Targeting High Ability Entrepreneurs Using Community Information: Mechanism Design In The Field*

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Abstract

Microentrepreneurs in low-income countries have high marginal returns to capital yet face significant credit constraints. Because returns are highly heterogeneous, the cost of assessing credit worthiness often makes lending to this sector unprofitable. In this paper, we show that (1) community knowledge can help overcome information asymmetries prevalent in poorly developed financial markets and that (2) appropriately designed elicitation mechanisms can extract truthful community reports. We asked entrepreneurs in Maharashtra, India to rank their peers on metrics of business profitability and growth potential. To assess the validity of their reports, we then randomly distributed cash grants of USD 100 to a third of these entrepreneurs. We find that information provided by community members is highly predictive of the marginal return to capital: entrepreneurs ranked in the top tercile earn returns of 23% per month, which is three times the average return within the sample. We horserace community rankings against a machine learning prediction built using entrepreneur characteristics and find that peer reports are predictive over and above observable traits. Yet community information is only useful if it is feasible to collect truthful statements. We experimentally vary the elicitation environment and demonstrate agency problems when community members have incentive to lie: accuracy of community reports decreases by a third when cash grants are at stake. But we also show that tools from mechanism design can be used to address these agency problems. Paying for truthfulness using a peer prediction rule fully corrects for strategic misreporting induced by the high-stakes environment. Public reporting and cross-reporting techniques motivated by implementation theory also significantly improve the accuracy of peer reports.

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1 Introduction

Not all entrepreneurs have what it takes to be successful. Both theory and empirical evidence on firm growth emphasize the wide distribution of talent among managers and business owners and, consequently, the significant heterogeneity in expected returns to capital (Lucas, 1978). But, to a lender in a peri-urban area of Maharashtra, India, identifying high-return entrepreneurs — applicants for whom larger or more flexible loans might be profitable for both borrower and creditor — is prohibitively difficult. Consider, for instance, an applicant who runs a convenience store next to her home. She cannot offer collateral and does not have verifiable income to establish a credit history. The shopkeeper is one of a dozen in her neighborhood and all sell a similar mix of grains, pulses, and packaged snacks. Though she might be motivated and highly skilled, the creditor has no means of assessing her potential.

The lender's information asymmetry problem is connected to an important puzzle in development economics. Experimental studies on the returns to capital for microentrepreneurs in low-income countries show that marginal returns to capital are far above standard microcredit interest rates (Fafchamps et al., 2014; McKenzie et al., 2008). Economic theory would suggest that reducing credit constraints should be an important factor in realizing enterprise growth, but the rapid spread of microcredit has had disappointingly low impact: a recent meta-analysis found that, on average, credit has only a modest effect on business profits (Banerjee et al., 2015).

Microcredit's low average impact is less puzzling when the distribution of entrepreneurial ability is taken into account. Numerous studies find that microentrepreneurs' marginal returns are high on average *and* highly heterogeneous. For instance, in a Sri Lanka capital grant experiment, quantile treatment effects imply a marginal return to capital of 0% - 45% per month (de Mel et al., 2008). Similarly, in our experiment, quantile treatment effects from cash grants vary from 0% to 28% per month (Appendix Figure 1). Theoretical and empirical studies of entrepreneurship in developing countries also emphasize that many self-employed individuals are business owners not because of personal ambition but because there are scarce opportunities for wage labor; these individuals are less likely to hire workers or otherwise expand their businesses (Schoar, 2010; De Mel et al., 2010). Yet lenders and policymakers tend to treat microentreprise owners as a relatively homogeneous group: credit and grant programs typically have minimal screening and little to no product differentiation by applicants' capital needs or business capabilities. As the shopkeeper example demonstrates, creditors may be impeded by their inability to differentiate between high and low return applicants. But little is known about how to overcome information asymmetries — or even what information is needed — to identify entrepreneurs with the most capacity to grow.

In the absence of formal financial information, there may be an alternative source of information that banks, governments, and non-profit institutions in developing countries could use to identify entrepreneurs with high potential: entrepreneurs' social network. Consider again the shopkeeper. Her customer and next-door neighbor might pay attention to how well she markets her business and whether the rice and lentils are clean and good quality. They may take note of her working hours and how fastidiously she keeps her shop floor clean. Several theoretical papers have studied the potential benefits of relying on community members to relax information asymmetries (e.g. Besley and Ghatak, 2005; Varian, 1990). In developing countries, neighbors are also more likely to be engaged in informal risk pooling agreements which require mutual knowledge of one another (Foster and Rosenzweig, 1996; Townsend, 1994).

On the other hand, relying on the community might lead the creditor astray. Among both academics and practitioners, there is a deep and divided literature on the predictors of selection into or success in entrepreneurship.[1] It not clear then that community members would themselves know which parameters to use to assess entrepreneurial ability. And even if community knowledge is accurate, the high stakes involved might introduce an incentive for community members to distort their predictions in favor of their friends and family.

In this paper, we show that community information — the knowledge that neighbors have about one another — is highly predictive of entrepreneurs' marginal returns to capital. Crucially, we also demonstrate that it is possible to collect credible reports even when the provision of important resources is at stake. Using methods from mechanism design theory, we develop a peer elicitation environment which aligns respondents' incentives with truthfulness. By experimentally varying these incentives, we also quantify the magnitude of misinformation when stakes are high and provide evidence on how community members trade off personal gain with benefits to family and peers.

We report on results from a field experiment that we conducted with 1,345 entrepreneurs from Amravati, a city in Maharashtra, India. We assigned respondents and their nearest neighbors to peer groups of 4-6 persons. After collecting detailed baseline data from all respondents, we asked entrepreneurs to rank their peer group members on predicted marginal returns to capital, profits, and other firm, owner, and household characteristics. Once the community reports were complete, we randomly assigned USD 100 grants to one third of entrepreneurs in order to induce growth and assess the accuracy of respondents' predictions. We evaluate the accuracy of community information by comparing how well the rankings predict individuals' true outcomes as reported at baseline or in subsequent follow-up surveys.

Our first main finding is that community members can identify high-return entrepreneurs with stunning accuracy. While the average marginal return to the grant was about 8% per month, our estimates of the marginal returns to capital of entreprenerus in the top third range from 17% to 27%. Had we distributed our grants using community reports instead of random assignment, we would have more than tripled the total return on our investment.

[1] For example, while some studies find a relationship between taste for risk and entrepreneurship, others do not (see Parker (2009) for a review).

To benchmark the value of community information, we compare its predictive accuracy against that of observable entrepreneur characteristics. We build a model to predict entrepreneurs' marginal return to capital using a causal forest (a machine learning technique developed by Wager and Athey (2017) to predict heterogeneous treatment effects). We find that entrepreneurs in the top third of the machine learning model's predicted marginal returns distribution have realized returns of 18% per month. But when we estimate marginal returns based on community information and control for the machine learning prediction, we still find that those in the top tercile of the community prediction distribution earn 17% higher monthly returns than those in the bottom tercile. This finding suggests that community information is valuable above and beyond information that can be captured by observables.

Our second main finding is that strategic misreporting is a first-order concern when eliciting community information. By random assignment, half of respondents were told that their reports would be used only for research purposes (the "*No Stakes*" treatment) and the other half were told that their reports would be used to allocate USD 100 grants to members of their community (the "*High Stakes*" treatment). The correlation between community reports and true outcomes is on average 24% to 35% lower when allocation of resources is at stake, which significantly lowers the value of peer elicitation. We also identify who benefits from misreporting and by how much: we quantify the extent to which participants favor themselves, their family members, and their close friends (as identified by other group members).

Given the importance of strategic misreporting, we explore whether it is feasible to realign incentives to report truthfully. Alongside the "*High Stakes*" treatment, we cross-randomized treatments which varied respondents' immediate benefit (or cost) for truthful responses. Respondents were assigned to report either in private or in a public setting, with their fellow neighbors observing their reports. Participants were also randomly assigned to receive monetary payments based on the truthfulness of their reports. Payments were calculated using the *Robust Bayesian Truth Serum* (RBTS), a peer prediction mechanism which determines participant scores as a function of the contemporaneous reports of other respondents. Importantly, RBTS does not utilize ex-post outcomes (which can be both manipulable and costly to verify) to determine payments.

Our third finding is that methods grounded in mechanism design theory can be used to design a peer-elicitation environment in which truthtelling is incentive compatible. Monetary payments and public reporting do little to improve the accuracy of self-reports. But payments double the predictive power of reports that entrepreneurs make about other group members. We show direct evidence that monetary payments reduce the likelihood that respondents favor their family members or their close friends. Thus monetary payments undo the strategic misreporting induced by shifting from a no-stakes to a high-stakes setting. Using the empirical distributions of reports, we also show that under RBTS truth-telling is empirically incentive-compatible. Finally, we find that public reporting doubles the predictive accuracy of reports about others when there are no stakes, but has no effect in a high-stakes setting. We shed light on this result by exploring two competing forces present in a public elicitation setting: family pressure and community policing.

Our findings contribute to several strands of literature. The idea that social networks — friends, family, colleagues — are a rich source of information has deep roots in development economics. Yet while there is an expansive literature on information diffusion within networks, there have been relatively few empirical studies on information extraction. Though there are many settings in which community knowledge could help private and public-sector actors overcome information asymmetries, the value of this information and the impact of incentives on disclosure are not well-understood. There are a few notable exceptions: first, in the community targeting literature, Alatas et al. (2012) investigate whether villagers in Indonesia can select the village's poorest residents to receive government transfers. They find that community targeting performs worse than a Proxy Means Test for assessing households' level of consumption but better at capturing a household's perception of their own poverty status. Basurto et al. (2017) find that village chiefs in rural Malawi are more likely to target fertilizer subsidies to households that self-report they would benefit from agricultural inputs than the standard PMT method. In the referrals literature, Beaman and Magruder (2012) find that high-quality workers in Kolkata, India can refer other high-quality laborers when incentivized to do so. In contrast, Bryan et al. (2015) find that borrowers in South Africa can do no better than the lending institution in selecting high-quality borrowers among their peers.[2] Lastly, Maitra et al. (2017) show that local traders in India can select microcredit borrowers for whom credit leads to larger increases in production and income than for borrowers selected by standard microcredit, with the caveat that both the selection method (traders' screening versus self-selection into microfinance) and the contract type (individual versus joint liability loans) covary.

Our findings provide new insight into the depth and breadth of social knowledge contained in rural and peri-urban networks. The Alatas et al. (2012) study demonstrates that community members have reliable information regarding observable characteristics (wealth) of persons across their social network. We show that community members can predict marginal returns to capital, a metric that is exceptionally difficult to estimate even using rich observables or expert opinions. This is evidence that community members have accurate knowledge of one another that is much deeper than what has been previously shown. The Beaman and Magruder (2012) and Bryan et al. (2015) studies evaluate the depth of knowledge that individuals have regarding one close peer or family member. We show that community members have more widespread knowledge of their peers: we find that participants can provide accurate reports on their neighbors, not only on persons with whom they have close social ties.

Community knowledge — even if accurate — is only useful for allocative decision-making if those eliciting the information can be confident that they will gather *truthful* reports. And when allocation of resources is at stake, there is reason to be concerned that community members will

[2] All referred applicants had to also meet the bank's eligibility criteria and, unlike in our setting, South Africa has a well-functioning credit bureau.

lie. Yet strategic misreporting is not typically addressed in the design of programs which rely on community information to make decisions. For example, community-driven development projects, which leverage community information or community action to make decisions regarding public goods expenditures, are rarely designed to account for strategic behavior (Mansuri and Rao, 2004; King, 2013).

We contribute to a young literature which addresses strategic misreporting in targeting programs. Alatas et al. (2013) examine whether elite capture poses a problem for community reporting, but elites are not the only group with the ability or incentive to lie. Though Alatas et al. (2013) conclude that elite capture is not a significant concern, we find that misreporting is common when community members are told that their reports will influence distribution of grants. Alatas et al. (2012) also elicit community reports in public in order to incentivize truthtelling. However, their experiment is not designed to evaluate the impact of public reporting on the accuracy of reports. Through random variation of the elicitation environment, we show that public reporting is not effective for realigning incentives with truthtelling when allocation of resources is at stake.

Finally, we contribute to an emerging literature which evaluates the implementability of methods developed within the theoretical mechanism design literature. The field of mechanism design offers tools which make truthtelling incentive compatible in theory, but the assumptions underlying these schemes may not hold in practice, and first order first order barriers to implementation are sometimes unmodeled. In this and a companion paper (Rigol and Roth, 2017), we adapt and deploy a peer prediction mechanism to incentivize truthful reporting. To the best of our knowledge, this is the first large-scale setting to use a peer prediction mechanism.

The rest of the paper proceeds as follows. Section 2 introduces the setting and study sample. Section 3 describes our conceptual approach to designing the elicitation environment, Section 4 describes our experimental setting and design, Section 5 describes the data, Section 6 is a brief discussion of the randomization, Section 7 discusses our results, and Section 8 concludes.

2 Study Sample and Context

Our study takes place in Amravati, a city of about 550,000 persons in the state of Maharashtra, India. Households in our sample come from nine neighborhoods along the perimeter of Amravati; we selected these neighborhoods because they have a relatively high proportion of microentrepreneurs.[3] These are densely packed peri-urban slums; in each of these neighborhoods, there are roughly 900 household dwellings in a 500 by 700 square ft. area. In September 2015, we conducted a complete door-to-door census of these neighborhoods, which encompassed 5,573 households. Based on households' responses to the census, we determined their eligibility for the study.

[3]Our selection of neighborhoods was based on advice from local officials in the District Collector's Office. The nine neighborhoods are: Belpura, Vilash Nagar, Mahajan Pura, Akoli, New Saturna, Old Saturna, Wadali, and Pathan Chawk.

In line with selection criteria of other recent "cash-drop" experiments (see e.g. de Mel et al. (2008)), all households in our sample have at least one enterprise with (i) USD 1,000 or less in total working and durable capital and (ii) no paid, permanent employees.[4] Almost 30% of households in these neighborhoods owned at least one business and were eligible (1,576 households). Entrepreneurs in 1,345 of these households agreed to participate in our study so our sample population is reasonably representative of the universe of eligible enterprises in Amravati.

Characteristics of Microenterprise Owners. The modal entrepreneur in our sample is 40 years old and has roughly 8 years of formal education. Approximately 60% are male and almost all are married. Most entrepreneurs operate their business close to home, but they operate across a wide range of activities. 30% of sample entrepreneurs work in manufacturing, typically as a tailor or stitcher. Another 30% work in services, mainly in food preparation and hair salons. Within the retail sector (30% of the sample), the most common business type is a grocery shop. Outside of these three sectors, entrepreneurs are spread evenly across construction and livestock rearing. On average, sample entrepreneurs earn profits of Rs. 4500 per month (USD 2.5 per day), which accounts for roughly half of their household income. Entrepreneurs also face a significant amount of risk: between the baseline and one year follow-up survey, about 10% of businesses in control group households were shut down. In over a third of these cases, the reason given for enterprise closure was illness of the business owner. Correspondingly, medical expenses make up a large fraction of household spending: on average, respondents report spending nearly 30% of their monthly earnings on health-related expenditures. Perhaps as a means of insuring against risk, households diversify across types of income-generating activities: in half of sample households, there is at least one fixed salary or daily wage worker and one fifth of households own more than one business.

Characteristics of Microentrepreneurs' Peer Networks. In order to elicit entrepreneurs' knowledge of one another, we assigned study participants to peer groups of roughly five persons based on geographical proximity. Peer groups are the unit of information collection: entrepreneurs are asked to report on only themselves and their other group members, not on the entire community. Importantly, we find that peers know their group members well. On average, peers reported that they visited another group member on 22 occasions in the previous 30 days. Respondents were not able to identify another group member in less than 1% of cases. Two-thirds of respondents identify at least one other group member as a family member or close friend. In 70% of groups, at least two people operate a business in the same (broad) industry category. Entrepreneurs also actively maintain strong social ties within their group: over 50% of respondents reported that they regularly discuss private family and business matters with at least one other group member. And, entrepreneurs have at least some knowledge of *every* group member: 87% of respondents correctly identified for all other group members whether that person owned a motorcycle (half of respondents are motorcycle owners) and 80% correctly identified who among their peers had young

[4] Following de Mel et al. (2008)'s selection criteria, we excluded farmers and self-employed service persons, such as domestic helpers and teachers. If there were multiple business owners in the household, we required that the household have at most USD 2000 in combined business capital.

children living in their home.

3 Mechanisms to Incentivize Truthful Revelation

Agents' knowledge is only valuable for decision-making if it is incentive compatible for agents to report truthfully. When the allocation of resources is at stake, strategic misreporting may be a first-order concern. Mechanism design offers an array of tools which make truthtelling incentive compatible in theory, and one of our goals is to understand which of these tools work to realign incentives in practice. In this section, we describe our conceptual approach for designing and evaluating the peer ranking elicitation environment.

Public Reporting. Fear of public reprisal is a powerful deterrent to socially undesirable behavior. This insight has been applied to incentivize costly actions across a number of settings (notable examples include using public notification of individuals' voting record (Gerber et al., 2008) or electricity usage (Allcott and Rogers, 2014) to encourage behavioral change). Intuitively, conducting peer elicitation in public may reduce strategic misreporting because participants care about their reputation for honesty. At the same time, publicity may exacerbate pressure to rank one's family, friends, and influential members of the community more highly. Because manipulating the observability of reports is cheap and straightforward to implement, resolving this ambiguity in practice may yield substantial benefit in disciplining community reports. To assess the relative strength of these competing effects, we randomly vary whether the peer elicitation exercise takes place in a private or public setting.

Paying for Truthfulness. Explicit monetary incentives for accuracy offer a promising deterrent to misreporting. One straightforward way to implement monetary incentives would be to pay respondents based on the closeness of their reports with an ex-post measure of accuracy. But often ex-post measures of accuracy are unavailable, or prohibitively costly to collect (such as in the case of estimating marginal returns to capital, which can never be confirmed for an individual entrepreneur). Even when signals of ex-post accuracy exist, using them necessitates a time-lag between the moment of elicitation and subsequent payment for reports. In settings with weak institutions, where trust in outsiders is minimal, respondents may demand to be paid contemporaneously with their reports.

To circumvent these concerns we evaluate monetary incentives delivered via a peer prediction scheme, which rewards respondents based exclusively on their own reports and the contemporaneous reports of their peers. The particular payment rule we use is the *Robust Bayesian Truth Serum,* described in detail in the next section.

Zero-sum Elicitation. During our peer elicitation exercise, entrepreneurs rank one another on metrics of business growth and profitability. Respondents are assigned to groups based on geographical proximity and each person ranks herself and the other members of her peer group (see Section 4.1 for details on our elicitation intervention). Within each $4-6$ person group of entrepreneurs, we evaluate two forms of community rankings: rankings relative to the particular members of the group, and reports placing each entrepreneur in quintiles relative to the community at large. The former has a zero-sum nature, in which promoting someone's position necessitates diminishing another's, and may therefore be more effective at inducing truthful reports (a respondent cannot merely place everyone in the highest position). However, if group members have correlated attributes, then these rankings may be less informative than rankings that assess each entrepreneur relative to the broader community. By examining both mechanisms we investigate which of these concerns dominates in practice.

Cross-Reporting. In the spirit of cross-reporting techniques which play a prominent role in mechanism design and implementation theory (see Maskin (1999)), we ask respondents to identify each group member's closest peer in the group, with the intention of exploring whether group members identified as close peers distort their reports to favor one another. We also ask respondents to identify who in their peer group has the most accurate information regarding each ranking metric.

3.1 The Robust Bayesian Truth Serum

Peer prediction mechanisms, including Witkowski and Parkes' (2012) *Robust Bayesian Truth Serum* (RBTS), incentivize truthful reporting of beliefs without reference to ex-post measures of accuracy.[5] Instead, these mechanisms determine payments as a function of the contemporaneous reports of several respondents.

We implemented a variant of RBTS, which requires elicitation of agents' first order beliefs (the ranking that an agent assigns to each of his peers) and second order beliefs (the probability distribution the agent assigns to each possible ranking his peers may give one another). RBTS rewards an agent's second order beliefs based on their proximity to the empirical distribution of stated first order beliefs. First order beliefs are evaluated based on how "surprisingly common" they are relative to other agents' stated second order beliefs. That is, agents are compensated for first order beliefs that have empirical frequencies higher than predicted by other agents' stated second order beliefs. Witkowski and Parkes (2012) show that under the assumption of a common and admissible prior, truthful reporting is a Bayesian Nash Equilibrium. See Appendix for details on RBTS as well as an intuition for its incentive compatibility.

Implementation of the Robust Bayesian Truth Serum. Peer prediction methods are attractive because they make truthtelling incentive compatible and circumvent the need for ex-post verification of outcomes. The principal challenge to implementation of RBTS is its complexity. It is infeasible to describe RBTS (and its incentive comparability) to respondents in our setting who are largely innumerate. This is a challenge shared by many mechanisms implemented in practice

[5] See Prelec (2004) for a seminal contribution to this literature.

(most notably, two-sided matching algorithms, versions of which are commonly used in education and entry-level labor markets). A common tactic, which we take in this study, is simply to assert to respondents that they can do no better than to tell the truth.[6]

In Rigol and Roth (2017) we provide evidence that this is a reasonable tactic. We report on an experiment among a sample drawn from a very similar population to that of our current study, in which compare the accuracy of peer reports when paying agents for truthfulness using a straightforward payment rule based on ex-post accuracy and when paying agents using peer prediction mechanisms. Surveyors carefully and completely explained the ex-post payment rule to respondents. For the peer prediction method, surveyors simply asserted to respondents that they would maximize their incentive payments by telling the truth. We elicit information regarding borrower reliability and entrepreneurial ability and we find that the additional accuracy induced by the simple ex-post incentive is statistically and economically indistinguishable from that induced by the peer prediction method. Both payment methods led to significantly more accurate reports than elicitation without monetary payments.

That respondents believe our assertion that they should tell the truth is reassuring, but it may nevertheless be desirable to verify that RBTS's theoretical properties hold in practice. While RBTS is incentive compatible in theory, it may be that given the empirical distribution of beliefs, respondents can indeed increase their payoff with deceptive reports. In Rigol and Roth (2017), we verify that the payment method is incentive compatible in practice. To do so, we estimate the higher order beliefs of respondents in the sample and used these beliefs to determine respondents' subjective expected payments from RBTS. Details of this exercise are replicated in the Appendix of this paper.

That RBTS is incentive compatible in practice is encouraging for several reasons. First, we do not want to deceive respondents when we tell them they can do no better than to tell the truth. Second, that assertion will only be reinforced with repeated use — because RBTS is incentive compatible, agents will receive experiential feedback over time that truth-telling is the highest paying strategy.

[6]The National Resident Matching Program, which matches new physicians to residency spots in the United States, has a video explanation of the steps involved in the mechanism and advises physicians that "To make the matching algorithm work best for you, create your rank order list in order of your true preferences, not how you think you will match." The video explanation and accompanying instructions do not attempt to explain why truthtelling is a dominant strategy. The website is: http://staging-nrmp.kinsta.com/matching-algorithm. For the Boston Public Schools matching system, parents are told "List a number of choices (BPS recommends at least five) and order them in the true order of preference to increase the chances of getting the school that you want."

4 Experimental Design

4.1 Design of the Peer Elicitation Exercise

Recruitment. In October 2015, we visited the 1,576 eligible households and invited them to participate in our study. At the time of recruitment, households were told that a research team was conducting a project to study entrepreneurship and business growth.[7] In December 2015 - April 2016, we conducted baseline surveys of the 1,345 sample households. Separately, we also assigned respondents to groups of five based on geographic proximity, for a total of 274 groups across all neighborhoods.[8] Once all baseline surveys in a given neighborhood were complete, surveyors returned to sample households to invite respondents to a meeting at the local town hall. Respondents were not given any information regarding the content of the meeting, or that they would be placed into groups with their peers. They were told, though, that to thank them for their participation in the study the research team would conduct a public lottery where some participants would be awarded a USD 100 grant.

Explanation of the Exercise to Respondents. Upon arrival at the town hall, respondents were each given 20 lottery tickets. They were told that, at the end of the activity, all people present would put their lottery tickets into an urn and grant winners would be selected by drawing lottery tickets. Participants were then separated and individually paired with a surveyor. Surveyors explained to participants that they would be asked to provide information about themselves and their neighbors. In order to ensure that participants were introduced to the elicitation exercise in a clear and consistent way, we created animated videos to introduce respondents to the concepts covered in the rankings questions and to guide them through the activity. When explaining the concept of marginal returns, we used examples to emphasize to respondents that an entrepreneur's projected marginal returns corresponds to their expected *change* in profits in response to the grant, and not their *level* of profits. After watching the videos, participants completed a series of quizzes to test their understanding of the activity and concepts. The introduction and subsequent ranking activity took place behind a privacy screen. The screen was there to ensure that coordination of responses would not be possible (as explained below, respondents in the public reporting treatment were later randomly assigned to complete a subset of their rankings among their peers). Surveyors also told participants which of their neighbors they would be ranking and gave them four to six placards, each with the name of a group member.

Questions Asked in the Ranking Exercise. First, we asked participants to rank themselves and their peers on predicted marginal returns to a USD 100 grant. We then asked respondents to rank themselves and their peers across several additional entrepreneur characteristics: educational

[7]No information regarding the community information nature of the project was disclosed to respondents at this time.

[8]We organized respondents into groups that would minimize the geographic distance between study households. The total number of respondents per neighborhood was not always a multiple of 5, so some groups had 4 or 6 clients.

attainment; average number of hours spent at work per week; performance in a digit span memory test; and, projected monthly profits 6 months post-grant disbursal, if the business owner were to receive a USD 100 grant. We also asked about a number of household-level characteristics: average monthly income over the past year, total value of assets; total medical expenses in the past 6 months; and, loan repayment trouble over the previous year. Finally, we asked respondents to report on whom they thought was most deserving of the grant. We deliberately did not provide any additional description or criteria to this question and instead emphasized that respondents should select based on criteria that they thought were important for this metric. Note that to minimize respondent fatigue peer groups completed the ranking exercise only for a randomly assigned subset of these metrics (but all respondents completed the marginal returns ranking). For details on the assignment of ranking questions by treatment group, see the Appendix. And, participants completed both relative and quintile rankings for questions on marginal returns, business profits, and household income and assets, but only relative rankings for the remaining questions (this was also done to reduce fatigue). Finally, respondents were asked to cross-report on their peers: they identified one another's closest peer in the group and, for each ranking question, respondents identified the group member they believed would have the information required to answer the question most accurately.

4.2 Description of Treatments

Respondents were cross-randomized (at the group level) to give their ranking reports under the following three treatment conditions, for a total of eight treatment cells: *No Stakes* vs. *High Stakes* (S_0 vs. S_1), *Private* vs. *Public* (P_0 vs. P_1), and *No Payments* vs. *Payments* (T_0 vs. T_1). We also randomly selected one-third of our sample to receive USD 100 grants. Grant randomization occurred at the individual level and was stratified by group. See Figure 1 for the randomization design.

High Stakes Environment (S_0 vs. S_1). For this treatment, participants were told that their responses in the ranking exercise would help determine the winner of the lottery that would occur at the completion of the activity. All participants across treatment groups were given twenty lottery tickets upon arrival at the town hall. Respondents in the high stakes treatment were told that, for each question, the peer ranked highest (on average) by group members would receive extra lottery tickets, and so would have a better chance of winning.[9] In order to ensure that we would have sufficient power to test predictions from the marginal returns rankings, all participants completed this ranking in a no-stakes setting (the marginal return ranking occurred prior to other rankings and to any mention of the high stakes treatment).[10]

[9] We did not tell participants how many extra lottery tickets would be awarded to the person ranked highest; in order to keep the randomization as close to uniform as possible, we awarded only one extra lottery ticket per ranking. Respondents were in a high stakes setting for four ranking questions, and so a person in this treatment group could win at most four extra lottery tickets. Participants completed all rounds of ranking questions prior to the disbursal of the extra lottery tickets.

[10] Measures of profits among microentrepreneurs in settings like this one are notoriously noisy (see, for instance,

Public Reporting (P_0 vs. P_1). Participants in both the Public and Private Reporting groups responded to each ranking question behind a privacy screen, in the presence of only their surveyor. But in the Public treatment, after completing each ranking question, peers came to the center of the room and sat in a circle with their response clipboard in front of them. Participants were told that they were doing this so that the survey coordinator could record their responses, but the true purpose was to give them the opportunity to observe one another's rankings.[11] Crucially, participants understood ahead of doing the ranking exercise that their peers would see their responses. This was described to them in their introductory animation video and, to ensure that participants understood the set-up, groups performed several practice rounds. In the privacy treatment, respondents completed all ranking questions before interacting with peers and, even after the activity was completed, group members did not see each other's individual responses.

Payments for Truthfulness (T_0 vs. T_1). The introductory video for participants in the monetary incentives group explained that respondents would be paid per ranking question, based on the truthfulness of their responses. As explained in Section 3, we did not explain the details of the RBTS scoring rule to participants. Instead, participants were told that people who reported what they truly believed would receive an extra Rs. 100 on average (which is equivalent to 2/3 of the average daily wage). Payments were calibrated using the empirical distribution of beliefs from Rigol and Roth (2017) to maximize strength of the incentive to tell the truth while adhering to a project budget constraint. Since RBTS incentive payments require respondents to report second-order beliefs, the introductory video also explained this concept to participants. Respondents expressed their beliefs about the distribution of first-order beliefs in the community by allocating coins to quintile bins. There were 20 coins to distribute, representing 20 hypothetical community members. For example: if $respondent_i$ believed that 8 out of 20 community members would rank $peer_j$ in the top quintile for household assets, she would place 8 coins into the top quintile bin, and so on. Groups that were not in the monetary payments treatment were not asked to report second order beliefs and were not paid for each ranking report; instead, they were given a lump sum payment to compensate them for their time.

Enterprise Grant. Upon completion of the peer elicitation exercise, group members came to the center of the room and placed their lottery tickets into an urn. One respondent was blindfolded and then drew tickets to award USD 100 grants to one or two group members (the number of winners per peer group was determined by random assignment). When surveyors earlier visited respondents to tell them the date of their town-hall meeting, they also gave respondents a business plan worksheet. Surveyors reminded respondents that grants were meant to be used for business purposes (respondents had been told about the grant lottery at the time of recruitment) and instructed them to describe in the worksheet what they would do with the grant money, if they

De Mel et al. (2009)). Due to budget constraints, our experiment is just powered to detect how well marginal returns rankings predict realized marginal returns when accuracy of reports is not confounded by the incentive to lie present in a high-stakes setting.

[11] Surveyors report that respondents did in fact almost always look at their peers' rankings.

won. Participants then brought their completed worksheets to the town-hall meeting and winners were again reminded of the grant purpose (but we did not enforce that winners put their winnings towards their business). Grant money was distributed to winners via bank transfer.

4.3 Identification Strategy

Random assignment allows us to use the difference between post-period profits of grant winners and post-period profits of grant losers as an estimate of the true average marginal return to the grant. We therefore identify the informational value of community members' reports by testing the predictive power of respondents' marginal return rankings against true marginal returns.

Next, we assess whether community information extraction is susceptible to strategic misreporting when allocation of resources is on the line. We measure accuracy by comparing peer reports to self-reported values that participants provided at the time of the baseline survey.[12] By comparing accuracy of peer reports for participants in the *No Stakes* and *High Stakes* groups (S_0 vs. S_1), we identify the effect on strategic misreporting of shifting the elicitation environment to one in which reports can have consequences for allocation of grants.

Finally, we measure the efficacy of mechanisms to realign incentives for truthful reporting: a comparison of the accuracy of peer reports in the *Private* versus *Public* treatments (P_0 vs. P_1), or in the *No Payments* versus *Payments for Truthfulness* treatments (T_0 vs. T_1), identifies the effect each of these mechanisms has on respondents' truthfulness. Because we cross-randomize treatments, we can separately identify the strength of these mechanisms in the benchmark, *No Stakes* setting, and in the *High Stakes* setting, where respondents have a counteracting incentive to lie.

5 Data

Data for analysis come from respondents' peer rankings during the elicitation exercise and from respondent surveys. Baseline surveys were conducted between December 2015 and April 2016, and three follow-up surveys were conducted between May 2016 and March 2017. For all survey rounds, each business owner in the household completed a detailed business module about her own enterprise and answered questions about her well-being. The business module included questions on enterprise costs; revenues; profits; seasonality; inventories; labor inputs; assets; and business history. At baseline, entrepreneurs also completed a digit span test and a set of psychometric questions.[13]

[12] In order to ensure that we would have sufficient power to test predictions from the marginal returns rankings, all participants completed this ranking in a no-stakes setting.

[13] Respondents answered each psychometric question in the module by providing their agreement with the given statement, where agreement was rated on a scale of one to five, with five indicating strong agreement and one indicating strong disagreement. A detailed description of the psychometric assessment module is in the Appendix. The psychometric module questions are organized according to categories developed by industrial psychologists: polychronicity measures the willingness to juggle multiple tasks at the same time (Bluedorn et al. 1999); impulsiveness is a measure of the speed at which a person makes decisions and savings attitudes (Barratt Impulsiveness Scale); tenacity measures a person's ability to overcome difficult circumstances (Baum and Locke 2004); achievement is a

In each survey round, the study respondent also provided information regarding her household's finances. The household-level module included questions on income, health expenditures, credit history and loan repayment issues, and assets. For the asset section, the respondent indicated whether the household owned a particular type of asset and its current resale value. Surveyors were trained to visually verify that the household owned each of the assets about which they reported. At baseline, the respondent also completed a full household roster with education and labor history for each household member. For a complete timeline of the project and data, please see Figure 2.

6 Randomization Checks

In Appendix Table 1, we present the randomization check of baseline characteristics by treatment. To check for balance we estimate the model

$$Characteristic_{ij} = \tau_0 + \tau_1 Treatment_j + \epsilon_{ij}$$

where i indexes the individual and j indexes the group. $Treatment_j$ is a dummy for whether the group was assigned to the *No Stakes*" vs. *High Stakes* treatment (columns 1 and 2), the *No Payments* vs. *Payments* treatment (columns 3 and 4), and the *Private* vs. *Public* treatment (columns 5 and 6).

The odd columns 1-7 show the average of each characteristic for the control group in each block. So column 1 shows the means of characteristics for groups that were assigned to *No Stakes*. The even columns show τ_1 for each treatment (the difference between treatment and control characteristics) . The characteristics in Panel A are about the entrepreneur who was ranked during the ranking exercise and in Panel B are about her primary business. In Panel C, we show household level baseline measures. The variables "Value of Business Assets" and "Avg. Monthly Profits" are shown as aggregates over all household businesses. So if the the ranked entrepreneur is the only business owner in the household, these reflect the values of only her businesses.

The majority of entrepreneur and household characteristics are balanced across treatment groups. Entrepreneurs assigned to *Payments* report lower household monthly income and entrepreneurs assigned to *Public* report lower value of household assets. At the bottom of the table, we presents the p-value from an F-test of whether the treatment group coefficients are jointly equal to zero. All of the joint tests of equality are rejected, suggesting that the randomization was effectively implemented.

We do not see significant differences between lottery winners and losers on income, profits,

measure of satisfaction in accomplishing a task well (McClelland 1985); and locus of control measures a person's willingness to put themselves in situations outside of their control (Rotter 1996).

and assets, which is important since for the $High\,Stakes$ group the grant was partly allocated using rankings for those three variables. Nonetheless, as we discuss below, to account for this feature of the design, we weigh all regressions that exploit variation between lottery winners and losers by the inverse number of lottery tickets that each person received. We also present the results of a joint test of statistical significance and cannot reject that all groups are drawn from the same population.

7 Results

7.1 Entrepreneurs' Average Marginal Returns to Capital

We begin by estimating average marginal returns to the grant. Following de Mel et al. (2008), our primary specification is

$$Y_{ijt} = \alpha_0 + \alpha_1 Winner_{it} + \gamma_i + \sum_{t=1}^{3} \delta_t + \theta_m + \tau_s + \epsilon_{ijt} \quad (1)$$

where Y_{ijt} measures either total household business profits or household income of person i in survey round t.[14] We measure business profits by asking entrepreneurs the following question: "Now that you have thought through your sales and your expenses from the past 30 days, I would like you to think about the profits of your business. By business profits, I mean taking the total income received from sales and subtracting all the cost of producing the items (raw material, wages to employees, fixed costs, etc). Can you tell me your business profits in the past 30 days?"[15] Household income is also measured using a single question: "What is your total household income over the past 30 days from all income generating activities?" Like de Mel et al. (2008), we trim the outliers of the household income and total profits distributions (levels) by trimming the top 0.5% of both the absolute and percentage changes in profits measured from one period to the next. We also estimate regression specification 1 for $log(Y_{ijt} + 1)$ of income and profits, using the untrimmed distributions.[16]

In the main specification, we utilize three rounds of follow-up surveys, so t ranges from 0 (baseline) to 3. [17] $Winner_{it}$ is an indicator for whether person i won a grant at or before survey

[14]Bernhardt et al. (2017) reanalyze data from several cash-drop experiments with microentrepreneurs and find that measures of returns to capital differ substantially when analyzed at the household versus enterprise level. We therefore aggregate profits of all household businesses, for all specifications.

[15](De Mel et al., 2009) find that asking one aggregate summary measure (rather than for the components) reduces noise in the estimation of profits.

[16]The results remain nearly identical whether we log-transform the trimmed or untrimmed income and profits distributions.

[17]The month before we began our fourth (last) round of data collection, the Indian government removed from circulation two currency notes - the Rs. 1000 and Rs. 500 bills - overnight. The result was a tremendous shock to the formal and informal economy. As Banerjee and Kala (2017) report, traders experienced a 20% drop in sales due to demonetization. In fact, in the last round of surveying, over 50% of our sample reported being adversely affected

round t. Note that $Winner_{it}$ is 0 at period $t = 0$ for all persons i. We also include the following fixed effects: person (γ_i), survey round (δ_t), survey month (θ_m), and surveyor (τ_s). Standard errors are clustered at the group level. In the *No Stakes* treatment group, assignment of grant winners was uniformly random: all participants received twenty lottery tickets and each group member was equally likely to have their tickets drawn from the urn. But, as described in Section 4.2, respondents in the *High Stakes* group were eligible to receive up to four extra lottery tickets, based on whether their peers ranked them highest for the treatment questions.[18] To account for this, we weigh all regressions by the inverse number of lottery tickets (inverse propensity score) that each person received (Rosenbaum, 1987). In Appendix Figure 2, we plot the distribution of lottery tickets in the sample.

The coefficient of interest in regression specification 1 is α_1, which measures average marginal return to the grant in the sample. Table 1 presents results from estimating Equation 1. We find that the grant had a large positive effect on household income and total household profits. On average, households that win grants report an extra Rs. 422.3 in household income and an extra Rs. 507.7 in total household profits over households that were not awarded grants. These gains in household income and profits represent very high marginal returns to the grant: on average, households earn returns of $7.6\% - 8.6\%$ per month. These estimates are in line with average returns estimated from cash grants in other settings: de Mel et al. (2008) find that profits increase by 7.6% per month in response to a USD 100 grant and Fafchamps et al. (2014) show that profits increase by 9.7% per month in response to a USD 120 grant.

We plot the quantile treatment effects in Appendix Figure 1 and find that while the average marginal returns to the grant are very high, returns vary between 0% and 28% per month. Replicating this exercise using data from de Mel et al. (2008) and Fafchamps et al. (2014) yields a similar result: in de Mel et al. (2008) returns range between 0% and 45% and in Fafchamps et al. (2014) they vary from 0% to 30%. The quantile treatment effects suggest that significant heterogeneity in returns to capital of microentrepreneurs is not uncommon.[19] We will dedicate the remainder of the section to evidence that communities can predict that heterogeneity.

7.2 Can Communities Predict Entrepreneurs' Marginal Returns To Capital?

Entrepreneurs have close social ties with peers in their neighborhood. Over half of respondents regularly discuss private family and business matters with at least one other group member and on average group members visit one another 22 times per month. Community members have

by demonetization. For this reason, we exclude the post-demonetization wave of data from the analysis presented in the main tables. We replicate all the main tables with all five data rounds in Appendix Tables 15-18. The results are qualitatively identical but marginally noisier in a few specifications.

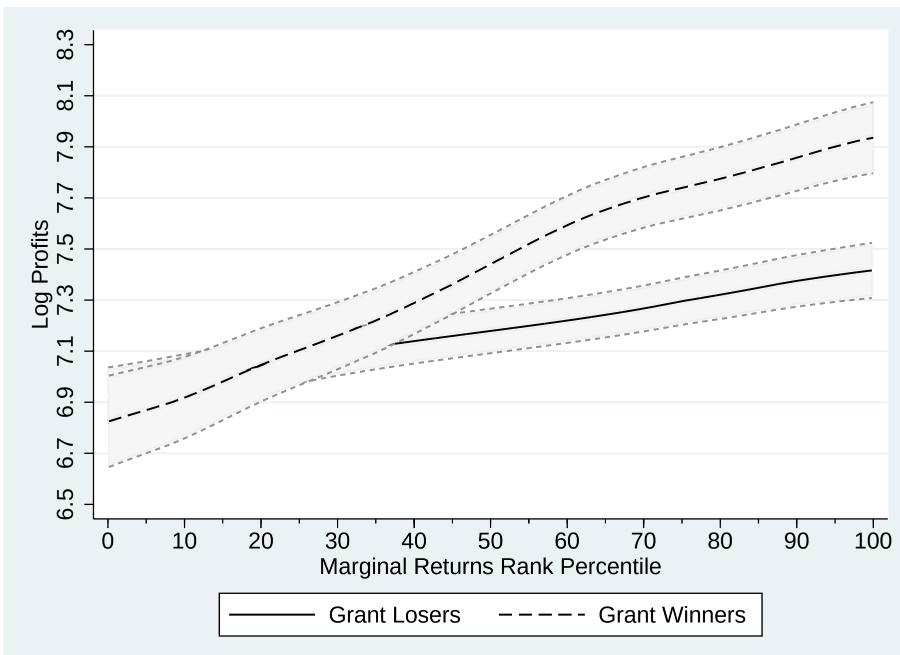
[18] For a more detailed description of the *High Stakes* treatment, please refer to Section 4.2.

[19] While quantile regressions are provide suggestive evidence that there they may be heterogeneity in returns in the sample, they cannot be interpreted causally without imposing strong assumptions. See Abadie et al. (2002) for a detailed discussion on the interpretation of quantile regressions.

close social ties and, as we will show in the following section, have accurate knowledge of one another's business and household finances. These observations lead us to our first main empirical question: Do peers have the depth of knowledge required to predict one another's entrepreneurial potential?

The striking accuracy of community members' predictions is illustrated in Figure 1. The x-axis of this figure is percentile of the average rank that respondents assigned to their peers when asked "Could you please rank your group members in order of who you think had the highest marginal returns to the Rs. 6000 grant? In other words, who would gain the most in monthly profits, or who would grow their business the most, from receiving a Rs. 6000 grant.".[20][21] We plot two kernel-weighted local polynomial regressions (degree 1) of log profits at followup for the treatment (grant winners) and control (grant losers) groups on rank percentile.

Figure 1: Marginal Returns to the Grant by Percentile of the Community Ranks Distribution



Notes: This figure plots two kernel-weighted local polynomial regressions of log profits on the marginal returns rank percentile, estimated separately for respondents who won and respondents who did not win grants. Log profits is the log value of average profits in the post grant disbursal periods. The marginal returns rank percentile is the percentile of the average rank assigned to person i by all of her peers in her group. 90% confidence bands are shown.

The vertical distance between the two regression lines in Figure 1 represents marginal returns

[20]To calculate the average marginal returns rank we take the simple mean of every individual rank given about person i by all of her peers in the group (this quantity is formally defined Specification 2). The value on the x-axis is the percentile of the average rank.

[21]All analysis in Section 7.2 uses the quintile community rankings. Results are very similar if we instead use the zero-sum ranks. These results can be found in Appendix Tables 19-22.

to the grant for a person at that rank percentile. As discussed in Section 7.1, there is significant heterogeneity in returns to the grant; the quantile treatment effects of the grant range from 0% to 28% returns per month. Impressively, community members are accurately able to identify the ordering of their peers' heterogeneous returns ex-ante. Figure 1 shows that an entrepreneurs' marginal returns rank is strongly correlated with her realized marginal profits: profits in the treatment and control groups below the $35th$ percentile of the marginal returns distribution are indistinguishable. But above the $35th$ percentile, distance between treatment and control profits increases with marginal returns rank – this increasing distance is a measure of respondents' prediction accuracy.

Importantly, community members' predictions map to economically significant differences in returns. The entrepreneur at the bottom of the marginal returns rank distribution has zero returns to the grant; conversely, the entrepreneur at the $99th$ percentile of peer ranks earns an extra 45% in profits per month. This increase in profits translates to an 18% monthly return to the grant for the entrepreneur at the $99th$ percentile of the ranks distribution. To gain intuition for the relative size of entrepreneurs' returns, note that in 2016 the average yearly APR for microcredit in India was 24%.[22] Had we instead asked our grant winners to repay their grants according to a 24% interest rate, the principal and interest payment would amount to Rs. 570 per month. [23] A simple back-of-the-envelope calculation shows that all entrepreneurs above the $58th$ percentile of the ranks distribution would have been able to earn a net positive return on their investments.

We also present a difference-in-differences estimate of community members' prediction accuracy, extending the model from Specification 1 to incorporate peer ranks:

$$Y_{ijt} = \alpha_0 + \alpha_1 Winner_{it} + \alpha_2 Winner_{it} \times \overline{Rank}_{ij} + \gamma_i + \sum_{t=1}^{3} \delta_t + \theta_m + \tau_s + \epsilon_{ijt}. \tag{2}$$

$Rank_{ikj}$ is the rank that person k in group j assigns to person i (also in group j). $\overline{Rank}_{ij} = \sum_{k=1}^{n} \frac{1}{n} * Rank_{ikj}$, where n is the total number of group members in group j. So $\overline{Rank}_{ij}$ is the average marginal returns rank assigned to person i by the members of group j. The coefficient α_2 identifies the average additional marginal return to capital associated with a one unit increase in marginal return rank. The differences-in-differences specification estimates α_2 for a model in which marginal return increases linearly in the value of average rank. We also estimate a non-linear model in which the ranks distribution is divided into terciles and rank tercile is interacted (as above) with $Winner_{it}$.

Table 2 shows results of the difference-in-differences estimation of respondents' ability to predict true marginal returns to capital. Outcome variables are household income and total household profits, in both levels and logs. For the linear-in-rank version of the estimation (*Panel A*), the

[22]This estimate comes from the Bharat Microfinance Report (2016).

[23]There are many possible reasons why a loan might have induced different selection and investment patterns, but it is useful to benchmark entrepreneurs' returns against market rates. See (Fiala, 2013) for an experiment which randomly allocates loans or grants to entrepreneurs.

coefficient α_2 is large and positive for all four outcome variables. Coefficients for income and log income are both significant at the 5% level; for profits, levels are noisy and not significant but the coefficient for log profits is significant at the 1% level. An extra rank is associated with increases in profits and income of between Rs. 283.2 and Rs. 848.1 per month. These amounts translate to increases in monthly returns to the grant of between 4.7% and 14%. Average marginal return to capital in the sample is about 7.1% per month and an entrepreneur ranked one standard deviation above the mean has monthly marginal return to capital of 16.4% (the mean and standard deviation of the marginal return rank are 3.46 and 0.66, respectively). For an entrepreneur ranked two standard deviations above the mean, monthly returns to capital are 25.7%.

Panel B in Table 2 shows results from the non-linear, tercile rank version of the difference-in-differences estimation. Consistent with results from the local polynomial regressions in Figure 1, we cannot reject that the entrepreneurs in the bottom tercile of the marginal returns rank distribution have zero returns to the grant. For three of the four outcome variables (all but level household profits), the coefficient on $Winner_{it}$ actually implies a negative return to the grant. Also consistent with Figure 1, the coefficients on log income and log profits for the middle tercile are positive, but not significant, and the level effects are almost precisely zero.[24] The strongest treatment effects of the grant are concentrated among entrepreneurs in the top tercile of the average rank distribution: depending on whether we use household income or profits , the coefficients on $Winner_{it} \times Top\bar{Tercile}_{ij}$ imply that monthly returns to the grant for the top tercile range from 16.6% to 26.7%. We can statistically reject that the grant has the same effect for entrepreneurs in the middle and top tercile.

Regression specification 2 identifies the treatment effect of the grant off of the within-person differences in profits and income in the pre- and post- grant disbursal periods for grant winners and losers. As a robustness check, we also present results using an alternative specification in which the treatment effects are identified by comparing the cross-sectional differences between treatment and control groups in the post-grant disbursal periods, controlling for the baseline value of the outcome characteristic. Our specification is:

$$Y_{ijt} = \beta_0 + \beta_1 Winner_{ijc} + \beta_2 Winner_{ijc} \times \overline{Rank}_{ijc} + \beta_3 \bar{Y}_{ijPRE} + \sigma_c + \theta_m + \tau_s + \epsilon_{ijt}, \tag{3}$$

where Y_{ijt} are post-treatment outcomes (so t ranges from 1 to 3 rather than 0 to 3 as in Specification 2) and $\bar{Y}_{ijPRE}$ is the pre-treatment (time 0) value of the outcomes. σ_c is a neighborhood cluster fixed effect. We present the analogue of Table 1 using Specification 3 in Appendix Table 2 and the analogue of Table 2 in Appendix Table 3. Results in the robustness specification are qualitatively very similar in terms of the size and significance of coefficients.

Across all specifications, we find that top-ranked entrepreneurs earn very high returns on their

[24]Mechanically, since the middle tercile is fixed, the difference between the level and log results occurs because there are some extreme right-tail observations in the distribution of income and profits for the middle tercile ranks. The weight of these outliers in the regression is diminished when the distributions are log-transformed.

grants, while bottom-ranked entrepreneurs see no (or negative) returns. In the next section, we explore whether differences in entrepreneurs' investment decisions can help explain these large gaps in returns. For ease of exposition, the remaining main tables show only the rank tercile specification. All tables with the linear-in-rank value specification can be found in the Appendix.

7.2.1 Entrepreneurs' Investment Decisions in Response to the Grant

How do the top-ranked entrepreneurs attain such high rates of return to the grant? We begin answering this question by analyzing how they invest the grant money. In follow-up rounds of data collection, we asked grant winners to report on whether and how they had invested the grant. Expenditures of the grant money were divided into business expenses (inventory, durable assets, labor, and other) and non-business expenses (loan repayment, relending, household repairs, and other household expenses). We also asked respondents if they had supplemented the grant money with their own funds to make a business purchase. In Appendix Table 4 we examine the relationship between self-reported investment decisions and marginal returns rank. To do so we regress total grant expenditures in each category (the sum of which is Rs. 6000) on whether an entrepreneur is in the top or middle terciles of the marginal returns ranks distribution. Since the omitted group are entrepreneurs in the bottom tercile, the coefficients on top and middle terciles tell us the differences in grant expenditures between the bottom and upper terciles. While we are underpowered to detect statistically significant differences between the top and middle tercile, business owners in the top tercile invest an extra Rs. 903.1, or 25% more of their grants, in their businesses than those in the bottom tercile. Most of this difference appears as higher expenditures in inventories. Both the top and middle terciles spend significantly less money on "Other Household Expenses" - generally medical expenses, education, food consumption, etc. - and are less likely to have saved their grant money.

Note that respondents who did not win the grant (our control group) were excluded from this exercise. Furthermore, money is fungible so reports of grant expenditures do not necessarily hold constant pre-grant consumption in these different categories. To investigate whether this pattern of grant investments translates to real marginal increases in business inputs, we compare the inventories, business assets, and labor outcomes of grant winners and losers.

In Table 3, we again utilize regression specification 2 to analyze differences in business inputs between grant winners and losers by terciles of the marginal returns distribution. Consistent with the pattern of investments in the previous table, the grant induces top and middle ranked entrepreneurs to accumulate higher capital stocks: top tercile grant winners report an extra Rs. 4541.0 worth of inventory and an extra Rs. 8281.1 of durable assets. The treatment increases the capital stock (inventory plus durable assets) by approximately 200% of the grant amount, which is large but within the confidence bound of increases in capital stock in McKenzie et al. (2008).

The grant also induces marginal increases in inputs that could be complementary to capital:

own, household, and non-household labor. In columns (1) and (2) we show that grant winners in the top tercile spend an extra 10 hours per week and an extra 4 days per month working when compared to their untreated counterparts. The treatment also has an impact on the amount of household and non-household labor. At baseline, 21% of households in our sample utilize household labor for an average of 30 hours per week (conditional on having a worker) and almost none of these workers are officially paid a wage. Despite our selection criteria (see Section 2 for a detailed explanation), 9% of households report utilizing non-household labor in their businesses.[25] Conditional on having a paid non-household laborer, the average weekly wage bill for these businesses at baseline is Rs. 3221. The grant induces top-ranked entrepreneurs to be 8.1% more likely to have a household laborer and 6.4% more likely to have a non-household laborer.

Overall, we see that top ranked households invest higher proportions of their grants into the business, turn those investments into higher business stock, and devote more time to working in their businesses.

7.2.2 Discussion

We find that for a significant portion of our sample, returns exceed the interest rates charged by banks and microfinance institutions. Why then are entrepreneurs, especially those at the top of the ranks distribution, not taking advantage of these high rates of returns?

One possibility is that, while communities have very good information about ability, entrepreneurs may not ex-ante know this information about themselves. Researchers have documented that decision-makers may not be well informed about the economic returns to different activities such as for example the returns to education (Jensen, 2010), the returns to migration (McKenzie et al., 2007)) or returns to saving for retirement (Duflo and Saez, 2003). If so, entrepreneurs may not be willing to borrow to find out where in the distribution of returns they fall. This is not the case in our setting. At baseline, we asked all entrepreneurs to predict their own returns to the grant.[26] As can be seen in Appendix Table 5, in which we regress an entrepreneur's own prediction on the community prediction, we see that the predictions of top-ranked entrepreneurs about their own marginal returns is Rs. 400 higher than the prediction of own marginal returns of the bottom-ranked entrepreneurs and this difference is significant at the 1% level.[27] Additionally in Appendix Table 6, we estimate regression Specification 2 but create terciles of entrepreneurs' predictions about themselves (rather than terciles of community ranks predictions). Again, we see that top-ranked entrepreneurs according to their own self-reports obtain higher observed marginal returns than those who are bottom ranked.

[25] In the vast majority of these cases, the business that employs non-household labor is a second household business that was not the firm that met our eligibility criteria.

[26] Specifically, we asked them to predict what their monthly profits would be in a year if they did and did not win the grant.

[27] Middle ranked entrepreneurs predict their own returns as significantly higher than those that are bottom ranked, but significantly lower than those that are top ranked.

More importantly, 92% of entrepreneurs in our sample report having a desire to borrow. There is a deep experimental and non-experimental literature arguing that credit constraints are an important impediment to microenterprise growth and, some argue, potentially responsible for the overabundance of small firms in low-income countries relative to the distribution of firm sizes in high-income countries Tybout (2000). Indeed, McKenzie et al. (2008) argue that heterogeneity in the marginal returns to microfirms in their sample is driven by credit constraints rather than missing insurance markets.

Yet, microfinance penetration in Maharashtra is substantial. In 2015, there were 27 MFIs operating in the state, the highest of any North Indian state.[28] The CEO of an MFI we consulted while designing this project told us that the market in urban Amravati was so saturated that they had abandoned plans to lend in the urban areas and were concentrating efforts in reach remote rural villages in the district. Moreover, screening of borrowers is almost nonexistent.[29] While most MFIs in India lend exclusively to women, nearly all entrepreneurs in our sample are married. Still, only 6% of our sample reported ever having borrowed from a formal bank and less than 20% had ever borrowed from a microfinance institution.

A plausible alternative theory is that top entrepreneurs may not borrow because the current structure of microfinance contracts is too restrictive to allow them to grow their businesses. Contractual flexibility is appealing to borrowers and can drastically increase the returns to credit, but it can also lead to higher rates of defaults (Field et al., 2013). As the authors note, asymmetric information is a tremendous problem since high-risk types are willing to pay higher interest rates for contractual flexibility, at par with high-productivity entrepreneurs. In this study, we asked entrepreneurs to tell us the maximum interest rate they would be willing to pay for a microfinance loan. Consistent with Field et al. (2013), we find that top ranked entrepreneurs are on average willing to pay the same for a microfinance loan as bottom ranked entrepreneurs. Without tools that allow lending institutions to screen in good entrepreneurs and screen out bad ones, giving entrepreneurs access to desirable contractual features may not be possible. In the remainder of the paper, we propose a set of tools to accomplish this goal.

7.3 Benchmarking the Value of Community Information Against Observables

Although community information is highly predictive of realized marginal returns, a first-order question is whether the information contained in the reports can be replicated using observable characteristics about business owners and her household.

[28] http://research.religarecm.com/INDIA/India%20Microfinance%20-%20Sector%20Report%2019Aug15.pdf

[29] Accessing credit is so easy that the Associate Director of India Rankings, a ratings agency, notes "there is definitive borrower overleveraging in Maharashtra." https://www.bloombergquint.com/business/2016/12/22/is-maharashtra-the-next-andhra-pradesh-for-the-microfinance-industry

7.3.1 Who are the Top-Ranked Entrepreneurs?

We compare the baseline characteristics of households and entrepreneurs in all three terciles of the marginal returns ranks distribution in Table 4. In Column 1, we present the mean of each characteristic for the bottom tercile group. We then estimate the following model:

$$Y_{ijc} = \beta_0 + \beta_1(Middle\,Tercile)_{ijc} + \beta_2(Top\,Tercile)_{ijc} + \sigma_c + \theta_m + \tau_s + \epsilon_{ij} \tag{4}$$

Columns 2 and 3 are the coefficients from a regression of the characteristic on whether the person is ranked in the middle (β_1) or top (β_2) terciles, respectively. So each coefficient can be interpreted as the impact of being in the upper terciles relative to being in the bottom tercile.

Top-ranked entrepreneurs are 8 percentage points more likely to be male, are younger, and are less likely to be married. While they do not appear to be more educated, they do remember an average of 0.57 digits more in the digitspan memory test than their counterparts in the bottom tercile. The business owners in top-ranked households work an extra 6.8 hours per week and 1.8 days per month. We asked business owners how much a salaried job would have to pay per month in order for them to exit self-employment. Top ranked entrepreneurs report that they would require 22% higher monthly wages to shut down their businesses. Top-ranked entrepreneurs are slightly more likely to be engaged in a food preparation business and less likely to engage in livestock than the bottom-ranked entrepreneurs, but otherwise they differ little by business type.

The total number of businesses in the households of top-ranked entrepreneurs is the same as those in the bottom, the businesses of top ranked entrepreneurs have 52% larger in terms of assets and earn 40% higher profits per month. Household composition is very similar across all three groups, but top and middle ranked households have fewer daily wage workers. The households of top-ranked entrepreneurs earn 13.3% higher monthly income.

For the most part, entrepreneurs in the middle tercile have baseline characteristic means that lie between the means of the bottom and top ranked entrepreneurs. Two notable exceptions are that they have higher levels of education and business assets.

7.3.2 The Value of Community Information

Entrepreneurs in the top tercile of the ranks distribution appear different from those ranked at the bottom. Can we predict which entrepreneurs have the highest marginal returns to grants using just their observable information? Table 5 examines how much the value of community reports diminishes when controlling for baseline business and household characteristics, by including in the regression model in the interaction of these characteristics with $Winner_{it}$. The odd columns in Table 5 control for a set of characteristics that would be easily observable and verifiable by a loan officer and which tend to be predictive of marginal returns: the entrepreneur's gender, marital status, age, education, digitspan memory test, household workers composition, and business type.

We find that community information is almost orthogonal to these characteristics; the estimates in Table 5 are strikingly similar to those obtained without controls (Table 2). In the even columns of Table 5 we also control for harder to observe baseline characteristics including household income, the value of household assets, hours worked, the value of business assets, average yearly profits,[30] and the other characteristics presented in Table 3. If anything, controlling for baseline profits seems to enhance the value of community information, as the estimates in Table 5 are substantially larger than the preceding ones. The reason for this is that the marginal returns rank is positively correlated with baseline profits and baseline profits are negatively correlated with the marginal return to capital (implying that there are diminishing returns to capital).[31] The analogue of this table using the robustness specification (Specification 3) can be found in Appendix Table 7, with qualitatively similar results.

Another set of characteristics that have been shown to be predictive of credit worthiness and entrepreneurial aptitude are psychological questions that identify characteristics such as tenacity, polychronicity, and optimism (see Klinger, Khwaja, and Carpio 2013). In Appendix Table 8, we therefore test how well psychometric questions perform at predicting marginal returns and how they compare to community rankings. The regressors are labeled according to the psychological trait for which they are meant to proxy (the specific wording of the statement is found in the Appendix). The traits that are strongly predictive of marginal returns fall into two categories: optimism and achievement. Optimism negatively predicts marginal returns: business owners who are more likely to agree with the statements "In times of uncertainty I expect the best" and "I'm always optimistic about the future" and those who are more likely to disagree with "If something can go wrong with me, it will" have lower self-reported marginal returns. People who agree with the statement "Part of my enjoyment in doing things is improving my past performance" tend to have higher marginal returns. Importantly, the value of the predictions remain almost identical to the original results presented in Table 2.

7.3.3 Predicting Marginal Returns with Observables

Overall, community information is valuable in identifying entrepreneurs with high marginal return to capital even if the implementing organization has access to a large variety of observable demographic and business information about respondents. A distinct question is how much value does community information add over what can be predicted using observables? The most straight-

[30] We asked respondents at baseline to tell us what had been their monthly profits for each month for the previous 12 months. This section of the survey (seasonality) is distinct from the section of the survey in which we ask respondents to report about business activities (including profits) in the previous 30 days. So the average yearly profits value is distinct from the profits in the previous 30 days, which is the outcome variable in Columns 5-8.

[31] To see this, we regress income and profits on the interaction of baseline profits with winner and winner with the fixed effects specified above. We find that the coefficient on the interaction between winner and baseline profits is negative and significant at the 1%. Regression available from the authors.

forward way to answer this question would be to estimate a simple OLS regression of profits on all of the characteristics used in the odd columns of Table 5 as well as the characteristic interacted with winner. The coefficient on $Winner * Characteristic$ tells us the predicted impact that characteristic has on the marginal return. For each household, we could then multiply each characteristic value by the coefficient from the regression model and sum across all characteristics to obtain a predicted marginal return.

One problem with the approach above is that it requires the researcher to form an ex-ante opinion on which covariates matter and on the optimal way of combining the information obtained from these covariates to formulate a prediction.[32] It can also lead to overfitting: the better the model does at predicting within sample, the worse it may do at making an out-of-sample prediction. Machine learning is a data-driven method to identify which characteristics are the best predictors of the marginal return and to combine those covariates in a disciplined manner so at to avoid overfitting.

While there is a vast statistical literature on prediction techniques, RCTs face a unique problem in using machine learning methods to identify treatment heterogeneity. No matter which specific machine learning technique is used, the key to training a predictive model is having a set of covariates X_i and a "ground truth"- a value of Y_i- for each observation in the sample. As with all randomized control trials, however, we cannot observe an individual treatment effect. Using notation from the Rubin Causal Model, let $W_i \in \{0, 1\}$ be an indicator of treatment, where $W_i = 0$ indicates that person i did not receive the treatment (say, a grant) and $W_i = 0$ indicates that person i did receive the treatment. For each individual i, we would like to observe an individual treatment effect $\tau_i = Y_i(1) - Y_i(0)$- this would allow us to train the model on τ_i as the ground truth. But each person only has one realized outcome ($Y_i(1)$ or $Y_i(0)$). So we can only observe the average treatment effect (ATE) for the population $E[Y(1) - Y(0)]$ or the conditional average treatment effect (CATE) $E[Y(1) - Y(0)|X = x]$.

Athey and Imbens (2015) and Wager and Athey (2017) develop a set of tools to modify standard regression tree and forest techniques and allow researchers to identify heterogeneity in treatment effects. The standard regression tree algorithm works by recursively partitioning the data into "leaves" of observations with the same set of characteristics. The decision of how to partition the data is taken so as to minimize mean square error across a partition. A prediction $\hat{Y}$ is then formulated by taking the average value of Y within each leaf. A regression forest extends the regression tree algorithm by growing and averaging across many trees.

Because the true mean squared error cannot be calculated for an average treatment effect, Athey and Imbens (2015)and Wager and Athey (2017) amend the standard algorithms to instead estimate heterogeneous treatement effects. While the regression tree estimates $\bar{y}$ within a leaf, the

[32] For example, the present model assumes covariates linearly predict the marginal returns of entrepreneurs and do not interact with one another. But, for example, the gender of the business owner may only matter in sectors that require interacting with the final consumers (such as retail), but not in manufacturing.

causal forest algorithm computes the average treatement effect $\hat{\tau} = \bar{y}_{treat} - \bar{y}_{control}$ within the leaf. Although the authors provide several functional options to estimate goodness-of-fit, the objective is to maximize the sum of squared treatment effects across leafs. Because the function is squared, the algorithm seeks to generate splits to maximize the difference in the treatment effects across either side of the split. The causal forest algorithm again extends the causal tree by generating a prediction for each i using the average of the average treatment effect of i across all terminal nodes where i appears. In the Appendix, we provide more detailed intuition for the machine learning techniques discussed here.

Aside from the issue of estimating treatment effects rather than observed outcomes, a second challenge in applying machine learning techniques to randomized control trials are small sample sizes. Most RCTs, including ours, due to budget constraints are just sufficiently powered to detect treatment effects. Machine learning, however, typically requires splitting the data into a training sample where the model is generated and a test sample used to evaluate the out-of-sample goodness of fit. To help boost our sample size, we will utilize data from McKenzie et al. (2008). We utilized the same sample selection criteria as the authors to make the treatment effects as comparable as possible. Their study takes place in Sri Lanka, which is physically and economically proximate to India. In Appendix Table 9, we show the average baseline characteristics across the two samples and find the two to be similar.

There are important differences between two studies: the authors gave out both in-kind and cash grants, while we only give cash grants. Additionally, they randomize \$100 and \$200 grants, while we only give \$100 grants. McKenzie et al. (2008) analyze the differences in treatment effects from in-kind versus cash grants and \$100 and \$200 grants and find that they cannot reject equivalency of treatment effects. In our exercise, we will consider an entrepreneur as treated if she received any of the four treatments.

Both our and the Sri Lanka experiment data share a lot of the same covariates. One important difference is that in Sri Lanka, the authors did not collect rankings information, which is the variable on which our experiment was powered. Since the goal of this exercise is to horserace our community information model with a machine learning prediction, we train the model on the Sri Lanka data exclussively and test it on the India data. We discuss robustness checks after the main analysis.

In the Appendix, we give a step by step instruction of how the algorithm was implemented. Here we highlight a few important features of the implementation. We use in-sample tests to determine which technique best fits our training data. An important feature of machine learning is penalizing algorithms for model complexity so as to avoid overfitting. The most recent version of the causal forest package does not provide tools for cross-validation, which is needed to determine optimal model complexity. We therefore follow Katz and Roth (2017) and build a cross-validation method to determine the minimum node size at which the tree should no longer split. The minimum node size is a proxy for model complexity since smaller terminal node sizes imply a larger number of splits. We implement a k-fold cross validation method and the results of this exercise are shown in Appendix Table 10. The largest $\bar{\beta}_{1n}$ exists for minimum node size 15. We fit the full model on all of the Sri Lanka data with these parameters and predict the marginal returns of entrepreneurs in the India data.

As an additional robustness exercise, we also do an in-sample fit using the India data. We follow the same technique as with Sri Lanka: we conduct a k-fold cross-validation exercise and present the results to choose the optimal minimum node size in Appendix Table 11. Using the minimum node size from the cross-validation exercise, we generate a prediction using the India trained model on the India data. The goal of this exercise is not to use the India model to generate an out-of-sample prediction. Rather, this exercise is a conservative estimate of the "best fit" of our covariates.

In Table 6, we present the results of the machine learning exercise. For ease of comparison in columns 1 and 2, we replicate the results of column 6 of Table 2 and column 6 of Table 5, respectively.[33] The machine learning exercises (from the model trained in Sri Lanka and the model trained in India) produce a numerical prediction of the marginal returns of each individual in the sample based on their baseline characteristics. For comparability with our preferred specification, we divide the predictions into terciles and in columns 3-6 test how well the machine learning estimation predicts the true marginal returns in our sample. In Appendix Table 12, we show the linear specification.

In columns 3 and 4, we present the results of the machine learning prediction trained in Sri Lanka. In column 3, the top tercile of entrepreneurs as identified by the Sri Lanka prediction earn an extra Rs. 879 in marginal returns to the grant over the bottom tercile of entrepreneurs. In column 4, we add the community information prediction. First note that the coefficient on $Winner * TopTercile$ is large and significant at the 5% level. Furthermore, the machine learning prediction estimate for the top tercile gets noisier and a bit smaller, but remains a good prediction of the best entrepreneurs. The correlation between Quintile Rank and the machine learning prediction is 0.1. Taken together, these observations indicate that community members are using additional information to rank beyond (detailed) covariates that are observable to the researcher and that information is very valuable in identifying high-ability entrepreneurs. Columns 5 and 6 demonstrate the same point: despite the fact that the model is clearly overfit in-sample, community ranks continue to be predictive above and beyond the machine learning prediction.

What would have been our monthly return on investment using the different allocation mechanisms presented? In Figure 4, we depict the return on investment for each allocation mechanism separately: random allocation (the equivalent of the population average return), allocation using

[33]The estimates (and number of observations) differ slightly to ensure a comparable sample with the machine learning exercise. So in the replication of Table 5 column 6, we only control for the variables that we use in the machine learning exercise (a subset of the variables used in Table 5)

the community information, allocation using the Sri Lanka machine learning prediction.[34] The top tercile of entrepreneurs using the community rankings method earn 22.5% monthly returns, while those in the top tercile of the Sri Lanka machine learning prediction distribution earn 18.0% monthly returns.

7.4 Do Peers Distort Their Responses When There Are Real Stakes?

The analysis in Tables 1-6 has shown that communities are well informed about the marginal returns of its members. Why is that information not being leveraged by lending institutions? One reason may be that acquiring this information *truthfully* is challenging. When faced with allocating a highly desirable resource (such as a grant), community members may alter their reports to benefit or hurt particular individuals in a social network. Aside from quantifying how much information neighbors have about one another, the second major goal of this project is to quantify whether and by how much peers misreport in high stakes settings.

Because we cannot observe a marginal return for each individual in the sample, in Sections 7.2 and 7.3 we evaluated the "accuracy" of community information by estimating whether the true marginal returns of more highly ranked people were higher than the true marginal returns of less highly ranked entrepreneurs.[35] In addition to the marginal returns reports, we asked respondents to rank peers on a series of dimensions such from lowest to highest household income. At baseline – prior to any respondents being aware of the peer information aspect of this study – we had asked each entrepreneur to report the answer to each of those questions about their own selves. For example, we asked respondents to tell us what their average monthly household income had been over the previous year. To evaluate the accuracy of community reports in the remainder of the paper, we therefore estimate how closely a report about each entrepreneur matches the true outcome observed for that individual. Specifically, we estimate the following regression model,

$$Y_{ijq} = \beta_0 + \beta_1 Rank_{ijmq} + \gamma_n + \theta_m + \tau_s + \delta_q + \epsilon_{ijmq} \tag{5}$$

where $Rank_{ijmq}$ is the rank that person m in group j assigns to person i (also in group j) on question and Y_{ijq} is the corresponding outcome for question q of person i. We have corresponding true outcomes from the baseline survey for the income, profits, assets, medical expenses, work hours, digitspan ranks. To allow us to stack the data, we convert the outcome and rank of each question into percentiles and add a question fixed effect to the regression (δ_q). We also add neighborhood (γ_n), survey month (θ_m), and surveyor (τ_s) fixed effects. A 1 percentile increase in the $Rank_{ijmq}$ is associated with a β_1 percentile increase in the outcome variable distribution Y_{ijq}.

After the completion of the marginal returns ranking exercise, half of our sample was informed

[34] Note that this regression tells us the returns for each tercile separately, while the regressions in Table 2, for example, tells us the difference in the marginal returns between the top/middle terciles and the bottom tercile.

[35] See a detailed discussion of this problem in Section 7.3.3.

that they could affect the probability that their peers (or themselves) would win the USD 100 grant (this is the *High Stakes* group). The other half continued to believe that as with the marginal returns, the rankings were purely for research purposes and that at the completion of the ranking exercise a lottery (with all group members having equal probabilities of winning) would allocate the grant. To test whether respondents behave strategically, we compare the accuracy of reports in groups in which ranks affected the grant allocation (*High Stakes*) and groups in which ranks had no effect on grant distribution.

7.4.1 How Much Do They Know?

We begin by estimating regression model 5 and showing that respondents have information about their peers' observables. In Table 7, we pool responses across all treatments (*High Stakes*, *Payments*, and *Public*). The outcome variables, denoted in the column headings, correspond exactly to the outcome that peers were asked to rank on during the ranking exercises. In columns 1 and 2, the outcome is average monthly household income over the past year and the *Rank* variables are the income quintile and income relative ranks, respectively, given to each person i. In columns 3 and 4, the outcome value is the clients' predicted monthly profits if they were to receive a USD 100 grant. In columns 5 and 6, the outcome is the total value of household assets, which were visually verified by our survey team. In column 7, we report a households total medical expenses in the past six months. In column 8, the outcome variable is the average number of hours the client works per week, and in column 9 we report the total number of digits the client remembered during a digit span memory test.[36]

In Panels A and B, both the outcome variables and *Rank* have been converted to percentiles of the distribution of observed outcome values. In Panel C, the outcome variable and regressors are presented in levels.

Panel A reports the results at the ranker-rankee pair level of observation for each question. For all outcome measures, the reports are highly predictive. Peers are informed about relatively observable aspects of their neighbors' lives, such as household assets, but also much less easily observable characteristics including working memory, work ethic, and business profits. The level of accuracy of the prediction varies depending on the question. Respondents are most accurately able to predict peers' household assets: a 1 percentile increase in the relative rank of assets is associated with a 0.154 percentile increase in the distribution of household assets in our sample population. To contextualize how "predictive" these estimates are, we regress the income percentile on the percentile of the education of the household head and percentile of assets: a 1 percentile increase in the education distribution is associated with a 0.128 percentile increase in the distribution of household income; the α_1 on households assets is 0.208.

[36]Digit span is a commonly used test for working memory. Respondents are shown flashcards with an increasing number of digits and asked to recall the numbers from memory. The surveyor records the total number of digits that the respondent correctly repeated back.

We asked respondents to rank their peers relative to others in the group and also relative to the community by reporting the quintile of the neighborhood distribution that they believe the peer to be in. In theory, quintile rankings could be more useful as they could contain more information about the true position of the peer vis-a-vis other similar microentrepreneurs. In both the even and odd columns 1-6 of Table 7 the outcome variable is the same, but what changes is the method of reporting. In the odd columns, the regressor is the percentile in the relative rank distribution and in the even columns the regressor is the percentile of the quintile rank distribution. By comparing the odd and even columns, we cannot reject that relative and quintile rankings are equally informative.

Respondents may have idiosyncratic preferences for misreporting about certain peers in their group and may otherwise make idiosyncratic errors. One way to reduce the influence of the errors is by averaging across all reports given about a particular group member. We do so and present these results in Panel B, where the unit of observation is the rankee. We observe that the average reports are significantly more predictive of all outcome variables. While a 1 percentile increase in the profits rank leads to a 0.145 percentile increase in the profits distribution in Panel A, it is associated with a 0.246 percentile increase in Panel B. Averaging reports is therefore a costless way to nearly double the predictiveness of community reports.

7.4.2 Do Peers Distort their Responses in a Real Stakes Setting?

Having established that respondents have valuable information about baseline data, we can evaluate whether they distort responses. Following model 5, we estimate

$$Y_{ijq} = \alpha_0 + \alpha_1 Stakes_j \times Rank_{ijmq} + \alpha_2 Stakes_j + \alpha_3 Rank_{ijmq} + \gamma_n + \theta_m + \tau_s + \delta_q + \epsilon_{ijmq} \quad (6)$$

The $Rank_{ijmq}$ variable captures the accuracy of the report in the control group ($No\,Stakes$). The $Rank \times High\,Stakes$ coefficient tells us whether the rankings are differentially informative when respondents are told their ranks will be used to help determine grant allocation.[37] For now, we pool across the *Public* and *Payments* treatments.

In Table 8, we stack the percentilized outcomes and ranks across all 9 columns presented in Table 7. Columns 1-3 show the regressions at the ranker-rankee level of observation (analogue of Panel A in Table 7) and Column 4-6 are the regressions with the average rank (analogue of Panel B in Table 7). First, as observed in the previous table, the average predictiveness of ranks in the control group increases significantly when reports are averaged: in Column 1, a 1 percentile increase in the rank distribution is associated with a 0.162 shift in the outcome distribution in the individual regressions and a 0.252 shift in the average regression (Column 4).

[37]To reduce clutter in the regression table, we have omitted the $High\,Stakes$ coefficient from the regression report as it does not contain information relevant for the interpretation of results, but rather simply adjusts the constant.

Secondly, the coefficient on $Rank \times High\,Stakes$ is large, negative, and significant. We should note that this was not ex-ante obvious: the $High\,Stakes$ treatment may have had a positive effect since revealing ranks may have caused respondents to focus or take the exercise more seriously. The regression implies that responses are significantly less accurate when respondents have an incentive to behave strategically: in the pooled individual regression in Column 1, the responses become 34.6% less accurate in the $High\,Stakes$ group. While averaging reports increases accuracy in the control group, it does not reduce the effect of misreports. While the loss in accuracy in Column 4 is smaller as a percent of the information obtained in the treatment group (24.0%), it has nearly the same size negative impact (-0.060 in Column 4 versus -0.056 in Column 1).

Lastly, we hypothesized that while quintile ranks could theoretically contain more valuable information about rankings because entrepreneurs are compared to the community more broadly than only the group, it could also mean that it is easier to lie about peers. We separate the pooled questions into quintile ranks questions (the aggregate of Columns 1, 3, and 5 in Table 7) and relative ranks questions (Columns 2, 4, 6, 7, 8, and 9 in Table 7) and test for distortions. The coefficients on *Rank* in the individual (Columns 2 and 3) and the average regressions (Columns 5 and 6) are very similar, implying that in the absence of high-stakes, the value of information from relative and quintile ranks is very similar. While the coefficient on $Rank \times High\,Stakes$ in the quintile regressions is larger in magnitude both in the individual and average models, we cannot reject that respondents misreport by the same amount in either type reporting method.

Who do respondents lie in favor of? At the start of the ranking exercise, we asked respondents to report what their relationship with each peer in the group was. We also asked each respondent to report who is person i's closest peer in the group. The *cross-reported peer* is the peer that is most frequently reported as person i's closest friend in the group. To analyze who respondents lie in favor of, in Table 9 we re-estimate regression Specification 6 but limit the sample to a respondent's reports about herself, her family members, and her cross-reported peers in the group. First, notice that the rankings of all three categories of persons, particularly family, are quite accurate in the $No\,Stakes$ group. When stakes are introduced, however, the rankings become between 31% and 58% less accurate. There does not appear to be any differential pattern in misreporting by quintile or relative question. But the fact that accuracy dramatically decreases in the quintile ranks implies that $High\,Stakes$ does not simply increase the general error rate due to re-rankings. As further corroboration, we analyze how the rankings themselves (not just accuracy) are affected by proximity between peers in Appendix Table 13. We see that respondents up-rank themselves, family members, and cross-reported peers relative to other peers in the group in the $No\,Stakes$ treatment but that family members are ranked even more highly when $High\,Stakes$ are introduced.

Overall, we find that misreporting is a first order problem if a principal wants to use community information to make valuable allocations.

7.5 Can Mechanism Design Tools Correct Incentives to Misreport?

7.5.1 Monetary Incentives and Public Reporting

In the previous section we provided evidence that respondents distort their reports when they have a strategic incentive to do so. These distortions have a substantial impact on the accuracy of reports, particularly when respondents have an incentive to misreport such as when their information is used to allocate a desired good. Can we use mechanism design tools to generate incentives for truthful reporting? We test two randomly assigned tools: incentive payments for the accuracy of reports and reporting in public versus private.

In Table 10, we provide evidence of the accuracy of reports in the *Public* and *Payments* treatments. Given that respondents lie substantially in favor of themselves, we split the results by whether a respondent is reporting about herself (Columns 1 and 2) or about her peers (Columns 3 and 4). Our main goal with these treatments was to test whether mechanism design tools can correct incentives to misreport created by elicitation in high-stakes settings. To answer how these tools perform in a high stakes setting, we split results by *No Stakes* (odd columns) and *High Stakes* (even columns). The coefficient on *Average Rank* indicates the accuracy of reports in groups in which respondents do not receive incentives and report in private. The coefficient on the three remaining interaction terms tell us the additional effect of reporting in public without monetary payments, in private with monetary payments, and in public with monetary payments (when added to the sum of the two previous coefficients), respectively.

First, we see in Columns 1 and 2 that providing stakes decreases the accuracy of reports about self by 28% in the private and no incentives treatments. Secondly, neither payments for truthfulness nor public reporting have any impact on the accuracy of reports about self. Notably, though, while our treatments were not successful in incentivizing respondents to be truthful about themselves in a high-stakes setting, even when they do lie, the accuracy of their reports about themselves (0.146) is approximately the same as the accuracy of reports about others in the group in the private and no incentives treatment (0.120 in Column 4).

Turning to Columns 3 and 4, we see that incentives significantly increase the informativeness of reports about others in both the *No Stakes* and *High Stakes* treatments: in both cases, monetary payments improve accuracy by 0.14, or over 100%. The fact that payments improve accuracy substantially even in the *No Stakes* treatment also implies that reporting in the no-stakes, private, and no incentives setting is not the best benchmark for the most accurate that a report could be.

The *Public* treatment in *No Stakes* increases accuracy by a similar amount as monetary payments (Column 3). But it yields no differential effect over reporting in private in the *High Stakes* setting (Column 4). We return to this result in the next paragraph. Lastly, the coefficient on the treatment in which respondents receive monetary incentives and report in public is large and negative (*Average Rank* $\times$ *Payments* $\times$ *Public*). We can, however, reject at the 10% level that the accuracy of information in this group is the same as in the private reporting and no monetary incentives group. We interpret the negative coefficient, therefore, as being indicative that monetary payments and public reporting are substitutes.

As discussed in Section 3, while monetary payments will unambiguously incentivize truth-telling, public reporting has an ambiguous prediction on accuracy: there may be pressure for the ranker to report that family members in the group are better than they actually. At the same time, there may also be pressure by non-family members and other peers for the ranker to be truthful. When we introduce stakes, both of these forces are intensified: family members and close friends want the ranker to sway the lottery in their favor, but it may also be especially important to the community that the ranker be truthful when there are high stakes.

To shed some light into how respondents trade off these allegiance, we turn to Table 11. In this table, we examine the rankings that respondents give to family and non-family members in the group under different treatment conditions. The outcome variable is what rank respondent i assigned to peer j in the group. We exclude ranks given to ones own self. *Family* indicates whether respondent i is related to peer j. We see that compared to non-family peers (the omitted group), family members receive 0.4 higher ranks on average when reports are given in private and in the no-stakes setting. The coefficient on *Family* $\times$ *Public* indicates the additional effect of ranking a family member in public without real stakes. The *Public* treatment fully corrects the extra ranks that are given to family members in private. This is consistent with the result in Column 3 of Table 10 which shows that public reporting in a no-stakes setting improves the quality of reports. We cannot reject that introducing stakes in a private setting has no additional effect over how family members are ranked.[38] Lastly, when respondents are asked to rank in public and with stakes, the correcting effect of the *Public* treatment is mostly undone: respondents revert to ranking their family members more highly than non-family members. This again is consistent with the result in Column 4 of Table 7 which shows that public reporting in a stakes setting has no differential impact over private reporting in a stakes setting.

7.5.2 Cross-Reporting

As shown in Table 9, community members are capable of successfully identifying which persons a peer may lie in favor of. A second non-randomized cross-reporting feature of our experiment was to ask respondents to name the person who would be best able to predict the true ranks (in other words, who would be the most accurate). In Table 12, we interact whether a respondent has been selected by her group as the one who would provide the most accurate answers. In column 1, pooling across all questions, we see persons who are selected provide information that is 50% more accurate than information provided by the standard respondent in the group.

[38] In fact, private stakes drive respondents to rank themselves more highly.

8 Conclusion

We find that community members have residual information about their peers that is valuable for targeting. Not only can community members identify characteristics of their peers' enterprises, they can also predict which of their peers have high returns to capital. But community information is also susceptible to strategic misreporting. In particular, we identify a tendency for respondents to favor their friends and family members in their reports. Moreover misreporting is exacerbated when respondents are told that their reports will influence the distribution of grants. If we assume that stakes would have reduced the accuracy of the marginal returns ranking by a third (the estimated average reduction in accuracy across the metrics evaluated in the high stakes treatment), then the marginal returns prediction for the top third of entrepreneurs would drop from 22.5% to 14.8% per month.[39]

However we also find that a variety of techniques motivated by mechanism design theory are effective in realigning incentives for truthfulness. Relatively small monetary payments for accuracy, eliciting reports in public rather than in private, and cross reporting techniques all substantially improve the accuracy of reports.

Is it worth it for principals to invest in collecting community information and providing incentives to respondents? We calibrated the payment rule to pay, on average, Rs. 25 per question per respondent. In total, we paid Rs. 17000 in incentives for the marginal returns question. If a lender were distributing 450 loans (as we did with grants), this would increase the cost on each loan by approximately Rs. 40 per month. In Section 7.2, we estimated that the cost of interest that an MFI would charge per grant is Rs. 570 per month. Adding the incentives costs (transferring it to the borrower) implies that the cost of the loan to each respondent per month would be Rs. 610. Using the returns estimate from our preferred specification (Table 2 Panel B, column 3), borrowers would still earn a net return of Rs. 388 per month if the full cost of the monetary incentives were passed on to the borrowers.

Our aim is that the peer elicitation method identified in this paper can be useful for targeting in poorly developed financial markets in low-income countries, where information asymmetries are prevalent.

References

Abadie, A., J. Angrist, and G. Imbens (2002). Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica 70*(1), 91–117.

Alatas, V., A. Banerjee, R. Hanna, B. A. Olken, R. Purnamasari, and M. Wai-Poi (2013). Does

[39] In Appendix Table 22, we re-estimate the same model as in Table 7, but analyze the results question by question rather than pooling across questions. We see that for 7 out of the 9 characteristics presented in Table 7, the reduction in accuracy due to *High Stakes* is between one and two thirds vis-a-vis the *No Stakes* group.

elite capture matter? local elites and targeted welfare programs in indonesia. Technical report, National Bureau of Economic Research.

Alatas, V., A. Banerjee, R. Hanna, B. A. Olken, and J. Tobias (2012). Targeting the poor: evidence from a field experiment in indonesia. *The American Economic Review 102*(4), 1206–1240.

Allcott, H. and T. Rogers (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *The American Economic Review 104*(10), 3003–3037.

Athey, S. and G. W. Imbens (2015). Machine learning methods for estimating heterogeneous causal effects. *stat 1050*(5).

Banerjee, A., D. Karlan, and J. Zinman (2015). Six randomized evaluations of microcredit: Introduction and further steps. *American Economic Journal: Applied Economics 7*(1), 1–21.

Basurto, P. M., P. Dupas, and J. Robinson (2017). Decentralization and efficiency of subsidy targeting: Evidence from chiefs in rural malawi. Technical report, National Bureau of Economic Research.

Beaman, L. and J. Magruder (2012). Who gets the job referral? evidence from a social networks experiment. *The American Economic Review 102*(7), 3574–3593.

Bernhardt, A., E. Field, R. Pande, and N. Rigol (2017). Household matters: Revisiting the returns to capital among female microentrepreneurs. Technical report, National Bureau of Economic Research.

Besley, T. and M. Ghatak (2005). Competition and incentives with motivated agents. *American Economic Review 95*(3), 616–636.

Bryan, G., D. Karlan, and J. Zinman (2015). Referrals: Peer screening and enforcement in a consumer credit field experiment. *American Economic Journal: Microeconomics 7*(3), 174–204.

de Mel, S., D. McKenzie, and C. Woodruff (2008). Returns to capital in microenterprises: Evidence from a field experiment. *The Quarterly Journal of Economics 123*(4), 1329–1372.

De Mel, S., D. J. McKenzie, and C. Woodruff (2009). Measuring microenterprise profits: Must we ask how the sausage is made? *Journal of development Economics 88*(1), 19–31.

De Mel, S., D. J. McKenzie, and C. M. Woodruff (2010). *International Differences in Entrepreneurship*, Chapter Who are the Microenterprise Owners?: Evidence from Sri Lanka on Tokman v. de Soto, pp. 63–87.

Duflo, E. and E. Saez (2003). The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *The Quarterly journal of economics 118*(3), 815–842.

Fafchamps, M., D. McKenzie, S. Quinn, and C. Woodruff (2014). Microenterprise growth and the flypaper effect: Evidence from a randomized experiment in ghana. *Journal of development Economics 106*, 211–226.

Fiala, N. (2013). Stimulating microenterprise growth: Results from a loans, grants and training experiment in uganda.

Field, E., R. Pande, J. Papp, and N. Rigol (2013, October). Does the classic microfinance model discourage entrepreneurship among the poor? experimental evidence from india. *American Economic Review 103*(6), 2196–2226.

Foster, A. D. and M. R. Rosenzweig (1996). Technical change and human-capital returns and investments: evidence from the green revolution. *The American economic review*, 931–953.

Gerber, A. S., D. P. Green, and C. W. Larimer (2008). Social pressure and voter turnout: Evidence from a large-scale field experiment. *American Political Science Review 102*(1), 33–48.

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics 125*(2), 515–548.

Lucas, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, 508–523.

Maitra, P., S. Mitra, D. Mookherjee, A. Motta, and S. Visaria (2017). Financing smallholder agriculture: An experiment with agent-intermediated microloans in india. *Journal of Development Economics 127*, 306–337.

Maskin, E. (1999). Nash equilibrium and welfare optimality. *The Review of Economic Studies 66*(1), 23–38.

McKenzie, D., S. de Mel, and C. Woodruff (2008). Returns to capital: Results from a randomized experiment. *Quarterly Journal of Economics 123*(4), 1329–72.

McKenzie, D., J. Gibson, S. Stillman, et al. (2007). *A land of milk and honey with streets paved with gold: Do emigrants have over-optimistic expectations about incomes abroad?*, Volume 2788. World Bank, Development Research Group, Finance and Private Sector Development Team.

Parker, S. C. (2009). *The economics of entrepreneurship*. Cambridge University Press.

Prelec, D. (2004). A bayesian truth serum for subjective data. *Science 306*(5695), 462–466.

Rigol, N. and B. Roth (2017). Paying for the truth: The efficacy of peer prediction in the field. *Working Paper*.

Rosenbaum, P. R. (1987). Model-based direct adjustment. *Journal of the American Statistical Association 82*(398), 387–394.

Schoar, A. (2010). The divide between subsistence and transformational entrepreneurship. *Innovation policy and the economy 10*(1), 57–81.

Townsend, R. M. (1994). Risk and insurance in village india. *Econometrica: Journal of the Econometric Society*, 539–591.

Tybout, J. R. (2000). Manufacturing firms in developing countries: How well do they do, and why? *Journal of Economic literature 38*(1), 11–44.

Varian, H. R. (1990). Monitoring agents with other agents. *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift Für Die Gesamte Staatswissenschaft*, 153–174.

Wager, S. and S. Athey (2017). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association* (just-accepted).

APPENDIX

Details for Robust Bayesian Truth Serum

This discussion is based on Rigol and Roth (2017).

Theory and Intuition

In this appendix section we discuss the details of the Robust Bayesian Truth Serum, an intuition for the underlying incentive properties, and our implementation of the payment rule in the field. The following discussion of the model is based on Witkowski and Parkes (2012).

Suppose there is a binary state of the world $t \in (h, l)$ (high, low) representing the entrepreneurial quality of a community member. Agents get a binary signal which is informative of the state of the world. That is each agent receives a signal $s \in \{h, l\}$ which may represent what they observe about their peer (e.g. they appear responsible, smart etc). Suppose further that all agents share a common prior about the state of the world such that they all agree on the prior probability of a high state, and they all agree on the distribution of signals conditional on the state. Let $p_h = P(s_j = h|s_i = h)$ be the probability an agent assigns to one of his peers receiving a high signal conditional on himself receiving a high signal, and analogously let $p_l = P(s_j = h|s_i = l)$. We say the common prior is *admissable* if $p_h > p_l$, which in English implies that the probability that one's peer receives a high signal is higher if the agent himself receives a high signal. Many natural distributions satisfy this weak requirement.

In order to define the RBTS we must first define the quadratic scoring rule. Let

$$R_q(y, \omega) = \begin{cases} 2y - y^2 & \text{if } \omega = 1 \\ 1 - y^2 & \text{if } \omega = 0 \end{cases}$$

Imagine an agent trying to predict whether some true state ω is 1 or 0. The quadratic scoring rule has the property that his expected score is maximized by reporting his true belief about the probability the state ω is 1 (see e.g. Selten, 1998).

The RBTS is implemented as follows. Every agent states their first order belief (their signal), in a report $x_i \in \{0, 1\}$ (imagine $x_i = 1$ corresponding to $s_i = h$). Further they report their second order belief $y_i \in [0, 1]$ (this is the fraction of the population they believe will report a high signal, $x_k = 1$). For each agent i, assign them a peer agent j, and a reference agent k, and calculate

$$y'_i = \begin{cases} y_j + \delta & \text{if } x_i = 1 \\ y_j - \delta & \text{if } x_i = 0 \end{cases}$$

for arbitrary δ. The RBTS payment for agent i is

$$u_i = R_q\left(y'_i, x_k\right) + R_q\left(y_i, x_k\right)$$

The main theorem of Witkowski and Parkes is that under the assumption of an admissable prior and risk neutral agents, there is a Bayes' Nash Equilibrium in which all agents report their first and second order beliefs truthfully.

The intuition behind the payment rule is fairly straightforward. The payment rule has two components. The second component incentivizes the agent to be truthful about his second order beliefs. That is, the agent is paid via the quadratic scoring rule to predict what some reference agent k will announce as his signal. And by the discussion above, agent i maximizes his expected payment from this component of the scoring rule by truthfully announcing his belief y_i about the likelihood agent k will announce a high signal. In simpler terms, the payment rule rewards agent i for choosing a second order belief as close as possible to the truth (the realized distribution of first order beliefs).

The first component of the payment rule incentivizes the agent to be truthful about his first order beliefs. The term y'_i takes an arbitrary person j's second order belief y_j and either raises or lowers it depending on i's report x_i. RBTS pays agent i $R_q\left(y'_i, x_k\right)$, and so i wants y'_i to be as near as possible to the true distribution of responses in the population. The admissibility assumption guarantees that if person j were to know that person i's signal were high, then person j would increase his assessment as to the number of people in the group who received high signals. Likewise, if j were to learn that i's signal were low, j would lower his assessment about the number of people in the group who received high signals. In effect the mechanism raises or lowers j's assessment based on i's report, and then pays i based on the closeness of this modified report to the truth. Thus i can do no better than to tell the truth.

Practical Implementation

We used this payment rule in the field to incentivize rank order responses about members of each group. The model and payment rule, however, were designed for binary responses. Thus while responses contain a rank ordering of 5 people, we treat each ranking as a composite response to 25 yes/no questions of the form "Is person i the highest ranking individual in the group?", "Is he the second highest?" and so on. We elicited second order beliefs of the form "How many people will say person i is the highest ranking individual in the group?" "How many will say he is the second highest?" and so on. From there we directly applied the payment rule, calibrated so that the expected difference between payments arising from truthful and deceptive answers was large. Note that the accuracy of responses across various questions in a single ranking were correlated, but under the assumption of risk neutrality (which is maintained throughout the peer prediction literature and may be empirically reasonable with respect to moderate sums of money), these correlations are irrelevant.

Incentive Compatibility Exercise for RBTS

Throughout the experiment we told respondents that they would maximize their personal payoffs if they reported truthfully. While RBTS is truthful under certain reasonable assumptions about how beliefs are formed, its incentive compatibility under the empirical distribution of beliefs in practice remains an open question. We therefore evaluate whether respondents are maximizing their subjective expected utility by telling the truth.

Due to the coarseness of our elicited measures of belief, we cannot verify directly whether or not the respondents' priors are admissable. However we can determine the distribution of payoffs respondents can expect to receive under alternative responses to see whether they succeeded in maximizing their subjective expected utility. Respondents' payments depend on the distribution of first order beliefs (i.e. the empirical distribution of responses about the question of interest) and on the distribution of second order beliefs. Therefore, to determine whether truth telling is incentive compatible, we must understand what the respondent believes are the distributions of first and second order beliefs in the population. We obtain the former for free; respondents' beliefs about the distribution of first order beliefs are their second order beliefs, and we elicited these in our survey. We did not, however, elicit their beliefs about the distribution of second order beliefs: their third order beliefs. We must therefore construct those. The intuition behind the construction is presented in the following three steps:

1. We assume that respondents hold a common prior. If so, we can back out their third order beliefs from (a) the distribution of second order beliefs conditional on each first order belief and (b) their belief about how probable each first order belief is. The latter corresponds to her second order beliefs. [40]

[40] If agents have common priors then conditional on the signal they receive, they would update to have the same

2. We approximate the distribution of second order beliefs in the population conditional on any given first order belief with the (sparse) empirical distributions we observe.

3. Given second and third order beliefs, we can calculate a respondent's subjective expected utility from reporting the truth (her stated first order belief) and from any other report.[41] Specifically, we assume that the report the respondent has given is her true belief and calculate her payment. Holding constant her own second order belief and the first and second order beliefs of her peers, we then calculate her payments for every other possible report she could have given.

The results from this exercise are presented in Figure 2 below. Column 1 of the figure depicts the percentage of instances in which telling the truth gives the largest payment, column 2 depicts the percentage of instances that telling the truth results in the second largest payment, etc. Taking the graph at face value, telling the truth maximizes the respondent's subjective expected utility in about 35% of instances and it minimizes her subjective expected utility in only about 10% of instances. An ideal graph would place all of its weight in the first column.

Figure 2: Incentive Compatibility of RBTS Using Collected Data

The observed departure from this ideal may be due to the failure of our assumptions required by RBTS holding in practice, or by our noisy approximation of third order beliefs. To evaluate this, we perform a simulation in which we generate data that perfectly abides by all of the assumptions required for the incentive compatibility of RBTS. We generate groups of artificial agents, each of

posterior belief. We stress here that we elicited ranks and not signals. Therefore two agents who report the same rank do not necessarily have the same posterior as the rank is a coarse measure of a signal.

[41] Notice that we only utilize incentivized data since it is only for these data that we collected second order beliefs.

whom holds a common prior and receives a signal about the skill level of their peers. Agents update their priors based on these signals and these form the basis of their second and third order beliefs, each of which we can compute.

Because the data is generated to be perfectly consistent with the assumptions of RBTS, the agent always maximizes his expected utility by telling the truth. Next we compress our simulation data to correspond exactly to the data we collected from our respondents: just first and second order beliefs about group rank. This allows us to have two data sets (collected and simulated) that contain identical level of detail. We then generate the same graph as we did for our collected data and present it in Figure 3.

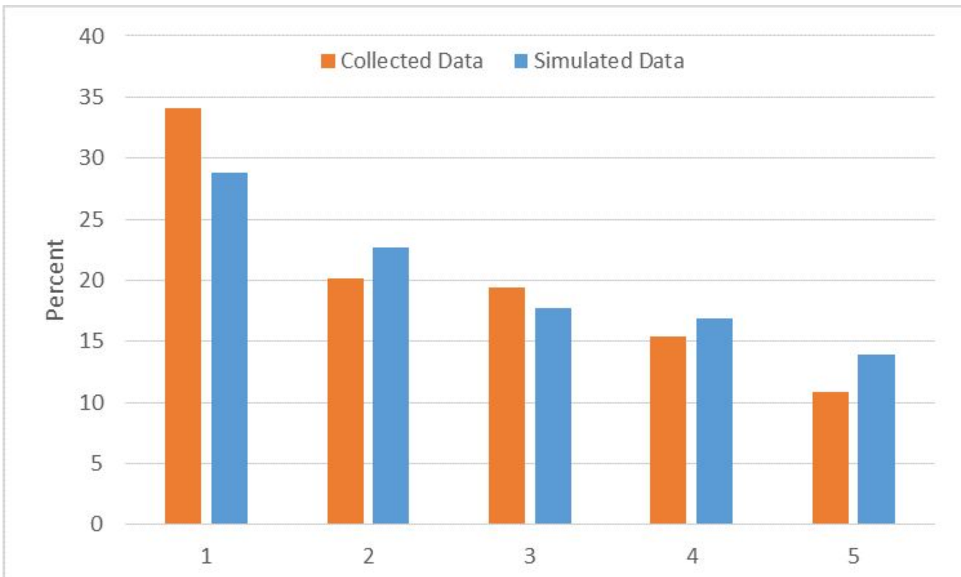


Figure 3: Incentive Compatibility of RBTS Using Collected and Simulated Data

The graph produced with the collected and with the simulated data are strikingly similar. We therefore conclude that our noisy approximation of third order beliefs could be to blame for the observed weights in columns 2 through 5, and argue that our test yields the strongest evidence in favor of the incentive compatibility that could be achieved via this method. Therefore, telling respondents that they will maximize their expected payments by reporting truthfully may indeed be good advice.

Entrepreneurial Psychology

Impulsiveness:

- I plan tasks carefully.
- I make up my mind quickly

- I save regularly.

Optimism:

- In uncertain times I usually expect the best.
- If something can go wrong for me, it will.
- I'm always optimistic about my future.
- Generally speaking, most people in this community are honest and can be trusted

Locus of Control

- A person can get rich by taking risks.
- I only try things that I am sure of.

Tenacity

- I can think of many times when I persisted with work when others quit
- I continue to work on hard projects even when others oppose me.

Polychronicity:

- I like to juggle several activities at the same time
- I would rather complete an entire project every day than complete parts of several projects.
- I believe it is best to complete one task before beginning another.

Achievement

- Part of my enjoyment in doing things is improving my past performance
- If given the chance, I would make a good leader of people.

Organized person:

- My family and friends would say I am a very organized person

Intuition for Machine Learning Prediction

Regression Tree/Forest The regression tree algorithm has two major tasks: (1) decide how to split the data at each step and (2) decide when to stop splitting. Broadly, the algorithm will consider every value of every covariate as a possible split point. To decide on the first split, the algorithm systematically partitions the data at each value of each of the covariates and computes the goodness of fit criterion for either side of the partition. It picks the split where the goodness of fit criterion is optimized. As a specific example, suppose there are j covariates and the goodness-of-fit criterion is the mean square error $\frac{1}{N}\sum_{i=1}^{n}(\bar{y}-y_i)^2$ where $\bar{y}$ is the average value of y within a partition.[42] The algorithm will choose covariate j and $X_{ij}=s$ such that the following function is minimized

$\frac{1}{N}\sum_{i:X_{ij}<s}(\bar{y}-y_i)^2+\frac{1}{N}\sum_{i:X_{ij}\geq s}(\bar{y}-y_i)^2$

For the second split, the algorithm will perform the same search but separately for $X_{ij}<s$ and $X_{ij}\geq s$. In each subsequent node, the data in the leaf will be split in the same manner to minimize mean squared error until a limit is reached. One important thing to note is that the algorithm is "greedy:" it does not search for partitions to globally minimize the mean squared error of all X_{ij}. To form a prediction, the algorithm computes $\bar{y}$ at each terminal leaf. [43] To deal with the problem of overfitting , the researcher can use cross-validation techniques to determine the optimal place to stop splitting.

A regression forest extends the regression tree algorithm using a bootstrapping technique. The algorithm selects (with replacement) a subset of all covariates and a subset of the data to grow a tree. This process is repeated for a user-selected number of trees. If there are B trees grown and observation i appears in $\{b : b \leq B\}$ trees, then to make a prediction for observation i the algorithm computes $\frac{1}{b}\sum_{n=1}^{b}\bar{y}_{in}$ where $\bar{y}_{in}$ is the average value of y in the leaf of tree n where observation i ends up.

Cross Validation Exercise

We partition the training (Sri Lanka or India) data into 5 non-overlapping parts. A very important part of this partitioning is that we have a panel data set and so all observations for one person have to fall in the same partition. We build a tree using the first 4 "training" folds and estimate model fit on the 5th "test" fold for a range of minimum node sizes. To estimate model performance, we estimate the following linear regression

$$Y_{ijt}=\beta_0+\beta_1(\hat{MR}*Winner)_{ij}+\beta_2(\hat{MR})_{ij}+\beta_3(Winner)_{ij}+\epsilon_{ij} \tag{7}$$

where Y_{ijt} are the observed post-treatment profits for the "test" fold and $\hat{MR}$ is the predicted marginal return for each individual in the "test" fold (using the model estimated in the "training" folds). For each node size, we record β_1. We begin this process leaving out 1 fold and training on the other 4 until the model has been tested on all 5 folds (so we have 5 total iterations of this process with a 5-fold partition). For each node size, we compute $\bar{\beta}_{1n}=\frac{1}{5}\sum_{f=1}^{5}\beta_{1nf}$ where β_{1nf} is the value of $\beta_1$for minimum node size n in test fold f. We select the minimum node size in which

[42] $\bar{y}=argmin_{\hat{y}}\ (\frac{1}{N}\sum_{i=1}^{n}(\hat{y}-y_i)^2)$

[43] For example, the minimum number of observations within a leaf. The fewer the minimum allowable number of observations within a leaf, the greater the number of splits the algorithm can perform.

the $\bar{\beta}_{1n}$ is highest. The intuition is that we would like to pick the model that allows us to estimate the biggest treatment effect in a test dataset.

Figure 1: Randomization Design

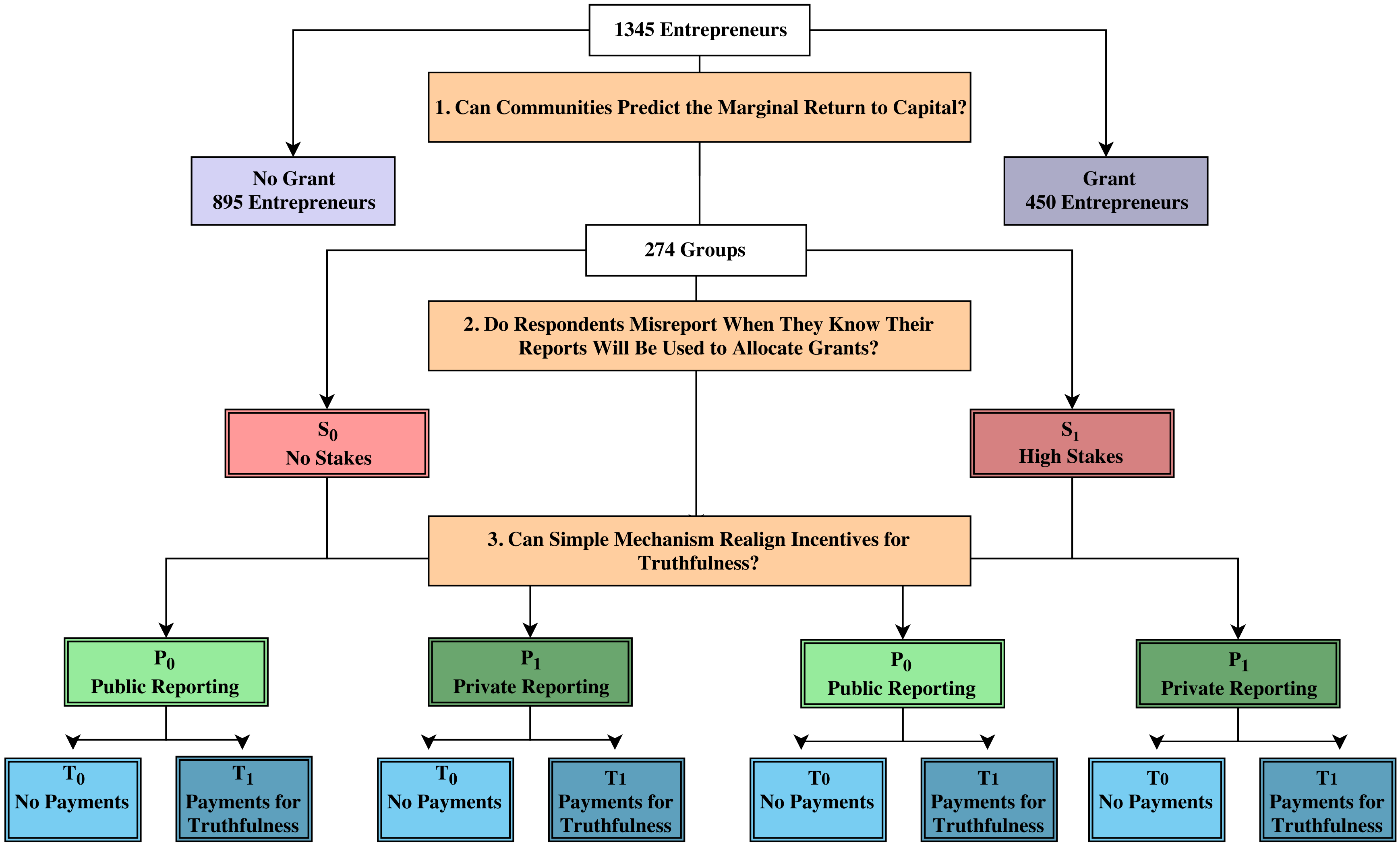


Figure 2: Timeline

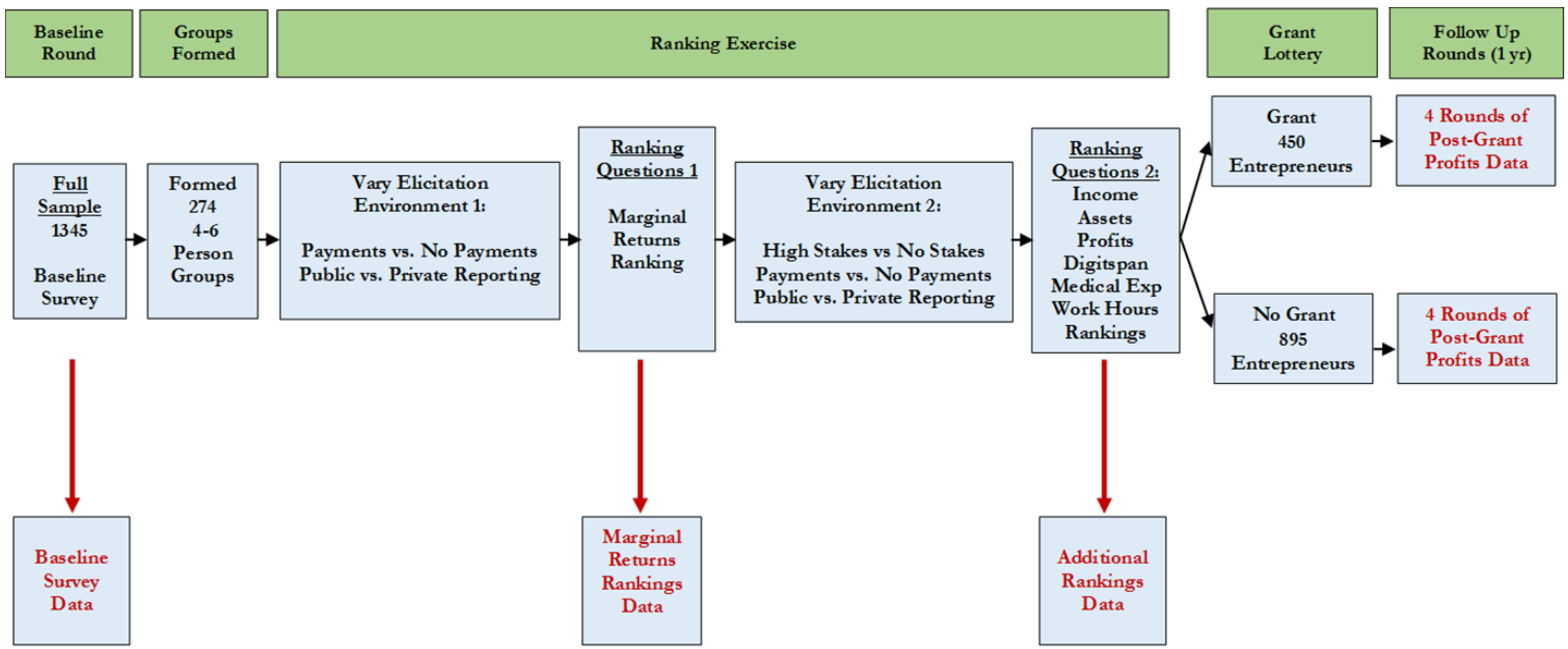
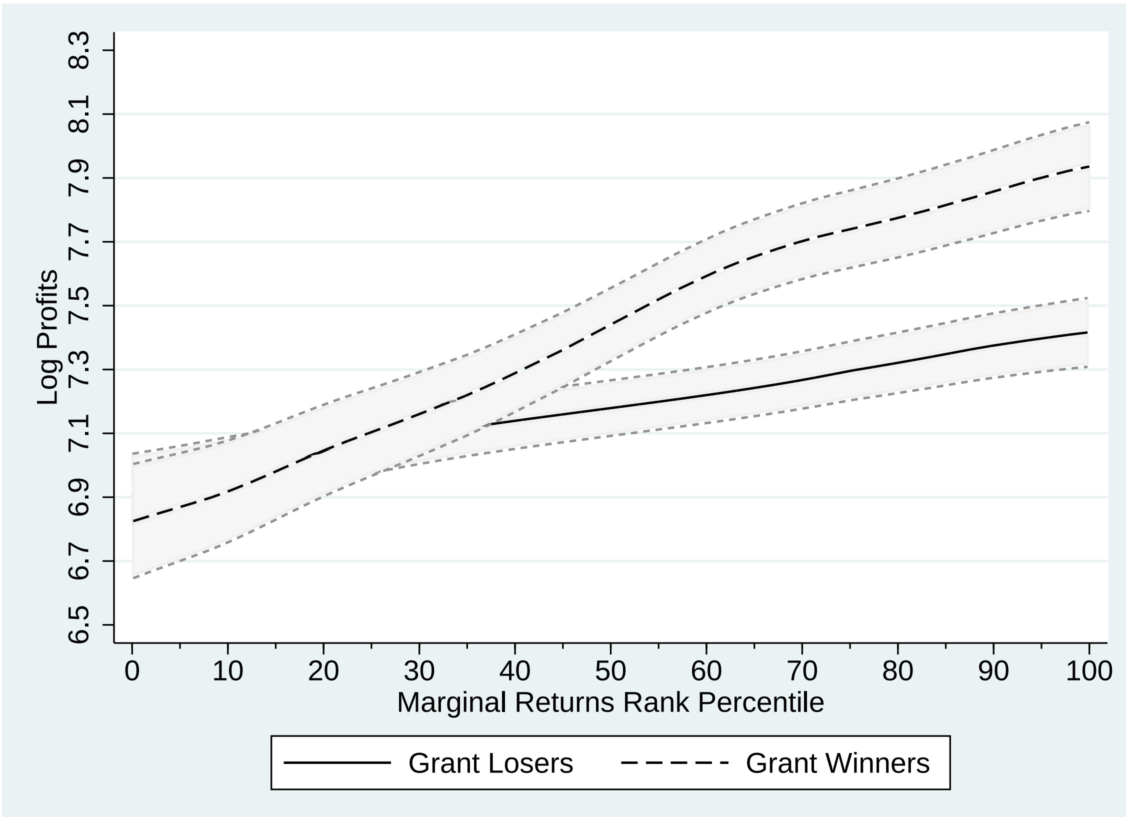


Figure 3: Marginal Returns to the Grant by Percentile of the Average Community Ranks Distribution



Notes: This figure plots two kernel-weighted local polynomial regressions of log profits on the marginal returns rank percentile, estimated separately for respondents who won and respondents who did not win grants. Log profits is the log value of average profits in the post grant disbursal periods. The marginal returns rank percentile is the percentile of the average rank assigned to person i by all of her peers in her group. 90% confidence bands are shown.

Table 1: Average Return to the Grant

	(1) Income	(2) Log Income	(3) Profits	(4) Log Profits
Winner	422.328	0.063	507.658*	0.279**
	(328.951)	(0.081)	(264.758)	(0.124)
Mean of Outcome for Grant Losers	8315.92	8.63	4608.60	7.37
	[6622.20]	[1.39]	[5183.78]	[2.51]
N	5323	5341	5307	5325
No. Obs	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). The unit of observation is the household. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. All regressions are weighed by the inverse number of lottery tickets a respondent received. Data in this table come from rounds 1-4 of data collection.

Table 2: Do Peer Reports Predict True Marginal Returns to Grants?

	(1) Income	(2) Log Income	(3) Profits	(4) Log Profits
Panel A: Rank Value				
Winner*Rank	836.944**	0.194**	296.549	0.428***
	(375.646)	(0.086)	(240.956)	(0.150)
Winner	-2491.763*	-0.613**	-524.477	-1.210**
	(1341.987)	(0.304)	(810.172)	(0.538)
Panel B: Rank Tercile				
Winner*Top Tercile Rank	1562.015**	0.436**	1001.836**	0.835***
	(628.584)	(0.170)	(431.784)	(0.255)
Winner*Middle Tercile Rank	34.524	0.114	-21.096	0.271
	(643.052)	(0.143)	(383.341)	(0.261)
Winner	-176.407	-0.138	139.500	-0.123
	(477.986)	(0.123)	(306.991)	(0.206)
P-value from F-Test				
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.024**	0.039**	0.026**	0.015**
Mean of Outcome for Grant Losers	8204.29	8.62	4578.28	7.35
	[6431.06]	[1.35]	[5173.75]	[2.52]
N	5323	5341	5307	5325
No. HHs	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Rank indicates the average ranking the entrepreneur was given by her peers for the marginal returns to grant ranking question. Top (Middle) Tercile Rank is a dummy for whether the entrepreneur is in the top (middle) tercile of the average marginal return rank distribution. Winner indicates that the household is a grant recipient after baseline (after round 1 of data collection). The unit of observation is the household. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. All regressions are weighed by the inverse number of lottery tickets a respondent received. Data in this table come from rounds 1-4 of data collection.

Table 3: Impact of Grant on Business Inputs

	Business Assets		Owner Labor		Household and Non-Household Labor					
	(1) Business Inventory	(2) Durable Business Assets	(3) Total Hours Worked Past Week	(4) Total Days Worked Past Month	(5) Uses Household Labor	(6) Household Labor Hours Past Week	(7) Household Labor Wage Bill Past Week	(8) Uses Non-Household Labor	(9) Household Labor Hours Past Week	(10) Non-Household Labor Wage Bill Past Week
Winner*Top Tercile Rank	1181.524	9041.525**	7.954***	1.913**	0.081*	5.236**	77.337	0.061*	5.874	244.503
	(966.431)	(3915.829)	(2.531)	(0.951)	(0.047)	(2.453)	(59.607)	(0.035)	(3.597)	(195.498)
Winner*Middle Tercile Rank	748.549	3801.906	2.041	0.987	0.061	3.583	75.034	-0.013	2.031	240.877
	(668.188)	(3197.899)	(2.648)	(0.955)	(0.049)	(2.217)	(59.177)	(0.036)	(4.082)	(290.729)
Winner	-367.225	-2200.190	-3.299	-0.680	-0.015	-3.931**	-55.217	-0.008	-2.198	-67.979
	(472.492)	(2040.598)	(2.204)	(0.770)	(0.034)	(1.844)	(60.019)	(0.026)	(2.610)	(153.985)
P-value from F-Test										
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.681	0.219	0.015**	0.303	0.700	0.436	0.754	0.056*	0.420	0.991
Mean of Outcome for Grant Losers	4799.10	39544.00	37.19	21.28	0.19	5.19	12.65	0.09	6.99	270.51
	[12351.64]	[89243.94]	[25.68]	[8.47]	[0.39]	[16.20]	[251.15]	[0.29]	[37.06]	[1709.47]
N	5301	5293	5228	5191	2672	2672	2672	2672	2672	2672
No. HHs	1335	1331	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Rank indicates the average ranking the entrepreneur was given by her peers for the marginal returns to grant ranking question. Top (Middle) Tercile Rank is a dummy for whether the entrepreneur is in the top (middle) tercile of the average marginal return rank distribution. Winner indicates that the household is a grant recipient after baseline (after round 1 of data collection). The unit of observation is the household. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. All regressions are weighed by the inverse number of lottery tickets a respondent received. The number of observations in columns 1-4 varies due to missing outcome data across the rounds and missing baseline covariates data. Data for these columns come from rounds 1-4 of data collection. Variables reported in columns 5-10 were only collected at baseline and in round 4.

Table 4: Baseline Differences Between Top, Middle, and Bottom-Ranked Entrepreneurs

	Mean	Difference from Column 1	
	(1) Bottom Tercile Rank	(2) Middle Tercile Rank	(3) Top Tercile Rank
Panel A: Entrepreneur Characteristics			
Male	0.606	-0.007	0.082***
Education	6.056	0.923***	0.234
Married	1.318	-0.053	-0.103**
Age	42.219	-1.051	-2.017***
Digitspan	4.969	0.153	0.569***
Wage to Exit Self-Employment	11426.573	874.195	2037.982***
Total Hours Worked Past Week	39.139	2.466	4.880***
Total Days Worked Past Month	22.015	0.897*	1.092*
Entrepreneur in 5 Yrs	0.817	0.033	0.020
Panel B: Enterprise Characteristics			
Business Type- Manufacturing	0.221	0.033	0.018
Business Type- Retail	0.298	0.031	0.049
Business Type- Service	0.244	-0.029	-0.030
Business Type- Piecerate	0.092	-0.020	-0.029
Business Type- Livestock	0.066	-0.027*	-0.035***
Business Type- Food Preparation	0.053	0.015	0.031*
Business Type- Construction	0.025	-0.004	-0.005
Business Type- Agricultural	0.000	0.002	0.002
Business Uses HH Labor	0.188	0.034	0.033
Business Uses Non-HH Labor	0.064	0.030	0.042**
Monthly Change in Sales Since 2013	345.064	186.634	392.329***
Panel C: Household Characteristics			
Household Size	3.700	0.123	0.105
No. Children 0-5	0.419	0.005	-0.037
No. Children 6-12	0.518	0.006	0.047
Total No. HH Businesses	1.117	0.044*	0.012
No. Salaried HH Members	0.498	-0.067	-0.075
No. Daily Wage HH Members	0.364	-0.092**	-0.179***
Business Capital	32303.541	37304.982**	17360.417**
Value of HH Assets	352368.600	167170.070***	154333.204***
Avg. Monthly Profits	4052.594	892.914***	1618.088***
Avg. Monthly Income	8267.387	150.909	1150.834***

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Notes: Data in this table come from round 1 (baseline) of data collection. The characteristics in Panels A and B are of the entrepreneur that was ranked in the elicitation exercise. Standard errors are clustered at group level. The model includes neighborhood cluster, surveyor, and date of survey fixed effects.

Table 5: Marginal Returns to Grants with Baseline Controls

	(1) Income	(2) Income	(3) Log Income	(4) Log Income	(5) Profits	(6) Profits	(7) Log Profits	(8) Log Profits
Winner*Top Tercile Rank	1323.464**	2018.212***	0.392**	0.466***	1131.549***	1590.046***	0.923***	0.988***
	(578.922)	(549.848)	(0.165)	(0.168)	(414.820)	(365.432)	(0.240)	(0.235)
Winner*Middle Tercile Rank	-108.850	463.308	0.082	0.132	144.744	506.769	0.307	0.346
	(603.640)	(569.329)	(0.151)	(0.149)	(385.168)	(337.918)	(0.251)	(0.257)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.026**	0.009***	0.037**	0.024**	0.023**	0.006***	0.006***	0.004***
Mean of Outcome for Grant Losers	8204.29	8204.29	8.62	8.62	4578.28	4578.28	7.35	7.35
	[6431.06]	[6431.06]	[1.35]	[1.35]	[5173.75]	[5173.75]	[2.52]	[2.52]
Controls	Loan Officer	All	Loan Officer	All	Loan Officer	All	Loan Officer	All
N	5304	5252	5322	5270	5287	5235	5305	5253
No. HHs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Rank indicates the average ranking the entrepreneur was given by her peers for the marginal returns to grant ranking question. Top (Middle) Tercile Rank is a dummy for whether the entrepreneur is in the top (middle) tercile of the average marginal return rank distribution. Winner indicates that the household is a grant recipient after baseline (after round 1 of data collection). The unit of observation is the household. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. All regressions are weighed by the inverse number of lottery tickets a respondent received. Regressions in the odd columns include Winner interacted with the following controls: gender, education, married, age, digitspan, household size, household demographics, number of fixed salary, daily wage, and self-employed workers, and business type. The regressions in the even columns include Winner interacted with all the variables listed in Table 4. Data in this table come from rounds 1-4 of data collection.

Table 6: Marginal Returns Predictions Using Machine Learning versus Community Information

	(1) Profits	(2) Profits	(3) Profits	(4) Profits	(5) Profits	(6) Profits
Winner*Top Tercile Rank	998.393**	1664.656***		935.745**		913.976**
	(446.935)	(353.060)		(436.108)		(421.854)
Winner*Middle Tercile Rank	-14.943	508.743		35.283		102.824
	(384.689)	(316.359)		(375.735)		(388.895)
Winner*ML Top Tercile Rank (SL)			879.408*	773.144		
			(516.550)	(493.098)		
Winner*ML Middle Tercile Rank (SL)			-24.786	-11.024		
			(415.525)	(410.948)		
Winner*ML Top Tercile Rank (In)					1824.006***	1713.140***
					(540.102)	(521.392)
Winner*ML Middle Tercile Rank (In)					908.860**	964.417**
					(369.302)	(373.717)
Winner	131.673		247.506	-98.014	-351.706	-721.956*
	(310.397)		(380.534)	(419.081)	(340.445)	(409.415)
ML Trained In?			Sri Lanka	Sri Lanka	India	India
Prediction Test			Out-of-Sample	Out-of-Sample	In -Sample	In -Sample
Mean of	4606.95	4606.95	4606.95	4606.95	4606.95	4606.95
Outcome	[5184.05]	[5184.05]	[5184.05]	[5184.05]	[5184.05]	[5184.05]
N	5307	5271	5307	5307	5307	5307
No. HHs	1336	1336	1336	1336	1336	1336

The first column replicates the main regression in Column 6 of Table 2. The second column replicates Column 6 of Table 5 The estimates (and number of observations) differ slightly to ensure a comparable sample with the machine learning exercise. So in the replication of Table 5 column 6, we only control for the variables that we use in the machine learning exercise (a subset of the variables used in Table 5). The ML Top Tercile Rank (SR) and ML Middle Tercile Rank (SR) are dummy variables for the top and middle tercile ranks of a marginal returns prediction generated by a generalized method of forests algorith. The model is trained using data from the Sri Lanka experiment. Cross-validation yields an optimal minimum node size of 15 and the model is produced by growing 10000 trees. The ML Top Tercile Rank (In) and ML Middle Tercile Rank (In) are dummy variables for the top and middle tercile ranks of a marginal returns prediction generated by a generalized method of forests algorith. The model is trained using data from the India experiment (therefore this is an in-sample estimate). Cross-validation yields an optimal minimum node size of 150 and the model is produced by growing 10000 trees. All models include surveyor, and date of survey fixed effects. Standard errors are clustered at the group level.

Table 7: What Respondents Know: Average Regressions in Percentiles

	(1) Income [Quintile]	(2) Income [Zero-Sum]	(3) Profits [Quintile]	(4) Profits [Zero-Sum]	(5) Assets [Quintile]	(6) Assets [Zero-Sum]	(7) Medical Exp. [Zero-Sum]	(8) Digitspan [Zero-Sum]	(9) Work Hours [Zero-Sum]
Panel A: Individual Rank Percentile									
Rank	0.135***	0.138***	0.106***	0.145***	0.133***	0.154***	0.103***	0.157***	0.067**
	(0.019)	(0.019)	(0.017)	(0.017)	(0.019)	(0.020)	(0.030)	(0.025)	(0.030)
N	4375	5051	4651	5116	4153	4887	1281	1362	1349
Panel B: Average Rank Percentile									
Average Rank	0.236***	0.218***	0.202***	0.246***	0.221***	0.233***	0.214***	0.280***	0.125**
	(0.032)	(0.029)	(0.035)	(0.029)	(0.032)	(0.030)	(0.061)	(0.040)	(0.061)
N	895	1029	942	1038	848	996	263	281	276
Panel C: Average Rank Level									
Average Rank Level	2140.556***	1753.333***	1482.495***	1643.552***	1.47e+05***	1.14e+05***	1335.464***	0.614***	3.875**
	(336.908)	(243.923)	(293.108)	(226.175)	(30157.622)	(22224.829)	(471.463)	(0.094)	(1.530)
Mean of Outcome	8870.25	8802.26	6872.76	6951.65	473101.96	477499.21	2866.78	5.19	47.69
	[6868.28]	[6826.21]	[6066.39]	[5965.52]	[729425.49]	[711400.77]	[5389.32]	[1.69]	[21.09]
N	895	1029	942	1038	848	996	263	281	276
No. HHs	895	1029	942	1038	848	996	263	281	276

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Data in this table come from round 1 (baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The outcome variable is the percentile of the outcome in the column header. The regressor is the percentile of the average rank given to a respondent, computed by question. The level of observation is the rankee. The number of observations varies across questions because each respondent answered only a subset of the questions. See the Implementation Appendix for details.

Table 8: Do Respondents Distort Responses?

	(1) Questions [Pooled]	(2) Questions [Quintile]	(3) Questions [Zero-Sum]	(4) Questions [Pooled]	(5) Questions [Quintile]	(6) Questions [Zero-Sum]
Rank	0.162***	0.159***	0.165***			
	(0.016)	(0.017)	(0.018)			
Rank*High Stakes	-0.056***	-0.065***	-0.050**			
	(0.021)	(0.024)	(0.023)			
Average Rank				0.252***	0.264***	0.246***
				(0.024)	(0.030)	(0.025)
Average Rank*High Stakes				-0.060*	-0.090**	-0.040
				(0.033)	(0.042)	(0.035)
Reports	Individual	Individual	Individual	Average	Average	Average
N	32225	13179	19046	6568	2685	3883
No. Obs	1336	1336	1336	1336	1336	1336

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Notes: Data in this table comes from Round 1 (Baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The left hand side variable is the percentile of the outcome in question. The regressor is the percentile of the average rank given to a respondent, computed by question. The level of observation is the ranker-rankee in Columns 1-3 and the rankee in Columns 4-6.

Table 9: Who Do Respondents Favor in High Stakes?

	(1) Questions [Pooled]	(2) Questions [Pooled]	(3) Questions [Pooled]	(4) Questions [Quintile]	(5) Questions [Quintile]	(6) Questions [Quintile]	(7) Questions [Zero-Sum]	(8) Questions [Zero-Sum]	(9) Questions [Zero-Sum]
Rank*High Stakes	-0.059*	-0.149**	-0.058	-0.086**	-0.153**	-0.042	-0.039	-0.149**	-0.068*
	(0.032)	(0.061)	(0.036)	(0.042)	(0.076)	(0.042)	(0.033)	(0.067)	(0.040)
Rank	0.189***	0.256***	0.157***	0.180***	0.230***	0.136***	0.195***	0.287***	0.170***
	(0.022)	(0.036)	(0.026)	(0.030)	(0.044)	(0.029)	(0.023)	(0.040)	(0.029)
Who is Ranked?	Self	Family	Close Peer (CR)	Self	Family	Close Peer (CR)	Self	Family	Close Peer (CR)
N	6538	2521	6921	2673	1044	2839	3865	1477	4082
No. Obs	671	207	445	671	207	445	671	207	445

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Data in this table come from round 1 (baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The outcome variable is the percentile of the outcome in the column header. The regressor is the percentile of the average rank given to a respondent, computed by question. The level of observation is the rankee. In each of the columns, the sample is limited to the observations specified in the "Who is Ranked?" row. For example, in Column 1, the observations are limited to the reports that the ranker gives about herself. In column 2, they are limited to the ranks that a family member gives about the rankee. The Close Peer (CR) variable indicates whether the ranker is predicted to be a close friend of the rankee by other group members.

Table 10: How Do Payments for Truthfulness and Public Reporting Affect Responses?

	(1) Questions [Pooled]	(2) Questions [Pooled]	(3) Questions [Pooled]	(4) Questions [Pooled]
Average Rank	0.212***	0.158***	0.141***	0.116**
	(0.036)	(0.041)	(0.046)	(0.047)
Average Rank*Public	0.003	0.002	0.166**	0.027
	(0.052)	(0.060)	(0.064)	(0.058)
Average Rank*Payments	-0.023	-0.079	0.141**	0.142**
	(0.061)	(0.065)	(0.067)	(0.071)
Average Rank*Payments*Public	-0.025	0.045	-0.243**	-0.118
	(0.091)	(0.098)	(0.094)	(0.098)
Who is Ranked?	Self	Self	Not Self	Not Self
Treatment	[No Stakes]	[High Stakes]	[No Stakes]	[High Stakes]
N	3241	3297	3254	3310
No. Obs	1330	1330	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Data in this table comes from Round 1 (Baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The left hand side variable is the percentile of the outcome in question. The regressor is the percentile of the average rank given to a respondent, computed by question. The level of observation is the rankee.

Table 11: How Does Public Reporting Affect Family Rankings in No Stakes and High Stakes?

	(1) Rank	(2) Rank	(3) Rank
Family	0.459***	0.250**	0.364***
	(0.140)	(0.124)	(0.095)
Family*Public	-0.548***	-0.076	-0.320**
	(0.162)	(0.184)	(0.125)
Who is Ranked?	All	All	All
Sample	No Stakes	High Stakes	Pooled
N	5905	6109	12014
No. Obs	338	338	676

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Notes: Data in this table comes from Round 1 (Baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The outcome variable is the rank assigned by the ranker to the rankee. The level of observation is the ranker-rankee.

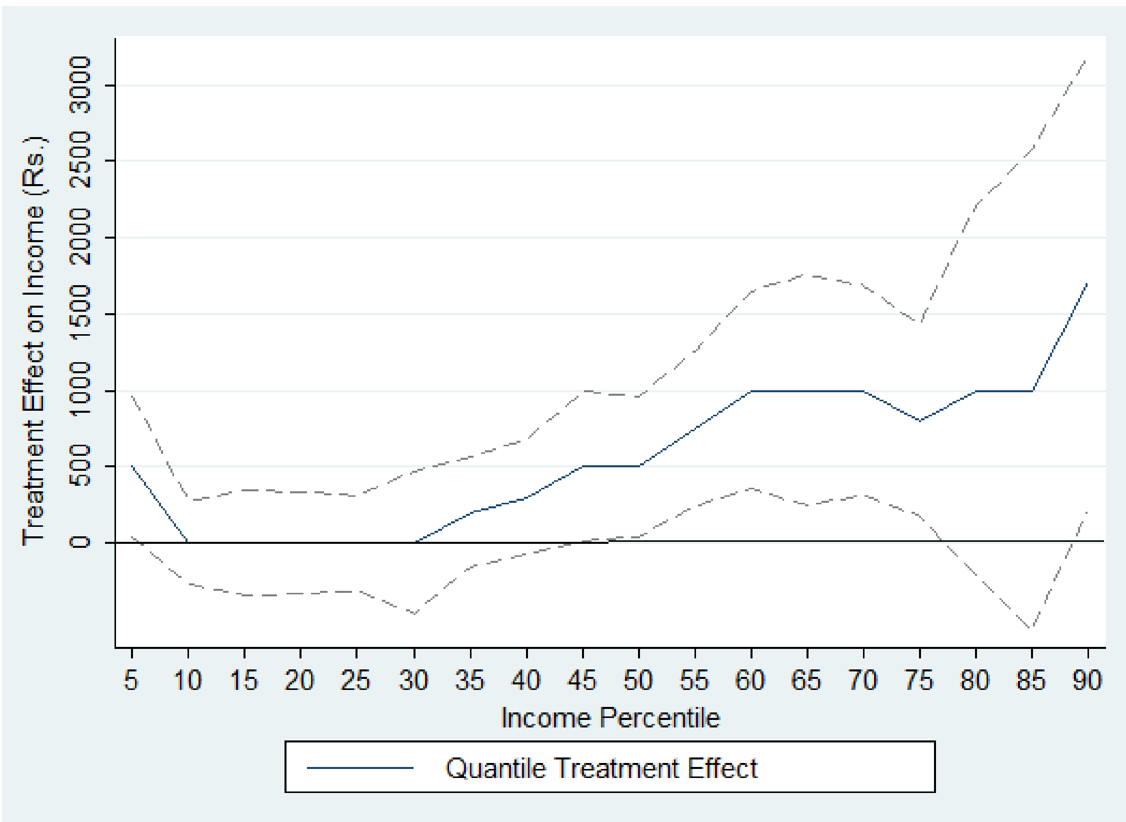
Table 12: Cross Report: Can Respondents Identify Who Has the Best Information?

	(1) Questions [Pooled]	(2) Questions [Quintile]	(3) Questions [Zero-Sum]	(4) Income [Quintile]	(5) Income [Zero-Sum]	(6) Profits [Quintile]	(7) Profits [Zero-Sum]	(8) Assets [Quintile]	(9) Assets [Zero-Sum]
Rank*Cross Report	0.074*	0.065	0.083	0.282***	0.059	0.053	0.090	-0.036	0.105
	(0.042)	(0.056)	(0.058)	(0.103)	(0.075)	(0.078)	(0.104)	(0.080)	(0.120)
Rank	0.132***	0.121***	0.144***	0.127***	0.136***	0.099***	0.144***	0.135***	0.151***
	(0.012)	(0.012)	(0.013)	(0.018)	(0.019)	(0.017)	(0.018)	(0.019)	(0.021)
Cross Report	-0.054*	-0.047	-0.062	-0.214**	-0.019	-0.028	-0.176***	0.026	-0.011
	(0.031)	(0.047)	(0.039)	(0.108)	(0.062)	(0.061)	(0.058)	(0.062)	(0.070)
Mean of Outcome	0.51	0.51	0.51	8870.25	8802.26	6872.76	6951.65	473101.96	477499.21
	[0.29]	[0.29]	[0.29]	[6868.28]	[6826.21]	[6066.39]	[5965.52]	[729425.49]	[711400.77]
N	28233	13179	15054	4375	5051	4651	5116	4153	4887
No. HHs	1344	1344	1344	895	1029	942	1038	848	996

Notes: Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The outcome variable is the percentile of the outcome in the column header. The regressor is the percentile of the average rank given to a respondent, computed by question. * p≤ 0.10, ** p≤ 0.05, *** p≤ 0.10. The outcome variable is the level of the outcome in the column header. The regressor is the percentile of the rank given to a respondent by each group member, computed by question. The level of observation is the ranker-rankee pair for each question.

1 Appendix Figures and Tables

Figure 1: Quantile Treatment Effects



Notes: This figure plots the quantile treatment effects obtained from quantile regressions from the 5th to the 95th quantile. The regressions include surveyor, survey month, and survey round fixed effects. Standard errors are clustered at the group level. The 90% confidence bands are represented by the dotted lines.

Table A1: Balance Check

	(1) No Stakes Mean	(2) Stakes Difference	(3) No Incentives Mean	(4) Incentive Difference	(5) Private Mean	(6) Public Difference	(7) Grant Loser Mean	(8) Grant Winner Difference	(9) N
Panel A: Individual Characteristics of Ranked Entrepreneur									
Male	0.603	0.038	0.641	-0.038	0.621	0.008	0.627	0.001	1345
Education	7.338	-1.455	7.355	-1.449	5.849	1.732	7.197	-1.880	1345
Married	1.269	-0.016	1.243	0.053	1.257	0.014	1.262	0.009	1345
Age	40.538	1.122	41.046	0.238	40.862	0.643	41.078	0.190	1345
Digitspan	5.275	-0.086	5.260	-0.001	5.244	0.016	5.226	0.051	1341
Wage Exit Self-Employment	13300.000	-785.744	12869.766	-623.592	13081.670	-923.951	12681.903	-250.374	1345
Total Hours Worked Past Week	44.228	2.773	40.566	-0.716	40.434	0.537	40.088	0.638	1345
Total Days Worked Past Month	24.930	0.309	23.779	0.024	23.600	0.713	23.413	-0.117	1345
Panel B: Characteristics of Ranked Entrepreneur's Business									
Business Type- Manufacturing	0.257	-0.026	0.245	-0.003	0.238	0.004	0.240	0.004	1345
Business Type- Retail	0.322	0.005	0.317	0.020	0.334	-0.011	0.333	-0.015	1345
Business Type- Service	0.221	-0.018	0.217	0.008	0.226	-0.016	0.215	0.008	1345
Business Type- Piecerate	0.079	-0.003	0.064	0.024	0.064	0.023	0.084	-0.017	1345
Business Type- Livestock	0.031	0.022**	0.048	-0.015	0.044	-0.004	0.045	-0.009	1345
Business Type- Food Preparation	0.058	0.028*	0.083	-0.027*	0.071	0.000	0.056	0.044***	1345
Business Type- Construction	0.022	-0.004	0.024	-0.008	0.022	-0.002	0.023	-0.007	1345
Business Type- Agricultural	0.001	-0.000	0.000	0.003	0.000	0.004	0.002	-0.002	1345
Panel C: Household Characteristics									
Household Size	3.802	-0.034	3.748	0.058	3.811	-0.072	3.798	-0.052	1345
No. Children 0-5	0.457	-0.088**	0.380	0.058	0.417	-0.022	0.427	-0.050	1345
No. Children 6-12	0.491	0.083	0.565	-0.057	0.541	-0.024	0.569	-0.106**	1345
No. Salaried HH Members	0.472	-0.061	0.426	0.053	0.446	-0.002	0.451	-0.013	1345
No. Daily Wage HH Members	0.284	-0.008	0.263	0.005	0.288	-0.031	0.283	-0.047	1345
Value of Business Assets	41086.113	24844.256	43151.760	21275.818	50360.009	-37668.828	40335.965	-15605.551	1345
Value of HH Assets	468091.306	48287.088	507025.233	-38965.522	505787.755	-84931.194*	486671.570	-48525.608	1345
Avg Monthly Profits	4981.301	161.486	5133.479	-102.735	4986.993	-161.331	4943.973	-15.907	1345
Avg Monthly Income	9030.522	-456.278	9051.766	-684.276*	8763.702	-27.021	8551.450	702.572	1345
P-Value Joint F-Test		.26		.43		.67		.20	

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Data in this table comes from Round 1 (Baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects.

Table A2: ANCOVA Average Returns to the Grant

	(1) Trim Income	(2) Log Income	(3) Trim Profits	(4) Log Profits
Winner	599.828**	0.036	312.999*	0.186*
	(241.962)	(0.052)	(173.209)	(0.101)
Mean of Outcome	8293.19	8.59	4517.65	7.25
	[6698.77]	[1.48]	[5001.28]	[2.66]
N	5317	5341	5270	5293
No. Obs	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A3: ANCOVA Returns by MR Rank

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	485.348		0.144*		596.619**		0.354**	
	(359.518)		(0.086)		(271.739)		(0.160)	
Winner*Top Tercile Rank		1622.271**		0.360**		1520.385***		0.698***
		(652.502)		(0.142)		(518.959)		(0.266)
Winner*Middle Tercile Rank		1226.988**		0.314**		584.621		0.301
		(519.885)		(0.142)		(371.557)		(0.268)
Winner	-1087.047	-394.678	-0.445	-0.181	-1758.620**	-431.006	-1.012*	-0.131
	(1190.689)	(390.060)	(0.308)	(0.112)	(877.383)	(261.660)	(0.575)	(0.211)
MR Rank	703.283***		0.110**		602.713***		0.289***	
	(205.549)		(0.052)		(162.869)		(0.103)	
Baseline Income	0.414***	0.414***						
	(0.037)	(0.037)						
Top Tercile Rank		543.315		0.110		722.048**		0.388**
		(336.256)		(0.078)		(288.742)		(0.161)
Middle Tercile Rank		-421.580		-0.055		45.287		0.184
		(319.509)		(0.079)		(267.123)		(0.153)
Baseline Log Income			0.232***	0.234***				
			(0.037)	(0.037)				
Baseline Profits					0.356***	0.360***		
					(0.085)	(0.085)		
Baseline Log Profits							0.439***	0.444***
							(0.039)	(0.039)
Linear Combination of Estimates								
Effect at Avg Rank	594.029**		0.053		307.860		0.214**	
	(252.78)		(0.05)		(187.37)		(0.10)	
Effect 1 SD Below	271.933		-0.043		-88.080		-0.021	
	(288.30)		(0.08)		(196.63)		(0.16)	
Effect 1 SD Above	916.125**		0.148**		703.800**		0.449***	
	(398.15)		(0.07)		(310.80)		(0.14)	
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.513		0.707		0.050**		0.083*
Mean of	8315.92	8315.92	8.63	8.63	4608.60	4608.60	7.37	7.37
Outcome	6622.20	6622.20	1.39	1.39	5183.78	5183.78	2.51	2.51
N	3987	3987	4005	4005	3952	3952	3969	3969
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A4: Do Marginal Returns Ranks Predict the True Marginal Returns to the Grant?

	(1) Rs. Added to Grant Amount	(2) Business Expenditures	(3) Inventory	(4) Equipment	(5) Labor	(6) Other Business Expenditures	(7) Household Expenditures	(8) Loan Repayment	(9) Household Repairs	(10) Other Household Expenditures	(11) Amt of Grant Saved
Top Tercile Rank	503.320	903.051***	692.839**	183.343	-4.119	30.987	-557.747**	-2.977	61.071	-615.840***	-357.152*
	(408.262)	(276.894)	(308.220)	(299.405)	(19.505)	(72.512)	(217.506)	(88.292)	(38.368)	(195.208)	(199.413)
Middle Tercile Rank	165.741	517.686*	364.869	0.097	-7.452	160.172*	-573.271**	-60.075	-1.019	-512.177**	47.548
	(240.434)	(305.849)	(333.065)	(294.817)	(14.342)	(92.349)	(222.125)	(89.715)	(12.014)	(203.649)	(241.655)
P-value from F-Test											
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.467	0.137	0.322	0.551	0.890	0.216	0.932	0.411	0.140	0.527	0.050*
Mean of	845.06	4548.20	2601.91	1780.90	14.16	151.24	737.02	82.39	27.09	627.54	718.09
Outcome	3099.42	2247.95	2606.45	2498.49	160.94	722.91	1633.86	624.25	348.48	1507.78	1719.77
N	445	445	445	445	445	445	443	443	443	443	445
No. HHs	445	445	445	445	445	445	443	443	443	443	445

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A5: Self Reported Marginal Returns

	(1) Self Reported MR
Top Tercile Rank	362.044***
	(107.278)
Middle Tercile Rank	189.177*
	(109.857)
P-value from F-Test	
Winner*Top Tercile Rank=	0.110
Winner*Middle Tercile Rank	
Mean of Omitted	1824.42
Group	[1662.78]
N	1336
No. HHs	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Self Reported MR is the marginal returns to grants that respondents predict of themselves at baseline. Robust standard errors clustered at the group level in parentheses. All regressions include survey month and surveyor fixed effects. Data in this table comes from round 1 of collection.

Table A6: Self Reported Marginal Returns

	(1) Profits	(2) Log Profits
Winner*Top Tercile Self MR	752.325	0.472
	(477.855)	(0.287)
Winner*Top Middle Self MR	713.664	0.759**
	(445.099)	(0.294)
Winner	-198.078	-0.218
	(330.554)	(0.244)
Top Tercile Self MR	1048.072***	0.330**
	(355.967)	(0.159)
Top Middle Self MR	472.174	0.113
	(312.790)	(0.158)
Baseline Profits	0.354***	
	(0.085)	
Baseline Log Profits		0.446***
		(0.041)
P-value from F-Test		
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.935	0.183
Mean of Outcome	4608.60	7.37
	[5183.78]	[2.51]
N	3952	3969
No. Obs	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). Self MR is the marginal returns to grants that respondents predict of themselves. This value is split into terciles. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. All regressions are weighed by the inverse number of lottery tickets a respondent received. Data in this table comes from rounds 1-4 of data collection.

Table A7: ANCOVA Returns by MR Rank with Controls

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	480.160		0.123		591.925**		0.372**	
	(349.755)		(0.082)		(259.219)		(0.154)	
Winner*Top Tercile Rank		1577.499**		0.322**		1509.863***		0.730***
		(619.183)		(0.134)		(488.878)		(0.255)
Winner*Middle Tercile Rank		1094.577**		0.258*		896.357**		0.404
		(537.873)		(0.140)		(379.653)		(0.267)
Winner	1418.188	2216.593	0.469	0.704**	-2875.008**	-1560.212	-2.109*	-1.152
	(1849.894)	(1488.045)	(0.381)	(0.283)	(1338.466)	(1067.418)	(1.085)	(0.907)
MR Rank	709.709***		0.111**		616.126***		0.291***	
	(206.372)		(0.052)		(165.449)		(0.103)	
Baseline Income	0.409***	0.409***						
	(0.038)	(0.038)						
Top Tercile Rank		554.549		0.113		734.627**		0.392**
		(337.620)		(0.078)		(292.252)		(0.161)
Middle Tercile Rank		-417.504		-0.052		47.476		0.189
		(320.304)		(0.080)		(266.351)		(0.152)
Baseline Log Income			0.221***	0.224***				
			(0.037)	(0.037)				
Baseline Profits					0.342***	0.346***		
					(0.083)	(0.083)		
Baseline Log Profits							0.427***	0.432***
							(0.040)	(0.040)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.415		0.604		0.169		0.146
Mean of	8315.92	8315.92	8.63	8.63	4608.60	4608.60	7.37	7.37
Outcome	6622.20	6622.20	1.39	1.39	5183.78	5183.78	2.51	2.51
N	3984	3984	4002	4002	3949	3949	3966	3966
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. This regression also includes business sector interacted with winner fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A8: Returns with Psychometric Controls

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	929.284**		0.218**		408.036		0.549***	
	(385.750)		(0.086)		(249.917)		(0.140)	
Winner*Top Tercile Rank		1622.724**		0.446***		1193.624***		1.022***
		(661.223)		(0.163)		(446.223)		(0.245)
Winner*Middle Tercile Rank		304.875		0.143		158.854		0.413
		(640.636)		(0.155)		(395.761)		(0.254)
Winner*Impulsiveness I	-897.563	-866.523	-0.121	-0.117	-929.673*	-915.687*	-0.075	-0.066
	(666.031)	(655.629)	(0.178)	(0.176)	(500.094)	(493.878)	(0.260)	(0.260)
Winner*Impulsiveness II	22.189	0.223	0.041	0.041	76.574	68.478	0.025	0.028
	(492.169)	(489.267)	(0.079)	(0.077)	(250.921)	(249.911)	(0.152)	(0.150)
Winner*Impulsiveness III	-201.754	-194.291	0.066	0.065	-21.353	-32.369	0.013	0.016
	(401.820)	(399.841)	(0.100)	(0.100)	(269.825)	(266.450)	(0.189)	(0.189)
Winner*Optimism I	-133.306	-102.688	0.101	0.108	258.880	280.845	0.026	0.038
	(453.237)	(453.720)	(0.119)	(0.120)	(312.793)	(318.141)	(0.213)	(0.211)
Winner*Optimism II	-297.881	-330.175	-0.028	-0.035	-341.811	-363.192	-0.035	-0.049
	(419.215)	(419.638)	(0.098)	(0.097)	(305.597)	(306.365)	(0.120)	(0.119)
Winner*Optimism II	599.643*	592.401*	0.075	0.072	563.448**	550.142**	0.239**	0.237**
	(344.562)	(346.624)	(0.059)	(0.059)	(227.348)	(227.177)	(0.101)	(0.101)
Winner*Optimism IV	-291.749	-315.759	-0.077	-0.083	491.439	505.835	0.209	0.187
	(708.141)	(711.048)	(0.146)	(0.149)	(439.379)	(445.124)	(0.266)	(0.267)
Winner*Tenacity I	1275.986	1196.212	0.185	0.169	320.392	258.104	0.272	0.241
	(783.999)	(771.517)	(0.134)	(0.134)	(301.953)	(302.541)	(0.209)	(0.211)
Winner*Tenacity I	-67.666	-55.268	0.054	0.056	142.351	165.469	0.114	0.110
	(379.525)	(384.652)	(0.091)	(0.094)	(229.308)	(231.686)	(0.149)	(0.151)
Winner*Polychronicity I	-445.206*	-419.471*	-0.074	-0.069	-176.612	-166.017	0.149	0.160
	(244.591)	(244.694)	(0.069)	(0.068)	(176.414)	(173.346)	(0.100)	(0.099)
Winner*Polychronicity II	-292.402	-311.609	-0.256**	-0.261**	-618.798**	-635.711**	-0.190	-0.196
	(425.839)	(427.950)	(0.121)	(0.122)	(304.120)	(306.698)	(0.132)	(0.132)
Winner*Polychronicity III	-394.524	-359.514	-0.031	-0.024	-172.470	-167.517	-0.213	-0.192
	(441.366)	(430.672)	(0.088)	(0.087)	(323.221)	(321.492)	(0.324)	(0.321)
Winner*Locus of Control I	294.240	322.321	0.123	0.137	776.696*	825.683*	0.588*	0.613*
	(564.994)	(573.613)	(0.186)	(0.184)	(435.644)	(435.579)	(0.313)	(0.313)
Winner*Locus of Control II	-408.509	-410.850	0.013	0.015	-307.584	-289.126	0.079	0.077
	(306.785)	(308.693)	(0.076)	(0.076)	(200.375)	(201.847)	(0.105)	(0.104)
Winner*Achievement I	-15.798	-2.666	0.098	0.102	-164.109	-165.004	-0.094	-0.082
	(408.999)	(404.877)	(0.093)	(0.093)	(261.345)	(262.460)	(0.155)	(0.156)
Winner*Achievement II	822.948	807.402	0.023	0.017	-127.694	-144.135	-0.443	-0.455
	(723.893)	(717.153)	(0.131)	(0.130)	(372.011)	(373.395)	(0.306)	(0.304)
Winner*Organization	-610.066	-555.985	-0.377**	-0.370**	-263.235	-259.842	-0.256	-0.237
	(700.794)	(700.158)	(0.164)	(0.161)	(489.885)	(482.680)	(0.299)	(0.294)
Winner	2016.843	4398.550	0.272	0.780	54.679	997.638	-4.225**	-2.920*
	(4953.557)	(4722.428)	(1.134)	(1.070)	(3598.980)	(3472.456)	(1.828)	(1.683)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.043**		0.040**		0.033**		0.006***
Mean of	8315.92	8315.92	8.63	8.63	4608.60	4608.60	7.37	7.37
Outcome	6622.20	6622.20	1.39	1.39	5183.78	5183.78	2.51	2.51
N	5295.00	5295.00	5313.00	5313.00	5279.00	5279.00	5297.00	5297.00
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: Data in this table comes from Round 1 (Baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A9: Balance Check

	(1) India Sample Mean	(2) Sri Lanka Difference	(3) N
Panel A: Individual Characteristics of Ranked Entrepreneur			
Male	0.625	-0.091***	1674
Age of entrepreneur	41.113	1.033	1673
Yrs of Education of the Owner	6.573	2.515*	1674
Dummy for married	0.835	-0.038*	1681
Digitspan	5.247	0.550***	1677
Hours Worked in Past Week	45.843	6.540***	1681
Panel B: Characteristics of Household Businesses			
Age of Business	13.027	-2.864***	1672
Business Located at Home	0.395	0.233***	1681
Retail Shop	0.329	0.031	1674
Food Preparation and Sales	0.072	0.103***	1674
Sewing	0.254	-0.134***	1681
Repair Services	0.005	0.061***	1681
Manufacturing	0.065	0.047***	1681
Services	0.219	-0.197***	1681
Other	0.243	-0.098***	1681
Panel C: Household Characteristics			
Borrowed from Bank	0.058	0.182***	1681
Household Size	3.772	1.225***	1673
Number of Children Under 12	0.946	-0.109	1681
Number of Wage Workers	0.265	0.441***	1681
Business Capital Value	62409.843	-34455.396	1681
Business Profits	4940.545	-973.628***	1681
Business Revenues	18514.380	-5673.549**	1681
Asset Index of Household Durables	-0.082	0.363***	1676

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. The first column are the baseline means from the India sample. In the second column is the difference between the India Data and the Sri Lanka samples.

Table A10: Sri Lanka Training Cross-Validation Exercise

Minimum Node Size	β Fold 1	β Fold 2	β Fold 3	β Fold 4	β Fold 5	Average β
3	-1.92	-0.95	1.00	1.00	-0.39	-0.25
10	-1.86	-2.26	1.71	1.71	-2.07	-0.56
15	-1.60	-2.15	2.67	2.67	-2.11	-0.11
30	0.47	-4.40	1.84	1.84	-4.07	-0.86
50	0.47	-4.40	1.84	1.84	-4.07	-0.86
75	1.85	-10.20	1.38	1.38	-6.58	-2.43
100	2.39	-9.36	-0.55	-0.55	-7.04	-3.02
150	3.84	-15.62	-1.55	-1.55	-8.62	-4.70
200	4.93	-18.48	-1.37	-1.37	-10.51	-5.36

* p$\leq$ 0.10, ** p$\leq$ 0.05, *** p$\leq$ 0.01. Notes: The βs in this table are the result of a 5-fold cross-validation exercise to decide on a minimum node size for the predictive model. The model is trained on the full Sri Lanka dataset. The Average β column contains the average β for each node size across all 5 folds. In this exercise, the optimal minimum node size is 15.

Table A11: India Training Cross-Validation Exercise

Min. Node Size	β Fold 1	β Fold 2	β Fold 3	β Fold 4	β Fold 5	Average β
3	1.17	-0.96	2.29	0.09	0.27	0.57
10	1.26	-1.06	2.07	0.17	0.57	0.60
15	1.25	-0.93	2.24	0.40	0.92	0.77
30	1.23	-0.56	2.02	0.44	1.59	0.94
50	1.23	-0.56	2.02	0.44	1.59	0.94
75	1.29	0.26	1.02	-0.13	2.74	1.04
100	0.96	0.96	0.60	-0.25	3.59	1.17
150	0.85	1.57	0.57	-0.45	4.28	1.36
200	0.59	2.86	0.03	-6.14	5.28	0.52

* p$\leq$ 0.10, ** p$\leq$ 0.05, *** p$\leq$ 0.01. Notes: The βs in this table are the result of a 5-fold cross-validation exercise to decide on a minimum node size for the predictive model. The model is trained on the full India dataset. The Average β column contains the average β for each node size across all 5 folds. In this exercise, the optimal minimum node size is 150.

Table A12: Marginal Returns Predictions Using Machine Learning versus Community Information

	(1) Profits	(2) Profits	(3) Profits	(4) Profits	(5) Profits	(6) Profits
Winner*Top Tercile Rank	998.393**	1664.656***		1033.354**		690.990*
	(446.935)	(353.060)		(450.020)		(381.559)
Winner*Middle Tercile Rank	-14.943	508.743		74.431		267.701
	(384.689)	(316.359)		(369.206)		(410.319)
Winner*ML MR Predict			0.391**	0.389**		
			(0.168)	(0.165)		
Winner*ML MR Predict					6.842**	6.687**
					(2.779)	(2.793)
Winner	131.673	2623.019**	170.839	-251.497	-1271.352*	-1585.345**
	(310.397)	(1232.936)	(323.075)	(363.588)	(697.380)	(772.833)
Mean of Outcome	4606.95 [5184.05]	4606.95 [5184.05]	4606.95 [5184.05]	4606.95 [5184.05]	4606.95 [5184.05]	4606.95 [5184.05]
N	5307	5271	5307	5307	5307	5307
No. HHs	1336	1336	1336	1336	1336	1336

The first column replicates the main regression in Column 6 of Table 2. The second column replicates Column 6 of Table 5. The ML Top Tercile Rank (SR) and ML Middle Tercile Rank (SR) are dummy variables for the top and middle tercile ranks of a marginal returns prediction generated by a generalized method of forests algorith. The model is trained using data from the Sri Lanka experiment. Cross-validation yields an optimal minimum node size of 15 and the model is produced by growing 10000 trees. The ML Top Tercile Rank (In) and ML Middle Tercile Rank (In) are dummy variables for the top and middle tercile ranks of a marginal returns prediction generated by a generalized method of forests algorith. The model is trained using data from the India experiment (therefore this is an in-sample estimate). Cross-validation yields an optimal minimum node size of 150 and the model is produced by growing 10000 trees. All models include surveyor, and date of survey fixed effects. Standard errors are clustered at the group level.

Table A13: How do Respondents Lie? Individual Regressions

	(1) Rank	(2) Rank	(3) Rank	(4) Rank Excluding Self	(5) Rank Excluding Self	(6) Rank Excluding Self	(7) Rank Excluding Self	(8) Rank Excluding Self	(9) Rank Excluding Self
Characteristic	0.292***	0.979***	0.632***	0.387***	0.248**	0.325***	0.378***	0.302***	0.340***
	(0.069)	(0.101)	(0.073)	(0.097)	(0.105)	(0.073)	(0.057)	(0.070)	(0.046)
Characteristic*Public	-0.101	-0.205	-0.141	-0.372***	-0.028	-0.203*	-0.137	-0.004	-0.071
	(0.104)	(0.146)	(0.105)	(0.137)	(0.164)	(0.108)	(0.095)	(0.107)	(0.072)
Characteristic*Incentives	-0.144	-0.407***	-0.268**	-0.146	-0.062	-0.126	-0.297***	-0.128	-0.210***
	(0.124)	(0.155)	(0.110)	(0.153)	(0.163)	(0.111)	(0.110)	(0.109)	(0.077)
Characteristic*Public*Incentives	0.275	0.236	0.239	0.250	-0.035	0.111	0.413**	0.165	0.287**
	(0.188)	(0.224)	(0.159)	(0.219)	(0.225)	(0.156)	(0.164)	(0.161)	(0.115)
Who is Ranked?	Self	Self	Self	Family	Family	Family	Peer (CR)	Peer (CR)	Peer (CR)
Treatment	No Stakes	Stakes	Pooled	No Stakes	Stakes	Pooled	No Stakes	Stakes	Pooled
N	15933.00	16292.00	32225.00	12680.00	13015.00	25695.00	12704.00	13015.00	25719.00
No. Obs	1336.00	1336.00	1336.00	1336.00	1336.00	1336.00	1336.00	1336.00	1336.00

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Notes: Data in this table comes from Round 1 (Baseline) of data collection. Robust standard errors clustered at group level in parentheses. The model includes randomization cluster, surveyor, and date of survey fixed effects. The outcome variable is the rank assigned by the ranker to the rankee. The level of observation is the ranker-rankee.

Table A14: Returns with and without Incentives

	(1) Income	(2) Log Income	(3) Profits	(4) Log Profits
Winner*Top Tercile Rank	427.951	0.235	-393.967	0.350
	(806.043)	(0.284)	(675.490)	(0.334)
Winner*Middle Tercile Rank	-554.393	-0.082	-64.581	0.467
	(1220.783)	(0.222)	(637.200)	(0.326)
Winner	226.730	-0.043	6.574	-0.181
	(502.851)	(0.187)	(347.244)	(0.252)
Incentives*Winner*Top Tercile Rank	932.016	0.057	2072.578**	0.775*
	(861.129)	(0.291)	(821.687)	(0.409)
Incentives*Winner*Middle Tercile Rank	1357.963	0.233	343.502	-0.305
	(1365.014)	(0.247)	(853.774)	(0.449)
P-value from F-Test				
Winner*Top Tercile Rank= Winner*Middle Tercile Rank	0.467	0.251	0.700	0.745
Mean of	8315.92	8.63	4608.60	7.37
Outcome	6622.20	1.39	5183.78	2.51
N	2743	2750	2736	2743
No. HHs	1345	1345	1344	1344

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. This regression also includes business sector interacted with winner fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A15: Average Return to the Grant

	(1) Trim Profits	(2) Log Profits	(3) Trim Income	(4) Log Income
Winner	448.567*	0.223*	412.246	0.037
	(257.858)	(0.119)	(314.799)	(0.078)
Mean of Outcome	4517.65	7.25	8293.19	8.59
	[5001.28]	[2.66]	[6698.77]	[1.48]
N	6637	6661	6653	6677
No. Obs	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-5 of data collection.

Table A16: Returns without Controls- All Survey Rounds

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	581.011*		0.148*		121.632		0.347**	
	(347.071)		(0.085)		(228.816)		(0.143)	
Winner*Top Tercile Rank		1210.806**		0.362**		719.534*		0.708***
		(566.905)		(0.162)		(398.629)		(0.249)
Winner*Middle Tercile Rank		151.398		0.112		-28.666		0.309
		(628.642)		(0.140)		(379.784)		(0.262)
Winner	-1622.303	-107.745	-0.482	-0.140	22.780	179.160	-0.992*	-0.151
	(1260.219)	(450.296)	(0.296)	(0.118)	(782.837)	(307.510)	(0.522)	(0.204)
Linear Combination of Estimates								
Effect at Avg Rank	390.114		0.032		444.070*		0.210*	
	(312.30)		(0.08)		(255.77)		(0.12)	
Effect 1 SD Below	4.533		-0.067		363.351		-0.020	
	(399.13)		(0.09)		(270.21)		(0.16)	
Effect 1 SD Above	775.695**		0.130		524.790		0.441***	
	(376.65)		(0.10)		(322.39)		(0.14)	
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.117		0.092*		0.085*		0.074*
Mean of	8293.19	8293.19	8.59	8.59	4517.65	4517.65	7.25	7.25
Outcome	6698.77	6698.77	1.48	1.48	5001.28	5001.28	2.66	2.66
N	6653	6653	6677	6677	6637	6637	6661	6661
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-5 of data collection.

Table A17: Returns with Observable Controls- All Survey Rounds

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	673.911*		0.163*		224.348		0.428***	
	(350.165)		(0.087)		(225.448)		(0.138)	
Winner*Top Tercile Rank		1299.229**		0.377**		876.992**		0.841***
		(562.334)		(0.166)		(393.397)		(0.243)
Winner*Middle Tercile Rank		192.334		0.102		83.689		0.410
		(628.850)		(0.153)		(393.601)		(0.253)
Winner*Male	76.079	-8.512	-0.061	-0.084	259.593	161.092	0.047	0.034
	(684.464)	(667.678)	(0.133)	(0.128)	(441.124)	(439.472)	(0.259)	(0.256)
Winner*Education	0.508	0.472	0.000	0.000	0.018	0.215	0.001**	0.001**
	(1.212)	(1.156)	(0.000)	(0.000)	(0.821)	(0.774)	(0.000)	(0.000)
Winner*Married	-183.704	-158.831	-0.113*	-0.103	-67.314	-37.775	0.125	0.144
	(282.923)	(283.231)	(0.062)	(0.063)	(200.489)	(201.124)	(0.123)	(0.122)
Winner*Age	41.354**	41.613**	0.014***	0.014***	31.672**	32.611**	0.016*	0.015*
	(18.608)	(18.752)	(0.005)	(0.005)	(13.950)	(14.223)	(0.008)	(0.009)
Winner	-2279.811	-453.242	-0.712	-0.310	-1884.609	-1432.277	-2.568**	-1.487
	(2247.501)	(1791.768)	(0.484)	(0.359)	(1269.874)	(1070.127)	(1.188)	(1.032)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.091*		0.057*		0.067*		0.056*
Mean of	8293.19	8293.19	8.59	8.59	4517.65	4517.65	7.25	7.25
Outcome	6698.77	6698.77	1.48	1.48	5001.28	5001.28	2.66	2.66
N	6648	6648	6672	6672	6632	6632	6656	6656
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-5 of data collection.

Table A18: Returns with Observable and Business Controls- All Survey Rounds

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	1101.789***		0.225**		708.501***		0.522***	
	(339.360)		(0.089)		(203.313)		(0.143)	
Winner*Top Tercile Rank		1791.543***		0.452***		1465.587***		0.955***
		(552.436)		(0.167)		(359.263)		(0.247)
Winner*Middle Tercile Rank		605.403		0.156		541.057		0.486*
		(624.663)		(0.153)		(336.327)		(0.257)
Winner*Male	825.963	755.653	0.042	0.021	1092.044**	1027.158**	0.203	0.186
	(687.959)	(674.701)	(0.143)	(0.138)	(435.119)	(429.685)	(0.266)	(0.264)
Winner*Education	2.612**	2.253*	0.001	0.001	2.298***	2.198***	0.001***	0.001***
	(1.205)	(1.147)	(0.000)	(0.000)	(0.811)	(0.768)	(0.000)	(0.000)
Winner*Married	-241.936	-211.355	-0.120*	-0.109*	-128.778	-93.913	0.115	0.136
	(267.370)	(268.986)	(0.061)	(0.061)	(152.402)	(156.116)	(0.119)	(0.117)
Winner*Age	19.849	19.606	0.011**	0.011**	7.375	7.184	0.011	0.011
	(16.976)	(17.131)	(0.005)	(0.005)	(11.429)	(11.630)	(0.008)	(0.008)
Winner*Avg. Yearly Profits	-0.313***	-0.302***	-0.000***	-0.000***	-0.363***	-0.360***	-0.000***	-0.000***
	(0.067)	(0.068)	(0.000)	(0.000)	(0.055)	(0.055)	(0.000)	(0.000)
Winner*Baseline Assets	-0.001***	-0.001***	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Winner	-1853.725	1101.428	-0.672	-0.107	-1449.930	330.986	-2.514**	-1.191
	(2152.375)	(1643.305)	(0.476)	(0.340)	(1095.208)	(901.154)	(1.199)	(1.056)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.059*		0.041**		0.017**		0.038**
Mean of	8293.19	8293.19	8.59	8.59	4517.65	4517.65	7.25	7.25
Outcome	6698.77	6698.77	1.48	1.48	5001.28	5001.28	2.66	2.66
N	6648	6648	6672	6672	6632	6632	6656	6656
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. This regression also includes business sector interacted with winner fixed effects. Data in this table comes from rounds 1-5 of data collection.

Table A19: Returns without Controls- MR Relative Ranking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Trim Income	Trim Income	Log Income	Log Income	Trim Profits	Trim Profits	Log Profits	Log Profits
Winner*MR Rank	632.402*		0.086		114.912		0.210*	
	(361.224)		(0.085)		(252.629)		(0.125)	
Winner*Top Tercile Rank		1365.451*		0.074		191.794		0.383
		(703.334)		(0.183)		(461.378)		(0.269)
Winner*Middle Tercile Rank		147.329		-0.116		182.473		0.466*
		(632.853)		(0.160)		(376.473)		(0.253)
Winner	-1451.565	-86.875	-0.186	0.087	165.486	379.486	-0.345	-0.013
	(1075.670)	(526.572)	(0.259)	(0.141)	(725.610)	(331.501)	(0.397)	(0.213)
Linear Combination of Estimates								
Effect at Avg Rank	471.858		0.075		514.985*		0.293**	
	(338.46)		(0.08)		(275.72)		(0.12)	
Effect 1 SD Below	-51.105		0.004		419.959		0.119	
	(398.82)		(0.10)		(285.71)		(0.16)	
Effect 1 SD Above	994.821**		0.146		610.011		0.467***	
	(498.52)		(0.12)		(397.12)		(0.16)	
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.062*		0.213		0.984		0.723
Mean of	8293.19	8293.19	8.59	8.59	4517.65	4517.65	7.25	7.25
Outcome	6698.77	6698.77	1.48	1.48	5001.28	5001.28	2.66	2.66
N	5325	5325	5341	5341	5309	5309	5325	5325
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A20: Returns with Observable Controls- MR Relative Ranking

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	677.070*		0.062		186.570		0.270**	
	(369.395)		(0.087)		(255.925)		(0.129)	
Winner*Top Tercile Rank		1452.456**		0.006		288.711		0.483*
		(726.657)		(0.187)		(455.214)		(0.278)
Winner*Middle Tercile Rank		255.744		-0.148		267.617		0.537**
		(662.963)		(0.166)		(385.497)		(0.258)
Winner*Male	333.350	324.615	0.046	0.042	302.179	330.276	-0.035	0.013
	(714.938)	(719.416)	(0.148)	(0.148)	(507.194)	(514.863)	(0.274)	(0.277)
Winner*Education	0.760	0.682	0.000	0.000	-0.111	-0.272	0.001**	0.001*
	(1.413)	(1.328)	(0.000)	(0.000)	(0.886)	(0.835)	(0.000)	(0.000)
Winner*Married	20.780	25.079	-0.127*	-0.147**	3.481	4.735	0.224*	0.239*
	(302.269)	(306.980)	(0.069)	(0.072)	(192.454)	(197.188)	(0.129)	(0.131)
Winner*Age	36.285*	35.330*	0.012**	0.011**	31.859**	31.799**	0.012	0.012
	(20.226)	(20.087)	(0.005)	(0.005)	(15.278)	(15.191)	(0.009)	(0.009)
Winner	-2235.375	-807.399	-0.303	-0.050	-1764.388	-1392.620	-1.820	-1.369
	(2301.977)	(1812.862)	(0.499)	(0.375)	(1546.823)	(1229.036)	(1.118)	(1.057)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.060*		0.320		0.964		0.817
Mean of	8293.19	8293.19	8.59	8.59	4517.65	4517.65	7.25	7.25
Outcome	6698.77	6698.77	1.48	1.48	5001.28	5001.28	2.66	2.66
N	5321	5321	5337	5337	5305	5305	5321	5321
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* p≤ 0.10, ** p≤ 0.05, *** p≤ 0.01. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. Data in this table comes from rounds 1-4 of data collection.

Table A21: Returns with Observable and Business Controls- MR Relative Ranking

	(1) Trim Income	(2) Trim Income	(3) Log Income	(4) Log Income	(5) Trim Profits	(6) Trim Profits	(7) Log Profits	(8) Log Profits
Winner*MR Rank	909.503**		0.101		465.603*		0.323**	
	(364.909)		(0.087)		(240.156)		(0.131)	
Winner*Top Tercile Rank		1886.998***		0.078		815.159*		0.582**
		(724.083)		(0.185)		(432.013)		(0.280)
Winner*Middle Tercile Rank		600.275		-0.100		647.306*		0.599**
		(656.502)		(0.165)		(361.984)		(0.258)
Winner*Male	1057.836	1069.882	0.159	0.154	1124.072**	1178.253**	0.109	0.161
	(730.853)	(738.264)	(0.160)	(0.160)	(509.216)	(514.864)	(0.285)	(0.288)
Winner*Education	2.712*	2.462*	0.001	0.001	2.064**	1.726*	0.001***	0.001**
	(1.435)	(1.358)	(0.000)	(0.000)	(0.953)	(0.920)	(0.000)	(0.000)
Winner*Married	-11.848	1.997	-0.131*	-0.149**	-28.040	-17.364	0.220*	0.236*
	(291.029)	(298.792)	(0.069)	(0.072)	(152.121)	(156.020)	(0.126)	(0.127)
Winner*Age	15.750	14.898	0.008*	0.008*	8.086	8.044	0.008	0.008
	(18.420)	(18.321)	(0.005)	(0.005)	(12.807)	(12.783)	(0.008)	(0.009)
Winner*Avg. Yearly Profits	-0.292***	-0.290***	-0.000***	-0.000***	-0.349***	-0.347***	-0.000***	-0.000***
	(0.067)	(0.065)	(0.000)	(0.000)	(0.057)	(0.056)	(0.000)	(0.000)
Winner*Baseline Assets	-0.001**	-0.001**	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Winner	-1162.979	669.569	-0.157	0.161	-605.112	281.096	-1.643	-1.089
	(2155.164)	(1676.173)	(0.478)	(0.359)	(1376.640)	(1091.491)	(1.130)	(1.076)
P-value from F-Test								
Winner*Top Tercile Rank= Winner*Middle Tercile Rank		0.036**		0.248		0.697		0.943
Mean of	8293.19	8293.19	8.59	8.59	4517.65	4517.65	7.25	7.25
Outcome	6698.77	6698.77	1.48	1.48	5001.28	5001.28	2.66	2.66
N	5321	5321	5337	5337	5305	5305	5321	5321
No. Obs	1336	1336	1336	1336	1336	1336	1336	1336

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Notes: The unit of observation is the household. Winner indicates that the household is a grant recipient after baseline (round 1 of data collection). MR Rank indicates the average ranking the entrepreneur was given by her peers. Robust standard errors clustered at the group level in parentheses. All regressions include household, survey month, survey round, and surveyor fixed effects. This regression also includes business sector interacted with winner fixed effects. Data in this table comes from rounds 1-4 of data collection.