Motivating Agents to Spread Information: The Role of Explicit Incentives and Social Identity-Matching[1]

Erlend Berg[#]
Maitreesh Ghatak[$]
R. Manjula*
D. Rajasekhar*
Sanchari Roy [‡]

I. Introduction

The literature on public service delivery usually focuses on supply side problems.[2] For example, a large literature studies the role of providing incentives to teachers and health care workers to show up for work and provide services at reasonable levels of quality (see Kremer and Holla, 2008). However, demand side problems, namely, the problem of beneficiaries not utilizing a service, are often under-appreciated. An important aspect of the problem of public service delivery to the poor is to make beneficiaries aware of what they are entitled to and how it benefits them. Even if there were no supply side problems - namely, the quality of schools and health care facilities were excellent and these facilities were widely available, if beneficiaries are not aware enough or do not value the service enough (for reasons of lack of information or present-bias), the resulting outcomes are going to be poor. A recent World Bank report (World Bank, 2011) on various public services in India shows that programme

[1]We gratefully acknowledge funding from iiG, a research consortium funded by DFID, as well as the International Growth Centre. The views expressed herein are those of the authors and do not reflect the views of any of the funders. All errors are our own.
[#] University of Oxford; email: erlend.berg@economics.ox.ac.uk
[$] London School of Economics; email: m.ghatak@lse.ac.uk
* Institute of Social and Economic Change; email: raja@isec.ac.in
* Institute of Social and Economic Change; email: manjula@isec.ac.in
[‡] University of Warwick; email: s.roy@warwick.ac.in

[2] For example, Besley and Ghatak (2006) in their overview of issues in public service delivery does not discuss demand-side problems at all. The World Development Report (2004) on providing public services to the poor does touch upon them but focuses mainly on supply side problems.

awareness is often very low among target groups. According to this report, in 2006, level of awareness regarding NREGA, one of the flagship anti-poverty schemes of the Government of India, was around 57% , with some of the poorer states like Jharkhand and Madhya Pradesh doing worse at 28.9% and 45% respectively.[3]

In the context of developed countries as well, information costs are argued to be one of the main reasons behind low take up rate of various welfare programmes (see Hernanz *et al*, 2004). For example, Aizer (2007) finds that eligible children do not sign up for free public health insurance (Medicaid) in the USA because of information costs and Daponte et al (1999) find that randomly allocating information about the Food Stamp Program significantly increases participation amongst eligible households in the US.

In this paper, we look at the role of providing incentives to agents whose job is to disseminate information regarding a government funded health insurance programme among beneficiaries and make them aware of their entitlements. We also compare the impact of such incentive provision to that of matching agents with beneficiaries in terms of socio-economic characteristics, in order to understand their relative efficacy in information dissemination. We do this with the help of a randomized experiment conducted in rural Karnataka in south India, where locally recruited agents (typically women) are hired in each village to spread information about the health insurance programme among fellow eligible villagers. The agents are randomly assigned to either flat pay or incentive pay that is based on measurable outcomes like score on a knowledge test about the programme administered to beneficiaries and programme utilization. This enables us to obtain causal estimates of the impact of alternative mechanisms of information dissemination, i.e. incentive pay and social identity-

[3] These figures were obtained from field studies carried out in 6 major states of India, namely Andhra Pradesh, Bihar, Chhattisgarh, Jharkhand, Gujarat and Madhya Pradesh.

matching, on key dimensions of public service participation from the target population, including awareness, take-up, knowledge and utilization.

Our main findings are as follows. Providing financial incentives to agents led to an improvement in awareness, enrolment (weakly) and knowledge about the public health insurance programme, but only for those agents whose incentive pay was linked to knowledge provision. Agents who were paid a flat rate had no impact on any of the above outcome variables. This is consistent with the theoretical prediction that since these agents were paid a constant amount irrespective of outcomes, they were not incentivized to exert effort. Agents who were incentivized on programme utilization also had no impact, primarily due to the dilution of incentives under this contract as utilization depends on many factors (e.g. hospital readiness, distance to hospital, morbidity etc.) and is only partly under the agent's control.

Secondly, we find that social matching plays a role in information dissemination. Specifically, we find that agents are better at communicating with households (knowledge scores are higher) with same caste and religious denomination as themselves. Moreover, this effect of matching is independent of the effect of incentive pay, implying that incentive pay and social matching may be regarded as competing mechanisms of information dissemination.

Our paper contributes to the broad literature on improving the quality of public service delivery in developing countries.[4] It focuses on the demand side, as opposed to supply side problems and in particular, looks at alternative mechanisms of improving information about a programme available to beneficiaries. To our knowledge, this study represents the first randomized evaluation of the impact of incentivizing agents to provide beneficiaries with

[4] See the World Development Report (2004), Besley and Ghatak (2006), Kremer and Holla (2008), and Banerjee and Duflo (2006) for surveys.

information about a public service with the aim of raising awareness and knowledge. We also provide the first field experimental evidence on the specific mechanism of social matching in the context of information delivery.

Our paper is also related to the literature that focuses on the importance of providing information on the efficiency of economic decisions, even though in our case we do not have data on eventual utilization of the relevant service. Banerjee *et al* (2010) study how information campaigns affect local participation and educational outcomes in India. Jensen (2010) finds that perceived returns to secondary school are very low even though measured returns are high in the Domincan Republic, and conducts a field experiment to find out that providing information on measured returns increases years of schooling. This is similar to the findings of Dupas (2011) on providing information about HIV prevalence on incidence of risky sexual behaviour among girls in Kenya and Duflo and Saez (2003) who find that providing incentives to attend information-sessions affect retirement plan decisions.

Finally, our paper is related to the large literature now on the role of monetary and non-monetary incentives on the performance of agents. This constitutes both incentives for teachers and health care workers, as mentioned above (the evidence from developing countries is surveyed in Kremer and Holla, 2008, Glewwe, Holla and Kremer, 2008, and Banerjee and Duflo, 2006) but also in standard settings of firms in developed countries where output or productivity is measurable but worker effort is not (Bandiera *et al*, 2011 survey this literature). An emerging literature looks at the role of identity of agents (in terms of how they identify with the task or the beneficiaries), and intrinsic motivation in reducing the need for giving explicit incentives (see Akerlof and Kranton, 2005, Benabou and Tirole, 2003, and Besley and Ghatak, 2005). However, as Bandiera *et al* (2011) point out, there is relatively little field-experimental evidence on this and by looking at the role of both explicit incentives and identity-matching (between agents and beneficiaries), our study contributes to our

understanding of this broader issue (beyond the specific context of public service delivery in developing countries) as well.

The rest of the paper is organized as follows. In Section II, we describe the health insurance programme in detail. Section III describes the experimental design and data. Section IV presents the results from the evaluation. Section V discusses the role of social matching. Section VI concludes.

II. The Programme

The Rashtriya Swasthya Bima Yojana (or the National Health Insurance Scheme, henceforth, the RSBY) was launched by the Indian government in 2008 with the aim of improving "access of BPL [Below the Poverty Line] families to quality medical care for treatment of diseases involving hospitalization and surgery through an identified network of health care providers" (Govt. of India, 2009). Each state follows its own timetable for implementation, and a few districts from each state were selected for the initial phase. In Karnataka, five districts were selected (Bangalore Rural, Belgaum, Dakshina Kannada, Mysore and Shimoga), and household enrolment in these districts commenced in February-March 2010 (Rajasekhar *et al* 2011).

The policy covers hospitalisation, day-care treatment and related tests, consultations and medicines, as well as pre- and post-hospitalisation expenses, for some 700 medical and surgical conditions and procedures. Pre-existing conditions are included, as is maternity care, and there is a provision for transport allowance. However, expenses related to outpatient treatment are not covered, and there is an annual expenditure cap of Rs 30,000 (630 USD) for a household of five.

The policy is underwritten by insurance companies selected in state-level tender processes. The insurer receives an annual premium per enrolled household, paid by the central (75%) and state (25%) governments. The beneficiary household only pays Rs 30 (0.63 USD) as an annual registration fee.

Each BPL household can enrol up to five of its members under the scheme. The names, ages, photographs and thumb impressions of enrolled members are stored on a smart card to be issued to the household on the day of enrolment. Beneficiaries are entitled to cashless treatment at any participating ('empanelled') hospital. Hospitals are issued with card-readers and software. Treatment costs are reimbursed to the hospital by the insurance company according to fixed rates. Both private and public hospitals can be empanelled.

III. Experimental design and data description

The main data used here were collected in two waves of post-intervention surveys conducted in 220 randomly selected first-phase RSBY districts (Bangalore Rural and Shimoga) in Karnataka. 3638 and 2955 households were interviewed in the first and second waves, respectively. The households were chosen at random from the villages for each survey wave, but there is a degree of overlap so that 1391 households were interviewed twice. For the analysis presented here, the first observation of twice-observed households was deleted so that each household is only observed once, 2224 in the first round and 2906 in the second round.

The 220 villages were randomly allocated between three treatment groups and one control group. In each treatment village, a meeting was arranged with local government-sponsored all-female self-help groups (SHGs). In the meeting, SHG members were given a brief introduction to RSBY and told that a local agent would be recruited to help spread awareness of the scheme in the village over a one-year period. They were told that the agents would be

paid, but the details of the payment were not further specified. In each case an agent was recruited on the same day, most often from the SHG itself but in a small number of cases a non-member recommended by the SHG was selected. In about a third of the cases, the president of the SHG was recruited. All agents were women.

Once the meeting was concluded and the agent selected, she was taken aside and given a more thorough introduction to the scheme ('Information Package I'). An agent background questionnaire was fielded. The payment scheme was also revealed to the agent at this time.[5] There were three payment schemes:

- 'Flat pay': The agent was told that she would be paid Rs 400 every three months.
- 'Knowledge pay': The agent was told that knowledge of RSBY would be tested in the eligible village population every three months. The agent's pay would depend partly on the results of this knowledge test. There would be a minimum payment of Rs 200 every three months, but the variable component would depend on the outcome of the knowledge tests in the village.
- 'Utilisation pay': The agent was told that her payment would consist of a flat component of Rs 200 every three months. In addition, there would be a variable component which would depend directly on the level of utilisation (frequency of hospital treatments booked on RSBY cards) in the village.

The purpose of not revealing the payment scheme until after recruitment was to isolate the incentive effect of the payment structure from its potential selection effect. None of the agents pulled out after learning about the payment scheme. However, two agents dropped out seven months after recruitment, and another three dropped out 12 months after recruitment.

[5] Information about the payment scheme was kept in a sealed envelope, so that even our field staff did not know about it until this point.

In each case, the reported reason was either the birth of child or migration away from the village. These agents and villages are excluded from the analysis. Agents were told that there would be other agents in other villages, but they were not told that there was variation in the payment structure.

The original plan was to set the variable part of the pay scale for knowledge and utilisation agents in such a manner that average pay would be equal to 400 Rs in each of the three treatment groups. The aim of equalising average pay across the treatment groups is to isolate the incentive effect of the contract structure from the 'income effect' of the average payment size. However, because scheme utilisation was virtually zero, the pay for utilisation agents was not much above 200 Rs (the fixed portion of the salary) for the first round and 332 Rs for the second round. For knowledge agents, the pay did indeed average Rs 400 for one district (Shimoga) in the first survey round and for both districts in the second round. But due to an administrative error, a majority of knowledge agents in Bangalore Rural were overpaid in the first round. In spite of the error, the rank ordering of agents was preserved in the sense that better-performing agents were indeed paid more. Due to this error we also present results only for Shimoga district, in which average pay in the knowledge group was approximately 400 Rs in both rounds.

Descriptive statistics on agents are presented in Table 1a. All agents are female. The average agent is 34 years old. 87% are married, 68% have at least one child under the age of 15 and 13% have at least one child under the age of 5. 61% of agents have completed at least some high school (8^{th} standard or more). 80% of agent households have a BPL card and 29% have a scheduled caste or tribe (SC/ST) background. 64% of agent households own some land, but the median land holding amongst these is only 2 acres. 19% of agents report working for wages. In 32% of the cases, the recruited agent is the president of the self-help group.

Note that income is reported as being in one of four brackets, so the mapping between true income and the income variable is not linear. The scales for personal and household income are not the same, which explains how average personal income can exceed average household income.

Table 1b presents descriptive statistics on the villages. About a quarter of them are GP headquarters villages. The average village has 222 households, and is 13 kilometres from the nearest town.

Table 1c presents summary statistics on household characteristics. Note that this table is based on data collected at baseline. As there is only a partial overlap between the baseline set of households and the set of households observed in the data used here, the number of observations in this table is smaller than in most of the regression tables that follow. Also, since a different control group was used at baseline, these background variables are not available for households in the control group used here.

The average household has 4.6 members. 42% are classified as scheduled caste or scheduled tribe (SC/ST). 6.4% are muslim. In 67% of households, at least one member has completed at least some high school. 50% of households own some land, and 88% have a BPL ration card. More than half of all households include at least one child below the age of 15. It is interesting to note that agents are less likely to be SC/ST than the target population, and also more likely to be a landowner.

Two of the constructed variables are worth describing in more detail. The household 'knowledge score' was computed on the basis of a knowledge test that was fielded to households in each of the two surveys. The tests consisted of eight questions about particulars of the RSBY scheme, including eligibility, cost, cover and exclusions. The exact questions used in the knowledge tests are provided in Appendix A. Each answer was recorded and later

coded as being correct or wrong. The number of correct answers, divided by eight, gives each interviewed household a knowledge score between 0 (least knowledgeable) and 1 (most knowledgeable). The tests used in the two surveys were different, so although the score can be compared across households within a survey, scores cannot easily be compared between the two surveys. The knowledge test was fielded to all interviewed households, and in the knowledge treatment group the agents' pay was directly linked to the scores obtained by eligible households in their village.

The 'female autonomy' score was constructed on the basis of the following question fielded to all agents after recruitment: 'Are you usually allowed to go to the following places? To the market; to the nearby health facility; to places outside the village.' The answer options were 'Alone', 'Only with someone else' and 'Not at all'. For each of the three destinations, agents were given a score of 0 if they were not allowed to visit it at all, 1 if they were only allowed to visit it with someone else and 2 if they were allowed to visit it on their own. These three scores were added up to give an autonomy score ranging from 0 (least autonomous) to 6 (most autonomous). 82% of agents received the score highest score, 6.

In the subsample for which there is household background information, 30% of agents were of a scheduled caste or tribe (SC/ST). The average proportion of SC/ST respondent households was 43%. On average, each agent matched the SC/ST status of 61% of respondent households in her village.

Following agent recruitment, the villages were revisited twice. Each time, a sample of households was interviewed to establish the state of their knowledge about the scheme and the level of scheme utilisation. At the outset, the primary purpose of the surveys was to provide information on agent performance so as to be able to pay them according to their contract. The households were drawn at random each time, so that in general there was a

partial overlap between the households in the baseline and those in the follow-up surveys. After the completion of a follow-up survey, the agents' pay was determined and the agents were revisited and paid. At the same time, the agents' knowledge of the scheme was refreshed and added to. The first round of information campaign covered details on the scheme, eligibility criteria, benefits under the scheme, the process to be adopted during the enrolment and other relevant information. The second round of information campaign focused mainly on utilisation of the scheme covering hospitalisation and utilisation procedures, diseases covered by RSBY, maternity benefits and transportation allowance.

This paper analyses the findings from the information collected from 5130 households over the two follow-up surveys.[6]

IV. Results

IV.A The effect of awareness-spreading agents

We estimate the impact of the information intervention on a number of outcomes related to the program: whether the household has heard of RSBY (awareness), whether the household has registered with RSBY (enrolment), score on the knowledge test (knowledge) and whether the household has used the card to obtain treatment (utilisation). For each outcome, we estimate the effect of being assigned to the treatment group using specification

$$Y_{hv} = \alpha_0 + \beta.Treat_v + \varepsilon_{hv}$$

where Y_{hv} is the outcome of interest for household h in village v and $Treat_v$ is a dummy equal to 1 if the household belonged to a village with an agent, irrespective of contract type

[6] Because the surveys described here were intended primarily as intermediate process checks and a means of calculating the agents' pay, rather than serving as the main follow-up survey for the study, they are short and contain limited background information on households. Also, they only partly overlap with the baseline household sample: there is baseline information on 746 of the households analysed here. All of these live in treatment villages, i.e. there is no baseline information on the households in the control villages analysed here.

('flat', 'knowledge' or 'utilisation'). Therefore, β captures the overall effect of information-spreading agents. Standard errors are clustered at the village level to address concerns of serial correlation and heteroscedasticity (Bertrand, Duflo and Mullainathan, 2004).

Table 2 presents the main results of the information treatment. Column 1 indicates that general awareness regarding RSBY is very high, with 87% of households in control villages having heard of RSBY (captured by the constant term), but there is no additional effect of the information treatment on awareness. Similarly, enrolment is quite impressive at around 69% (column 2), but households in the treatment villages are no more likely to enrol in RSBY than those in control villages.

The main effect of the information treatment appears to be along the dimension of increased knowledge regarding the RSBY scheme. Column 3 of Table 2 indicates that being assigned to a treatment village had a positive and significant impact on the level of knowledge regarding RSBY among eligible households, as proxied by the score on the knowledge test administered to a randomly selected sample. Households in treatment villages score on average 0.057 points higher than the control group score of 0.302 (knowledge scores are on a scale from 0 to 1). This represents a gain of around 19% or 0.21 standard deviations.

The increased knowledge due to the presence of an agent did not translate into increased utilisation of RSBY, as indicated by column 4 of Table 2.

Table 3 presents the results of similar regressions but where district and survey fixed effects are included. The qualitative findings are unchanged. In addition, the coefficients in column 4 indicates that there was virtually no scheme utilisation at the time of the first survey, though by the time of the second survey it had picked up somewhat. Other evidence corroborates the view that at the time of the first survey, utilising the scheme in Karnataka was hardly possible

at all. A large proportion of households had not received their cards six months after enrolment, and there were severe problems operating the scheme on the hospital side.[7]

In addition to the treatment effects, there appears to be a time effect in most of the outcome variables. This is captured by the coefficient on the "second survey" fixed effect. Over time, awareness, enrolment and utilisation of RSBY increased irrespective of whether the village had an agent or not, although there is no such trend in knowledge score. The "Bangalore Rural" effect suggests that there is no significant difference in outcomes between the two districts.

IV.B Disaggregated effects by contract type

As described above, the agents (who, as mentioned earlier, are all female) were randomly assigned to a payment structure. Flat-pay agents were paid a fixed amount, knowledge-pay agents were paid on basis of the level of knowledge about the scheme amongst the RSBY-eligible households in her village, and utilisation-pay agents were paid on the basis of the frequency of scheme utilisation in her village.

Table 4 presents results of regressions where the effect of the awareness-spreading agents is disaggregated by contract type. Columns 1-3 indicate that households in villages with a knowledge agent have higher awareness as well as knowledge regarding RSBY. Compared to an awareness level of 83% in the control group, households in villages with knowledge-pay agents are 4.3 %-points more likely to have heard of RSBY, though the coefficient is significant only at the 10% level. Compared to the mean knowledge score of 0.30 in the

[7] A phone survey of empanelled hospitals was conducted in October 2010. We were able to interview a senior official at 39 of the 46 hospitals in Karnataka that were empanelled at the time. One problem that emerged was that a majority of hospitals in the sample were empanelled after the enrolment of households, so that at the time of enrolment only very limited information on participating hospitals could have been made available to the beneficiaries. There is no evidence that supplementary information was provided later. Furthermore, many hospitals reported severe difficulties using the card-reading technology and in obtaining correct and timely reimbursements from the insurer. Six months into the one-year policy period, nine of the empanelled hospitals had not treated a single patient under the RSBY scheme, and a further 22 had treated fewer than ten patients each (Rajasekhar et al 2011).

control group, villages with knowledge pay-agents score 0.08 higher in the knowledge test, representing a gain of 27% or 0.30 standard deviations.

For enrolment, the coefficient for knowledge pay treatment is positive and sizeable although not statistically significant. In contrast, the magnitude of the coefficient for flat pay treatment for enrolment is actually negative and that for utilisation pay treatment is small. We can reject pairwise equality of the former with the latter two coefficients at 10% significance, suggesting that the effect of knowledge pay treatment in case of enrolment is moving in the same direction as awareness and knowledge.

These results suggest that providing financial incentives to agents that are linked to imparting knowledge did indeed improve knowledge of the scheme as well as raise general awareness. There is also weak evidence for an impact on enrolment.

In contrast, villages with flat-pay agents display no differential impact compared to control villages in any of the outcome variables, and in case of awareness and enrolment, the magnitudes are actually negative though not statistically significant. This is consistent with the theoretical argument that since these agents are paid a constant amount irrespective of the outcomes, they are not incentivized to provide exert effort.

Villages with utilisation pay agents also do not display differential effect on any of the outcome variables. Even allowing for the difficulty in obtaining actual treatment, one might have expected these agents to have an effect on the awareness and knowledge of the scheme in their villages. It may be that the agents were aware that obtaining treatment under the scheme was very difficult and therefore chose to not put much effort into the job. More generally, it is possible that the lack of any significant effect is due to the diluted agent incentive under this contract: utilisation depends on many factors (e.g., hospital readiness, distance to hospital, morbidity) and is only partly under the agents' control.

Table 5 presents the results of similar regressions but where survey and district fixed effects are included. The effect of knowledge-pay agents on scheme awareness is now highly significant. Otherwise, the qualitative findings are unchanged.

As mentioned earlier, an administrative error caused knowledge agents in one of the districts (Bangalore Rural) to be overpaid after the first survey. To allay fears that the higher rates of pay are driving the findings, Table 6 presents results of the same regressions as above but where data from Bangalore Rural has been deleted. The coefficient representing the effect of knowledge agents on knowledge increases to 0.11 and remains highly significant. The effect of knowledge agents on awareness is still significant at the 10% level. Oddly, there is now a *negative* (but only marginally significant) effect of utilisation-pay agents on scheme awareness. Otherwise the qualitative findings are unchanged, and it appears safe to conclude that findings are not driven by the erroneous payments in Bangalore Rural.

Table 7 exploits the fact that 1391 households were interviewed in both follow-up surveys. By interacting the 'second survey' time variable with the treatment variables and introducing household fixed effects, it is possible to look at whether the effect of the agents grew stronger over time. This exercise is less meaningful for the knowledge scores than for the other outcome variables, because different tests were given at each survey and therefore the change in score between the surveys cannot be directly interpreted as the household's knowledge either increasing or diminishing. None of the coefficients on the interacted variables are significant (though some coefficients are quite large), indicating that the effect of the agents did not grow stronger over time. The large and significant positive coefficient on the uninteracted 'second survey' variable in column 1 confirms that there was a strong secular increase in the awareness of the programme between the surveys, and to some extent also in enrolment (column 2). It should be noted, however, that being contacted and interviewed about the scheme is in itself likely to make households more aware of it, so that it is natural

that awareness has increased when the surveyors return to the same household. But this learning-from-the-surveyor effect cannot explain the marginally significant increase in enrolment between the surveys, although in principle it is possible that being interviewed about the programme may have encouraged some households to enrol.

IV.C Agent characteristics and heterogeneous treatment effects

The questionnaire that was administered to the agents at the time of their appointment contains detailed information on a range of individual characteristics including age, marital status, number of children, education, income, caste, land ownership and personal autonomy.

Table 8 looks at how the effect of appointing awareness-spreading agents depends on agent characteristics. The outcome variable is the score on the 'knowledge test' about the scheme given to eligible households, as this outcome was found above to be the most responsive to the intervention. Column 1 replicates column 3 of Table 3 for ease of reference. In column 2, the main treatment variable is interacted with variables on agent age, education, caste and whether she has children under the age of five. It would appear that the best-performing agents are those below the age of 50, without high school education and with at least one child below the age of five. Caste on its own does not seem to matter for agent effectiveness.

The negative coefficient on education may suggest that the result is partly driven by opportunity costs. If uneducated women have fewer outside options, they might be expected to work harder under the contract that was offered to them. In order to investigate this, column 3 includes the agent household's poverty (BPL) status and land holdings, as well as personal and household income levels. A binary variable indicating whether the agent is the president of her SHG and the female autonomy metric are also included. None of the income or wealth-related coefficients is significant, while the coefficient on education remains significant. Hence it would seem that the heterogeneous treatment with respect to education is

not driven by income or wealth. Autonomy is positively related to treatment effect, which is to be expected if autonomy allows the agent to move around freely to provide information to her fellow villagers.

One possible explanation for the results presented in Table 8 is that agents are more effective at transmitting information the more they have in common with their target audience. If the eligible population is characterised by low education levels, relatively young adults and the presence of small children, then perhaps agents that match these characteristics are more effective at communicating information about the scheme. In order to investigate this possibility, some regressions were run using a subset of the data for which we have more detailed information about the households. This subsample does not include any households from control villages, but it is still possible to look at factors that affect agent effectiveness differentially.

Table 9 presents the results of this analysis. Column 1 regresses the household knowledge score on agent and household characteristics. It still appears that agents aged 50 or above are less effective, but the negative effect of agent education and the positive effect of the agent having small children are not replicated in this subsample. On the other hand, it appears that households with at least some high school education do better irrespective of agent characteristics. It does not seem to matter whether the household has a female member aged 50 or above, whether there is a small child in the household or whether the household is SC/ST. In column 2, variables are included to indicate how well the agent's characteristics match those of the household. Whether or not there is a female within five years of the agent's age in the household does not seem to matter, and nor does it seem to matter whether or not the household's education level matches that of the agent. It also does not seem to matter whether the household matches the agent in terms of the presence or absence of young children.

However, though the agent's and the household's SC/ST status do not seem to matter separately, there is a strong positive effect of matching SC/ST status. This indicates that agents are better at communicating with households of the same binary SC/ST status as themselves.

The result on SC/ST status highlights the importance of social markers. Religion is another major social identifier in rural India, and column 3 therefore introduces binary variables for whether the agent and respondent households are Muslim (Muslims being the main religious minority in the study area). It appears that Muslim households generally do better on the knowledge test.

Column 4 introduces variables indicating whether the agent and the household matches in terms of Muslim status (they are both either Muslim or not), and also whether the agent and household match on a more fine-grained caste categorisation than the binary SC/ST status. The five caste categories underlying this variable are SC, ST, minorities, backward caste and forward caste, and the agents are coded as matching with a household if they belong to the same category. The coefficient on matching Muslim with Muslims and non-Muslims with non-Muslims is significant at the 10% level. There is no effect of matching on the more fine-grained caste category variable.

Taken together with the results in Table 8, it appears that the caste of the agent does not matter in itself. But the agent is better able to communicate with households that have the same SC/ST status as herself. Matching caste on a more fine-grained level than SC/ST binary does not add any explanatory power. In addition, there is some evidence that agents are more effective at communicating at households with whom they share religious affiliation (Muslim vs non-Muslim). But it also appears that Muslims are just better agents, and also more receptive learners than non-Muslims, aside from the matching effect. Note that agent and

household landownership are controlled for and their coefficients are not significant. Therefore, the Muslim binary does not appear to be simply proxying for poverty, though it is the case that in the sample Muslims are less likely to own land than non-Muslims.

The findings on the importance of social identification correspond with results seen in other recent work from India: Cole *et al* (2010) find that demand for rainfall insurance is significantly affected by whether the picture on the associated leaflet (a farmer standing in front of either a Hindu temple or a mosque) matches the religion of the potential buyer.

V. Social matching and incentives

The analysis up to this point suggests that monetary incentives matter for agent performance, and so does social matching. In this section this finding is examined more closely. The question asked here is whether matching agents with target households has an effect on knowledge scores that is independent of the effect of incentive pay. Also, it is of interest to see whether *combining* social matching and incentive-pay contracts can boost agent performance still further.

The regressions in Table 10 draws on the same subsample as those in Table 9; that is, the subsample of households who are observed both in the baseline and in one of the follow-up surveys. In column 1, the knowledge score is regressed on a binary for whether the agent is on the knowledge-pay contract. There are also district and time fixed effects, and control variables for the SC/ST status of agents and households. Reflecting earlier findings, the regression indicates that knowledge agents are more effective than flat or utilisation at imparting knowledge about the scheme, though the coefficient is significant only at the 10% level. (The p-value is 0.059.) Note that, based on previous results, utilisation-pay agents are grouped with the flat-pay agents and regarded as non-incentivised with respect to knowledge acquisition.

In column 2, the agent/household SC/ST matching variable is added, and its coefficient is positive and significant. This suggests that incentive pay and social matching have independent effects on agent performance. Again, this is subject to the caveat that the coefficient on incentive pay is only marginally significant. (The p-value is 0.072.) It also of interest to note that, as before, the SC/ST status of either agent or household in itself does not seem to matter, emphasising that this is a pure matching effect.

Column 3 adds the interaction of SC/ST matching and knowledge-incentive pay. The coefficient on this variable can be interpreted as a test of whether combining matching and incentive pay has an additional effect, positive or negative, on top of the individual contributions of matching and incentive pay. This coefficient is small and not significantly different from zero. That is, matching agent and household on SC/ST status will have a positive effect on knowledge transfer, and so will introducing incentive pay, and combining these two mechanisms is a matter of adding up the two individual effects. In other words, the difference in agent effectiveness between a matching and a non-matching household is positive and does not depend on contract type. And likewise, the difference in effectiveness between an incentivised and a non-incentivised agent is positive and does not depend on whether the agent's SC/ST characteristics match those of the household. Note, however, that although un-interacted coefficient on the knowledge incentive pay increases somewhat in magnitude, it just loses its 10% significance in column 3 (p-value 0.102). Furthermore, the un-interacted matching variable is here significant only at the 10% level (p-value 0.085).

In addition to the results presented in Table 10, two similar sets of regressions were run in which (1) agents were matched with households on the Muslim/non-Muslim dimension rather than SC/ST, and (2) agents were matched with households along Muslim as well as SC/ST dimensions. Both these sets of regressions (not reported) produce the same qualitative findings as above.

VI. Conclusion

This paper reports the findings of an impact evaluation of provision of financial incentives to local agents for spreading information regarding a public health insurance programme among the target population in Karnataka, India. The results suggests that providing financial incentives linked to provision of knowledge about the programme had a positive impact on agent performance and led to an improvement in awareness, enrolment and knowledge with regard to the programme. We also find that social matching plays a significant role in information dissemination, independent of the effects of incentive pay. Agents are better at communicating with households with the same caste and religious denomination as themselves, resulting in these matched households performing better at knowledge tests. This corresponds well with the findings obtained in other recent work on India, e.g. on the role of trust in the context of financial market participation (Cole et al., 2011). Thus, incentive pay for agents and identity-matching between agents and beneficiaries may be regarded as competing mechanisms for information dissemination.

Our results, therefore, have broad implications for public service delivery in the context of developing countries where, aside from common supply side problems like staff absenteeism, corruption and red tape, lack of awareness regarding available welfare schemes represents a demand side problem that may short-circuit the process of lifting the masses out of poverty. The experimental evidence from our study points to key mechanisms that can address this problem and raise awareness and knowledge of government programmes targeted at the poor, such that the desired outcome is achieved.

Our future research agenda aims to investigate the impact of spreading information about the health insurance scheme on potential health outcomes of the beneficiaries. Although utilization of the scheme has overall been quite low so far, there are indications that it might

pick up over time, and we aim to capture this in future follow-up surveys of our sample villages. In particular, we would like to test if incentivizing information dissemination, which is found to improve awareness, enrolment and knowledge of the programme, also translates into improved health outcomes for the beneficiaries.

References

Aizer, Anna (2007), "Public health insurance, program take-up, and Child health," *The Review of Economics and Statistics*, 89(3): pp. 400-415

Bandiera, Oriana, Iwan Barankay, and Imran Rasul (2011), *"Field Experiments with Firms," Journal of Economic Perspectives*, 25(3): pp. 63–82

Banerjee, Abhijit and Esther Duflo (2006), "Addressing Absence," *Journal of Economic Perspectives*, 20(1): pp. 117–132

Banerjee, Abhijit, Rukmini Banerji, Esther Duflo, Rachel Glennerster and Stuti Khemani (2010) "Pitfalls of Participatory Programs: Evidence from a Randomized Evaluation in Education in India," *American Economic Journal: Economic Policy*, 2(1): pp. 1-30

Benabou, Roland and Jean Tirole (2003), "Intrinsic and Extrinsic Motivation," *Review of Economic Studies*, 70(3): 489–520

Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan (2004), "How Much Should We Trust Differences-in-Differences Estimates?," *The Quarterly Journal of Economics*, 119(1): pp. 249-75

Besley, Timothy and Maitreesh Ghatak (2005), "Competition and Incentives with Motivated Agents," 95(3): pp. 616-637

Besley, Timothy and Maitreesh Ghatak (2006), "Public Goods and Economic Development," in Abhijit Banerjee, Ronald Benabou and Dilip Mookherjee (eds.) *Understanding Poverty*, Oxford University Press

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend and James Vickery (2010), "Barriers to household risk management: Evidence from India," *Working paper downloaded from http://www.people.hbs.edu/scole/*, dated November 2010

Daponte B.O., Sanders S., Taylor L. (1999), "Why do Low-Income Households not Use Food Stamps? Evidence from an Experiment," *The Journal of Human Resources*, 34(3): pp. 612-628

Duflo, Esther and Emmanuel 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): pp. 815-842

Dupas, Pascaline (2011), "Do Teenagers Respond to HIV Risk Information? Evidence from a Field Experiment in Kenya," *American Economic Journal: Applied Economics*, 3(1): pp.1-36

Glewwe, Paul, Alaka Holla and Michael Kremer (2009), "Teacher Incentives in the Developing World," in Matthew Springer (ed.) *Performance Incentives: Their Growing Impact on K-12 Education*, Washington D.C.: Brookings Institution Press

Government of India (2009), "Tender document: Implementation of Rashtriya Swasthya Bima Yojana," *Template for use by state governments downloaded from www.rsby.gov.in*

Hernanz, V., F. Malherbet and M. Pellizzari (2004), "Take-Up of Welfare Benefits in OECD Countries: A Review of the Evidence," *OECD Social, Employment and Migration Working Papers*, No. 17, OECD Publishing

Jensen, Robert (2010), "The (Perceived) Returns to Education and the Demand for Schooling," *The Quarterly Journal of Economics*, 125(2): pp. 515-548

Kremer, Michael and Alaka Holla (2008), "Pricing and Access: Lessons from Randomized Evaluation in Education and Health," in William Easterly and Jessica Cohen (eds.) *What Works in Development: Thinking Big and Thinking Small*, Washington D.C.: Brookings Institution Press

Rajasekhar, D, Erlend Berg, Maitreesh Ghatak, R Ramachandran Manjula and Sanchari Roy (2011), "Implementing Health Insurance: The Roll-out of Rashtriya Swasthya Bima Yojana in Karnataka," *Economic and Political Weekly*, XLVI(20), pp. 56-63.

World Bank (2004): *World Development Report 2004: Making Services Work for Poor People*, World Bank and Oxford University Press.

World Bank (2011), "Social Protection for a Changing India: Volume 2" pp. 162-165

Appendix A: The knowledge tests

In the first survey, the knowledge test consisted of the following eight questions (correct answers in brackets):

1. Does the programme cover the cost of treatment received while admitted to a hospital (hospitalisation)?
   Yes.

2. Does the programme cover the cost of treatment received while not admitted to a hospital (out-patient treatment)?
   No.

3. Who can join this programme?
   BPL card-holders.(Those who said 'the poor', 'low income' or similar were marked as correct.)

4. What is the maximal annual expenditure covered by the scheme?
   Rs 30,000.

5. How much money do you have to pay to get enrolled in the scheme?
   Rs 30 per year.

6. How many members of a household can be a part of the scheme?
   Up to five.

7. What is the allowance per visit towards transportation to the hospital that you are entitled to under the RSBY scheme?
   Rs 100. (This was the expected answer, although strictly speaking the transportation allowance is subject to a maximum of Rs 1000 per year, i.e. ten visits.)

8. Is there an upper age limit for being covered by the scheme? If yes, what is it?
   There is no upper age limit.

In the second survey, the knowledge test consisted of the following eight questions:

1. What is the maximum insurance cover provided by RSBY per annum?
   Rs 30,000.

2. Does the beneficiary have to bear the cost of hospitalisation under the RSBY scheme up to the maximum limit?
   No.

3. Are pre-existing diseases covered under RSBY?
   Yes.

4. Are out-patient services covered under RSBY?
   No.

5. Are day surgeries covered under RSBY?
   Yes.

6. Does the scheme cover post-hospitalization charges? If yes, up to how many days?
   *Yes, up to **5** days. (Anyone who answered 'yes' was marked as correct.)*

7. Are maternity benefits covered?
   Yes.

8. If a female RSBY member has given birth to a baby during the policy period, will the baby be covered under RSBY?
   Yes.

Table 1a: Agent summary statistics by treatment group

	flat	knowledge	utilisation
Agent age	34.76	34.77	34.04
	(8.808)	(8.084)	(8.687)
Agent personal income bracket	3.333	3.326	2.977
	(1.111)	(0.990)	(1.102)
Agent household income bracket	2.686	2.901	3.127
	(1.231)	(1.185)	(1.108)
Agent is SC/ST	0.270	0.225	0.356
	(0.450)	(0.421)	(0.482)
Agent is Muslim	0.0811	0.0141	0.0274
	(0.277)	(0.119)	(0.164)
Agent is married	0.811	0.915	0.863
	(0.397)	(0.280)	(0.346)
Agent has at least some high school	0.568	0.592	0.658
	(0.502)	(0.495)	(0.478)
Agent works for wages	0.108	0.183	0.247
	(0.315)	(0.390)	(0.434)
Agent household has BPL card	0.892	0.789	0.753
	(0.315)	(0.411)	(0.434)
Agent has a child under 15	0.649	0.732	0.644
	(0.484)	(0.446)	(0.482)
Agent has a child under 5	0.108	0.183	0.0959
	(0.315)	(0.390)	(0.296)
Agent autonomy score (the higher, the more autonomous)	5.568	5.676	5.562
	(0.929)	(0.841)	(0.986)
Agent owns land	0.595	0.690	0.603
	(0.498)	(0.466)	(0.493)
Agent is SHG president	0.297	0.282	0.370
	(0.463)	(0.453)	(0.486)
Agent pay in round 1	400	507.7	200.3
	(0)	(478.5)	(2.341)
Agent pay in round 2	400	403.0	332.6
	(0)	(209.1)	(282.8)

Proportion of households matching agent's SC/ST status	0.720 (0.381)	0.749 (0.354)	0.623 (0.405)
Proportion of households matching agent's religion (Muslim or non-Muslim)	0.920 (0.205)	0.928 (0.173)	0.923 (0.222)
Proportion of households matching agent's high school status	0.118 (0.109)	0.0960 (0.0923)	0.127 (0.126)
Proportion of households matching agent's young-child status	0.736 (0.307)	0.715 (0.331)	0.741 (0.316)
Proportion of households with a female matching agent's age (within five years)	0.309 (0.265)	0.443 (0.292)	0.484 (0.301)
Observations	181		

Table 1b: Village summary statistics by treatment group

	control	flat	knowledge	utilisation
Village distance to GP headquarters	2.923 (3.463)	2.257 (2.153)	2.345 (2.208)	2.356 (1.959)
Village population (number of households)	205.1 (193.0)	222.6 (167.7)	237.2 (248.8)	214.8 (170.1)
Village distance to nearest Primary Health Centre	. (.)	4.319 (3.124)	4.913 (4.564)	5.723 (4.577)
Village distance to nearest government hospital	. (.)	19.01 (16.41)	18.50 (16.22)	14.93 (12.45)
Village distance to nearest private nursing home	. (.)	17.61 (16.65)	22.11 (24.59)	18.80 (17.72)
Village distance to nearest town	11.51 (6.198)	15.84 (12.86)	13.34 (10.38)	13.38 (10.03)
Village is GP headquarters	0.179 (0.389)	0.297 (0.463)	0.254 (0.438)	0.247 (0.434)
At least 20% of village land is irrigated	0.692 (0.468)	0.595 (0.498)	0.634 (0.485)	0.521 (0.503)
Approximate proportion of wage labourer households in village	0.479 (0.244)	0.456 (0.176)	0.495 (0.197)	0.458 (0.195)
Observations	220			

Table 1c: Household background summary statistics by treatment group

	flat	knowledge	utilisation
Household size	4.887	4.522	4.569
	(2.199)	(1.686)	(2.061)
Household is SC/ST	0.377	0.438	0.422
	(0.486)	(0.497)	(0.495)
Household is Muslim	0.0629	0.0766	0.0543
	(0.244)	(0.267)	(0.227)
Household has at least one member with at least some high school	0.673	0.741	0.617
	(0.471)	(0.439)	(0.487)
Household has at least one child under 5	0.176	0.186	0.192
	(0.382)	(0.390)	(0.394)
Household has at least one child under 15	0.579	0.536	0.565
	(0.495)	(0.500)	(0.496)
Household has female member aged 30+	0.925	0.916	0.936
	(0.265)	(0.278)	(0.245)
Household has female member aged 50+	0.535	0.376	0.409
	(0.500)	(0.485)	(0.492)
Household owns agricultural land	0.478	0.489	0.514
	(0.501)	(0.501)	(0.501)
Household has BPL ration card	0.868	0.905	0.872
	(0.340)	(0.294)	(0.334)
Observations	746		

mean coefficients; sd in parentheses

Table 2: The effect of awareness-spreading agents

	(1) Heard of RSBY	(2) Have enrolled	(3) Knowledge	(4) Have utilised
Agent in village	0.00209	0.0160	0.0563***	-0.000117
	(0.0227)	(0.0418)	(0.0187)	(0.00188)
Constant	0.872***	0.688***	0.302***	0.00246
	(0.0174)	(0.0368)	(0.0157)	(0.00171)
Observations	5087	5087	5087	5087

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 3: The effect of awareness-spreading agents, with district and time fixed effects

	(1) Heard of RSBY	(2) Have enrolled	(3) Knowledge	(4) Have utilised
Agent in village	0.00542	0.0197	0.0550***	0.0000676
	(0.0231)	(0.0417)	(0.0189)	(0.00187)
Bangalore Rural	0.0133	-0.0159	0.00836	0.0000520
	(0.0249)	(0.0353)	(0.0177)	(0.00143)
Second survey	0.0524***	0.0432***	-0.0135	0.00256*
	(0.0128)	(0.0162)	(0.0144)	(0.00134)
Constant	0.833***	0.668***	0.306***	0.000824
	(0.0224)	(0.0411)	(0.0179)	(0.00189)
Observations	5087	5087	5087	5087

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Disaggregated by agent contract type

	(1) Heard of RSBY	(2) Have enrolled	(3) Knowledge	(4) Have utilised
Flat-pay agent in village	-0.0215	-0.0381	0.0425	-0.000212
	(0.0377)	(0.0595)	(0.0296)	(0.00230)
Knowledge-pay agent in village	0.0434*	0.0632	0.0831***	-0.0000985
	(0.0225)	(0.0442)	(0.0211)	(0.00220)
Utilisation-pay agent in village	-0.0270	-0.00291	0.0366	-0.0000845
	(0.0329)	(0.0506)	(0.0224)	(0.00207)
Constant	0.872***	0.688***	0.302***	0.00246
	(0.0174)	(0.0368)	(0.0157)	(0.00171)
Observations	5087	5087	5087	5087

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 5: Disaggregated effect by agent contract type, with district and time fixed effects

	(1) Heard of RSBY	(2) Have enrolled	(3) Knowledge	(4) Have utilised
Flat-pay agent in village	-0.0171	-0.0344	0.0415	-0.00000142
	(0.0375)	(0.0591)	(0.0295)	(0.00224)
Knowledge-pay agent in village	0.0473**	0.0683	0.0816***	0.000115
	(0.0226)	(0.0442)	(0.0213)	(0.00221)
Utilisation-pay agent in village	-0.0243	-0.0000599	0.0358	0.0000566
	(0.0330)	(0.0505)	(0.0224)	(0.00206)
Bangalore Rural	0.0103	-0.0197	0.00645	0.0000481
	(0.0238)	(0.0345)	(0.0173)	(0.00141)
Second survey	0.0536***	0.0442***	-0.0127	0.00256*
	(0.0128)	(0.0162)	(0.0144)	(0.00134)
Constant	0.834***	0.669***	0.307***	0.000825
	(0.0223)	(0.0411)	(0.0179)	(0.00188)
Observations	5087	5087	5087	5087

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 6: Disaggregated effect by agent contract type, Shimoga district only

	(1) Heard of RSBY	(2) Have enrolled	(3) Knowledge	(4) Have utilised
Flat-pay agent in village	-0.0471	-0.0641	0.00235	0.00201
	(0.0580)	(0.0765)	(0.0395)	(0.00350)
Knowledge-pay agent in village	0.0429*	0.0347	0.106***	0.000299
	(0.0225)	(0.0568)	(0.0277)	(0.00288)
Utilisation-pay agent in village	-0.0898*	-0.0893	0.00138	-0.00106
	(0.0526)	(0.0740)	(0.0314)	(0.00253)
Second survey	0.0308**	0.0291	-0.0807***	0.00102
	(0.0150)	(0.0229)	(0.0179)	(0.00178)
Constant	0.876***	0.724***	0.356***	0.00164
	(0.0199)	(0.0455)	(0.0196)	(0.00219)
Observations	2583	2583	2583	2583

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 7: Does the effect get stronger over time? Exploiting the panel aspect of the data

	(1) Heard of RSBY	(2) Have enrolled	(3) Knowledge	(4) Have utilised
Flat-pay agent in village x second survey	-0.0338	-0.0321	0.0802	0.00340
	(0.0499)	(0.0330)	(0.0489)	(0.00757)
Knowledge-pay agent in village x second survey	-0.00509	0.0169	0.0366	0.00340
	(0.0419)	(0.0297)	(0.0434)	(0.00757)
Utilisation-pay agent in village x second survey	-0.0499	0.0221	0.0125	0.00340
	(0.0414)	(0.0316)	(0.0376)	(0.00856)
Second survey	0.0816**	0.0374*	-0.0323	-0.00340
	(0.0357)	(0.0209)	(0.0297)	(0.00757)
Observations	2782	2782	2782	2782

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 8: Agent characteristics

	(1) Knowledge	(2) Knowledge	(3) Knowledge
Treatment (agent in village)	0.0550***	0.0678**	-0.0207
	(0.0189)	(0.0277)	(0.0703)
Bangalore Rural	0.00836	0.0111	0.0127
	(0.0177)	(0.0169)	(0.0160)
Second survey	-0.0135	-0.0119	-0.0115
	(0.0144)	(0.0145)	(0.0145)
Treatment x agent is 30+		0.0323	0.0185
		(0.0233)	(0.0230)
Treatment x agent is 50+		-0.0799**	-0.0836**
		(0.0356)	(0.0361)
Treatment x agent has at least some high school		-0.0524***	-0.0561***
		(0.0200)	(0.0211)
Treatment x agent is SCST		-0.0364	-0.0289
		(0.0235)	(0.0225)
Treatment x agent has a child under 5		0.0884***	0.0847***
		(0.0244)	(0.0224)
Treatment x agent is BPL			-0.0119
			(0.0258)
Treatment x agent owns land			-0.00385
			(0.0212)
Treatment x agent personal income			0.000992
			(0.00590)
Treatment x agent household income			-0.00513
			(0.00800)
Treatment x agent is SHG president			-0.000253
			(0.0200)
Treatment x agent autonomy			0.0221**
			(0.0103)
Constant	0.306***	0.304***	0.303***
	(0.0179)	(0.0178)	(0.0175)
Observations	5087	5087	5087

Standard errors in parentheses
Standard errors are clustered at the village level.

* p<0.10, ** p<0.05, *** p<0.01

Table 9: Social identification. Subsample analysis within treatment villages.

	(1) Knowledge	(2) Knowledge	(3) Knowledge	(4) Knowledge
Agent is 50+	-0.111*	-0.121**	-0.136**	-0.136**
	(0.0605)	(0.0589)	(0.0552)	(0.0531)
Agent has at least some high school	-0.0125	-0.0169	-0.0230	-0.0244
	(0.0279)	(0.0277)	(0.0273)	(0.0276)
Agent has a child under 5	-0.00673	-0.0185	-0.0107	-0.00844
	(0.0325)	(0.0352)	(0.0354)	(0.0350)
Agent is SC/ST	-0.0243	-0.0231	-0.0241	-0.0217
	(0.0311)	(0.0310)	(0.0307)	(0.0312)
Agent owns land	-0.00959	-0.0121	-0.00818	-0.0191
	(0.0278)	(0.0272)	(0.0272)	(0.0297)
Household has female member aged 50+	-0.0268	-0.0258	-0.0209	-0.0194
	(0.0207)	(0.0212)	(0.0213)	(0.0219)
Household has at least one member with at least some high school	0.0620**	0.0611**	0.0639***	0.0593**
	(0.0242)	(0.0240)	(0.0236)	(0.0236)
Household has a child under 5	0.00309	-0.00630	-0.00276	0.00200
	(0.0252)	(0.0380)	(0.0382)	(0.0381)
Household is SC/ST	-0.00625	0.0169	0.0342	0.0311
	(0.0236)	(0.0259)	(0.0256)	(0.0261)
Household owns land	0.00422	0.00120	0.00955	0.00710
	(0.0227)	(0.0225)	(0.0224)	(0.0231)
Bangalore Rural	-0.0249	-0.0285	-0.0299	-0.0308
	(0.0276)	(0.0274)	(0.0272)	(0.0284)
Second survey	0.0360	0.0336	0.0345	0.0401
	(0.0246)	(0.0242)	(0.0241)	(0.0245)
Household has female matching agent age (within 5 years)		-0.00973	-0.00780	-0.0112
		(0.0209)	(0.0208)	(0.0211)
Highest educated household member matches agent's education		0.0121	0.0152	0.0227
		(0.0229)	(0.0226)	(0.0224)
Household binary for		-0.0165	-0.0132	-0.0156

presence of child under 5 matches that of agent		(0.0374)	(0.0372)	(0.0372)
Household's SC/ST status matches that of agent		0.0591**	0.0613**	0.103***
		(0.0252)	(0.0251)	(0.0361)
Agent is Muslim			0.0616	0.129**
			(0.0669)	(0.0533)
Household is Muslim			0.129***	0.191***
			(0.0405)	(0.0577)
Household's caste category matches that of agent				-0.0549
				(0.0373)
Household's Muslim binary matches that of agent				0.105*
				(0.0632)
Constant	0.386***	0.362***	0.331***	0.236***
	(0.0373)	(0.0573)	(0.0573)	(0.0867)
Observations	746	746	746	716

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01

Table 10: Identity and incentives.

	(1) Knowledge	(2) Knowledge	(3) Knowledge
Knowledge-pay agent in village	0.0548**	0.0523**	0.0585*
	(0.0253)	(0.0253)	(0.0337)
Agent is SC/ST	-0.00870	-0.00879	-0.00827
	(0.0297)	(0.0293)	(0.0294)
Household is SC/ST	-0.0156	0.00537	0.00466
	(0.0229)	(0.0258)	(0.0255)
Bangalore Rural	-0.0172	-0.0199	-0.0203
	(0.0262)	(0.0257)	(0.0258)
Second survey	0.0363	0.0351	0.0352
	(0.0241)	(0.0238)	(0.0238)
Household's SC/ST status matches that of agent		0.0527**	0.0559*
		(0.0255)	(0.0320)
Household's SC/ST status matches that of agent x Knowledge-pay agent			-0.00973
			(0.0430)
Constant	0.376***	0.338***	0.336***
	(0.0281)	(0.0341)	(0.0358)
Observations	746	746	746

Standard errors in parentheses
Standard errors are clustered at the village level.
* p<0.10, ** p<0.05, *** p<0.01