

MOTIVATING KNOWLEDGE AGENTS: CAN INCENTIVE PAY OVERCOME SOCIAL DISTANCE?*

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This article studies the interaction of incentive pay with intrinsic motivation and social distance. We analyse theoretically as well as empirically the effect of incentive pay when agents have not only pro-social objectives but also preferences over dealing with one social group relative to another. In a randomised field experiment undertaken across 151 villages in South India, local agents were hired to spread information about a public health insurance programme. In the absence of incentive pay, social distance impedes the flow of information. Incentive pay increases overall agent effort and appears to cancel the negative effects of social distance.

Economists tend to believe in the power of incentives and prices to improve efficiency, whether the aim is to motivate workers or eliminate social ills such as discrimination.¹ Yet both theory and evidence suggest that there are circumstances in which there are grounds for caution: First, if there are multiple tasks or output is hard to measure, financial incentives may have undesirable consequences (Holmstrom and Milgrom, 1991; Gneezy *et al.*, 2011). Second, in jobs with an aspect of social service, as in public goods provision, or if reputation matters, workers may not be ‘in it just for the money’. It has been argued that financial incentives may interfere with or even ‘crowd out’ such intrinsic motivation (Gneezy and Rustichini, 2000b; Bénabou and Tirole, 2006). Third, theory suggests that aligning the identities of economic agents can increase efficiency (Francois, 2000; Besley and Ghatak, 2005), and there is evidence that ethnic fragmentation and ‘social distance’ can lead to worse economic outcomes (Easterly and Levine, 1997). Akerlof and Kranton (2005) argue that when group identity is salient, monetary incentives can be ‘both costly and ineffective’.

However, evidence on the effect of incentive pay on performance in pro-social tasks is still limited. Ashraf *et al.* (2014) find that both non-financial and financial rewards have stronger effects for socially motivated agents. Dal Bó *et al.* (2013) conclude that higher wages do not have adverse selection effects in terms of public service motivation. Rasul and Rogger (2016) suggest that the use of incentives can negatively affect aspects of performance in the Nigerian Civil Service.²

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¹ Bandiera *et al.* (2011) and Prendergast (2015) review the evidence. Becker and Posner (2009) and Sandel (2012) provide different perspectives.

² Finan *et al.* (2017) survey recent evidence on the role of incentives in the public sector.

Moreover, very little is known about the interaction of incentive pay and social distance, although the literature on discrimination has suggested that competitive markets can remove the effects of social distance where these cause inefficiencies (Lang and Lehmann, 2012).

In this article, we develop a theoretical model and provide empirical evidence on the role of incentive pay in spreading information about a public service in a socially heterogeneous population. We study whether incentive pay is effective in settings where output is noisy and crowding out is a possibility, and whether incentive pay ameliorates or exacerbates the potentially detrimental effects of social distance.

A simple theoretical framework is developed which combines elements of a motivated agent framework (Besley and Ghatak, 2005) with the multi-tasking model (Holmstrom and Milgrom, 1991). The framework predicts that when there is a single task and the agent is intrinsically motivated, effort is always weakly increasing in the part of the agent's compensation that is dependent on success (the 'bonus'). But when there are two tasks, which differ in terms of the agent's intrinsic motivation to succeed and in the marginal cost of effort, the effect of bonus pay will depend in part on the degree of substitutability in the cost of effort across the two tasks. If substitutability is low, increasing bonus pay will lead to an increase in the agent's effort with respect to both tasks. But if the two tasks are relatively substitutable in the cost function, an increase in bonus may cause effort in one task to decrease while effort in the other increases. This can be interpreted as incentive pay 'crowding out' intrinsic motivation for one of the tasks.

We then analyse data from a field experiment conducted across 151 villages in Karnataka, India, in the context of a government-subsidised health insurance scheme aimed at the rural poor. In a random sub-sample of the villages (the treatment groups), one local woman per village was recruited to spread information about the scheme. These 'knowledge agents' were randomly assigned to either a flat-pay or an incentive-pay contract. Under the latter contract, the agents' pay depended on how a random sample of eligible households in their village performed when surveyed and orally presented with a knowledge test about the scheme.

Our main empirical findings are as follows: first, hiring agents to spread information has a positive impact on the level of knowledge about the programme. The effect is driven by agents on incentive-pay contracts. Households in villages assigned an incentive-pay agent score on average 0.25 standard deviations higher on the knowledge test than those in the control group, and are also 8 percentage points more likely to enrol.

Second, social distance between agent and beneficiary has a negative impact on knowledge transmission. But putting agents on incentive-pay contracts appears to increase knowledge transmission by cancelling (at our level of bonus pay) the negative effect of social distance. In contrast, incentive pay has no impact on knowledge transmission or enrolment for socially proximate agent–beneficiary pairs. This result appears to be symmetric across social boundaries, in the sense that it holds whether the agent is from a high or low-status caste group. Our preferred interpretation is that, with respect to their 'own' group (socially proximate households), agents were already at a maximum effort level and hence, introducing bonus pay has no impact. However, non-incentivised agents choose a lower level of effort with respect to the 'other' group (socially distant households). With incentive pay, effort goes up to the same level as for the agent's own group. One might say that incentives appear to 'price out prejudice', although social

distance barriers can operate through channels other than prejudice. We do not observe crowding out empirically, but cannot rule it out for unobserved parameter values.

Third, incentivised agents appear to achieve higher knowledge scores by reallocating time away from socially proximate households (their ‘own group’) towards socially distant households (their ‘cross-group’), without increasing aggregate time spent. The findings are consistent with a story in which non-incentivised agents spend more time than needed with their ‘own group’ because it is enjoyable rather than productive (‘idle chatter’). Incentivised agents channel some of this time toward productive use with households in the ‘cross-group’.

The article makes three main contributions. First, to the best of our knowledge, it presents the first randomised evaluation of incentive pay for agents tasked with providing information about a public service. An important aspect of service delivery is to make intended beneficiaries aware of their entitlements. Even if there were no supply-side problems – if the quality of schools and health centres were excellent and these facilities were widely available – the outcome would be disappointing if beneficiaries were unaware of the services or did not value them sufficiently (due to, say, a lack of information or present bias). While this is a recognised problem in rich countries,³ the issue has not received much attention in developing countries. There is, however, reason to believe that the problem is no less important there: a report on public services in India shows programme awareness to be low among target groups (World Bank, 2011).⁴ It is thus important to understand the role of incentives in raising awareness of social programmes, a context in which pro-social motivation is likely to feature.

Second, we contribute to the broader literature on financial incentives and performance by showing that incentives can matter, even in the context of a pro-social task, a soft objective and agents with possible intrinsic motivation. As Finan *et al.* (2017) point out, we do not know enough about the effect of financial incentives in these settings; in particular, when incentives may cause agents to prioritise dimensions that are easy to measure to the detriment of those that are less so, or when incentives could crowd out intrinsic motivation.

Third, the article extends our understanding of the interaction between incentive pay and social distance. While we are not the first to document the detrimental effects of social barriers, the question of whether incentive pay alleviates or exacerbates the negative consequences of social distance has not received much attention. This is particularly important in developing countries, many of which are highly stratified along socio-economic lines. The novelty of our findings is that what is ‘crowded out’ is an anti-social tendency to favour interactions with one’s own group, whereas most previous studies have focused on financial incentives crowding out pro-social tendencies, such as picking up one’s children on time from day care (Gneezy and Rustichini, 2000a).

³ Information costs are often argued to be one of the main reasons for low take-up of welfare programmes in developed countries (Hernanz *et al.*, 2004). For example, in the US, Aizer (2007) finds that eligible children do not sign up for free public health insurance (Medicaid) because of high information costs, and Daponte *et al.* (1999) find that randomly allocating information about the Food Stamp Program significantly increases participation among eligible households.

⁴ According to this report, the level of nationwide awareness regarding the National Rural Employment Guarantee, one of the flagship anti-poverty schemes of the Government of India, was around 57% in 2006, with some of the poorer states like Jharkhand and Madhya Pradesh, where one would expect demand for such schemes to be high, doing worse at 29% and 45% respectively.

Our article is related to that of [Bandiera *et al.* \(2009\)](#), who study the interplay of social connections and financial incentives in the context of worker productivity in a private firm in the UK. They find that when managers are paid fixed wages, they favour workers with whom they are socially connected; but when incentive pay is introduced, managers' efforts do not depend on social connections. But as [Bandiera *et al.* \(2011\)](#) point out, provision of incentives for pro-social tasks raise different issues compared to private tasks for several reasons, including the possibility of crowding out.

Another article looking at the effects of social distance in a for-profit setting is [Fisman *et al.* \(2017\)](#). They analyse data from an Indian bank, and find that the volume of credit is larger, and repayment rates higher, when the borrower and the loan officer are matched on social identity. While they are able to exploit quasi-random variation in social distance, they do not study the interaction of social distance and pay.

There is a growing literature on the importance of information campaigns in economic decision-making and, in particular, in determining demand for public services. Previous work has explored how information campaigns affect local participation and educational outcomes in India ([Banerjee *et al.*, 2010](#)), how providing information on measured returns increases years of schooling ([Jensen, 2010](#)) and how creating awareness about HIV prevalence reduces incidence of risky sexual behaviour among Kenyan girls ([Dupas, 2011](#)).⁵

There is substantial evidence that ethnic heterogeneity is linked to poor economic outcomes, including sub-optimal provision of public goods and poor governance ([Easterly and Levine, 1997](#); [La Porta *et al.*, 1999](#); [Kimenyi, 2006](#)). A possible explanation for this is that people prefer to interact with those who are similar to themselves, leading to fragmented markets, lower social mobility ([Bertrand *et al.*, 2000](#)) and reduced gains from trade ([Anderson, 2011](#)). Several studies find evidence of strong own-group bias ([Banerjee and Munshi, 2004](#); [Kingdon and Rawal, 2010](#)), with potentially adverse implications for the flow of information. In the context of awareness campaigns, if people prefer to liaise with their own kind, information constraints on the demand for public services may be more severe in socially heterogeneous settings. However, micro-level evidence on the role of social distance in the spreading of awareness about public services is rare.

This article is also related to the rich literature on the impact of monetary and non-monetary incentives on the performance of agents. This body of work encompasses studies in the 'standard setting' of firms in developed countries where output or productivity is measurable but worker effort is not ([Lazear, 2000](#)), as well as articles on incentives for teachers and health workers in developing countries as surveyed by [Kremer and Holla \(2008\)](#) and [Glewwe *et al.* \(2009\)](#). [Muralidharan and Sundararaman \(2011\)](#) and [Duflo *et al.* \(2012\)](#) study the effect of financial incentives for teachers on absenteeism and test scores, while [BenYishay and Mobarak \(2014\)](#) look at the role of incentives in leveraging peer learning to promote the adoption of agricultural technologies in Malawi.

There are also studies looking at the role of agents' intrinsic motivation and identification with either the task at hand or the intended beneficiaries in reducing the need for explicit incentives ([Bénabou and Tirole, 2003](#); [Akerlof and Kranton, 2005](#); [Besley and Ghatak, 2005](#)). In a laboratory setting, [Gneezy and Rustichini \(2000b\)](#) find

⁵ In the context of the government health insurance scheme studied here, [Das and Leino \(2011\)](#) analyse an information campaign in North India and get mixed results.

non-monotonicities in the effect of incentive pay on effort. As [Bandiera *et al.* \(2011\)](#) point out, there is little field-experimental evidence in this area, although [Ashraf *et al.* \(2014\)](#) is a recent exception.

The rest of the article is organised as follows: In [Section 1](#), a simple theoretical framework is presented with the aim of analysing the impact of incentive pay on agents' effort and its interaction with social-identity matching. [Section 2](#) describes the context, experimental design and data. [Section 3](#) presents the empirical evidence and [Section 4](#) concludes.

1. Theoretical Framework

In this Section, we develop a simple model of motivated agents. It extends the study by [Besley and Ghatak \(2005\)](#) by incorporating features of the multi-tasking model ([Holmstrom and Milgrom, 1991](#)). The aim is to provide a theoretical framework that can generate predictions about the effects of incentive pay and how these might interact with the effects of social distance.

Suppose agents exert an unobservable effort in spreading awareness of a scheme to potential beneficiaries. The goal may be either the transmission of knowledge itself or to increase programme enrolment. The principal can be thought of as a planner (say, the relevant government agency) who values either awareness of or enrolment in the programme among the eligible population. A given agent can interact with an exogenously fixed number of target households.

1.1. A Single Task

First, assume there is a single task. This could correspond to a situation in which the potential beneficiaries of the public service are relatively homogeneous. Let e be the unobservable effort exerted by the agent. Let the outcome variable Y be binary, with the value 0 denoting 'bad performance' or 'failure', and the value 1 denoting 'good performance' or 'success'. For example, a household doing well in a knowledge test (say, scoring above a certain threshold level), or enrolling in the programme, might be considered a success.

Agent effort stochastically improves the likelihood of a good outcome. To keep things simple, assume that the probability of success is $p(e) = e$, so that attention is restricted to values of e that lie between 0 and 1. Let us further assume that the lowest value e can take is $\underline{e} \in (0, 1)$, and the highest value e can take is $\bar{e} \in (\underline{e}, 1)$. This means that there is some minimum effort that any agent supplies and that even with this minimum effort, there is some chance that the good outcome will happen. There is also a maximum level of effort, and even at that level, the good outcome is not guaranteed to occur. Therefore, as is standard in agency models, there is common support. That is, either outcome (0 or 1) is consistent with any level of effort in the feasible range. It is also assumed that both the principal and the agent are risk neutral.

Let the agent's disutility of effort be $c(e) = (1/2)ce^2$. If the project succeeds, the agent receives a non-pecuniary pay-off of θ – this is her intrinsic motivation for the task – and the principal receives a pay-off of π , which may have a pecuniary as well as a non-pecuniary component. The planner's pay-off π incorporates both the direct

benefit to the beneficiaries and how the rest of society values their welfare. With perfect enforcement, the problem is:

$$\max_e (\theta + \pi)e - \frac{1}{2}ce^2,$$

subject to $e \in [\underline{e}, \bar{e}]$. The solution is:

$$e^{**} = \max \left\{ \min \left\{ \frac{\theta + \pi}{c}, \bar{e} \right\}, \underline{e} \right\}.$$

It should be noted that the effect of θ and c on e are similar although opposite in sign: an agent puts in more effort when the disutility of effort decreases or the non-pecuniary pay-off from success increases. This makes it hard to distinguish between the two empirically.

If effort is contractible, the principal can simply stipulate e^{**} . For the problem to be interesting, and for incentive pay to have an effect, assume that there is moral hazard in the choice of effort. Also, agents have zero wealth and there is limited liability: the agent's income in any state of the world must be above a certain minimum level, say, $\omega > 0$. From the principal's point of view, this creates a tension between minimising costs and providing incentives. In the absence of a limited liability constraint (LLC), the principal could have achieved the first-best outcome by imposing a stiff penalty or fine for failure. With limited liability, the only way the principal can motivate the agent, beyond relying on her intrinsic motivation θ , is to pay her a bonus that is contingent on performance. When setting the bonus, the principal has to respect the LLC and the incentive compatibility constraint (ICC). There is also a participation constraint (PC) which requires the agent's expected pay-off to be at least as high as her outside option. To keep things simple, it is assumed that the outside option is relatively unattractive so that the PC does not bind – the analysis would be qualitatively unchanged if this assumption were relaxed.

Let $\bar{w}$ be the pay the principal offers to the agent in the case of success, and let $\underline{w}$ be the pay in the case of failure. Define $b \equiv \bar{w} - \underline{w}$, which can be interpreted as bonus pay with $\underline{w}$ as the fixed-wage component. Then the agent's objective is:

$$\max_e (\theta + \bar{w})e + \underline{w}(1 - e) - \frac{1}{2}ce^2,$$

subject to $e \in [\underline{e}, \bar{e}]$, which yields:

$$e = \max \left\{ \min \left\{ \frac{\theta + b}{c}, \bar{e} \right\}, \underline{e} \right\}. \quad (1)$$

This is the ICC. Since $b \leq \pi$, effort will, in general, be lower than in the first-best scenario. This can be shown formally as follows. The principal's objective is:⁶

$$\max_{\bar{w}, \underline{w}} (\pi - \bar{w})e - \underline{w}(1 - e),$$

⁶ In the formulation presented here it is assumed that the principal does not put any direct weight on the agent's welfare but does take into account the welfare of the beneficiaries. An alternative formulation would be to put a weight λ on the welfare of the beneficiaries and a weight $1 - \lambda$ on the welfare of the agents. This would lead to higher incentive pay and higher effort.

subject to the ICC (1), the LLCs $\bar{w} \geq \omega$ and $\underline{w} \geq \omega$ and the PC:

$$(\theta + \bar{w})e + \underline{w}(1 - e) - \frac{1}{2}ce^2 \geq \underline{u}.$$

Since we ignore the PC (which is justified if $\underline{u}$ is small enough), the optimal contract is easy to characterise (see Besley and Ghatak, 2005, for details). As the agent is risk neutral, $\underline{w}$ will be at the lowest limit permitted by the LLC, namely $\underline{w} = \omega$. The solution for optimal bonus then follows:

$$b = \max \left\{ \frac{\pi - \theta}{2}, 0 \right\}.$$

Note that optimal bonus is strictly smaller than π .

Experimentally, we only observe outcomes for two given values of b , so the focus here will be on the ICC (1) rather than the optimal bonus. If there is no bonus pay and the agent is not sufficiently intrinsically motivated, we may get a lower corner solution, namely $e = \underline{e}$. This will be the case if $\underline{e} \geq \theta/c$. At the other extreme, if the agent is sufficiently motivated (namely, $\theta/c \geq \bar{e}$), then even without any bonus pay the agent chooses the maximum level of effort, $\bar{e}$. Otherwise, effort is increasing in bonus pay. The solution is illustrated in Figure 1. The slope of the interior-solution segment ($1/c$) is positive and so is its intercept (θ/c). However, depending on parameter values, the value of e for any given value of b could range from $\underline{e}$ to $\bar{e}$. For example, the case of a relatively unmotivated agent is captured by the dashed vertical line marked by $c\underline{e} > \theta$. In this case, the vertical axis (at which $b = 0$) intersects the effort curve at a flat section where $e = \underline{e}$. Similarly, a case where the agent is relatively highly motivated is captured by the line marked $\theta > c\bar{e}$, and an intermediate level of motivation is captured by the line marked $c\underline{e} < \theta < c\bar{e}$. In the former case, the agent is at the minimum effort level for $b = 0$ and initially the marginal effort with respect to bonus pay is zero. As bonus pay increases further, the marginal effort becomes positive, before returning to zero once the effort curve has hit the upper bound. If the vertical axis is at the right-most dashed vertical line, then the agent is already at the maximum effort level when $b = 0$ and effort will be unresponsive to incentive pay at any level. If the vertical axis is at the middle dashed line, effort level is at an interior value when $b = 0$ and the marginal effort with respect to bonus pay is positive.

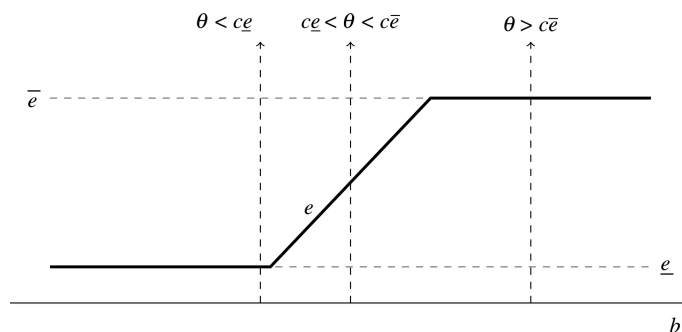


Fig. 1. *The One-task Solution*

1.2. Two Tasks

Assume now that the agent has two tasks, as in the multi-tasking model. The tasks may be thought of as the agent exerting effort to transfer knowledge to, or enrol, two different types of beneficiary households. However, unlike in the classic multi-tasking model, the outcomes associated with the two tasks are assumed to be equally measurable. Instead, the differences between the two tasks are in the agent's intrinsic pay-off from success and her cost of effort. Extending the notation from the previous section, let Y_1 and Y_2 be the binary outcomes for the two tasks and e_1 and e_2 the corresponding effort levels.

It is assumed that the principal is constrained to offer the agent the same conditional payments for the two tasks. That is, the payment in the case of success must be the same for tasks 1 and 2, as must the payment in the case of failure. This is justified if the principal is politically, socially or legally constrained to offer the same pay rates for all tasks. The assumption is also justified if the relevant characteristics of the households are not observable to the principal. For example, a knowledge agent may be biased in favour of some social or economic group or may have purely idiosyncratic biases, but if the principal does not observe the relevant dimension, the remuneration scheme cannot correct for it.

Let $\underline{e}$ and $\bar{e}$, where $0 < \underline{e} < \bar{e} < 1$, define lower and upper bounds for both e_1 and e_2 , and let θ_1 and θ_2 denote the non-pecuniary pay-offs to the agent from success in tasks 1 and 2 respectively. Let the agent's cost of effort be given by:

$$c(e_1, e_2) = \frac{1}{2} c_1 e_1^2 + \frac{1}{2} c_2 e_2^2 + \gamma e_1 e_2.$$

The parameter γ can be thought of as a measure of the cost-function substitutability of effort between tasks 1 and 2. To ensure that the marginal cost of effort in each task is always positive, it is assumed that $\gamma \geq 0$.

Note that if $c_1 = c_2 = \gamma = c$ and $\theta_1 = \theta_2 = \theta$, the set-up collapses to the single-task model. Abstracting from the special case $c_1 = c_2$ we can, without loss of generality, assume that $c_1 < c_2$ and refer to task 1 and 2 as the easier and the harder task respectively.

The principal values the tasks equally and so receives the same pay-off π from success in both. Then the first-best is characterised by:

$$\max_{e_1, e_2} (\theta_1 + \pi) e_1 + (\theta_2 + \pi) e_2 - \left(\frac{1}{2} c_1 e_1^2 + \frac{1}{2} c_2 e_2^2 + \gamma e_1 e_2 \right).$$

The first-order conditions yield the following interior solutions:

$$e_1(\pi) = \frac{(c_2 - \gamma)\pi + c_2\theta_1 - \gamma\theta_2}{c_1 c_2 - \gamma^2},$$

$$e_2(\pi) = \frac{(c_1 - \gamma)\pi + c_1\theta_2 - \gamma\theta_1}{c_1 c_2 - \gamma^2}.$$

For this to be a local maximum, the second-order condition requires:

$$c_1 c_2 > \gamma^2.$$

As before, corner solutions may be possible, and if e_i assumes a corner solution, then e_j ($j \neq i$) would take a different form.

Define the pair:

$$\hat{e}_1(\pi) = \begin{cases} \frac{\theta_1 + \pi - \gamma \underline{e}}{c_1} & \text{if } e_2(\pi) \leq \underline{e} \\ e_1(\pi) & \text{if } \underline{e} < e_2(\pi) < \bar{e} \\ \frac{\theta_1 + \pi - \gamma \bar{e}}{c_1} & \text{if } e_2(\pi) \geq \bar{e}, \end{cases}$$

$$\hat{e}_2(\pi) = \begin{cases} \frac{\theta_2 + \pi - \gamma \underline{e}}{c_2} & \text{if } e_1(\pi) \leq \underline{e} \\ e_2(\pi) & \text{if } \underline{e} < e_1(\pi) < \bar{e} \\ \frac{\theta_2 + \pi - \gamma \bar{e}}{c_2} & \text{if } e_1(\pi) \geq \bar{e}. \end{cases}$$

Now the complete first-best solution for the two-task model is given by:

$$e_1^*(\pi) = \max\{\min\{\hat{e}_1(\pi), \bar{e}\}, \underline{e}\},$$

$$e_2^*(\pi) = \max\{\min\{\hat{e}_2(\pi), \bar{e}\}, \underline{e}\}.$$

The second-best is characterised as follows. Let $\bar{w}$ be the wage the principal offers to the agent conditional on success in a task, let $\underline{w}$ be the wage conditional on failure and define $b \equiv \bar{w} - \underline{w}$. The agent's objective is to maximise:

$$\max_{e_1, e_2} (\theta_1 + \bar{w})e_1 + (\theta_2 + \bar{w})e_2 + \underline{w}(1 - e_1) + \underline{w}(1 - e_2) - c(e_1, e_2).$$

The first-order conditions yield:

$$e_1(b) = \frac{(c_2 - \gamma)b + c_2\theta_1 - \gamma\theta_2}{c_1c_2 - \gamma^2},$$

$$e_2(b) = \frac{(c_1 - \gamma)b + c_1\theta_2 - \gamma\theta_1}{c_1c_2 - \gamma^2}.$$

As in the single-task model, we expect effort levels to be lower than first-best because the PC of the agent is assumed not to bind. As in the first-best case, corner solutions may be possible, and following the same steps as above, we can derive $\hat{e}_1(b)$ and $\hat{e}_2(b)$:

$$\hat{e}_1(b) = \begin{cases} \frac{\theta_1 + b - \gamma \underline{e}}{c_1} & \text{if } e_2(b) \leq \underline{e} \\ e_1(b) & \text{if } \underline{e} < e_2(b) < \bar{e} \\ \frac{\theta_1 + b - \gamma \bar{e}}{c_1} & \text{if } e_2(b) \geq \bar{e}, \end{cases}$$

$$\hat{e}_2(b) = \begin{cases} \frac{\theta_2 + b - \gamma \underline{e}}{c_2} & \text{if } e_1(b) \leq \underline{e} \\ e_2(b) & \text{if } \underline{e} < e_1(b) < \bar{e} \\ \frac{\theta_2 + b - \gamma \bar{e}}{c_2} & \text{if } e_1(b) \geq \bar{e}. \end{cases}$$

The complete second-best solution for the two-task model is given by:

$$\tilde{e}_1(\pi) = \max\{\min\{\hat{e}_1(b), \bar{e}\}, \underline{e}\},$$

$$\tilde{e}_2(\pi) = \max\{\min\{\hat{e}_2(b), \bar{e}\}, \underline{e}\}.$$

Several aspects of the solution are worth noting. First, effort in the easier task, e_1 , is always weakly increasing in b .

Second, e_2 is also non-decreasing in b , except when both tasks are at internal solutions and $c_1 < \gamma < c_2$, when it is decreasing in b . The intuition for the negative slope is that when effort in the two tasks are relatively substitutable and both effort levels are at internal solutions, providing a monetary incentive leads the agent to substitute effort towards the easier task to a degree that causes effort in the harder task to decrease. We view this as a form of ‘crowding out’ since increasing incentive pay leads the agent to work less in one of the tasks. However, it is not quite crowding out in the sense of [Bénabou and Tirole \(2006\)](#), where the term is taken to imply a decrease in effort overall. In our case, the sum of effort across the two tasks is always weakly increasing in b . This follows trivially from the above except when both efforts are internal. But then:

$$e_1(b) + e_2(b) = \frac{(c_1 + c_2 - 2\gamma)b + (c_2 - \gamma)\theta_1 + (c_1 - \gamma)\theta_2}{c_1 c_2 - \gamma^2},$$

and $c_1 + c_2 - 2\gamma > c_1 + c_2 - 2\sqrt{c_1 c_2} = (\sqrt{c_1} - \sqrt{c_2})^2 > 0$, where the first inequality follows from the second-order condition, $c_1 c_2 > \gamma^2$.

Third, when both effort curves are internal, the slope of e_1 is always greater than the slope of e_2 .

Fourth, the slopes of all internal curves are completely determined by γ , c_1 and c_2 . The role of θ_1 and θ_2 is to shift the intercepts, and hence the lengths and meeting points, of the effort curves’ constituent line segments.

Before classifying the types of possible solutions, it is helpful to define the ‘intrinsically preferred task’ as the task in which the agent exerts the greatest effort when there is no bonus pay, that is, at $b = 0$. Task 1 is the intrinsically preferred task iff $\hat{e}_1(0) > \hat{e}_2(0)$, or:

$$\frac{\theta_1}{c_1 + \gamma} > \frac{\theta_2}{c_2 + \gamma}.$$

Otherwise, task 2 is the intrinsically preferred task. (With equality in the above expression, effort in each task is equal at $b = 0$.) Intuitively, a higher θ_i and a lower c_i both contribute to the agent’s intrinsic preference for task i . Note that it is possible that task 2, the harder task, is intrinsically preferred by the agent. This is the case if her intrinsic pay-off for the harder task (θ_2) is large enough to outweigh the cost disadvantage.

The main types of solutions can be classified using the relative magnitudes of γ , c_1 and c_2 . Above, it was assumed without loss of generality that $c_1 < c_2$, and the second-order condition requires $c_1 c_2 > \gamma^2$. The substitutability parameter γ must therefore be either less than both c_1 and c_2 , or equal to c_1 and less than c_2 , or lie between c_1 and c_2 .

[Figures 2–4](#) illustrate representative cases⁷ where task 1 is intrinsically preferred (effort in task 1 is greater at $b = 0$), and moreover, e_1 is already at the highest possible level $\bar{e}$ but e_2 has an interior solution. The latter corresponds to the condition

⁷ Online Appendix A discusses how these relate to the universe of possible cases.

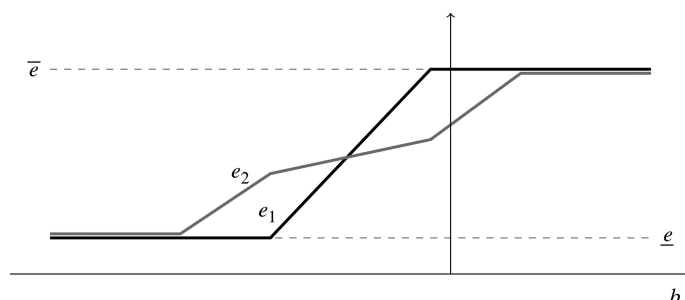


Fig. 2. A Solution without Crowding Out ($\gamma < c_1 < c_2$)

$(\theta_2 - \gamma \bar{e})/c_2 < \bar{e} < (c_2\theta_1 - \gamma\theta_2)/(c_1c_2 - \gamma^2)$. As in the single-task model, other solutions can be generated by drawing the vertical axis just to the left of the crossing point of the two effort curves, in which case task 2 would be intrinsically preferred. Also illustrated are the ‘kinks’ in e_2 that arise as e_1 meets the upper or lower bounds.

Solutions with $\gamma < c_1 < c_2$ (relatively low task substitutability) are illustrated in Figure 2. In the centre of the Figure, both effort curves are internal and positively sloped, while the slope of e_1 is greater than that of e_2 .

Figure 3 illustrates the case $\gamma = c_1 < c_2$. Here, effort in task 2 is temporarily satiated while both effort curves are internal. Again, which task is intrinsically preferred depends on the position of the vertical axis.

Figure 4 illustrates the case $c_1 < \gamma < c_2$ (relatively high task substitutability). This is the only case that permits ‘crowding out’, that is, a phase in which effort in one task (task 2) decreases with increasing bonus pay. As illustrated, crowding out can only happen when both effort curves are internal. Again, the intrinsically preferred task is determined by the position of the vertical axis.

Mapping the theory to the experimental setting, each of the model’s two tasks can be thought of as corresponding to a group of eligible households in the agent’s village. In the empirical analysis we find that, in the absence of bonus pay, agents tend to exert a greater effort with respect to households who are similar to themselves in terms of social characteristics. The model’s ‘intrinsically preferred task’ therefore corresponds to households who are socially proximate to the agent. These households will also be

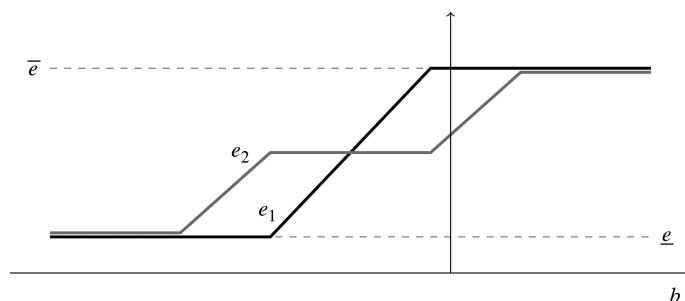


Fig. 3. A Solution with Temporary Satiation in e_2 ($\gamma = c_1 < c_2$)

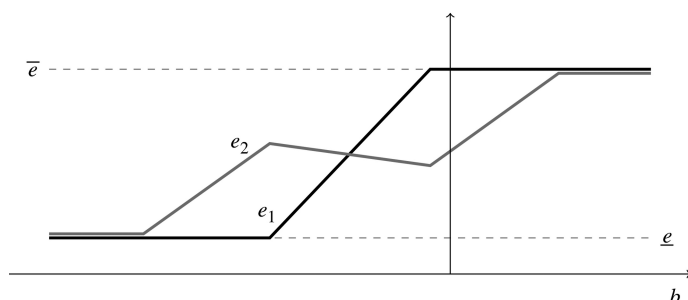


Fig. 4. A Solution with Crowding Out ($c_1 < \gamma < c_2$)

referred to as the agent's 'own group'. Households who are socially distant from the agent (the 'other group') correspond, in the model, to the task that is not intrinsically preferred.

Which task is intrinsically preferred depends on θ_i and c_i , both of which are in principle unobservable. Therefore, while the agent's 'own' group will be mapped to the intrinsically preferred task, it is not always possible to deduce whether this is task 1 (the easier task) or 2 (the harder task).

Note that we have modelled the agent's effort but not her time use. Some of the results presented below suggest that these are not the same: agents appear to be able to hold effort constant while varying the time spent on a task. Our interpretation is that agents can control the intensity of effort (effort exerted per unit of time) – in particular, they may engage in enjoyable but unproductive 'idle chatter' with their friends.

2. Context, Experimental Design and Data

2.1. The Programme

The experiment was conducted in the context of India's National Health Insurance Scheme (Rashtriya Swasthya Bima Yojana – henceforth, RSBY). The scheme was launched by the central government in 2007 with the aim of improving the 'access of BPL (Below the Poverty Line) families to quality medical care for treatment of diseases involving hospitalisation and surgery through an identified network of health care providers' (Government of India, 2009). Each state followed its own timetable for implementation, and a few districts from each state were selected for the first stage. 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 covered hospitalisation expenses for around 700 medical and surgical conditions, with an annual expenditure cap of 30,000 rupees (US\$ 652) per eligible household.⁸ Each household could enrol up to five members. Pre-existing conditions were covered, as was maternity care, but outpatient treatment was excluded.

⁸ Here and later, we use the currency exchange rate as per 1 July 2010 according to www.oanda.com (46 rupees/US\$).

The policy was underwritten by insurance companies selected in state-wise tender processes. The insurer received an annual premium per enrolled household,⁹ paid by the central (75%) and state (25%) governments. The beneficiary household paid only a 30 rupee (US\$ 0.65) annual registration fee.

Biometric information was collected from all members on the day of enrolment and stored, along with photographs, in a smart card issued to the household.¹⁰ Beneficiaries were entitled to cashless treatment at any participating ('empanelled') hospital across India. Both public and private hospitals could be empanelled. Hospitals were issued with card readers and software. The insurance companies reimbursed the hospitals for the cost of treating patients, according to fixed rates.

2.2. *Experimental Design*

One hundred and fifty-one villages were randomly selected from two of the first-phase RSBY districts in Karnataka: Shimoga and Bangalore Rural. In the first stage of randomisation, some villages in our sample (112 of 151) were randomly selected to be part of the treatment group, that is, receive an agent, while the remaining form the control group. In each treatment village, our field staff arranged a meeting with the local self-help groups (SHGs).¹¹ All contacted SHGs were female-only. In the meeting, SHG members were given a brief introduction to RSBY and told that we were looking to recruit a local agent to help spread awareness of the scheme in the village over a period of one year. They were told that the agent would be paid, but no further details about payment were given at that time. In each case, a single candidate was nominated by the group and recruited on the same day. The nominated agent was a member of the SHG, except in two cases where the selected agent was a non-member recommended by the SHG. In about a third of the cases, the president of the SHG became the agent. All agents were female.

Once the meeting was concluded and the agent selected, she was taken aside and given a more thorough introduction to the scheme, including details on eligibility criteria, enrolment, benefits and other relevant information. An agent background questionnaire was also fielded at this time.

The payment scheme was revealed to the agent only after recruitment. Each treatment village had been randomly allocated to a payment structure, which constituted the second stage of randomisation, but this information was kept secret. Even our field staff did not know about the contract type until after the agent had been selected. The day after recruitment, the agent was called and informed of her payment scheme. There were two payment schemes, defining the two treatment groups: flat-pay agents were told that they would be paid 400 rupees every three months. Incentive-pay agents were told that knowledge of RSBY would be tested in the eligible village population every three months. The agent's pay would depend on the results of these knowledge tests. There

⁹ The annual premium was determined at the state (and sometimes district) level, and was at the time in the range 400–600 rupees (US\$ 9–13). In Karnataka, the annual premium in the first year of operation was 475 rupees.

¹⁰ According to RSBY guidelines, smart cards should be issued at the time of registration, but this was often not adhered to. For more detail, see [Rajasekhar *et al.* \(2011\)](#).

¹¹ Self-help groups are savings-and-credit groups of about 15–20 individuals, often all women, who meet regularly. All government-sponsored SHGs in the village were invited to the meeting.

would be a fixed payment of 200 rupees every three months, but the variable component would depend entirely on the outcome of the knowledge tests in the village.¹²

The bonus payments were determined as follows: a random sample of households eligible for RSBY in each village was surveyed and orally presented with the knowledge test.¹³ A household was classified as having ‘passed’ the test if it answered at least four of eight questions correctly. The proportion of passing households in a village was multiplied by the number of eligible households in that village in order to estimate the total number of eligible village households that would have passed if everybody had taken the test. The bonus was calculated as a fixed amount per eligible household estimated to pass the test in a village, and set in such a manner that the average bonus payment across each of the two study districts would be 200 rupees per agent. The households taking the tests were not told how they scored, nor were they provided with the correct answers.

Thirty-eight villages/agents were assigned to the flat-pay treatment group, and 74 to the incentive-pay treatment group. Agents were told that there would be other agents in other villages, but not that there was variation in the payment scheme.

The purpose of not revealing the payment scheme until after recruiting the agent was to isolate the incentive effect of the payment structure from its potential selection effect. None of the agents pulled out after learning of the payment scheme. However, four agents dropped out 6–12 months after recruitment (after at least two rounds of payments). Three of these were in incentive-pay villages, while the fourth was in a flat-pay village.¹⁴ In each case, the reported reason was either childbirth or migration away from the village. The agents were replaced, but the villages in question are excluded from the analysis. Hence, in the analysis presented here, there are 37 villages with flat-pay agents and 71 villages with incentive-pay agents, for a total of 108 agents in 108 treatment villages. The number of control villages remains 39, so the total number of villages in our final sample is 147.

One question of interest is whether eligible households knew the type of payment scheme the agent in their village was on. We do not have data on this, but on balance we believe that most did not. When asked to nominate an agent, the self-help group was told the work would be remunerated but given no further details. We were careful to tell the agent about the type of contract in private, after selection, and away from the group. When we returned to make payments, these were also always made in private. The agents were of course free to tell others how they were paid, but people locally tend to be reticent in talking about money. Anecdotally, we know that at least some agents on incentive pay were careful not to reveal this information because, once spread, it might reduce their credibility as pro-social volunteers and thereby the villagers’ willingness to listen. In any case, from a policy point of view, one would probably want to capture the

¹² As part of the original experimental design, we also provided a second type of incentive pay to some agents based on programme utilisation by the beneficiaries in their village. But because the scheme was hardly operational during the period of our study, overall utilisation of RSBY across Karnataka was very low. See [Rajasekhar *et al.* \(2011\)](#) for details. These agents and the corresponding villages are excluded from the analysis presented here.

¹³ For each survey wave, a fixed number of households per village were targeted, and on average 13 households were interviewed per village per wave. The average sample village had 50 eligible households.

¹⁴ Assuming that attrition is Poisson distributed, we are unable to reject the null hypothesis that the rate of attrition was the same across the two treatment groups.

total effect of the contract types inclusive of any additional effect on eligible households who learn how their agent is paid.¹⁵

The original plan was to set the variable part of the pay scale for incentive-pay agents in such a manner that average pay would equal 400 rupees in each of the two treatment groups. The aim of equalising average pay across the incentive-pay and flat-pay groups was to isolate the incentive effect of the contract structure ('incentive effect') from that of the expected payment amount ('income effect'). The pay did in fact average 400 rupees for one district (Shimoga) in the first survey round and for both districts in the second, third and fourth rounds. But due to an administrative error, a majority of incentive-pay agents in Bangalore Rural were overpaid in the first round of payments. In spite of the error, the rank ordering of agents was preserved in the sense that better-performing agents were indeed paid more. Nevertheless, we also present results only for Shimoga district, where average pay in the knowledge group was equal to that of flat-pay agents (400 rupees) in all rounds.

2.3. Data

Following agent recruitment, four consecutive rounds of 'mini-surveys' were fielded.¹⁶ In each wave, randomly selected eligible households in each sample village were interviewed to establish the state of their knowledge about the scheme and determine their test scores, as well as measure their enrolment status. An important purpose of these surveys was to provide information on agent performance so as to be able to pay the incentive-pay agents. The households were drawn at random (with replacement) for the first, second and fourth survey rounds, so that there is a partial overlap between the households in these rounds. The first, second and fourth rounds of mini-surveys were based on face-to-face interviews. For the third survey, the sample from the second survey was re-used, but this time the households were contacted by telephone. Although not everyone could be reached by phone, the re-survey rate was significant. A sample of 2,360 households were interviewed in the first mini-survey wave, 1,931 in the second, 1,346 in the third and 2,093 in the fourth. In all, the mini-surveys cover 3,998 households, of which 1,068 were interviewed twice, 642 were interviewed three times and 460 were interviewed four times. As the tests were conducted in every sample village, there was no difference between incentive and flat-pay agents in the intensity of monitoring.

Using each household observation as an equally-weighted data point would give more weight to households that were observed more than once. Observation weights were introduced to take account of this, so that the total weight across observations equals 1 for all households. All regressions using data from more than one mini-survey are weighted least squares. In addition, standard errors are clustered at the village level

¹⁵ In this sense, side payments or doing favours to incentivised agents would be not regarded as possible threats to our story, but rather as mechanisms through which incentive pay might work. In practice, however, we believe that the scope for collusion was limited: agents and households were never notified in advance of the knowledge tests. The households were not given the questions in writing, and they were not told whether they had answered the questions correctly or not, nor their overall score. The sample of households to whom the knowledge test was fielded was drawn independently each time. The agent did not know exactly how household knowledge test scores mapped into her bonus pay. Also, as pointed out by one referee, households similar to the incentivised agent would be the ones more likely to do her a favour by trying harder, yet we find the opposite: incentivised agents do relatively better with households who are socially different from her.

¹⁶ The data and do-file used to generate the Tables are available online.

Table 1
Agent Summary Statistics

	Flat pay	Incentive pay	Difference
Agent age	34.8 (8.81)	34.8 (8.08)	0.018 [1.73]
Agent is married	0.81 (0.40)	0.92 (0.28)	0.10 [0.073]
Agent is of forward/dominant caste	0.43 (0.50)	0.35 (0.48)	-0.080 [0.10]
Agent's household head has completed primary school	0.62 (0.49)	0.56 (0.50)	-0.058 [0.10]
Agent household has ration card	0.89 (0.31)	0.79 (0.41)	-0.10 [0.071]
Agent owns her home	0.86 (0.35)	0.87 (0.34)	0.0084 [0.069]
Agent is self-help group president	0.30 (0.46)	0.28 (0.45)	-0.016 [0.093]
Agent autonomy score (the higher, the more autonomous)	5.57 (0.93)	5.68 (0.84)	0.11 [0.18]
Observations	37	71	-

Notes. Standard deviations are in parentheses. Robust standard errors for the difference tests are in brackets.
*p < 0.10, **p < 0.05, ***p < 0.01.

(Bertrand *et al.*, 2004). Since serial correlation is probably more severe within a household than across households within a village, clustering at the village level yields consistent, but not necessarily efficient, estimates.

After the completion of each mini-survey, the agents were revisited and paid. At the same time, the agents' knowledge of the scheme was refreshed and added to.

Descriptive statistics on agents are presented in Table 1. Recall that all agents are female. The average agent is around 35 years old, 88% are married, 58% of the agents' household heads have completed primary school and 82% of agent households have a ration card,¹⁷ and 38% are from a forward or dominant caste.¹⁸ In 29% of the cases, the recruited agent was the president of a self-help group. We also constructed a 'female autonomy' score for the agents.¹⁹

Table 2 presents summary statistics for the villages. The average village has a little over 200 households, of which about 50 are eligible for the scheme. About a quarter of sample villages are gram panchayat (village council) headquarters, and the distance from the

¹⁷ These cards entitle the holders to purchase certain foods at subsidised rates. The cards are intended for the poor, but because of mis-allocation issues they are an imperfect indicator of poverty.

¹⁸ In Karnataka, two castes officially classified as 'backward', Vokkaliga and Lingayath, tend to dominate public life. These two have therefore been classified together with the forward caste groups in one category as 'dominant castes'.

¹⁹ 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 allowed to visit it only 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 highest score, 6.

Table 2
Village Summary Statistics

	Control	Flat pay	Inc'tive pay	Flat – Control	Inc'tive – Control	Inc'tive – Flat
Village size (households)	205.1 (193.0)	222.6 (167.7)	237.2 (248.8)	17.5 [41.7]	32.2 [42.8]	14.6 [40.7]
Eligible population (households)	42.9 (45.1)	56 (51.5)	56.2 (53.9)	13.1 [11.1]	13.3 [9.6]	0.17 [10.6]
Village is GP headquarters	0.18 (0.39)	0.30 (0.46)	0.25 (0.44)	0.12 [0.098]	0.074 [0.081]	–0.044 [0.092]
Distance to GP headquarters in km (0 if headquarters)	2.92 (3.46)	2.26 (2.15)	2.35 (2.21)	–0.67 [0.66]	–0.58 [0.61]	0.088 [0.44]
Distance to nearest town in km	11.5 (6.20)	15.8 (12.9)	13.3 (10.4)	4.33* [2.33]	1.83 [1.59]	–2.49 [2.44]
Proportion of village land irrigated	0.69 (0.47)	0.59 (0.50)	0.63 (0.49)	–0.098 [0.11]	–0.059 [0.094]	0.039 [0.10]
Village has drainage sanitation	0.79 (0.41)	0.89 (0.31)	0.89 (0.32)	0.097 [0.083]	0.092 [0.075]	–0.0046 [0.064]
Average social distance between households in village	0.30 (0.081)	0.28 (0.083)	0.29 (0.082)	–0.017 [0.019]	–0.0089 [0.016]	0.0078 [0.017]
Observations	39	37	71	–	–	–

Notes. Standard deviations are in parentheses. Robust standard errors for the difference tests are in brackets. GP, gram panchayat. *p < 0.10, **p < 0.05, ***p < 0.01.

village to the nearest town is about 13 kilometres. None of the village-level variables differ significantly across treatment groups.

Table 3 presents summary statistics for households. The average household has 4.8 members, 17% are from a forward/dominant caste. In 27% of households, the household head has completed primary school, 92% have a ration card. It is interesting to note that agents are more likely than the average eligible household to belong to the forward/dominant caste category. Agent households are also more highly educated than the average eligible household.

The main outcome variable is the household ‘knowledge score’. A knowledge test was fielded, in each of the four mini-surveys, to all interviewed households across the three experimental arms. Each test consisted of eight questions about particulars of the RSBY scheme, including eligibility, cost, cover, exclusions and how to obtain care. The exact questions used in the knowledge tests are provided in online Appendix B. Each answer was recorded and later coded as being correct or incorrect. The number of correct answers gives each interviewed household a score between 0 (least knowledgeable) and 8 (most knowledgeable).²⁰

The test questions asked in the four surveys were different, so although the raw scores can be compared across households within a survey, they are not necessarily directly comparable across surveys, even for a given household. The scores on each test were

²⁰ Question 8 on the third test is difficult to mark as correct or incorrect, as there are several ways in which an RSBY member might plausibly check whether a particular condition will be covered ahead of visiting a hospital. For this reason the question is omitted when computing the overall score and the maximum score on the third test is taken to be 7.

Table 3
Household Summary Statistics

	Control	Flat pay	Inc'tive pay	Flat – control	Inc'tive – control	Inc'tive – flat
Household is of forward/dominant caste	0.22 (0.42)	0.18 (0.39)	0.15 (0.36)	–0.041 [0.046]	–0.068* [0.037]	–0.027 [0.036]
Household head has completed primary school	0.29 (0.45)	0.23 (0.42)	0.30 (0.46)	–0.057* [0.032]	0.0042 [0.029]	0.061** [0.026]
Household has ration card	0.93 (0.26)	0.93 (0.26)	0.92 (0.27)	0.0040 [0.020]	–0.0037 [0.019]	–0.0077 [0.018]
Household owns its home	0.65 (0.48)	0.63 (0.48)	0.64 (0.48)	–0.024 [0.042]	–0.010 [0.034]	0.014 [0.038]
Household knowledge score, mean	–0.11 (0.74)	–0.028 (0.79)	0.11 (0.80)	0.077 [0.094]	0.21*** [0.077]	0.14 [0.087]
Household is enrolled, mean	0.67 (0.38)	0.68 (0.40)	0.73 (0.37)	0.0029 [0.051]	0.058 [0.039]	0.055 [0.044]
Social distance to agent	–	0.39 (0.24)	0.37 (0.26)	–	–	–0.023 [0.035]
Agent time spent with household, in minutes	–	15.9 (26.6)	15.6 (33.4)	–	–	–0.33 [3.23]
Observations	919	886	1,634	–	–	–

Notes. Standard deviations are in parentheses. Standard errors for the difference tests, clustered at the village level, are in brackets. *p < 0.10, **p < 0.05, ***p < 0.01.

therefore standardised by subtracting the test-wise mean and dividing by the standard deviation.

3. Evidence

3.1. *The Impact of Agents on Knowledge*

Consider first the impact of knowledge agents on household knowledge score. The basic specification is:

$$Y_{hv} = \alpha + \beta T_v + \epsilon_{hv}. \tag{2}$$

The outcome variable Y_{hv} is the test z -score for household h in village v . T_v is a binary variable equal to 1 if the household lives in a treatment village (a village with a knowledge agent of either type) and 0 otherwise. The coefficient β captures the average effect on test score of being in a treated village, and α is a constant reflecting the average test score in the control group.

The results of regression (2) are presented in Table 4, column (1). Households living in a treatment village score 0.18 standard deviations higher on the knowledge test compared to households in the control villages. Column (2) indicates that this effect is robust to the inclusion of fixed effects for taluk (the administrative unit below district) and time (survey wave).

In column (3), the treatment effect is estimated separately for flat-pay and incentive-pay agents, while still including taluk and time fixed effects. The estimated effect

Table 4
The Effect of Agents on Knowledge

	(1) Knowledge	(2) Knowledge	(3) Knowledge
Agent in village	0.175*** (0.0662)	0.190*** (0.0611)	
Flat-pay agent in village			0.0677 (0.0842)
Incentive-pay agent in village			0.252*** (0.0623)
Survey wave fixed effects	No	Yes	Yes
Taluk fixed effects	No	Yes	Yes
Observations	7,730	7,730	7,730
t-test: flat = incentivised (p-value)			0.0198

Notes. Weighted least-squares regressions. Each household is given the same weight, divided equally between all observations of that household. Standard errors, in parentheses, are clustered at the village level. *p < 0.10, **p < 0.05, ***p < 0.01.

of flat-pay agents on test scores, while positive, is not statistically significant. This is consistent with the argument that, since these agents are paid a constant amount irrespective of outcome, they are not incentivised to exert any effort beyond the level determined by their intrinsic motivation. In contrast, households in villages assigned an incentive-pay agent score 0.25 standard deviations higher on the knowledge test than those in the control group. Hence, providing agents with financial incentives leads to an improvement in knowledge about the scheme among beneficiaries. Moreover, equality of these two coefficients is rejected. This suggests that, looking at the sample overall, the effect of knowledge-spreading agents is driven by the agents on incentive-pay contracts.

As mentioned, an administrative error caused incentive-pay agents in one district (Bangalore Rural) to be overpaid after the first survey. To allay concerns that our findings are driven by these higher rates of pay, Table 5 presents results using only data from Shimoga district, where no error was made. Overall, the qualitative findings are similar to those obtained in Table 4, if not stronger. Hence, it appears that the main findings are not driven by the larger payments made to agents in one district for one of the four rounds.

Effects by survey round and by agent characteristics are presented in online Appendix C.

3.2. *The Impact of Agents on Enrolment*

Next consider the impact of knowledge agents on programme enrolment. Although the agents were not incentivised to enrol households into the scheme, it is conceivable that increasing households' knowledge about the scheme might induce enrolment. Enrolment is also of primary policy relevance.

The results are presented in Table 6. Households living in a treatment village are on average 4.5 percentage points more likely to enrol in the scheme than households

Table 5
The Effect Agents on Knowledge, Shimoga District Only

	(1) Knowledge	(2) Knowledge	(3) Knowledge
Agent in village	0.222*** (0.0752)	0.202*** (0.0699)	
Flat-pay agent in village			0.0315 (0.106)
Incentive-pay agent in village			0.301*** (0.0694)
Survey wave fixed effects	No	Yes	Yes
Taluk fixed effects	No	Yes	Yes
Observations	3,954	3,954	3,954
t-test: flat = incentivised (p-value)			0.0190

Notes. Weighted least-squares regressions. Each household is given the same weight, divided equally between all observations of that household. Standard errors, in parentheses, are clustered at the village level. *p < 0.10, **p < 0.05, ***p < 0.01.

in the control villages, although this effect is not statistically significant (column (1)). Controlling for taluk and wave fixed effects does not change this result (column (2)). Once we disaggregate the treatment effect by agent contract type, we find that households living in a treatment village where the agent was on an incentive-pay contract are 7.5 percentage points more likely to be enrolled relative to control group, significant at 5%. No significant impact is found for those living in a treatment village where the agent was on a flat-pay contract. As with the knowledge score results reported above, we are able to reject the equality of the two coefficients at the 5% level. Hence, incentivising agents to disseminate programme knowledge also boosted enrolment.

Table 6
The Effect of Agents on Enrolment

	(1) Enrolled	(2) Enrolled	(3) Enrolled
Agent in village	0.0445 (0.0352)	0.0465 (0.0325)	
Flat-pay agent in village			-0.0102 (0.0434)
Incentive-pay agent in village			0.0754** (0.0332)
Survey wave fixed effects	No	Yes	Yes
Taluk fixed effects	No	Yes	Yes
Observations	7,730	7,730	7,730
t-test: flat = incentivised (p-value)			0.0294

Notes. Weighted least-squares regressions. Each household is given the same weight, divided equally between all observations of that household. Standard errors, in parentheses, are clustered at the village level. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 7
Difference in Differences: Mean Knowledge Scores by Contract Type and Social Distance

	Socially proximate pairs	Socially distant pairs	Difference
Flat pay	0.05 (0.03)	-0.09 (0.03)	-0.14** (0.05)
Incentive pay	0.12 (0.02)	0.13 (0.03)	0.01 (0.04)
Difference	0.07 (0.04)	0.22*** (0.04)	0.15*** (0.06)

Notes. Standard errors are in parentheses. ‘Socially proximate pairs’ is a binary variable equal to 1 if the composite social distance metric is equal to or less than 0.5 and 0 otherwise. These regressions use data only from the treatment villages, that is, villages with agents, since social distance is not defined for villages without agents. *p < 0.10, **p < 0.05, ***p < 0.01.

3.3. *Incentives and Social Distance*

The results so far suggest that monetary incentives matter for how effective agents are at disseminating information about the scheme and increasing enrolment. But previous work suggests that social identity is also an important determinant of insurance take-up. Cole *et al.* (2013) find that demand for rainfall insurance is significantly affected by whether the picture on the associated leaflet (a farmer in front of either a Hindu temple or a mosque) matches the religion of the potential buyer.

This subsection asks whether matching agents with target households in terms of social characteristics has an effect on knowledge scores that is independent of the effect of incentive pay. Also, it investigates whether the effects of social distance and incentive pay are purely additive or whether they reinforce or weaken each other.

A simple metric of social distance was constructed as follows. First, we created four binary variables which capture basic social dimensions and for which we have data for both the agent and eligible households: forward/dominant caste status (0/1), whether the household head has completed primary school (0/1), ration-card status (0/1) and home ownership (0/1). In each of these four dimensions, the social distance between an agent and a household is defined as the absolute difference in the agent’s and the household’s characteristics. To take ration-card status as an example, ration-card distance is set to 0 if either both have a ration card or if neither does. Ration-card distance is 1 if any one of them has a ration card and the other does not.²¹

The composite social distance metric is the simple sum across the four individual distance measures, normalised to lie between zero and one by dividing by four.

Before turning to the main specification, consider the basic difference-in-differences calculation in Table 7. We create a binary variable, ‘socially proximate pair’, indicating whether or not the composite social distance metric is equal to or less than 0.5. The mean knowledge scores for socially proximate and socially distant household–agent pairs are tabulated by agent contract type. Reading the Table row by row, flat-pay agents

²¹ The choice of variables for use in the calculation of social distance was severely constrained, as only a small number of variables were observed for both agents and eligible households. That said, our social distance metric does incorporate measures of caste, education, asset ownership and poverty status. A more sophisticated social distance metric for rural India would probably include measures of most, if not all, of these.

are significantly more effective at transmitting knowledge to socially proximate households than to the socially distant households – average scores are higher by 0.14 standard deviations. For incentivised agents there is no significant difference in performance between close and distant pairs, and the difference in differences is significant. Alternatively, reading the Table column by column, incentive pay seems not to affect knowledge transmission in proximate pairs, but it does increase knowledge transmission in distant agent–household pairs, up to about the same level as for proximate pairs. Note that the socially distant households who are assigned a flat-pay agent score significantly lower than any of the other three groups, which is indicative of the disadvantage created by social distance in the absence of incentive pay. In summary, the difference-in-differences analysis suggests that incentive pay has the effect of neutralising social distance as an impediment to the transmission of knowledge – a finding that will be corroborated in what follows.

The main empirical specification for this subsection is:

$$Y_{hv} = \alpha + \beta D_{hv} + \gamma T_v + \delta D_{hv} T_v + \pi X_{hv} + u_{hv}. \quad (3)$$

Here, D_{hv} denotes social distance between household h in village v and the agent in village v . T_v is a binary variable indicating whether the agent in village v is on an incentive-pay contract. (The control villages drop out from this analysis since the distance metrics are not defined when there is no agent.) X_{hv} are level variables for each of the agent and household characteristics that are considered in the construction of the social distance metrics.

The coefficient β captures the effect²² of social distance on knowledge when the agent is not incentivised. The coefficient γ captures the effect of incentive pay for socially proximate (non-distant) agent–household pairs. Finally, δ captures the differential effect of incentive pay for socially distant agent–household pairs relative to socially proximate ones.

The results are presented in Table 8. Column (1) confirms that incentive-pay agents have a significant and positive impact on knowledge compared to flat-pay agents, even when controlling for agent and household caste, education, ration-card status and home-ownership as well as taluk and time-fixed effects.

Column (2) presents results for the composite social distance metric. The un-interacted treatment effect is not significant, while the coefficients on social distance and the interaction of incentive pay with social distance are both highly significant and roughly opposite in magnitude. We interpret this in three steps: first, it confirms that social distance has a negative impact on knowledge transmission. Second, putting agents on an incentive-pay contract has a positive effect on knowledge transmission, but only for socially distant agent–household pairs. And third, the effect of providing financial incentives (at our level of bonus pay) is more or less exactly the level required to cancel the negative effect due to social distance. In other words, the effect of incentive pay seems to be to cancel the negative effect of social distance, but no more. Loosely speaking, we may say that incentive pay appears to ‘price out prejudice’, although the effects of social distance are not necessarily a function of prejudice alone. For example, socially proximate pairs may meet more often socially, reducing the cost of effort

²² The words ‘effect’ and ‘impact’ are used for ease of exposition, but we cannot make the same claims of causality in this part of the analysis since social characteristics were not randomly allocated.

Table 8
Incentives and Social Distance – Effect on Knowledge

	(1) Knowledge	(2) Knowledge	(3) Knowledge	(4) Knowledge	(5) Knowledge	(6) Knowledge	(7) Knowledge	(8) Knowledge
Incentive pay	0.156** (0.0781)	-0.0499 (0.114)	-0.0894 (0.133)	-0.100 (0.131)	0.0529 (0.0940)	0.220** (0.102)	0.0799 (0.0805)	0.0901 (0.0894)
Social distance		-0.429** (0.183)	-0.372* (0.210)	-0.328 (0.228)	-0.226** (0.0992)	0.0862 (0.0881)	-0.240** (0.118)	-0.123 (0.0798)
Incentive pay × social distance		0.559*** (0.194)	0.483** (0.212)	0.517** (0.234)	0.254** (0.122)	-0.123 (0.105)	0.398*** (0.136)	0.188** (0.0898)
Castes live apart			-0.278** (0.122)					
Incentive pay × castes live apart			0.260 (0.165)					
Physical distance				-0.0272 (0.0716)				
Incentive pay × physical distance				0.00673 (0.0834)				
Agent and household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave and taluk fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social distance metric	-	Composite	Composite	Composite	Caste only	Education only status only	Ration-card ownership only	Home ownership only
Observations	4,854	4,854	3,877	3,189	4,854	4,854	4,854	4,854

Notes. Weighted least-squares regressions. The regressions use data only from treatment villages, that is, villages with agents, since the distance measures are not defined for villages without agents. Each household is given the same weight, divided equally between all observations of that household. Standard errors, in parentheses, are clustered at the village level. In all columns, agent and household characteristics are binary indicators for whether the agent and household are of forward/dominant caste, whether the head has completed primary school, whether they have a ration card and whether they own their home. The simple social distance metrics in columns (5)–(8) are binary variables equal to the absolute difference between the corresponding household and agent characteristic binaries. The composite social distance metric in columns (2)–(4) is the sum of the binary distance metrics for caste, education, ration-card status and home ownership, divided by 4. 'Castes live apart' is a binary indicator for whether castes are separated into separate zones in the village, and 'physical distance' is the great-circle distance in metres between the agent and household dwellings. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

required to transmit information. See online Appendix D for a discussion of the magnitude of the main effect relative to the incentive.

In Indian villages, caste groups sometimes live in distinct sub-villages called hamlets. This means that the social distance between a pair of households in the village may be positively correlated with the physical distance between them. To the extent that this is the case, it is possible that the results so far confound the effect on knowledge transmission of social distance with that of physical distance. After all, it seems natural that the cost of knowledge transmission increases with the physical distance between the agent and a household.

We control for the role of physical distance using two separate measures. The first is whether or not caste groups in a village tend to live apart. This information is based on enumerator recall and hence only available for 107 of the 147 villages. Based on this information, we construct a binary indicator which is equal to 1 if, in a given village, the settlements of the major caste groups are physically separated, and 0 otherwise. The indicator is equal to 1 for 26 of 107 villages. Returning to Table 8, this indicator and its interaction with the incentive-pay variable are included in the regression in column (3).

While the sample size drops, the results in column (3) confirm that physical separation does have a negative effect on knowledge transmission. Like for social distance, the coefficient on the interaction of incentive pay and physical distance is of opposite sign and roughly equal magnitude to the un-interacted physical distance term. While the interaction term is not statistically significant, this may indicate that incentive pay can overcome barriers to physical distance. But the results also show that the social distance indicator and its interaction with incentive-pay are still significant at the 10% and 5% levels, respectively, and do not drop much in magnitude. This indicates that social distance matters, even after controlling for physical distance.

The measure of physical distance used above is crude, and it is conceivable that the social distance measure still captures some physical distance effect. Hence, we use a second and more accurate measure of physical distance in the form of the actual straight-line distance in metres between the agent's and the household's dwellings, constructed from GPS coordinates collected in the field. Since these data were only collected during the fourth survey wave, the analysis can only be undertaken for a subset of the total sample. Using this second measure, we find results in column (4) that are qualitatively similar to those obtained with the crude measure in column (3). The coefficient on social distance is no longer statistically significant at conventional levels, possibly due to the fact that the sample size drops by almost a quarter. But the coefficient continues to be of opposite sign to that of its interaction term with incentive-pay. In addition, both the coefficient on social distance and that on the interaction term are not significantly different from those obtained in column (2) without the inclusion of physical distance (p-values for the F-tests are 0.38 and 0.74 respectively), which increases our confidence that these results are less likely to be driven by confounding factors. Moreover, this measure of physical distance does not appear to exert any independent influence on knowledge scores.

Columns (5)–(8) repeat the exercise in column (2) for each of the component social distance metrics. For distance in caste, ration-card status and home ownership, the story appears to align with the findings for the composite metric presented above, albeit not always with full significance. However, for education, there appears to be no significant disadvantage due to social distance. In other words, agent–household communication

Table 9
Testing for Symmetry: Differences in Differences in Knowledge Score, by Agent Caste Category

	Dominant household	Non-dominant household	Difference (dom – non)
Dominant-caste agent			
Flat pay	0.05 (0.09)	–0.11 (0.04)	0.16* (0.09)
Incentive pay	0.06 (0.07)	0.09 (0.03)	–0.03 (0.07)
Difference (inc – flat)	0.01 (0.11)	0.20*** (0.05)	–0.19 (0.12)
Non-dominant-caste agent			
Flat pay	–0.13 (0.08)	0.06 (0.04)	–0.19** (0.09)
Incentive pay	0.07 (0.06)	0.15 (0.02)	–0.09 (0.07)
Difference (inc – flat)	0.20** (0.10)	0.10** (0.04)	0.10 (0.11)

Notes. Standard errors are in parentheses. This Table uses only the sample of treatment villages, that is, villages with agents, since distances are not defined in the control villages (where there are no agents). *p < 0.10, **p < 0.05, ***p < 0.01.

appears to be hampered by differences in caste, ration-card status and possibly home ownership, but not by differences in education. Correspondingly, in this specification, un-interacted incentive pay has a large and positive co-efficient. That is, agents do not appear to be at a disadvantage when communicating with households with a different educational background (having completed primary school or not) from themselves, and the introduction of incentives correspondingly boosts results for socially proximate and distant households alike.

It is of interest to examine whether the impact of social distance and its interaction with incentive-pay is symmetric across the caste hierarchy. In other words, is the impact of social distance between agent and beneficiary household more severe when a lower caste agent interacts with a higher caste household than *vice versa*? To test this, we compute differences in differences in mean effects by agent caste group. The results, presented in Table 9, suggest that the qualitative findings are symmetric: irrespective of the agent’s own caste group, the coefficient representing the effect of introducing incentive pay is greater with respect to the cross-group than to the own group. This is reassuring, although in this basic analysis the differences in differences are not statistically significant.

Table 10 presents results for our other main outcome variable, enrolment. The results are qualitatively similar to those obtained for knowledge scores, and with somewhat greater significance for the composite measure of social distance (columns (2)–(4)). Once again the main effect of incentives appears to be to cancel the negative effects of social distance. This finding is robust to the inclusion of controls for either measure of physical distance. Taken together, the analysis in this subsection suggests that social distance can lower the efficacy of welfare programmes through reduced knowledge transmission and enrolment, and that the use of incentive pay can counteract this effect.

Table 10
Incentives and Social Distance – Effect on Enrolment

	(1) Enrolled	(2) Enrolled	(3) Enrolled	(4) Enrolled	(5) Enrolled	(6) Enrolled	(7) Enrolled	(8) Enrolled
Incentive pay	0.0648* (0.0388)	−0.0700 (0.0548)	−0.100 (0.0674)	−0.115 (0.0768)	0.0116 (0.0398)	0.0527 (0.0424)	0.00664 (0.0354)	0.0529 (0.0472)
Social distance		−0.238** (0.0983)	−0.212* (0.112)	−0.348** (0.138)	−0.0630 (0.0507)	−0.0286 (0.0355)	−0.237*** (0.0664)	−0.00297 (0.0420)
Incentive pay × social distance		0.368*** (0.132)	0.313** (0.134)	0.396** (0.174)	0.133** (0.0651)	0.0221 (0.0467)	0.306*** (0.0942)	0.0348 (0.0483)
Castes live apart			−0.0727 (0.0642)					
Incentive pay × castes live apart			0.173** (0.0820)					
Physical distance				−0.0544 (0.0446)				
Incentive pay × physical distance				−0.00202 (0.0592)				
Agent and household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave and taluk-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social distance metric	–	Composite	Composite	Composite	Caste only	Education only	Ration-card status only	Home ownership only
Observations	4,854	4,854	3,877	3,189	4,854	4,854	4,854	4,854

Notes. Weighted least-squares regressions. The regressions use data only from treatment villages, that is, villages with agents, since the distance measures are not defined for villages without agents. Each household is given the same weight, divided equally between all observations of that household. Standard errors, in parentheses, are clustered at the village level. In all columns, agent and household characteristics are binary indicators for whether the agent and household are of forward/dominant caste, whether the head has completed primary school, whether they have a ration card and whether they own their home. The simple social distance metrics in columns (5)–(8) are binary variables equal to the absolute difference between the corresponding household and agent characteristic binaries. The composite social distance metric in columns (2)–(4) is the sum of the binary distance metrics for caste, education, ration-card status and home ownership, divided by 4. ‘Castes live apart’ is a binary indicator for whether castes are separated into separate zones in the village, and ‘physical distance’ is the great-circle distance in metres between the agent and household dwellings. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11
Agent Time Spent with Household

	(1) Minutes	(2) Minutes	(3) Minutes	(4) Minutes
Incentive pay	−1.059 (1.683)	−5.178** (2.510)	−5.884* (3.178)	−6.369** (2.944)
Social distance		−8.298** (3.570)	−6.570 (4.123)	−9.965** (3.862)
Incentive pay × social distance		10.96** (5.256)	9.112 (5.776)	13.04** (5.779)
Castes live apart			−4.297 (4.262)	
Incentive pay × castes live apart			5.901 (5.258)	
Physical distance				−1.544 (1.831)
Incentive pay × physical distance				−0.347 (1.983)
Agent and household characteristics	Yes	Yes	Yes	Yes
Taluk fixed effects	Yes	Yes	Yes	Yes
Observations	1,539	1,539	1,221	1,459

Notes. Ordinary least-squares regressions. Only data from treatment villages are used, that is, villages with agents, since the distance measures are not defined for villages without agents. Standard errors, in parentheses, are clustered at the village level. The dependent variable is the number of minutes the agent spent with the household talking about the programme in minutes in the fourth round of the intervention, as reported by the household. In all columns, agent and household characteristics are binary indicators for whether the agent and household are of forward/dominant caste, whether the head has completed primary school, have a ration card and own their home. *p < 0.10, **p < 0.05, ***p < 0.01.

3.4. *Potential Mechanism: Time Spent with Households*

One likely mechanism by which agents may boost the knowledge scores and enrolment rates of eligible households in their village is by spending time with them to talk about the scheme. It is, therefore, of interest to look at how agent time allocation varies with contract type and social distance. In the fourth survey round, households were asked how much time their agent had spent with them talking about the scheme over the past three months.²³

The results for time spent are presented in Table 11. The analysis is again restricted to treatment villages since the distance measures are not defined in villages without an agent. In column (1), the time spent by the agent with the household talking about the scheme is regressed on incentive pay, and the results suggest that total time spent with households by the agent does not depend on contract type. So while it was found above that incentivised agents are more successful at transmitting knowledge and inducing enrolment overall, this does not seem to be because she spends more time with households in aggregate.

²³ This question was introduced only in the fourth and final survey wave. At that time, the households were also asked to recall how much time the agent had spent with them earlier in the intervention. However, we focus on the most recent period as it is probably the most accurately recollected.

Column (2) introduces social distance and the interaction of incentive pay and social distance. The coefficients on un-interacted incentive pay and social distance are negative and significant, while the coefficient on the interaction term is positive and significant. Moreover, the magnitudes are such that coefficient on the interaction is close to cancelling the sum of the un-interacted terms.

In column (3), physical distance measured in terms of separation of castes and its interaction with incentive pay are introduced. While the magnitudes suggest that physical distance may matter for time spent, the coefficients are not statistically significant. The coefficients on un-interacted incentive pay and social distance and their interaction lose significance but do not change much in magnitude. Using the GPS-based measure of physical distance gives stronger results (column (4)). While physical distance continue to matter little in terms of time spent, those on social distance and its interaction with incentive-pay are now larger in magnitude and highly significant. Thus, as in the case of knowledge scores, these results suggests that social distance matters in its own right as far as time spent by agent is concerned, and not just as a proxy for physical distance. Once again the magnitude of the interaction term comes close to cancelling the uninteracted terms.

We interpret these results as follows: the type of contract does not appear to make a great difference to the average time spent with each household across the sample. However, while agents on flat-pay contracts spend on average 8 minutes less with each socially distant households than they do with socially proximate households (based on column (2) of Table 11), agents on incentive-pay contracts spend on average 3 minutes more on socially distant households compared to socially proximate households. In other words, incentives have little effect on the time spent with households overall, but they do appear to cause a large shift of agents' focus from socially proximate to socially distant households.

It was shown above that incentivised agents achieve superior results overall in terms of both knowledge scores and enrolment. The results presented in this subsection suggest that this was achieved without investing more time in talking to households overall. Instead, relative to flat-pay agents, incentivised agents spend less time with their 'own group' and more time with their 'cross-group'. One interpretation of these findings is that agent 'intensity of effort per minute' may vary. Spending time with one's friends may be pleasurable and hence, in the absence of incentives, agents chose to spend more time at a lower intensity with socially proximate households. The implication is that when incentives are introduced, agents are able to increase intensity and hence free up time to spend on socially distant households without sacrificing effort or output with respect to their friends.

Separate results (not reported) indicate that the time-use effect is exclusively on the 'intensive margin': incentive-pay agents did not talk to a greater number of households overall than did flat-pay agents.

3.5. *Relating the Empirical Results to the Theoretical Model*

The aim of this subsection is to tie the empirical findings back to the model. It should, however, be noted that what follows is subject to statistical inaccuracy. That is, while we cannot reject the equality of certain quantities, it is also possible that the true values of

these quantities are different, but not different enough to be detectable by the econometric tests. While for simplicity we will proceed as if these equalities hold exactly, a full discussion would consider a broader range of cases in which the effort curve is nearly flat, effort across the two tasks nearly equal and so on.

Let $e_f(b)$ denote the effort of a knowledge agent when dealing with her own social group ('friends'), and let $e_o(b)$ denote the effort with respect to dealing with the other group. We observe four points empirically: $e_f(0)$, $e_f(b')$, $e_o(0)$ and $e_o(b')$; that is, the effort with respect to the agent's own and cross-group, with and without bonus. Using this notation, the empirical findings can be summarised as follows:

$$e_o(0) < e_f(0) = e_f(b') = e_o(b').$$

In words, the task of transmitting information to the agent's own group is intrinsically preferred. The introduction of bonus pay induces no change in effort in the intrinsically preferred task, but it does increase effort in the non-preferred task, up to the same level as for the intrinsically preferred task.

The most straightforward interpretation is that with respect to their own group, agents were already exerting the maximum effort, and, therefore, bonus pay induces no additional effort. With respect to the other group, the agents were choosing a sub-maximal effort level without bonus, but with bonus pay the effort goes up to the maximum level.

We do not observe crowding out, but we cannot rule it out outside the observed parameter values. Specifically, given more variation in b , we might encounter a region in which effort with respect to one of the groups decreases with b . Unfortunately, from the four points we observe, we cannot tell whether or not we are in a 'crowding-out world'.

In Figures 2–4, the position of the vertical axes correspond to cases that are consistent with the empirical findings. At $b = 0$, e_1 has reached the maximum effort level while e_2 has not. A sufficiently high bonus b would bring e_2 up to $\bar{e}$ where it would be equal to e_1 . If this reflects the empirical reality, then task 1, the easier task, corresponds to the agent's own group.

However, another possibility is generated by shifting $\bar{e}$ in Figures 2–4 down until it meets, or crosses, the meeting point of the internal solutions. The vertical axis would now need to be placed to the left of the crossing point. This configuration would generate a solution in which e_2 , the harder task, corresponds to the agent's own group. For this to be the case, θ_2 , the intrinsic motivation for success in the own-group task would need to be not only greater than θ_1 but large enough to outweigh the cost disadvantage.

As an example of the latter, imagine that, irrespective of the agent's own identity, it is easier to transmit knowledge to high-caste than low-caste households, perhaps because high-caste households tend to be better educated. Then, irrespective of the caste of the agent, task 1 (the easier task) corresponds to high-caste households and task 2 to low-caste households. If so, for a low-caste agent to intrinsically prefer the task of transmitting information to her own caste group, which is what we observe, her intrinsic motivation for the own-group task, θ_2 , needs to be large enough, relative to θ_1 , to outweigh the cost disadvantage. While the cost-of-effort parameters c_i and the preference parameters θ_i are distinct concepts theoretically, empirically we are unable to distinguish the effect of low task preference ('prejudice') from high cost of effort.

It is also possible that the apparent convergence of the effort curves is not due to having reached the maximum effort level as assumed above, but rather that one of the effort curves is flat, as in Figure 3. If the vertical axis were to the left of the crossing point, and the positive bonus pay observation $b = b'$ were exactly at the crossing point, this could explain the empirical findings. However, we find this possibility less likely than the two described above, because it would require the arbitrarily chosen experimental value for bonus pay to have hit exactly the 'sweet spot' (the crossing point).

Although the empirical findings are supportive of the model's assumption of an upper limit to agent effort, the theory does not explain why such an upper limit should exist in the first place. One possibility is that households 'max out' on the knowledge tests, thereby creating an upper bound on agent performance. If households attain the maximum score, any further effort would be unobservable and hence, from the point of view of an incentive-pay agent, futile. However, a quick look at the distribution of test scores reveals that the households are generally nowhere near the level of test scores where such saturation could become important. In particular, only 5% of households answered seven or eight of eight questions correctly.

Another, and in our view more likely, possibility is that the upper bound $\bar{e}$ is not imposed by the test or the agent but by the households. The agent might be willing to sit with the households for long periods of time to teach them the intricacies of RSBY, especially if they are incentivised to do so, but households may have limited time or patience for this. Field anecdotes suggest that households think of the agent as a resource person who can be contacted if the need arises: if a household member falls ill or otherwise needs health care, they would turn to the agent and ask her advice on how to obtain treatment under the scheme. If this perspective is widespread, it would not be surprising if the households' motivation for learning details about the insurance policy is limited. They only need basic knowledge about the scheme, and for this reason their patience with listening to details will probably 'max out' relatively quickly.

Our model is mute on the relationship between effort and time. But the results suggest that, relative to flat-pay agents, agents on incentive pay are able to increase overall effort/output without spending more time in aggregate. Instead, we observe a reallocation of time away from socially proximate towards socially distant households. If intensity of effort can vary over time, non-incentivised agents may be spending more time with socially proximate households (their 'friends') than strictly necessary, presumably because they enjoy it. When incentives are introduced, agents are able to shift time away from socially proximate households towards time spent with socially distant households by increasing the intensity (i.e. reducing idle but enjoyable 'chatter') of the time spent with their 'friends'.

4. Conclusion

This article sheds light on the role of financial incentives and social proximity in motivating local agents to transmit knowledge about a public service. The results suggest, first, that hiring agents to spread knowledge about welfare programmes has a positive impact on the level of knowledge, but that the entire effect is driven by agents on incentive-pay contracts. Second, agents on incentive-pay contracts also have a positive and

significant impact on programme enrolment. Third, social distance between agent and beneficiary has a negative impact on knowledge transmission and enrolment, but putting agents on incentive-pay contracts increases knowledge transmission and enrolment by cancelling (at our level of bonus pay) the negative effect of social distance. On the other hand, incentive pay has no impact on knowledge transmission or enrolment for socially proximate agent–beneficiary pairs. A likely mechanism is a reallocation of time spent by incentive-pay agents towards socially distant households at the expense of socially proximate ones.

Our results may have implications for public service delivery in developing countries, where, in addition to common supply-side problems like staff absenteeism, corruption and red tape, a lack of awareness and knowledge regarding available welfare schemes represents an important barrier to the take-up of government programmes. The experimental evidence presented here points to a key mechanism that may in some circumstances alleviate this problem.

Our findings concerning the relative importance of financial incentives and social distance have implications for contexts in which strong own-group bias can lead to adverse welfare effects. In India, caste and religious identities, in particular, have been found to create social divisions that impede the efficient functioning of markets (Anderson, 2011) and access to public goods (Banerjee *et al.*, 2005; Banerjee and Somanathan, 2007). It would be hasty to extrapolate from our findings in the context of information transmission about welfare schemes to wider societal effects of own-group bias. Still, in the setting studied, a relatively small piece rate was sufficient to overcome the negative consequences of entrenched social barriers.

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Additional Supporting Information may be found in the online version of this article:

Appendix A. Cases Not Captured by Figures 2–4 for the Two-task Model.

Appendix B. The Knowledge Tests.

Appendix C. Effects over Time and by Agent Characteristics.

Appendix D. On Magnitude.

Appendix E. Village-level Analysis.

Appendix F. More on Agent Attrition.

Appendix G. For Whom is Information a Binding Constraint?

Appendix H. Direct Comparison of the Flat-pay and Incentive-pay Groups with the Control Group.

Appendix I. Triple Differences by Caste Segregation.

Data S1.

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