Motivating Knowledge Agents: Can Incentive Pay Overcome Social Distance?*

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Abstract

This paper studies the interaction of incentive pay and social distance in the dissemination of information. We analyse theoretically as well as empirically the effect of incentive pay when agents have 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. Relative to flat pay, incentive pay improves knowledge transmission to households that are socially distant from the agent, but not to households similar to the agent.

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1 Introduction

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 under which there are grounds for caution: First, if output is hard to measure, financial incentives may not have undesirable consequences (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' intrinsic motivation (Bénabou and Tirole, 2006; Gneezy and Rustichini, 2000). But evidence on the effect of incentive pay on performance in pro-social tasks is limited.[2] Third, theory suggests that aligning the identities of economic agents can itself be productivity-enhancing (Besley and Ghatak, 2005; Francois, 2000), 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, incentive pay 'as the sole motivator can be both costly and ineffective'. But very little is known about the interaction of social distance and incentive pay.[3] Specifically, does incentive pay ameliorate or exacerbate the potentially detrimental effect of social distance?

In this paper we develop a theoretical model and provide empirical evidence on the interaction of incentive pay and social distance in spreading information about a public service. This allows us to shed light on the question of whether incentive pay is effective in settings where output is noisy and crowding out is a possibility, and whether it can 'price out prejudice'.

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

[1] Bandiera et al. (2011) and Prendergast (2013) review the evidence. See Becker and Posner (2009) and Sandel (2012) for different perspectives.

[2] Ashraf et al. (2012) is a notable exception. In related work, Dal Bó et al. (2013) find that higher wages do not have adverse selection effects in terms of public service motivation.

[3] However, the literature on discrimination suggests that competitive markets can remove the effects of social distance to the extent that these cause inefficiencies (Lang and Lehmann, 2012).

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 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 they were surveyed and orally presented with a knowledge test about the scheme.

The main 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 entirely driven by agents on incentive-pay contracts. Households in villages assigned an incentive-pay agent score 0.25 standard deviations higher on the knowledge test than those in the control group.

Second, using the random assignment of incentivised agents as an instrument for knowledge, it is found that improved knowledge increases programme take-up. An increase of one standard deviation in knowledge score increases the likelihood of enrolment by 39 percentage points.

Third, 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. Incentive pay has no impact on knowledge transmission for socially proximate agent–beneficiary pairs.

Our preferred interpretation is that, with respect to their 'own' (socially proximate) group, 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' (socially distant) group. With incentive pay, effort goes up to the same level as for the agent's own group. This is what we refer to as 'pricing out prejudice'. We do not observe crowding out empirically, but it could still happen outside of the observed parameter values.

To the best of our knowledge, this paper presents the first randomised evaluation of incentive pay for agents tasked with providing information about a public service. It contributes to the growing literature on the importance of information costs in economic decision-making and, in particular, the demand for public services. Previous work has explored how information campaigns affect local participation and educational outcomes in India (Banerjee et al., 2010a), 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).[4]

Most existing work on the role of incentives in public services emphasises the supply side. For example, a number of studies look at whether teacher and health worker incentives can reduce problems of absenteeism and under-performance in the public sector (Duflo et al., 2012; Glewwe et al., 2009; Muralidharan and Sundararaman, 2011; Banerjee et al., 2008) . But the importance of incentives in the context of *demand* for public services is relatively under-studied.[5]

In developed countries, low take-up of welfare programmes has been linked to information costs (Hernanz et al., 2004). Aizer (2007) finds that eligible children do not sign up for free public health insurance (Medicaid) in the US 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. The evidence presented here suggests that information costs can act as a barrier to take-up also in developing countries. This is in line with Keefer and Khemani (2004), who argue that information constraints and social barriers, along with a lack of credibility of political promises, are important reasons for inadequate social services in India.

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). In the context of awareness campaigns, if people prefer to liaise with their own kind,

[4]In the context of the specific government health insurance scheme that we use in this paper, an early study by Das and Leino (2011) finds mixed results regarding the effects of a general information campaign on enrolment in North India.

[5]Banerjee et al. (2010b) is a notable exception.

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 scarce.

This paper is also related to the rich literature on the role 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).Bandiera et al. (2009) study the interplay of social connections and financial incentives in the context of worker productivity in a private firm in the United Kingdom. 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. Our paper is related, 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. This literature also includes studies on incentives for teachers and health workers in developing countries, as surveyed by Kremer and Holla (2008) and Glewwe et al. (2009). 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 (Akerlof and Kranton, 2005; Bénabou and Tirole, 2003; Besley and Ghatak, 2005). In a laboratory setting, Gneezy and Rustichini (2000) find non-monotonicities in the effect of incentive pay on effort. However, as Bandiera et al. (2011) point out, there is little field-experimental evidence in this area, although Ashraf et al. (2012) is a recent exception.

The rest of the paper is organised as follows: In Section 2, 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 to guide our empirical analysis. Section 3 describes the context, experimental design and data. Section 4 presents the empirical evidence and Section 5 interprets it. Section 6 concludes.

2 Theoretical Framework

In this section we develop a simple model of motivated agents. It extends 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 payment and how these might interact with the effects of social distance.

Suppose agents exert 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.

2.1 A Single Task

First, assume there is a single task. This may 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 and of value 0 or 1, with the former denoting 'bad performance' or 'failure' and the latter, 'good performance' or 'success'. For example, a group of beneficiaries doing well in the knowledge test (say, scoring above a certain threshold level), or enrolling in the programme, might be considered a success. The agent's 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 $\overline{e} \in (\underline{e}, 1)$. 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, but 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 value of the outcome is consistent with any value 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 $c(e) = \frac{1}{2}ce^2$. 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 incorporates both the direct benefit to the beneficiaries and how the rest of society values their welfare. In the absence of incentive problems, the problem is

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

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

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

It should be noted here 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 payoff from success increases. Conceptually, and hence empirically, it is hard to distinguish between the two.

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, $\underline{\omega} > 0$. 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, 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. In choosing the bonus for the agent, the principal has to respect the limited-liability constraint (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, assume that the outside option is relatively unattractive so that the PC does not bind—the analysis is qualitatively unchanged if this assumption is relaxed.

Let $\overline{w}$ 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 $b \equiv \overline{w} - \underline{w}$, which can be interpreted as bonus pay with $\underline{w}$ as the fixed wage component. Then the agent's objective is

$$\max_{e}(\theta + \overline{w})e + \underline{w}(1-e) - \frac{1}{2}ce^2$$

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

$$e = \max\left\{\min\{\frac{b+\theta}{c}, \overline{e}\}, \underline{e}\right\}. \tag{1}$$

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

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

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

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

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). Since the agent is risk-neutral, $\underline{w}$ will be at the lowest limit permitted by the LLC, namely $\underline{w} = \underline{\omega}$. 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.

The effort response is only observed experimentally for two 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 for $\underline{e} \geq \frac{\theta}{c}$. At the other extreme, if the agent is sufficiently motivated (namely, $\frac{\theta}{c} \geq \overline{e}$), then even without any bonus pay the agent chooses the maximum level of effort $\overline{e}$. Otherwise, effort is increasing in bonus pay. The solution is illustrated in Figure 1. The slope of the interior-solution segment $(\frac{1}{c})$ is positive and so is its intercept $(\frac{\theta}{c})$. However, depending on parameter values, the value of e for any given value of b could range from $\underline{e}$ to $\overline{e}$. 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 dashed vertical line marked by $\theta > c\overline{e}$, and an intermediate level of motivation is captured by the line marked $c\underline{e} < \theta < c\overline{e}$. 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

[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.

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.

2.2 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 task 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 the relevant dimension, the remuneration scheme cannot be contingent on it.

Let $\underline{e}$ and $\overline{e}$, where $0 < \underline{e} < \overline{e} < 1$, 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 task 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 substitutability of effort in tasks 1 and 2 in the cost function. 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:

$$\begin{aligned} e_1(\pi) &= \frac{(c_2 - \gamma)\,\pi + c_2\theta_1 - \gamma\theta_2}{c_1 c_2 - \gamma^2} \\ e_2(\pi) &= \frac{(c_1 - \gamma)\,\pi + c_1\theta_2 \ - \gamma\theta_1}{c_1 c_2 - \gamma^2} \end{aligned}$$

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. Also, if e_i assumes a corner solution, e_j $(j \neq i)$ would take a different form.

Define the pair:

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

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

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

$$\begin{aligned} e_1^*(\pi) &= \max\{\min\{\hat{e}_1(\pi), \overline{e}\}, \underline{e}\} \\ e_2^*(\pi) &= \max\{\min\{\hat{e}_2(\pi), \overline{e}\}, \underline{e}\} \end{aligned}$$

The second-best is characterised as follows. Let $\overline{w}$ 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 $b \equiv \overline{w} - \underline{w}$. The agent's objective is to maximise

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

The first-order conditions yield:

$$\begin{aligned} e_1(b) &= \frac{(c_2 - \gamma)\, b + c_2\theta_1 \ - \gamma\theta_2}{c_1c_2 - \gamma^2} \\ e_2(b) &= \frac{(c_1 - \gamma)\, b + c_1\theta_2 \ - \gamma\theta_1}{c_1c_2 - \gamma^2} \end{aligned}$$

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

$$\begin{aligned} \hat{e}_1(b) &= \begin{cases} \frac{\theta_1 + b - \gamma\underline{e}}{c_1} & \text{if} e_2(b) \leq \underline{e} \\ e_1(b) & \text{if} \underline{e} < e_2(b) < \overline{e} \\ \frac{\theta_1 + b - \gamma\overline{e}}{c_1} & \text{if} e_2(b) \geq \overline{e} \end{cases} \\ \hat{e}_2(b) &= \begin{cases} \frac{\theta_2 + b - \gamma\underline{e}}{c_2} & \text{if} e_1(b) \leq \underline{e} \\ e_2(b) & \text{if} \underline{e} < e_1(b) < \overline{e} \\ \frac{\theta_2 + b - \gamma\overline{e}}{c_2} & \text{if} e_1(b) \geq \overline{e} \end{cases} \end{aligned}$$

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

$$\tilde{e}_1(\pi) = \max\{\min\{\hat{e}_1(b), \overline{e}\}, \underline{e}\}$$
$$\tilde{e}_2(\pi) = \max\{\min\{\hat{e}_2(b), \overline{e}\}, \underline{e}\}$$

Several aspects of the solution are worth noting. First, 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 curves 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, this 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 $c_1 + c_2 - 2\gamma > c_1 + c_2 - 2\sqrt{c_1 c_2} = \left(\sqrt{c_1} - \sqrt{c_2}\right)^2 > 0$, 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 cases[7] 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 $\overline{e}$ but e_2 has an interior solution. The latter corresponds to

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

the condition $\frac{\theta_2-\gamma\bar{e}}{c_2} < \bar{e} < \frac{c_2\theta_1-\gamma\theta_2}{c_1c_2-\gamma^2}$. 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 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).

3 Context, Experimental Design and Data

3.1 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 health insurance policy covers hospitalisation expenses for around 700 medical and surgical conditions, with an annual expenditure cap of 30,000 rupees (652 USD) per eligible household.[8] Each household can enrol up to five members. Pre-existing conditions are covered, as is maternity care, but outpatient treatment is excluded.

The policy is underwritten by insurance companies selected in state-wise tender processes. The insurer receives an annual premium per enrolled household,[9] paid by the central (75%) and state (25%) governments. The beneficiary household pays only a 30 rupees (0.65 USD) annual registration fee.

Biometric information is collected from all members on the day of enrolment and stored in a smart card issued to the household on the same day.[10] Beneficiaries are entitled to cashless treatment at any participating (‘empanelled’) hospital across India. Both public and private hospitals can be empanelled. Hospitals are issued with card readers and software. The cost of treating patients under RSBY are reimbursed to the hospital by the insurance company according to fixed rates.

3.2 Experimental Design

151 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 out of 151) were randomly selected to be part of the treatment group, i.e. receive an agent, while the remaining form the control group. In each treatment village, our field staff arranged a meeting with the

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

[9] The annual premium is determined at the state (and sometimes district) level, and is currently in the range of 400–600 rupees (9–13 USD). 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 is often not adhered to. For more detail, see Rajasekhar et al. (2011).

local Self-Help Groups (SHGs).[11] All SHGs contacted were female-only. In the meeting, SHG members were given a brief introduction to RSBY and told that a local agent would be recruited to help spread awareness of the scheme in the village over a period of one year. They were told that the agents would be paid, but no further details on the payment were given at that time. In each case, a single candidate was nominated by the group and recruited on the same day. Except in two cases where the selected agent was a non-member recommended by the SHG, the nominated agent was a member of 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 up 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 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. A household was classified as having 'passed' the test if it answered at least four out of eight questions correctly. The proportion of passing households in a village was multiplied by the number of eligible households in

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

[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.

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.

38 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. Three of these were in incentive-pay villages, while the fourth was in a flat-pay village. 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 presented here. 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.

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 round. 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 both rounds.

3.3 Data

Following agent recruitment, three consecutive rounds of 'mini-surveys' were fielded. For 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. One 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 for the first and second survey rounds, so that there was a partial overlap between the households in the first two rounds of surveys. The first and second 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. 2369 households were interviewed in the first mini-survey wave, 1933 in the second and 1348 in the third. In all, the mini-surveys cover 3296 households, of which 908 were interviewed twice and 723 were interviewed three times. However, 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 empirical results presented here are based on weighted least squares regressions. In addition, standard errors are clustered at the village level (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 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 35 years old. 88% are married. 59% of the agents' household heads have completed primary school. 82% of agent households have a ration card,[13] and 39% are from a forward or dominant caste.[14]

[13]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.

[14]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.

In 29% of the cases, the recruited agent was the president of a Self-Help Group.

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 presents summary statistics for households. The average household has 4.6 members. 19% are from a forward/dominant caste.[15] In 26% of households, the household head has completed primary school. 93% 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 to all households interviewed in each of the three mini-surveys. 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 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).[16]

The test questions asked in the three surveys were different, so although the raw scores can be compared across households within a survey, they cannot easily be compared across surveys, even for individual households. The scores on each test were therefore standardised by subtracting the test-wise mean and dividing by the standard deviation.

[15] As mentioned, eligibility is determined on the basis of BPL ('Below the Poverty Line') status, not caste.

[16] 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.

4 Evidence

4.1 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 3, 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. Flat-pay agents have no significant impact on test scores. This is consistent with the argument that, since these agents are paid a constant amount irrespective of the outcome, they are not incentivised to exert any extra effort beyond some level determined by their intrinsic motivation as in the theoretical model. In contrast, households in villages assigned an incentive-pay agent score 0.25 standard deviations higher on the knowledge test relative to those in the control group. Hence, providing agents with financial incentives leads to an improvement in knowledge about the scheme among beneficiaries. Moreover, the equality of these two coefficients is rejected with a p-value of 0.06. This suggests that the entire effect of knowledge-spreading agents in the village is due to the agents that are on incentive-pay contracts.

As already mentioned, an administrative error caused incentive-pay agents in one of the districts (Bangalore Rural) to be overpaid after the first survey. To allay concerns that our findings are driven by these higher rates of pay, Table 4 presents results using data only from Shimoga district, where no error was made. Overall, the qualitative findings concerning the main coefficients of interest are similar to those obtained in Table 3. Hence it appears that the main findings are not driven by the larger agent payments in Bangalore Rural in one of the rounds.

Given that the three survey waves were conducted at different times after the recruitment of agents, it is also possible to look at dynamics. For example, does the difference in knowledge score (or enrolment) between households in the different experimental groups increase over time? In fact, the gap between households in the incentive-pay group and those in flat-pay and control areas is established already in the first survey wave, and does not increase significantly over time (not reported). This suggests that the extra effort by the agents in the incentive-pay villages was exerted early on. This is consistent with rational behaviour on the part of the agents if knowledge is persistent: any extra effort should be exerted early on since the knowledge imparted will then be rewarded in all subsequent payment rounds. Alternatively, it could be that household knowledge does decay and that subsequent effort by the agent is required to maintain it. The finding is also consistent with households having a bounded 'appetite' for knowledge about the scheme; this is a possibility that will be revisited below.

4.2 The Impact of Knowledge on Enrolment

Does increased knowledge about the programme cause higher enrolment rates? In order to estimate the causal impact of knowledge on enrolment we consider the following equation:

$$E_{hv} = \alpha_E + \gamma Y_{hv} + u_{hv}, \tag{3}$$

Here, E_{hv} captures the enrolment status of household h in village v. OLS estimation of equation (3) could lead to biased estimates of the causal impact of knowledge, because of either unobserved factors (for example, ability) that might influence both knowledge score and enrolment, or reverse causality: being enrolled in the programme may itself spur people to acquire more knowledge.

In order to address these concerns, we use the random assignment of our experimental treatment as an instrument for knowledge. Since we find that the households assigned a flat-pay agent did not exhibit a significantly different impact on knowledge scores compared to those in the control group (Table 3, column 3), we club these two groups together and use assignment to the incentive-pay group, compared to either flat-pay or pure control, as the instrument for knowledge.

The results are shown in Table 5. Column 1 presents the OLS estimate, which is positive and highly significant. Column 2 reports the reduced-form estimates obtained by regressing enrolment on the instrument, and the result indicates that households assigned an incentive-pay agent are 8 percentage points more likely to enrol in the programme compared to those assigned a flat-pay agent or no agent. Column 3 reports the first stage of the IV regressions and indicates that the instrument has good explanatory power. This regression is similar to that reported in column 3 of Table 3, except that in this case the omitted group consists of not only the pure control villages but also those that were assigned a flat-pay agent.

Column 4 presents the second-stage regression, and the results indicate that an increase of one standard deviation in knowledge score increases the likelihood of enrolment by 39 percentage points. Hence, we find robust evidence that improving knowledge about the welfare scheme had a positive impact on enrolment.

The fact that the co-efficient of interest nearly doubles between the OLS and IV regressions suggests that the effect of knowledge on enrolment is particularly strong for those whose knowledge levels are influenced by the presence of an incentivised agent (local average treatment effect). In other words, those households for whom the knowledge transfer is the most successful are also the households for whom increased knowledge is most likely to lead to take-up.

A concern with this instrumental variable analysis might be that, in addition to imparting knowledge, the agents are associated with an 'endorsement effect'. Having been selected by the Self-Help Group, the typical agent probably represents someone of considerable standing and respect among her peers. Therefore, it may be argued that in addition to getting knowledge of the scheme, the households perceive the agent's involvement as a form of endorsement and might therefore be more likely to enrol irrespective of their level of knowledge.

To address this concern, the above analysis was repeated while excluding the pure control villages. Hence the comparison is now only between flat-pay and incentive-pay village, and the instrument is 'putting the agent on an incentive contract'. Since the agents were selected before the contract type was revealed, and there was very little attrition at any point, the flat-pay and incentive-pay agents are drawn from the same distribution and should not differ on average. In other words, if there is an endorsement effect associated with the agents, it will be the same for both types, assuming that the households did not know their agent's payment type. Note that the difference between the two forms of payment contract changes the incentives to impart knowledge, but neither type is incentivised to enrol households into the scheme.

Dropping the control villages means that there is now only data on 71 incentive-pay agents/villages and 37 flat-pay agents/villages. In spite of the reduced sample size, the results are qualitatively similar to the above, although the reduced-form and first-stage estimates are significant only at the 10% level. The second-stage estimate of the effect of knowledge on enrolment is 0.54 and highly significant (column 5).

Another concern might be that the households learn of their agent's payment type and that it might somehow influence the enrolment decision. We believe it is unlikely that the households will learn of the agent's payment structure since this was revealed to the agent in private and she has little incentive to discuss it with the households. Even if she did, we believe that the most likely effect of such information would be to trust the incentive-agent relatively *less*, since households might be suspicious of an agent who stands to gain personally from their engagement with the scheme. If so, any 'endorsement effect' of the incentive-pay scheme should actually be negative so that the regression co-efficients are under- rather than over-estimates.

A final concern might be that the incentivised agent might try harder than the flat-pay agent to get the household enrolled *because* she thinks that will make it easier to boost their knowledge level. Although it is not possible to rule out this possibility, we find it quite unlikely.

4.3 Agent Characteristics and Heterogeneous Treatment Effects

The questionnaire that was administered to the agents at the time of their appointment collected information on some individual and household characteristics including age, marital status, education of household head, caste, house ownership and personal autonomy.

Table 6 looks at how the impact of knowledge agents on knowledge test scores depends on agent characteristics. Column 1 replicates column 2 of Table 3 for ease of reference. In column 2, the main treatment variable (whether or not there is an agent in village) is interacted with variables on agent age, caste, education, ration-card status, home ownership, whether the agent is president of an SHG and her personal autonomy. None of these interacted effects are significant except for the autonomy metric. (The autonomy variable is described in the data section.) It seems intuitive that an important factor determining the effectiveness of an agent is whether she is free to move around the village.

4.4 Pricing Out Prejudice: Financial 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 that improving knowledge in turn increases enrolment. But previous work suggests that social identity is also an important determinant of insurance take-up. For example, Cole et al. (2010) 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 section 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, define the social distance between an agent and a household 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 of them does. Ration-card distance is 1 if any one of them has a ration card and the other does not.

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

The empirical specification is of the following form:

$$Y_{hv} = \alpha + \beta D_{hv} + \gamma T_v + \delta D_{hv} T_v + \pi X + u_{hv} \tag{4}$$

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 are necessarily dropped from this analysis.) X 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 effect[17] 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 7. 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 out 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.

This finding is emphasised in Table 8. We create a binary variable denoting 'socially proximate pairs' if the composite social distance metric is equal to or less than 0.5 and 0 otherwise, and tabulate the mean test scores for socially proximate and socially distant households by agent contract type. Flat-pay (non-incentivised) agents are found to be significantly more effective at transmitting knowledge to their own group/socially proximate households than to the cross-group/socially distant households (average scores are higher by 0.18 standard deviations), while for incentivised agents there is no significant difference in performance between the agent's own group and the cross-group. Moreover, the socially distant households who are assigned a flat-pay agent scores significantly lower than any of the other three groups, which is indicative of the disadvantage

[17] 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.

created by social distance in the absence of incentive pay.

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.

While we do not have good measures of physical distance at the household level, a rough test can be constructed for a subset of villages for which we know whether caste groups tend to live apart or not. This information is available for 107 out of the 147 villages. Based on this information, a binary indicator is constructed which is equal to 1 if, in a given village, the settlements of the major caste groups are physically separated, and 0 otherwise. This indicator is 1 for 26 out of 107 villages. Returning to Table 7, 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 and that this effect, like the one for social distance, is completely counter-acted by the introduction of incentive pay. But the results also show that the social distance indicator and its interaction with incentive-pay is still significant and qualitatively unchanged. While the measure of physical distance is crude, and, therefore, it is conceivable that the the social-distance measure still captures some physical-distance effect, the fact that the coefficients on the social-distance measure and its interaction with the treatment variable are virtually unchanged suggests that this is not the case. Social distance matters, even after controlling for physical distance.

Columns 4–7 repeat the exercise of column 2 for each of the sub-component distance metrics. For distance in caste group, ration-card status and home ownership, the story appears to align with the findings for the overall distant metric presented above. However, for education, there appears to be no significant disadvantage due to social distance. In other words, agent–household communication appears to be hampered by differences in caste, ration-card status and home ownership, but not by differences in education. Correspondingly, in this specification, un-interacted incentive pay has a large and positive co-efficient, though it is statistically significant only at the 10% level.

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.

4.5 Relating the Empirical Results to the Theoretical Model

The aim of this section 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 for the differences to be detectable by our 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 $e_s(b)$ denote the effort of a knowledge agent when dealing with her own social group, and let $e_o(b)$ denote the effort with respect to dealing with the other group. We observe four points empirically: $e_s(0)$, $e_s(b')$, $e_o(0)$ and $e_o(b')$; that is, the effort with respect to the agent's own and cross-group, with and without bonus. Given this notation, the empirical findings can be summarised as follows:

$$e_o(0) < e_s(0) = e_s(b') = e_o(b')$$

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 of 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 $\overline{e}$ 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 $\overline{e}$ 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.

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), which is unlikely.

Though 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 incentive-pay, 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 out of eight questions correctly.

Another, and in our view more likely, possibility is that the upper bound $\overline{e}$ is not imposed by the test or the agent but by the household. 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 will 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. This explanation is also corroborated by regressions (not reported) showing that more households in the incentive-payment group report having spoken to the agent, but that the average time spent per household is unchanged relative to the flat-payment group.

5 Discussion

In the experiment, the agents were paid a bonus of 8 rupees (0.17 USD) for each household that answered at least four out of eight knowledge test questions correctly. Since the average effect of incentive pay is to increase knowledge levels by about 0.25 standard deviations or about 0.6 correctly answered questions on the knowledge test, crude extrapolation would suggest that a bonus of 13 rupees (0.28 USD) per household would suffice to increase by one the average number of correctly answered questions. The reduced-form estimate in column 2 of Table 5 suggests that a 8 rupees (0.17 USD) bonus per household raises the enrolment rate by 8 percentage points. This modest rate of bonus pay also appears to completely wipe out the knowledge gap between beneficiary groups that are socially proximate to the agent and those that are not.

It may appear that the effect of incentive pay is rather large compared to the rates of pay that were offered to the agents. After all, an average payment of 400 rupees (9 USD) for work over a period of several months is not all that much, even for India's poor. However, whether the job was well paid or not is also a function of the hours put in. While we do not have survey data to back this up, examination of field notes indicates that agents spend in the region of 4–5 days of full-time work equivalents per payment period. This is a very rough estimate, and clearly there will be substantial variation around the mean, but if reasonably accurate, it would suggest that the average pay per day of work is around 100 rupees (2.17 USD), which is of the same order of magnitude as what agricultural labourers earn. A hundred rupees per day is also the wage rate that was offered by the government's large-scale public-works programme, the National Rural Employment Guarantee, in Karnataka at the time of the surveys.

An alternative and more behavioural explanation for the finding that relatively small bonus rates can have large effects on outcomes is that agents may be more sensitive to the fact that there *is* an incentive than to its size. This is in line with Bénabou and Tirole (2003), who suggest that the fact that incentive pay is offered can itself convey information to the agent about the task, the principal or the principal's view of the agent. Clearly there is no presumption from theory that these effects will always be positive, and indeed Gneezy and Rustichini (2000) suggests they can be negative. Our finding corresponds with results obtained in other recent work on conditional cash transfers, where the size of transfer was not found to matter beyond the fact that there is a positive transfer (Filmer and Schady, 2009), as well as in the context of preventive health behaviour, where demand for services were found to be sensitive to small incentives (Thornton, 2008; Banerjee et al., 2010b).

6 Conclusion

This paper 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, using the random assignment of our experimental treatment as an instrument for knowledge, we find that improved knowledge in turn increases programme take-up. An increase of one standard deviation in knowledge score increases the likelihood of take-up by 39 percentage points. Third, we find that social distance between agent and beneficiary has a negative impact on knowledge transmission, but putting agents on incentive-pay contracts increases knowledge transmission by cancelling out (at our level of bonus pay) the negative effect of social distance. On the other hand, incentive pay has no impact on knowledge transmission for socially proximate agent–beneficiary pairs.

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 our findings from the current context of information transmission about welfare schemes to the wider societal effects of own-group bias, but our results do suggest that in this particular context, a relatively small piece rate was sufficient to overcome the negative consequences of entrenched social barriers.

In future work, we hope to investigate the impact of spreading information about the health insurance scheme on health outcomes of the beneficiaries. Although utilisation of the scheme has been low so far, there are indications that it may pick up over time, and we hope to capture this in future follow-up surveys of our sample villages. In particular, we would like to know whether providing incentives for information dissemination, which was found to improve knowledge and enrolment of the programme, also leads to improved health outcomes for the beneficiaries.

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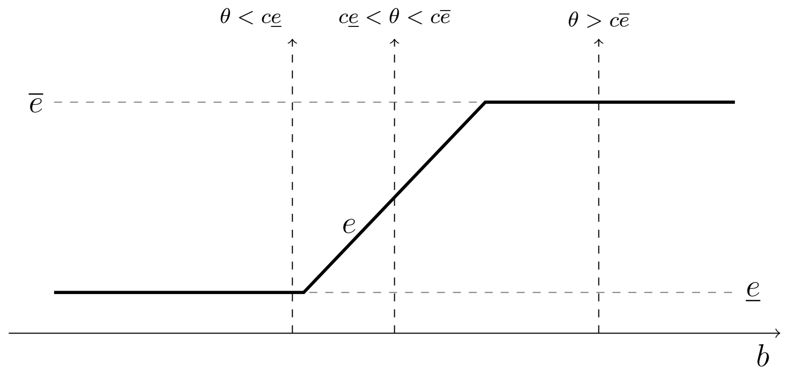

Figure 1: The one-task solution

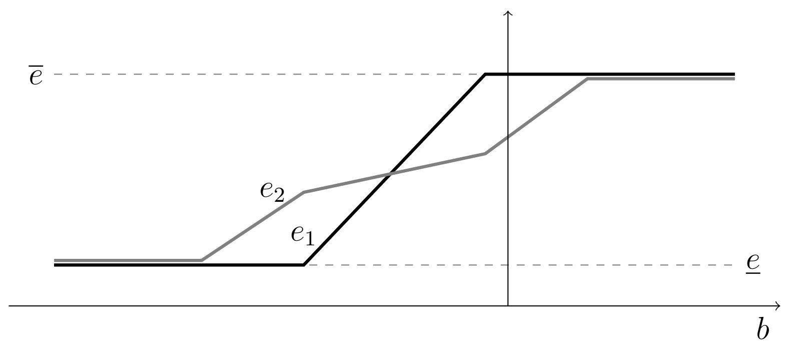

Figure 2: A solution without crowding out ($\gamma < c_1 < c_2$).

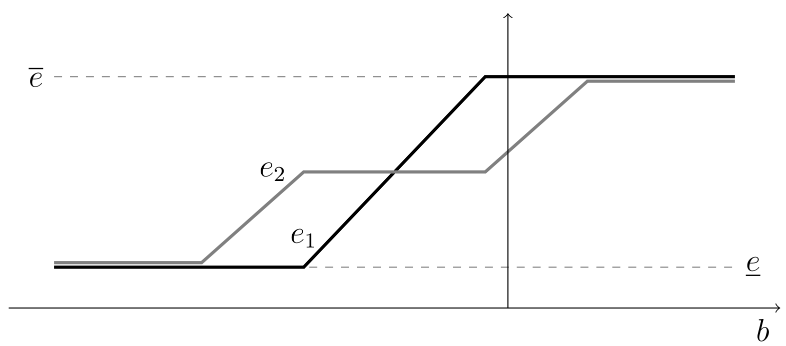

Figure 3: A solution with temporary satiation in e_2 ($\gamma = c_1 < c_2$)

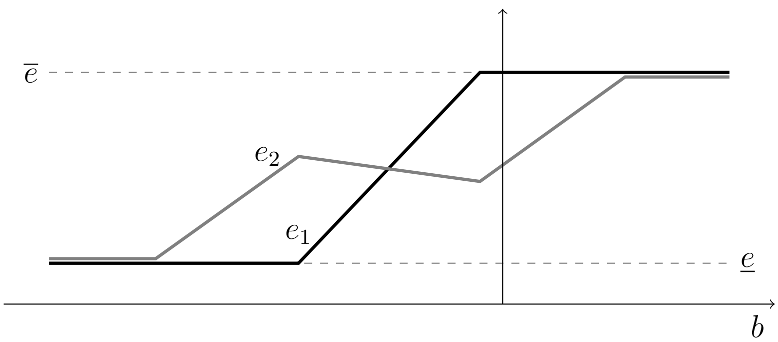

Figure 4: A solution with crowding out ($c_1 < \gamma < c_2$)

Table 1: Agent Summary Statistics

	Flat pay	Incentive pay	Difference
Agent age	34.8	34.8	0.018
	(8.81)	(8.08)	(1.73)
Agent is married	0.81	0.92	0.10
	(0.40)	(0.28)	(0.073)
Agent is of forward/dominant caste	0.43	0.35	-0.080
	(0.50)	(0.48)	(0.010)
Agent's household head has completed primary school	0.62	0.56	-0.058
	(0.49)	(0.50)	(0.10)
Agent household has ration card	0.89	0.79	-0.10
	(0.31)	(0.41)	(0.071)
Agent owns her home	0.86	0.87	0.0084
	(0.35)	(0.34)	(0.069)
Agent is Self-Help Group president	0.30	0.28	-0.016
	(0.46)	(0.45)	(0.093)
Agent autonomy score (the higher, the more autonomous)	5.57	5.68	0.11
	(0.93)	(0.84)	(0.18)
Observations	37	71	

Note: Standard deviations / robust standard errors in parentheses.

Table 2: Household Summary Statistics

	Control	Flat pay	Inc'tive pay	Flat −Control	Inc'tive −Control	Inc'tive −Flat
Household is of forward/ dominant caste	0.25	0.18	0.17	-0.070	-0.084*	-0.015
	(0.43)	(0.39)	(0.37)	[0.054]	[0.046]	[0.041]
Household head has completed primary school	0.30	0.25	0.31	-0.051	0.011	0.062*
	(0.46)	(0.43)	(0.46)	[0.042]	[0.036]	[0.035]
Household has ration card	0.94	0.94	0.92	0.00078	-0.019	-0.020
	(0.25)	(0.24)	(0.28)	[0.020]	[0.023]	[0.022]
Household owns its home	0.67	0.64	0.68	-0.023	0.017	0.040
	(0.47)	(0.48)	(0.47)	[0.047]	[0.035]	[0.045]
Household knowledge score, mean	-0.12	-0.050	0.13	0.065	0.24***	0.18*
	(0.70)	(0.76)	(0.77)	[0.100]	[0.081]	[0.096]
Household is enrolled, mean	0.71	0.68	0.79	-0.034	0.076	0.11**
	(0.41)	(0.42)	(0.37)	[0.061]	[0.046]	[0.053]
Observations	375	348	625			

Note: 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.

Table 3: The Effect of Knowledge Agents

	(1) Knowledge	(2) Knowledge	(3) Knowledge
Agent in village	0.175***	0.187***	
	(0.0645)	(0.0572)	
Flat-pay agent in village			0.0722
			(0.0919)
Incentive-pay agent in village			0.246***
			(0.0569)
Time fixed effects	No	Yes	Yes
Taluk fixed effects	No	Yes	Yes
Observations	5641	5641	5641
t-test: flat=incentivised (p-value)			0.060

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. This table uses all sample villages, including the control villages with no agent. 'Agent in village' indicates presence of an agent in the village with either contract.

Table 4: The Effect of Knowledge Agents, Shimoga District Only

	(1) Knowledge	(2) Knowledge	(3) Knowledge
Agent in village	0.210**	0.191**	
	(0.0823)	(0.0743)	
Flat-pay agent in village			-0.0289
			(0.121)
Incentive-pay agent in village			0.317***
			(0.0683)
Time fixed effects	No	Yes	Yes
Taluk fixed effects	No	Yes	Yes
Observations	2885	2885	2885
t-test: flat=incentivised (p-value)			0.007

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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. This table uses all sample villages in Shimoga, including the control villages with no agent. 'Agent in village' indicates presence of an agent in the village with either contract.

Table 5: Knowledge Drives Enrolment: Two-Stage Least Squares

	(1) Enrolled (OLS)	(2) Enrolled (Reduced form)	(3) Knowledge (First stage)	(4) Enrolled (IV)	(5) Enrolled (IV)
Knowledge	0.206***			0.390***	0.537***
	(0.00910)			(0.128)	(0.192)
Incentive-pay agent in village		0.0816**	0.209***		
		(0.0362)	(0.0618)		
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Taluk fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5641	5641	5641	5641	4160

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. This table uses all sample villages. The comparison group in columns 2–4 consists of flat-pay and control villages. In column 5, the comparison group is flat-pay villages only.

Table 6: The Effect of Knowledge Agents, by Agent Characteristics

	(1) Knowledge	(2) Knowledge
Treatment (agent in village)	0.187***	-0.499
	(0.0572)	(0.331)
Treatment x agent is 30+		0.0453
		(0.0916)
Treatment x agent is 50+		-0.0826
		(0.0938)
Treatment x agent of forward/dominant caste		-0.102
		(0.0894)
Treatment x agent household head has completed primary school		-0.105
		(0.0931)
Treatment x agent has ration card		-0.0642
		(0.123)
Treatment x agent owns her home		0.148
		(0.108)
Treatment x agent is Self-Help Group president		0.00918
		(0.0865)
Treatment x agent autonomy		0.121**
		(0.0466)
Time fixed effects	Yes	Yes
Taluk fixed effects	Yes	Yes
Observations	5641	5641

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: Incentives and Social Distance

	(1) Knowledge	(2) Knowledge	(3) Knowledge	(4) Knowledge	(5) Knowledge	(6) Knowledge	(7) Knowledge
Incentive pay	0.179*	-0.139	-0.217	0.019	0.244*	0.079	0.078
	(0.0940)	(0.144)	(0.162)	(0.110)	(0.127)	(0.0972)	(0.111)
Social distance		-0.792***	-0.795***	-0.433***	0.117	-0.392***	-0.215*
		(0.231)	(0.257)	(0.115)	(0.0972)	(0.139)	(0.113)
Incentive pay x social distance		0.839***	0.806***	0.369***	-0.127	0.488***	0.272**
		(0.235)	(0.260)	(0.129)	(0.115)	(0.136)	(0.118)
Castes live apart			-0.373**				
			(0.171)				
Incentive pay x castes live apart			0.426**				
			(0.192)				
Agent & hh chars, village size	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and taluk fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Social distance metric	-	Composite	Composite	Caste only	Education only	Ration-card status only	Home ownership only
Observations	2435	2435	1949	2435	2435	2435	2435

Notes: Weighted least squares regressions, using only treatment villages. 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, have a ration card and own their home. The simple social distance metrics in columns 4–7 are binary variables equal to the absolute difference between the corresponding household and agent characteristic binaries. The composite social distance metric in columns 2 and 3 is the sum of the binary distance metrics for caste, education, ration-card status and home ownership, divided by 4. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. This table uses only the sample of treatment villages, i.e. villages with agents, since control villages contain no agents.

Table 8: Mean Scores by Contract Type and Social Distance

	Socially proximate pairs	Socially distant pairs	Difference
Flat pay	0.07	-0.11	0.18***
	(1.01)	(1.01)	(0.06)
Incentive pay	0.13	0.15	-0.02
	(1.01)	(0.96)	(0.05)
Difference	-0.06	-0.26***	0.20***
	(0.05)	(0.06)	(0.08)

Notes: Standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01. '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. This table uses only the sample of treatment villages, i.e. villages with agents, since control villages contain no agents.

Table 9: Mean Scores by Contract Type and Social Distance, for each Caste Category

	Dominant household	Non-dominant household	Difference (Dom-Non)
Dominant-caste agent			
Flat pay	0.26	-0.20	0.46***
	(0.13)	(0.05)	(0.13)
Incentive pay	0.15	0.10	0.05
	(0.10)	(0.05)	(0.10)
Difference (Inc-Flat)	-0.11	0.30***	-0.41**
	(0.16)	(0.07)	(0.16)
Non-dominant-caste agent			
	Dominant household	Non-dominant household	Difference (Dom-Non)
Flat pay	-0.13	0.09	-0.22*
	(0.11)	(0.05)	(0.12)
Incentive pay	0.05	0.17	-0.12
	(0.09)	(0.03)	(0.09)
Difference (Inc-Flat)	0.18	0.08	0.10
	(0.14)	(0.06)	(0.15)

Notes: Standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01. This table uses only the sample of treatment villages, i.e. villages with agents, since control villages contain no agents.

A Cases Not Captured by Figures 2–4 for the Two-Task Model

Figures 2–4 illustrate the main classes of solutions for the two-task model. However, it is worth noting some features of the solution space that are not captured by the figures.

First, in all three illustrated solutions, when moving from left to right (that is, increasing b from minus infinity), task 2 is the first to move into the internal solution space. While it is possible for task 1 to 'leave' the lower bound first, the two effort curves cannot then cross. This is because task 1 would have a 'head start', and when both tasks are internal, the slope of task 1 is always greater so that effort in task 2 cannot 'catch up'. These cases can, therefore, be generated graphically from Figures 2–4 by shifting the lower effort boundary, $\underline{e}$, up until it meets the crossing point of e_1 and e_2, or beyond.

Second, there is a set of sub-cases of Figure 4 where e_2 'temporarily' hits the upper and/or lower bound only to re-emerge into the internal solution space. Graphically, the first of these cases can be generated from Figure 4 by shifting the maximum effort level $\overline{e}$ down until it crosses the first kink in the internal e_2 curve. The second is generated by shifting the minimum effort level $\underline{e}$ up until it crosses the second kink in the internal e_2 curve. The third of these special cases is a combination of the first two; that is when e_2 is first temporarily saturated at $\overline{e}$ and then at $\underline{e}$ before it re-emerges and finally reaches $\overline{e}$.

Third, while Figures 2–4 show the kinks in e_2 when e_1 reaches the upper or lower bound, they do not illustrate that e_1 will be similarly kinked if e_2 reaches the upper or lower bound while e_1 is internal.

Fourth, it should be noted that, depending on the position of the vertical axis, not all regions of a solution type may be feasible when b is constrained to be non-negative, as is the case in our model.

B The Knowledge Tests

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

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

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

3. Who can join this programme?
   Households designated as being Below the Poverty Line.(Those who said 'the poor', 'low income' or similar were marked as correct.)

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

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

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

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

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

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

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

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

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

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

5. Are day surgeries covered under RSBY?
   Yes.

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

7. Are maternity benefits covered?
   Yes.

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

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

1. Under RSBY, how many family members can be enrolled in the scheme?
   Five.

2. What is the maximum insurance cover provided by RSBY per policy period?
   30,000 rupees.

3. If hospitalised, does an RSBY cardholder have to pay separately for his/her medicines?
   No.

4. If hospitalised, does an RSBY cardholder have to pay separately for his/her diagnostic tests?
   No.

5. Is it compulsory for an RSBY cardholder to carry the smart card while visiting the hospital for treatment?
   Yes.

6. If an RSBY cardholder is examined by a doctor for a health problem but not admitted to the hospital, will the treatment cost be covered under RSBY?
   No.

7. What is the duration/tenure of the RSBY policy period?
   1 year.

8. How can an RSBY cardholder check if a particular health condition is covered under RSBY prior to visiting the hospital for treatment?
   Multiple correct answers; see text.