2022

Targeting Using Differential Incentives: Evidence from a Field Experiment

Yubraj Acharya
The Pennsylvania State University

Jiyoon Kim
Bryn Mawr College, jkim4@brynmawr.edu

Citation

Acharya, Y. and J. Kim. 2022. "Targeting Using Differential Incentives: Evidence from a Field Experiment." *Economic Development and Cultural Change* 70.2: 763-790.

Targeting Using Differential Incentives: Evidence from a Field Experiment

YUBRAJ ACHARYA
Pennsylvania State University

JIYOON KIM
Bryn Mawr College

I. Introduction

The uptake of health care services in developing countries is low, even for simple cost-effective technologies (Kremer and Glennerster 2011). This study explores whether we can use financial incentives to raise the uptake of health care services by traditionally disadvantaged groups. Unequal access and uptake of health care services is a major problem in both developed and developing countries (Braveman and Tarimo 2002). Outreach workers are often used to solve the problem of low access. The expectation from policy makers is that outreach workers would reach individuals who would not otherwise access services. However, the advantaged groups are often overrepresented in the health workforce (Agency for Healthcare Research and Quality 2014; Snyder et al. 2015). Literature in

We thank Edward C. Norton and Dean Yang for providing mentorship throughout this project. We have benefited tremendously from the guidance of Richard A. Hirth, Andrew D. Jones, Jeremy Magruder, an associate editor, and two anonymous reviewers from this journal. Thanks are also due to Qing Zheng, Anup Das, Betsy Cliff, Morris Hamilton, Ryoko Sato, and Dhiraj Sharma as well as seminar participants at the University of Michigan, the 89th Health Economics Study Group meeting in Spain (June 2016), the Northeast Universities Development Economists Consortium conference in Boston (November 2016), and the International Health Policy Conference in the United Kingdom (February 2017) for comments on earlier analyses. The study would not have materialized without the support received from Dirgha Ghimire and in the field from Prem Pandit, Ramesh Ghimire, Beena Mahato, the late Krishna Ghimire, Bishnu Adhikari, Indra Chaudhary, the Female Community Health Volunteers, and the health posts in charge at the site where this experiment was conducted. We thank them all. All errors in this paper are our own. Acharya acknowledges funding support from four sources at the University of Michigan: Department of Health Management and Policy's McNerney Award, School of Public Health's International Travel Award, the Rackham Graduate Student Research Grant, and the Rackham Predoctoral Fellowship. The University of Michigan's Institutional Review Board and Nepal Health Research Council approved this project. Contact the corresponding author, Yubraj Acharya, at yua36@psu.edu.

Electronically published November 3, 2021

Economic Development and Cultural Change, volume 70, number 2, January 2022.

https://doi.org/10.1086/713883

sociology suggests that individuals find it easier to reach out to others like themselves (Barnes-Mauthe et al. 2013). If the advantaged groups reach out primarily to their own groups, inequality could be worsened by the existing outreach efforts; more individuals from advantaged groups would access services with only a small increase, if any, in the number of individuals from disadvantaged groups. Therefore, in order to improve access for disadvantaged groups and thus address inequality in general, it is important to find a mechanism to encourage outreach workers to reach out to those from disadvantaged groups.

In this study, we attempt to answer two research questions. First, can we incentivize health outreach workers to refer individuals from disadvantaged groups through differential incentives favoring recruitment from the disadvantaged groups? Second, on the demand side, does providing financial incentives directly to disadvantaged clients encourage them to utilize health care services?

To answer these questions, we recruited health volunteers within a geographic region in a semiurban district in Nepal, randomized them into four arms, provided them with basic training on diabetes, and asked them to recruit clients from the community for a free sugar level assessment at their local health center. Across four arms, we varied the amount of financial incentives that the health volunteers received. Specifically, in the Low and High arms, the amount of incentive did not depend on the type of the referral. In the two remaining arms, the amount depended on the ethnicity of the client the health volunteers recruited—in one of these arms, we offered a higher amount for recruiting a client from their own ethnicity, whereas in the other arm, we offered a higher amount for recruiting a client from a different ethnicity. This resulted in two sets of differential incentives: one targeted toward referring disadvantaged clients (NudgeDis) and another targeted toward referring advantaged clients (NudgeAdv). This setup allowed us to test whether different incentives for health volunteers influence the likelihood of a disadvantaged client being referred.

We included a second level of randomization in which we varied the amount of financial incentives provided directly to the clients. For disadvantaged clients to increase their uptake of health services on the basis of a health worker's persuasion, they should be receptive to the health worker's message. It is possible for the clients not to act on the health worker's suggestion, even after the health worker provides a referral. By randomizing incentives received by clients for showing up for a checkup, we are able to assess whether incentives can help offset the barriers faced by prospective disadvantaged patients in coming to the checkup once a health volunteer refers them.

To preview the results, we find that our differential incentive in the ratio of 2.5 : 1, geared toward encouraging a disadvantaged referral, raises the chances of such a referral by 11.6 percentage points (95% confidence interval [CI], 1.1–22.1). This effect translates to an incentive elasticity of referral of about 0.2. The proportion of disadvantaged individuals referred by health volunteers at baseline is 43%, which is lower than their population share of 56%. The incentives geared toward disadvantaged referral thus raise disadvantaged referrals to approximately 55%, roughly equal to their share in the population. The increased share of disadvantaged referrals does not come at a cost of reduced overall referrals; nor do the health volunteers refer less sick patients to benefit from the incentive. The increased chances of a disadvantaged referral is due to disadvantaged health volunteers referring more of their own type in response to the differential incentives rather than the advantaged health volunteers referring more of the disadvantaged clients. We find that there is no difference in the proportion of disadvantaged referrals between advantaged and disadvantaged health volunteers at baseline, which suggests that disadvantaged health volunteers are no more likely to target their own group than advantaged health volunteers are, if there were no incentives. Hiring more disadvantaged health volunteers and providing them a differential incentive geared toward a disadvantaged referral may be the most effective way to raise the uptake of preventive health services by the disadvantaged groups.

On the demand side, conversely, we find no evidence that a financial incentive provided directly to a disadvantaged individual raises the uptake of preventive health services. Conditional on being referred by a health volunteer, the disadvantaged clients are less likely to come to a health center for a checkup than are advantaged clients. However, financial incentives do not sufficiently offset the barriers they face.

Our study contributes to the broad body of literature that centers on incentivizing public service workers to improve their performance in prosocial tasks. In the context of our study, the public service workers are the health volunteers, and the measure of prosocial task is whether they reach out to individuals from traditionally disadvantaged groups. To date, researchers have focused on the roles of financial incentives on hiring and keeping capable agents who work for public programs to help public good provision, often testing them against the effects of nonfinancial incentives (for a review of these studies, see Finan et al. 2017). However, evidence on the effect of financial incentives on public workers has been substantially limited, with mixed findings. For example, Dal Bo et al. (2013) study a recruitment drive for public sector positions in Mexico and conclude that higher wages help attract a better candidate pool in terms of both quality and motivation. In other words, financial incentives to public service workers do not have adverse selection effects in terms of public service motivation. Conversely, using a field experiment among candidates for a health promoter position in Uganda, Deserranno (2019) finds that stronger financial incentives discourage applications from agents with strong prosocial preferences, showing that financial incentives can crowd out prosocial motivation.

Relatively fewer studies have documented the role of incentives on health workers. Ashraf et al. (2014) conducted an experiment in Zambia that was designed to compare the effects of monetary and nonmonetary incentives on the performance of workers in a public health organization to promote human immunodeficiency virus (HIV) prevention. They find that nonfinancial rewards are effective in delivering health services and that the effect of both nonfinancial and financial rewards is stronger for prosocially motivated workers. Their study is informative in evaluating the effect of extrinsic rewards on the performance of health agents. However, the study provides little insights about whether these incentives could encourage health workers to reach out more to those from disadvantaged groups and address inequality in general. In other words, the extent of the effect of financial incentives on outreach effort—and thus health care utilization by disadvantaged groups—vis-à-vis multiethnic interactions is poorly understood in the literature. This is an important omission, given the centrality of outreach efforts in improving access and utilization and the need for health workers to interact frequently with individuals from different backgrounds than their own.

A recent exception is Berg et al. (2017). They study the impact of social distance between agent and beneficiary household across the caste hierarchy in India, documenting whether incentive pay could alleviate the negative consequences of the tendency to favor interaction with one's own groups. They find that putting agents on incentive pay contracts increases knowledge transmission and enrollment of cross groups by cancelling the negative effect of social distance. They find this result to be symmetric, in the sense that it holds whether the agent is from a high- or low-status caste group. They suggest that a likely mechanism is a reallocation of time spent toward cross-group households at the expense of one's own group.

While both the work of Berg et al. (2017) and our study involve the use of financial incentives to offset barriers to health care utilization, there are two key differences, which also highlight our key contributions to the literature. First, the incentive pay in Berg et al. is based on the results of the knowledge test among a group of randomly selected households, which was used to identify how well the knowledge was conveyed from agents to households. In our experiment, the incentive is directly attached to the type of clients referred by the health volunteers, and the performance is measured by the number of clients who were referred and showed up at the clinic. In that sense, our indicators measure outreach effort made by health volunteers more directly. On the basis of the difference between who is referred and who comes to the health center, we are also able to comment on the extent to which efforts from health volunteers translate to actual utilization of health services by disadvantaged groups. In Berg et al.'s study, the incentive pay incentivizes the agent to put in general effort toward improving the knowledge of their villagers. In our study, the health volunteer is incentivized to reach a specific type of client. By design, we thus cater more directly to the targeting of disadvantaged groups.

Second, Berg et al. explore whether incentive pay alleviates the negative consequences of social distance from the perspective of the health workers only. In our experiment, we add a second layer of experiment by varying the amount of financial incentives offered to clients. This allows us to examine the effect of incentives on barriers the clients face and the effectiveness of both supply- and demand-side incentives in the utilization of health services. Most existing studies have exclusively focused on incentivizing the supply side, or public agents, and measured the effects of incentives on their performance to reach out to the public. To our knowledge, this is the first study that brings together the two types of incentives as a way to raise the uptake of health care services by traditionally disadvantaged groups.

II. The Study Setting

We conducted this experiment in Nepal, which is an appropriate place to study health care utilization and ethnic barriers for two main reasons. First, the prevalence of health disparities between ethnic groups and the low uptake of preventive health services has been persistent in Nepal. Specifically, significant disparities exist in both access to health care services and health outcomes between ethnic groups (Pandey et al. 2013). Second, the prevalence of diabetes, the medical condition of interest in this study, is rapidly rising in Nepal, with the current prevalence at 9.1% (World Health Organization 2016).

The Nepalese government has categorized the country's more than 100 ethnicities into six main categories based on religion, caste, and ethnicity: Brahmin/Chhetri, Newar, Muslim, Madhesi, Janajati, and Dalit. They have been further categorized into advantaged and disadvantaged groups based on historical access to resources. Brahmin/Chhetri and Newar are considered advantaged, while the rest are considered disadvantaged. In this study, we use these two broad categories. Although there are within-category differences—in both access and outcomes—they are more pronounced between these categories (Pandey et al. 2013). An improvement in the health status of individuals from the disadvantaged group would help raise the overall health status of the population significantly. From a practical perspective, it would be easier to target a policy intervention to the disadvantaged group in general rather than a subgroup within it. Therefore, the categorization used in this study also has a political appeal. Not surprisingly, other studies have also used this categorization as a basis for ethnicity (e.g., Mishra, Joshi, and Khanal 2014).

The level of social interaction between the groups depends on the type of activity. They share the same schools and health facilities. However, marrying across ethnic lines is uncommon, and Dalits in particular continue to be barred from sharing water facilities and from religious sites (although such restrictions are now illegal).

The subjects in this study are the Female Community Health Volunteers (health volunteers) in a semiurban area in western Nepal and the clients they recruited for a free sugar level assessment. The government created the health volunteers in 1989 initially to help administer vitamin A supplements to children. There are nearly 48,000 health volunteers, all female, in the country (Andersen et al. 2013). The health volunteers are primarily tasked to create awareness about available health services and to encourage individuals in their community to utilize those services. Over the years, the health volunteers' role has expanded significantly, and they have been praised in the international development community for their success in reducing child and maternal mortality (Center for Global Development 2011). On the basis of the country's past experience in reducing child and maternal mortality, the health volunteers can potentially play an integral role in the management of the new health conditions as well. The extent to which this can happen, however, has not been evaluated. Apart from answering the research questions listed earlier, this paper also helps fill that gap.

Each health volunteer is responsible for her ward, which is the lowest administrative unit in the country (before the new federal setup was implemented in 2017). In the study site, a ward had 284 households on average in 2011 (the latest year of the census), ranging from 28 households in the smallest one to 760 in the largest. The share of advantaged households ranged from 3% to 97%, with an average of 23%. The share of the advantaged population is 44% (authors' calculations based on the 2011 census data). As discussed later, because the health volunteers have worked in their ward for several years, the advantaged or disadvantaged status of a household is known to them even without asking for the individual's name. The public can also infer it from the individual's last name.

III. The Study Design

There are two levels of randomization in this study. In the first level, we randomly assigned 72 health volunteers into four arms stratified by their ethnic category (advantaged vs. disadvantaged), experience, and education. We stratified in order to ensure that each arm had a reasonable number of health volunteers from the traditionally advantaged and disadvantaged ethnic groups.

We collected information on ethnicity, experience, and education from local health centers before the experiment.

We invited the health volunteers for 1-day training on diabetes at their local health center. A practicing endocrinologist provided information to the health volunteers—in Nepali, the dominant local language—on basic risk factors for diabetes, prevention, symptoms, and implications if not treated on time.

After the training, 2 days before the checkup, the research team visited the health volunteers at their home and explained to them the incentive structure in private. We told the health volunteers that they should refer only one individual (above 18 years of age) per household on the basis of their understanding of the risk factors learned during the training. As the checkup was only for diagnosis and not for treatment, we also told the health volunteers that they should not refer individuals who they knew were already diagnosed with diabetes. Nonreferred individuals were welcome to come to the checkup, but they would not be a part of the study.

We told each volunteer that she would receive an amount of money based on the number of clients who came for the checkup at their local health center on the prespecified date and time and according to the schedule in table 1. To summarize, in the Low and High arms, the amount of incentive per referral did not depend on the ethnicity of the client the health volunteers recruited. In the Low arm, the health volunteers received 20 Nepalese rupees (Rs) per referral. The exchange rate between the US dollar and the Nepalese rupee was US$1 = Rs 100 at the time of the experiment. Therefore, Rs 20 is approximately US$0.2 (or 20 cents). In the High arm, they received Rs 50 per referral. In the remaining two arms, the amount depended on the ethnicity of the client the health volunteers recruited. In the NudgeDis arm, the amount was higher for recruiting a client from a disadvantaged group (Rs 50) than for recruiting a client from an advantaged group (Rs 20). In the NudgeAdv arm, the amount was higher for recruiting a client from an advantaged group (Rs 50) than for recruiting a client from a disadvantaged group (Rs 20). The comparison of the Low and High arms allows us to examine the effect of higher, nondifferential incentives on motivation in the

TABLE 1
INCENTIVES PROVIDED TO HEALTH VOLUNTEERS

	Arm 1 (Low)	Arm 2 (NudgeDis)	Arm 3 (NudgeAdv)	Arm 4 (High)
Number of health volunteers	17	19	16	17
Refer advantaged	Low	Low	High	High
Refer disadvantaged	Low	High	Low	High

Note. The exchange rate at the time of the experiment was approximately US$1 = 100 Rs. Low = Rs 20/referral; High = Rs 50/referral.

presence of ethnic heterogeneity. The comparison of the Low and NudgeDis arms allows us to examine whether differential financial incentives can be used to improve the likelihood of a disadvantaged client being referred. The NudgeAdv arm is not policy relevant, and we use it only for comparison.

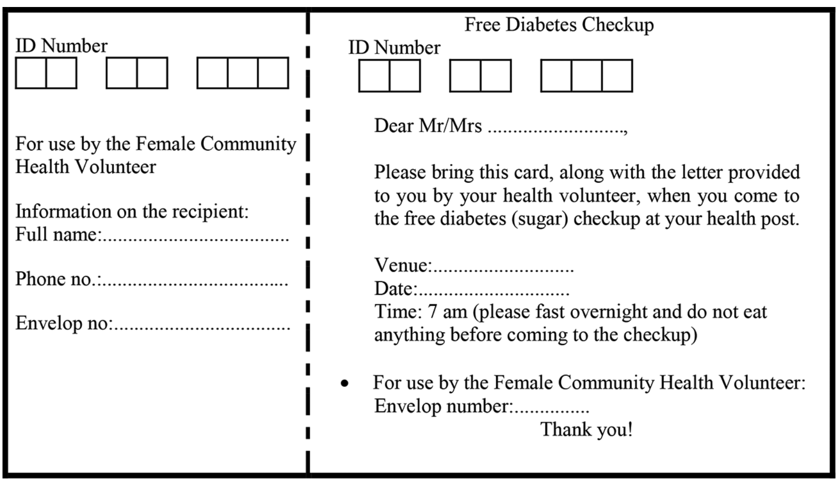
To put the incentive amount in context, the health volunteers are generally not paid a salary but receive some incentives (not based on performance) from the government, including transport stipends for training and meeting allowances. In this study, the health volunteers were provided a lump sum of Rs 600 (approximately US$6) on the day of the training to cover the cost of transportation and to offset their opportunity cost of time that day. A semiskilled worker in the area earns approximately Rs 400 per day, close to the Rs 8,000 per month minimum wage set by the government. If a health volunteer in the Low arm recruited 50 clients, and if all showed up, she would receive Rs 1,000, which is 2.5 times the daily wage of a semiskilled worker in the area.

We gave each health volunteer one full day to recruit clients. If the checkup was scheduled for Friday morning, for example, the health volunteer received the referral cards and the letters on Wednesday afternoon. Given the short duration between the time we explained the incentives to the health volunteers and the time of the checkup, it is reasonable to expect that the health volunteers did not share information about their incentive with other health volunteers. Although it is not possible to confirm this empirically, anecdotally, husbands of two health volunteers approached the research team during the checkup and asked why we had not paid any money to the health volunteers for their work, indicating that at least in those two cases, the health volunteers had not revealed the incentive even to their husbands. After the experiment was over, we paid all health volunteers Rs 2,500, which was the incentive amount of the highest earning volunteer.

The second level of randomization is at the client level. We randomized incentives received by the clients for showing up for the sugar level assessment. As discussed in section I, this additional randomization allows us to evaluate the effect of incentives on the decision to appear for the sugar level assessment and whether incentives can help offset the barriers to health care utilization from the clients' perspective. Through the health volunteers, we sent each client an invitation letter that specified a randomly assigned amount between Rs 20 and Rs 50 (in intervals of Rs 10) that the client would receive if she or he came to the health center for the checkup. The health volunteers gave clients the letter along with the referral card. The health volunteers themselves did not know the amount the client would receive for coming to the checkup, and we told them not to open the letters themselves. Without opening the envelopes, it was not possible to know the amount mentioned in the letter. However, given the low literacy in the area, we instructed the health volunteers to read the letters to the clients if the clients asked.

We gave 50 letters along with 50 referral cards to each health volunteer. We told the health volunteers that they could call the research team if they needed more cards and letters or if the clients had questions about the study. Although no health volunteer called for additional cards, several of them used all 50 cards. Like in the case of the health volunteers, there was a short duration between the time a client received the letter specifying the amount and the time of the checkup; hence, the chances of spillovers—specifically, the chances of one client's decision to come to the checkup being altered by the knowledge of what other clients were receiving—are low. However, such spillovers remain a possibility, a limitation we turn to in section VII.

To keep track of all clients to whom the health volunteers provided the referral cards, the referral card had the design of a boarding pass (fig. 1). The health volunteers gave one part of the card to clients and kept the other part. In the part that she kept, the volunteer was asked to write the name and contact information of the individual she spoke to and the code on the envelope that she gave the individual. The research team collected the cards from the health centers at the time of the checkup and from the volunteers the same morning. The coding system in referral cards, the envelopes, and the survey questionnaire allowed us to match each individual client to the health volunteer and


ID Number

For use by the Female Community Health Volunteer

Information on the recipient:
Full name:....................................

Phone no.:....................................

Envelop no:..................................

Free Diabetes Checkup

ID Number

Dear Mr/Mrs ....,

Please bring this card, along with the letter provided to you by your health volunteer, when you come to the free diabetes (sugar) checkup at your health post.

Venue:...........................
Date:.............................
Time: 7 am (please fast overnight and do not eat anything before coming to the checkup)

- For use by the Female Community Health Volunteer:
Envelop number:...............

Thank you!

Figure 1. Referral card provided to health volunteers. Health volunteers were asked to provide one side of the referral card to the client they referred and keep the stub. We collected the stubs from the health volunteers on the day of the checkup in their respective health centers. The identification number on top enabled us to match the health volunteer to the clients. For each client, we were able to identify the health volunteer who referred them and, on the basis of the envelop number (of the letter provided by the health volunteer along with this referral card), the amount the client would have received if the client came to the health center for the sugar level assessment.

to know how many clients each health volunteer referred, their ethnicity, whether they showed up, and the financial incentives the clients received (or would have received, for those who did not come).

We collected additional information on the health volunteers and the clients who came to the checkup using a survey. We administered the survey to the health volunteers on the day of their training and to the clients when they appeared for the checkup.

We held checkups in eight health centers. On a prespecified date, the research team visited the centers to conduct the checkup and to administer the survey to the clients who came. The nurses recruited for this experiment tested the blood sugar levels using a handheld Nova-Stat Glucometer. The Nova-Stat Glucometer has been found to be reliable and accurate for the determination of blood glucose levels (Rabiee et al. 2010). Nonetheless, the nurses advised those with high sugar levels to go to a hospital for further diagnosis.

The study was not registered and a preanalysis plan was not submitted. A brief discussion of the statistical power in the study is in order. Our main intervention is at the level of the health volunteers, while we evaluate the outcome at the level of the individual client. We assumed that in the Low arm, health volunteers would recruit 40% disadvantaged clients (roughly the proportion of disadvantaged health volunteers) and that an increase to 60% in the NudgeDis arm (roughly the proportion of underlying disadvantaged population) would be meaningful as a policy, given that the incentive for a disadvantaged referral increases by 150% between the Low and the NudgeDis arms. With the short duration given to health volunteers for referral, we expected that they would refer 25 clients on average in each arm. Assuming an intraclass correlation of 0.14, we had 82% power to detect a 20 percentage point change in the proportion of disadvantaged clients between the Low and the NudgeDis arms.[1] Although the study was sufficiently powered for the main outcome (probability of a disadvantaged referral), we did not have enough power to evaluate several intermediate outcomes with larger variances, including the *number* of disadvantaged referrals. Therefore, in our results, we report *p*-values from a randomization inference test, which is more amenable to analysis involving small samples. Following Cohen and Dupas (2010), we report coefficients and clustered standard errors and the *p*-values from the randomization inference test. For our main results, we also report the 95% CIs throughout the text.

[1] The assumptions about intraclass correlation were taken from the pilot of Goldberg et al. (2018), in which the randomization is at the level of the health centers. The details of that pilot are now available at https://www.socialscienceregistry.org/trials/773.

IV. Empirical Approach

A. The Effect of Incentives on Disadvantaged Referrals

In order to evaluate whether incentives geared toward encouraging the referral of disadvantaged individuals increase their chances of receiving a referral, we estimate the coefficients in the following equation:

$$Y_{ij} = \beta_1 + \beta_2 \mathrm{NudgeDis}_j + \beta_3 \mathrm{NudgeAdv}_j + \beta_4 \mathrm{High}_j + \delta \mathbf{X} + \varepsilon_{ij}. \quad (1)$$

In equation (1), Y_{ij} is a binary indicator that equals 1 if the individual i referred by a health volunteer j is from the disadvantaged group. The arms differ by the health volunteer. The Low arm is the excluded arm. The vector $\mathbf{X}$ includes a set of health volunteer characteristics that may influence their ability to recruit clients or their choice of client. These include the health volunteer's age, education level, experience, distance to the health center (measured as the number of minutes it takes the volunteer to reach the health center), ethnicity, occupation, and household income. They also include the amount of money they received for their work as a health volunteer in the previous month, the number of households they usually visit per month, and the proportion of disadvantaged households in their ward based on the 2011 census. We cluster the standard errors at the health volunteer level—the level of randomization.

To further check the validity of randomization and the stability of coefficients, we first estimate the equation with only the variables used for stratification (ethnicity, experience, and education). We then estimate it with additional characteristics of the health volunteer (occupation, number of households normally visited per month, amount received for work as a health volunteer the previous month, and distance to the health center). Finally, we add two variables related to accessibility: the proportion of disadvantaged households in the ward and whether the ward is extreme (defined as a ward with less than 10% population of one of the two groups), both based on the data available from the 2011 census.

While we do not present a formal model, the underlying assumption in our study is that a health volunteer maximizes her objective function, which is the sum of extrinsic motivation (financial incentive) and intrinsic motivation (such as reciprocity) minus the cost of recruiting. We assume that reciprocity is higher for an own-type referral (such as a disadvantaged health volunteer referring a disadvantaged client) and that the cost of recruiting is higher for an other-type referral (i.e., when an advantaged health volunteer refers a disadvantaged client, or vice versa).

It is difficult to predict the signs of the coefficients on equation (1) ex ante. If the differential incentives geared toward a disadvantaged referral are enough to offset the cost of reaching out to them and do not crowd out the intrinsic motivation, we expect $\beta_2 > 0$. If the cost of reaching out to disadvantaged clients are substantially higher for advantaged health volunteers than for disadvantaged health volunteers, $\beta_2 > 0$ only for disadvantaged health volunteer. β_3 is not policy relevant. If higher incentives, which are not conditional on any specific type of referral, offset the cost of referring a disadvantaged client and do not crowd out the intrinsic motivation, then $\beta_4 > 0$.

We estimate the coefficients in equation (1) separately using two different samples: first using all the clients who received a referral card from the health volunteers and then using only the clients who showed up to the checkup. We told health volunteers that the amount of incentive they received would depend on the number of clients who showed up. However, the first part is a better measure of the health volunteers' response to financial incentives and reflects the disadvantaged clients' chances of being reached out. Therefore, it is logical to conduct analyses using both samples.

The incentives provided to health volunteers to change their behavior have the potential to distort their behavior in a way that is inefficient. For example, driven by financial motivation, a health volunteer in the NudgeDis arm may recruit disadvantaged clients who are less likely to be diabetic, even though there may be other less healthy advantaged clients. In order to test whether such behavior occurs, we run a regression of whether an individual who came to the health center is diabetic (i.e., had a blood sugar level greater than 125 mg/dL) on the four arms and various characteristics of the health volunteer and the individual.

Likewise, the increased chances of a disadvantaged referral in the NudgeDis arm may come at the expense of a reduced total number of referrals if the health volunteers spend additional time convincing the disadvantaged clients to go for the checkup or if the health volunteers have a target income. This issue is particularly relevant in our setting because the health volunteers had a limited amount of time to refer clients. Therefore, we estimate the relationship between total number of referrals (both in absolute terms and as a share of the 2011 population in the ward) and the incentive.

Last, to assess whether the increased disadvantaged referrals are due to advantaged health volunteers referring more of the disadvantaged clients or due to disadvantaged health volunteers referring more of their own type, we interact the incentive arm of the health volunteer with her ethnicity and estimate coefficients in a regression similar to equation (1). Our expectation is that the increased disadvantaged referrals may be more strongly driven by the disadvantaged health volunteers than by the advantaged workers since disadvantaged health workers have (1) lower cost of reaching out to their own type and (2) higher expected reciprocity from the disadvantaged referral.

B. *Demand (Client's) Response*

On the clients' side, the key outcome of interest is whether a disadvantaged client who received a referral card from a health volunteer showed up for the checkup. In order to evaluate the general effect of the incentives and whether a higher incentive encourages a disadvantaged client to come to the checkup, we estimate the coefficients in the following equation:

$$\begin{aligned} \mathrm{Y}_{ij} = {} & \alpha + \beta_{1,\mathrm{demand}}\mathrm{Disadvantaged}_i + \beta_{2,\mathrm{demand}}\mathrm{Amount\ of\ incentive}_i \\ & + \beta_{3,\mathrm{demand}}(\mathrm{Amount\ of\ incentive}_i \times \mathrm{Disadvantaged}_i) + \delta\mathbf{X} + \varepsilon_j. \end{aligned} \tag{2}$$

In equation (2), Y_{ij} is a binary variable that equals 1 if an individual *i* referred by health volunteer *j* showed up for the checkup and 0 otherwise. Again, **X** is a vector of health volunteer characteristics; **X** also includes a categorical variable for the arm that the health volunteer belongs to because health volunteers in different arms may put different effort toward convincing the disadvantaged client to come to the checkup, which in turn may affect the client's decision. Finally, **X** includes health center fixed effects, so the effect is identified from the within–health center variation in financial incentives to the clients.

Given historical patterns in health care utilization in Nepal, the disadvantaged clients can be expected to be less likely to show up than the advantaged ones. Therefore, in equation (2), we expect $\beta_{1,\mathrm{demand}} < 0$. Because the clients receiving a higher incentive should be more likely to show up, we expect $\beta_{2,\mathrm{demand}} > 0$. We hypothesize that with higher incentives, the disadvantaged clients will be more likely to show up than with lower incentives; therefore, we expect $\beta_{3,\mathrm{demand}} > 0$.

C. *Interaction between Health Volunteers' and Clients' Incentives*

In the demand analysis above, we have controlled for the incentive arm of the health volunteer. However, to test formally whether there exists any potential interaction between the two types of treatments—incentives offered to the health volunteers and incentives to the clients—we run regressions of the form in equation (2) but include an interaction between the two layers of incentives. The equation we estimate the coefficients is thus

$$\begin{aligned} Y_{ij} = {} & \alpha + \beta_{1,\mathrm{demand}}\ \mathrm{Disadvantaged}_i + \beta_{2,\mathrm{demand}}\ \mathrm{Client\ incentive}_i \\ & + \beta_{3,\mathrm{demand}}(\mathrm{Client\ incentive}_i \times \mathrm{Disadvantaged}_i) \\ & + \beta_{4,\mathrm{demand}}\ \mathrm{HV\ incentive}_j \\ & + \beta_{5,\mathrm{demand}}(\mathrm{Client\ incentive}_i \times \mathrm{HV\ incentive}_j) + \delta\mathbf{X} + \varepsilon_j. \end{aligned} \tag{3}$$

Here, our main outcome Y_{ij} is a binary variable that equals 1 if an individual i referred by health volunteer j showed up for the checkup. To evaluate the effect only on the disadvantaged clients, we estimate the coefficients in the following equation on the subsample of disadvantaged clients:

$$\begin{aligned} Y_{ij} = \alpha &+ \beta_{1,\text{demand}} \text{ Client incentive}_i + \beta_{2,\text{demand}} \text{HV incentive}_j \\ &+ \beta_{3,\text{demand}}(\text{Client incentive}_i \times \text{HV incentive}_j) + \delta \mathbf{X} + \varepsilon_j. \end{aligned} \tag{4}$$

V. Descriptive Statistics and the Validity of Randomization

Of the 72 health volunteers who had been randomized into four groups, 69 showed up for the training and were recruited for the experiment. The three health volunteers who did not show up were one each from the Low, NudgeAdv, and High arms. Of the 69 health volunteers, there were 17 each in the Low and High arms, 19 in the NudgeDis arm, and 16 in the NudgeAdv arm. Forty-three of them (62%) were from the advantaged ethnic category, while the remaining 26 (38%) were from the disadvantaged category (table 2). This mix is different

TABLE 2
SUMMARY STATISTICS FOR ANALYTIC SAMPLE

	Mean	SD
	A. Health Volunteers (N = 69)	
Age (years)	46.09	9.28
Experience (years)	18.96	7.54
Education higher than grade 10 (1 = yes)	.28	.45
Had informal schooling (1 = yes)	.10	.30
Ethnicity (1 = advantaged)	.62	.49
Number of households visited per month	50.26	42.65
Received money for work as health volunteer in previous month	.78	.42
Distance to health center (minutes)	29.74	19.89
Primary occupation is agriculture (1 = yes)	.83	.38
Has one of five neighbors from a different ethnicity	.20	.41
	B. Clients (N = 2,333)	
Gender (1 = female)	.60	.49
Age (years)	52.07	12.33
Ethnicity (1 = advantaged)	.56	.50
Same ethnic category as that of health volunteer	.66	.47
Marital status (1 = married)	.89	.31
Years of schooling	4.11	4.64
Distance to health center (minutes)	26.93	24.32
Primary occupation is agriculture (1 = yes)	.82	.38
Knew about diabetes before health volunteer's visit	.61	.49
Knew about checkup from health volunteer	.99	.09
Health volunteer informed client by visiting client's house	.98	.12

Note. Clients include individuals who received a referral card from a health volunteer, showed up for the checkup, and answered the questionnaire administered by the research team. As mentioned in the text, of the 2,825 individuals who received a referral card, 2,403 showed up. Of those, 2,365 were interviewed and 2,333 provided complete information on the various indicators above.

from the one in the underlying population in the study site in which the share of the advantaged population is 44% (authors' calculations based on the 2011 census data). For comparison, in the country as a whole, advantaged health volunteers constitute 52% of their total number relative to a population share of 35% (authors' calculations based on New Era [2007, 10]). In the analytical sample, on average, a health volunteer is 46 years old and has 19 years of experience. All are women. Less than one-third of health volunteers have completed the school-leaving certificate (equivalent to the sophomore year of high school in the United States), and 10% have only informal education. On average, a health volunteer in the sample visited 50 households in the month preceding the survey and lives half an hour away from the nearest local health center. Seventy-eight percent of health volunteers received honorarium for their work in the month before the survey, and 82% of health volunteers reported agriculture as their main occupation.

The health volunteers distributed the referral cards to 2,825 clients (average = 40.9 cards per health volunteer). This is our main analytic sample. Of these, 2,403 (85.1%) showed up for the checkup and 2,365 (98.4% of all those who showed up) were interviewed. The remaining 38 include clients who showed up after the interviewers had left. For clients who received the cards from the health volunteers but did not show up, we have data on their ethnicity and the amount of incentive they would have received for showing up. Of the 2,365 clients who were interviewed, information on some of the covariates is missing for a total of 32 clients, leaving a second analytical sample of 2,333 (97% of all clients who showed up and 98.6% of all clients who were interviewed).

Among those who showed up and provided complete information, 60% of clients are women, the average age is 52 years, and 56% are from an advantaged ethnic category (table 2). Sixty-six percent are from the same ethnic category as that of the health volunteer. Eighty-nine percent are married, and the average education level is grade 4. On average, clients live 27 minutes away from the nearest health center, 82% are engaged in agriculture, and 61% had heard about diabetes before the study. Almost all of them heard about the sugar level checkups from their health volunteer. In 98% of cases, the health volunteer visited the individual at home to talk about diabetes and to give the referral card and the letter.

Randomization divided the health volunteers into four similar arms (table 3). For many health volunteers, their actual experience, age, and level of education—self-reported during the interviews—were different from the information collected from the health centers before randomization (not shown). On the basis of the self-reported information, there is a decrease in age and experience going from the Low arm to the High arm. The differences in experience levels are also

TABLE 3
BALANCE IN KEY CHARACTERISTICS OF HEALTH VOLUNTEERS BETWEEN ARMS

	Low	NudgeDis	NudgeAdv	High	*p* (All Arms)
Age (years)	49.35	47.95	45.31	41.47	.06
	(1.74)	(1.81)	(2.72)	(2.36)	
Experience (years)	21.29	20.63	18.81	14.88	.05
	(1.72)	(1.50)	(1.84)	(1.97)	
Education higher than grade 10 (1 = yes)	.24	.11	.38	.41	.16
	(.11)	(.07)	(.13)	(.12)	
Had informal schooling (1 = yes)	.12	.11	.13	.06	.62
	(.08)	(.07)	(.09)	(.06)	
Ethnicity (1 = advantaged)	.65	.58	.63	.65	.97
	(.12)	(.12)	(.13)	(.12)	
Income category	2.29	2.05	2.06	1.88	.57
	(.19)	(.19)	(.17)	(.26)	
Number of households visited per month	38.29	60.53	54.38	46.88	.45
	(9.69)	(10.14)	(9.87)	(11.30)	
Received money in previous month	.88	.84	.69	.71	.43
	(.08)	(.09)	(.12)	(.11)	
Distance to health center (minutes)	27.94	35.79	30.75	23.82	.33
	(3.79)	(5.32)	(5.06)	(4.63)	
Primary occupation is agriculture	.76	.84	.81	.88	.84
	(.11)	(.09)	(.10)	(.08)	

Note. The *p*-values are from the joint orthogonality test of the arms. All variables reported here were self-reported by the health volunteers. Income was categorized into four groups: 1 = less than Rs 50,000 per year; 2 = Rs 50,000–100,000 per year; 3 = Rs 100,000–200,000 per year; 4 = Rs 200,000–500,000 per year; 5 = more than Rs 500,000 per year. The mean income category reported in this table is based on those categories.

not negligible, particularly for the high group. Further, even with the stratification, the differences in education levels are substantively large, although the null of equality cannot be rejected at standard levels. The *p*-values are from a joint orthogonality test of all arms. The *p*-values from pairwise comparison of all arms are in table A1 (tables A1–A5 are available online). The health volunteers in the Low and NudgeDis arms—the key arms—are not statistically different from each other in any of the observable characteristics (col. 1). However, the health volunteers in the High arm differ significantly from those in the Low arm in terms of age and experience (col. 3) and from those in the NudgeDis arm in terms of age, experience, and distance to the health center (col. 5). We control for these characteristics in all regressions.

As mentioned in section III, we gave 50 letters along with 50 referral cards to each health volunteer and informed them that they could call the research team if they needed more cards and letters or if the clients had questions. None of them called. The extent to which the health volunteers used all referral cards can affect the validity of our findings if the proportion of health volunteers who use all 50 cards differs by arm. Thirty-five (50.7%) volunteers used all 50 referral cards. Ten of them were from the Low arm, eight from the NudgeDis arm, seven from the NudgeAdv arm, and 10 from the High arm. We created a binary variable for whether the health volunteers used all 50 cards and regressed that variable on the nudge arm as well as the covariates used in the main analysis, and we found that the proportions of health volunteers who distributed all 50 cards did not vary statistically by arm (not shown),

On the demand side, the health volunteers in all arms had similar probabilities of receiving letters offering Rs 20, Rs 30, Rs 40, and Rs 50, which confirms the validity of randomization of incentives to the clients (fig. A1, available online). There is no evidence that the health volunteers opened the envelopes beforehand to give letters mentioning a higher amount to their own-type clients—the proportion of envelopes going to own-type clients were 64.7% for Rs 20, 66% for Rs 30, 63.2% for Rs 40, and 64.4% for Rs 50. The characteristics of clients across four different incentive arms are also balanced, except for the proportion of clients who reported that they had heard about diabetes even before the health volunteers visited them (table A2).

VI. Main Empirical Results

A. The Effect of Incentives on Disadvantaged Referral

On the basis of the number of referral cards distributed by the health volunteers, approximately 43% of the clients receiving them were disadvantaged (table 4). Recall that the share of disadvantaged individuals in the population in the study site is approximately 56%. On the basis of the fully specified model (panel A, col. 3), incentives geared toward a disadvantaged referral increased the chances of such a referral by 11.6 percentage points (95% CI, 1.1–22.1). This effect represents an increase in the number of disadvantaged referrals of nearly 27% ($= 100 \times 0.12/0.43$). From the Low arm to the NudgeDis arm, the amount of incentive changed by 150% (i.e., went up from Rs 20 to Rs 50), which means that the incentive elasticity of referral is approximately 0.2 ($= 27/150$). The coefficient on NudgeDis is stable across the three specifications, suggesting that the effects are likely not driven by factors other than the differential incentives, including those related to accessibility.

The results are similar, if not larger, when we use the sample of clients who showed up to the checkup at the health center. The coefficient of 0.12 on NudgeDis (panel B, col. 3; 95% CI, 0.015–0.224) implies that the number of disadvantaged referrals increased by 29% ($= 100 \times 0.12/0.41$) in response to the incentives geared toward a disadvantaged referral. The corresponding incentive elasticity of referral is again close to 0.2.

In columns 1–3 of table 4, the coefficients on the NudgeAdv and High arms are close to zero and statistically insignificant, and the CIs are wide (not shown). The *p*-values from the randomization inference test for the coefficient

TABLE 4

REGRESSION RESULTS OF DISADVANTAGED CLIENT REFERRAL

	Probability of Disadvantaged Client Referral			Number of Disadvantaged Referrals
	(1)	(2)	(3)	(4)
	A. Based on Initial Referrals (n = 2,825; N = 69; Baseline Proportion of Disadvantage Clients = .43; Baseline Number of Disadvantage Clients = 17.35)			
NudgeDis	.138*	.117	.116**	3.629
	(.082)	(.076)	(.052)	(3.525)
RI p	.134	.221	**.078**	.343
NudgeAdv	−.056	−.077	−.006	−2.220
	(.080)	(.075)	(.061)	(3.814)
RI p	.538	.413	.932	.578
High	−.002	−.008	.037	−4.064
	(.075)	(.081)	(.059)	(3.791)
RI p	.977	.938	.594	.287
R^2	.115	.142	.211	.534
	B. Based on Clients Who Showed Up (n = 2,403; N = 69; Baseline Proportion of Disadvantage Clients = .41; Baseline Number of Disadvantage Clients = 14.53)			
NudgeDis	.134	.122	.120**	4.094
	(.086)	(.079)	(.052)	(3.227)
RI p	.180	.232	**.091**	.232
NudgeAdv	−.044	−.059	.018	−2.430
	(.086)	(.078)	(.065)	(3.429)
RI p	.636	.564	.840	.488
High	.006	−.001	.050	−4.414
	(.082)	(.085)	(.062)	(3.216)
RI p	.952	.990	.490	.167
R^2	.119	.153	.233	.569
	C. Additional Covariates (for Panels A and B)			
Stratification variables	Yes	Yes	Yes	Yes
Other health volunteer characteristics	No	Yes	Yes	Yes
Accessibility-related variables	No	No	Yes	Yes

Note. The results in this table are from estimating equation (1) separately for the sample of all clients who received a referral card from their health volunteer (panel A) and those who came to the health center for the checkup (panel B). Standard errors are in parentheses and are clustered at the health volunteer level. In cols. 1–3, the dependent variable is whether a client referred by a health volunteer is from a disadvantaged group. In col. 4, the dependent variable is the number of disadvantaged referrals. Stratification variables include ethnicity, experience, and education. Other health volunteer characteristics include age, annual household income, number of households the health volunteer visited in the past month, the amount of money she received for working as a health volunteer, distance to the nearest health center, and primary occupation. The accessibility-related variables include the share of disadvantaged households in the ward and whether the ward had less than 10% population of any of the two groups. The p-values are from randomization inference (RI). When estimating the randomization p-values, we reassign treatment status at the health volunteer level. The Stata codes used to generate these p-values are available from the authors on request. N = number of health volunteers; n = number of clients.

* $p < .10$.

** $p < .05$.

on NudgeDis in column 3 is small enough for us to reject no effect. Finally, the results are also robust to using bootstrapped standard errors (table A3).

Higher incentives as well as the incentives geared toward an advantaged referral (which, as mentioned earlier, are policy irrelevant) had no effect on the chances of a disadvantaged referral—using both samples. The lack of an effect of higher incentives on disadvantaged referral suggests that while such incentives may improve health services utilization in general, they are not particularly effective in improving health service utilization by the disadvantaged groups.

In column 4 of table 4, we report results on the absolute number of disadvantaged referrals. On average, the NudgeDis incentives induce the health volunteers to recruit 3.6 (95% CI, −3.4 to 10.7) additional disadvantaged clients on the basis of the initial number of referrals (panel A, col. 4) and 4.1 (95% CI, −2.3 to 10.5) additional disadvantaged clients on the basis of the clients who came to the health center for the checkup (panel B, col. 4). Given the high variance in the number of disadvantaged referrals within each arm, our study is not sufficiently powered to detect this effect.

The higher chances of a disadvantaged referral in the NudgeDis arm do not seem to come at the cost of reduced total number of referrals. In fact, there is no evidence that the incentives offered to health volunteers differentially affect the total number of referrals (table 5) or total referrals as a share of the total population in the health volunteer's ward (table A4). Regarding whether the health volunteers engage in gaming—that is, referring healthier disadvantaged clients to benefit from higher incentives even when there are sicker advantaged clients—we find no evidence supporting such gaming. Approximately 4.4% of the clients who were provided a referral card and came to the checkup were diabetic (table 6). Clients in the NudgeDis, NudgeAdv, and High arms were all more likely to be diabetic than those in the Low arm. These findings show that higher incentives, irrespective of who they are induced to recruit, encourage the health volunteers to identify and target patients who are more in need of the service. However, we do not find any statistically significant difference in the effect between the three arms.

The higher chances of a disadvantaged referral in response to the NudgeDis incentives seem to come from disadvantaged health volunteers referring more of their own type than from the advantaged health volunteer referring more disadvantaged clients. Figure 2 shows the probability of a disadvantaged referral in each incentive arm by the ethnicity of the health volunteer—again separately based on initial referrals (fig. 2*a*) and based on the sample of clients who came to the health center (fig. 2*b*). The full set of regression results behind these figures is in table A5. The figures show that at baseline, there is no difference between advantaged and disadvantaged health volunteers in terms of

TABLE 5
REGRESSION RESULTS OF TOTAL NUMBER OF REFERRALS ON INCENTIVE ARMS

	(1)	(2)	(3)
	A. Based on Initial Referrals (n = 2,825; N = 69; Baseline Total Number of Referrals = 40.11)		
NudgeDis	1.225	1.325	1.356
	(4.570)	(3.647)	(3.703)
RI p	.805	.763	.750
NudgeAdv	1.419	1.291	2.261
	(4.510)	(4.278)	(4.466)
RI p	.790	.806	.675
High	−.695	−3.323	−4.439
	(5.526)	(4.389)	(4.626)
RI p	.891	.480	.344
R^2	.043	.236	.280
	B. Based on Clients Who Showed Up (n = 2,403; N = 69; Baseline Total Number of Referrals = 35.59)		
NudgeDis	.358	1.716	2.290
	(4.591)	(3.776)	(3.697)
RI p	.946	.679	.569
NudgeAdv	−2.509	−2.181	−.515
	(4.517)	(3.995)	(4.101)
RI p	.611	.670	.914
High	−1.600	−4.443	−5.886
	(4.925)	(3.938)	(4.071)
RI p	.744	.313	.188
R^2	.067	.289	.378
	C. Additional Covariates (for Panels A and B)		
Stratification variables	Yes	Yes	Yes
Other health volunteer characteristics	No	Yes	Yes
Accessibility-related variables	No	No	Yes

Note. The results in this table are from estimating regressions of the total number of referrals on the incentive arms separately for the sample of all clients who received a referral card from their health volunteer (panel A) and the sample of those who came to the health center for the checkup (panel B). Standard errors are in parentheses. Stratification variables include ethnicity, experience, and education. Other health volunteer characteristics include age, annual household income, number of households the health volunteer visited in the past month, the amount of money she received for working as a health volunteer, distance to the nearest health center, and primary occupation. The accessibility-related variables include the share of disadvantaged households in the ward and whether the ward had less than 10% population of any of the two groups. The p-values are from randomization inference (RI). N = number of health volunteers; n = number of clients.

whether they refer a disadvantaged client. For advantaged health volunteers, the chances of a disadvantaged referral do not change across the incentive arms. For the disadvantaged health volunteers, the chances of a disadvantaged referral increase significantly from baseline to the NudgeDis arm. Put together, table 4 and figure 2 suggest that if the policy goal is to increase health care utilization by disadvantaged groups in this setting, recruiting more individuals from disadvantaged health volunteers will be insufficient, as will providing differential

TABLE 6

REGRESSION RESULTS OF CLIENTS' DIABETIC STATUS ON HEALTH VOLUNTEERS' INCENTIVES

	(1)	(2)	(3)
NudgeDis	.025**	.024**	.032***
	(.012)	(.011)	(.009)
NudgeAdv	.030*	.034**	.034***
	(.015)	(.015)	(.011)
High	.010	.021**	.026***
	(.010)	(.010)	(.009)
R^2	.002	.005	.012
Number of clients	2,354	2,354	2,354
Additional covariates:			
Stratification variables	No	Yes	Yes
Health volunteer characteristics	No	No	Yes

Note. The results in this table are from estimating equation (1) on the sample of clients who received a referral card from their health volunteer and came to the health center for the checkup. The proportion of individuals who are diabetic in the Low arm is 0.04. Standard errors are in parentheses and are clustered at the health volunteer level. Health volunteer characteristics include ethnicity, experience, education, age, annual household income, number of households the health volunteer visited in the past month, the amount of money she received for working as a health volunteer, distance to the nearest health center, and primary occupation.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

incentives to the advantaged health volunteers. Instead, an effective approach will be to recruit more disadvantaged health volunteers and provide them incentives geared toward a disadvantaged referral.

Given the similar propensity to refer disadvantaged clients at baseline by advantaged and disadvantaged clients, the ethnic barrier prevalent in this setting does not appear to be one of taste-based discrimination (from advantaged to disadvantaged). In fact, as the demand-side analysis suggests (discussed next),

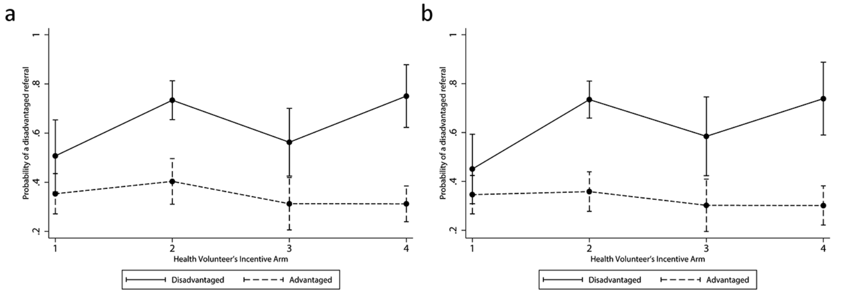


Figure 2. Probability of a disadvantaged referral by health volunteer's incentive arm for disadvantaged and advantaged health volunteers. The figure is based on the sample of all clients who were referred by the health volunteers (*a*) and all clients who were referred by the health volunteers and came to the health center for the sugar level assessment (*b*). The probabilities were obtained from estimating equation (1) by interacting health volunteers' ethnicity with the incentive arm in the sample of clients who came to the health center. The full set of numbers corresponding to *a* and *b* are in columns 1 and 2, respectively, of table A5.

the low number of disadvantaged referrals seem to originate in health volunteers' knowledge about the disadvantaged groups' low likelihood of showing up.

B. Effect of Incentives on Demand (Decision to Access Services)

On the demand side, overall, the incentives to the clients—in the range tested, that is, between Rs 20 and Rs 50—were inconsequential in affecting the clients' decision to come to the checkup after the health volunteers referred them (table 7, col. 1). Consistent with our expectation, the disadvantaged clients were less likely to come to the checkup compared with the advantaged clients even after receiving a referral card (col. 2). Conditional on being referred, the disadvantaged clients are approximately 5 percentage points less likely to show up to the health center than advantaged clients. It is possible that the health volunteers are aware of the disadvantaged clients' lower inclination to access health care and therefore are less likely to refer them at baseline. To clarify further why disadvantaged

TABLE 7
REGRESSION RESULTS OF CLIENTS' DECISION TO SHOW UP FOR CHECKUP

	(1)	(2)	(3)	(4)
Incentive amount (Rs)	−.0008	−.0006		−.0016
	(.0007)	(.0008)		(.0012)
Disadvantaged client		−.0511***	−.0417	−.0359
		(.0181)	(.0444)	(.0450)
Incentive amount × disadvantaged client			−.0003	−.0004
			(.0013)	(.0013)
NudgeDis	.0050	.0087	.0098	−.0558
	(.0336)	(.0331)	(.0332)	(.0769)
NudgeAdv	−.1170***	−.1226***	−.1217***	−.1429*
	(.0419)	(.0411)	(.0410)	(.0779)
High	−.0718**	−.0718**	−.0710**	−.1255**
	(.0311)	(.0301)	(.0300)	(.0596)
NudgeDis × incentive amount				.0019
				(.0018)
NudgeAdv × incentive amount				.0006
				(.0020)
High × incentive amount				.0016
				(.0016)
R^2	.053	.056	.057	.058
N	2,760	2,760	2,760	2,760
Additional covariates:				
Health volunteers characteristics	Yes	Yes	Yes	Yes
Health center fixed effects	Yes	Yes	Yes	Yes

Note. Each column represents a separate regression. Standard errors are in parentheses and are clustered at the health volunteer level. The health volunteer characteristics include ethnicity, experience, education, age, annual household income, number of households the health volunteer visited in the past month, the amount of money she received for working as a health volunteer, distance to the nearest health center, and primary occupation.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

individuals are less likely to be targeted at baseline, one could argue that it is because disadvantaged clients suffer less from diabetes. To our knowledge, population-level prevalence rates broken down by ethnicity are not available for our geographic area. The prevalence rates of diabetes are similar in the study setting on the basis of the clients who came to the checkup (5.7% for advantaged clients and 5.8% for disadvantaged clients). Put everything together, it is likely that disadvantaged clients are less receptive to the information provided by the health worker on diabetes and are hence less likely to show up to the clinic conditional on being referred.

A few additional observations from columns 1–3 of table 7 are noteworthy. Even controlling for health volunteer's arms and other characteristics, the standard errors on the key variable—interaction of being disadvantaged and incentive amount—are large relative to the coefficient (col. 3). Overall, higher incentives provided directly to the clients do not seem to increase the chances of appearing for the checkup. In section VII, we provide a few setting-specific conjectures for why this might be happening.

C. Interaction between Health Volunteers' and Clients' Incentives

We have so far shown that incentives geared toward a disadvantaged referral yield expected results without distorting health volunteers behavior (i.e., encouraging them to refer fewer individuals overall or to refer less sick patients). We have also shown that the effects are driven by the disadvantaged health volunteers who behave similar to advantaged health volunteers at baseline but increase own-type referrals in the NudgeDis arm. The low chance of a disadvantaged referral at baseline seems to be due to the fact that disadvantaged clients are generally less likely to come to the checkup—the premise of our study.

It is worth checking whether the two layers of the incentives interacted in an unintended way and biased the estimates of the effect of incentives to the clients on their decision to show up. In column 4 of table 7, we confirm that there are no interaction effects between the two types of treatments (incentives for health volunteers and incentives for clients).

In figure 3, we show the probability of coming to the checkup conditional on being referred, generated from equation (3). It shows that a client's chances of coming to the checkup are significantly higher when referred by a health volunteer in the NudgeDis arm than when referred by a health volunteer in the NudgeAdv or High arm. This indicates that substantially higher efforts are exerted by health volunteers in the NudgeDis arm when talking to the targeted clients, which is successfully translated into the actual output. We see a similarly high chance of coming to checkup for the clients referred by a health volunteer in the Low arm.

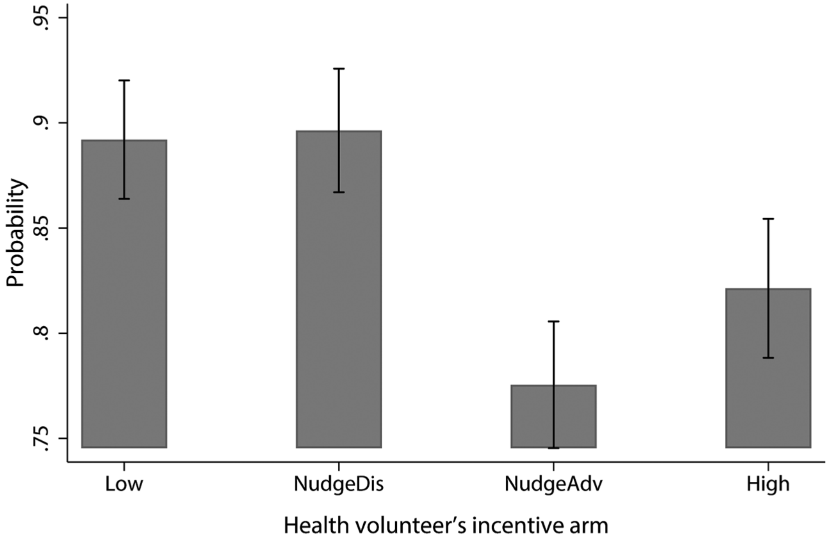


Figure 3. Client's probability of coming to checkup conditional on being referred by health volunteer, by health volunteer's incentive arm. The probabilities were generated by estimating equation (3) on the sample of clients referred by the health volunteers. The outcome is whether a client referred by a health volunteer came to the checkup.

That we observe a higher likelihood of workers' efforts being translated into the output under the Low arm and NudgeDis arm than under the High arm may have been caused by extrinsic motivations being crowded out by the intrinsic motivations. However, we cannot test it empirically.

VII. Discussion and Conclusion

In this study, we showed that the uptake of health care services by traditionally disadvantaged groups can be raised by providing differential incentives—ones geared toward a disadvantaged referral—to health outreach workers. We showed that without incentives (specifically, small incentives), health workers would refer disproportionately fewer disadvantaged individuals. In our case, the workers referred 43% disadvantaged individuals relative to a population share of 56%. Incentives geared toward disadvantaged referrals raised the proportion by 11.6 percentage points (95% CI, 1.1 to 22.1), bringing them close to the proportion of the disadvantaged population. Such differential incentives do not have adverse effects on efficiency—in fact, the likelihood of having diabetes was similar for clients recruited in all arms except the low incentive arm. From a policy perspective, these are encouraging findings. The higher share of the disadvantaged referrals does not seem to come at the cost of reduced total referrals; put differently, incentive geared toward disadvantaged referrals does not suffer from trade-off between better targeting and lower coverage. Upon closer examination, we showed that the increased disadvantaged referrals primarily come through higher own-type referrals by disadvantaged health volunteers.

Although the study was not set up to parse out the discrimination from other barriers, the low number of disadvantaged referrals at baseline by both advantaged and disadvantaged health volunteers suggests that taste-based discrimination is not a major barrier among ethnic groups in this setting. While this is good news, it also threatens the external validity of our findings. The study site is a semiurban area with better availability of schools, health facilities, drinking water, and electricity than in the rest of Nepal, and a large share of the residents are permanent migrants from other parts of the country. Therefore, it is likely that the level of barriers between ethnic groups is higher elsewhere in the country.

The reader should understand our findings, especially the magnitudes of the effects, in light of a number of other limitations. We gave the volunteers only one full day to recruit clients. While the short duration was appropriate given our interest in the mix of clients, it is difficult to imagine real-world outreach efforts where agents have so limited time to deliver outcomes. From the onset, the health volunteers were aware of the temporary nature of the financial incentives. It is possible that they would behave differently if similar incentives were to be provided as a policy, thus making these incentives a regular income. We conducted the study at a time when the health volunteers did not have any other major activity (such as visiting households to encourage them to take the kids for vitamin A supplementation). Our incentives may have also crowded out other activities if we had conducted the study at a busier time.

Likewise, as the checkup took place on a specific day (by design, as we did not want to disrupt regular business of the health centers), it is possible that the clients who came were nonrepresentative of the underlying population. For example, poorer individuals who valued the incentives may have been more likely to show up. We expect this not to be a significant issue in this study, as we conducted the study during a postcultivation season and the checkup took place in the mornings between 7 and 10 a.m. (the regular businesses open at 10 a.m.). Nonetheless, the short duration for showing up is a possible threat to the external validity of our results.

The short duration provided to the health volunteers for recruiting clients and to the clients for the checkup likely reduced spillovers, which we confirmed anecdotally. An immediate area for investigation is the nature of the barrier that health workers and disadvantaged clients face when interacting with each other—in other words, the barriers that the differential incentives seem to offset in our study. Our analysis suggests that the primary barrier in this setting is not taste-based discrimination and that the health volunteers are likely optimizing their effort by focusing on the clients who are more likely to come to the checkup—in this case, the advantaged clients. A larger sample size would be required to confirm this and to investigate the reasons why disadvantaged clients are less likely to utilize health care even after health volunteers have reached them.

The finding that incentives to the clients—which were exogenous—had no effect on the decision to come to the checkup also warrants further research. It is possible that the amount of incentive offered to the clients signaled the service's quality, with higher incentives signaling lower quality. It is also possible that the lowest incentive amount provided to the client—Rs 20—was already high enough in terms of offsetting the costs they faced when going for the checkup, and therefore the additional amount had no effect on their decision. This second argument is consistent with the high uptake in this study—approximately 85% of the clients approached by the health volunteers came to the sugar level assessment—and a number of other studies that have similarly found a weak association between demand and the size of the incentive beyond the fact that it is a positive incentive (Thornton 2008; Filmer and Schady 2009; Banerjee et al. 2010). Nonetheless, more research will be needed to understand why demand is not responsive to incentives in this setting. We collected a limited amount of information (namely, information on the incentive amount and ethnicity) from the clients who were referred by the health volunteers but did not come to the checkup. This limited our ability to comment on whether the effect of incentives to clients on the decision to come to the checkup varies by factors such as education level, gender, previous experience with the health sector, and distance from the health center.

In the meantime, the high uptake in this study suggests that the health volunteers can continue to play an important role in encouraging preventive health behavior in Nepal, even for newer health conditions. The policy challenge now is to build an incentive structure so that the significant disparities prevalent in the uptake of common, communicable diseases and their outcomes do not extend to the newer, noncommunicable conditions, such as diabetes.

Beyond Nepal, the methodological approach we adopted—differential incentives based on the ethnicity of the individual that a client interacts with—may be applied to several settings as a way to improve health care utilization by disadvantaged and minority groups. In fact, the disproportionate representation of advantaged groups in the relevant workforce and the resulting uneven uptake by and gains for individuals from different groups is a common problem in many government programs. Examples of potential applications of our method beyond health include efforts to raise diversity in universities and to raise the uptake of government services by disadvantaged groups.

References

Agency for Healthcare Research and Quality. 2014. "National Healthcare Disparities Report 2013." Rockville, MD: US Department of Health and Human Services. http://www.ahrq.gov/sites/default/files/publications/files/2013nhdr.pdf.

Andersen, K., A. Singh, M. K. Shrestha, M. Shah, E. Pearson, and L. Hessini. 2013. "Early Pregnancy Detection by Female Community Health Volunteers in Nepal Facilitated Referral for Appropriate Reproductive Health Services." *Global Health: Science and Practice* 1:372–81.

Ashraf, N., O. Bandiera, and K. Jack. 2014. "No Margin, No Mission? A Field Experiment on Incentives for Pro-Social Tasks." *Journal of Public Economics* 120:1–17.

Banerjee, Abhijit Vinayak, Esther Duflo, Rachel Glennerster, and Dhruva Kothari. 2010. "Improving Immunisation Coverage in Rural India: Clustered Randomised Controlled Evaluation of Immunisation Campaigns with and without Incentives." *BMJ* 340:c2220.

Barnes-Mauthe, M., S. Arita, S. D. Allen, S. A. Gray, and P. S. Leung. 2013. "The Influence of Ethnic Diversity on Social Network Structure in a Common-Pool Resource System: Implications for Collaborative Management." *Ecology and Society* 18, no. 1:23.

Berg, E., M. Ghatak, R. Manjula, D. Rajasekhar, and S. Roy. 2017. "Motivating Knowledge Agents: Can Incentive Pay Overcome Social Distance?" *Economic Journal* 129, no. 617:110–42.

Braveman, P., and E. Tarimo. 2002. "Social Inequalities in Health within Countries: Not Only an Issue for Affluent Nations." *Social Science and Medicine* 54:1621–35.

Center for Global Development. 2011. "Reducing Child Mortality with Vitamin A in Nepal." Washington, DC: Center for Global Development. http://www.cgdev.org/doc/millions/MS_case_4.pdf.

Cohen, J., and P. Dupas. 2010. "Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Experiment." *Quarterly Journal of Economics* 125, no. 1:1–45.

Dal Bo, E., F. Finan, and M. A. Rossi. 2013. "Strengthening State Capabilities: The Role of Financial Incentives in the Call to Public Service." *Quarterly Journal of Economics* 128, no. 3:1169–218.

Deserranno, E. 2019. "Financial Incentives as Signals: Experimental Evidence from the Recruitment of Village Promoters in Uganda." *American Economic Journal: Applied Economics* 11, no. 1:277–317.

Filmer, D., and N. Schady. 2009. "Are There Diminishing Returns to Transfer Size in Conditional Cash Transfers?" Policy Research Working Paper Series 4999, World Bank, Washington, DC.

Finan, F., B. A. Olken, and R. Pande. 2017. "The Personnel Economics of the Developing State." *Handbook of Economic Field Experiments* 2:467–514.

Goldberg, J., M. Macis, and B. Chintagunta. 2018. "Incentivized Peer Referrals for Tuberculosis Screening: Evidence from India." Working Paper no. w25279, NBER, Cambridge, MA. http://www.nber.org/papers/w25279.

Kremer, M., and R. Glennerster. 2011. "Improving Health in Developing Countries: Evidence from Randomized Evaluations." *Handbook of Health Economics* 2:201–315.

Mishra, S., M. P. Joshi, and V. Khanal. 2014. "Family Planning Knowledge and Practice among People Living with HIV in Nepal." *PLoS ONE* 9, no. 2:e88663.

New Era. 2007. "An Analytical Report on National Survey of Female Community Health Volunteers of Nepal." Kathmandu: United States Agency for International Development. https://dhsprogram.com/pubs/pdf/FR181/FCHV_Nepal2007.pdf.

Pandey, J. P., M. R. Dhakal, S. Karki, P. Poudel, and M. S. Pradhan. 2013. "Maternal and Child Health in Nepal: The Effects of Caste, Ethnicity, and Regional Identity." http://www.dhsprogram.com/pubs/pdf/FA73/FA73.pdf.

Rabiee, A., J. T. Magruder, C. Grant, R. Salas-Carrillo, A. Gillette, J. DuBois, R. P. Shannon, D. K. Andersen, and D. Elahi. 2010. "Accuracy and Reliability of the Nova StatStrip® Glucose Meter for Real-Time Blood Glucose Determinations during Glucose Clamp Studies." *Journal of Diabetes Science and Technology* 4:1195–201.

Snyder, C. R., B. Stover, S. M. Skillman, and B. K. Frogner. 2015. "Facilitating Racial and Ethnic Diversity in the Health Workforce." Seattle, WA: Center for Health Workforce Studies, University of Washington. https://depts.washington.edu/fammed/chws/studies/facilitating-racial-and-ethnic-diversity-in-the-health-workforce/.

Thornton, R. 2008. "The Demand for and Impact of Learning HIV Status: Evidence from a Field Experiment." *American Economic Review* 98:1829–63.

World Health Organization. 2016. "Diabetes Country Profiles 2016." http://www.who.int/diabetes/country-profiles/npl_en.pdf?ua=1.