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Targeting through Social Norms: Experimental Evidence from India's #GiveItUp Campaign*

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Abstract

Social norms about who is deserving may help target public benefits, by making sure people in need receive benefits or by excluding people with lesser need to reduce costs. The Government of India launched a campaign to use norms to improve the targeting of a cooking gas subsidy used by 220 million households. The campaign, called Give It Up, asks beneficiary households to voluntarily forfeit cooking gas subsidies so the money can be used to subsidize the poor instead. We propose a field experiment to test whether this approach to change social norms affects subsidy use. The randomized saturation design encourages individual households to forfeit their own subsidies though a direct-mail solicitation, and varies the proportion of their neighbors who are similarly encouraged, in order to measure whether subsidy use decisions spill over across neighbors. The main policy outcome, usage of the cooking gas subsidy, will be measured with high-quality administrative data in a sample of 1.2 million gas-using households.

Timeline. The intervention was carried out in a mass marketing experiment from October through December 2018. The analysis will use data from two sources, a household survey and an administrative data set on gas consumption. The household survey was run in December 2018 through April 2019. We have completed the household survey but not accessed the survey data.

Our main outcomes are from administrative data on gas consumption and subsidy transfers. We have collected this data for the baseline period, up through April 2018, and use it for power analysis. We have not collected any post-intervention administrative data. We will collect the administrative data for a period of roughly 12 months after the intervention, up through December 2019. We expect to get access to this administrative data by March 2020, and complete the study shortly thereafter.

I Introduction

Governments often do not know who is poor (Besley and Persson, 2013) even when the poor themselves, and their neighbors, know well. Anti-poverty programs therefore use local knowledge, including self targeting and community-led targeting, to improve the targeting of benefits like subsidies and transfers (Alatas et al., 2012, 2016; Bandiera et al., 2017; Alderman, 2002).

Social norms about who is deserving may improve the accuracy of such targeting (Moffitt, 1983; Besley and Coate, 1992; Lindbeck, Nyberg and Weibull, 1999). For example, if it is shameful to use food stamps, for those who can afford to buy food themselves, only people who cannot afford to buy food may take the benefit. Norms may not only improve targeting, but also reduce costs, since this kind of selection would imply that the government could screen beneficiaries less rigorously.

Whether social norms actually improve targeting is an empirical question. Social norms need not improve the targeting of benefits, or align with the aims of policy. A poor person forgoing benefits may establish a starkly low threshold of need in one community.[1] In another community, a rich person claiming a subsidy may make everyone feel entitled.

This paper tests whether social norms are useful as a means of targeting, in the context of a campaign by the Indian government to improve the targeting of a huge subsidy for cooking gas (also known as liquefied petroleum gas, or LPG). The subsidy is provided to 224 million beneficiary households and has a value of USD 2.9 billion (MoPNG, 2019). For the median household, the value of the subsidy, at 30% of the sticker price of gas, equals 1.3% of household income or 20% of energy expenditures.[2]

This large subsidy is abysmally targeted. It is meant, nominally, as a lifeline to reduce the cost of cooked meals for less-well-off households, but used mainly by middle-class urbanites. Households in the top quintile of expenditure draw 60% of the total subsidy value, while households in the bottom half of the expenditure distribution draw none (Figure 1). Most poor households in India cook with biomass rather than natural gas, which is more expensive. The Government of India is wary of removing the gas subsidy for higher income households outright, but concerned with its growing cost.

The Government of India therefore launched, in 2015, a campaign to improve targeting by getting richer households to voluntarily give up their gas subsidies. The campaign, called "Give It Up," urged households to give up their subsidies so that the government could use the money saved to subsidize set-up costs for poor, rural households using gas for the first time. The program was heavily advertised in the media, with messages appealing both to people's sense of altruism and to national pride. To change the norm on who is deserving of gas subsidies, the Government stressed the benefit of giving up one's subsidy for the poor, to the point of linking the name of each person to Give It Up to the poor household their forgone subsidies helped fund. In the first three years of the program, the Government reports more than 10 million households have given up their subsidy (4% of gas consumers).

[1] A growing body of work examines the reason for apparently low benefit take-up of welfare programs and tax benefits in the United States (Currie, 2006; Kopczuk and Pop-Eleches, 2007; Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019). The stigma of take-up, an example of a social norm against benefit receipt, is one reason why, it is argued, take-up may be low (Moffitt, 1983; Friedrichsen, König and Schmacker, 2018).

[2] Based on our calculation using CMIE (2018) and 2011-12 National Sample Survey data.

We use a field experiment to test whether social norms, used as a policy instrument, can improve subsidy targeting. Our research design layers a direct marketing experiment on top of the existing Give It Up campaign. The experiment, a randomized encouragement design, asks households in a direct mail campaign to enroll in Give It Up and thus forgo their gas subsidy. The intensity of the campaign varies in saturation across neighborhoods to test whether subsidy use decisions spill over across neighbors. We measure whether this appeal changes awareness about the campaign, its beliefs about entitlements and, the main policy aim of the government, household usage of natural gas and subsidy funds.

The campaign could plausibly act on household subsidy use decisions for a number of reasons, which we gather under three classes of mechanisms: consumption utility, intrinsic benefits, and social norms. The first class of mechanism, consumption utility, refers to the direct utility and costs of taking an action. In our context, this is the utility of gas consumption net of household expenditures on gas. Forgoing the subsidy raises the price of gas and tightens the household's budget constraint, reducing utility from consumption. Households that forgo the subsidy expose themselves to a higher price for natural gas, which should reduce gas consumption, in particular, and decrease utility. The second class of mechanisms, intrinsic benefits, refers to a household's own warm glow from giving up the subsidy, or other such benefits that are purely internal to the household, and not dependent on the perception of others. The third class of mechanisms is social norms. Social norms refer to shared beliefs about appropriate behavior: one's beliefs about what others do and how others would judge one's own actions (Bicchieri, 2016).[3] For example, if I believe that other people in my social class will forgo the subsidy, and would look badly on me for not doing so, I may decide to forgo the subsidy myself.

Our experimental design has treatment arms and data meant to provide evidence for whether household subsidy use responds to each of these mechanisms. The basic experimental treatment asks households to Give It Up with an appeal to support gas take-up by the poor. We vary the content and level of randomization in order to study how this appeal operates. On consumption utility, we provide households information about the subsidy amount. Since the subsidy is volatile (it changes monthly according to international market price for gas) and households may not track it precisely, this may cause households to update on the consumption utility of forgoing the subsidy. On intrinsic benefits, the basic appeal may motivate people to forgo the subsidy to help the poor. We strengthen this channel with a treatment that makes an explicit connection between the decision to forgo the subsidy and the receipt of gas subsidies for a poor household.

On social norms, our experimental design randomizes at the cluster level in order to test for spillover effects between neighbors in their subsidy use decisions. This design randomly encourages a random fraction of all households in a neighborhood to give up their subsidies, and allows us then to measure the spillover effects of this subsidy disadoption on others within the same neighborhood. The existence of a spillover effect is consistent with social norms. If my neighbors give up their

[3]Under the parsing of Bicchieri (2016), both empirical expectations and normative expectations are necessary for social norms to affect actions. Empirical expectations are one's belief about what others will do. Normative expectations are one's belief about what others believe one should do. A normative social norm is then a social norm founded jointly on empirical and normative expectations. I believe that others will act well, and that others believe that I should act well, therefore I do act well, to earn their praise or avoid their scorn.

subsidies, it may change my empirical expectations about what behavior is common, or my normative expectations, about what behavior is acceptable to my neighbors. The existence of spillovers, while suggestive, does not alone imply that social norms must be at work. If my neighbors give up their subsidy, that may also give me information relevant to my own consumption utility, for example, that the subsidy is not as big as I thought.

We therefore also vary the content of the treatment, in several ways, to test whether social norms drive any estimated spillovers. In a signaling treatment, we make it easier for households to signal to others that they have given up their subsidy. In a social distance treatment, we vary the perceived social distance between households and the beneficiaries who would receive the subsidy, if a household were to forgo it. Finally, a moral appeal treatment, drawn from the teachings of Mahatma Gandhi, reminds households of the social norm in India to help the needy. We use these experimental treatments and several tests for treatment effect heterogeneity by characteristics of the local social network, to test whether spillover effects are due to social norms.

We collect rich administrative in order to trace effects of the campaign on subsidy use. The goal of the experimental design is to identify changes in natural gas use and reliance on subsidies, and whether the campaign has any spillover effects, of a type or force related to changes in norms towards subsidy usage. Measuring spillovers is in general difficult due to power concerns. Our study sample consists of 3,802 clusters in total with 1.2 million gas-using households, of whom 100,000 households are treated. We observe administrative records on Give It Up enrollment and all natural gas transactions and subsidy use for these households. We show that this large sample is sufficient to detect even small treatment effects on Give It Up enrollment and gas usage.

To understand the mechanisms behind changes in household subsidy use, we gather further data on household information and beliefs through a large household survey. We survey a subsample of about 8,000 households and measure whether the Give It Up appeal changed their awareness of the campaign, their beliefs about the value of the subsidy, the fairness of subsidizing the well-off versus the poor, or the signal that is sent when one gives up their subsidy, among other outcomes. We use this data, along with variation in the content of the campaign, to understand whether households are responding to the appeal out of concerns for the poor, new information they acquired, or social norms, for example, concern for their own self-image or the stigma that may face as a rich household that relies on subsidies.

The study relates most directly to the literature on the targeting of public benefits. Within development economics and public economics, there is a large theoretical and empirical literature on targeting welfare programs. The basic trade-off is between stringent targeting, which may deny welfare to worthy recipients and raise administrative and screening costs, and looser targeting, which reduces screening costs but raises program expenses (Kleven and Kopczuk, 2011; Currie and Gahvari, 2008; Currie, 2006).[4][5] A recent pair of studies from Indonesia shows that raising program applica-

[4]A growing literature in developed countries explores how transactions costs or a lack of information may reduce the take-up of public benefits (Deshpande and Li, 2019; Finkelstein and Notowidigdo, 2019; Chetty, Friedman and Saez, 2013; Bhargava and Manoli, 2015), with one branch of work focusing on the role of peer effects on take-up in particular (Bertrand, Luttmer and Mullainathan, 2000; Åslund and Fredriksson, 2009; Dahl, Løken and Mogstad, 2014; Figlio, Hamersma and Roth, 2015; Aizer and Currie, 2004; Grossman and Khalil, 2020).

[5]Group identities may influence household preferences for redistribution and other social-welfare-maximizing decisions

tion costs can improve targeting, through self-selection, but that community targeting does somewhat worse than a simple asset-based test in identifying the poorest households (Alatas et al., 2016, 2012).

Our contribution, relative to to this body of work, is to measure the effect of social norms on benefit targeting with a randomized saturation design.[6] Studies of self-targeting have focussed more on ordeal mechanisms, rather than social norms. Whether an ordeal mechanism improves targeting depends on how the cost of the ordeal relates to need (Nichols and Zeckhauser, 1982); whether social norms improve targeting depends on who is sensitive to changes in norms. Methodologically, measures of social pressure, in the literature, come from direct manipulation of perceived pressure, such as due to the experimenter varying whether an action is observable. By contrast, our cluster-based design will vary social pressure by varying the share of one's neighbors that are solicited.[7]

The study also relates to a broader literature on the role of social norms or stigma in personal decisions in a variety of domains, including charitable giving (Bursztyn and Jensen, 2017; DellaVigna, List and Malmendier, 2012; Ariely, Bracha and Meier, 2009; Frey and Meier, 2004), educational investments (Bursztyn, Egorov and Jensen, 2017; Bursztyn and Jensen, 2017; Bursztyn, Fujiwara and Pallais, 2017), and consumption (Allcott, 2011; Allcott and Rogers, 2014; Bursztyn et al., 2018; Bertrand and Morse, 2016). Despite this broad body of evidence on the existence of social norms, it is not clear when norms are strong or pliable enough to be useful as a policy instrument. High-stakes policy experiments, such as for tax compliance, have generally found weak effects of informational, social and moral appeals (Fellner, Sausgruber and Traxler, 2013; Blumenthal et al., 2001).[8] The effects of social comparisons on behavior may also decay over time (Ito, Ida and Tanaka, 2018).

Our study provides a test not of whether social norms exist but whether they can serve as a policy tool for targeting benefits. Motivating richer households to opt out of benefits may particularly improve efficiency in developing country settings, where poor enforcement (Barnwal, 2018) and a lack of hard data on which to target may limit how well the state can directly target transfers without using local information. The policy question of how to reform fuel or other in-kind subsidies is relevant for a wide set of developing countries. Subsidy reform, in a traditional mode, pairing cuts in subsidies with offsetting tax or benefit replacements, has proven politically disastrous.[9] Social norms may improve targeting without the large political costs of screening explicitly or of removing subsidies outright.

(Alesina and Ferrara, 2005; Klor and Shayo, 2010). Two of the most socially and politically salient identities in India are one's religion and, within the Hindu religion, one's place in the caste hierarchy. Our social distance treatment and heterogeneity analysis using data on the religion and caste composition of neighborhoods test how these identities may shape social norms.

[6]This design has become the standard to measure spillover effects (Crépon et al., 2013; Baird et al., 2018), but is sparsely used because of the cost and logistical difficulty of operating at a large enough scale to measure spillover effects.

[7]Also, contrary to much of the literature, which is concerned with the stigma of benefit receipt discouraging benefit take-up, we study a setting in which the government wants to change social norms to cultivate a stigma, of taking benefits when they are not needed, in a setting with near-universal subsidy adoption.

[8]Hallsworth et al. (2017) find "a rare example of social norm messages affecting tax compliance behavior" with a direct mailing experiment in the United Kingdom.

[9]See Davis (2014) on the costs of global fuel subsidies. As an example of the costs of reform, consider Indonesia. The Indonesian government was widely praised for removing distortionary fuel subsidies and replacing them with cash transfers in 2005. In 2018, Indonesia retreated, under immense political pressure, and again increased diesel subsidies by more than 100% (Suzuki and Nakano, 2018).

II Context

II.A Cooking gas in India

Most Indian households use biomass and not modern fuels, like fossil fuels or electricity, to cook. Biomass fuels include firewood, dried cow dung chips and charcoal, and have the great advantage of being cheap to purchase or produce with one's own labor. Of all Indian households in rural areas, 67% use biomass. Only 15% of households across rural India use LPG (National Sample Survey, 2011-12), though its market share is rapidly growing. In urban areas the market shares of these fuel types are practically reversed, with 68% of urban households using liquefied petroleum gas (LPG) and 14% using biomass. LPG is a mixture of propane and butane gas that is liquefied when under pressure. LPG is easy to light and extinguish, is extremely energy dense, and burns clean, producing less indoor air pollution than cooking with biomass (Pope et al., 2017; Rosenthal et al., 2018). For all of these reasons, the Government of India, as a matter of policy, is concerned to increase the market share of LPG.

The market for LPG is tightly controlled by the Government. There are three publicly-owned gas distributors, known as Oil Marketing Companies (OMCs), that form a triopoly in the country. These are: Indian Oil Corporation Limited (IOCL), Bharat Petroleum Corporation Limited (BPCL) and Hindustan Petroleum Corporation Limited (HPCL). Through government coordination, the market shares of these companies are deliberately maintained in a ratio of 50% IOCL, 25% BPCL and 25% HPCL. These companies have distributors in each city who supply gas cylinders and refills to consumers. Most consumers receive their natural gas in 14.2 kilogram cylinders. Small trucks or heavy-duty tricycles carrying gas to consumers, and retrieving empty cylinders, are a ubiquitous sight in India's cities.

The government updates the regulated price of LPG on a monthly basis to pass through changes in world market prices. Household consumption of LPG is subsidized up to a yearly cap of 12 cylinders. Households can buy more than 12 cylinders, but at the full regulated price. The price net of subsidy is changed infrequently and only by small increments, to protect households from price volatility, which implies that the value of the subsidy fluctuates with world prices (Figure 2).

The subsidy represents a significant portion of household energy expenditures and consumption. The median LPG-using household in 2018 used 7 cylinders, each of which had an average price of INR 777 and subsidy of INR 280 (in Delhi). The median household income in urban India during 2018 was about INR 156 thousand (CMIE, 2018). The LPG subsidy therefore represents 1.3% of income or about 20% of energy expenditure for an urban household.[10]

Subsidies are disbursed to households through Direct Benefit Transfers for LPG (DBT-L, also known as the Pahal Scheme) (Barnwal, 2018). Under DBT-L households pay the full regulated price for each cylinder and afterwards receive a bank transfer for the subsidy amount. The transfer usually arrives about 7 days after a gas purchase. The subsidy not being given at the time of purchase could arguably make it more salient to households, since they receive the subsidy as a separate transfer in their accounts, or less salient, since the transaction itself occurs at the sticker price.

[10]We assume that urban households spend 10% of their total expenditure on energy (2011-12 NSS data) and that total expenditure is 60% of income (Shukla, 2010).

II.B Give It Up campaign

As more households adopt LPG and as international market LPG prices rise, the Government of India's expenditures on the LPG subsidy have ballooned. LPG subsidy expenditure in 2019-20 is projected to be about USD 4.7 billion (INR 32,989 crores), up 62% from 2018-19 and 111% increase from 2017-18 (MoPNG, 2019). The Government, in an effort to get more poor households to use LPG, has expanded gas distribution into rural areas and launched a separate subsidy program, the Ujjawala Yojana, to subsidize gas set-up costs (the initial deposit on cylinders and a stove) for needy households. This big push has further strained the subsidy budget and raised awareness that, while poor households are very price sensitive, most urban households would continue cooking entirely with gas if subsidies were removed (Parikh et al., 2013).

The Government has therefore moved to reduce subsidy usage among richer households through both direct and indirect means. The direct means is that, starting in 2016, gas connection owners or their spouse that paid income tax and had a taxable income of more than INR 1 million were ruled ineligible for subsidies. This rule barred 7 million households, 0.3% of the gas-using population, from receiving subsidies. The indirect means is through the Give It Up program that we study in this paper.

The Give It Up program is a marketing campaign launched by the government to encourage households to give up their natural gas subsidies voluntarily. The program was launched in 2015 by the Prime Minister of India, to appeal to well-to-do parts of Indian society to Give Up their subsidies, so that the money saved could be used to provide additional one-time subsidies to poorer, more deserving recipients enabling them to switch from biomass fuel to LPG. The campaign's main theme was of charity towards the poor. A secondary, nationalist theme was that, by contributing to the progress of the poor, households that Give It Up would aid in building their own nation.

The Give It Up advertising campaign has been massively funded across television and print media, in billboards and through the oil-marketing companies' distribution networks. Figure 3 provides some examples of prominent advertising for the campaign, which featured endorsements from parties ranging from film and sports stars to the Prime Minister. Households who Give It Up are named in a "Scroll of Honour" on the website of their gas distribution company, and their names explicitly linked to the names of poor beneficiaries that newly received subsidies. Households who gave up their subsidy received personalized letters of thanks, over the facsimiled signature of the Prime Minister. Public companies such as banks and the OMCs themselves were asked to urge their employees to Give It Up. Some private sector companies followed suit (BI India Bureau, 2015).

The program was designed to make giving up one's subsidy as simple and painless as possible. Households who give up their subsidy continue to receive LPG deliveries as before, but do not receive subsidy transfers in their bank account. Giving up subsidies does not affect the gas distributor or deliveryman's commission. If households regret giving it up, they can re-enroll in the subsidy in the next fiscal year. Households could enroll in the Give It Up campaign through many different means, including paper forms, text messages, downloading an app, or through the website of their gas distributor.

We have obtained administrative baseline data from the OMCs (described below), which shows that 6.82% of consumers who are active LPG users have given up their subsidy. This rate is much lower, only 1.40%, among those customers who have enrolled in the DBT-L program to receive subsidies directly in their bank accounts. The rates of participation in Give It Up are considerably higher in some of India's larger and richer cities: 10.83% of active consumers in Delhi, 6.8% of active consumers in Mumbai and 7.9% in Bangalore.

II.C Theory of social norms and targeting

The campaign could plausibly act on household subsidy use decisions in a number of ways. We do not give a formal model of the effects of norms on subsidy use, but instead discuss three classes of mechanisms that may determine whether households choose to forgo subsidies. These mechanisms are (a) consumption utility; (b) intrinsic benefits; and (c) social norms. The distinction between intrinsic benefits and social norms is common in the literature on charitable giving and other contexts (Edwards and List, 2014; Luttmer and Singhal, 2014).

Consumption utility. The first class of mechanisms, consumption utility, refers to the direct consumption utility of taking an action. In our context, this is the utility of gas consumption net of household expenditures on gas. Forgoing the subsidy raises the price of gas, tightens the household budget constraint, and thereby lowers consumption utility from other goods through an income effect. If households are poor and have a high marginal utility of income, then forgoing the subsidy will be especially costly, and they will choose not to do so.

The effect of forgoing the subsidy on consumption utility may be greatest through changing gas usage. Households that forgo the subsidy voluntarily expose themselves to a higher price for natural gas. The increase in gas prices should cause a substitution effect, reducing gas consumption and lowering utility from gas consumption in particular. The strength of this effect will depend on the elasticity of demand for gas. Rich households with inelastic gas demand may not change gas consumption much in response to higher prices.

Households may not know the value of the subsidy for sure at a given time, but have only an idea of its value. The value of the subsidy varies monthly with international market gas prices. A median household consumes 7 gas refills in a year, while the subsidy per gas refill may change 12 times. Therefore it is the expected change in consumption utility from forgoing subsidies that is relevant for household decision-making.

Intrinsic benefits. The second class of mechanisms, intrinsic benefits, refers to a household's own utility from the act of giving up the subsidy. This intrinsic benefit includes motivations such as warm glow and altruism (Dwenger et al., 2016; Andreoni, 1989, 1990). Experiments on charitable appeals have parsed these distinct intrinsic motivations for giving (Tonin and Vlassopoulos, 2014; List et al., 2019). The important commonality is that intrinsic benefits are internal to the household and not dependent on the perception of others. (In the long run, it is reasonable to think that many intrinsic benefits have their origins in the internalization of social norms.)

Social norms. The third class of mechanisms relates to social norms about subsidy usage (Lindbeck, Nyberg and Weibull, 1999). Social norms are the gain or loss in utility of a households resulting from the interaction of a household's decision with the attitudes or actions of other households (Edwards and List, 2014). Social norms refer to shared beliefs about appropriate behavior: one's beliefs about what others do and how others would judge one's own actions (Bicchieri, 2016). Social norms could take various kinds. Particularly relevant here are social preferences for redistribution (Moffitt, 1983; Besley and Coate, 1992). Households that take a benefit that they are not seen to deserve may be stigmatized and experience this as a loss of utility. Households that forgo a benefit they may need may be seen as generous, or be mistakenly perceived as richer than their neighbors had thought.

In this framework, spillovers between neighbors in their subsidy use decisions may arise for two reasons. First, information on the costs and benefits of gas consumption may spread across households, which has a direct bearing on consumption utility. Second, changing actions or attitudes on the part of one's neighbors may affect household decision-making through social norms. For example, even if I knew about the Give It Up program already, I may not forgo the subsidy myself, unless a significant share of my neighbors have chosen to do so, since only then do I fear being stigmatized for drawing a subsidy I do not need. If social norms are strong enough, there may be multiple equilibria in benefit adoption. In one neighborhood all households draw the subsidy. In another, similar neighborhood, with a few households advocating for giving up the subsidy, other households may go along, which further shifts the norm and other household's decisions.

III Research Design

The research design is a cluster-randomized experiment that varies the saturation of the Give It Up appeal across different areas. In addition, within clusters, the design varies the content of the appeal to test the reasons why households respond to the appeal. We first describe the sample of households in the study and then the experimental design and treatments.

III.A Sample selection

The study population consists of cooking gas users in seven major Indian cities who currently use subsidized gas. The cities are: Delhi, Chennai, Ahmedabad, Hyderabad, Kolkata, Bangalore and Mumbai. The urban, relatively well-off population was selected because these consumers are more likely to Give It Up.

We impose several sample selection criteria to get a population of households who use the subsidy at baseline. Households are identified by their gas account with one of the Oil Marketing Companies (OMCs). We keep in the sample consumer households who (a) are active LPG consumers (as defined by OMCs), (b) have been receiving subsidies since at least April 1st, 2013 and (c) have taken at least one subsidized refill in the prior financial year and had some subsidy payout in that time.

The sample of households is drawn in clusters. We use two different definitions of a cluster to balance logistical constraints against the likely spatial decay of spillover effects. The two cluster definitions are the "society" and the "delivery area". A "society" is a residential complex defined under the Co-operative Societies Act wherein a group of households register with the state government and contribute to the upkeep of public goods like common spaces and utilities. Societies, in Indian cities, are similar to condominiums, where an apartment building or group of buildings is owned separately but with some common responsibilities for maintenance, security and the like. A "delivery area" is defined by being on a common LPG delivery route, within a particular gas distributor. We limit societies to have at least 10 and at most 500 consumers and areas to have at least 30 and at most 1000 consumers.

There are probably stronger social ties under the society cluster, where households would interact in the management of the society and in common areas, then in the delivery area. Regardless, in both cases households within a cluster would live nearby, and we therefore will generically call both cluster definitions "neighborhoods" henceforth, though the scale of the delivery area is slightly larger. We use both cluster types because it is only possible, in our data, to define societies in Hyderabad, Chennai and Delhi. In cities where it is possible to define both cluster types, we ensure that these two samples are mutually exclusive by dropping distributorships that serve clusters in the sample of societies, before sampling areas in the same city.

Our sample therefore consists of a random group of clusters in each city. For the society clusters, we first sample gas distributors with probability proportional to size and then, within a distributor, map consumers to their housing society with a combination of address matching and field verification. The delivery area variable is directly observed in the data. There are a total of 3,802 neighborhood clusters (449 societies and 3,353 delivery areas) in the sample, serving a total of 1,201,052 consumers that meet our sample selection criteria. We discuss the power of the experiment below.

III.B Experimental design

The experimental design assigns treatment status in two tiers: first, a neighborhood is assigned a fraction of households to receive the Give It Up appeal. Second, households within a neighborhood are assigned to treatment arms that vary whether they receive an appeal and the content of that appeal. The exogenous variation in the fraction of a neighborhood receiving the direct-mail allows us to test for spillovers between neighbors in their subsidy use decisions.

Table 1 shows the number of society and delivery area clusters in each of the five saturation bins – 0%, 25%, 50%, 75% and 100%. The number of households assigned to receive an appeal is to be roughly 100,000 out of the total sample of 1.2 million sample households. In order to achieve this relatively low treatment probability, most neighborhoods (3,128) are assigned to be pure control neighborhoods, in which 0% of households receive an appeal. Allocating a higher proportion of clusters to the pure control bin is helpful for power, in randomized saturation designs, because a household in pure control neighborhood serves as a counterfactual for both non-treated households in treated neighborhoods and treated households (Baird et al., 2018). A total of 674 neighborhoods are then evenly distributed across the four treatment arms with positive treatment saturation.

Households within each neighborhood are randomly assigned to treatment using their neighborhood's treatment probability. Figure 4 shows the letter sent to customers. The letter is printed in color and includes the seal of the Government of India (top-right corner) and the logos of the three Oil Marketing Companies (bottom-right) that serve LPG customers. The top of the letter shows the logo for the Give It Up campaign. The appeal would be perceived as coming from a customer's gas supplier with the endorsement of the Government. The letter, for all customers, describes the purpose of the

#GiveItUp campaign and asks the customer to enroll. The envelope also includes a pre-filled subscription form the customer can return by mail or via their local LPG distributor. Customers receiving letters also received several text message solicitations to Give It Up over the following month.[11]

Table 2 describes the different treatment arms in detail. Conditional on being assigned to any treatment, households are randomly assigned to different treatment arms that vary the content of the appeal. The different treatment messages are meant to separate different reasons why forgoing the gas subsidy may spill over across neighbors. In particular, we are interested to test whether social pressure in giving up the subsidy may work because it provides information about consumption utility or acts on utility through social norms. Here we describe the treatments. In the next section we discuss the hypotheses to be tested.

- The *basic appeal*, in all letters, gives the basic message of the campaign that subsidies forgone would be used to fund subsidies for the poor. The treatment tests whether raising the salience of poverty, which may alter the intrinsic benefits of household decisions, decreases subsidy usage.
- The *social distance* treatment gives the household an example of a pair of households that have given it up and that have received a new LPG connection funded through the program. The letter additionally varies the religion and identity of the giver and the recipient. The treatment tests whether households given an example of a donor or of a recipient more like themselves reduces subsidy usage, which would suggest a role for social norms.
- The *information* treatment informs households what the value of the subsidy has been in a recent time period, either the current value or the value over the past year on average. The treatment tests whether information about the value of the subsidy relevant for consumption utility changes household beliefs and changes the usage of the subsidy.
- The *signaling* treatment encloses a shiny sticker in the envelope that households may use to affix on their door or car to show that they have enrolled in Give It Up. Some households in the signaling treatment are also told that better off households are more likely to Give It Up. The treatment tests whether giving households a way to signal their generosity and adhere to social norms decreases usage of the subsidy.
- The *moral appeal* closes the letter with the following quote, known as Gandhi's Talisman: "Recall the face of the poorest and the weakest man [woman] whom you may have seen, and ask yourself, if the step you contemplate is going to be of any use to him [her] ... In other words, will it lead to swaraj for the hungry and spiritually starving millions?" This quote, from the leader of India's independence movement and its moral conscience, is widely printed in school books in India. The treatment tests whether moral suasion, making salient the social norm of charity, decreases subsidy usage.

[11] We monitor the letter treatment in two ways. First, we track letters which could not be delivered and were returned. About 9.8% letters were undelivered and returned by the Indian Post, likely due to household did not update after address change or due to incomplete address information in the OMC database. Second, we conduct back-check over the phone with a sub-sample of households to ask if the household has received the letter. Among the respondents who received the call, about 48.9% report receiving the letter.

III.C Data

The analysis uses data from three sources that together form a hierarchy of outcomes: administrative data on gas and subsidy usage, and survey data on beliefs.

The main administrative datasets cover gas consumption, subsidy usage and Give It Up status. The OMCs keep data on which households have enrolled in Give It Up. We have obtained this data set at baseline and will update it through at least 12 months after the appeal. We also obtain administrative data on gas usage, consumption and payments. Even households that do not Give It Up may still alter their gas consumption behavior in response to the appeal. We have data on gas consumption and subsidy usage from all sample consumers from April 2013 till April 2018. We will update this data to provide outcome measures.

We survey a subset of roughly 8,000 sample households on awareness about the Give It Up campaign, beliefs and attitudes towards subsidies, their perception of the fairness of the natural gas subsidy, and the characteristics of their households (such as income). We also ask households about their support for a range of government programs to gauge their political affiliation. We survey a random sample of households within the administrative data and additionally survey a sample of households who have already enrolled in the #GiveItUp campaign (before our intervention) to understand how they differ from other households.

III.D Randomization balance and experimental power

We check for balance across treatment arms and study the likely power of the experiment using administrative baseline data on gas consumption and subsidy usage.

Appendix A shows the balance tests for the two different kinds of neighborhoods (delivery areas and housing societies). Within each subsection we show separate balance tests for the two neighborhood types. For each type, we show in sequence (a) the balance across neighborhoods by treatment saturation (b) the balance between households assigned to receive any treatment letter versus not (c) the balance between households assigned to receive any treatment letter versus not, conditional on neighborhood fixed effects (d) the balance between households assigned to different treatment arms. We consider balance on several variables: the number of subsidized cooking gas refills, the number of non-subsidized refills, and the total amount of subsidy transferred to a household, all measured in the prior year.

The experimental design is balanced in nearly all of these tests and shows, in general, very small differences in baseline outcome variables across treatment arms. For example, Table A1 tests for the equality of prior gas usage and subsidies by treatment saturation in the delivery route area sample. We perform F-tests of the null hypothesis that dummy variables representing each positive saturation level are all jointly significant. We find p-values of 0.86, 0.55, 0.98 and 1.00 for these tests, for the outcomes of subsidized gas usage, non-subsidized gas usage, subsidy transferred and the number of consumers in each area. Thus we cannot reject the equality of these baseline outcomes across different saturations of the treatment.

The balance tests indicate that we will have ample power to test hypotheses regarding spillover effects by comparing mean outcomes across clusters. Consider the amount of subsidy transferred in a year in Table A1. The mean level in the control is INR 1359. The standard error of the estimated mean effect in each treatment arm, other than the control, is about INR 25, and the standard error in the control is INR 5. Therefore, the standard error for a test of the difference between the means of any treatment arm with positive saturation and the control will be approximately 25, and the standard error for a test of the difference between the means of any two treatment arms with positive saturation will be 35. The experiment would therefore reject the null of no difference between the control and 100% saturation at the 5% level in a two-sided test for an effect size of INR 50, or 3.6% of mean consumption. Analogously, the experiment would reject the null of no difference between the 25% and 100% saturation arm at the 5% level in a two-sided test for an effect size of about INR 70, or 5% of the mean subsidy usage.

These simple calculations understate the power of the design for two reasons. First, we intend to pool, for nearly all specifications, the two neighborhood definitions for all cluster-level comparisons. Second, more importantly, with administrative baseline data for all households, we can control for the baseline levels of all administrative outcome variables at the household level.

We can get a sense of the expected gain in power by comparing, in baseline data, the standard error of the coefficient on treatment status in regressions of subsidy drawn on treatment and a constant, in specifications with and without delivery route area fixed effects. These specifications appears in column 3 of Tables A2 and A3, respectively. Likewise, column 3 of Tables A6 and A7 show equivalent specifications with and without society fixed effects. Including these neighborhood fixed effects reduces the standard errors in this regression by a factor of roughly four, which would imply that our experiment has a minimum detectable effect of roughly 1% of baseline subsidy usage across clusters. Controlling for household-level baseline values of the outcome variable would result in even smaller minimum detectable effects across clusters.

Our power for gas usage and subsidy drawl at the individual level, as opposed to the cluster level, is stronger still. We estimate we will have more than 80% power to detect a treatment effect of INR 4 (about 6 US cents, or 0.3% of the mean) in subsidy transfers, in specifications using household-level baseline values of the outcome as a control. Thus, the fact that our experiment is well-powered at the level of the cluster implies that it is somewhat over-powered at the level of the individual.

IV Planned hypotheses and specifications

Table 3 gives an overview of the hypotheses. The panels of the table correspond to a series of interlinked research questions. Under each panel (question), we present the hypotheses we will test. For each hypothesis, the respective columns of the table give the statement of the hypothesis, the data or sample used to test it, the outcome variables and whether the analysis will allow for any hetrogeneity (by household baseline characteristics or across treatment arms). The following subsections motivate and discuss our hypotheses and give our empirical specifications.

IV.A Do treated households reduce subsidy usage?

We test whether treated households reduce their subsidy usage in response to the GIU appeal. The main policy aim of the Government is that the appeal should reduce subsidy expenditure.

A1. H_0 : *The treatment solicitation to Give It Up has no effect on subsidy usage.* The alternative is that the receipt of the GIU appeal reduced subsidy usage. The sample is the full sample of 1.2 million households in the administrative data. The outcome variables are a dummy variable for whether the household enrolled in Give It Up and a continuous variable for the amount of subsidy used by the household in the twelve months period following the appeal. The continuous amount of subsidy usage is an important outcome. Even if households do not Give It Up altogether, they may be persuaded by the appeal to reduce their gas consumption on the intensive margin, and therefore the amount of subsidy they use.

We use the following specification to test the hypothesis:

$$y_{in} = \alpha_1 + \beta_1 D_{in} + y_{in,base}\gamma_1 + \epsilon_{in} \tag{1}$$

where y_{in} is the outcome for household i in neighborhood n, D_{in} is an indicator for households randomly assigned to the Give It Up solicitation and $y_{in,base}$ is the baseline value of the dependent variable.

IV.B Is there a spillover effect?

We test whether solicitations to forgo subsidy cause a spill over effect between neighbors in their subsidy use decisions. One's neighbors' action and attitude towards using subsidy may affect one's own decision to use subsidy, as discussed in Section II.C. Social norms may be more useful as a policy tool to the extent that they are self-reinforcing. If the government succeeds, for example, in shifting the norm from the universal entitlement to that the cooking gas subsidy is a benefit for the poor only, then it may not have to do any advertising or screening and social forces can help enforce it. We are therefore interested in the extent to which household's action and attitude towards forgoing subsidy may spill over across neighbors, as indicative of the strength of social norms in this domain. In Section IV.D, we test underlying mechanisms behind the spillover effect, such as learning from neighbors, moral concerns of neighbors and signaling value of not using the subsidy.

B1. H_0 : *The treatment solicitation has no effect on the subsidy usage of the neighbors of the household treated (pooled).* The alternative is that solicitations decrease the subsidy usage of a treated household's neighbors. The sample is the full sample of 1.2 million households in the administrative data. The outcome variables are a dummy variable for whether the household enrolled in Give It Up and a continuous variable for the amount of subsidy used by the household in the twelve months following the appeal.

We test for spillovers by using the experimental variation in the treatment fraction across neighborhoods. Each neighborhood (cluster) n is assigned to a treatment fraction τ_n , where $\tau \in \{0, 0.25, 0.50, 0.75, 1.0\}$. In a cluster with $\tau > 0$, households are randomly assigned to the Give It Up solicitation treatment ($D_{in} = 1$), as per the value of τ. Clusters with $\tau \in \{0.25, 0.50, 0.75\}$ contain both assigned and unassigned households, while clusters with $\tau = 0$ include only unassigned households, and clusters with $\tau_n = 1$ have only assigned households. We will use $T_n = 1$ for a treated cluster that contains both treated and untreated households, that is, when $\tau \in \{0.25, 0.50, 0.75\}$, and $T_n = 0$ otherwise.

$$y_{in} = \alpha_1 + \beta_1.D_{in}.T_n + \beta_2.T_n + y_{in,base}\gamma_1 + \epsilon_{in} \tag{2}$$

Specification 2 estimates the pooled intention to treat effect (ITT) and the pooled spillover effect on the non-treated households (SNT). The coefficient β_1 is the difference in outcomes between treated households and their control neighbors in the same neighborhood. The coefficient β_2 estimates the difference between the expected outcome for individuals not offered treatment in a neighborhood with a positive saturation and the expected outcome for individuals in a control neighborhood (SNT). Therefore the hypothesis stated is equivalent to $H_0 : \beta_2 = 0$. The sum $\beta_1 + \beta_2$ is the pooled (across saturations) treatment effect for treated households.

The estimated coefficients will depend on the distribution of saturation levels. We use saturation weights for households in the treated clusters to estimate the pooled ITT and SNT (Baird et al., 2018). Treated households have weight with $1/\tau_n$ and non-treated households have weight $1/(1 - \tau_n)$.

B2. H_0 : The treatment solicitation has no effect on the subsidy usage of the neighbors of the household treated (by saturation). The strength of norms on an individual may be nonlinear in the underlying beliefs of a neighborhood. For example, spillover effects may require a person to hear the same thing from multiple other people in their network (Beaman et al., 2018). Pooling all neighborhoods with varying τ together increases the statistical power to detect any spillover effect, but does not allow measurement of the functional form of spillover effect.

Equation 3 estimates the slope of spillover effects over the proportion of assigned households within a cluster using a reduced form model that is saturated in neighborhood treatment saturation dummies.

$$\begin{aligned} y_{in} = \beta_{25}.D_{in}.T_{25n} + \beta_{50}.D_{in}.T_{50n} + \beta_{75}.D_{in}.T_{75n} + \beta_{100}.D_{in}.T_{100c}X_n \\ +\delta_{25}.T_{25n} + \delta_{50}.T_{50n} + \delta_{75}.T_{75n} + X_n\gamma_1 + Z_{in}\gamma_2 + \epsilon_{in} \end{aligned} \tag{3}$$

Here, $T_{\tau n}$ for $\tau \in \{0.0, 0.25, 0.50, 0.75, 1.0\}$ are dummy variables denoting the saturation of a neighborhood. The coefficients of interest β_τ will measure the effect on the outcome variable y when τ fraction of the population is assigned, compared to not being assigned in a neighborhood of the same treatment-fraction type τ. For β_{100}, the comparison is to the pure control neighborhoods. The coefficients δ measure the spillover effect on the households not treated in a neighborhood where some of their neighbors are treated. We test for the homogeneity of spillover effects by running the following post-estimation tests: first $H_0 : \delta_{25} = \delta_{50} = \delta_{75} = 0$ for the hypothesis that all spillover effects are jointly zero and second $H_0 : \delta_{25} = \delta_{50} = \delta_{75}$ for the hypothesis that all spillover effects are equal.

B3. H_0 : The treatment solicitation has no effect on the subsidy usage of the neighbors of the household treated (pooled) regardless of neighborhood characteristics. Spillover effects may be stronger in some neighborhoods than others, because people are more or less alike or have stronger social ties.

We will test for the heterogeneity of spillover effects with respect to two variables. First, the Gini coefficient, within the cluster, of subsidy usage across households. We use Gini coefficient as a measure of inequality in the reference network, which may be useful to understand the mechanism for change in norms. For example, familiarity with relatively poor households, when they live in the same neighborhood, may lead to more generosity (Rao, 2019). Second, the homogeneity of the cluster with respect to religion and caste. This test is motivated by prior work on the effect of ethnic links on welfare take-up (Bertrand, Luttmer and Mullainathan, 2000; Åslund and Fredriksson, 2009).

Equation 4 interacts treatment and the neighborhood treatment fraction with a neighborhood characteristic variable H_n.

$$\begin{aligned} y_{in} = \alpha_1 + \beta_1.D_{in}.T_n + \beta_2.T_n + \beta_{11}.D_{in}.T_n.H_n + \beta_{21}.T_n.H_n + \beta_3.H_n \\ +X_n\gamma_1 + \gamma_2 y_{in,base} + \epsilon_{in} \end{aligned} \tag{4}$$

We will demean H_n measures so that the β_1 coefficient will give the estimated spillover effect at the mean of the neighborhood characteristic. Our post-estimation tests will compare coefficients for the interaction with is statistically different from the coefficient for non-interacted term: $H_0 : \beta_{11} = 0$ and $H_0 : \beta_{21} = 0$.

IV.C Do norms improve targeting?

Even very strong norms that change household subsidy use and the use of their neighbors may not improve targeting. It depends on the character of the norm and who it touches. For example, the rich may be moved by an appeal to give up the subsidy, but so too may households who are closer to poverty themselves. Asking households to Give It Up may induce as many lower-middle-class households as rich households to Give It Up. For households that do give up their subsidies, the further endogeneous response of gas consumption to newly higher prices may be stronger for the middle class than for the rich, if the gas demand of the middle class is more elastic.

We therefore test several hypotheses with respect to what households respond to norms. The first hypothesis is that household income, proxied by past gas usage, has an effect on who reduces subsidy usage in response to the treatment. This can be taken as a test of whether the government is meeting its aim in improving targeting. The second hypotheses is that social mobility may make people more sensitive towards the pro-poor welfare programs. More specifically, since the government's appeal to enroll in Give It Up includes the promise to help the poor switch from dirty fuel like wood to clean fuel like gas, households who have used wood in the past for cooking may become more likely to the shift in norms. The third hypotheses is that households' political orientation, i.e. whether they favor programs by the current National Democratic Alliance (NDA) government, may affect the response to the treatment (Li et al., 2011). If we see strong responses to social mobility or political orientation, this would show that social norms affect behavior but on dimensions that may not improve subsidy targeting.

C1. H_0 : The appeal has an equal effect on households regardless of income. The goal of the Government is for the rich to give up their subsidies. The rich likely have inelastic gas demand, because they are rich and because they would not substitute to biomass in any case, and so their use of subsidies is a pure transfer.

We do not observe income in our administrative data set and so use two proxies for income based on past gas consumption. The first proxy is whether the household has used any unsubsidized gas in the past year. Households can buy up to 12 subsidized gas cylinders per year at subsidized prices, but must purchase any additional gas at market prices. Whether households buy more than 12 cylinders is therefore a salient measure, in the gas market, of whether a household is dependent on the subsidy. The second proxy is whether a household is in the top decile of baseline gas consumption.

$$y_{in} = \alpha_1 + \beta_1 D_{in} + \beta_2 . D_{in} . Z_{in} + y_{in,base} \gamma_2 + \epsilon_{in} \tag{5}$$

The specification for the test is given by equation 5, a slight variant of 1 that includes an interaction between the treatment assignment D_{in} and household baseline characteristic Z_{in}. We demean Z_{in} and test $H_0 : \beta_2 = 0$ against a two-sided alternative. The household income proxies are the baseline gas consumption measures described in the previous paragraph, and the outcome variables, as before, are whether a household gives up the subsidy (Give It Up $=$ 1) and the continuous amount of subsidy usage.

C2. H_0 : *The appeal has an equal effect on households regardless of social mobility.* Households may respond to the appeal not because they are rich btu because they have greater sympathy for the poor. We proxy for this sympathy using a measure of social mobility: whether your mother cooked with biomass fuel when you were a child. We expect that the answer to this question will be yes for first-generation rural-urban migrants and therefore having a mother who used biomass will be a sign that you have come up in social class. This measure may therefore proxy for being upwardly mobile, particularly in the domain, cooking fuel, which the Give It Up campaign highlights as a source of inequality. We test this hypothesis using equation 5 again.

C3. H_0 : *The appeal has an equal effect on households regardless of political orientation.* The Give It Up campaign was based in part on personal appeals from India's Prime Minister, Narendra Modi. The Prime Minister appeared in advertisements and letters with his signature were sent to congratulation households who had given up their subsidies. We therefore test whether people who support the Prime Minister's political alliance, the center-right National Democratic Alliance (NDA), are more likely to respond to the campaign than those who support the opposition center-left United Progressive Alliance (UPA). We measure support by taking the average support of a household for three programs, aside from Give It Up, started by the NDA government and subtracting the average support for three programs started by the UPA government. We then include this measure of differential support as a household characteristic interacted with treatment assignment in equation 5.

IV.D Why do households forgo subsidies?

If there are spillover effects across households, they could be due to several factors, such as learning from one's neighbors, the salience of moral concerns when others are also concerned, or the signaling value of a not using the welfare (Section II.C) . The discussion in Section III of the treatment arms in Table 2 lays out the variations in message content and the motivation of each treatment arm.

We have three ways of identifying the mechanism behind any spillovers. First, the analysis of treatment effect heterogeneity discussed above, particularly whether spillovers are stronger in areas that are more homogenous with respect to income proxies or religion. Second, variation in the content of the individual treatments. Certain treatments (*social distance*, *signaling* and *moral appeal*) are designed explicitly to act via changes in social norms, whereas *information* treatment is included to test for the learning effect relevant to consumption utility. Third, survey data on households' awareness and beliefs about the Give It Up campaign. If spillovers are due to information relevant for consumption utility, then we may see spillover effects on knowledge of the gas subsidy. If, to the contrary, spillovers are due to changes in norms, we may see instead changes in beliefs about the decision to Give It Up and what that decision signals for other households. The following hypotheses formalize these tests.

D1. H_0 : *The content of the appeal has no effect on subsidy usage.* We estimate whether the content of the appeal affects household responses using the specification

$$y_{in} = \alpha_1 + \beta_0.Basic\_appeal_i + \beta_1.Info\_subsidy\_value_i + \beta_2.Moral\_suasion_i + \beta_3.Social\_distance_i + \beta_4.Signal_i + y_{in,base}\gamma_2 + \epsilon_{in} \tag{6}$$

The outcome variables are giving up the subsidy and subsidy usage, in the administrative data sample, as before. The omitted group, in this specification, does not receive any letter. We will test for the joint equality of coefficients for the different treatment arms, $H_0 : \beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4$. We will check for the efficacy of each message arm by testing the statistical significance of its corresponding coefficient, with one or two sided tests as implied by the discussion in Section III. For example, if we are testing whether moral suasion reduces subsidy usage this would correspond to $H_o : \beta_2 = 0$ against $H_a : \beta_2 < 0$.

Two of the treatment arms, social distance and price information, have sub-arms. For example, the social distance comparison randomizes the religion and caste of the potential recipient of the subsidy. We will test for the heterogeneity of these two treatments across sub-treatments: for instance, if a household responds to the social distance treatment only if the example recipient of the gas subsidy is likely to be a member of their own religion or caste group. Likewise, the average LPG subsidy over the last year will be different from the current month LPG subsidy (Figure 2), which will allow us to test for the heterogeneity of information treatment across low and high subsidy amount sub-treatments.

D2. H_0 : *The appeal does not change household beliefs about government or forgoing subsidy.* Households may wish to help the poor but believe that the government is not a reliable way to transfer resources to the poor, or that the gas subsidy is an inefficient means of redistribution. Our household survey asks, in a smaller sample, about household awareness and beliefs about the Give It Up campaign and the government's intentions with respect to this campaign. We test whether these beliefs respond to the treatment. These tests would explain the underlying mechanism by which any reduction in treatment usage came about; however, we will perform them regardless of whether we observe effects on subsidy usage. It is possible that the treatment moves awareness and beliefs about the campaign but does not change subsidy usage if households consider it too costly to curtail subsidy usage.

The survey therefore asks households whether they would give up the gas subsidy if the value were very low.

The questions on beliefs correspond roughly to the beliefs that we anticipate each treatment arm tested in hypothesis D1 would change. In particular, we consider the following beliefs as outcomes:

- The *basic appeal* treatment may change awareness of the campaign i.e. whether the household has heard of the Give It Up campaign (=1), and whether the household can explain what it means (=1)
- The *social distance* treatment may change whether the household supports the removal of the LPG subsidy, or whether the household believes the subsidy saved from the Give It Up program is used to help the poor (=1).
- The *information* treatment may change beliefs about the value of the subsidy (in INR) and household's stated willingness to Give It Up if the subsidy value were low.
- The *signaling* treatment whether the household believes that those who Give It Up are likely to have above average incomes (=1)
- The *moral appeal* treatment may change whether the household supports the removal of the LPG subsidy, or whether the household believes the subsidy saved from the Give It Up program is used to help the poor (=1).

We will first test whether the treatment, in any form, had an effect on each belief, and then we will test whether the hypothesized treatments changed the specific beliefs that we associate with each treatment above. The specification is as equation 1, except that we will control for baseline subsidy usage but not the baseline values of the dependent variables (since variables on beliefs are only available in our household survey).

V Administrative Information

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Institutional Review Board (ethics approval): We obtained IRB approval from JPAL South Asia at IFMR, Michigan State University and Yale University.

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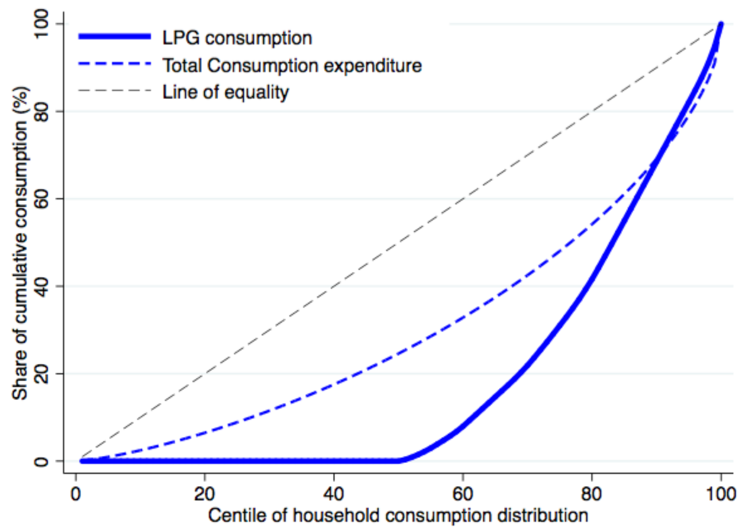
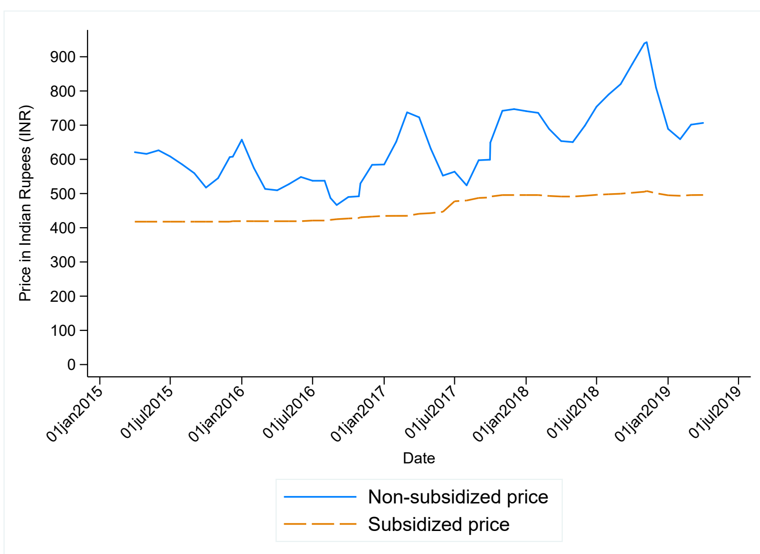
VI Figures

Figure 1: Distribution of LPG subsidy usage



The figure shows distribution of cumulative proportion of natural gas subsidy drawn ($\sim$ subsidized gas purchased by households) plotted against households ordered on horizontal axis in terms of gas consumption. It also shows the distribution of cumulative proportion of consumption expenditure of these households. National Sample Survey 68^{th} round (July 2011- June 2012) for uniform reference period (30 days) is used. For simplicity, it is assumed that all LPG purchased by households was subsidized. During this period, there was no cap on subsidized LPG refills for households.

Figure 2: Value of LPG subsidy over time



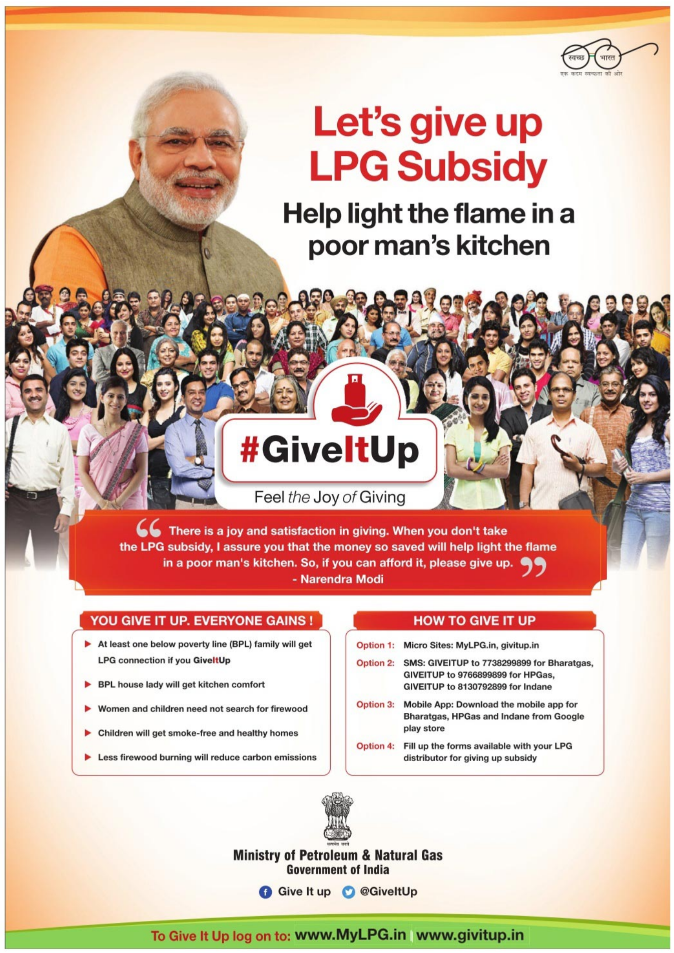
The figure shows the price of one 14.2 kilogram cylinder of LPG in New Delhi at monthly frequency from 2015 through early 2019. The solid (blue) line is the price set by the government to reflect world prices for LPG. The dashed (red) line is the price net of subsidies. The exchange rate during this period is in the range of INR 60 per USD at the start to INR 70 per USD at the end of the period.

Figure 3: Give It Up Marketing

A. Billboard

B. Olympian endorsement

C. Prime Minister's endorsement



The figure shows several parts of the ubiquitous marketing campaign for Give It Up. Panel A shows a roadside billboard with the message "Let's Give Up LPG Subsidy: Help light the flame in a poor man's kitchen." Panel B shows olympian badminton player Saina Nehwal releasing balloons to Give It Up. Panel C shows Prime Minister Narendra Modi's endorsement of the program, with the quote "There is joy and satisfaction in giving. When you don't take the LPG subsidy, I assure you that the money so saved will help light the flame in a poor man's kitchen. So, if you can afford it, please give up."

Figure 4: Give It Up appeal letter

Sanchita Ohri
XXIIIOOOOOOOOXXXX
XXXXIOOOIIIOOXXX
XXXIIOOOIIIOOXXXX

Dear Valued Customer <NAME> ,

Feel the joy of giving! We are writing to invite you to join the Government of India's #GiveItUp campaign to Give Up the LPG subsidy. If you #GiveItUp, it would help the poorest to afford an LPG connection.

Over 1 crore families have felt the joy of giving their LPG subsidy to a needy household. <HOUSEHOLD HEAD FIRST NAME><LAST NAME> in <NEIGHBORHOOD> chose to Give Up the LPG subsidy. Consequently, the family of <HOUSEHOLD HEAD> in <NEIGHBORHOOD> received LPG connection for the first time.

Last month, your subsidy was worth only <AMOUNT> for each cylinder of LPG. Given the current value of your subsidy, we hope you can join #GiveItUp.

Please find enclosed a sticker as a token of our appreciation. If you give up your LPG subsidy, please put up this sticker on your vehicle or door to show your pride from participating in the #GiveItUp campaign.Customers with high income are most likely not to avail the LPG subsidy.

Please return the form enclosed to your distributor in order to Give Up the LPG subsidy. Or, you could SMS GIVEITUP to <respective number for OMC> or log onto www.myLPG.in or www.givitup.in to #GiveItUp.Thank you for your contribution!

As a token of our appreciation, we would like to offer you a mobile recharge of Rs. 100. In order to avail of this recharge, please SMS <CODE> to <NUMBER>. For recharge-related queries, write to cre@jritechnologies.in

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प्रिय उपभोक्ता<NAME>,

खुशियां बाँट कर खुशियां पाएं! हम आपको एलपीजी सब्सिडी छोडने के लिए भारत सरकार के #GiveItUp अभियान में जुड़ने के लिए आमंत्रित करते है। अगर आप #GiveItUp का हिस्सा बनते हैं तो इससे गरीबों को एलपीजी कनेक्शन प्राप्त करने में सहायता मिलेगी।

एक करोड़ से भी ज्यादा परिवार अपनी एलपीजी सब्सिडी किसी जरूरतमंद परिवार को देने की ख़ुशी काअनुभव कर चुके हैं।<HOUSEHOLD HEAD FIRST NAME> ने अपनी एलपीजी सब्सिडी को छोड़ने का निर्णय किया जो<CITY>में रहते है। इसके कारण, <HOUSEHOLD HEAD> के परिवार को पहली बार एलपीजी कनेक्शन मिला जो <CITY> में रहते है।

पिछले महीने, प्रत्येक एलपीजी सिलिंडर के लिए आपकी सब्सिडी की राशि केवल <AMOUNT> थी। आपकी वर्तमान सब्सिडी राशि को देखते हुए, हमें आशा है आप #GiveItUP से जुडने का निर्णय लेंगे|

कृप्या हमारे आभार के प्रतीक के रूप में संलग्न स्टिकर को स्वीकार करें| अगर आप एलपीजी सब्सिडी छोड़ने का निर्णय लेते है, तो कृपया इस स्टिकर को अपने वाहन या दरवाजे पर लगाकर ,अपने #GiveItUp अभियान से जुड़े होने का गर्व प्रदर्शित करें| उच्च आय वर्ग के एलपीजी उपभोक्ता आमतौर पर एलपीजी सब्सिडी नहीं लेते हैं|

एलपीजी सब्सिडी छोड़ने के लिए कृपया साथ में दिया फॉर्म भर करअपने एलपीजी वितरक (डिस्ट्रीब्यूटर) को दें।अथवा, #GiveItUp में शामिल होने के लिए आप<respective number for OMC>पर GIVEITUP SMS कर सकते हैं| आप www.myLPG.in या www.givitup.in पर लॉग इन करके भी #GiveItUp कर सकते हैं।आपके योगदान के लिए धन्यवाद!

इस अभियान में हिस्सा लेने के लिए प्रशंसा स्वरूप, हम आपको 100 रुपये के मूल्य का मोबाइल रिचार्ज उपहार के रूप में देना चाहते है। इस रिचार्ज को पाने के लिए, कृपया <Number> पर <CODE>SMS करें। रिचार्ज से सम्बंधित किसी भी जानकारी के लिए कृपया cre@jritechnologies.in पर संपर्क करे।

Gandhi's Talisman: Recall the face of the poorest and the weakest man [woman] whom you may have seen, and ask yourself, if the step you contemplate is going to be of any use to him [her] ... In other words, will it lead to swaraj for the hungry and spiritually starving millions?

Treated households receive the above letter by mail. The contents of the letter and their variation across customers by treatment arm are described in Table 2. The first half of the letter is in English and the second half in the local language, which varies by city (here, the Hindi version is shown).

VII Tables

Table 1: Treatment saturation across neighborhoods

Saturation	Number of societies	Number of delivery areas
0% treated	193	2935
25% treated	64	105
50% treated	64	105
75% treated	64	104
100% treated	64	104
Total	449	3353
Grand total	3,802	

The table shows the number of neighborhoods assigned to each bin of treatment saturation.

Table 2: Content of Give It Up appeal by treatment arm

Letter paragraph # (1)	Treatment arm (2)	Description (3)	Text (4)
1	Basic appeal	The opening message in every letter.	Feel the joy of giving! We are writing to invite you to join the Government of India's campaign #GiveItUp campaign to Give Up the LPG subsidy. If you #GiveItUp, it would help the poorest to afford an LPG connection.
2	Social distance	An example of someone who has given it up in the same city. Additionally vary the identity of the giver and recipient on lines of religious and caste similarity.	Over 1 crore families have felt the joy of giving their LPG subsidy to a needy household. <HOUSEHOLD HEAD FIRST NAME> <LAST NAME> in <CITY> chose to Give Up the LPG subsidy. Consequently, the family of <HOUSEHOLD HEAD> in <CITY>, <DISTRICT> received LPG subsidy for the first time.
3 (a)	Information (average subsidy value)	Information on the average value of the subsidy in the last financial year.	Last year, your subsidy was worth Rs. <AMOUNT> for each cylinder of LPG. Given the current value of your subsidy, we hope that you can join #GiveItUp.
3 (b)	Information (current subsidy value)	Information on the current value of the subsidy	Last month, your subsidy was worth Rs. <AMOUNT> for each cylinder of LPG. Given the current value of your subsidy, we hope that you can join #GiveItUp.
4 (a)	Signaling	Enclose a shiny OMC sticker stating that customer has given it up, and suggest in the letter that the customer may affix it outside their door or on their vehicle.	Please find enclosed a sticker as a token of our appreciation. If you give up your LPG subsidy, please put up this sticker on your vehicle or door to show your pride from participating in the #GiveItUp campaign
4 (b)	Signaling (with update)	As above in 4 (a), with an additional sentence which says that customers with high income are most likely to not take the subsidy.	Please find enclosed a sticker as a token of our appreciation. If you give up your LPG subsidy, please put up this sticker on your vehicle or door to show your pride from participating in the #GiveItUp campaign. Customers with high income are most likely not to avail the LPG subsidy.
5	Basic appeal	The closing message in every letter.	Please return the form enclosed to your distributor in order to Give up the LPG subsidy. Or, you could SMS GIVEITUP to <respective number for OMC> or log onto www.myLPG.in or www.givitup.in to #GiveItUp. Thank you for your contribution!
6	Moral appeal	Give customer information on Gandhi's Talisman	Gandhi's Talisman: Recall the face of the poorest and the weakest man [woman] whom you may have seen, and ask yourself, if the step you contemplate is going to be of any use to him [her] ... In other words, will it lead to swaraj for the hungry and spiritually starving millions?

The table gives the content of the letter sent to households as part of the Give It Up appeal. The content varies across treatment arms. All treated households get a basic letter consisting of paragraphs 1 and 5. The other paragraphs may or may not appear depending on treatment status. Column 1 gives the paragraph number in the letter in which the treatment appears. Column 2 gives the name of the treatment arm to which the paragraph corresponds. Column 3 gives a brief description of the treatment. Column 4 gives the literal text of the treatment. Figure 4 shows the full text of the appeal, as formatted and sent to treated households, with all treatments switched on together.

Table 3: Summary of hypotheses

Hypothesis	Data	Outcomes	Heterogeneity
A. Do treated households reduce subsidy usage?			
A1. H_0 : The treatment solicitation to Give It Up has no effect on subsidy usage.	Admin	Give It Up (=1), Subsidy amount (INR)	
B. Do solicitations spillover across neighbors?			
B1. H_0 : The treatment solicitation has no effect on the subsidy usage of the neighbors of the household treated (pooled).	Admin	Give It Up (=1), Subsidy amount (INR)	
B2. H_0 : The treatment solicitation has no effect on the subsidy usage of the neighbors of the household treated (by saturation).	Admin	Give It Up (=1), Subsidy amount (INR)	Saturation arms
B3. H_0 : The treatment solicitation has no effect on the subsidy usage of the neighbors of the household treated (pooled).	Admin	Give It Up (=1), Subsidy amount (INR)	Subsidy Gini, religious homogeneity
C. Do norms improve targeting?			
C1. H_0 : The appeal has an equal effect on households regardless of income.	Admin	Give It Up (=1), Subsidy amount (INR)	Any unsubsidized gas (=1), gas use in top decile (=1)
C2. H_0 : The appeal has an equal effect on households regardless of social mobility.	Survey	Give It Up (=1), Subsidy amount (INR)	Mother cooked with biomass (=1)
C3. H_0 : The appeal has an equal effect on households regardless of political orientation.	Survey	Give It Up (=1), Subsidy amount (INR)	Support for NDA less UPA
D. Why do households forgo supsidies?			
D1. H_0 : The content of the appeal has no effect on subsidy usage.	Admin	Give It Up (=1), Subsidy amount (INR)	Table 2 treatment arms
D2. H_0 : The appeal does not change household beliefs about government or charity.	Survey	Heard of GIU (=1), Support no subsidy (=1), Subsidy to poor (=1), GIU signals wealth (=1), Price belief (INR)	Table 2 treatment arms (selected)

The table shows the hypotheses laid out in the pre-analysis plan. The columns give the hypothesis, the data set in which it will be tested, the outcome variables and the variables or treatment arms used to test treatment effect heterogeneity, if any. Section IV discusses the variables and specifications used to test each hypothesis.

A Appendix: Balance checks and experimental power

The appendix uses administrative baseline data to present balance checks across treatment arms. We use the precision of the balance checks, in the main text, to discuss the power of the experiment.

Table A1: Delivery route clusters: Balance by treatment saturation

	Num. of subsidized refills in 17-18	Num. of non-subsidized refills in 17-18	Amount of subsidy transferred in 17-18	Number of consumers in each area
	(1)	(2)	(3)	(4)
treat_frac_area==25	-0.007	0.044	15.098	-1.101
	[0.121]	[0.042]	[25.420]	[27.021]
treat_frac_area==50	-0.021	0.056	-2.886	1.242
	[0.121]	[0.042]	[25.420]	[27.021]
treat_frac_area==75	0.090	0.027	-6.161	-7.009
	[0.122]	[0.043]	[25.537]	[27.146]
treat_frac_area==100	0.106	-0.001	5.110	-1.067
	[0.122]	[0.043]	[25.537]	[27.146]
Constant	8.241***	0.609***	1358.984***	351.625***
	[0.022]	[0.008]	[4.724]	[5.022]
Number of Areas	3353	3353	3353	3353
R-squared	0.00	0.00	0.00	0.00
F-value	0.33	0.76	0.12	0.02
p-value	0.86	0.55	0.98	1.00

The table shows balance checks for each saturation bin at the area cluster level. No. of subsidized refills represents the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders. Each row of the table shows percentage of consumers who will receive treatment of getting letters with different messages. Standard errors in parantheses with * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Delivery route cluster sample: Balance by treatment status dummy

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)
Letter treatment (=1)	0.017	0.023	2.339
	[0.072]	[0.029]	[15.003]
Constant	8.303***	0.620***	1386.491***
	[0.024]	[0.008]	[4.893]
Number of Consumers	1173608	1173608	1178173
R-squared	0.00	0.00	0.00

This table shows balance checks between treatment and control group at area cluster level. No. of subsidized refills is the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders. If in treatment group, the household receives a letter [=1]. Standard errors clustered at area level in parantheses with *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Delivery route cluster sample: Balance by treatment status dummy, with area fixed effects

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)
Letter treatment (=1)	0.004	-0.024**	0.482
	[0.018]	[0.010]	[3.692]
Constant	8.304***	0.624***	1386.635***
	[0.001]	[0.001]	[0.285]
Number of Consumers	1173608	1173608	1178173
R-squared	0.13	0.06	0.14

This table shows regressions for balance checks between treatment and control groups with area fixed effects. No. of subsidized refills is the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders.If in treatment group, the household receives a letter [=1]. Standard errors clustered at area level in parantheses with *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Delivery route cluster sample: Balance across letter content arms

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)
Signaling	0.021	0.009	0.677
	[0.031]	[0.014]	[6.649]
Social Distance	-0.021	0.010	-2.737
	[0.032]	[0.014]	[6.611]
Information	0.012	0.012	1.059
	[0.036]	[0.015]	[7.035]
Moral Suasion	0.021	0.004	3.490
	[0.031]	[0.015]	[6.629]
Constant	8.303***	0.621***	1386.576***
	[0.024]	[0.008]	[4.840]
Number of Customers	1173608	1173608	1178173
R-squared	0.00	0.00	0.00
F-value	0.92	0.27	0.35
p-value	0.45	0.90	0.85

This table shows balance checks for 4 main message groups at the area level. No. of subsidized refills is the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders. Each dummy (=1) if that message is there in the letter sent to the customer. Standard errors clustered at area level in parantheses with *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Society clusters: Balance by treatment saturation

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)	Number of consumers in each society (4)
treat_frac==25	0.029	-0.000	-3.850	-0.974
	[0.152]	[0.058]	[26.788]	[11.165]
treat_frac==50	0.034	-0.023	-7.336	-9.958
	[0.152]	[0.058]	[26.788]	[11.165]
treat_frac==75	0.085	0.048	-6.210	-6.958
	[0.152]	[0.058]	[26.788]	[11.165]
treat_frac==100	0.155	0.114**	-4.397	-4.630
	[0.152]	[0.058]	[26.788]	[11.165]
Constant	6.914***	0.506***	1355.564***	65.036***
	[0.076]	[0.029]	[13.368]	[5.571]
Number of Societies	449	449	449	449
R-squared	0.00	0.01	0.00	0.00
F-value	0.29	1.32	0.03	0.26
p-value	0.88	0.26	1.00	0.90

The table shows balance checks for each saturation bin at the society cluster level. No. of subsidized refills represents the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders. Each row of the table shows percentage of consumers who will receive treatment of getting letters with different messages. Standard errors in parantheses with * p<0.10, ** p<0.05, *** p<0.01.

Table A6: Society cluster sample: Balance by treatment status dummy

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)
Letter treatment (=1)	0.037	0.049	-18.922
	[0.104]	[0.031]	[20.478]
Constant	6.948***	0.461***	1385.352***
	[0.074]	[0.021]	[16.471]
Number of Consumers	27444	27444	27760
R-squared	0.00	0.00	0.00

This table shows balance checks between treatment and control group at society cluster level. No. of subsidized refills is the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders. If in treatment group, the household receives a letter [=1]. Standard errors clustered at area level in parantheses with *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Society cluster sample: Balance by treatment status dummy, with society fixed effects

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)
Letter treatment (=1)	-0.018	-0.033	4.074
	[0.025]	[0.030]	[4.351]
Constant	6.967***	0.489***	1377.536***
	[0.009]	[0.010]	[1.479]
Number of Consumers	27444	27444	27760
R-squared	0.09	0.04	0.07

This table shows regressions for balance checks between treatment and control groups with society fixed effects. No. of subsidized refills is the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders.If in treatment group, the household receives a letter [=1]. Standard errors clustered at area level in parantheses with *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Society cluster sample: Balance across letter content arms

	No.of subsidized refills in 17-18 (1)	No.of non-subsidized refills in 17-18 (2)	Amount of subsidy transferred in 17-18 (3)
Signaling	-0.005	0.005	-10.783
	[0.066]	[0.029]	[13.408]
Social Distance	0.037	0.012	-9.451
	[0.060]	[0.029]	[12.113]
Information	0.006	0.045	-4.980
	[0.069]	[0.029]	[13.551]
Moral Suasion	-0.016	-0.012	-9.711
	[0.061]	[0.032]	[12.546]
Constant	6.957***	0.469***	1384.857***
	[0.070]	[0.020]	[15.402]
Number of Customers	27444	27444	27760
R-squared	0.00	0.00	0.00
F-value	0.12	0.69	0.37
p-value	0.98	0.60	0.83

This table shows balance checks for 4 main message groups at the society level. No. of subsidized refills is the total amount of subsidized refills taken by a customer in the year 17-18. It is capped at 12 refills per customer per year. No. of non-subsidized refills is the total amount of non-subsidized refills taken by a customer in the year 17-18. Amount of subsidy transferred is the total amount of subsidy a customer received in the year 17-18 from purchasing subsidized cylinders. Each dummy (=1) if that message is there in the letter sent to the customer. Standard errors clustered at society level in parantheses with *** p<0.01, ** p<0.05, * p<0.1.