Impact of Self- or Social-regarding Health Messages: Experimental Evidence Based on Antibiotics Purchases

By DAIXIN HE, FANGWEN LU AND JIANAN YANG*

We study two interventions that provide patients with information on antibiotic resistance through text messages in Beijing, China. The "self-health" intervention emphasizes the threat to one's own health and is found to have negligible effects. In contrast, the "social-health" intervention highlighting the threat to society reduces antibiotic purchases by 17% without discouraging healthcare visits and other medicine purchases. Survey evidence shows social consequences are viewed graver but equally likely to occur, suggesting the perceived severity being a potential explanation. The messages were sent once every month for five months, and gradual decrease of the effect size is observed over time.

Keywords: Social-regarding message; Antibiotics; Field experiment

JEL codes: C93, D83, I12

* He: Chinese Academy of Social Sciences (email: hedaixin@cass.org.cn); Lu: Renmin University of China (email: lufangwen@ruc.edu.cn); Yang: UC San Diego (email: jiy346@ucsd.edu). The financial support from the National Natural Science Foundation of China through grant no.71822303 and 72173129 to Lu, and 71973149 and 71603273 to He are gratefully acknowledged. Yang is grateful to Karthik Muralidharan, Paul Niehaus, Prashant Bharadwaj and Craig McIntosh for their constant support and guidance. AEA Trial Registry RCT ID: 0005118. IRB at EconLab, Renmin University of China: RUCecon-201811-2.

1 Introduction

The increasing availability of antibiotics saves lives. However, its byproduct—antibiotic resistance—has become one of the biggest threats to global health, food security, and development (World Health Organization, 2018). The resistance emerges naturally with any use of antibiotics, however appropriate and justified, and could be disseminated rapidly worldwide (Laxminarayan et al., 2013). Failure to account for externalities results in antibiotics overuse. Patients' lack of information further intensifies the problem. Likewise, misconceptions abound across many contexts, leading to the irrational use of these drugs (Widayati et al., 2012; Yu et al., 2014; Vaz et al., 2015; Sakeena et al., 2018; Wang et al., 2018; Wang et al., 2019).

The standard economic approach to negative externalities is to use taxes or subsidies to bridge the gap between private and social benefits. However, in this case, the price mechanism works to exacerbate the problem because of the first-order importance of ensuring medicine access. Health systems in many countries seek to lower the out-of-pocket cost for antibiotics, often by reducing production cost and providing coverage through health insurance (Frost, 2019). An alternative is to utilize intermediaries like doctors for prescribing antibiotics with the hope that the doctors will take into account the negative externalities and discourage overuse. However, patients' expectations and requests could directly affect doctors' prescription decision (Cockburn and Pit, 1997; Macfarlane et al., 1997; Scott et al., 2001; Mangione-Smith et al., 2006; Iizuka and Shigeoka, 2018; Lopez et al., 2018), weakening doctors' gate-keeping role.

Another compelling approach would be to use insights from behavioral economics, given that people often voluntarily consider the social impact of their behavior when provided with relevant information. The appeal of "non-price" interventions as nudges can effectively shift behaviors in socially desirable ways, which has been demonstrated in different contexts, including energy conservation (Allcott, 2011; Ferraro and Price, 2013; Ito et al., 2018) and tax collections (Hallsworth et al., 2017). In this study, we test such a nudge approach by studying whether patients' antibiotics purchases respond to text messages with information on the potential negative self or social impact of antibiotic resistance. Text message interventions are easily scalable, highly inclusive, and cheap to implement. They have the potential to be a very cost-effective tool in problems involving externality and lack of information.

We implemented an experiment of sending differently framed text messages in a community healthcare center in Beijing, China. China is among the world's largest consumer of antibiotics (Song et al., 2020). The percentage of prescriptions that include antibiotics in China is way above the recommended threshold by the World Health Organization (WHO), with around half of the antibiotics being estimated to be unnecessarily prescribed (He et al., 2019). Moreover, public misperception about antibiotics is staggering. A WHO survey (2015) reports that 61% of respondents in China think, incorrectly, that colds and flu can be treated by antibiotics.

We design the experiment to include three different messages. The first is a placebo message that reminds patients to take good care of themselves during the flu season, without any information on antibiotics. This message is sent to all patients. Patients in the two treatment groups receive additional treatment messages. Both treatment messages have the same opening statement on a common case of antibiotics misuse and overuse, and then differ in how they describe the consequences of the resulting resistance issue. The "self-health" message describes how resistance might affect one's own health, whereas the "social-health" message talks about how it could pose a threat to public health. Both conclude with the same sentence calling for rational drug use.

As evidence shows the short-lived effect of this type of intervention (Ferraro et al., 2011; Allcott and Rogers, 2014; Ito et al., 2018), we sent the text messages repeatedly once every month for five months, with the treatment assignment kept the same for each subject. We took note of their subsequent antibiotics purchases and other healthcare-seeking behaviors from the patients' visiting record.

Our study site is a community healthcare center located in the central part of Beijing, China. It serves an area with around 100,000 residents, with a population density close to that of Manhattan in the U.S. We use administrative visiting records from the healthcare center, which allows us to measure patients' healthcare utilization accurately from several dimensions and in particular, frees us from social desirability bias which would be a nontrivial concern of any self-reported data in this context. The study sample is collected from the patients who visited the healthcare center from August 1, 2018 to October 31, 2019, and the final sample consists of 14,063 patients.

Results show that patients receiving social-health messages significantly reduced their antibiotics purchases compared with both the control and self-health groups. The effect is meaningful in magnitude: over the six-month period since the first message was sent, the social-health group reduced their total dosage (days) of antibiotics purchased by 17.0% and reduced spending on antibiotics by 22.4% relative to the control group. Although we also find some reduction in the self-health group, the effect size is much smaller and not statistically significant. The response in the social-health group comes mainly from the extensive margins of the reduction in times of antibiotics purchases. Conditional on making a purchase, the distribution of dosage in the social-health group is not significantly different from that in the control group, suggesting that patients did not shorten the course of antibiotics treatment. In the analysis of heterogeneity by antibiotics purchase history, those who purchased antibiotics before the experiment experienced a larger absolute reduction, but in the percent term, the magnitude is comparable to the group without a purchase history. The time trajectory of the effect size reveals a gradual decrease toward the latter rounds of messaging.

To explore the potential mechanism behind the main finding, we conducted a short survey with 200 respondents on perceptions of the two intervention messages. The survey response demonstrates that the consequences described in the two messages are considered equally likely to occur (51% versus 49%), but a larger share of respondents (63%) perceive the social-health consequence of antibiotic resistance as being more severe compared with the self-health one. This could partially explain why the social-health message leads to a larger reduction in antibiotics purchases.

An intervention designed to reduce the usage of low-value care through price mechanisms faces the problem of discouraging potentially valuable care utilization (Haviland et al., 2012; Brot-Goldberg et al., 2017). To address this concern, we examine whether the text message intervention delivered any undesirable impacts. First, none of the number of visits, expenditure on examinations and services, or the purchase of medicine other than antibiotics is negatively affected. Second, patients in the treatment groups are not less likely to be diagnosed with an illness that might require antibiotics for treatment, suggesting that they are not scared away from seeing a doctor when they have symptoms that could be treated with antibiotics. We also observe that most of the reduction in antibiotics purchases comes from purchases that did not succeed any examination for bacterial infections and, thus, were highly likely to be illegitimate. Overall, our findings suggest that this intervention effectively reduced improper antibiotics purchases without any observable undesired effects.

We believe that our study could contribute to the literature on the utilization of low-cost nudges to promote socially desirable behavior. This approach has been applied to encourage water (Ferraro et al., 2011; Ferraro and Price, 2013) and electricity conservation (Allcott, 2011; Allcott and Rogers, 2014; Ito et al., 2018), deter traffic violations (Lu et al., 2016; Chen et al., 2017), increase payment rates for tax and fees (Fellner et al., 2013; Hallsworth et al., 2017), increase rates of saving (Karlan et al., 2010) and loan repayments (Karlan et al., 2012; Du et al., 2020), and decrease the share of delinquency (Bursztyn et al., 2019). In promoting health-preserving behaviors, Banerjee et al. (2020) found that SMS containing a 2.5-minute clip that encourages reporting of COVID-19 symptoms significantly increased reporting and other behaviors that are critical in preventing the spread of the virus. Banerjee et al. (2021) also examined the impact of SMS reminders on demand for immunization.

With ample evidence on the general effectiveness of prosocial nudges, some elements have been explicitly tested to be essential in inducing behavioral changes, including personal touch (Karlan et al., 2012) , social norm (Allcott, 2011; Ferraro and Price, 2013; Hallsworth et al., 2017) , and moral suasion (Bursztyn et al., 2019). However, the gap between self and social cost or benefit is the root of inefficiency in markets with externality. For behaviors like antibiotics usage, its externality might not be as well understood as that of tax payments or energy conservation and thus, information, might be the first-order constraint. To the best of our knowledge, the effectiveness of messaging regarding the social impact of individual behavior has not been directly tested, nor its comparison with messaging regarding the potential cost to oneself, with one exception being the recent work by Banerjee et al. (2020) on COVID-19 symptoms reporting, which did not find any significant effect of adding social impact information on top of only the self one. Thus, our work contributes to the literature by showing that providing people with information on the potential social impacts of their behaviors can be effective in inducing behavioral changes. This study also discovers a new perspective for social regarding message – the social consequences can be perceived more severe, which may be the channel for its effectiveness.

Moreover, we expect to contribute to the discussion on the tension between access and targeting in healthcare settings. Price mechanism is the most explored approach to regulate care utilization but it is often found to trade off access and targeting against each other. To promote access, lowering patients' cost-sharing was shown to increase misuse and overuse of care (Cohen et al., 2015; Iizuka and Shigeoka, 2018). To address mis-targeting, increasing cost-sharing is effective in reducing overall usage but does poorly in targeting at the part of the demand where the marginal cost exceeds the benefit (Haviland et al., 2012; Brot-Goldberg et al., 2017). Lack of information could be an important barrier to optimal healthcare-seeking behaviors (Dupas, 2011). Indeed, the provision of information to patients has been shown to effectively reduce the unnecessary use of anti-malaria drugs (Cohen et al., 2015) and underuse of care for vulnerable children (Sautmann et al., 2016). Currie et al. (2011) documented that doctors are more likely to provide information and reduce prescription to patients who demonstrate some antibiotics-related knowledge. Our study aims to show that a simple patients' side information intervention by text messaging could be effective in alleviating the tension between access and targeting.

The rest of the paper is organized as follows. Section 2 discusses the background of the study. Section 3 describes the research design. Section 4 presents the results. Section 5 discusses the external validity of the results and conclude.

2 Background

China is among the countries with the highest per capita usage of antibiotics (Lin et al., 2016). It also has a high level of antibiotic resistance and high growth rate of resistance (Zhang et al., 2006). As part of the global effort to combat antibiotic resistance, in 2012, the Chinese Ministry of Health issued a regulation to limit antibiotic prescription to 20% of outpatient prescriptions for all patients[1]. It also eliminated doctors' financial incentive to prescribe antibiotics, which has been argued to be a major driver of antibiotics over-prescribing (Currie et al., 2014; Lu, 2014). The combined effort has effectively reduced antibiotics consumption at tertiary hospitals but has failed to deliver much improvement in primary care and rural settings (Yin et al., 2013; He et al., 2019).

The other side of the story involves the patients. According to a survey by WHO (2015), 61% of respondents in China think antibiotics can treat a common cold and do not know that they are ineffective against viral diseases; 35% say that antibiotics can be used to treat headaches, which is also against scientific guidance. People tend to keep antibiotics as a household medicine and self-medicate when they have mild cold or infection-like symptoms (Wang et al., 2018). The other feature that makes demand-side factors more relevant lies in the local nature of the study context. In the case of a community healthcare center, it is common for patients and doctors to have repeated interactions and be acquainted. Given that patients can directly affect doctors' prescribing behavior (Cockburn and Pit, 1997; Macfarlane et al., 1997; Scott et al., 2001; Mangione-Smith et al., 2006; Lopez et al., 2018), doctors who are familiar to their patients may have even more difficulty rejecting a prescription request.

In China, community healthcare centers are state-owned, not-for-profit healthcare facilities. They provide residents with basic healthcare services, including vaccination, physical examinations, and treatment for minor illnesses like colds, flu, and chronic diseases. Since 2009, price markups have been removed for drugs sold in community healthcare centers[2], which means that these centers no

[1] Chinese Ministry of Health, "The announcement of carrying out intensive nation-wide intervention on antimicrobial clinical use", http://www.nhc.gov.cn/zwgkzt/wsbysj/201104/51376.shtml

[2] In April 2009, the State Council of China launched the National Essential Medicine System. A key component is the zero-markup policy, which means that medicines are sold to patients at the procurement price, with no profits for the

longer make any extra revenue from drug sales[3]. Moreover, the center's pharmacies receive their drug stocks through a centralized procurement platform and thus offer lower prices than private retail drugstores. The coinsurance of the public health insurance for medicine spending is lower at community healthcare centers than at other public healthcare facilities. As such, patients have strong incentives to purchase antibiotics at these centers.

Aside from providing healthcare, the community healthcare centers also play the role of promoting healthy lifestyle and providing health related knowledge to the local residents. Their common strategies include organizing workshops, handing out flyers and sending text messages. During our intervention period, patients on average received two messages from the center each month, excluding the one sent by us.

In the community healthcare center, patients can purchase antibiotics only if they have a prescription from the doctors. However, due to the fact that doctors prescribing decision are often affected by patients' expectation and request, a prescription does not necessarily justify the legitimacy of antibiotics purchases from a clinical perspective[4]. According to a regulation effective in 2004 issued by the National Medical Products Administration (NMPA)[5], all pharmacies, public and private, are only permitted to dispense antibiotics with a prescription. Though nationwide there is still a large share of antibiotics sold without a valid prescription (Gong et al., 2020), Beijing, and especially the district that our partner center

healthcare facilities. This applies to all public healthcare facilities. http://www.gov.cn/zwgk/2009-04/07/content_1279256.htm

[3] However, this does not rule out the possible kickbacks from pharmaceutical firms.

[4] Even in cases when healthcare practitioners know antibiotics won't be effective, facing request from patients, busy physicians would prefer just writing prescriptions to educating the patients (Ding et al., 2019). A study in the U.S. also found that nearly half of all antibiotics prescribed are without the diagnosis of an infection and 1 in 5 prescriptions was written even without an in-person visit (https://www.eurekalert.org/news-releases/834810).

[5] National Medical Products Administration (Oct 14th. 2003): https://www.nmpa.gov.cn/directory/web/nmpa/xxgk/fgwj/gzwj/gzwjyp/20031024010101310.html

locates in, has better implementation of the regulation due to its proximity to the central administration. And thus, purchasing antibiotics without a prescription from private retail drugstores is not quite feasible, though patients could still get a prescription from the drugstore's own physician, who has the authority to write prescriptions.

The physicians are not made aware of the interventions. Even if they happened to know about intervention messages, it is not easy for physicians to tell which patients are in the treatment group and which are not. There are usually a large number of patients waiting to be seen, and physicians have limited time to chat with each patient during the visit[6]. Besides, 66% of the post-intervention patient-visits were made by those who did not receive any treatment messages. Therefore, it is unlikely for physicians to make conversation with patients about text messages. Even if physicians become aware of the intervention by any chance, it is difficult for them to target behaviors to patients in the treatment groups. If they respond to the messages by reducing the overall prescription of antibiotics to everyone, we get an underestimate of the effect.

3 Research Design

3.1 Text Message Interventions

Our experiment includes one control group and two treatment groups. The details of the treatment design are shown in Table 1. The control group receives a "placebo message" with no information on antibiotics, called "usual reminder" in our study. Patients in each of the two treatment groups receive the placebo message, plus either the "self-health" or "social-health" message. The placebo message is

[6] A physician in our partner healthcare center is estimated to see 40-50 patients a day.

included to catch any impact of simply receiving a message from a local healthcare provider, thereby capturing possible Hawthorne effect.

The three text messages can be translated as follows. The different portions between the self-health and social-health messages are highlighted in bold below[7].

Usual Reminder:

"Please keep warm and ensure adequate sleep/hydration during winter and flu season. We are here to provide medical service, should you have symptoms of cold, flu, inflammation, etc."

In April, the winter and flu season had passed, and the message was changed accordingly as follows:

"Please keep warm and ensure adequate sleep/hydration amid the fickle weather of spring. We are here to provide medical service, should you have symptoms of cold, flu, inflammation, etc."

Self-Health Message:

"Antibiotics have little benefit for acute respiratory infections, including cold or flu. Misuse and overuse of antibiotics will contribute to **the evolution of antibiotic-resistant bacteria in your body. This might make it necessary for you to use stronger antibiotics in treating future infections.** This might also make infections no longer treatable by currently available antibiotics. Please follow doctors' instructions in using medicine."

Social-Health Message:

"Antibiotics have little benefit for acute respiratory infections, including cold or flu. Misuse and overuse of antibiotics will contribute to **the evolution and spread of antibiotic-resistant bacteria among people. This might make it necessary for society to develop stronger antibiotics in treating future infections.** This might

[7] The bold part is not highlighted in the actual text messages.

also make infections no longer treatable by currently available antibiotics. Please follow doctors' instructions in using medicine."

The beginning sentence, identical for the two treatment messages, is a statement based on medical research (Hirschmann, 2002; Meropol et al., 2013), included to provide potential patients with an idea of what would be an example of antibiotics misuse and overuse. Both messages conclude the threat with the possible unavailability of drugs for future infections. The end of the messages emphasizes the expectation for patients to follow doctors' instructions in using medicine, phrased in such a way as to alleviate the concern that patients might be scared away from even the legitimate use of medication.

We word the two treatment messages in a similar manner, with the only difference being in the mention of the consequences of antibiotic resistance to the self or society. They also contain roughly the same number of Chinese characters (120 versus 123), which allows us to rule out salience effects. Therefore, we could attribute any differential responses between the two treatment groups to the self or social dimension of the message.

The first round of messages was sent on December 3, 2019. Four subsequent rounds were sent on the 3rd of each month for January, February, and March 2020, and the 8th of April 2020. The repeated messaging is motivated by evidence on the short-lived effect of non-price nudges (Ferraro et al., 2011; Allcott and Rogers, 2014; Ito et al., 2018). The message each individual received did not change across rounds. The timeline is illustrated in Figure 1. The messages were all sent by the community healthcare center, and the patients could identify the sender by the format of the message and the sender's number.

3.2 Data, Sample, and Randomization

We collected data covering all the hospital visits from August 1, 2018 to June 9, 2020. Patients' demographics include gender and age. For each visit, the community healthcare center recorded their diagnosis, service and examination performed, drug purchased, and spending details. The community healthcare center de-identified the data prior to us working with it; names of patients, dates of birth, phone numbers, and national IDs were all replaced by generated IDs that are not personally identifiable. And there is no information available to identify the relationship among patients, for example, whether they come from the same household.

The study sample includes patients who visited the healthcare center from August 1, 2018 to October 31, 2019. The sample selection criteria are as follows. First, given the nature of the intervention, we focused on individuals with a valid mobile phone number on record. Those who share a phone number with three or more different patients were excluded from the study. We also restricted the sample to those with available national ID information, which could enable the accurate tracking of visits by each patient over time. Finally, we included patients aged between 18 and 75 years. Our final sample consists of 14,063 individuals.

Table 2 presents the summary statistics for the study sample. Around 42% of the sample are male, and the average age is 53.6 years. Sixty-two percent of the sample have been diagnosed with chronic conditions[8]. An average patient visited the community healthcare center 0.85 times per month. Of the sample, 39% purchased antibiotics in the sample collection period. And on average, patients in our sample purchase antibiotics without a set of bacterial infection related exams 0.063 times per month pre-intervention. The spending value in the data is as total amount to be paid, which consists of both the portion covered by insurance and patients' out-of-

[8] The chronic conditions considered here include cardiovascular system related conditions (hypertension, high blood cholesterol, coronary artery disease, atherosclerosis, stroke), diabetes, cancer, and chronic obstructive pulmonary disease (COPD).

pocket payment. The average spending on bacterial infection related exams is RMB 1.44 per month pre-intervention and the number for the other exams and services is RMB 38.41. The medicine purchases are measured in three metrics: dosage, quantity, and spending. We define dosage as the number of days for which the medicine had been prescribed. Quantity is measured by the number of units in which the medicine was sold at the healthcare center's pharmacy (e.g., boxes or bottles). Spending is measured in RMB. The statistics reported for these three measures are all at the monthly average level. Antibiotics takes only a small share of patients' total spending on medicine, owing to both the relatively low price of antibiotics and abundant types of drugs included in the other medicine category, of which drugs for chronic conditions accounted for a significant share.

The randomization is blocked on gender, age, and an indicator for whether a patient had any antibiotics purchases during the sample collection period. We divide the age range of 18–75 years into 6 age groups: 18–30, 30–40, 40–50, 50–60, 60–70, and 70–75. Table 3 reports the means and standard deviations for key variables at baseline, separated by treatment. There are no statistical differences between the treatment groups and control group, indicating that the randomization yields a balanced sample. The joint p-values for the self- and social-health treatment assignments are equal to 0.96 and 0.82 respectively.

4 Results

We report intent-to-treat estimates, comparing mean outcomes in two treatment and control groups, given that we could not guarantee whether the messages were actually read. The estimation equation is as follows:

$$Y_{is} = \alpha + \beta_1 SelfHealth_{is} + \beta_2 SocialHealth_{is} + \gamma Y_{is}^0 + \delta_s + \varepsilon_{is}$$

where Y is the outcome, $SelfHealth$ and $SocialHealth$ are the indicators for treatment assignment, and Y^0 is the pre-experiment value of the outcome variable, if available. Indices denote individual i in stratum s, which is determined by the individual's age, gender, and antibiotics purchase history. Treatment is strictly exogenous, conditional on the randomization stratum fixed effects δ_s.

4.1 Effect on Antibiotics Purchases

Table 4 presents the effect of the intervention on antibiotics purchases. Although the self-health group experienced reductions in purchases, the effect sizes are small and not significant. The social-health messages have a much larger and statistically significant effect on antibiotics purchases across the three measures. The preferred specifications are column 2, 4 and 6, in which we control for pre-period antibiotics purchases (dosage, quantity or spending), age and gender. Relative to the control means of 0.41 days in dosage purchased, 0.11 units in quantity, and RMB 1.28 in spending, the effects of the social-health messages are equivalent to a reduction of 17.0% in dosage, 13.3% in quantity, and 22.4% in spending. Moreover, the hypothesis that self-health and social-health messages would have the same effect could be rejected at the 5% level for dosage and spending and at the 10% level for quantity. Overall, the patients respond much more strongly to the social-health message than the self-health one in reducing antibiotics purchases.

Table 5 shows the results on the total reduction by extensive and intensive margins (i.e., whether reduction comes from patients purchasing antibiotics fewer times or buying fewer antibiotics per purchase or both). Columns 1 and 2 present the extensive margin effect, with the outcome variable in column 1 being an indicator variable on whether any antibiotics is purchased during the post-experiment period and column 2 being the average number of antibiotics purchase per month. The social-health group shows a small but insignificant reduction in the overall likelihood of having an antibiotics purchase, but the times of antibiotics purchases per month drop by 0.0065 (11.1% relative to the control mean). With the caveat of endogenous sample selection, we then restrict the analysis to the subsample that has positive antibiotic purchases in the post intervention period and examine explicitly the intensive margin on antibiotics per purchase. Columns 3-4 in Table 5 shows that the estimates are not significant for dosage and quantity, and are small in magnitude relative to the control mean (4% reduction in dosage and 0.1% in quantity). Column 5 shows a significant reduction in spending per purchase and the effect size of 1.99 RMB is equivalent to 9.4% of the control mean. This might be a result of patients in the social-health group purchasing antibiotics with lower cost per daily dose or per box[9].

However, though the intensive margin impact is small, it may raise the concern that patients might not take the full course of antibiotics treatment, which will also lead to drug resistance. To test this possibility, we plot the distribution of antibiotics dosage in each purchase from the post intervention period in Figure 2, overlaying the distribution for the social-health group on top of that for the control group. Visually the distribution for the social-health group is not more concentrated at the lower end with dosage smaller than 5 days. In fact, the recommended duration for antibiotics treatment is 5-7 days for common infections (Pouwel et al., 2019). Formally testing the difference between the two distributions, the p-value from a Kruskal-Wallis test is 0.50 and from a Kolmogorov-Smirnov test is 0.92, both not rejecting the null hypothesis that the distributions from the social-health group and the control group are identical. Therefore, the effects are unlikely to come from individuals reducing their purchases by not taking the full course of antibiotics treatment.

Antibiotics is only effective in treating bacterial infections. It usually requires a blood or urine test to verify that the symptoms are caused by bacterial infections. Thus, we identify a set of exams that could be used to check for bacterial

[9] In fact, another margin of antibiotics overuse is the unnecessary use of stronger and more expensive drugs when regular and cheaper ones are sufficient for the condition.

infections[10], and then examine the effect of the messages on the spending of those exams and the purchases of antibiotics by whether they succeed any of those exams. We define an antibiotics purchase to be "with exam" if the purchase occurs after the patient underwent an exam up to three days prior to the purchase. Similarly, a purchase is categorized as "without exam" if no exam was recorded in the three-day window prior to the purchase. Redefining the two outcome variables using 0- to 5-day windows prior to the purchase would not affect the results. First, we do not observe a significant increase in spending on the set of bacterial infection related tests, though the estimates have positive signs (column 1 in Table 6). Second, the effect of social-health messages was only significant for "without exam" purchases with a reduction of 0.0676 in dosage days purchased per month, which is equivalent to 17.4% of the control mean (column 2 in Table 6). In fact, most of antibiotics purchases falls in the "without exam" category (93.7% in dosage[11]). Though these are not necessarily all illegitimate purchases, this number is in line with the findings from the medical literature that a large proportion of antibiotics prescriptions are inappropriate in Chinese primary care and ambulatory care settings (Wang et al., 2014; Zhao et al., 2021)[12].

Lastly, we explore the heterogeneous effect along the dimension of pre-intervention antibiotics purchases. Table 7 shows the effects on antibiotics purchases separately for patients who had never purchased any antibiotics (Panel A) and those with antibiotics purchase history in the sample collection period (Panel B). The comparison of the control means shows that the sample with a purchase history continues to have a higher level of antibiotics purchases after the

[10] Under the assistance from physicians out of sample, the set of exams that could be used to identify bacterial infections in the sample include: complete blood count, clinical urine tests, urine sediment examination, C-reactive protein (CRP) test, and 13c urea breath test.

[11] This number is calculated from the control means: 93.7% = 0.3879/(0.3879+0.0264)

[12] Zhao et al. (2021) documented that only 15.3% of outpatient antibiotics prescriptions are deemed appropriate in a survey of 139 secondary-level and tertiary-level hospital nationwide from 2014-2018.

intervention, suggesting persistent differences in patients' use of antibiotics. The effects of social-health message are much larger in magnitude in the history subsample. We can reject the hypothesis that the social-health message has the same effect on the two subsamples at 5% level for both dosage and spending (Table 7 Panel C). In the no-history sample, the absolute magnitude of the effects is small owing to the low base level, but the percentage reduction relative to the control in the social-health group is comparable with that in the with-history sample (16.3% versus 17.3% in dosage). In contrast, self-health messages have a much smaller impact compared with social-health messages in both sub-samples across the three measures of antibiotics purchases. And the hypotheses that the effects of the self-health message are the same for the two subsamples cannot be rejected.

4.2 Effect on Other Healthcare Utilization

In this subsection, we will provide evidence on potential changes in other dimensions of healthcare utilization. The outcome variables include number of total visits, spending on medical examinations and services, diagnosis patterns, and purchase of other medicine.

First, to address the concern that the message might have discouraged people from seeking healthcare from the provider in this study, we examine the effect of our intervention on visits and spending on health products and services apart from antibiotics. Columns 1 to 4 in Table 8 indicate that none of them are negatively affected. We find no significant impact on the overall likelihood of having any visit nor the total number of visits (columns 1 and 2). The point estimates are small, and the magnitude of coefficients for the social-health message is smaller than that for the self-health message. Neither the spending on medical exams, services excluding those exams related to bacterial infections (column 3), nor on other medicines (column 4) is significantly affected.

The fact that the social-health message does not have negative effects on those other dimensions of healthcare seeking behaviors at the experiment center provides suggestive evidence against the possibility that patients shift to purchase antibiotics at other places due to a social judgement concern. Because these results suggest that for such a story to hold, patients will need to make additional trips to other drugstores only for buying antibiotics. Together with a higher price they need to pay for the drugs at other places, the social judgement concern will need to be sufficiently large to justify this additional cost.

Second, to address the concern that the message might have prompted reluctance to seek care when having bacterial-related symptoms, we check whether the messages affect the diagnosis compositions. The diagnosis a patient receives from a single visit typically includes multiple illnesses. And we assign all the illnesses into two categories, labelled as Type Antibiotics and Type Not, based on whether the illness might require antibiotics for treatment. Diseases categorized as Type Antibiotics are those that might require antibiotics for treatment, such as conjunctivitis and upper respiratory infections. Type Not include illnesses that do not require antibiotics for treatment, such as chronic conditions like diabetes and cardiovascular diseases. The dependent variables in columns 5 and 6 of Table 8 are the number of times that a patient's diagnosis contains each of the two types of illnesses. The results show that the diagnosis pattern is not affected by the messages, indicating that the treatment message did not scare patients away from seeing a doctor when they had relevant symptoms. This finding could alleviate the concern that patients do not purchase antibiotics when they truly need one. In fact, the malfunction of providers' gate-keeping function in this setting tends to be over-prescribing antibiotics in order to satisfy patients' expectations, as extensively documented in the medical literature (He et al., 2019; Fletcher-Lartey et al., 2016).

The reduction in antibiotics purchases might be a result of patients substituting antibiotics with alternative medicines. Table 9 shows the result for medicines other than antibiotics in two categories to clarify potential substitution behaviors. The first category, “substitutes”, contains medicines that could treat Type Antibiotics illnesses. For example, medicines for cough, fever, and other cold/flu-related symptoms are considered “substitutes”. Medicines in the category “unrelated” are those not related to any disease that could be treated by antibiotics. Where substitution occurs, an increase in the purchases of “substitutes” could be expected. However, the results do not support such a scenario. The effects of the treatment on “substitutes” and “unrelated” medicines are both insignificant and small relative to the control mean. If antibiotics are clinically needed, physicians will switch to substitute drugs when the prescription of antibiotics is constrained. Our findings are consistent with evidence from several survey studies mentioned earlier (WHO, 2015; Wang et al., 2019), which find that the prevalence of misperception on antibiotics leads to antibiotic overuses that do not provide any clinical benefits (for example, as prophylaxis for cold or alleviation for headache).

In sum, in the social-health group, we find a sizeable reduction in antibiotics purchases, and the effect mainly comes from the extensive margin of a reduction in times purchasing antibiotics. We address the concern of patients not taking the full course of treatment by showing that the distribution of dosage per purchase in the social health group is not significantly different from that in the control. Other dimensions of healthcare seeking behaviors in the study site are not affected, which provides support that this intervention only affected the antibiotics purchases that are clinically unnecessary. Specifically, treated patients are not seeking care less frequently from the study site, purchasing less of other drugs, exams, and services. And the concern that patients might not use antibiotics when they truly need one is alleviated by the result that patients are similarly likely to seek care for antibiotics related symptoms. The fact that the purchase of substitute drugs does not increase suggests the discouraged antibiotics purchases should be those that do not provide any clinical benefits. More importantly, the finding that the majority of the reduction happens under antibiotics purchases without any exam to check for bacterial infections directly supports a scenario of reduction in the illegitimate purchases. The overall results together point toward a potential welfare improvement.

4.3 Time Trajectory of Effect Size

We also pay attention to the evolution of the effects of the two messages over time. Figure 3 graphs the time trajectory of the effects for the self-health (left panel) and social-health messages (right panel). To obtain the estimates plotted in the figures, we run the main specification separately for each time frame, with the dependent variable being the cumulative antibiotics purchases within that time frame. For the period before the experiment, the time frame is a calendar month. For the period after the first message, given that repeated messages were sent roughly once a month, the time frame is the period between two adjacent messages. The time span plotted is June 1, 2019 to June 9, 2020, or six months before and six months after the first message.

As shown in the graph, before the messages were sent (June to November 2019), neither self nor social-health group had any significant differences from the control, suggesting that the treatment and control are balanced in pre-treatment antibiotics purchases. In the period between the first and second rounds, antibiotics purchases in the social-health group dropped significantly relative to the control but not in the self-health group. The effects are muted in the period between the second and third rounds. This could be explained by an overall low levels of healthcare utilization during this period owing to the Chinese New Year (January 25, 2020) holiday and the outbreak of COVID-19 (the lockdown in Wuhan started on January 23, 2020). The trends rebounded after the third round of messaging in the social-health group, and then we observe a gradual decrease in effect size over time. In contrast, the effect of the self-health messages is only statistically significant between the second and third messages, and the effect sizes fluctuate at around 0. Although the coefficients in the post period are not statistically different, there seem to be a gradual decrease in effect size of the social-health messages, which might suggest habituation as documented by Ito et al. (2018) in the use of moral suasion to stimulate energy conservation. Thus, repeated messages alone might not be sufficient to induce persistent behavioral change.

4.4 Potential Mechanisms

As both messages emphasize the resistance effect of antibiotics and highlight the possible unavailability of drugs for future infections, it is puzzling to find that the social-health message is effective while the self-health message is not. Aside from other-regarding preferences, the perceptions about the self and social consequences of antibiotics resistance might also contribute to the differential response. Though we do not have evidence on patients' baseline knowledge and perceptions about antibiotics resistance and thus are unable to access how they are shifted by the treatment, a short survey conducted among patients visiting the community healthcare center reveals that the scenario described in the social-health message is viewed as being more serious by patients.

In late December 2020 and early January 2021, we collected a survey sample from patients that were waiting to be seen by the doctors at the community healthcare center. If they were willing to fill out the survey, we presented respondents with the self and social-health messages together but in a random order for each respondent, and asked them three questions on their perception of the two messages. The survey had a total of 200 respondents. Table 10 shows the distribution of answers.

The first question is on which message describes a more serious and consequential scenario. A total of 63% of the respondents chose the social-health one as being more of a concern, which deviates substantially from a half–half situation. The second question is on which scenario described in the two messages is more likely to occur. The social-health consequence was perceived as being roughly equally likely to happen as the self-health one (49% versus 51%). The combined results for the first two questions are consistent with the distribution of answers to questions 3: a higher share of people (58.5%) reported that the social-health message would be more effective than the self-health one in addressing the issue of antibiotics misuse and overuse. The pattern in this survey suggests that one of the potential mechanisms to social-health messages being more effective is that people perceive the social-health consequences of antibiotic resistance as being more severe than those of self-health.

5 Conclusion

Antibiotic resistance leads to higher medical costs, prolonged hospital stays, and increased mortality, and is rising to dangerously high levels worldwide (WHO, 2018). In a recent report, WHO (2020) warns that there are not enough antibacterial treatments in development to keep up with the growing resistance. Given the global scope of this issue, regulating antibiotics use has important implications for public health.

We conducted a randomized controlled trial to evaluate whether text messages with information on the externality of antibiotics usage could induce behavioral changes. We sent messages once every month for five months to the patients of a community healthcare center in China. In response to the message with information on the social impact of antibiotic resistance, the patients reduced their antibiotics purchases by 17% relative to the control group. Meanwhile, the message with information on self-health consequences had limited impact. This reduction did not come at the cost of any decrease in other observed dimensions of healthcare utilization, including number of visits, examination and service spending, and purchase of other medicines.

As with most experimental work, the interpretation of the results and their wider applicability would depend on the key features of the specific setting. We acknowledge several caveats that might limit the generalizability of our results, such as the relatively high socioeconomic status of the patient sample, and the collectivism culture in the East-Asian society. However, the salience of social cost is common in many issues related to public health; external cost or benefit could far exceed the private ones. Getting vaccination and wearing mask in the COVID-19 pandemic are examples. Insufficient knowledge of the social impact of one's behavior also widely exist in those contexts.

Nevertheless, the results identify a cost-effective means of addressing concerns over antibiotics misuse and overuse, which are particularly serious in developing countries (Okeke et al., 2005; The Economist, 2018). The rapid increase in mobile phone penetration makes text messaging easily scalable, highly inclusive, and cheap to implement. Externality problems like this exist in many other public health issues where the strategy explored in our study could also be a powerful tool. For example, many governments have been attempting to increase the COVID-19 vaccination rates among the population, which is critical in slowing the spread of the virus. People might be more willing to act if they receive relevant information on the social impact of their behavior from an institution that they trust. With the caveats of potential threats to generalizability in mind, this approach might also be relevant for the design of policies to deal with negative externalities in other domains, given that the usual price mechanisms—taxes, subsidies, or punishments—though effective, are much more expensive to implement. The fact that people are willing to correct themselves given a simple nudge provides a means of changing behavior at low cost. This approach is particularly relevant in settings with limited state capacity, where administering a price intervention, in the form of taxes or subsidies, would be difficult.

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Tables

Table 1: Treatment Design

	Control	Treatment 1	Treatment 2
Message: Usual Reminder	✓	✓	✓
Message: Self-Health		✓	
Message: Social-Health			✓

Notes: This table shows the treatment design. There are three types of messages, as shown in the first column. See Section 3.1 for the exact message framing. The control group only receives the “Usual Reminder” message. Patients in Treatment 1 receive both “Usual Reminder” and “Self-Health” messages. Patients in Treatment 2 receive both “Usual Reminder” and “Social-Health” messages.

Table 2: Summary Statistics

	Mean	SD	Min	Max
Baseline Characteristics (8/1/2018 –10/31/2019)				
Male	.42	.49	0	1
Age	53.57	13.10	18	75
Chronic Conditions	.62	.49	0	1
Any Antibiotics	.39	.49	0	1
Times Visited	.85	.93	0.07	9.47
Times: Antibiotics Without Exam	.063	.13	0	2.33
Antibiotics Related Exam: Spending (RMB)	1.44	6.46	0	353.8
Other Exam/Services: Spending (RMB)	38.41	88.28	0	1533.50
Antibiotics Purchases				
Dosage (Days)	.59	1.37	0	35.80
Quantity	.19	.44	0	11.60
Spending (RMB)	2.62	7.30	0	275.04
Other Medicine Purchases				
Dosage (Days)	55.20	82.97	0	794.07
Quantity	91.79	418.39	0	9989.07
Spending (RMB)	405.22	645.27	0	8688.91
Post-experiment Outcomes (12/6/2019 –6/9/2020)				
Any Antibiotics	.19	.39	0	10
Times Visited	.50	.68	0	7.17
Times: Antibiotics Without Exam	.051	.14	0	2.17
Antibiotics Related Exam: Spending (RMB)	1.19	6.74	0	266.67
Other Exam/Services: Spending (RMB)	15.94	55.73	0	648.54
Antibiotics Purchases				
Dosage (Days)	.38	1.14	0	26.17
Quantity	.10	.31	0	6.17
Spending (RMB)	1.14	4.10	0	101.75
Other Medicine Purchases				
Dosage (Days)	40.98	66.31	0	587.33
Quantity	39.48	248.66	0	8895.83
Spending (RMB)	227.00	394.46	0	6994.35
Observations	14063			

Notes: Variables are measured at the monthly average level except for “Male”, “Age”, “Chronic Conditions”, and “Any Antibiotics”. “Chronic Conditions” is an indicator for whether the patient has been diagnosed with chronic conditions. “Any Antibiotics” is an indicator for the purchase of any antibiotics either during the sample collection period or in the outcome collection period. “Times: Antibiotics Without Exam” is the average monthly times of purchasing antibiotics without a set of bacterial infection related exams (details in footnote 10). “Antibiotics Related Exam: Spending (RMB)” is the average monthly spending on the set of bacterial infection related exams and “Other Exam/Services: Spending (RMB)” is the average monthly spending on all other exams and services.

Table 3: Balance Checks

Variable	(1) Control	(2) Treatment 1: Self-Health	(3) Treatment 2: Social-Health	(4) p-value
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	(C = T1 = T2)
Male	0.42	0.41	0.42	0.83
	(0.49)	(0.49)	(0.49)	
Age	53.56	53.54	53.59	0.98
	(13.05)	(13.14)	(13.10)	
Any Antibiotics	0.39	0.39	0.39	0.91
	(0.49)	(0.49)	(0.49)	
Chronic Conditions	0.62	0.61	0.61	0.87
	(0.49)	(0.49)	(0.49)	
Times Visited	0.86	0.86	0.84	0.47
	(0.95)	(0.93)	(0.91)	
Times: Antibiotics Without Exam	0.07	0.06	0.06	0.28
	(0.13)	(0.13)	(0.12)	
Antibiotics Related Exam:	1.40	1.40	1.51	0.64
Spending (RMB)	(7.37)	(5.74)	(6.17)	
Other Exam/Services:	38.28	37.74	39.21	0.72
Spending (RMB)	(88.47)	(83.43)	(92.72)	
Antibiotics Purchases				
Dosage (Days)	0.60	0.59	0.57	0.69
	(1.43)	(1.33)	(1.35)	
Quantity	0.20	0.18	0.18	0.21
	(0.48)	(0.40)	(0.43)	
Spending (RMB)	2.76	2.55	2.54	0.27
	(8.02)	(6.85)	(6.98)	
Other Medicine Purchases				
Dosage (Days)	55.85	55.64	54.10	0.54
	(83.29)	(82.06)	(83.57)	
Quantity	98.03	90.78	86.55	0.41
	(467.49)	(406.01)	(376.56)	
Spending(RMB)	409.16	409.05	397.45	0.6
	(643.76)	(640.85)	(651.24)	
Joint p-value (Treatment 1)				0.96
Joint p-value (Treatment 2)				0.82
Observations	4,683	4,697	4,683	

Notes: To obtain the p-values reported in column 4, we run regressions of the variables of interest on treatment dummies and then perform tests on the hypothesis that the estimates on treatment dummies would be jointly zero. The joint p-value tests whether the covariates are jointly significant as predictors of treatment assignment. All the variables in this table were collected before the interventions (August 1, 2018 to October 31, 2019). Variables are measured at the monthly average level except for "Male", "Age", "Any Antibiotics", and "Chronic Conditions". "Any Antibiotics" is an indicator for the purchase of any antibiotics during the sample collection period. "Chronic Conditions" is an indicator for whether the patient has been diagnosed with any chronic conditions.

Table 4: Effect on Antibiotics Purchases

	Dosage (Days)		Quantity		Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
Message: Self-Health	-.0151	-.0108	-.0061	-.0037	-.1216	-.1050
	(.0235)	(.0217)	(.0063)	(.0059)	(.0846)	(.0793)
Message: Social-Health	-.0763***	-.0704***	-.0161**	-.0143**	-.2946***	-.2864***
	(.0235)	(.0217)	(.0063)	(.0059)	(.0847)	(.0794)
Lag&Age&Gender	N	Y	N	Y	N	Y
p value: T1=T2	.0093	.0060	.1166	.0715	.0409	.0222
Control mean	.4143	.4143	.1074	.1074	1.2812	1.2812
N	14063	14063	14063	14063	14063	14063

Notes: Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

This table reports the impacts on antibiotics purchases in three different measures. The dependent variables are at the monthly average level, that is, cumulative antibiotics purchases post-intervention (December 6, 2019 to June 9, 2020) divided by six. The three outcome variables are dosage (number of days), quantity (unit sold at the pharmacy), and spending (RMB) regarding antibiotics purchases. Lag&Age&Gender indicates controlling for pre-period antibiotics purchases (dosage, quantity or spending), age and gender.

Table 5: Effect on Extensive and Intensive Margins of Antibiotics Purchase

	Positive Purchase		Per Purchase		
	(1) Any	(2) Times	(3) Dosage	(4) Quantity	(5) Spending
Message: Self-Health	-.0036	-.0012	.0809	.0159	-.9329
	(.0077)	(.0027)	(.1848)	(.0491)	(.8956)
Message: Social-Health	-.0103	-.0065**	-.2811	-.0022	-1.9945**
	(.0077)	(.0027)	(.1867)	(.0496)	(.9056)
Lag&Age&Gender	Y	Y	Y	Y	Y
p value: T1=T2	.3807	.0494	.0539	.7170	.2434
Control mean	.1971	.0584	7.0097	1.7830	21.1102
N	14063	14063	2700	2700	2700

Notes: Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, *** $p < 0.01$.

This table reports the breakdown of the intensive and extensive margins of the main result. All dependent variables except that in column 1 are measured at the monthly average level. Outcome in column 1 is a dummy variable for any antibiotics purchase. Column 2 reports the effects on average times of antibiotics purchases per month. Dependent variables in columns 3, 4, and 5 are calculated by dividing the total antibiotics purchased by the times of antibiotics purchases in the post-intervention period, restricting to those who have positive purchases. Lag&Age&Gender indicates controlling for pre-period value of the outcome of interest, age and gender.

Table 6: Effect on Antibiotics Purchases by Examination

	Exam	Without Exam			With Exam		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Spending	Dosage	Quantity	Spending	Dosage	Quantity	Spending
Message: Self-Health	.0107	-.0128	-.0049	-.0961	.0021	.0011	-.0089
	(0.1171)	(.0206)	(.0054)	(.0732)	(.0046)	(.0016)	(.0212)
Message: Social-Health	0.0835	-.0676***	-.0138**	-.2536***	-.0028	-.0006	-.0328
	(0.1172)	(.0206)	(.0054)	(.0733)	(.0046)	(.0016)	(.0212)
Lag&Age&Gender	Y	Y	Y	Y	Y	Y	Y
p value: T1=T2	0.5342	.0077	.1016	.0314	.2908	.2862	.2606
Control mean	1.1350	.3879	.0998	1.1729	.0264	.0076	.1082
N	14063	14063	14063	14063	14063	14063	14063

Notes: Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports the effects on the spending of antibiotics related examinations and antibiotics purchases with and without any of those examinations. A “With Exam” purchase is one where the patient bought antibiotics after undergoing an exam to check for a bacterial infection (up to three days prior to the purchase). The contrary is categorized as “Without Exam”. The outcome variables are at the monthly average level. Lag&Age&Gender indicates controlling for pre-period value of the outcome of interest, age and gender.

Table 7: Heterogeneous Effects by Antibiotics Purchase History

	Antibiotics Purchase		
	(1) Dosage	(2) Quantity	(3) Spending
Panel A. Sample with NO Antibiotics Purchase History			
Message: Self-Health	-.0162	-.0030	-.0573
	(.0167)	(.0047)	(.0594)
Message: Social-Health	-.0293*	-.0060	-.0865
	(.0167)	(.0047)	(.0594)
Age&Gender	Y	Y	Y
p value: T1=T2	.4317	.5149	.6233
Control mean	.1802	.0460	.5339
N	8965	8965	8965
Panel B. Sample with Antibiotics Purchase History			
Message: Self-Health	-.0021	-.0057	-.1934
	(.0519)	(.0138)	(.1911)
Message: Social-Health	-.1426***	-.0289**	-.6354***
	(.0521)	(.0139)	(.1917)
Lag&Age&Gender	Y	Y	Y
p value: T1=T2	.0070	.0955	.0212
Control mean	.8232	.2147	2.5863
N	5098	5098	5098
Panel C. p-value for equal estimates from the two subsamples			
Message: Self-Health	0.8041	0.8558	0.5217
Message: Social-Health	0.0363	0.1196	0.0063

Notes: Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, *** $p < 0.01$.

We categorize an individual as "with Antibiotics Purchase History" if they had purchased any antibiotics during the sample collection period. Panels A and B report the results for the two subgroups separately. Lag&Age&Gender indicates controlling for pre-period value of the outcome of interest, age and gender. Panel C reports the p-values for testing the hypotheses that the coefficients from the two subsamples are equal.

Table 8: Effects on Other Healthcare-seeking Behaviors

	Visits		Exam/Services	Other Med	Diagnosis	
	(1) Any	(2) Times	(3) Spending	(4) Spending	(5) Type Antibiotics	(6) Type Not
Message: Self-Health	-.0085	.0144	1.2845	4.9016	.0504	.1076*
	(.0095)	(.0096)	(.9472)	(5.4801)	(.0380)	(.0566)
Message: Social-Health	-.0075	.0103	1.2412	-2.1773	.0056	.0832
	(.0095)	(.0096)	(.9749)	(5.4843)	(.0380)	(.0566)
Lag&Age&Gender	No Lag	Y	Y	Y	Y	Y
p value: T1=T2	.9207	.6723	.9636	.1965	.2384	.6657
Control mean	.6056	.5002	15.0586	228.0375	1.3598	2.8783
N	14063	14063	14063	14063	14063	14063

Notes: Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The first two columns report the effects on visits, respectively, whether one has visited at all and total number of visits. Column 3 reports the effects on the spending on medical exams and services other than those exams related to bacterial infections, and column 4, the spending on medicines other than antibiotics. Columns 5 and 6 report the effects on diagnosis patterns. “Type Antibiotics” include the illnesses that might require antibiotics for treatment. The illnesses categorized as “Type Not” are those that do not need antibiotics. Outcome variables in columns 5 and 6 are the number of times that a patient’s diagnosis contains Type Antibiotics or Type Not illnesses, respectively. Lag&Age&Gender indicates controlling for pre-period value of the outcome of interest, age and gender.

Table 9: Effects on Substitute and Non-related Medicine Purchases

	Substitutes			Unrelated		
	(1) Dosage	(2) Quantity	(3) Spending	(4) Dosage	(5) Quantity	(6) Spending
Message: Self-Health	.0437	-.0028	.1885	.3486	-6.1180	4.7131
	(.0417)	(.0270)	(.3675)	(.9290)	(4.7687)	(5.4010)
Message: Social-Health	.0041	-.0099	.2876	-.8688	-2.0663	-2.4649
	(.0418)	(.0271)	(.3678)	(.9297)	(4.7725)	(5.4052)
Lag&Age&Gender	Y	Y	Y	Y	Y	Y
p value: T1=T2	.3428	.7930	.7875	.1901	.3956	.1839
Control mean	.9271	.3138	7.0571	40.6002	43.0906	220.9804
N	14063	14063	14063	14063	14063	14063

Notes: Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, *** $p < 0.01$.

This table reports the effects on the purchases of drugs other than antibiotics. The drugs are categorized into two types. “Substitutes” are medicines used to treat the illnesses in category “Type Antibiotics.” Drugs in category “Unrelated” are those that are not related to any illness that could be treated by antibiotics. The outcome variables are at the monthly average level. Lag&Age&Gender indicates controlling for pre-period value of the outcome of interest, age and gender.

Table 10: Mechanism: Survey on Perception of Self- and Social-Health Messages

	Self-Health Message	Social-Health Message	p value for difference from 50%
Q1: Which scenario is more consequential	37.0%	63.0%	0.00
Q2: Which scenario is more likely to occur	51.0%	49.0%	0.78
Q3: Which message will be more effective	41.5%	58.5%	0.02

Notes: This table reports the survey responses from a sample of 200 patients. In the survey, the respondents were presented with both the self- and social-health messages and then asked the following: Q1: Which scenario in the two messages do you think is more consequential? Q2: Which scenario in the two messages do you think is more likely to occur? Q3: Which of the two messages do you think will be more effective in reducing antibiotics misuse and overuse?

Figure 1: Timeline

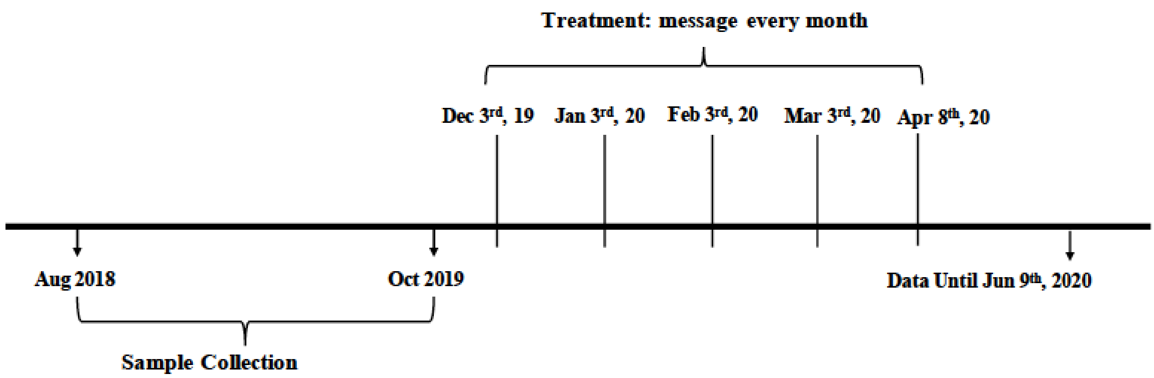
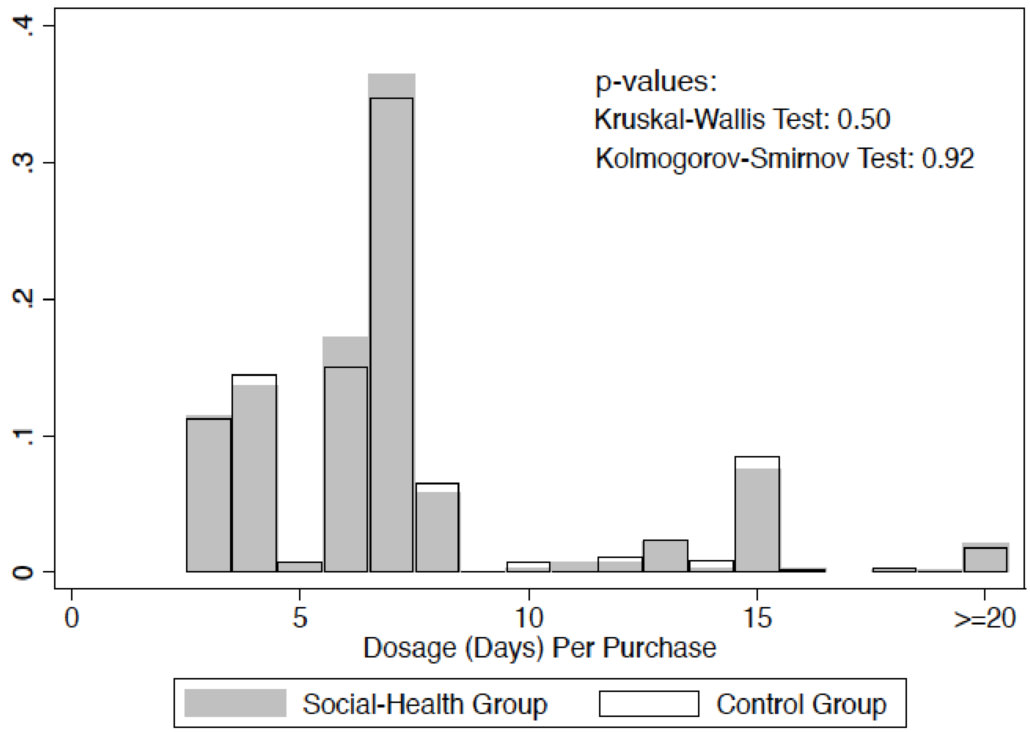
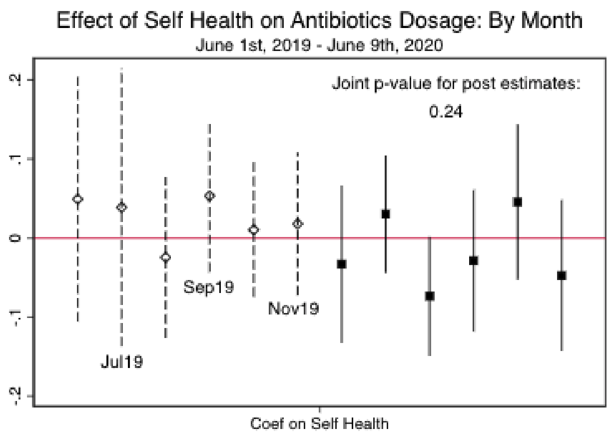


Figure 2: Distribution of Antibiotics Dosage Per Purchase

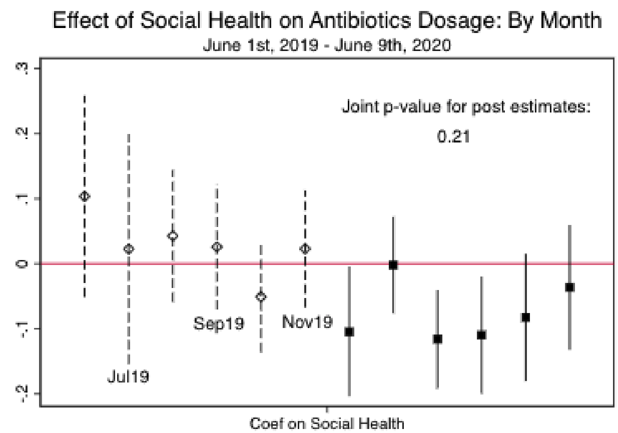


Notes: This figure plots the distribution of antibiotics dosage in each purchase in the post intervention period, for social-health group and control group separately. P-values reported in the graph are from Kruskal-Wallis test and Kolmogorov-Smirnov test, with the null hypothesis being the two distributions are identical.

Figure 3: Time Trajectory of Effects on Antibiotics Purchases (Dosage)



(a) Self-Health Message



(b) Social-Health Message

Notes: This figure plots the effects of the self-health (left) and social-health messages (right) on dosage of antibiotics purchases by month. Each dot is a coefficient estimate from a regression on treatment dummies, pre-intervention antibiotics dosage purchased and randomization block variables. Dependent variables are cumulative antibiotics purchases within a calendar month for the period before the experiment and cumulative purchases between two messages for the period after the first message. The time span plotted in the figure covers June 1, 2019 to June 9, 2020. The figure gives the 95% confidence intervals of the estimates. Estimates with confidence intervals shown in dash lines and solid lines are from the pre-intervention and post-intervention periods, respectively. The joint p-values for post estimates reported in the graph test the hypothesis that all the estimates from the post period are equal.