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Essays on Development and Health Economics

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by

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The Dissertation of Jianan Yang is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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DEDICATION

To my parents.

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ABSTRACT OF THE DISSERTATION

Essays on Development and Health Economics

by

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This dissertation is a collection of three essays on development and health economics. In the first essay, we studied 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 suggests the perceived severity being a potential explanation. The messages were sent once every month for five months, and a gradual decrease in the effect size is observed over time.

The second essay evaluated the affordability and overuse trade-off in pharmaceutical

pricing by studying a drug procurement program in China, which brought down the prices of 10 chronic condition drugs by an average of 78%. Using a difference-in-differences design with a set of comparable drugs as controls, we find that this improvement in affordability led to a significant increase in demand by uninsured patients, whose purchases of treated drugs increased by 28.4% more than the insured. This demand response came both from new and existing medication takers. Drug adherence was improved for the uninsured who had poorer adherence at baseline but overuse was not affected.

The third essay proposes two experiments related to low disease awareness, treatment take-up, and adherence in developing countries. Because of lacking access to primary care services, chronic condition awareness in developing countries is usually low. The first experiment proposes to provide people in low-income areas with physical exams and health reports to examine whether raising disease awareness could increase control. The second experiment proposes to provide patients with information on the expected benefit from treatment including the expected reduction in risk if their condition is under control, and the cost of a major health event. This experiment is designed to test the hypothesis that misperception of treatment benefits is one of the underlying causes for low take-up and adherence rates conditional on disease awareness in developing countries.

Chapter 1

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

1.1 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, 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 et al., 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 (World Health Organization, 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), etc. 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), 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, 2011b). 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 1.2 discusses the background of the study. Section 1.3 describes the research design. Section 1.4 presents the results. Section 1.5 discusses the external validity of the results and concludes.

1.2 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

[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

prescribe antibiotics, which has been argued to be a major driver of antibiotics over-prescribing (Currie et al., 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 World Health Organization (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 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

[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 were sold to patients at the procurement price, with no profits for the 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.

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), all pharmacies, public and private, are only permitted to dispense antibiotics with a prescription.[5] 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 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

[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

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.

1.3 Research Design

1.3.1 Text Message Interventions

Our experiment includes one control group and two treatment groups. The details of the treatment design are shown in Table 1.1. 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 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:

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

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

"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:

"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:

"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 the society to develop 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."

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 1.1. 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.

1.3.2 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 1.2 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-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 1.3 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.

[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).

1.4 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 individual's age, gender and antibiotics purchase history. Treatment is strictly exogenous, conditional on the randomization stratum fixed effects δ_s.

1.4.1 Effect on Antibiotics Purchases

Table 1.4 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 1.5 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 1.5 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 1.2, 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 (Pouwels 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

[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.

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 infections, 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.[10] 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 1.6). 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 1.6). 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 1.7 shows the effects on antibiotics purchases separately for patients who had never purchased any antibiotics (Panel A) and those with antibiotics purchase

[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.

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 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 1.7 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.

1.4.2 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 1.8 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 1.8 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 1.9 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 (World Health Organization, 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.

1.4.3 Time Trajectory of Effect Size

We also pay attention to the evolution of the effects of the two messages over time. Figure 1.3 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.

1.4.4 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 1.10 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.

1.5 Conclusion

Antibiotic resistance leads to higher medical costs, prolonged hospital stays, and increased mortality, and is rising to dangerously high levels worldwide (World Health Organization, 2018). In a recent report, World Health Organization (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.

1.6 Acknowledgments

This chapter, in part, is currently being prepared for submission for publication of the material. He, Daixin; Lu, Fangwen; Yang, Jianan. "Impact of Self- or Social-regarding Health Messages: Experimental Evidence Based on Antibiotics Purchases." The dissertation author was a primary investigator and author of this material.

1.7 Tables and Figures

Table 1.1: 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 message, as shown in the first column. See Section 1.3.1 for the exact message framing. The control group will only receive 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 1.2: 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	.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 1.3: Balance Checks

Variable	(1) Control	(2) T1: Self Health	(3) T2: 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 Spending (RMB):	1.40	1.40	1.51	0.64
	(7.37)	(5.74)	(6.17)	
Other Exam/Services Spending (RMB):	38.28	37.74	39.21	0.72
	(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 1.4: 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

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: 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 1.5: 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

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: 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 1.6: Effect on Antibiotics Purchases by Examination

	Exam	Without Exam			With Exam		
	(1) Spending	(2) Dosage	(3) Quantity	(4) Spending	(5) Dosage	(6) Quantity	(7) 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

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: 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 1.7: Heterogeneous Effect by Antibiotics Purchase History

Panel A. Sample with NO Antibiotics Purchase History			
	Antibiotics Purchase		
	(1) Dosage	(2) Quantity	(3) Spending
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

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: 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 1.8: Effect 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

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: 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 1.9: Effect on Substitute and Unrelated 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

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: 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 1.10: Mechanism: Survey on Perception of Self and Social Health Message

	Self Health Message	**Social Health Message**	**p value for difference from 50%**
Q1: Which scenario is more consequential	37%	63%	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?

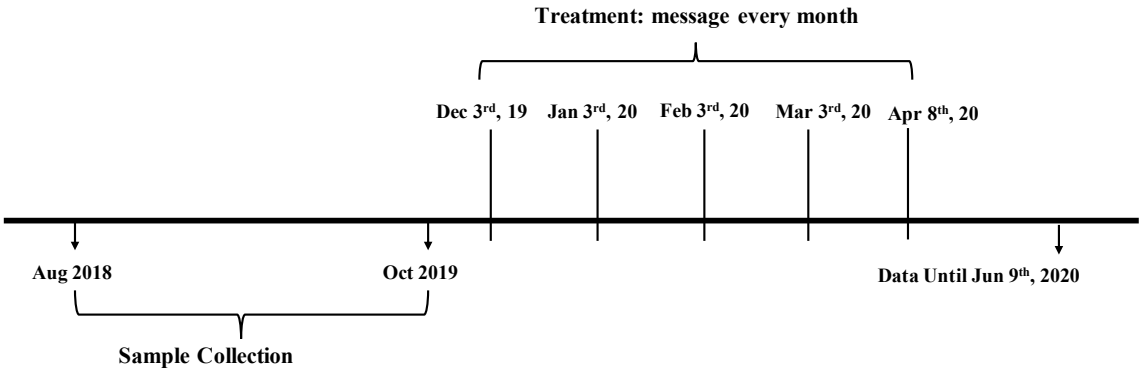


Figure 1.1: Timeline

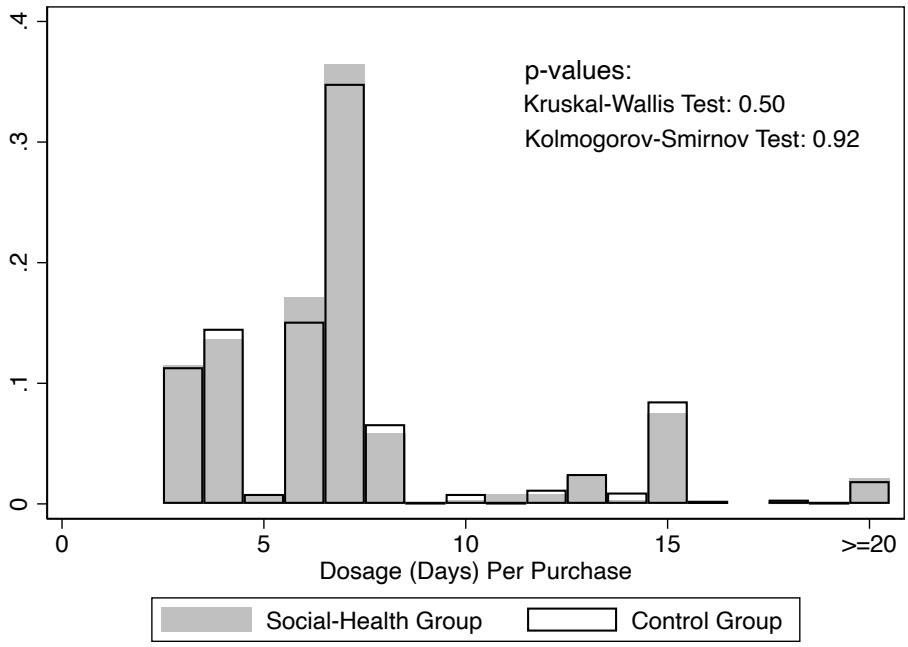
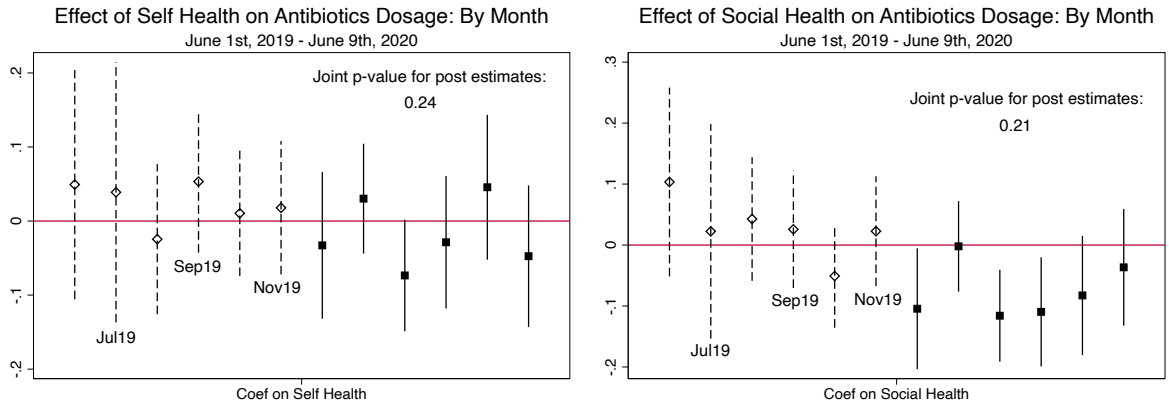


Figure 1.2: Distribution of Antibiotics Dosage Per Purchase

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.



(a) Self Health Message

(b) Social Health Message

Figure 1.3: Time Trajectory of Effects on Antibiotics Purchases (Dosage)

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.

Chapter 2

Affordability versus Overuse: Evidence from a Prescription Drug Price Reduction in China

2.1 Introduction

Globally high and rising pharmaceutical prices are challenges faced by both governments and patients (Abbott, 2016). While government interventions to lower drug prices may improve affordability, the possible costs include squeezing out innovation incentives and the risk of overuse of drugs. The possibility of overuse has both been argued theoretically (Arrow, 1963; Pauly, 1968) and documented empirically by the existence of moral hazard in healthcare settings (Einav and Finkelstein, 2018). In particular, patients may increase the utilization of low-value or even unnecessary care in response to lower out-of-pocket costs (Newhouse and the Insurance Experiment Group, 1993; Iizuka and Shigeoka, 2018).

In developing countries, both the affordability and overuse concerns are amplified. On one hand, the cost of care may seem exorbitant for the low income, given the potential crowd-out of basic necessities (Dupas, 2011b; Gross et al., 2020; McIntyre et al., 2006). Further, low insurance coverage exposes patients to higher out-of-pocket costs (Pauly et al., 2006; Habib et al., 2016). On the other hand, the concern of overuse is also greater since healthcare markets in developing countries are usually characterized by providers' gate-keeping function

being poorly performed, leading to unregulated supply of prescription drugs (Das et al., 2016; Zhao et al., 2021). As a result, the affordability and overuse trade-off is more salient and needs to be carefully evaluated as making drugs affordable is an increasingly urgent task for governments in the developing world due to its vital necessity for public health (World Health Organization, 2017b). However, there is little evidence on this trade-off for developing countries in prescription drug settings.[1]

In this paper, we evaluate this trade-off by studying a national drug procurement program in China. The idea of the program was to increase buyers' bargaining power by demand aggregation. In the pilot stage in 2019, with demand aggregated from 11 major Chinese cities with a total population of 130 million, the program successfully negotiated down the price of 25 commonly prescribed drugs by an average of 52%.[2] Following the success of the pilot, this reform got quickly expanded for the whole country and as of August 2021, four more rounds of procurement were conducted, affecting an additional 194 drugs.

We focus on the 10 drugs for chronic conditions related to the cardiovascular system in the pilot stage. The conditions treated by the 10 drugs are Hypertension (HTN), High Cholesterol (HC), and Atherosclerosis, among the most common chronic conditions people suffer from. Because those conditions require long-term medication with as little interruption as possible, drug adherence and overuse could then be measured by tracking patients' prescription refills. The incentives of patients and the social planner should also in principle coincide in this case because these conditions are not contagious and medication does not generate drug resistance concerns. The 10 drugs we study are all off-patent drugs and the negotiation mainly happens with domestic generic drug producers.[3] The average price drop of the 10 drugs in our

[1] There is evidence from over-the-counter health products (bednets, water purification kits and antimalarials). Studies on the pharmaceutical price control policies in India (Dean, 2019; Mohapatra and Chatterjee, 2021) have mainly focused on the strategic responses from the pharmaceutical companies.

[2] Drugs are considered at generic name (chemical compound) level during the procurement process. Throughout this paper, we refer to a drug by its generic name.

[3] The focus of this paper is primarily on the impacts on patient behavior. However, the fact that this is done in the context of generics suggests that the innovation incentive margin is less likely to be affected.

study context is 78%.[4]

However, there are known to be many non-price barriers to the adoption of high-return health products, making it ex-ante unclear to what extent improvement in affordability could increase utilization. Empirical evidence has shown that individuals' willingness to pay could be much lower than their expected benefits among the low-income population (Finkelstein et al., 2019) and in developing countries (Dupas, 2011b; Banerjee et al., 2010). Lack of trust (Lowes and Montero, 2021) and information (Dupas and Miguel, 2017) are two important constraints. In our particular setting, behavioral bias could also play an essential role. Because chronic condition medication does not provide immediate symptom relief but mainly lowers the future risk of health shock, salience and present bias will lead to underutilization as in the case of preventative care (Baicker et al., 2015; Bai et al., 2017; Carrieri and Bilger, 2013). The awareness of these chronic conditions is also found to be low, further adding to the ambiguity of whether the cost is a key barrier to take-up. Therefore, the magnitude of demand response is an empirical question.[5]

Using as controls a set of drugs that also treat chronic conditions but belong to different therapeutic classes than the treated drugs, we implement a difference-in-difference strategy to identify the effect of this program. We define all drugs that belong to the same therapeutic class as the price-reduced drugs as treated and the classification is based on the Anatomical Therapeutic Chemical (ATC) code system from the World Health Organization (WHO) and medical treatment guidelines.

We split the sample by their insurance status and examine both the absolute and differential responses of the insured and uninsured. The uninsured are not only paying the full cost out-of-pocket, but are also more likely to be the migrant workers without formal sector

[4]This is calculated by comparing the prices of the bid-winning drugs and that of the most popular drugs sold under the same generic name before the reform, which are primarily brand name drugs by multinationals. Thus it is mainly a reduction in markups due to monopolistic power.

[5]Lu et al. (2017) shows that in a large-scale population-based screening project among adults aged 35-75 years in China, only 44.7% of those who have hypertension were aware of their diagnosis. Similar rates of awareness are documented in other developing countries (Chow et al., 2013; Mirzaei et al., 2020).

jobs and earning lower wages. In contrast, insured patients have a coinsurance rate of 10% after a deductible and are more likely to have higher income.[6] For an uninsured patient with one chronic condition in our sample, the average drug cost could take up 9.5% of the monthly income for someone located at the 20th percentile of the income distribution in our study area.[7] 78% price reduction would thus meaningfully increase affordability to the uninsured.

Drug purchases were measured from the visiting records of more than 300 community healthcare centers covering one entire district in Beijing. The district has a population of over 3 million and in the two-year period that our data covers, we observe the visiting record of 1.4 million patients. The community healthcare centers are the major healthcare facilities providing care for chronic conditions.[8] The community healthcare centers do not generate any revenue from drug sales following the Zero Markup Policy (ZMP) implemented in 2017, which requires that medicines be sold to patients at the purchase price. This data allows us to track patients' prescription refills over time and thus we can measure treatment adherence at the individual level.

We first document a stronger demand response from the uninsured than from the insured. The uninsured, who experienced greater improvement in affordability, increased purchases of drugs in the treated therapeutic classes by 28.4% more than the insured, for whom the absolute response is insignificant. Breaking down the total effect, we find that the increase in drug purchases from the uninsured was largely driven by the increases in the number of prescriptions with the treated drugs and the number of patients purchasing them (accounting for 94.2% of total effect), as opposed to an increase in dosage purchased per prescription. A

[6]There are three types of public health insurance in China. The type of insurance patients are covered under is determined by the employment and Hukou registration status and thus is not subject to individual's preference. Those with formal sector jobs have the insurance with the most generous coverage. In the main analysis, we consider those with the most generous insurance coverage as the "insured" sample.

[7]Monthly drug cost is estimated using the pre-period monthly drug expenditure of the insured. The 20th percentile of monthly income is RMB1993.8 in 2018 according to Beijing Municipal Bureau of Statistics (http://tjj.beijing.gov.cn/tjsj_31433/yjdsj_31440/jmsz_32036/2018/202002/t20200217_1647256.html).

[8]Nationwide public health facilities delivers 90% of healthcare services and account for around 80% of drug sales (Yip et al., 2012). Prescription drugs are even more frequently filled at public health facilities.

further decomposition shows that 37.6% of the overall increase in drug purchases came from patients purchasing those drugs for the first time in the uninsured group. This implies that the price reduction brought in new patients to initiate the treatment, and meanwhile boosted the demand from the patients who had been undergoing treatment before the program. The stronger response from the uninsured suggests that the program achieved its goal of making drugs affordable and cost is a key barrier to the take-up of medication for those in need.

To measure drug adherence and overuse, we borrow a measure from the medical literature - Medication Possession Ratio (MPR) (Peterson et al., 2007), which is calculated by dividing the dosage purchased (days) over the days between two prescription refills. We use the average maintenance dose per day provided by the ATC classification system to convert the drug purchases into the number of days it can cover. For the set of chronic conditions we study, patients are supposed to be on long-term medication, which implies an optimal benchmark of MPR being 1.

Regarding the effect of the program on drug adherence, we find a significant reduction in drug underuse for the uninsured and a corresponding increase in the likelihood of being around the clinically optimal level as measured by MPR. Regression analysis shows that the shift in MPR distribution mainly happened in prescriptions with MPR below 0.77 moving to between 0.77 and 1. Quantifying the effects on mean MPR by the difference-in-difference framework, the program closed 19.9% of the gap in drug adherence of treated drugs between the insured and uninsured. There is better drug adherence for both the new and existing drug takers for the uninsured.

If anything, there was a shrinkage of the upper tail of the distribution for MPR, showing that the overuse was not exacerbated by the price reduction. For the uninsured, we find that the distribution of MPR anywhere greater than 2 was not affected. For the insured, there were actually reductions in the likelihood of prescriptions with any MPR larger than 2. In particular, the likelihood of MPR greater than or equal to 4 decreased by 0.005, a 7.7% reduction of

baseline. This likely reflects a reduction in hoarding or reselling, because the price reduction lowers the dollar value difference in the out-of-pocket cost of the insured and the retail price.

This paper makes several contributions to both research and policy. First, we contribute to the literature on the price responsiveness of prescription drugs. In particular, we document a stronger responses from the uninsured, suggesting that elasticities among the low-income population and in developing countries might be different from a high-income, highly-insured setting. With many people lacking insurance, the extensive margin response driven by increases in the number of patients seeking care can be sizable. Most of the existing evidence documents moderate elasticities and is from high-income countries based on the discontinuous change in insurance plan coverage (Goldman et al., 2004; Einav et al., 2015, 2018). Our findings also relate to the literature on the low take-up of potentially cost-effective health services and products in developing countries (see Dupas and Miguel (2017) for a review). And our evidence confirms the importance of price as a key barrier to the take-up of effective healthcare (Finkelstein et al., 2019).

The reason why there is no increase in overuse is worth discussing for consideration of the generalizability of the finding. The first possibility is that the Chinese healthcare system is playing an exceptionally good role as gatekeepers for preventing over-prescription. However, given the scale of antibiotics over-prescription (Zhao et al., 2021), and the fact that the MPR distribution has a long right tail, good gatekeeper is not likely to be the story. Another plausible explanation is that chronic condition patients often suffer from biases that lead to below-optimal drug utilization. And lower prices correct for them.

In a related manner, this study highlights the heterogeneity in the tradeoff between affordability and overuse among different health products and services. While overuse is often discussed in a broad way (Arrow, 1963; Pauly, 1968; Finkelstein et al., 2012; Brot-Goldberg et al., 2017; Einav and Finkelstein, 2018; Iizuka and Shigeoka, 2018), it depends crucially on the nature of the illnesses and treatment, and in particular, the specific biases that lead to

sub-optimal utilization. For treatment of chronic diseases, the concern for overuse might be second-order relative to affordability, given the high cost-effectiveness of treatment (Park et al., 2017) and the behavioral biases that often lead to under-utilization (Baicker et al., 2015). This also relates to the discussion of value-based health insurance design (VBID) (Chernew et al., 2007), which argues for cost-sharing to vary by the value of services or products instead of a uniform coinsurance schedule.

On the policy side, we provide the first evidence on the impact of the government using its bargaining power to negotiate down drug prices from a developing country setting. High and rising pharmaceutical price is a growing challenge for all countries (Abbott, 2016). Drug productions exhibit increasing returns to scale and thus governments countervailing bargaining power to negotiate down the rents might lead to welfare gains, especially for the off-patent drugs.[9] Chronic conditions impose an increasingly heavy burden for not only the developed countries but also the developing world as a result of demographic and epidemiological changes (Bollyky et al., 2017). They are the leading cause of death and a significant challenge to development due to the loss of productive life years (World Health Organization, 2011; Stevens et al., 2016).

The rest of the paper is organized as follows. Section 2.2 discusses the background. Section 2.3 presents a conceptual framework. We describe the data and research design in Section 2.4 and the result in Section 2.5. In Section 2.6 we discuss the policy implications and conclude.

[9]This would, however, rely on assumption that the chosen length of the patent provides the optimal trade-off in innovation incentive and efficiency loss from market power. In fact, Morgan et al. (2020) argues drug prices often exceed reasonable compensation for firms' investment in research.

2.2 Background

2.2.1 Chronic Condition Drugs and National Procurement Program

Drugs in developing countries are often found to be beyond the reach of the people who need them most due to cost (Silverman et al., 2019). The missing "patent cliff", characterized by elevated prices and high market shares of brand name drugs even after the generics are legally introduced to the market, is often observed in the pharmaceutical markets of developing countries as a contributing factor to the high drug prices (Danzon et al., 2015). Prevalence of substandard and falsified medicines leads to the low competitiveness of generics, which further dampens patients' trust in domestically produced cheaper substitutes on top of the issue of asymmetric information that patients usually face when seeking healthcare. China is no exception. In our data coverage period before the reform (Mar-Dec 2018), Lipitor, the brand name drug of atorvastatin (chemical name) by the famous multinational Pfizer, took up 80% of the market share of atorvastatin, and 47% of the market share of all statins in spending, even though the brand name drug had lost its patent protection for almost 7 years (since November 2011). And the most popular branded generics cost around only half of the price of the brand-name drug with the same packaging, dosages, and strengths. The 10 chronic condition drugs we study all had similar market structures at the time that the centralized procurement program was carried out.

Like the rest of the world, China is facing an increasing burden of chronic diseases, and the fact that it usually requires continuous treatment imposes high economic burdens for households (World Health Organization, 2011). Chronic conditions related to cardiovascular systems including hypertension (HTN) and high cholesterol (HC) are becoming increasingly common among the population, for which proper and timely treatment is essential and effective in preventing costly complications including stroke and heart attack. Yet the level of treatment is low - according to several studies, only around 30.1% of people in China with hypertension

are taking prescribed antihypertensive medications (Lu et al., 2017).

As an effort to make drugs more affordable to patients, and also to contain the rising healthcare expenditure, in November 2018, the Chinese National Healthcare Security Administration announced that a National Procurement Program would be launched and it would be first piloted in 11 major Chinese cities. Before this program, procurement and negotiation were usually conducted at the provincial or municipal level. The idea is to increase buyers' bargaining power by aggregating demand from previously segmented markets. Besides, this program would also lower the transaction cost due to decreases in the procurement processes each pharmaceutical company needed to go through. To further create incentives for the bidders to offer lower prices, the bid winning drugs would be included in the National Reimbursement Drug List (NRDL), and were promised 60-70% of the market share of all public healthcare facilities in the participating regions.[10] The benefits from winning the bid for pharmaceutical companies were truly meaningful - it came not only from the huge population size in China, but also the fact that the basic public health insurance now covers 95% of the population, and public healthcare facilities deliver more than 90% of the country's healthcare services (Yip et al., 2012). The program also has a component for quality control - the eligibility of making a bid includes a requirement for the generics having passed the "Generic Quality Consistency Evaluation (GQCE)".[11] Passing the evaluation implies the generic is bioequivalent to the original drug. Though there are debates about the equivalence in actual clinical efficacy, in principle generics are considered equal substitutes for the corresponding brand name drugs once passed the GQCE.[12]

The 11 major cities in the pilot have a total population of around 1.3 hundred million. A total of 25 drugs specified at the chemical compound level were included in the pilot, of

[10]State Council of the People's Republic of China, Jan 1st, 2019. http://www.gov.cn/zhengce/content/2019-01/17/content_5358604.htm

[11]State Council of the People's Republic of China, Feb 6th, 2016. http://www.gov.cn/zhengce/content/2016-03/05/content_5049364.htm

[12]Food and Drug Administration. Generic Drugs: Questions & Answers: https://www.fda.gov/drugs/questions-answers/generic-drugs-questions-answers

which 10 drugs are for cardiovascular system related chronic conditions. On Dec 17th, 2018, the list of bid-winning pharmaceutical manufactures was announced, together with the drug strengths, packaging, and retail price. In Beijing, the context of our study, the reduced-price drugs became available to patients in all public healthcare facilities on Mar 22nd, 2019. The reform got quickly rolled out to the rest of the country in September 2019. As of August 2021, there had been 4 rounds of subsequent procurement conducted, affecting an additional 194 drugs. And the private retail drugstores were also allowed to participate in the program starting from the second round.

The program successfully achieved its goal of lowering drug prices. The 25 drugs included in the pilot had an average price decrease of 52% according to the official document. As for the 10 chronic condition drugs this study focuses on, compared with the most popular brand name versions before the reform, the observed average price drop in our study context is 78.6%. The maximum price drop is 96.5% from Amlodipine Besylate Tablets, a commonly used drug for high blood pressure. 9 out of the 10 chronic drugs contracts were won by domestically produced generics, except for fosinopril sodium tablets. Bristol-Myers Squibb Company, the producer of the originator drug known under the brand name "MONOPRIL", won the bid with a price cut of 69.2%. Drugs included in the program are mainly those that have a high overall demand among the population.

2.2.2 Public Health Insurance and Community Healthcare Center

Since 2003, China has started to introduce universal basic healthcare coverage for the entire population. According to government statistics, as of 2018, 95% of the citizens are covered by some form of public basic health insurance.[13] There are a total of three different types of public health insurance, one for rural residents, called New Rural Cooperative Medical Scheme (NRCMS), and two for urban residents, named Urban Employee Basic

[13]Source: National Healthcare Security Administration http://www.nhsa.gov.cn/art/2019/10/15/art_26_1852.html

Medical Insurance (UEBMI) and Urban Resident Basic Medical Insurance (URBMI). UEBMI is provided to those with formal sector jobs and is funded by payroll deduction, employer contributions, and government subsidies. URBMI is designed for other urban residents, including children, the elderly, and the self-employed. URBMI and NRCMS are both funded by individual premiums and government subsidies. The way insurance type is determined leaves almost no room for individual choice. The public health insurance fund is usually managed at the provincial level and thus coverage details for the same type of insurance have substantial variations across regions. Another issue that comes with unintegrated management is a barrier to getting insurance coverage in locations other than one's registration place. As a result, though 95% of citizens are covered by public insurance, many people still need to pay the full cost out-of-pocket when seeking care, especially for the migrant workers who have their insurance registered at home and do not have a formal job in the big cities. In fact, we observe 24% of the sample in our data showing up as having no insurance coverage, who are highly likely to be the migrant workers in Beijing. There are no financing options available - patients need to pay all the out-of-pocket cost at the point of care.

Beijing, the context of this study, is one of the most economically developed provincial units in the country and thus offers more generous insurance coverage for its residents. The specific area that our community healthcare centers are located in is an urban area without any rural administrative region. Therefore the local residents would be covered by either one of the two types of insurance for urban residents. The coverage details for UEBMI and URBMI at the primary care facilities are shown in Table 2.1. There is an annual deductible that the out-of-pocket payment needs to reach before patients enjoy the low coinsurance rate. For people with UEBMI, the coinsurance is 10%. The coverage is less generous for URBMI patients, featuring a higher coinsurance and lower maximum benefit.

Community healthcare centers are state-owned, not-for-profit primary care facilities. They provide residents with basic healthcare services, and chronic disease management is one

of their major services. The prescriptions for the set of chronic condition drugs we study are most likely to be filled at these centers due to the following reasons. First, in Beijing, these centers are densely located and private drugstores do not have the advantage in accessibility except for their longer hours of operation than the public facilities. Over 90% of all residents in Beijing have access to a community healthcare center within 1km of their residence. Second, they offer lower prices than other private retail drugstores even before this national centralized procurement program, because these centers' pharmacies get their drug stocks through a city-level procurement platform. The public centers, in contrast to retail drugstores, have a zero mark-up on drug sales, due to the Zero Markup Policy (ZMP), a policy that has been in place for all public healthcare facilities in Beijing since Apr 8th, 2017.[14] Thirdly, patients with public insurance only need to pay their copayment part at the time of care at those centers, a feature that is not available at all private drugstores. And the coinsurance rate under the public health insurance for medicine spending is lower at these community health care centers compared to other (secondary or tertiary) hospitals. Finally, due to the lack of competitive advantage on those basic prescription drugs, private retail drugstores usually specialize in over-the-counter drugs or some higher-end prescription drugs that are not available in public healthcare facilities.

2.3 Conceptual Framework

In this section, we will present a conceptual framework to briefly discuss some primitives that could be driving the outcomes and their welfare implications.

Let us consider a simplified setup in the spirit of human capital theory (Grossman, 2000) with health as a commodity that households value in itself. For those who are diagnosed with the chronic conditions we study, pharmaceutical treatments are similar to preventive care in that they lower the risk of future severe health events (for example, strokes and heart attacks).

[14]The Zero Markup Policy is first brought up in the national medical and healthcare system reform guidelines in 2009 (http://www.gov.cn/zwgk/2009-04/07/content_1279256.htm). The policy is implemented in Beijing on Apr 8th, 2017 (The People's Government of Beijing Municipality 3/22/2017: http://www.beijing.gov.cn/zhengce/zhengcefagui/201905/t20190522_60088.html).

Let s_t indicate the occurrence of such health events, meaning that utility will be a decreasing function of s_t.[15] Suppose that the disutility from the health shock is x. In each period, health shock occurs with probability π_t. We will consider medication taking (med_t) as a continuous variable with support being [0,1]. med_t being 0 indicates non-takeup and 1 indicates fully adhering to the treatment regimens. For simplicity, we consider a two period problem, where households take π_0 as given and consume all their endowment in period 1. Assuming that utility is additively separable, the household problem could then be described as follows:

$$\max_{c_0, med_0} U(c_0, s_0) + \delta \mathbb{E}_0[U(c_1, s_1)] \tag{2.1}$$

$$U(c, s) = u(c) - \mathbb{1}(s)x \tag{2.2}$$

$$s.t.\ c_0 + p_m med_0 = w \tag{2.3}$$

$$\pi_1 = f(\pi_0, med_0) \tag{2.4}$$

We assume that the utility function is well-behaved.[16] δ is the discount factor. Equation (2.3) describes the budget constraint, where w represents the endowment in each period. With the price for consumption being our numéraire, we denote the price for medication with p_m. Equation (2.4) describes that the probability of health shock in period 1 (π_1) is a function of both π_0 and med_0.[17] Then the household will choose to take the medication if

$$u'(w)p_m \leq \delta[-xf'_{med}(\pi_0, 0)] \tag{2.5}$$

[15] s_t should be thought of as an adverse health shock that lowers the household's existing health stock, which we do not model explicitly.

[16] $U'(c) > 0$ and $U''(c) < 0$

[17] We can reasonably assume $f'_{\pi} > 0$ and $f'_{med} < 0$. And for tractability, we assume $f''_{med} = 0$ in equations (2.5) and (2.6), i.e. the return to medication is constant.

If there is interior solution, the optimal level of medication needs to satisfy the following condition

$$u'(w - p_m med_t^*)p_m = \delta[-xf'_{med}(\pi_0, med_t^*)] \tag{2.6}$$

Intuitively, patients will take medication up to the point where marginal cost equals the marginal benefit from treatment. The model first implies that the uninsured in our context are more likely to choose not to take medication at baseline.[18] They face higher out-of-pocket prices (p_m) and lower endowment levels (w) and thus higher marginal utility of consumption, which together makes the participation constraint (2.5) less likely to hold.

A reduction in p_m will generate increased medication utilization through both an income and substitution effect by reducing the relative price of medication and expanding the household's budget set. On the extensive margin, we should expect an increase in takeup. On the intensive margin (those who have been undergoing treatment before the price reduction), the model predicts an increase in drug utilization if the individual had not been fully adhering to their treatment regimens.

There are potential inefficiencies in the demand response because the private cost and privately perceived benefit from treatment might deviate from the social costs and benefits. In this setting, wedges between private and social costs and benefits can arise through several channels. The first is the traditional moral hazard issue. With insurance, the out-of-pocket cost of medication (p_m) is lower than the price paid by the society, which leads to overuse of medication because the cost of the individual's excess usage is spread over all other insurees or governments in cases of government subsidized social insurance.

In our empirical context, one of the primary populations of interest is the uninsured.

[18] In a population-based screening project covering 1.7 million adults in China, Lu et al. (2017) documented that among people with hypertension, no insurance coverage, lower household income and education level are strong predictors for not getting treated for the condition. In particular, the odds ratio of getting treatment for the uninsured is 0.76 relative to the insured.

Note that the prices the uninsured pay for pharmaceutical treatments coincide with the prices the government pays to manufacturers. For this population, we are thus analyzing a case in which the social and private cost of treatment decline together, which eliminates the standard moral hazard consideration. As discussed below, however, there are additional reasons why these individuals might engage in either over-use or under-use of care.

Even among the insured, however, the welfare losses from the moral hazard response could be counteracted if there are wedges between private and social benefits that tend to cause underutilization. In the context of chronic condition treatment, this is indeed the most frequently discussed issue by health practitioners and policymakers. Pharmaceutical treatment is highly cost-effective in preventing costly complications, yet the treatment take-up and adherence are low.[19]

The wedge between social and private benefits could first come from the fact that the cost of health events is usually partly borne by the society, as there are increasing efforts to provide protection for catastrophic health expenditure by social insurance (Xu et al., 2007; World Health Organization, 2005). Secondly, lower-income individuals are documented to have lower willingness to pay for a Quality-Adjusted Life Year (QALY) (Martín-Fernández et al., 2014), while in consideration of health equity the society imposes equal value for QALY regardless of gender, race, socioeconomic status.[20] Both of these considerations raise the possibility that individuals may undervalue the cost of adverse health events (x in our framework) relative to the value assigned to such events by society and thus undervalue the benefit of the risk reduction from pharmaceutical treatments.

Finally, behavioral hazard, which argues that people may make mistakes in healthcare utilization (Baicker et al., 2015), might also result in privately perceived benefit different from

[19]Park et al. (2017) shows that all antihypertensives were cost-effective by summarizing the abundant evidence from randomized controlled trials. Yet in China, Lu et al. (2017) shows that only 30.1% of those who have hypertension were taking prescribed antihypertensive medications.

[20]Cost-effectiveness for health interventions is usually accessed by the cost per Disability-Adjusted Life Year (DALY). WHO: Cost-effectiveness analysis for health interventions: https://www.who.int/heli/economics/costeffanalysis/en/

social benefit of treatment. It has been documented that patients respond to small increases in copayment by reducing highly cost-effective treatment, which can not be reconciled with a rational household model without the behavioral factors (Brot-Goldberg et al., 2017; Chandra et al., 2010, 2021). Salience and time inconsistency ($\delta < \delta^{social\ planner}$) are the first possible contributors to this wedge because chronic conditions like hypertension and high cholesterol do not have salient symptoms and because the benefits of treatment may only be realized in future periods. Besides, households might fail to assess the true risk reduction brought by medication ($f'_{med} \neq f'^{actual}_{med}$). In the discussion before, for simplicity, we assumed f to be a linear function of *med*, but clinically, f could take a more complicated form with increasing returns to medication as patients get closer to full adherence. Failure to understand how adherence specifically enters the production function f could lead to under-utilization even conditional on take-up.[21]

With all the forces discussed above, the welfare implications from the increase in medication utilization is ambiguous. In the empirical analysis, we will use the Medication Possession Ratio (MPR) as the measure for rational drug utilization and examine how the price reduction shifts the distribution of MPR.

2.4 Data and Empirical Strategy

2.4.1 Data

Our primary data source is the transaction records from all community healthcare centers in one administrative district of Beijing, covering the period of 3/23/2018-3/22/2020, which is one year before and one year after the implementation of the program. The administrative data allow us to accurately measure drug purchases, our primary outcome of interest. For each visit, the data records the patient's age, gender, diagnosis, drugs purchased, and examinations,

[21] Zhou et al. (2018) shows that treated but uncontrolled hypertensive patients were still at significantly higher risk of mortality than normotensives, but treated and controlled hypertensive patients were not. In a multinational study, Chow et al. (2013) shows that only 32.5% of those under antihypertensive treatment had their blood pressure controlled. In China, the corresponding number is 23.9% (Lu et al., 2017).

services acquired. Apart from total spending, the data also show the breakdown of out-of-pocket and insurance-covered portions, from which we identify the insurance scheme each patient is covered under, though it is not directly reported in the data.

For each entry of drug purchases, the data records the generic name of the drug, the strengths, packaging, unit price, and total quantity purchased. With this information, we are able to measure the total dosage purchased for drugs under the same generic name in a unified way (the most common unit is milligrams). For example, for an atorvastatin purchase record with drug strength being "20mg/tablet" and packaging being "7 tablets/bottle", we record the dosage purchased in this transaction as 140mg if the patient purchased 1 bottle, 280mg if 2 bottles, and so on.

To characterize the relationship among drugs under different generic names, we complement the administrative data with the Anatomical Therapeutic Chemical (ATC) Classification system from the World Health Organization.[22] Under this system, a unique code is assigned to each medicine (at the chemical compound level) according to the organ or system on which they act and their therapeutic, pharmacological, and chemical properties. The code has a total of five levels. Two drugs that only differ in the fifth level ATC code would be considered close substitutes for each other. For example, the ATC code is "C10AA05" for atorvastatin and "C10AA07" for rosuvastatin. Both are statins ("HMG CoA Reductase Inhibitors") that lower cholesterol levels and work by blocking a substance the body needs to make cholesterol. We manually match all the drugs treating cardiovascular system related chronic conditions and diabetes to their corresponding ATC codes. With this information and medical treatment guidelines for HTN, HC, and Diabetes, we are able to classify drugs commonly used for these three conditions into therapeutic classes (see Appendix 2.A for details).

In the ATC classification system, Defined Daily Dose (DDD) are assigned for some medicines given an ATC code. DDD is defined as the assumed average maintenance dose per

[22] Anatomical Therapeutic Chemical (ATC) Classification: https://www.who.int/tools/atc-ddd-toolkit/atc-classification

day for a drug used for its main indication in adults. With this information, we are able to convert the unified measure of drug dosage purchased into dosage measured in the number of days that the drug can cover, which yields a measure that is comparable across drugs under different generic names and also easier to interpret. For example, the DDD for atorvastatin is "20mg". So a purchase of 280mg will be equivalent to 14 days of dosage purchased. We use this as the main outcome of interest in the drug level analysis.

Table 2.2 presents the summary statistics at the patient (Panel A) and drug levels (Panel B, C, and D). The patient level statistics show that more than half of the patients (58%) are men and the average age is 51 years old. Around 36% of the sample have purchased at least one of the 10 treated chronic condition drugs during the sample collection period, indicating that consistent with the policy document, the drugs included in the reform are indeed commonly used drugs among patients. Patients with UEBMI take up more than half of the sample (53%) and even though 95% of people in China are covered by some form of public health insurance as stated in official statistics, there are still 24% of patients showing up as having no insurance coverage. As mentioned earlier, they are likely to be migrant workers in Beijing without a formal sector job. A sufficient share of patients seeks care for chronic conditions at these primary care facilities. Of the several conditions we study, hypertension is the most common one, which 28% of the patients have been diagnosed with.

We aggregate the total dosage (days) purchased of each drug (at chemical compound level) by year-month to estimate the effect of the price change on overall drug purchases. Drug level statistics (Panel B, C, and D in Table 2.2) show that the dosage purchased by patients with UEBMI is much higher than twice that by the uninsured, though the share of patients with UEBMI is around twice the share of uninsured from the patient level statistics. This implies that on a per capita basis, the uninsured are purchasing much fewer drugs than the insured. The average daily dosage cost per drug is RMB 5.86 for the insured. The out-of-pocket cost is reduced to RMB 0.95 due to insurance coverage. This overall coinsurance rate is higher than

10% since some patients might be under deductible at the time of the drug purchases. The cost per daily dosage is slightly lower in the uninsured group because the uninsured tend to choose the cheaper options under drugs with the same generic name (for example, choose generics over the brand name). The drug purchases and cost of patients with URBMI lie in between that of patients with UEBMI and the uninsured.

2.4.2 Empirical Strategy

We use difference-in-differences (DiD) as the main specification to estimate the effect of the price change on various outcomes of interest. To take into account the potential substitution, we consider all drugs in the therapeutic classes that include the drugs directly affected by the program as treated. The 10 reform drugs belong to four therapeutic classes. One class is for the treatment of Thrombosis (ATC Classification B01 "Antithrombotic Agents"). Two classes are for Hypertension (ATC Classification C08 "Calcium Channel Blockers" and C09 "Agents Acting On The Renin-Angiotensin System"). And the fourth class is "HMG CoA Reductase Inhibitors" for high blood cholesterol, commonly known as "statins" (ATC Classification C10AA). As such, we have an additional 29 drugs that are considered treated, besides the 10 drugs that are centrally procured.

The set of control drugs includes those in the other therapeutic classes for the treatment of Hypertension, High Cholesterol, and all the other drugs with the first level ATC Code being "C", which is the category of drugs for "Cardiovascular System". We also include drugs that treat diabetes as control, which is another common chronic condition among the population. Drugs for diabetes are classified under ATC Code "A10". We will test the robustness of the main result when excluding the diabetes drugs as control. The details of treated and control drugs are presented in Appendix 2.A.

The other dimension of variation is before and after the program. The program is announced on 12/17/2018 and the price reduction is in place on 3/23/2019. In the main

specification, we consider April to December in 2018 as the pre-period and April to December 2019 as the post-period, dropping the observation from January to March in both 2019 and 2020. This will give us the cleanest effects of the price reduction itself because first, in the period between the announcement and the actual implementation (January to March 2019), patients might have already started to change their behavior in anticipation of the actual price change. Second, the COVID-19 hit in January 2020 (the lockdown in Wuhan happened on January 23, 2020), which severely limited people's mobility and generated irregular patterns in the healthcare seeking behaviors in the first few months of 2020. Lastly, comparing drug purchases from the same months of the two years could difference out the potential seasonality across different months of the year in healthcare demand. We will check the robustness of the main result when including the observation from Jan to Mar.

For each outcome of interest, we did the estimation separately for the insured and uninsured. The DiD estimation equation is as follows:

$$log(Y_{d,i,m}+1) = \alpha + \beta Treat_d * Post_m + \gamma_d + \delta_m + \varepsilon_{d,m} \tag{2.7}$$

$Y_{d,i,m}$ is the outcome of interest. At drug level we examined total dosage (days) purchased, dosage (days) purchased per prescription and per patient for drug d from patients with insurance status i in year-month m. We include drug level fixed effects γ_d and year-month fixed effects δ_m to control for seasonality. And we define drugs at the chemical compound (ATC code) level, and thus are not distinguishing drugs with the same chemical compound but with different brands. The standard errors are clustered at the drug level. We use $log(Y_{d,i,m}+1)$ as the dependent variable to include the observations from several drugs with 0 total purchases in some months. We check the robustness of the main result when we drop the 0s and use $log(Y_{d,i,m})$ as the outcome variable, and when we use inverse hyperbolic sine transformation in Appendix 2.B.

The sample that is the main focus of our analysis is the uninsured group because they

are the ones that experience the largest out-of-pocket price change, and have the lowest level of per capita drug utilization at baseline. The analysis on the insured is of interest by itself, but we also view it as a placebo to gauge the effect size from the uninsured. Therefore, in the main analysis, we only examine the effects on the patients with UEBMI as the insured, who have the most generous insurance coverage and also have the highest income level. We will also report the effect on the main outcome for patients with URBMI in Appendix 2.B, as our conceptual framework suggests the effect sizes there should lie in between the other two groups.

To test the differential response between the insured and uninsured group, we estimate a triple difference specification, combining data from both the insured and uninsured groups and including a triple interaction term. With the same notation and indices as above, the estimation equation is as follows:

$$\begin{aligned} log(Y_{d,i,m}+1) = \alpha + \eta Treat_d * Post_m * Uninsured_i + \beta Treat_d * Post_m + \\ \theta Treat_d * Uninsured_i + \rho Post_m * Uninsured_i + \tau Uninsured_i + \gamma_d + \delta_m + \varepsilon_{d,m} \end{aligned} \tag{2.8}$$

The DiD approach relies crucially on a parallel trend assumption. One of the potential threats to identification would be the existence of unobserved post-treatment shocks that affect treatment and control drugs differently. The first possibility is that though not subject to centralized procurement, the prices of the control drugs will also be adjusted in response to changes in the overall market environment. We examine this possibility and Figure 2.1 shows the evolution of prices for directly treated drugs, other drugs in the same therapeutic class as the directly treated drugs, and the control drugs separately. The directly treated drugs experienced a sharp decline in price following the program implementation as expected. But the prices of other drugs included in the analysis are not affected, neither for other drugs in the treated therapeutic classes, nor for the control drugs. Second, substitution across drugs might invalidate the parallel trend assumption. Because we examine drug purchases at the chemical compound

level and consider all drugs within the same therapeutic class with the reduced price drugs as treated, substitution between different brands among drugs with the same chemical compound and substitution among drugs in the same therapeutic classes will be captured. Lastly, what would affect the purchase of both the treated and control drugs would be the underlying demand for chronic condition treatments. However, this should not affect the demand for treated and control drugs differently in absence of the price change brought by this reform. Moreover, diabetes drugs in the control group should not be subject to any demand shock that is specific to cardiovascular system conditions. We find that whether excluding the diabetes drugs as control does not have much impact on the result. If the program boosted the overall demand for all chronic condition drugs, the bias will lead to an underestimation of the actual demand response to the price reduction.

2.5 Results

2.5.1 Effect on Drug Purchases

Overall, the uninsured responded much more strongly to the drug price drop than the insured by increasing the purchases of drugs in the treated therapeutic classes. Figure 2.2 plots the monthly pattern of the dosage purchased for drugs in the treated classes and control drugs for insured and uninsured separately. Before the actual implementation of the program, the purchases of drugs in the treated classes and control drugs were following very similar trajectories, justifying the parallel trend assumption. Since March 2019 (price adjustment took place on the 22nd), the purchases of treated drugs in the no insurance group experienced a growth trajectory that is at a visibly higher level than the control drugs. The purchases of drugs in the treated class in the insured group were also at an elevated level relative to the control after the price reduction but at a much smaller magnitude.

We first plot the coefficients from an event study estimation in Figure 2.3. Consistent with the pattern in raw data, there are no significant effects in the period before the price

reduction, reassuring that the parallel trend assumption is satisfied. And in periods after the price reduction, the estimates are larger in magnitude in the uninsured group and statistically significant, though much nosier. Quantifying the effects with the DiD framework, Table 2.3 shows that the uninsured increased the purchases of drugs in the treated therapeutic classes by 40.5% (34 log points) relative to the control drugs (column 2). Though in the graphs the growth of treated drugs seems to outpace the control for the insured as well, we do not detect the effect with statistical significance (column 1). The triple difference estimator suggests that the difference between the two groups was statistically significant. The uninsured patients increased their purchases of the drugs in the treated therapeutic classes by 28.4% (25 log points) more than the insured, suggesting an improvement in drug affordability under the implication of the human capital framework of health investment.

We check the robustness of the finding when excluding diabetes drugs from the control. The statistical significance and the relative magnitude of the estimates were not affected (Table 2.B.1). We also examined the results when including Jan to March observations in the analysis in Table 2.B.2, which again did not have much impact on the estimates.

Besides the demand response to the price changes, the other potential driver of the effect is "physician induced demand", that is, physician induces patients to purchase drugs due to their own financial or other considerations (Currie et al., 2014). This is not likely to be a relevant factor in this case due to the following reasons. First, financial interest is not relevant in this context due to the Zero Markup Policy, which was documented to have decreased the drug sales (Fang et al., 2021). There might be concerns that there is still room for physicians to get kickbacks from the pharmaceuticals in forms other than direct price markups. But this program will only negatively affect this margin due to the substantial drop in price. Secondly, physicians at these public healthcare facilities might face pressure in meeting some sales targets from upper-level administrations following this program, given that it is a national pilot carried out by the central government. In fact, there are indeed implicit sales targets as part of the

procurement contract, which is that 60% of last year's sales of the drugs under the generic name is promised to the bid-winning drug manufacturer. However, this should not affect the interpretation of our finding as demand responses to price due to the following reasons. First, given the relatively stable demand for chronic condition drugs, doctors do not need to induce additional purchases from patients to fulfill this 60% target. Second, this target might push physicians to prescribe the bid-winning drugs over the drugs from the other manufacturers under the same generic name. But this substitution is captured by our design since we look at the total purchase of drugs under the same generic name and are not distinguishing drugs from different manufacturers. Moreover, with all drugs in the same therapeutic classes as the reduced-price ones considered as treated, we capture a wider possibility of substitution if doctors induced patients to substitute other drugs in the therapeutic class with the directly treated drugs.

With substantial increases in drugs purchases, the next question is whether this is driven by more prescriptions with the treated drugs and more patients purchasing them, or it simply reflects patients purchasing more drugs per prescription. In Table 2.4, we report the results when replacing the dependent variable from the main specification with the number of prescriptions and number of patients. There were substantial increases in the two extensive margin measures for the uninsured group. The number of prescriptions and number of patients both increased by 31% (27 log points) compared to the control. Assuming no change in the dosage purchased per prescription (or per patient), a back of envelope calculation suggests that the extensive margin response accounts for 94.2% of the overall increase in dosage purchased for the uninsured. The similar effect sizes from the two measures imply that the effect is not simply driven by patients increasing their frequency of refilling their prescriptions. Instead, following the price reduction, more uninsured patients started initiating treatment with the affected drugs.

Having seen that the effect on drug purchases is largely driven by an increase in number of patients purchasing the treated drugs, we next examine explicitly to what extent it is driven

by new patients entering the sample. Table 2.5 tests the differential responses between the new and existing patients, interacting the double difference interaction further with an indicator for whether the purchases came from the sample that were in the data from the pre-period. The outcome variables examined include drug purchases, number of prescriptions and number of patients. We do not detect any differential responses with statistical significance between the new and existing patients from both groups across all outcome measures. Though the estimates on the triple interaction term is not statistically significant, a simple back of envelope calculation using the estimates suggests that 62.4% of the overall increase of drug purchases in the uninsured group came from the existing patients. The price reduction not only brought in more new patients to initiate the treatment, but also boosted the demand from the patients who had been undergoing treatment before the program. In fact, the monthly pattern of drug purchases from the uninsured existing patients (panel a of Figure 2.4) shows a gradual decline overtime for both the treated and control drugs, which is presumably a result of both the high mobility and a high treatment dropout rate among the uninsured. The fact that we see an elevated overall purchases and significant positive effect on number of patients purchasing the treated drugs from this sample indicates that not all of the decline is from mobility. And the price reduction improved treatment persistence, though there is a high overall dropout rate. The insured existing patients' drug purchases are staying relatively stable except for some seasonal fluctuations (panel b).

2.5.2 Drug Adherence and Overuse

In this section, we will examine whether the increase in drug purchases translates to improved drug adherence, or is driven by elevated drug overuse. We will first introduce our measure of drug utilization and show some descriptive patterns. Then we will apply the difference in difference framework on this measure and presents the effect of the price reduction on drug adherence and overuse.

Measure: Medication Possession Rate

To measure and benchmark drug utilization, we borrow a concept from the medical literature called Medication Possession Ratio (MPR), which is calculated by taking the ratio of the dosage (days) purchased of a drug in one prescription and the days between this prescription and the next refill with drugs that treat the same condition. For the analysis in this subsection, we consider MPR at the prescription level. To define a "refill" of a certain drug, we take a relatively generous approach. The next prescription refill of a patient with any of the drugs that treat the same illness as the drug in the current prescription would be considered a refill, thus allowing the possibility that patients need to switch drugs. For the set of drugs that treat those conditions, there is a benchmark of 1 we can refer to in a clinically optimal sense because patients are supposed to be under long-term medication treatment with as little interruption as possible.

In the analysis of this part, we consider only drugs for HTN, HC, and diabetes, for which we have a clear and exhaustive set of therapeutic classes to be considered as treatment. The drugs included in the previous drug level analysis but not included here are other drugs with ATC Code starting with "C" and "B01", which are for the treatment of the broad "cardiovascular system" diseases. Without a specific disease that it can be used to treat, it is hard to define a refill because we are not sure what are the drugs that could be used to treat the same illness that the patients might be switching to. We will check the robustness of the main result in the next subsection when we consider refills to be only the refill of drugs within the same therapeutic class and thus are able to include all the drugs from the previous analysis.

The underlying assumption for defining refill as the subsequent purchases of any drugs treating the same condition is that as long as patients come to seek care for the condition they have, they will be getting the appropriate medication treatment that they need. Not purchasing drugs from the same therapeutic classes as in previous prescriptions will imply the current therapeutic classes do not suit their condition anymore. This might lead to an underestimate

of underuse if patients are under multi-drug therapy and they do need to refill drugs from the same therapeutic class, but they choose to only purchase drugs from other therapeutic classes for that condition. This might also lead to an overestimate for overuse if patients come to refill prescriptions for drugs in other therapeutic classes for the same illness before they run out of the drugs from the current therapeutic classes. By defining refill at the therapeutic class level we check the robustness of the main result to address the potential biases from our main definition of refill.

The other thing to note about this measure is that the dosage supplied measured in days is calculated by dividing the total dose purchased (usually in milligrams) by the Defined Daily Dosage, which is an average measure of drug dose needed per day at the population level. The true clinically optimal dose of a drug each patient needs might differ and not necessarily be equal to the DDD. Thus, an MPR less than 1 might not necessarily represent underuse and an MPR greater than 1 might not necessarily indicate overuse. To address this concern, we will present the full distribution of this measure and examine the effect of the price reduction on the entire distribution as well in the next subsection. Moreover, to demonstrate the existence of overuse and underuse in this setting, we collect the maximum and minimum daily dose needed for treated drugs to construct lower and upper bound estimates of the true MPR.

There are drug purchases in the data with no following refills, especially in the data from the post period close to the end of the data coverage. To deal with this imbalance in the pre and post period, we find the set of last prescription refills in the pre-period data as if we do not observe any subsequent refills from the next year. And we drop those "last time" observations in the main analysis of MPR. However, if the pre-post changes in the share of those "last time" purchases are different for the treated and control drugs, dropping those observations might bias our results, the direction of which depends on whether we think the prescription is never filled afterward or filled somewhere else due to mobility. We will check the sensitivity of the results when we impute MPRs to be either 0 or 1 for the "last time" purchases, that is, we

assume either the treatment is discontinued or patients perfectly adhere to the treatment but are purchasing drugs at other locations that are not captured by our data.

Descriptive Patterns of MPR

Table 2.6 reports the summary statistics of MPR for the main analysis. Because the distribution of MPR has a super long right tail, the mean could be misleading in describing the underlying distribution. Therefore, we reported the min, max, the three quartiles, and the 99th percentile of MPR for insured and uninsured separately. The extremely high values of MPR at the maximum could be driven by measurement errors in the data.[23] But as long as the likelihood of the presence of measurement error does not evolve differently for treated and control drugs, before and after the reform, this should not bias our estimate. Furthermore, in the analysis of the effect of the price reduction, we will report the result on the entire distribution of MPR.

To have a sense of how the MPR is distributed at baseline, we first plot the distribution of MPR from the pre-program period in Figure 2.5 for the uninsured (panel a) and insured (panel b) separately. It can be seen clearly from the figure that the distribution of MPR for the uninsured is much more concentrated in the region with MPR below 1 (78.6%) than the insured (55.7%). Correspondingly there is a substantially higher mass in the region above one in the insured group than the uninsured. Assuming the underlying clinically appropriate daily dose for the insured and uninsured are distributed similarly, this pattern suggests the prevalence of underuse in the uninsured group and overuse in the insured group. In particular, there are 6.1% of prescriptions with MPR greater than 4 in the insured group, which could be more confidently considered as overuse despite the potential variation in daily dose needs.

To check whether the cost would be a predictor for the discrepancy between the two groups, for each insurance group, we divide the prescriptions by whether the daily cost of the

[23]For example, if the drug purchase should be recorded in units of "milligram" but is recorded with the unit of "gram", this will lead to the true MPR be inflated by 1000 times.

drugs included in that prescription is above or below the median cost of all prescriptions in that insurance group, and plot the MPR distributions separately, shown as hollow and orange bars in the graph. First, we find that the median daily dose cost is much lower for the uninsured (RMB 4.38) than the insured (RMB 10.95), demonstrating that the uninsured tend to purchase fewer drugs and choose cheaper ones for treating the same set of chronic illnesses.[24] The graph shows that for the group with no insurance, the prescriptions with above-median daily cost are more likely to associate with very low MPR (in particular, with MPR between 0 and 0.5). No such pattern exists for the group with insurance. These patterns suggest that cost is indeed a constraint for drug adherence for patients with no insurance coverage. Furthermore, in the insured group and the below-median cost prescriptions of the uninsured, we both see a concentration of MPR in the region around 1, reassuring that our measure is capturing how well patients are adhering to the treatment and 1 is an appropriate benchmark in this setting.

To further establish the existence of under- and over-use in this setting, as mentioned earlier we plot the distribution of the lower and upper estimates bound of MPR for the treated drugs in Figure 2.6, by replacing the DDD with either the maximum or minimum daily dose in the MPR calculation. Because we use the maximum daily dose allowed to obtain a lower bound estimate of MPR, any value above 1 should be more confidently considered as overuse. In the graphs showing the distribution for these lower bound estimates (panel a and b), there are still prescriptions with MPRs above 1, especially in the insured group (12% versus 2.8% in the uninsured group). In the distribution of upper bound estimates for MPR (panel c and d), there is a higher concentration below 1 in the uninsured group, which could be confidently thought of as underuse (30.9% in the insured group versus 55.7% in the uninsured group). These patterns provide further evidence on the existence of both drug underuse and overuse in this setting though there might be variations in the actual daily dose needed which drives

[24] In Table 2.2 we report that at the drug level, the mean daily dose costs are 5.86 and 4.61 for the insured and uninsured, respectively. The comparison with the prescription level median cost shows that the insured are more likely to purchase more than one drug in a prescription.

individual optimal MPR either above or below 1.

Impact of the Price Reduction on Medication Possession Ratio

To examine the effect of the price reduction on drug adherence, we first plot the distribution of MPR in the pre- and post-period for insured and uninsured separately in Figure 2.7. The hollow bars represent the distribution from the pre-reform period (Apr-Dec 2018) and the colored bars represent the post-reform period (Apr-Dec 2019). For prescriptions with drugs in the treated classes in the uninsured group (panel a), after the reform, there was an increase in density around the area with MPR being 1, and the decrease in density was mostly observed at the lower end of the distribution, indicating that there were fewer prescriptions associated with severely under-using of medication. There seems to be a slight increase in drug adherence for the control drugs in the post-period for the uninsured as well, but at a smaller magnitude (panel c). Visually there were no such movements in the insured group from both treated and control drugs (panel b and panel d).

Though as discussed earlier, an MPR above 1 does not necessarily indicate drug overuse, the fact that we do not see much increase in density in the part of the distribution with MPR above 1, especially the part with extremely large MPRs (≥ 4) suggests that overuse should not be exacerbated. To quantity the shift in the distribution observed in Figure 2.7, we next examine the effect of the program on the entire distribution of MPR in a Diff-in-Diff framework. Specifically, we estimate the following specification:

$$\mathbb{1}(MPR <= k)_{p,m,i} = \alpha + \beta_k Treat_p * Post_m + \gamma Treat_p + \delta Post_m + \varepsilon_{p,m,i} \tag{2.9}$$

$\mathbb{1}(MPR <= k)_{p,i}$ is an indicator for the MPR associated with prescription p is smaller than or equal to k. $Treat_p$ is an indicator for whether the prescription includes any treated drugs and m denotes the month in which the prescription is filled. We estimate the specification for k

from 0.01 to 4, with 0.01 increments in between. i denotes insurance status and the estimation is conducted separately for the insured and uninsured group.

Figure 2.8 plots the CDF of MPR and the regression results from the specification above. Panel (a) shows the CDF of MPR for prescriptions with treated drugs for the uninsured group. We can see that the distribution of MPR from the pre period (green line) first-order dominates that from the post period (orange line). The difference between the two distributions is plotted in the blue line with the 95% confidence interval shown in grey lines. For any value k less than 2, the probability of MPR smaller than k is significantly lower in the post-period compared to the pre. The largest estimate in absolute value appears at the MPR of 0.8 with the magnitude being -0.066. From that point on, the difference is gradually reducing. At MPR being 1, the estimate has reduced to 0.022 in absolute value and gradually moving toward 0 as MPR gets larger. From an MPR of 2 on, the two CDFs are no longer statistically distinguishable from each other. This first difference results suggest that in the uninsured group, the movement of MPR for prescriptions with treated drugs is mainly a shift of MPR below 0.8 to the interval between 0.8 and 1. Though the overall likelihood of MPR between 1 and 2 also significantly increased, the magnitude is small (0.022). And the overall density of MPR between 1 and 2 for the uninsured is still lower than that of the insured. In the MPR distribution of treated drugs for the insured group, the differences in distribution are at a much smaller magnitude compared to the uninsured. Although we also observe a statistically significant decrease in the probability of MPR lower than k for k below 1, the maximum reduction in absolute value is 0.012 when k equals 0.82.

Panel (c) and (d) plot the MPR distribution of prescriptions with control drugs for the insured and uninsured desperately. Though the differences between the pre and post CDF are not visibly obvious, the distribution of MPR from the pre-period both first order dominates that from the post period in the insured and uninsured groups. And the reduction in relative probability lower than or equal to k only happens with k lower than 1. For the uninsured, the

estimate reaches the maximum absolute value of 0.018 at MPR being 0.19 and reduces to 0.003 at MPR equal to 1. For the insured, the estimate reaches the maximum absolute value of 0.018 at MPR being 0.77 and becomes no longer negative once MPR reaches 1.03. This pattern suggests improved drug adherence in prescriptions with control drugs in the post period from both insurance groups, though at a smaller magnitude than those with treated drugs in the uninsured group. This could be a result of patients getting better at adhering to treatment over time. We can not rule out a possibility of spillover from the treatment though, especially for the uninsured group, that is, patients become better adhering to the treatment of control drugs if their budget constraint is relaxed by the price reduction of the treated drugs and if they are taking both the treated and control drugs at the same time. However, such spillover will bias downwards our estimate from the true effect of the price reduction on drug adherence.

Panel (e) and (f) of Figure 2.8 plot the DiD estimates from specification (2.9). Because there is overall not much shift in the MPR distribution of control drugs, for the uninsured, the DiD result demonstrates a similar pattern as the first difference results in panel (a). The estimates at low values of MPR (between 0 and 0.25) are not statistically different from 0, which is mainly driven by the countervailing shift of MPR in this range of the control drugs as shown in panel (c). The maximum estimate in absolute value is 0.059 and shows up at MPR being 0.77. At MPR equal to 1, the estimate is reduced to 0.018 in absolute value and not statistically significant. The DiD estimate suggests that the price reduction mainly moved the prescriptions of treated drugs with MPR between 0.25 and 0.77 to between 0.77 and 1, which could be interpreted as an improvement in treatment adherence from underuse to our benchmark of the clinically appropriate level (MPR around 1).

For the insured (panel f of Figure 2.8), the estimates are much smaller in general compared to the uninsured but are positive and significant in both MPR between 0 and 1 and MPR greater than 2. The positive estimates in the region of 0 to 1 are driven by a larger reduction in density from the control drugs. While in the region with MPR above 2, it is a

result of an absolute reduction in density from the prescriptions with the treated drugs. This might reflect the reduction in incentives of hoarding or reselling of the insured. Though we do not have a definitive cutoff of MPR for overuse, the fact there is no increase in the part of distribution anywhere with MPR greater than 2 suggests that overuse of the treated drugs should not be increased by the price reduction. Though there is a slight increase in the density of MPR in regions between 1 and 2 for the uninsured group, the overall density is still lower than that of the insured group. This may reflect the drug needs of patients who need higher daily doses than the population average.

To show more clearly where the movement in MPR happens, Figure 2.9 draws the difference-in-difference estimates for the pdf of MPR, with the dependent variable being the likelihood of MPR being in a 0.1 bin from 0 to 4. The last bin shows the estimate on the likelihood of MPR greater than 4. Consistent with what we see in the CDF graphs, for the uninsured, there are significant drops in the likelihood of being in the range between 0.2 to 0.8, and a significant increase in mass in the bin of [0.9,1]. There is not much movement for each bin with MPR greater than 2, both for the insured and uninsured.

To further quantify the improvement, we next estimate the effect on mean MPR under the DiD framework. Restricting to prescriptions with MPR lower than 4, Figure 2.10 shows the parallel trends of mean MPR between prescriptions with treated and control drugs in the pre-period, and the differential growth after the price change in the uninsured group (panel a). Mirroring the observation from the distribution, we can first see that the MPR for the uninsured is not only at a much lower level than the insured but more importantly, also at a level lower than 1. For the uninsured the average MPR for the treated drugs is moving toward the value of 1 and the gap is widening between the treated and control drugs. For the insured, on the other hand, the average MPR for both the treated and control drugs are evolving similarly and with absolute levels either around or slightly greater than our optimal benchmark of 1. With *id* denoting patients and other notations same as before, the estimation is as follows:

$$MPR_{id,p,m,i} = \alpha + \beta Treat_p * Post_m + \gamma Treat_p + \delta Post_m + \gamma_{id} + \delta_m + \varepsilon_{id,p,m,i} \quad (2.10)$$

We include patient fixed effects γ_{id} so that the effects are estimated within patients. The standard errors are clustered at the patient level to allow for potential correlation in drug refill behavior within individual patients. Table 2.7 presents the estimates from equation (2.10). For the uninsured, the MPR in prescriptions with treated drugs increased by 0.046 relative to the ones without treated drugs (column 2). There was a reduction of MPR in the insured group, though the magnitude is small (0.0038). And from the distribution in Figure 2.8 we know that this was driven by an increase in adherence of the control drugs, not an absolute reduction of MPR for the treated drugs. The effect closes the gap in adherence to treated drugs between the insured and uninsured as measured by MPR by 19.9% (based on the gap in mean MPR of treated drugs in the pre-period). Because the MPR is the ratio of dosage prescribed and gaps between refills, plotting the distributions of the two variables shows that the increase in mean MPR of the uninsured mainly came from a reduction in the gaps between two refills, not an increase in dosage purchased per prescription (Figure 2.B.1 and Figure 2.B.2 in Appendix 2.B). In particular, there is a substantial reduction in the possibility of the gap between two prescriptions greater than 100 days (from 7.7% to 5.4%) and a corresponding increase in the density of gaps around 30 days, which is the common time interval that chronic condition patients are supposed to get their prescription refilled. There was not much change in the distribution of dosage purchased per prescription, for both insurance groups and across treated and control drugs.

Columns (3) and (4) of Table 2.7 report the effect on an indicator of MPR greater than or equal to 4. Consistent with what we observe from the distribution, there is a significant reduction from the insured group, representing a 7.7% decrease from the pre-period mean. And no significant change on this measure is observed for the uninsured group. From panel (e) and

(f) in Figure 2.8, we should expect similar effects in Column (3) and (4) if we replace the cutoff with any number greater than 2 (we report the result when replacing the cutoff with 2 or 3 in Table 2.B.4). In the distribution of gaps between refills plotted in Figure 2.B.1 panel (b), we observe a decrease in density where days are small (less than 10), which could be driving the decrease in the large value of MPR we observe in the data.

As discussed in Section 2.5.2, the way we calculate MPR might introduce some bias to measuring the underlying actual drug adherence. We check the robustness of the result taking those potential biases into account. First, the fact we dropped all the prescriptions that do have subsequent refills may introduce bias to the estimates if the pre-post changes in the share of those "last time" purchases are different for the treated and control drugs. We check the robustness of the result by imputing the MPR for the "last time" purchases to be either 0 or 1. By imputing 0, we are assuming that the prescription is never refilled and treatment is discontinued. By imputing 1, we are assuming that the prescription is refilled exactly on time at some other places not captured by our data. Table 2.B.3 in Appendix 2.B shows the result. There are slight changes in magnitudes of the estimates but not the sign and the statistical significance. The estimates on mean MPR conditional on $MPR < 4$ is either 0.036 or 0.065 under the two imputations, equivalent to 20.2% and 15.8% of the corresponding baseline gap between the insured and uninsured group, respectively. The estimates from the main specification (0.046 and 19.9% of the baseline gap) lie in between the two.

We also examine the robustness of the result when we define refill at the therapeutic class level, and when we include other drugs besides the ones for the treatment of HTN, HC and Diabetes. Table 2.B.5 shows the result when we only include drugs for HTN, HC and Diabetes and Table 2.B.6 reports the result when we include all drugs. Though there are some changes in the magnitude of the estimates and the baseline mean, the effect on mean MPR remains positive and significant for the uninsured. The findings that the likelihood of MPR larger than 4 is not increased are also preserved for both insured and uninsured groups. The

estimates on mean MPR conditional on $MPR < 4$ closes 11.7% and 17.2% of the baseline gap between insured and uninsured group respectively.

Heterogeneous Effect on New and Existing Patients

Because the price reduction brings in more patients purchasing the treated drugs in the uninsured group, we next will examine whether the improvement in drug adherence is driven by new patients entering the sample. We add a triple interaction term based on equation (2.10) and estimate the following specification:

$$\begin{aligned} MPR_{id,p,m,i} = \alpha + \beta' Treat_p * Post_m * NewPatient_{id} + \beta Treat_p * Post_m \\ + \gamma Treat_p + \delta Post_m + \gamma_{id} + \delta_m \varepsilon_{id,p,m,i} \end{aligned} \tag{2.11}$$

$NewPatient_{id}$ is an indicator for patients only showing up in the sample from the post-period. Table 2.8 shows the result. Patients fixed effects are included and the standard errors are clustered at the patient level. For the uninsured, we do not find significant differences between the new and existing patients on the two MPR outcomes examined (column 2 and column 4), suggesting that the overall improvement in drug adherence was not merely driven by the selection of patients newly entering the sample following the price reduction. In the insured group, however, there were significant differences between new and existing patients (column 1 and column 3). The negative estimates on both the mean MPR and the likelihood of $MPR >= 4$ from the pooled effect were driven by existing patients. The new patients, on the other hand, had responses with similar magnitude as the new uninsured patients (0.0631 versus 0.064 on mean MPR conditional on $MPR < 4$, 0.0032 versus 0.0026 on likelihood of $MPR >= 4$). Regardless of insurance status, drug adherence of marginal patients, in terms of initiating treatment following the price reduction, responded to the price change in a similar way.

2.6 Conclusion

High pharmaceutical prices make essential drugs unaffordable to a sufficient share of the population in need especially in low- and middle-income countries (Stevens and Huys, 2017; World Health Organization, 2017b). As governments and organizations around the world put enormous efforts in making drugs affordable by lowering out-of-pocket costs faced by patients, making sure the drugs will not get overused is another key challenge, as the gate-keeping function of the healthcare system is usually not well-performed in low- and middle-income countries (Das et al., 2016).

In this study, we evaluated the affordability and overuse trade-off by studying a national procurement program in China, which brought down the prices of 10 commonly used chronic condition drugs by an average of 78%. With data from the universe of primary care facilities in one administrative district in Beijing, we find that the program significantly improved drug affordability for those in need in the nine-month period following the program implementation. There was a much higher demand response from the uninsured, who are not only facing the full cost out-of-pocket, but are also more likely to be those without formal sector jobs and have lower income. The increase in drug purchases came both from the existing patients who had been undergoing treatment before the program, and new patients entering the sample following the price reduction. Meanwhile, drug adherence as measured by the medication procession ratio (MPR) was significantly improved for the uninsured. For prescriptions with treated drugs, fewer of them were associated with severe drug under-use and more were located near the clinically optimal level (MPR around 1). On the other hand, there was not much response from the insured, and drug overuse was not aggravated as evidenced by the distribution of MPR in the region that presumably represents overuse not being affected. Overall, this program has benefited those in need, without pushing patients who have already been consuming drugs at the near-optimal level too far toward overuse. We documented that affordability need not come at a cost of overuse, at least in the specific context of chronic condition drugs that we study.

Our findings provide insights into the understanding of demand responses to prescription drug prices in developing countries. With many patients having difficulty with drug access due to cost, lowering prices could induce demand responses that are much higher than the existing estimates from the developed countries among the patients that are covered by insurance. Furthermore, though our study context is a developing country, Beijing is still a more economically developed area in China, whose affordability issue might be less severe than other parts of the developing world. It is reasonable to expect a more substantial demand response in even lower income settings under similar price reductions.

The limited impact on drug overuse might be specific to chronic condition drugs and further study in the context of other types of drugs is needed. Nevertheless, the chronic condition is in itself an important illness category to both researchers and policymakers. As the leading cause of death globally, it now also imposes an increasingly heavy burden on developing countries as a result of demographic and epidemiological changes (Bollyky et al., 2017; World Health Organization, 2011). Timely and proper medication treatment is essential and extremely cost-effective in preventing costly complications like stroke and heart attack. But the fact that it requires long-term treatment makes the cost an even greater barrier to access for households.

To improve affordability, the scale and coverage level of universal basic healthcare is usually constrained by fiscal and state capacity. Pharmaceutical price is where the government could leverage their bargaining power to lower the cost people face because the production of pharmaceutical products exhibits increasing returns to scale, a property that other parts of healthcare expenditure (doctor fees and hospitalization) do not have. This is especially relevant for the drugs that are already off-patent and the high prices are driven by the missing "patent cliff", which is commonly observed in developing countries (Danzon et al., 2015). Giving power to the consumer is an effective tool to get the prices down and has advantages over direct price controls where pharmaceutical companies might respond strategically in a way that would

actually hurt the most vulnerable patients (Dean, 2019; Mohapatra and Chatterjee, 2021). This is also relevant for developed countries where government-provided health insurance covers an increasingly large population and thus the bargaining power due to scale is easily achievable (Duggan and Scott Morton, 2010; Hong, 2015).

2.7 Acknowledgements

This chapter, in part, is currently being prepared for submission for publication of the material. He, Daixin; Yang, Jianan. "Affordability versus Overuse: Evidence from a Prescription Drug Price Reduction in China." The dissertation author was the primary investigator and author of this material.

2.8 Tables and Figures

Table 2.1: Insurance Coverage for Outpatient Care

	Urban Resident (URBMI)	**Urban Employee (UEMI)**	
		Working	Retired
Annual Deductible (RMB)	100	1,800	1,300
Coinsurance	45%	10%	
Maximum Benefit (RMB)	4,000	20,000	

Table 2.2: Summary Statistics

	N	Mean	SD	Min	Max
Panel A. Patient Level Characteristics					
Male	1,420,257	.58	.49	0	1
Age(2020)	1,420,257	50.96	20.11	0	112
Reform Drug	1,420,257	.36	.48	0	1
Insurance Status					
Urban Employee (UEBMI)	1,420,257	.53	.50	0	1
Urban Resident (URBMI)	1,420,257	.08	.27	0	1
No Insurance	1,420,257	.24	.43	0	1
Common Chronic Conditions					
High Cholesterol (HC)	1,420,257	.09	.29	0	1
Cardiovascular Disease (CVD)	1,420,257	.20	.40	0	1
Hypertension (HTN)	1,420,257	.28	.45	0	1
High Blood Glucose(HBG)	1,420,257	.13	.34	0	1
Panel B. Drug Level Statistics: UEBMI					
Dosage Days (in thousands)	1,349	279.45	450.30	.01	2955.70
Cost Per Daily Dosage	1,349	5.86	7.40	.09	54.78
Out-of-pocket Cost Per Daily Dosage	1,349	.95	1.13	.01	9.01
Panel C. Drug Level Statistics: URBMI					
Dosage Days (in thousands)	1,330	12.77	20.85	.00	146.37
Cost Per Daily Dosage	1,330	5.59	6.76	.03	55.34
Out-of-pocket Cost Per Daily Dosage	1,330	3.31	4.50	.02	53.94
Panel D. Drug Level Statistics: Uninsured					
Dosage Days (in thousands)	1,208	1.45	3.14	.002	29.24
Cost Per Daily Dosage	1,208	4.61	4.64	.06	25.91

Notes: This table reports sample summary statistics. The top panel reports patient-level statistics. Age as of 2020 is calculated based on year of birth. Reform Drug is an indicator of whether a patient has ever purchased the drugs included in the reform. Variables under Insurance Status and Common Chronic Conditions are all indicator variables. Drug level statistics are reported with the observations at drug(chemical compound)*year-month level. Year-month included are Apr-Dec 2018 and Apr-Dec2019, consistent with the time horizon included in the regression analysis.

Table 2.3: Effect on Dosage Purchases

	log(Dosage(Days) + 1)		
	(1)	(2)	(3)
	Urban Employee	No Insurance	Triple-Diff
Treat*Post*Uninsured			.25**
			(.11)
Treat*Post	.093	.34***	.093
	(.08)	(.12)	(.078)
Uninsured			-5.9***
			(.17)
Treated Pre Mean	11	5.6	
N	1350	1350	2700

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the DiD analysis of the effect on drug dosage purchased. Dependent variables are log(Dosage + 1) and observations are at drug*year-month level. The first two columns reports the effect on insured (UEMI) and uninsured separately. Columns (3) reports the estimate from a triple difference analysis pooling the observations from the insured and uninsured together. The time horizon included in the analysis is Apr-Dec 2018 (pre) and Apr-Dec2019 (post). Year-month fixed effects and ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

Table 2.4: Extensive Margin Effect: Prescriptions and Patients

	Number of Prescriptions			Number of Patients		
	(1) Insured	(2) Uninsured	(3) Triple-Diff	(4) Insured	(5) Uninsured	(6) Triple-Diff
Treat*Post*Uninsured			.18**			.18**
			(.078)			(.075)
Treat*Post	.092	.27***	.092	.087	.27***	.087
	(.068)	(.071)	(.066)	(.065)	(.07)	(.064)
Uninsured			-5.5***			-5.4***
			(.16)			(.16)
Treated Pre Mean	7.9	2.8		7.8	2.7	
N	1350	1350	2700	1350	1350	2700

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the effect on the number of prescriptions and number of patients with the drugs in the treated therapeutic class. Column (1), (2) and (4), (5) present the DiD estimates for insured and uninsured separately. Columns (3) and (6) report the estimate from a triple difference analysis pooling the observations from the insured and uninsured together. Dependent variables are log(Y+1) and observations are at drug*year-month level. The time horizon included in the analysis is Apr-Dec 2018 (pre) and Apr-Dec2019 (post). Year-month fixed effects and ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

Table 2.5: Effect on Dosage Purchases: Pre-Subsample

	Urban Employee			Uninsured		
	(1) Dosage	(2) #Prescriptions	(3) #Patients	(4) Dosage	(5) #Prescriptions	(6) #Patients
Treat*Post*New Patients	-.061	.01	.006	-.29	-.059	-.063
	(.13)	(.12)	(.12)	(.29)	(.14)	(.14)
Treat*Post	.12	.11	.1	.73***	.31***	.31***
	(.099)	(.078)	(.074)	(.23)	(.099)	(.098)
New Patients	-2.3***	-2.3***	-2.2***	.66***	.31***	.3***
	(.11)	(.11)	(.1)	(.24)	(.11)	(.1)
Treated Pre Mean	11	7.9	7.8	5.6	2.8	2.7
N	2025	2025	2025	2025	2025	2025

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports differential response between the existing patients who had been undergoing treatment before the reform, and the new patients who enter the sample after the price reduction. "Treat*Post*New Patients" is the triple interaction term. Dependent variables are log(Y+1) and observations are at drug*year-month level. The time horizon included in the analysis is Apr-Dec 2018 (pre) and Apr-Dec2019 (post). Year-month fixed effects and ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

Table 2.6: Summary Statistics of Medication Possession Rate (MPR)

	N	Min	p25	p50	p75	p99	Max
MPR (UEBMI)	9,571,831	.002	.67	.97	1.47	22.50	4000.00
MPR (URBMI)	409,476	.01	.50	.86	1.08	7.50	666.67
MPR (Uninsured)	34,634	.01	.43	.75	1.00	3.11	60.00

Notes: This table reports the minimum, 25th percentile, median, 75th percentile, 99th percentile and maximum of MPR for the three insurance groups separately.

Table 2.7: Effect on Medication Possession Rate (MPR)

	MPR($MPR < 4$)		$1(MPR >= 4)$	
	(1) Urban Employee	(2) No Insurance	(3) Urban Employee	(4) No Insurance
Treated Class*Post	-.0038***	.046***	-.005***	.00087
	(.0013)	(.015)	(.00045)	(.0027)
Treated Class	.19***	.46***	.0042***	.0078**
	(.0014)	(.018)	(.00044)	(.0032)
Treated Pre Mean	1.1	.85	.065	.0078
Individual FE	YES	YES	YES	YES
N	8937836	34373	9571760	34633

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the effect on medication possession rate (MPR). The unit of observation is at the prescription level. A prescription is considered "treated" if it contains drugs in the treated therapeutic classes. And the MPR for each prescription is calculated based on the dosage prescribed and days until the next prescription with drugs treating the same illnesses. The first two columns report the effect on mean dropping the prescriptions with $MPR >= 4$. The dependent variables in Columns (3) and (4) are indicators for a prescription with $MPR >= 4$. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

Table 2.8: Effect on MPR: Heterogeneity by New and Existing Patients

	MPR(<4)		$1(MPR >= 4)$	
	(1) Urban Employee	(2) No Insurance	(3) Urban Employee	(4) No Insurance
Treated*Post*New Patients	.07***	.022	.0086***	.0022
	(.0051)	(.038)	(.0014)	(.0077)
Treated Class*Post	-.0069***	.042***	-.0054***	.00044
	(.0013)	(.015)	(.00046)	(.0024)
Treated Class	.19***	.46***	.0042***	.0075**
	(.0014)	(.02)	(.00044)	(.0033)
Treated Pre Mean	1.1	.85	.065	.0078
Individual FE	YES	YES	YES	YES
N	8937853	34373	9571831	34634

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the heterogeneous effect on MPR by whether the patients only show up in the observation from post-period. "Treat*Post*New Patients" is the triple interaction term. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

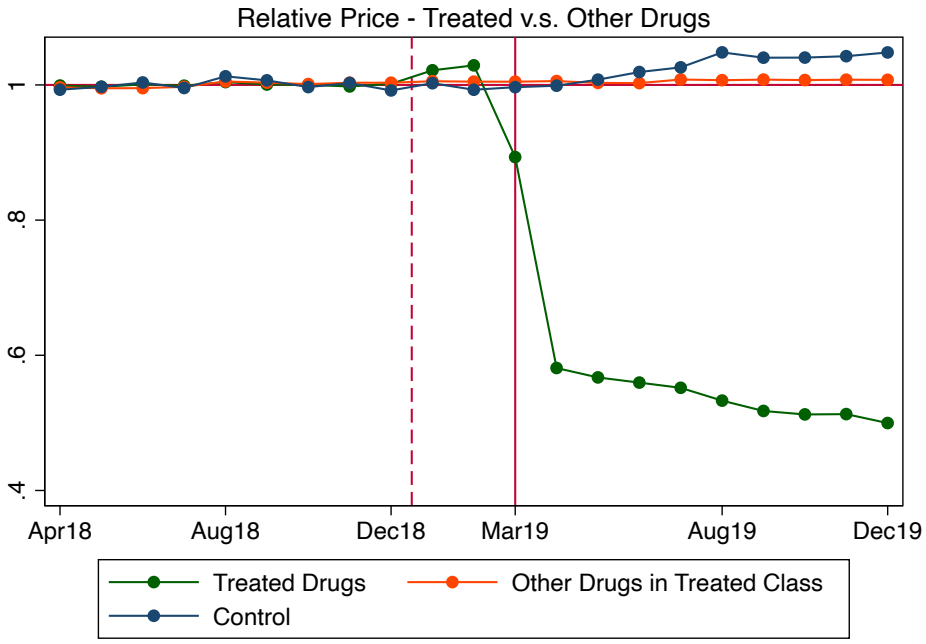
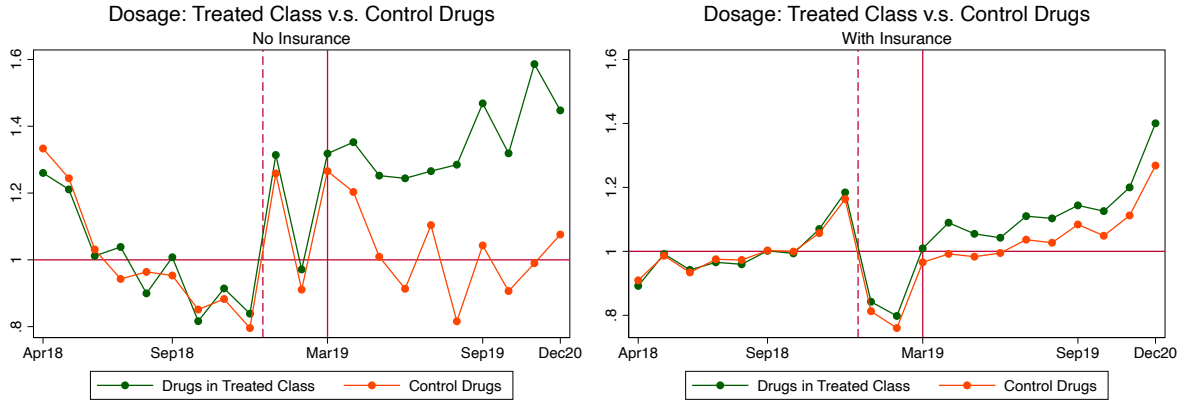


Figure 2.1: Drug Price

Notes: This figure plots the evolution of price level for directly-treated drugs, other drugs in the treated therapeutic classes and control drugs separately. The price in each month for each drug is calculated by taking the ratio of total cost and total dosage purchased. The price level is then normalized by the mean price in 2018 for each drug before taking the average for all drugs in each of the three categories. The dashed line indicates the end of the year (between Dec 2018 and Jan 2019), with the program announced in Dec 2018. And the solid red line indicates the month that the actual price change happens (March 2019).

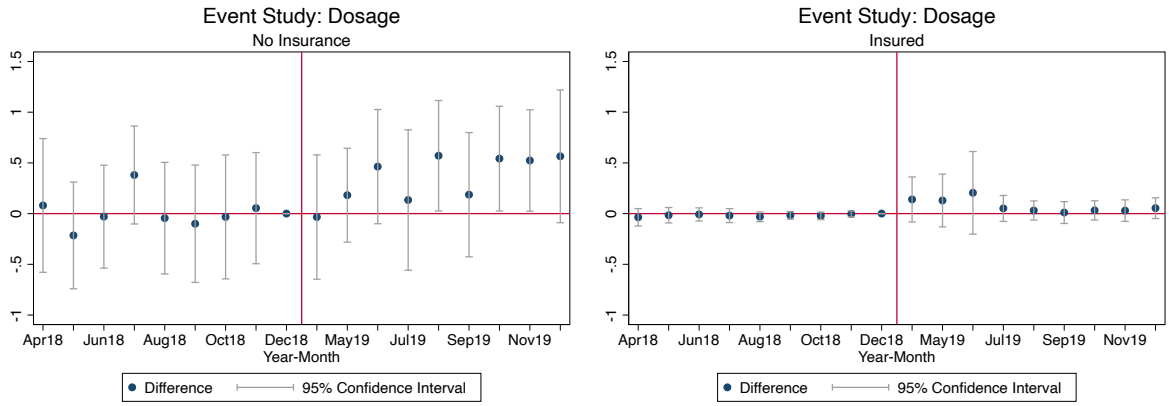


(a) No Insurance

(b) With Insurance

Figure 2.2: Monthly Drug Purchases

Notes: This figure plots the monthly pattern of drug purchases for the insured and uninsured separately. In each graph, drugs in treated therapeutic classes are plotted in green and control drugs in orange. Drug dosage purchases for each drug are normalized by the monthly mean of 2018 before taking the average of all drugs within the same category.

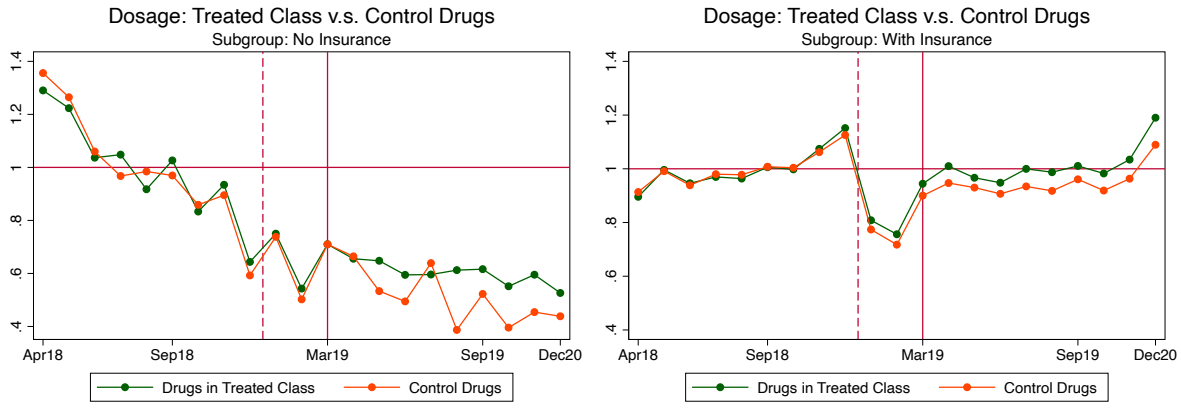


(a) No Insurance

(b) With Insurance

Figure 2.3: Event Study of the Effect on Drug Purchases

Notes: This figure plots the event study coefficients of the effect of price reduction on drug purchases for the insured and uninsured separately. Year-month included are Apr-Dec 2018 and Apr-Dec2019 and the estimate for Dec 2018 is normalized to 0. ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

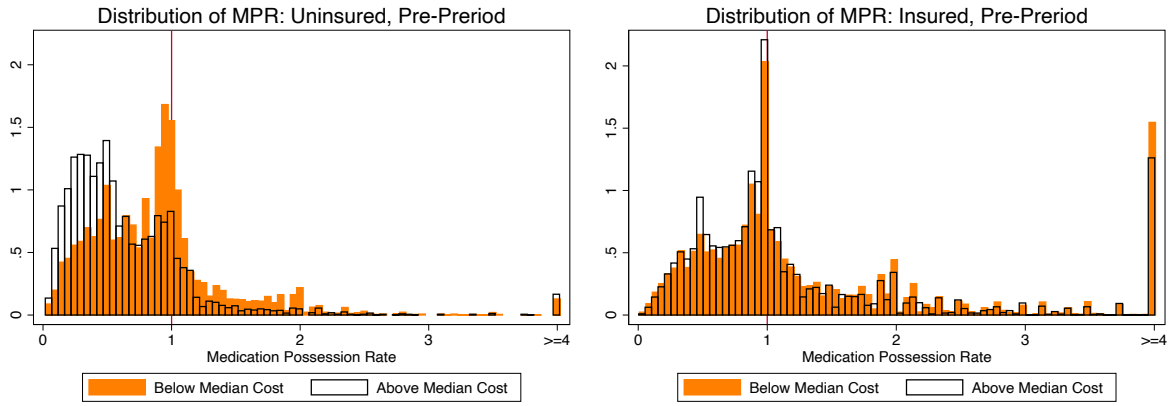


(a) No Insurance

(b) With Insurance

Figure 2.4: Monthly Drug Purchases: Existing Patients

Notes: This figure plots the monthly pattern of drug purchases for the subsample that had been undergoing treatment in the pre-period (4/1/2018-12/31/2018). The way values are constructed is the same as in Figure 2.

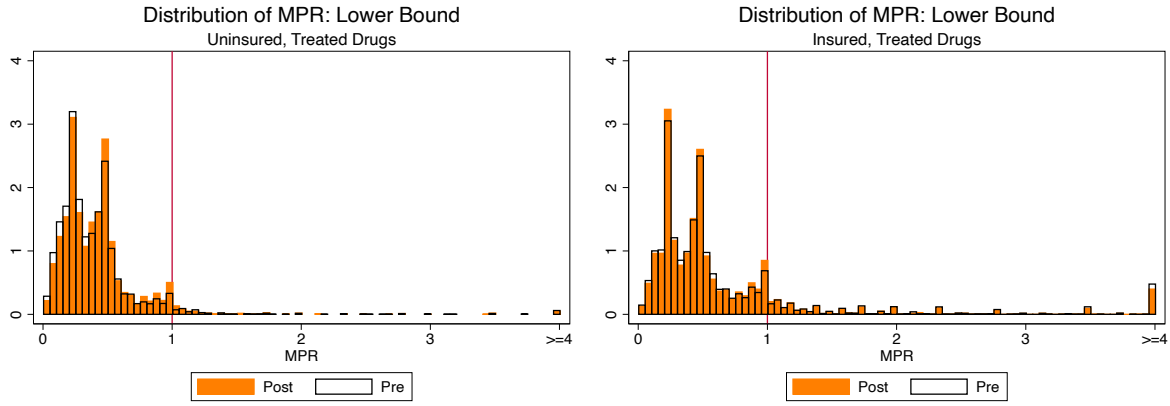


(a) No Insurance

(b) With Insurance

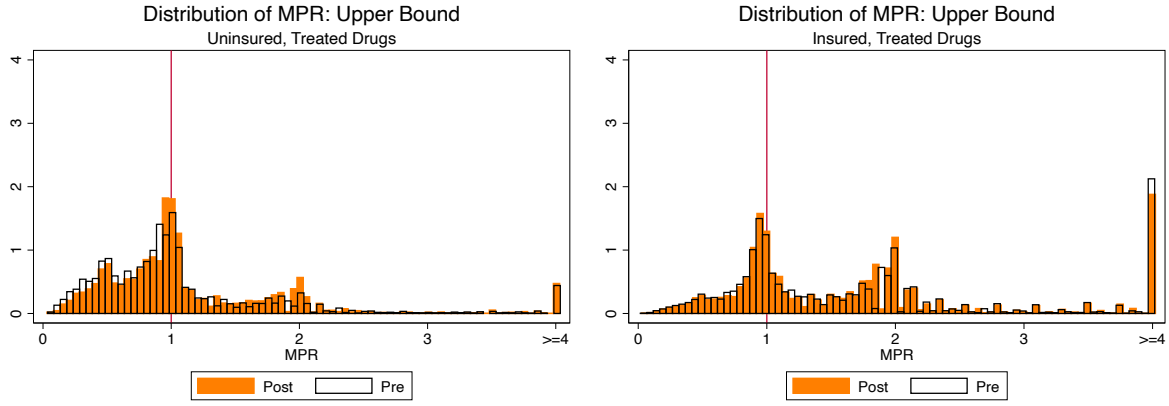
Figure 2.5: Distribution of MPR by Above and Below Median Cost of Daily Dose

Notes: This figure plots the distribution of medication possession ratio (MPR) in the pre-period (Apr-Dec 2018) for the insured and uninsured separately. Observation is at the prescription level. For each panel, MPR for prescriptions with above or below median daily dosage cost is plotted separately, shown as orange or hollow bars. Prescriptions with MPR greater than or equal to 4 are grouped together.



(a) Lower Bound: No Insurance

(b) Lower Bound: With Insurance

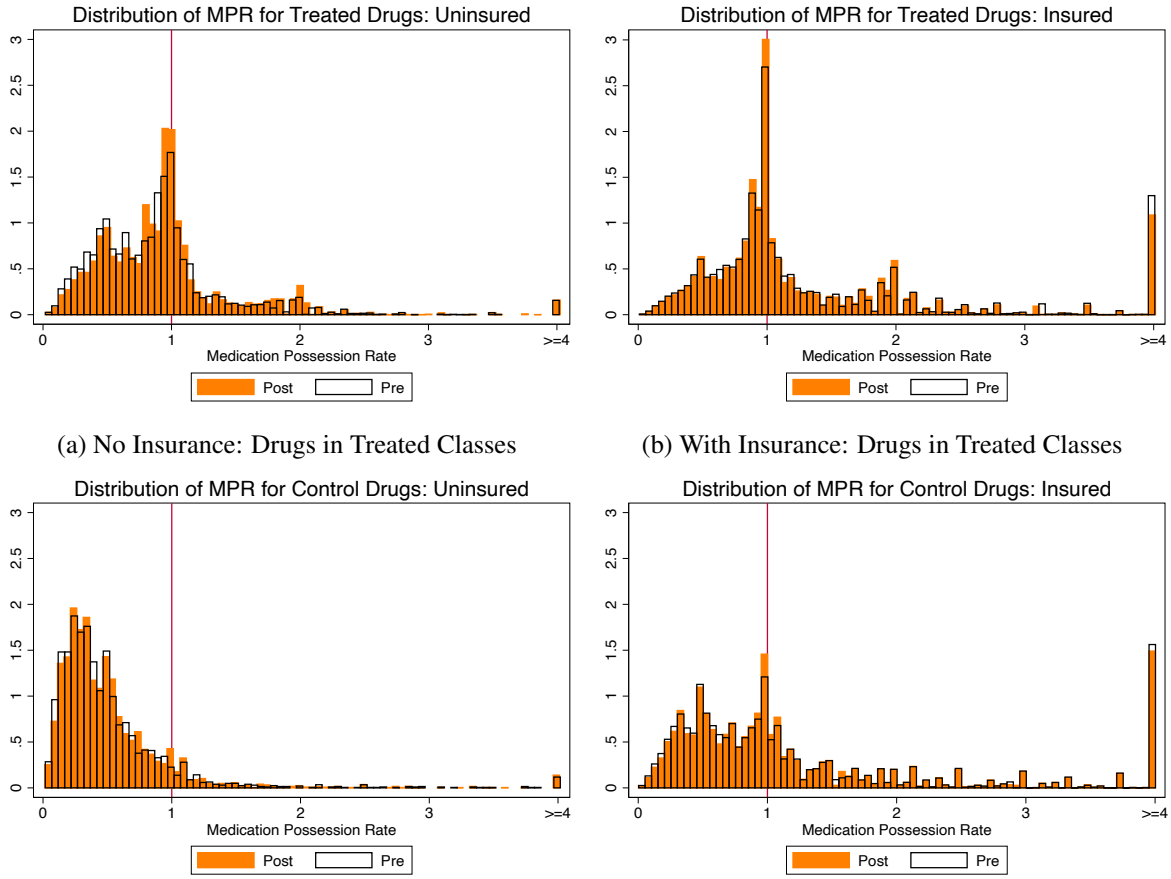


(c) Upper Bound: No Insurance

(d) Upper Bound: With Insurance

Figure 2.6: MPR Lower and Upper Bound: Treated Classes, Before and After

Notes: This figure plots the distribution of lower and upper bounds estimates of MPR for the treated drugs in both the pre-period and post period. Observation is at the prescription level. The lower bound estimate is obtained by assume patients need the maximum daily dose allowed for a drug. The upper bound estimate is obtained by assume patients need the minimum daily dose allowed for a drug. Distributions from pre and post period are graphed separately, show as hollow or orange bars in each panel. Prescriptions with MPR greater than or equal to 4 are grouped together.



(a) No Insurance: Drugs in Treated Classes

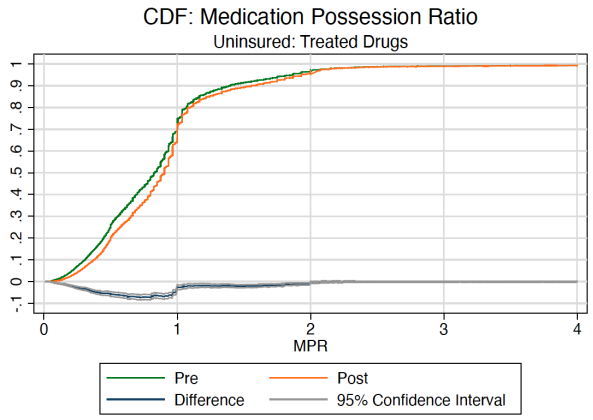
(b) With Insurance: Drugs in Treated Classes

(c) No Insurance: Control Drugs

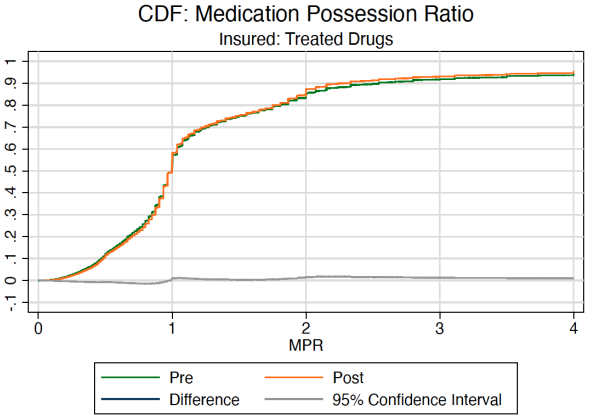
(d) With Insurance: Control Drugs

Figure 2.7: Distribution of MPR: Treated Classes, Before and After

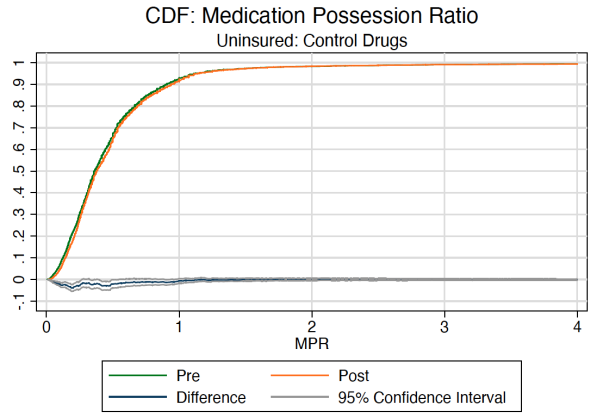
Notes: This figure plots the distribution of medication possession ratio (MPR) for the insured and uninsured separately. Panel (a) and (b) show the distribution of MPR for drugs in treated classes. Panel (c) and (d) show distribution for control drugs. In each sub-graph, distribution from the post period (orange bars) is overlaid on top of that from the pre-period (hollow bars). Observation is at the prescription level.



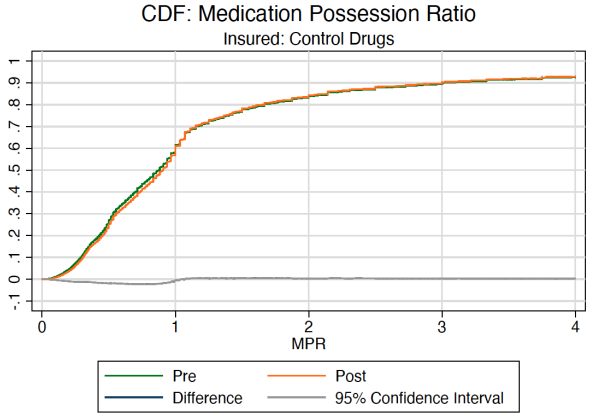
(a) No Insurance - Treated



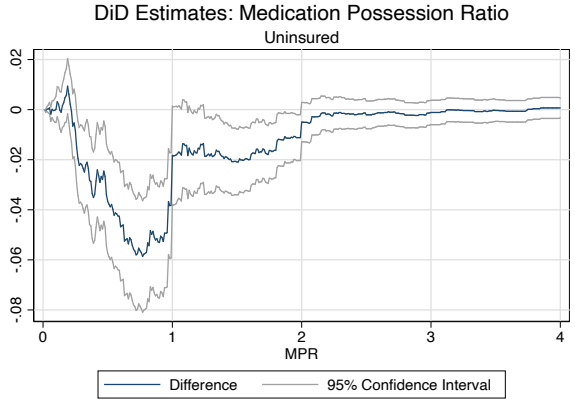
(b) With Insurance - Treated



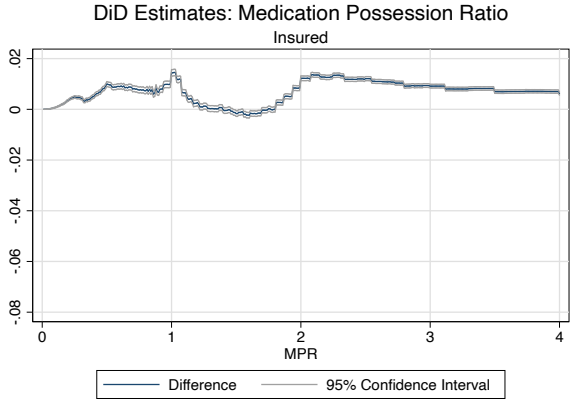
(c) No Insurance - Control



(d) With Insurance - Control

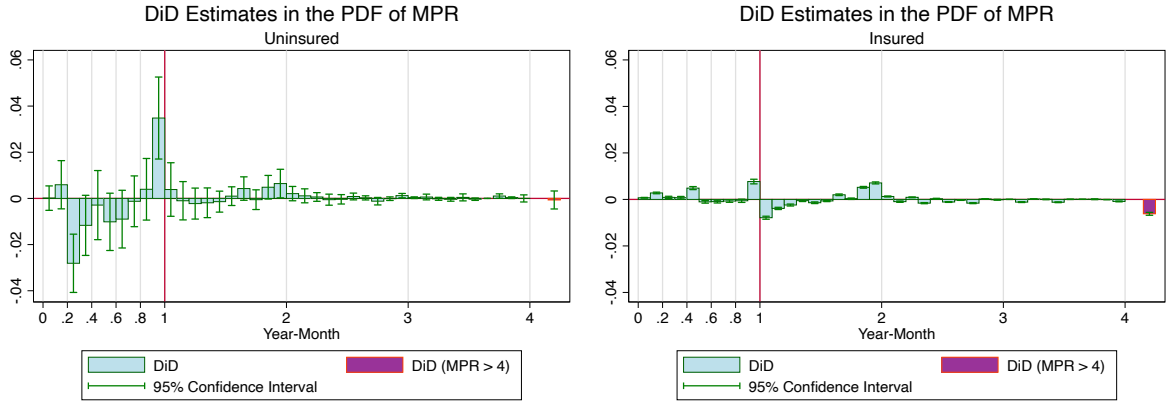


(e) No Insurance - DiD



(f) Insurance - DiD

Figure 2.8: Effects on MPR Distribution (CDF)
Notes: This figure plots the CDF of MPR and regression results from equation 2.9. Panel (a)-(d) plots the CDF of MPR from the pre and post period separately, with the difference in CDF shown by the blue lines and 95% confidence interval plotted in grey lines. Panel (e) and (f) present the DiD estimation results for uninsured and insured separately.

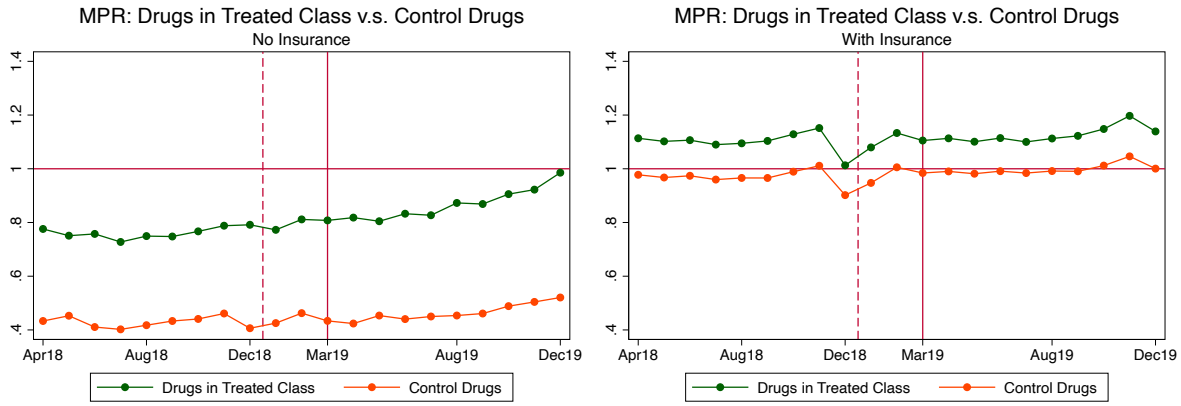


(a) No Insurance

(b) With Insurance

Figure 2.9: Effects on MPR Distribution (PDF)

Notes: This figure plots DiD estimation results for the pdf of MPR for uninsured and insured separately. The dependent variable in this figure is the likelihood of MPR in each of the 0.1 width bins from 0 to 4. And the last bar shows the estimates on the likelihood of MPR greater than 4.



(a) No Insurance

(b) With Insurance

Figure 2.10: MPR: Monthly Patterns

Notes: This figure plots the monthly means of MPR (conditional on $MPR \leq 4$) for prescriptions with treated and control drugs, and for insured and uninsured separately.

2.A Appendix: ATC Code and Therapeutic Classes

This appendix shows the list of drugs included in the analysis and the assignment of therapeutic classes based on medical treatment guidelines and the ATC classification system.

In the Anatomical Therapeutic Chemical (ATC) classification system, the active substances are divided into different groups according to the organ or system on which they act and their therapeutic, pharmacological and chemical properties. Drugs are classified in groups at five different levels. Drugs that share more levels of the ATC code are more similar in their therapeutic use and chemical properties. We first assign all drugs in our data with an ATC codes based on their chemical substance.

The 10 drugs that are included in the reform are for the treatment of Hypertension (7 out of 10), High Cholesterol (2) and Atherosclerosis (1). To find all the other drugs that are in the same therapeutic class as the 10 treated drugs, we use the medication treatment guidelines of hypertension, high cholesterol to find which therapeutic class those drugs belong to and then find corresponding ATC sub-categories. For example, treated drug with chemical name "amlodipine" and ATC code "C08CA01" is considered as "Calcium Channel Blockers" in the treatment guideline of hypertension. And the corresponding ATC sub-category representing "Calcium Channel Blockers" is "C08". Therefore we consider all drugs with ATC code starting with "C08" as treated. The ATC sub-categories for all treated drugs are shown in Table 2.A.1. For the selection of control, we first include all drugs in the other therapeutic classes for hypertension and high cholesterol. And we also include all the other drugs with ATC Code starting with "C" because "C" is the category of drugs for "Cardiovascular System". Finally, we include the drugs for diabetes as control as well, which is also a common chronic conditions among. The diabetes drugs are labeled by ATC code "A10" as "Drugs Used In Diabetes" in the ATC classification system.

Table 2.A.1: Treated and Control Therapeutic Class

Price-Reduced Drugs			**Treated Therapeutic Classes**			**Control Therapeutic Classes**		
Illness	ATC Code	Generic Name	Illness	ATC Code	Drug Group	Illness	ATC Code	Drug Group
Cardiovascular System	B01AC04	clopidogrel	Cardiovascular System	B01	Antithrombotic Agents	Cardiovascular System	C01 C04 C05	Cardiac Therapy Peripheral Vasodilators Vasoprotectives
HTN	C08CA01 C09AA02 C09AA03 C09AA09 C09CA01 C09CA04 C09DA04	amlodipine enalapril lisinopril fosinopril losartan irbesartan irbesartan and diuretics	HTN	C08	Calcium Channel Blockers	HTN	C02	Antihypertensives
				C09	Agents Acting On The Renin-Angiotensin System		C03	Diuretics
							C07	Beta Blocking Agents
HC	C10AA05 C10AA07	atorvastatin rosuvastatin	HC	C10AA	HMG CoA Reductase Inhibitors	HC	C10\C10AA	Lipid modifying agents
						Diabetes	A10	Drugs Used In Diabetes

Table 2.A.2: List of Treated and Control Drugs

Treated Drugs			Control Drugs		
Therapeutic Class	ATC Code	Name	Therapeutic Class	ATC Code	Name
B01	B01AC04	clopidogrel	C01	C01AA05	digoxin
	B01AC06	acetylsalicylic acid		C01DA14	isosorbide mononitrate
	B01AC19	beraprost		C01EA01	alprostadil
	B01AC23	cilostazol		C01EB15	trimetazidine
	B01AC24	ticagrelor	C04	C04AE02	nicergoline
	B01ACXX	platelet aggregation inhibitors excl. heparin	C05	C05AXXX	aluminium preparations
	B01ADXX	enzymes		C05BX01	calcium dobesilate
	B01AXXX02	other antithrombotic agents		C05CA03	diosmin
	B01XXXX	lumbrukinase		C05CA04	troxerutin
C08	C08CA01	amlodipine	C02	C02LA51	reserpine and diuretics, combinations with other drugs
	C08CA02	felodipine	C03	C03BA11	indapamide
	C08CA05	nifedipine		C03CA04	torasemide
	C08CA09	lacidipine		C03DA01	spironolactone
	C08CA14	cilnidipine		C03DB01	amiloride
	C08CA15	benidipine	C07	C07AB02	metoprolol
	C08DB01	diltiazem		C07AB07	bisoprolol
C09	C09AA02	enalapril		C07AG02	carvedilol
	C09AA03	lisinopril		C07AGXX	arotinolol hydrochloride
	C09AA04	perindopril	C10\C10AA	C10AB05	fenofibrate
	C09AA07	benazepril		C10AD06	acipimox
	C09AA09	fosinopril		C10AX02	probucol
	C09BBXX	amlodipine and benazepril		C10AXXX02	ethyl polyenoate
	C09BX01	perindopril, amlodipine and indapamide	A10	A10AB01	insulin (human)
	C09CA01	losartan		A10AB04	insulin lispro
	C09CA03	valsartan		A10AC01	insulin (human)
	C09CA04	irbesartan		A10AE04	insulin glargine
	C09CA06	candesartan		A10AE05	insulin detemir
	C09CA07	telmisartan		A10BB07	glipizide
	C09CA08	olmesartan medoxomil		A10BB08	gliquidone
	C09DA01	losartan and diuretics		A10BB12	glimepiride
	C09DA04	irbesartan and diuretics		A10BD02	metformin and sulfonylureas
	C09DA07	telmisartan and diuretics		A10BF01	acarbose
	C09DX01	valsartan, amlodipine and hydrochlorothiazide		A10BF03	voglibose
C10AA	C10AA01	simvastatin		A10BG03	pioglitazone
	C10AA03	pravastatin		A10BX02	vildagliptin
	C10AA04	fluvastatin		A10XAXX	epalrestat
	C10AA05	atorvastatin			
	C10AA07	rosuvastatin			
	C10AA08	pitavastatin			

2.B Appendix: Robustness of Main Results on Drug Purchases

Table 2.B.1: Robustness of Main Result: Excluding Diabetes Drugs

	log(Dosage(Days) + 1)		
	(1) Urban Employee	(2) No Insurance	(3) Triple-Diff
Treat*Post*Uninsured			.21*
			(.13)
Treat*Post	.12	.34**	.12
	(.12)	(.15)	(.11)
Uninsured			-5.6***
			(.23)
Treated Pre Mean	11	5.6	
N	1098	1098	2196

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the robustness of result in Table 2.3 when we exclude the set of diabetes drugs from control. The time horizon included in the analysis is Apr-Dec 2018 (pre) and Apr-Dec2019 (post). Year-month fixed effects and ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

Table 2.B.2: Robustness of Main Result: Jan to March

	log(Dosage(Days) + 1)		
	(1)	(2)	(3)
	Urban Employee	No Insurance	Triple-Diff
Panel A. Include Jan-Mar 2019			
Treat*Post*Uninsured			.21*
			(.11)
Treat*Post	.086	.29***	.086
	(.073)	(.11)	(.072)
Uninsured			-5.9***
			(.17)
Treated Pre Mean	11	5.6	
N	1575	1575	3150
Panel B. Include Jan-Mar 2019 and Jan-Mar2020			
Treat*Post*Uninsured			.2*
			(.11)
Treat*Post	.16	.36***	.16
	(.11)	(.12)	(.11)
Uninsured			-5.9***
			(.17)
Treated Pre Mean	11	5.6	
N	1800	1800	3600

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the robustness of result in Table 2.3 when include observations from January to March in the analysis. Year-month fixed effects and ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

2.B.1 Robustness of MPR

Table 2.B.3: Robustness of MPR Result: Last Time Purchase

	MPR(<4)		$1(MPR >= 4)$	
	(1) Urban Employee	(2) No Insurance	(3) Urban Employee	(4) No Insurance
Panel A. Impute MPR for the Last Purchase to be 1				
Treated Class*Post	-.0025**	.036***	-.0043***	-.00062
	(.0011)	(.011)	(.00039)	(.0019)
Treated Pre Mean	1.1	.91	.054	.0046
N	10704363	57090	11338287	57350
Panel B. Impute MPR for the Last Purchase to be 0				
Treated Class*Post	-.0029**	.065***	-.0043***	-.00062
	(.0012)	(.012)	(.00039)	(.0019)
Treated Pre Mean	.92	.49	.054	.0046
N	10704363	57090	11338287	57350

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the robustness of result in Table 2.7 when we impute either 0 or 1 for the "Last Time" drug purchases. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

Table 2.B.4: Robustness of MPR Result: Cutoff of Two or Three

	(1) Urban Employee	(2) No Insurance	(3) Urban Employee	(4) No Insurance
Panel A	MPR(<2)		$1(MPR >= 2)$	
Treated Class*Post	.0013*	.028**	-.0047***	.013**
	(.00076)	(.011)	(.00069)	(.006)
Treated Class	.19***	.44***	.027***	.031***
	(.00089)	(.015)	(.00073)	(.0074)
Treated Pre Mean	.94	.8	.17	.038
N	7973814	33346	9571831	34634
Panel B	MPR(<3)		$1(MPR >= 3)$	
Treated Class*Post	.00015	.039***	-.0069***	.0034
	(.001)	(.013)	(.00053)	(.0034)
Treated Class	.22***	.47***	-.004***	.0075**
	(.0012)	(.017)	(.00053)	(.0037)
Treated Pre Mean	1.1	.84	.084	.01
N	8710326	34276	9571831	34634

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the effect on MPR when we consider the "large" MPR cutoff to be either 2 or 3. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

Table 2.B.5: Robustness of MPR Result: Refill of Therapeutic Class
(HTN, HC, Diabetes Drugs Only)

	MPR(<4)		$1(MPR >= 4)$	
	(1)	(2)	(3)	(4)
	Urban Employee	No Insurance	Urban Employee	No Insurance
Treated Class*Post	.0093***	.028**	-.0042***	.0002
	(.00098)	(.014)	(.00022)	(.0018)
Treated Class	.28***	.47***	.017***	.0018
	(.0012)	(.018)	(.00025)	(.0023)
Treated Pre Mean	1	.84	.027	.0026
yearmonth FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
N	8902839	33173	9051232	33248

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the robustness of result in Table 2.7 when we define "refill" by the purchases of drugs from the same therapeutic class. The analysis is restricted to drugs treating Hypertension, High Cholesterol, and Diabetes only. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

Table 2.B.6: Robustness of MPR Result: Refill of Therapeutic Class (All Drugs)

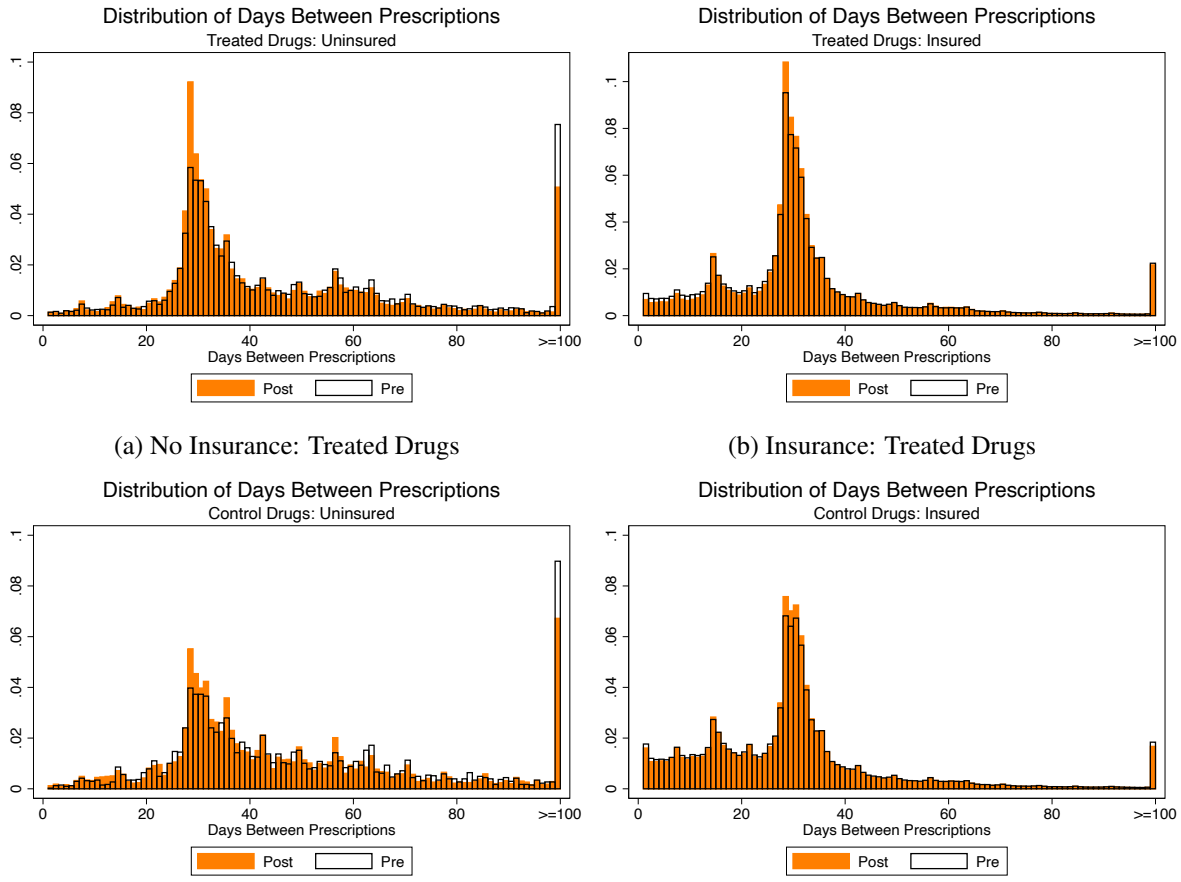
	MPR(<4)		$1(MPR >= 4)$	
	(1) Urban Employee	(2) No Insurance	(3) Urban Employee	(4) No Insurance
Treated Class*Post	.0069***	.038***	-.003***	.0019
	(.00093)	(.014)	(.00024)	(.0017)
Treated Class	.13***	.33***	.023***	.0032
	(.0011)	(.021)	(.00028)	(.002)
Treated Pre Mean	.94	.76	.034	.0022
yearmonth FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
N	11166531	39005	11433082	39107

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table reports the robustness of result in Table 2.7 when we define "refill" by the purchases of drugs from the same therapeutic class. The analysis includes all drugs in the sample. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

2.B.2 Distribution of Dosage Per Prescription and Gaps Between Refills



(a) No Insurance: Treated Drugs

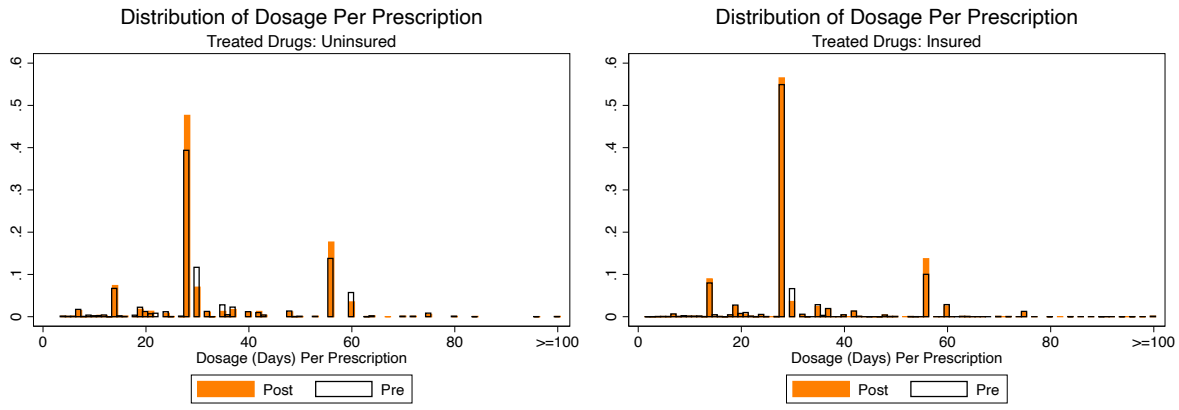
(b) Insurance: Treated Drugs

(c) No Insurance: Control Drugs

(d) Insurance: Control Drugs

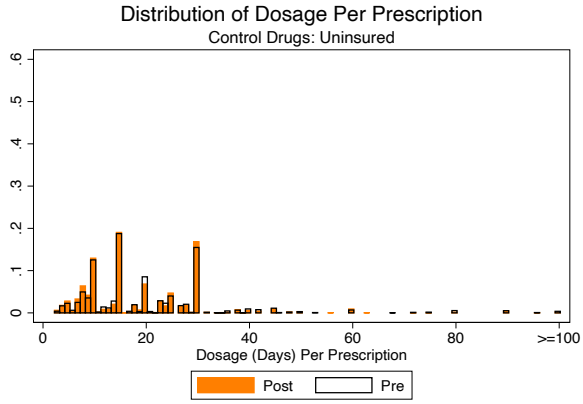
Figure 2.B.1: Distribution of Gaps Between Refills

Notes: This figure shows the distribution of gaps between two refills for the insured and uninsured separately. Panel (a) and (b) show the distribution for drugs in treated classes. Panel (c) and (d) show distribution for control drugs. In each sub-graph, distribution from the post period (orange bars) is overlaid on top of that from the pre-period (hollow bars). Observation is at the prescription level.

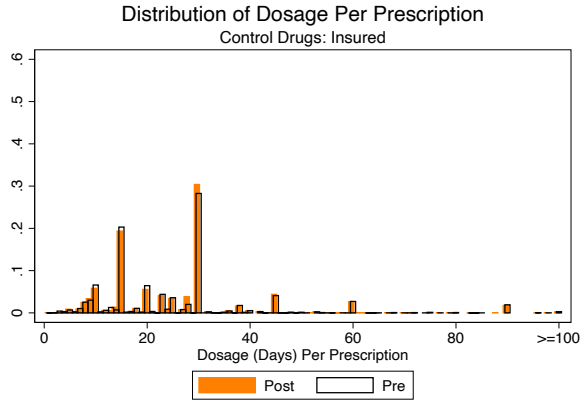


(a) No Insurance: Treated Drugs

(b) Insurance: Treated Drugs



(c) No Insurance: Control Drugs



(d) Insurance: Control Drugs

Figure 2.B.2: Distribution of Dosage Per Prescription

Notes: This figure shows the distribution of dosage per prescription for the insured and uninsured separately. Panel (a) and (b) show the distribution for drugs in treated classes. Panel (c) and (d) show distribution for control drugs. In each sub-graph, distribution from the post period (orange bars) is overlaid on top of that from the pre-period (hollow bars). Observation is at the prescription level.

2.B.3 Results on Urban Resident Insurance Sample

Table 2.B.7: Effect on Dosage Purchases

	log(Dosage(Days) + 1)		
	(1) Urban Employee	(2) Urban Resident	(3) No Insurance
Treat*Post	.093	.11*	.34***
	(.08)	(.068)	(.12)
Treated Pre Mean	11	8.2	5.6
N	1350	1350	1350

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table adds the result on drug dosage purchased from the sample with Urban Resident Basic Medical Insurance (URBMI) (column 2). Column (1) and column (3) replicate the results show in Table 2.3. The time horizon included in the analysis is Apr-Dec 2018 (pre) and Apr-Dec2019 (post). Year-month fixed effects and ATC fixed effects are included. Standard errors are clustered at the drug (ATC Code) level.

Table 2.B.8: Effect on Medication Possession Rate (MPR)

	MPR(<4)			$1(MPR >= 4)$		
	(1) Employee	(2) Resident	(3) Uninsured	(4) Employee	(5) Resident	(6) Uninsured
Treated Class*Post	-.0038***	.0082	.046***	-.005***	-.00022	.00087
	(.0013)	(.0051)	(.015)	(.00045)	(.0013)	(.0027)
Treated Class	.19***	.25***	.46***	.0042***	.00094	.0078**
	(.0014)	(.0061)	(.018)	(.00044)	(.0011)	(.0032)
Treated Pre Mean	1.1	.96	.85	.065	.021	.0078
Individual FE	YES	YES	YES	YES	YES	YES
N	8937853	399992	34373	9571831	409815	34634

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: This table adds the result on Medication Possession Rate (MPR) from the sample with Urban Resident Basic Medical Insurance (URBMI) (column 2 and column 4). Column (1) (3)and column (4) (6) replicate the results show in Table 2.7. Patient fixed effects and year-month fixed effects are included in the analysis. Standard errors are clustered at patient level.

Chapter 3

Disease Awareness, Treatment Take-up and Adherence in Developing Countries: Experiment Proposals

3.1 Introduction

Health is a fundamental component of human capital and health gaps across countries are a major contributor to global inequities. Health issues and healthcare cost have been documented to be overwhelmingly the most common reason that drives descent into poverty. They could also exacerbate the prevalence and depth of poverty not only in developing countries but also in higher-average-income regions, such as North Carolina in the United States (van Doorslaer et al., 2006; Krishna, 2010). Many people are living "one illness away from poverty" (Anirudh Krishna, 2010).

Households in low-income countries usually have low levels of preventative health expenditures, which contributes to and meanwhile contrasts with the fact that out-of-pocket health expenditure could account for up to 10% of total household expenditure (Dupas, 2011b). Lack of information has been shown to be an important barrier to optimal health investment. The insufficient provision of primary healthcare services both in quantity and quality makes people in developing countries lack access to regular physical exams. This could cause many illnesses to be left undiagnosed and untreated until it progresses into a stage that is not only

financially costly to treat but might also have a permanent negative impact on an individual's productive human capital (Gauer and Bragg, 2017). Lu et al. (2017) documents that among those who have hypertension in China, only 44.7% were aware of their diagnosis and 30.1% were taking prescribed medications. And uncontrolled hypertension accounted for almost half of all cardiovascular disease deaths (approximately 750,000) at ages 35-59 years in China in 2010 (Lewington et al., 2016).

This is especially concerning because the noncommunicable disease has become the top disease burden in many developing countries as a result of economic development, globalization, urbanization, and changes in population demographics (Nabel et al., 2009; Institute of Medicine, 2010). Many chronic conditions are often preventable, and early detection and proper management have been shown medically to be cost-effective in preventing costly complications (Ettehad et al., 2016). Yet because they do not usually have salient symptoms, people tend not to seek care until they result in severe health events like strokes or heart attacks.

Therefore, in the first experiment, I propose an intervention that provides people in low-income areas with physical exams and health reports. Based on their test results, the health report will provide people with information on whether they have those widely under-diagnosed conditions like hypertension, high cholesterol, and diabetes. Together with other information like age, smokers, and family health history, it will also report whether they are in the group with high cardiovascular risk.

This study is especially motivated by the fact that people have documented low awareness rates of chronic conditions across the developing world including China (Lu et al., 2017), India (Prabhakaran et al., 2005; Deepa et al., 2003), Indonesia (Kim and Radoias, 2016; Hussain et al., 2016), Latin America (Lamelas et al., 2019), and Africa (Dzudie et al., 2012). Awareness should be the first order constraint to seeking care on the patient side. This is in line with the development health literature where many studies have found that providing information is effective in changing the household's healthcare-seeking behaviors (Dupas, 2011b; Dupas and

Miguel, 2017; Kremer and Glennerster, 2011).

Given the low awareness rate, and the fact that households are often responsive to information on health risks (Jalan and Somanathan, 2008; Dupas, 2011b), there are reasons to expect a potentially large return to investment on the margin of raising awareness. Furthermore, because these conditions are not contagious, the incentives of patients and the social planner should in principle coincide. The story of insufficient take-up due to not taking into the positive externality generated by individual behavior should not hold in this context (Kremer and Miguel, 2007). Some facts in the medical literature also provide promising evidence on the potential effectiveness of the intervention. In China, treatment take-up rate is 66.7% conditional awareness (Lu et al., 2017). In Indonesia, previously diagnosed with hypertension is associated with better blood pressure control and lower probability of remaining hypertensive (Kim and Radoias, 2018).

However, there might exist some constraints that will limit the effectiveness of the information intervention. First, chronic conditions are disproportionally affecting the elderly, and the elderly might demonstrate different patterns of processing and reacting to information in healthcare settings (Abaluck and Gruber, 2011). Second, though aware of their conditions, patients might not seek care because of the financial or time cost.[1] The education level of the population might also play a role in how people respond to the information because of the potential complementarity between education and information (Schultz, 1975). Moreover, health care providers in developing countries are often found to be of insufficient quantity and poor quality (Das et al., 2016), which could lead to misuse and overuse of care due to a lack of professional guidance (Cohen et al., 2015). The welfare effects could be further complicated if there is a market for falsified and substandard drugs (Roger and Boateng, 2007; World Health Organization, 2017a). And because the cost of treatment is immediate but the benefit is delayed, chronic condition treatment is usually considered to suffer from negative behavioral hazard

[1] Studies have documented that the take-up of preventative care is sensitive to price and distance. See Kremer and Glennerster (2011) for a review.

(Baicker et al., 2015).

With the ex-ante ambiguity in the effect size in mind, one set of outcomes we are interested in would be lifestyle changes, for example, dietary choices and physical activities. Another set will be patients' healthcare-seeking behaviors: whether they have visited a health-care provider, whether they have been taking medications, whether they have been adhering to the treatment regimens prescribed by the doctor, and whether they have their condition better managed. I hope to collect all of that information through a baseline and an endline survey. Patient demographics will be also collected in the survey to facilitate the analysis of effect heterogeneity, which would allow us to better understand the underlying constraint to health investment. There are at least two important dimensions of heterogeneity to examine. The first would be an individual's baseline risk scores of cardiovascular disease. Those with a higher baseline risk score should have a higher expected benefit from treatment and theory would predict a higher take-up rate and treatment adherence (Kim and Radoias, 2016). The other dimension would be whether an individual knows someone who has had severe health events associated with cardiovascular disease in the past. It has been documented in the literature that such spillover exists within a family network (Fadlon and Nielsen, 2019). This could come from a channel of salience and/or information, meaning that people learn about their own risk if the event happens to family members, or people learn about the cost of such health events. The survey could be designed accordingly to disentangle these channels.

One other potential extension of the experiment is the question of social learning in the context of disease management. Studies have shown that social learning through networks is effective in promoting the take-up of not only health products (Kremer and Miguel, 2007; Dupas, 2014; Oster and Thornton, 2012), but also other products like agriculture production technologies (Foster and Rosenzweig, 2010), microfinance (Banerjee et al., 2013), etc. But the fact that the treatment of chronic conditions usually involves prescription drugs raises additional concern regarding the welfare impacts of social learning, especially when the gate-keeping

function of the healthcare providers is not well performed. If people follow others and take the drugs that are not prescribed based on their own conditions, there could be a welfare loss because the side effects could have a detrimental impact on a patient's health. If capacity allows, I would like to collect the network data within a village, and information on sources of patient's treatment plans to examine this aspect.

The central question this experiment tries to answer is whether improving disease awareness could induce behavioral changes in patients themselves. As governments around the developing world put enormous effort into improving population health and identifying chronic disease prevention and control as a key policy priority, it is usually a tough decision to allocate scarce resources across different sectors of the healthcare system. Governments have engaged in providing basic health insurance coverage, initiating public programs including tobacco control, primary health care management (Srinath Reddy et al., 2005; Eggleston and Jain, 2020; Ding et al., 2021), etc. These efforts have been shown to be effective but with such a large margin of disease unawareness in the population, there are likely substantial returns to investment at the awareness margin that has not been realized. Overall there has not been enough emphasis on this margin. Beyond contributing to the economic literature by identifying the constraints to health investment, this experiment also hopes to contribute to the policymaking by examining the cost-effectiveness of raising patients' awareness of the disease. Furthermore, we would also like to examine whether raising awareness could complement other government efforts in managing chronic conditions from the supply side.

The other margin of improvement that has been focused on by both the policymakers and researchers is the low adherence conditional on disease awareness and treatment take-up. Lu et al. (2017) documented that among all who are aware of their hypertension, only 17.2% achieved control in China. Hypertension patients in India only made 5 - 10% of the recommended number of doctor visits in an experiment conducted by Bai et al. (2017). Figure 2.5 of Chapter 2 also shows that a substantial fraction of drug purchases are associated with

drug underuse characterized by the Medication Possession Ratio (MPR) below 1 among the chronic condition patients visiting primary care centers in Beijing, China. And this is true both for the insured and uninsured, both before and after the reform that introduced a 78% reduction in prices. Even in the U.S., The blood pressure control rate is only around 43.7% in 2017-2018 among those with hypertension (Muntner et al., 2020).

Behavioral bias has been argued to be an important barrier to the take-up and adherence of care that have a preventative nature because the care would not provide immediate benefit. Chronic condition medication treatment has exactly that feature. It does not provide immediate symptom relief but mainly lowers the risk of future health shock. Hence salience and present bias will lead to underutilization (Baicker et al., 2015; Carrieri and Bilger, 2013). And because the chronic condition treatment usually requires regular doctor visits and prescription refills, the possibility that people might simply forget to take the medication or refill their prescription is also higher. However, studies have shown that tools designed to address those behavioral biases do not usually work in this context, including commitment devices and appointment reminders (Bai et al., 2017; Boone et al., 2020), though reminders have been shown to effectively improve adherence to curative care (Pop-Eleches et al., 2011). Researchers have explored different text message framing strategies to improve chronic condition medication adherence in the U.S. but they either find no effect (Choudhry et al., 2017; Dai et al., 2017a) or very modest effect (Dai et al., 2017b). This highlights the difficulty of improving medication adherence, especially in chronic care settings, and raises the question of whether there exist other constraints to adherence.

The perceived future benefit from treatment is another component in the patient decision-making model that has not been explicitly discussed in the literature. As shown in equation 2.6 of the conceptual framework in section 2.3, besides the discount factor, there are two other components on the benefit side of the equation. One is the expected reduction in the likelihood that a health event will occur in the future. The other is the cost associated with a health shock,

including the direct financial cost of treatment and the loss of productive labor. From the model, it is clear that these two variables will affect patients' decisions. It has also been well documented empirically that risk perception is correlated with health behavior (Brewer et al., 2007; Spitzer and Shaikh, 2022).

Therefore, in the second experiment, I propose an intervention that provides patients who have related chronic conditions with information on their cardiovascular disease risk scores, and the expected cost of a health event. Risk scores could be a 10-year risk of heart disease or stroke based on the patient current health indicators, and a reduction in risk could be calculated counterfactually assuming the condition is under control. The expected cost of a health event will include the cost estimates from the population, including the financial cost of treatment under different health coverage plans in the local area, and the loss of productive labor both in terms of lost labor time due to illness, and the loss of productivity after recovery.[2]

The main outcome of interest here would be a comprehensive set of health behavior measures, collected through both administrative healthcare-seeking records and surveys. Healthcare-seeking records like the one we used in Chapters 1 and 2 would allow us to measure the frequency of doctor visits, medication adherence, and whether the information has any spillover effect on the take-up and adherence of other preventative care. A survey would allow us to understand other aspects of health-related activities that could not be measured in the administrative record, including physical activities and dietary choices.

Studies have shown that risk perceptions affect individuals' decisions (Barseghyan et al., 2013; Spinnewijn, 2013), and correcting for misperception could change the willingness to pay and improve consumer welfare in the insurance market (Abito and Salant, 2018). Overconfidence in one's own health has also been widely documented in healthcare settings (Hoorens, 1994; Robb et al., 2004; Kreuter and Strecher, 1995). If patients do hold inaccurate

[2]All the information provided to patients should be carefully evaluated by the health professionals to make sure it is clinically accurate. There is also medical literature discussing strategies for communicating risk information to patients (for example, Paling (2003)), which needs to be carefully considered.

beliefs about their risk scores, we should expect correcting for misperceptions to have an impact on health behaviors. Apart from the level of risk perception, we also hope to correct the misperception about the reduction in risk through proper treatment, which patients usually do not have an accurate evaluation of either (Dupas, 2011a; Rhee et al., 2005).

Again, because there is no health externality associated with chronic conditions, the incentives of patients and the social planner should in principle coincide. And the information would be directly provided to patients themselves, which should make the effectiveness of the information not limited by factors documented by previous studies including the perception of transmissibility of the illness between oneself and others, or bargaining power within the household (Boozer and Philipson, 2000; Kremer and Miguel, 2007; Dupas, 2009; Ashraf et al., 2014). However, though we expect less of some aforementioned barriers to investment, information itself might not be sufficient to move decisions to the optimal level. We would also like to evaluate the role of other factors in explaining the remaining discrepancy if condition permits, for example, cost, trust, education, supply-side constraints, etc. People's beliefs and the process of belief updating might also be subject to a trade-off between accuracy and desirability, referred to by the literature as motivated reasoning, which might also limit the effectiveness of the information (Oster et al., 2013; Epley and Gilovich, 2016; Bénabou and Tirole, 2016; Schwardmann, 2019).

3.2 Chronic Condition in Developing Countries

In this section, I will discuss the scale of noncommunicable condition issues in developing countries, and highlight why the two issues targeted by the experimental proposals could be particularly important in this context.

Noncommunicable conditions (NCD) have become the top disease burden of many developing countries as a result of economic development, globalization, urbanization, and changes in population demographics (Nabel et al., 2009; Institute of Medicine, 2010). In fact,

77% of all NCD deaths are in low- and middle-income countries (World Health Organization, 2021b). NCD is estimated to cost developing countries up to 6.77% of GDP (Institute of Medicine, 2010). NCD strikes disproportionately among people of lower social positions and the "disease of affluence" is not an illness that only the high-income populations bore anymore. Because most health-care costs are paid by patients out-of-pocket in developing countries, the cost of care for NCDs could create a significant strain on household budgets (World Health Organization, 2011). As Nabel et al. (2009) put in a Lancet article:

> The health catastrophe provoked by this global surge of chronic disease is also an underappreciated cause of poverty that impedes the economic development of many countries. Thus, we believe it is vital that the international public health community makes chronic disease prevention a worldwide priority.

Though as the leading cause of death globally, NCDs are to a great extent preventable (World Health Organization, 2011). Cardiovascular diseases (CVD) are the major category of NCDs. Hypertension, elevated cholesterol, and blood sugar are significant risk factors for major cardiovascular events (World Health Organization, 2021a). But they can be managed through behavioral changes and medication treatment. Early detection and proper management of those conditions are cost-effective in preventing costly complications (Ettehad et al., 2016).

However, studies have documented very low awareness, treatment take-up, and adherence in the set of condition conditions that takes up the major disease burden in developing countries nowadays. In a population-based screening project in China that involves a sample size of 1.7 million, Lu et al. (2017) shows that the prevalence rate of hypertension among those aged 35-75 is 44.7%. The awareness rate, medication-taking rate, and control rate are surprisingly low among those who are diagnosed with the condition (44.7%, 30.1%, and 7.2%, respectively). Similar statistics have been shown in India. Srinath Reddy et al. (2005) shows that the prevalence rates of hypertension and diabetes are 30% and 15%, respectively, which are both high risk factors for CVD. But the awareness and control rate among those who are diagnosed with the conditions are disappointingly low (around 30% and 9%, respectively).

In Indonesia, 67% of the men and 54% of the women who are found to be hypertensive in a national survey had never been previously diagnosed by a doctor (Kim and Radoias, 2016).

The lack of awareness and control has important implications for population health. A large-scale study involving 500,223 people in China by Lewington et al. (2016) shows that uncontrolled hypertension accounted for about one-third of all CVD deaths at ages 35 to 79 years (approximately 750,000 CVD deaths). Given the scale of the problem, many governments around the world have identified chronic disease prevention and control as a key policy priority in public health. For example, the Chinese government included managing noncommunicable conditions as a key policy target in its national healthcare policy plan.[3] The government of India has launched the National Programme for Prevention and Control of Cancer, Diabetes, CVD, and Stroke (NPCDCS).[4]

3.3 Experimental Proposal: Raising Disease Awareness

In this section, I will illustrate an experimental design that addresses the low disease awareness in developing countries. The context I have in mind is China. But the proposed design would be applicable to the context of other countries as well. The details of the design will be subject to modification according to guidance from health experts, budget capacity, and other constraints.

3.3.1 Intervention and Randomization

The intervention will involve providing a basic physical exam for people who might not have had access to such healthcare services before (residents in rural areas or the low-income population in urban areas). Ideally, the randomization will happen at the village level. A public healthcare worker will go door to door and hand a free physical exam voucher to all adults in each household within a village. Residents will be given a time window of one week to go

[3] http://www.gov.cn/zhengce/content/2017-02/14/content_5167886.htm

[4] https://dghs.gov.in/content/1363_3_NationalProgrammePreventionControl.aspx

redeem the voucher. If there is a public primary care facility, the physical exam will take place there. If the village does not have such facilities, temporary health camps would be set up in the village to conduct the exams.[5]

Subjects will go through the basic standard physical exam procedure at the point of care. The health conditions we will be particularly interested in include their height, weight, blood pressure, blood lipids, blood sugar level, and other indicators that are relevant for the diagnosis of hypertension, hyperlipidemia, and diabetes, the set of chronic conditions related to cardiovascular disease. They will be told to come back and get their health report a few days later, depending on the capacity of the healthcare provider. When they come back and receive the health report, the healthcare provider will explain to them the indicators in their report if they are out of the normal range and give patients suggestions on whether they should have a follow-up visit to further examine their condition. If their exam results are indicative of those chronic conditions, or if other characteristics of the patients suggest that they are in a high CVD risk group (for example, age, sex, BMI, smoking status, family health history, etc), patients will be informed with their diagnosis and will be suggested to go to a clinic to get a doctor's more comprehensive evaluation on their condition and to determine whether medication treatment is necessary.[6] They will be given a flyer with information on suggested lifestyle changes, including getting regular physical exercises, reducing the diet that's high in fat, salt, sugar, and cholesterol, and increasing the consumption of fruit and vegetables, etc.[7]

A baseline survey will be conducted during the visit for the physical exam to collect information on the individual's demographics and other health-related characteristics that wouldn't be observed in the test results. This would include patients' age, gender, education level, marital status, household income level, and working status. Related to health, we will

[5] As of 2019, 95% of the villages in China has a public primary care facility according to National Bureau of Statistics of China. https://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A0O04&sj=2019

[6] Risk factors for developing heart disease (Mayo Clinic) https://www.mayoclinic.org/diseases-conditions/heart-disease/symptoms-causes/syc-20353118

[7] A sample flyer is the one designed by Chinese National Bureau of Disease Control and Prevention for the 2020 national hypertension day. http://www.nhc.gov.cn/jkj/s5879/202009/b37f099ecbe049a6910e6074a95b8cb5.shtml

collect information on health insurance coverage status, family health history related to CVD, self-awareness of chronic condition, current medication, and some information on their physical activity, dietary habits, and smoking status.

At the endline, we will survey the household who took up the physical exams and collect endline data. The survey will collect information mainly on their healthcare-seeking behaviors during the period between the baseline and endline. The survey will ask whether they have visited a healthcare provider to check their condition if they were suggested to do so, their medication-taking behavior, and some information on their physical activity, dietary habits, and smoking status. We would like to take another measure of their blood pressure (and blood lipids, blood sugar level if capacity permits) so that we could look at some actual health outcomes.

Because the baseline data collection comes together with the intervention itself, we would like some villages to get the treatment later and serve as a control group for the villages that receive the intervention earlier. This has several desirable features beyond making causal identification feasible. First, it will make sure that the control group also gets the treatment to ensure equity. Second, this type of staggered rollout might make the implementation more feasible if the resources needed for the intervention is limited. Finally, with appropriate time spacing in between, this design would also allow us to examine the trajectory of the treatment effect over time. A similar design has also been utilized by previous work (Miguel and Kremer, 2004).

Figure 3.1 shows an example of the research timeline. The second set of treatment villages will receive the treatment and baseline survey 3 months after the first set of treatment villages, and the third group of treatment villages will receive the treatment 6 months after. After 12 months of the start of the experiment, we will conduct the endline survey in all the three treatment groups simultaneously and offer the intervention to one control group. They are the control group in the sense that they have not yet been treated at the time we collect

the endline data of the three treatment groups. And the baseline data we collected there could be used to identify the treatment effect of the physical exam six months, nine months, and twelve months after the intervention, by comparing the control to treatment 3, treatment 2, and treatment 1 respectively. However, we need to think carefully about the natural evolvement of the outcome variables during the study period in the control villages.

The main hypothesis is that the physical exam and health report should induce health-related behavioral changes including seeking a doctor, getting medication if necessary, and changes in lifestyle through increasing patients' awareness of their chronic conditions. Given the high prevalence and low awareness documented in the population study (Lu et al., 2017), we could reasonably expect the first stage effect on awareness to be large. The main outcome of interest would be whether patients have seen a doctor, whether they have been taking medication, whether they have taken up recommended healthy lifestyle, and ultimately, whether their health indicators like the blood pressure levels are better controlled compared to the baseline.

There could be many barriers that make awareness difficult to turn into action. Examples include the cost of seeking care both financially and non-financially (for example, time cost), whether people could correctly perceive the benefit from treatment, behavioral biases, and supply-side constraints. Several dimensions of heterogeneity could be examined to help identify the barriers to behavior changes if we find the overall responses are limited. We could examine the heterogeneous response by the distance and transport cost to the nearest healthcare providers. Education level and having members in their family or social network who have had CVD-related health events could serve as a proxy for patients' understanding of the health risk and thus the benefits of timely and proper treatment. The second experiment proposal in section 3.4 tries to examine exactly the role of misperception of treatment benefits in take-up and adherence. If capacity allows, we will also include some questions in the endline survey to ask people explicitly about barriers to adoption.

3.3.2 Extension

There are two potential extensions we could add to this experiment design if capacity allows. The first one is to examine the spillover effect on take-up and adherence within social networks if we could collect network information within a village. Social learning has been widely documented to improve the take-up of new health technologies and products (Kremer and Miguel, 2007; Dupas, 2014; Oster and Thornton, 2012). We therefore could reasonably expect whether people you know have been diagnosed with the condition, and what behavioral changes adopted by others might affect one's own decision.

The question of interest will be whether having someone in the network who has been diagnosed with chronic conditions or taking the medication treatment increases the likelihood that an individual himself is more likely to see a doctor, initiate treatment, or take on a more healthy lifestyle, etc. While social learning has been generally thought of as a way of promoting the take up of cost-effective care which leads to welfare gains, we want to pay special attention to the potential welfare cost in this particular context. The ideal scenario of social learning would be that someone would learn from others' experiences and seek care from health professionals to get a treatment regimen that suits his own condition. But in a context with limited provider availability and unsatisfactory quality, and prevalence of substandard drugs (Das et al., 2016; Roger and Boateng, 2007; World Health Organization, 2017a), if people simply learn from others and copy their treatment regimens, it could lead to a welfare loss in terms of ineffective treatment and detrimental effect on one's health caused by the side effects of the medication.

The other potential extension would be to examine the complementarity between different policies that target the chronic condition control and management issue among the population. Both the Chinese and Indian government has identified chronic condition management as one of the health policy priorities and have been implementing many programs including providing health insurance coverage, tobacco control, strengthening primary health

care management, encouraging healthy diets, and drug procurement reforms aiming at improving affordability like what we have studied in Chapter 2 (Srinath Reddy et al., 2005; Eggleston and Jain, 2020; Ding et al., 2021). Though some have been shown effective, the efforts have mainly been on the supply side. Raising the patients' awareness of the conditions might be a complement to those other programs that the governments have been trying to promote. If there are other programs the governments are implementing regarding chronic condition management, we could cross randomize the implementation of those programs and the awareness intervention proposed in this section to examine their complementarities.

3.3.3 Additional Information Needed

There is additional information that needs to be collected and incorporated into the design before the experiment proposed in this section could be implemented. The first is medical experts' evaluation on what would be the set of the most cost-effective screening to provide, and what medical advice is the most appropriate to provide to patients with different conditions. There will be a trade-off between the coverage of the exams and the implementation capacities. There will also be a trade-off between providing more health information and the risk of overwhelming people with information. We also need to be careful about the potential psychological effect of receiving a diagnosis. All of these mentioned would require consultation with health experts to further polish the design. Before finalizing the design of the experiment, we also need to run a survey to understand the baseline prevalence and awareness rate of the conditions in the local context.

The other set of information that needs to be collected is what actions have the governments taken so far in addressing the challenges of chronic conditions, and what are the scales in terms of population coverage and impacts. This would require more data collection as well as field visits and conversations with the health experts. This is important both for thinking about the feasibility of the experiment and the possibility of examining the complementarity of

policies as mentioned in the previous subsection.

3.4 Experimental Proposal: Addressing Misperception of Treatment Benefits

In this section, I propose an experiment to provide patients who have chronic conditions with information on the expected benefit of treatment. The experiment tests the hypothesis that misperception of treatment benefits is one of the underlying reasons for low take-up and adherence rates conditional on awareness in developing countries. I will illustrate the design using the context of China. But the proposed design could be applicable to the context of other countries.

3.4.1 Intervention and Randomization

Because this intervention addresses the persistence and adherence issue conditional on awareness, our sample will consist of patients that have been diagnosed with chronic conditions and who are already aware of it. The intervention could happen at the time of a doctor's visit and the doctors will be delivering the information to the patients.

The information provided to the patient will include his individual cardiovascular disease risk score based on his current health indicators and demographics. The tool for generating the risk score will be developed with the help of health professionals to ensure the accuracy of the information. But such tools already exist and are available online, which are based on the guidelines developed by the American College of Cardiology (ACC) and the American Heart Association (AHA) (Goff et al., 2014).[8] The tool could generate a 10-year risk of heart disease or stroke based on patients' age, gender, and some health indicators like blood pressure and blood cholesterol levels. This could also generate a counterfactual risk factor, replacing the health indicator with the values in the normal range. The current and

[8]One example would be this tool that is readily available online: https://www.cvriskcalculator.com/

counterfactual risk score could provide the patient with an estimate of the reduction in risk if his condition would have been controlled.

Besides the reduction in risk, we will also provide patients an estimate of the cost associated with an event like a heart attack or stroke. This number should ideally be calculated using data from patients that are admitted to hospitals in the local area with such conditions. The average total financial cost of treatment could be estimated from hospital administrative records. Besides, information on the average length of hospital stay, spending on hiring care workers, and the extent to which the health capital has been permanently reduced could be collected through surveys and consultation with health professionals to provide patients an estimate of other financial costs besides the treatment itself and the nonfinancial cost associated with such health events (McHorney et al., 2021).

Because we want to test the effect of correcting for misperception, at baseline we need to collect data on beliefs. Before presenting patients with all the information, we will ask the patients their estimate of their current risk scores, the reduction in risk scores if the conditions have been well managed, and the cost of a major health event. This will first give us a sense of whether and to what extent misperception exists, and serves as the first stage results of the experiment. The questions should be carefully designed in an incentive-compatible way.

The outcome of interest would be patients' treatment adherence and their health conditions. Ideally, the data on drug adherence would come from the health provider's administrative record, which has a similar structure as those we used in the previous two chapters. And drug adherence could be measured using the same method as we illustrated in section 2.5.2. If we could collect more information on individual patients' prescription details at the point of care, we will be able to measure drug adherence more accurately by taking into account the heterogeneity in drug needs. At the endline, we will also measure the blood pressure or blood cholesterol levels of the study sample. If possible, we would like to conduct an endline survey to collect information on patients' perceptions of risk, and physical activities, dietary

choices, which are also critical for managing those conditions but wouldn't be captured in the administrative healthcare-seeking records.

3.4.2 Potential Context and Sample Size

This experiment could be conducted in a population with relatively high socioeconomic status because the information provided in this experiment might require patients to have a certain level of health literacy to process.[9] Complementarities between education and information have also been documented in the literature (Dupas, 2011b). I will therefore use the study context of Chapters 1 and 2 as an example to illustrate a possible design. As shown in Table 3.1, residents in Beijing have relatively higher socioeconomic status compared to the general population in China in terms of education and income levels. I will show the characteristics of a possible study sample with the data we used in Chapter 2 below.

To have a sense of the size of the primary care centers in the study area, Table 3.2 shows the summary statistics of patient visits at the clinic-month level. The sampling period included in the table is the full calendar year of 2019. We can see that patients with chronic conditions account for an average of 78% of the patients served by those healthcare centers, confirming that chronic condition management is one of the major services these primary healthcare centers provide to the local residents.[10] Compared with an average patient, those with chronic conditions are slightly older and have higher average spending per visit. But they are more likely to be covered by the most generous public health insurance scheme (Urban Employee Basic Medical Insurance) and are less likely to have no insurance coverage. This is consistent with the finding from previous work that those without insurance coverage are less likely to seek care for chronic conditions or take any medication treatment (Lu et al., 2017).

[9] According to the U.S. Health Resources and Services Administration, health literacy is defined as "the degree to which individuals have the capacity to obtain, process, and understand basic health information needed to make appropriate health decisions." (https://www.hrsa.gov/about/organization/bureaus/ohe/health-literacy/index.html#:~:text=Health%20literacy%20is%20the%20degree,Older%20adults)

[10] The set of chronic conditions we include here are hypertension, hyperlipidemia, diabetes, and cardiovascular artery disease.

Table 3.2 also shows that the size of the clinic varies in terms of the number of patients they serve and the composition of patients. The smallest among them have only seen 3 patients in some months. But those of larger sizes could be seeing tens of thousands of patients a month. Given the high share of patients with chronic conditions, if we could work with one or two clinics with larger overall sizes, there would be enough sample size to give us statistical power. The experiment will ideally be conducted at the end of the calendar year because there is usually a larger number of patients seeking care. We also need to restrict the age of the sample to between 40 to 80 years old or whatever the medical experts suggest.[11] With two clinics that locate at around the 60th percentile of the size in terms of the number of patients they serve, this could give us a sample size of around 2,000 chronic condition patients between 40 to 80 years old per month. The randomization will be conducted at the patient level.

[11]This preliminary thought on age restriction is based on the age range that the CVD risk score calculation tool could be used for. (https://www.cvriskcalculator.com/)

3.5 Tables and Figures

Table 3.1: Population Characteristics

Variable	Measure	Beijing	China
Average Education (2010)	Years	11.78[c]	8.8[c]
Rural	% of Total	13.5[a]	40.4[b]
Life Expectancy (2015)	Years	81.95[d]	76.34[b]
Disposable Personal Income	Per Capita, RMB	62,361[a]	28,228[b]

Notes: This table shows some population demographic characteristics for Beijing and China separately.
Data Source:
[a] Beijing Area Statistical Yearbook (2019)
[b] National Bureau of Statistics
[c] Sixth National Population Census of the People's Republic of China (2010)
[d] Beijing Annual Report of Population Health (2015)

Table 3.2: Primary Care Centers: Summary Statistics of Patient Visits

	Mean	SD	Min	Max
Panel A. All Visits				
Male	.57	.05	.25	.77
Age (as of 2020)	62.96	7.27	31.23	87.36
Total Number of Visits	3864.74	6026.52	3	63,242
Total Number of Patients	1960.89	2884.80	3	24,205
Share of Patients with Chronic Condition	.78	.16	.05	1
Average Total Spending per Visit (RMB)	612.33	243.06	43.86	2119.23
Average Out-of-pocket Spending per Visit	156.72	116.71	-.43	1052.57
Share of Patients with Urban Resident Insurance	.10	.18	.00	.89
Share of Patients with Urban Employee Insurance	.81	.22	.07	1
Share of Patients with No Insurance	.05	.06	.00	.60
Panel B. Visits by Patients with Chronic Conditions				
Male	.56	.06	.16	1
Age (as of 2020)	66.54	4.95	48.67	88.14
Average Total Spending per Visit (RMB)	653.29	235.23	-15.63	2053.43
Average Out-of-pocket Spending per Visit	154.57	109.31	-32.67	912.76
Share of Patients with Urban Resident Insurance	.09	.19	.00	.91
Share of Patients with Urban Employee Insurance	.87	.20	.06	1
Share of Patients with No Insurance	.01	.02	.00	.38
Observations	3,348			

Notes: This table shows the summary statistics of patient visits at the primary care center*month level. The sampling period is the full calendar year (Jan to Dec) of 2019. Panel A shows all the patient visits and Panel B shows the characteristics of patients and visits made by those with chronic conditions. Male is an indicator of gender male. "Total Number of Visits" is the average number of visits made by patients to a primary care center per month in 2019. "Total Number of Patients" is the average number of patients that have visited a primary care center per month in 2019. "Patients with Chronic Condition" are those that have been diagnosed with hypertension, hyperlipidemia, diabetes, and cardiovascular artery disease in the sampling period.

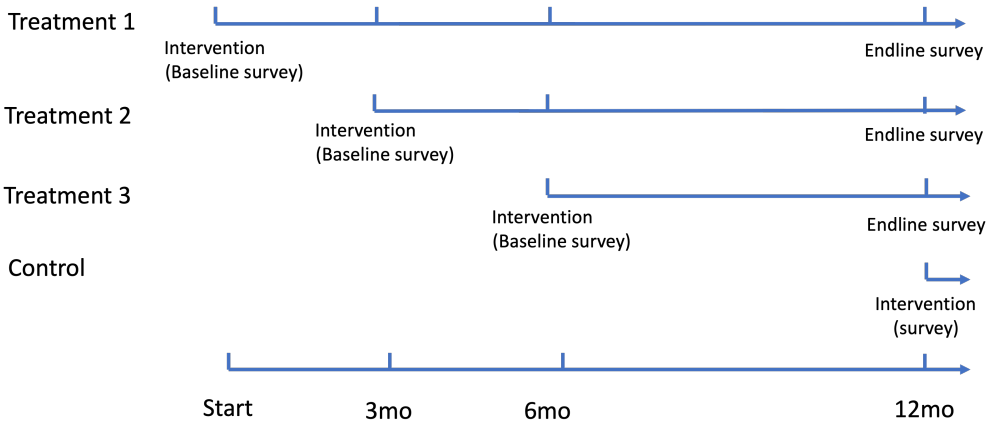


Figure 3.1: Proposed Intervention Timeline for the Awareness Experiment

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