Essays in Physician Prescribing Behavior

by

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Abstract

This dissertation consists of three separate studies with the central focus of better understanding physician prescribing behavior by examining their responses to three different policy interventions using patient level data from China. In the first study, I assess the cost-effectiveness of an antibiotic stewardship program for patients with acute respiratory infections (ARIs) by taking account of physician responses. I employ a net benefit regression approach, which demonstrates that the program has a positive net benefit and that it has the potential to be scaled-up with moderate resources required from the perspective of a publicly funded health care system.

The second study investigates the spillover effects of scientific information diffusion on physician prescribing behavior utilizing a difference-in-difference framework. I find that physicians increased their prescribing of Traditional Chinese Medicine (TCM) after learning about the negative consequences of prescribing antibiotics to patients with ARIs. I also find that prescriptions which contain a higher proportion of TCMs are associated with lower total expenditures, lower non-medicine expenditures, lower out-of pocket expenditures but higher medicine expenditures. These findings suggest that information about one type of medicine and its effects can lead to changes in prescribing behavior of other medicines (i.e., those that may not be the direct target of the policy), which in turn, may result in unintended financial implications.

The third study investigates how physicians in rural China respond to financial incentives. Faced with the introduction of a policy by the government in 2018 which aimed to increase physician income and increase non-medicine service expenditures as

a percentage of total medical expenditure, physicians increased non-medicine expenditure while decreasing medicine expenditure. This change in the expenditure mix aligns with the predicted effects of current financial schemes based on capitated global budgets with a zero-markup for prescription medicines that had been implemented by the government. In addition, physicians decreased medicine expenditures by reducing the value on each type of medicine they prescribed rather than reducing the number of medicines prescribed to patients. These results suggest that physician agency (the physicians maximizing their own financial returns) is an important driving factor of physician prescribing behavior.

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Chapter 1

Introduction

Physicians play a critical role in the delivery of health care. Their decisions and actions have an impact on both the cost and quality of care, which can in turn affect the performance of health care systems. For this reason, it is crucial to understand physician behavior and how physician behavior responds to external influences. These findings have the potential to inform policies regarding healthcare finance and population health.

Physician behavior has been recognized by many researchers as a central issue in health economics (McGuire (2000)). Nevertheless, how external factors such as intervention programs, new scientific information, and financial incentives affect physician behavior remain understudied. What is more, empirical evidence from rural settings of low-and-middle-income countries is particularly limited. This dissertation aims to contribute to the literature by conducting three studies designed to provide greater insights into how external factors may be expected to affect physician behavior and what impacts such behavior changes would have on the healthcare system. This dissertation follows the three manuscript format, which may result in some repetition of content, such as the description of the data sources.

The first study focuses on the economic evaluation of an intervention program designed to improve the appropriateness of physician prescribing. Specifically, using a net benefit regression approach, this study evaluates the cost-effectiveness of an antibiotic stewardship program designed to reduce inappropriate antibiotic prescribing for acute respiratory infections (ARIs). The study provides evidence as to whether the introduction of such a program, by changing physician prescribing behavior in relation to antibiotics represents an affordable option from the perspective of a publicly funded health care system.

The second study aims to understand the spillover effects of the introduction of scientific information on physician prescribing. One source of new information is related to national treatment guidelines for COVID-19 in January 2020, which contain recommendations on the use of Traditional Chinese Medicine (TCM) for the treatment and prevention of COVID-19. I hypothesize that the impact of such information may "spill over" to physician prescribing of TCM for (non-COVID-related) ARIs. The other source of new information analyzed is the introduction of an antibiotic stewardship program in February 2020, in which physicians were exposed to information about the reasons of not prescribing antibiotics for ARIs and the serious consequences associated with inappropriate use of antibiotics. This study hypothesizes that the information provided through the stewardship program would also have positive spillover effects on physician prescribing of TCMs, in that physicians would increase the relative use of TCMs. The study employs a difference-in-differences (DID) framework to estimate the spillover effects of the introduction of these two sources of information, using data collected over both the pre-COVID and in-COVID periods. Lastly, in order to examine whether there were unintended financial consequences to both patients and the public health care system resulting from such behavioral spillovers, I evaluate healthcare costs of prescriptions with varying proportions of TCMs.

The third study addresses the issue of physician agency. While there is certain to be a degree of altruism (i.e. physician acts in the best interest of the patient) in the treatment relationship between physicians and patients, it has also been noted in the literature that physicians may take advantage of their agent role to induce patient demand (i.e. to recommend treatment that is not strictly in the patient's best interest) to suit their own interests (usually to enhance their income). The literature suggests that physicians may be able to exert such influence because of the asymmetry of information that exists between patients and physicians, and patients are less informed about the causes of disease and the appropriate treatments for a given disease (Culyer et al. (2000); Glied and Smith (2013)). Using the financial incentives associated with a policy reform introduced in 2018, this study investigates the extent of demand inducement on the part of physicians by analyzing physician responses in terms of prescribing patterns of medicines and non-medicine services. Furthermore, the study examines the more detailed channels by which physicians may have shifted the expenditure mix in response to the policy.

Based on the agreements approved by the Research Ethics Board, the primary data set used across all three chapters is provided on a confidential, limited-use basis by 34 township hospitals located in two counties of Shaoguan City, Guangdong province in China[1]. Even though Guangdong is one of the most economically developed provinces in China, the two sample counties are from the poor area of Guangdong with a per capita GDP that is less than 40 percent of the provincial average.

The hospitals were randomly assigned to the intervention or the control group in a one-to-one ratio in the antibiotic stewardship program (Zhuo et al. (2020)). The data covered all outpatient records from January 2019 to December 2019, and from March 2020 and February 2021 during which the antibiotic stewardship program was implemented. For each visit, the total expenditure, the expenditure on medicines and non-medicine services, as well as the out-of-pocket expenditure on the part of patients were recorded. The visit date, diagnosis, patient's insurance status, ba-

[1] In China, there are five levels of local government: provincial level, prefecture level, county level, township level, and village level. Shaoguan is a prefecture-level city.

sic demographic information (age and sex), medicines prescribed, and the attending physician were also recorded. The primary data set is complemented with a survey distributed to all attending physicians collecting the physician's age, sex, level of education, and years of experience. The survey was sent to township hospital directors in August 2021, and was gathered in March 2022. There was no missing information on attending physicians. The raw data source contains about 1 million outpatient records associated with treatment visits provided by 360 physicians. The visits related to ARIs were selected according to the International Classification of Disease, version 10 (ICD-10) as shown in Table A1 in the Appendix.

From March 2020 to February 2021, there were no COVID-19 cases reported in the two study counties [2]. However, in comparison with the pre-COVID period, patients with certain respiratory related symptoms, such as fever, were restricted to seek care in township hospitals. According to the government guideline to combat COVID-19, patients who were suspected COVID-19 cases had to be treated at designated tertiary hospitals located in the city area. In addition, many patients may have elected to forgo or delay in-person care during the pandemic (Modesti et al. (2020)).

My dissertation is structured as follows: The remainder of Chapter 1 gives a brief introduction of the institutional background of the Chinese health system, health care delivery and structure in rural China, the public health insurance program and the reform policies related to prescription medicines. Chapter 2 presents my first empirical study evaluating the cost-effectiveness of the antibiotic stewardship program. Chapter 3 presents my second study on the spillover effects of new information on physician prescribing behavior. Chapter 4 investigates the impacts of physician agency on physician prescribing patterns. A discussion of the study results and a synthesis of key policy insights are presented in Chapter 5.

[2]Data on COVID-19 cases are updated daily by local health authorities, and are summarized by many news network. For example, see https://www.ipe.org.cn/MapGZBD/GZBDMap.html.

1.1 Institutional Background

1.1.1 Health care system in China

Unlike in the U.S. where the most common type of hospital is private not-for profit (NFP) (Gaynor and Town (2011)), the hospital industry in China has been dominated by public hospitals meaning publicly funded care as well as public delivery of care. Hospitals that provide secondary and tertiary care are located in the urban areas, and can be further categorized as general hospitals, Traditional Chinese Medicine (TCM) hospitals and specialised hospitals based on the range of services delivered. The primary health-care (PHC) system in China has urban components and rural components (Li et al. (2017)). Urban components include community health centers (93% publicly owned) and subordinate health stations. Rural components include township hospitals ($>$ 99% publicly owned) and village clinics that are guided by township hospitals. In 2019, the PHC system delivered about 52% of outpatient services and 16 % of inpatient services (National Health and Family Planning Commission (2020)). The prices of medical services in the public hospitals are regulated by the government. Physicians are salaried staff employed by public hospitals to provide healthcare (Daemmrich (2013)).

It is worth noting that there is no formally developed gate-keeping and referral system between PHC facilities and secondary/tertiary hospitals. Patients could use secondary or tertiary hospitals for PHC services. Patients are encouraged to use PHC facilities through more generous reimbursement terms under public health insurance. Figure 1.1 summarizes the categorization of health care providers in China. Although pharmacies are common in China, 80% of medicine sales are through public hospitals [3]. There are two reasons that prescription medicines are usually purchased in hospitals

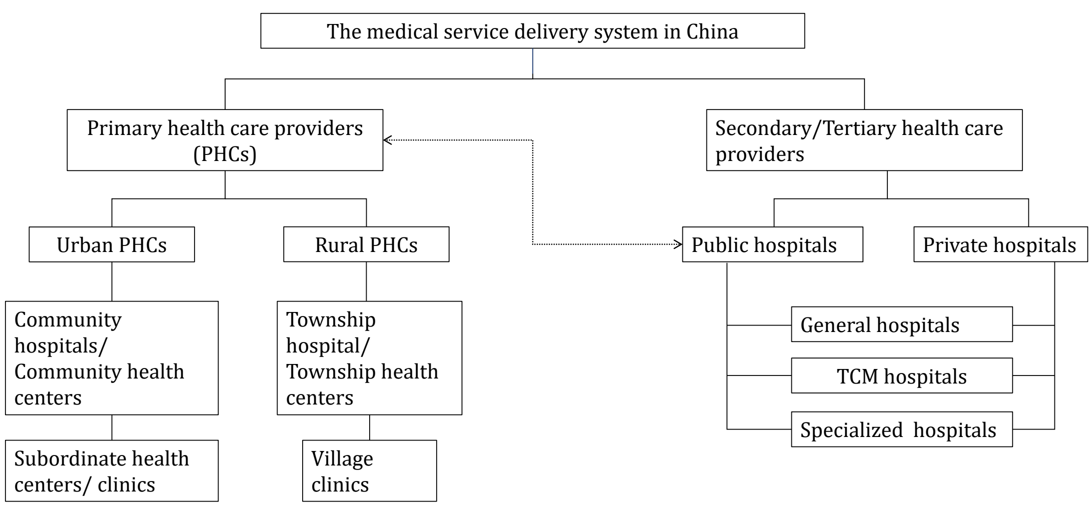
[3]Many industrial research reach to this conclusion. For example, see https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/life-sciences-health-care/ch_Studie_Pharmaceutical_China_05052014.pdf

rather than in pharmacies. First, pharmacies are concentrated in urban areas and are difficult to access for rural residents. Second, some pharmacies are excluded from the insurance network under which reimbursements of prescriptions are eligible.

Township hospitals

Township hospitals play an essential role in the rural healthcare system: they are non-profit institutions owned and partially funded by the government with the main function of providing primary care ranging from vaccination and basic laboratory tests to outpatient visits and inpatient care (Li et al. (2017); Hillier and Shen (1996)). Township hospitals are the backbone of the health care system in rural areas in that they provide a link between grassroots level village health clinics and higher level hospitals in the county/city. The size of the township hospitals is relatively small with typically 20-100 beds and 5-30 affiliated family physicians.

Figure 1.1: Primary care and secondary/tertiary care providers in China



Note: The dashed lines denote potential two-way referral channels between primary care and secondary (tertiary) care providers

1.1.2 The public health insurance program for rural residents

The universal coverage of the public insurance program was largely achieved in 2011 through a system that consisted of three main social health insurance schemes: 1) Urban Employee Basic Medical Insurance (UEBMI), 2) Urban Resident Basic Medical Insurance (URBMI), and 3) Rural Newly Cooperative Medical Scheme (RNCMS) (Yip et al. (2012); Yu (2015); Yip et al. (2019)). The UEBMI is predominantly funded through payroll taxes from both employers and employees and it is compulsory for urban employees to participate in this scheme. On the other hand, the URBMI covers self-employed urban residents and unemployed individuals such as children and students. Similarly, the RNCMS provides healthcare coverage for rural residents.

In 2016, the URBMI and RNCMS were integrated to form the new "urban and rural resident basic medical insurance" (URRBMI) scheme. URRBMI is voluntary at the individual level, and is financed through annual fixed premiums. Individuals only pay a portion (about 30%) of the total premiums, and the rest is subsidized by the government. The estimated coverage rate of the rural population by URRBMI is well over 90% since 2015, and there are few rural residents who purchase supplementary private health insurance (Shi and Liu (2018)).

In China, there are five levels of local government: provincial level, prefecture level, county level, township level, and village level. Each prefecture-level government organizes its own URRBMI program.[4] To obtain annual coverage, enrollees of URRBMI need pay the individual portion premiums between September and December of the previous year. After paying the premiums, rural enrollees can freely choose a township hospital as the contracted hospital. Although rural enrollees are allowed to choose a contracted hospital each year, they rarely switch to another township hospital. Enrollees of URRBMI only have outpatient coverage when they receive care from or are transferred by the contracted township hospital. In addition, there is

[4] Note that the two counties in our study belong to the same prefecture-level city.

usually an annual coverage limit with zero-deductible. Before reaching the coverage limit, enrollees have a coinsurance rate around 30% to 40% when seeking care at the contracted township hospital.

1.1.3 The reform of prescription medicines

To restrain the over-prescription of medicines in public hospitals, China initiated three important policy reforms since 2009: the zero markup policy (ZMP), the National Essential Medicines List (NEML), and provincial centralized medicine procurement (Yip et al. (2012); Hogerzeil and Jing (2013); Yip et al. (2019); He et al. (2019)).

Prior to the reform, public hospitals were allowed to charge a markup of up to 15% over the procurement price on all three categories of medicines including (1) chemical and biological medicines (Western medicines), (2) Traditional Chinese Medicine (TCM) patent drugs, and (3) TCM decoction pieces. The ZMP was first implemented in community/township hospitals to eliminate the markup on Western medicines and TCM patent drugs listed on the NEML. The drugs chosen for NEML are selected by the government based on various factors, such as the level of need corresponding to the disease burden, ensuring safety and clinical effectiveness, considering affordability, taking into account past usage patterns, and assessing the availability of supply. Since 2017, the ZMP has been expanded to any medicine other than TCM decoction pieces dispensed in all types of public hospitals across China.[5]

The procurement price of medicines is determined by a bidding system on the provincial medicine procurement platform. Every quarter, the platform aggregates orders from all hospitals, and allows the pharmaceutical companies to place bids based on the demand for each medicine. Only the winning bidders are allowed to sell

[5]According to the "Notice on comprehensive reform of public hospitals", the National Health Commission of China promotes eliminating markup for medicines except TCM decoction pieces in all public hospitals by September 2017.

medicines to hospitals according to the allocated volume. The provincial platform equalizes the procurement prices across hospitals for the same medicine purchased at the same time, which eliminates direct price negotiations between hospitals and pharmaceutical firms. Since 2017, the reform policies have been implemented in all public hospitals across China. These policy reforms constitute an important context within which the three studies to follow evaluate the impact of external influences on physicians prescribing behavior.

Chapter 2

Economic evaluation of an antibiotic stewardship program to reduce inappropriate antibiotic prescribing for acute respiratory infections in rural China: a net benefit regression approach

2.1 Introduction

One of the main approaches of modern medicine to combat infections is antibiotic treatment (Aslam et al. (2018)). Unfortunately, the efficacy of antibiotics has been endangered by the rapid emergence of antimicrobial resistance in the world, especially in low and middle-income countries (World Health Organization (2009)). Inappropriate antibiotic prescribing is a major contributor to the antibiotic resistance crisis (Michael et al. (2014)). Rising levels of antibiotic-resistant infections pose a serious global threat to human health, and place a substantial clinical and financial burden on health care systems (Golkar et al. (2014)).

Over 50% of antibiotic prescriptions in the United States are for outpatients with acute respiratory infections (ARIs) (Rattinger et al. (2012)). Similar results were reported by Dong et al. (2008) using data from 40 counties in 10 provinces of Western China. In addition, Li (2014) found that on average, each resident in China consumes ten times the number of antibiotics as are consumed in the United States; and antibiotics are regarded as a panacea in many rural primary care facilities due to the more limited health service capability. However, most uncomplicated respiratory infections are caused by viruses, and cannot be effectively treated with antibiotics (Dasaraju and Liu (1996)). Inappropriate use of antibiotics to treat ARIs in particular is unfortunately prevalent. Some examples include, Bianco et al. (2018) who found 67% of Italian general practitioners exemplified inappropriate use of antibiotics to treat ARIs; Sharma et al. (2017) which used Canadian data to uncover a 84% inappropriate antibiotics prescription rate when treating respiratory diseases commonly caused by viral infections; and Butt et al. (2017) examined an outpatient Qatari population, among which 45% had inappropriate indication for prescribing antibiotics. In China, Zhang et al. (2017) estimated an antibiotic prescriptions rate for children with upper respiratory track infections (URTIs) to be 34% in county hospitals versus 68% in township hospitals (primary care facilities in rural area). Sun et al. (2015) identified the misuse rate of antibiotics for the common cold as 44% in county hospitals versus 71% in township hospitals in China.

Substantial improper antibiotic use occurs in the primary care setting of rural China. This is primarily due to inadequate educational and skill levels of primary care physicians and weak oversight (Wang et al. (2014)). Interventions are urgently needed to reduce inappropriate antibiotic prescribing. Nevertheless, to date most intervention trials have been conducted in high-income countries with health care settings very different from China (Hu et al. (2016); Arroll (2005)). A notable exception is the paper by Zou et al. (2016), which evaluated an intervention program to reduce inappropriate antibiotic prescribing for children (2-14 years old) with upper respiratory tract infections (URTIs) who visited rural township hospitals in Guangxi Province. Using trial data collected to evaluate the program, the same group of researchers found a 29% decrease in the antibiotic prescription rate in the intervention group (Wei et al. (2017)), and this effect was achieved at an average upfront cost of $390.65 per township hospital with an incremental cost of $1.02 per patient (Zhang et al. (2018)).

Based on the intervention in Guanxi province by Zou et al. (2016), an enhanced antibiotic stewardship program was introduced in Guangdong province which incorporates the social media App (WeChat[1]) and electronic medical records (EMR) to address inappropriate antibiotic prescribing for patients of all ages with any form of ARI except pneumonia. The authors conducted a cluster-randomised controlled trial (cRCT) alongside this intervention to evaluate its cost and effectiveness. Briefly, the intervention targeted both physicians and patients/caregivers. For township hospitals in the intervention arm, family physicians were provided with (1) results from monthly peer-review meetings assessing their own antibiotic prescription rates through WeChat compared to the hospital target, (2) both a printed and WeChat-based operation guidelines on reducing antibiotic prescribing for ARIs, (3) a half-day training workshop on appropriate antibiotic prescribing, and (4) an improved electronic prescription system in the EMR with embedded modules to facilitate appropriate prescribing. Patients/caregivers in the intervention arm received printed and WeChat-based educational material describing appropriate antibiotic use for ARIs. Additionally, educational materials and education videos were accessible in the public areas of the township hospitals. In contrast, township hospitals in the control arm received no intervention components, and patients/caregivers received no educational materials. Full details of the development and implementation of the program are available in the trial protocol (Zhuo et al. (2020)).

In this paper, we employ a net benefit regression approach with outpatient visit data to provide cost-effectiveness evidence of the aforementioned antibiotic stewardship program which has shown promise as an effective intervention in reducing inappropriate prescribing of antibiotics. This paper contributes to the literature in several ways. First it is the first study to provide evidence as to whether the introduction of such a program represents an affordable option from the perspective of a

[1]A Chinese multi-purpose app with functions such as instant messaging, social media and mobile payment. It currently has a monthly active user base over a 1 billion people.

publicly funded health care system. Second, it applies the net benefit regression approach which allows for the control of a range of patient and physician characteristics between the intervention and control groups. Our analysis illustrates that net benefit regression offers a useful option for cost-effectiveness analyses using patient-level data. By estimating cost-effectiveness within one regression framework, we are able to adjust for imperfect randomization and can make use of established econometric methods. Evidence from such a program can be of great use to policy makers interested in the potential for scaling up comparable programs both in China and in a wider global context.

The remainder of this chapter is structured as follows. In Section 2, we describe the intervention. Section 3 describes the data and variables. Section 4 presents a net-benefit model to estimate the incremental cost, incremental effectiveness, and cost-effectiveness of the intervention. In Section 5 we close with a discussion and concluding remarks.

2.2 Intervention and Trial

There are existing antibiotic stewardship programs in most township hospitals, and a national guideline on using antibiotics. However, these measures are rarely used in practice to promote appropriate prescribing of antibiotics (Yin et al. (2013)). To address this issue within rural primary care settings, Zhuo et al. (2020) developed a comprehensive antibiotic stewardship program to work with family physicians and patients using multiple components, including electronic medical records (EMR) and smart phone apps. Table 1 provides a summary of the intervention package associated with the program as well as the existing processes in the control hospitals.

A parallel, two-arm, cluster-randomized controlled trial was conducted to test the effectiveness of the intervention. The trial was conducted in township hospitals

Table 2.1: Summary of the intervention and the existing processes in control-arm

Targeted group	Intervention arm	Control arm
Physician	1. An improved antibiotic stewardship program: (1) an antibiotic stewardship working team in each township hospital led by hospital executive, (2) monthly peer review meetings in township hospitals that promote appropriate use of antibiotics, and (3) monthly supervisory visits are made by the research team.	1. There is an existing antibiotic stewardship program in most township hospitals. However, these programs are usually not functioning and there are no monthly peer review meets on antibiotic prescribing.
	2. Operational guidelines to reduce inappropriate antibiotic prescribing for ARIs are provided to physicians.	2. Physicians practice using their own discretion based on their existing knowledge
	3. A four-hour training workshop is given to physicians.	3. No training is provided to physicians in the control arm.
	4. An improved electronic prescription system in the EMR with embedded modules such as pop-ups and alarm system to facilitate prescribing practices. The pattern of antibiotic prescribing from the EMR system can be monitored through a WeChat mini program.	4. Township hospitals have a similar electronic prescriptions system in the EMR with no embedded modules to help physicians make appropriate decisions when treating patients with ARIs. The WeChat mini program is not available for control hospitals.
Patient	1. Printed and WeChat-app version educational materials about inappropriate using antibiotics for treating ARIs are available to patients. Educational videos are played in the township hospital public areas.	1. No educational materials are available in control hospitals.
	2. Patients are invited to subscribe the township hospital public WeChat account for receiving educational information and making queries.	2. Township hospitals in the control-arm do not have WeChat public accounts.
	3. Improvede patient education during the consultation.	

Note: ARI acute respiratory infection, EMR electronic medical records located in two rural counties in Shaoguan city, Guangdong province. There are 17 township hospitals in each county, and an overall 1:1 intervention-to-control ratio stratified by county (8:9 within-county ratio) was used. The intervention package was provided to all physicians working in the township hospitals that were randomly selected into the intervention arm. It is worth noting that most of physicians in China practice only in one hospital (Sun et al. (2016); Fang (2018)).

2.3 Data

Our main data set is drawn from the outpatient records of all ARIs-related patient visits from the 34 township hospitals over a 24 month period.[2] This includes a 12-month baseline period from January to December 2019 and a 12-month study period from March 2020 to February 2021. Patients were excluded if they were diagnosed with the following: (1) pneumonia, and (2) chronic conditions such as asthma, non-respiratory infections, tuberculosis, immunological deficiencies or any form of cancer. The EMR data contain rich information about each outpatient visit, including the patient's ID, age, sex, visit date, diagnosis, detailed expenditures on medicines and medical services, and payment method (coinsurance/self-pay). Each record also contains the attending physician's ID, as well as the details of the prescribed medicines including medicine names and units.

In addition, we use two supplemental data sets. The first is a bespoke questionnaire which collected data about physician-level characteristics, including age, sex, education level, years of working experience. Physicians also reported average consultation time for patients who receive a primary diagnosis of an ARI and the amount of time spent checking the App based mini-program and participating review meetings. The second dataset contains cost information associated with implementation of the program itself.

[2]The ICD-10 codes used to define ARI can be found in Table A1 in Appendix.

2.3.1 Variables

Measuring costs and effectiveness

Costs from the regional publicly funded system's perspective are adopted for this study, and all costs are presented in USD ($) using a conversion rate from 2020 of USD 1 = RMB 6.9. There was a $ 50,000 cost associated with developing the intervention tools (WeChat mini program and modules in prescription system), representing a one-time investment, and is therefore assumed not to recur over the time horizon of the analysis and is not included in the analysis. The end products are used by all township hospitals in the intervention arm, and could be made available to other facilities at low cost across the province of Guangdong. However, these tools may need to be modified first before being implemented in other provinces.

There are upfront implementation costs associated with the intervention which are assumed to be recurring: maintenance costs of the intervention tools, facility costs, and training costs. Unit costs of items within each component collected from the trial are presented in Table 2.2. The total facility costs and total training costs are facility specific. They vary according to the number of items used by a township hospital. It is worth noting that the implementation costs refer to the expenses incurred during the process of actually implementing the intervention, and are not research costs incurred during the process of conducting research or evaluating the feasibility of an intervention.

In the intervention arm, a township hospital has on average 11 (SD=8.33)[3] physicians trained for the interventions, and to train a physician requires that they are provided with one handbook (which outlines the guidelines for appropriate prescribing of antibiotics) and receive four hours of in-person training. Each township hospital receives one copy of printed education material per physician, three posters and three

[3] SD for standard deviation.

Table 2.2: Implementation costs by unit

Source: Trial data	Cost ($)	Unit of measure
Maintenance Costs of Intervention Tools		
WeChat mini program	150	Per year for one hospital
Facility Costs		
Printed educational materials†	1.00	Per copy
Poster†	3.00	Per poster
Educational video†	1.00	Per video
Training costs		
Average trainee*	5.48	Per hour
Trainer	20.00	Per hour
Handbook (guideline)†	1.00	Per handbook

Notes: *Weighted average of all reported salaries across all physicians participated in training. †The costs of these materials refer to the costs of making copies and do not include the costs of development as hospitals can scale up using existing materials.

copies of an educational video for patients to review. Thus, the total implementation cost per hospital is $304.08 (SD=160.61) with an additional $150 yearly maintenance cost. The implementation cost and maintenance cost of a hospital are spread across all outpatient visits to that hospital in the 12-month study period[4]. Overhead costs not related to the intervention, such as the operation of facility, administration, and supporting staff are assumed to be the same between hospitals in the intervention arm and in the control arm.

In the net-benefit regression, the total per outpatient visit cost also takes into account the expenses linked with the utilization of healthcare resources, including: (1) cost of medication and medical services associated with the prescription, (2) cost of consultations, and (3) cost of prescription reviews. The prescription records include detailed cost information of medicines, non-medicine services, and consultations. However, the consultation fee per outpatient visit listed in the prescription record is a flat fee set by the government that does not necessarily reflect total time spent by the physicians with their patients. Instead, we re-calculate consultation fee per visit at the physician level by multiplying the physician's average consultation time and

[4]This is a rather conservative treatment on the implementation cost, since the intervention materials last more than one year.

hourly wage for each physician. We then apply the re-calculated consultation fee per visit to all outpatient visits attended by that physician. In addition, costs associated with the prescription review process in both the control and the intervention arms are calculated in the following steps. First, the total amount of physician time spent on the prescription review process (i.e., the time spent on using the WeChat Mini-program and participating the peer-review meetings) in the period of study across all physicians for each hospital. Second, the total amount of physician time spent on the review process is multiplied by a weighted physician average hourly wage to get the total cost associated with review time for each hospital. Third, the cost associated with the review process per visit was calculated using the hospital's total cost divided by the total number of ARI related outpatient visits to the hospital. The total cost for a given visit is then calculated as the sum of the following elements: (1) the implementation cost and maintenance cost per visit, (2) the per visit cost related to the review process, and (3) cost of medication and consultation associated with each visit.

As noted above, the major objective of the antibiotic stewardship program is to reduce inappropriate antibiotic prescribing in treating ARIs. Considering that most of the ARIs are viral infections and cannot be effectively treated with antibiotics, the outcome by which we measure the effectiveness of the program is the probability of a patient with an ARI being prescribed with any antibiotics. The effectiveness measure is equivalent to the antibiotic prescription rate (APR) at the sample-level, and the APR at the outpatient visit-level is either 1 (i.e., the prescription contains antibiotics) or 0 (i.e., the prescription does not contain any antibiotics).

The mean values for some key characteristics for the costs and the effectiveness for each of the control and intervention arm, before and after the intervention, are presented in Table 2.3. On average, patients treated by physicians working in intervention hospitals had lower average costs for medications and consultations, and they had slightly higher total costs in the study period. Table 2.3 also indicates a difference between the probability of being prescribed with antibiotics between outpatient visits in the control arm and in the intervention arm. In the study period, the antibiotic prescription rate (APR) in the intervention arm is about 41.6 % (i.e., $67.93\% - 26.29\%$) lower than the rate observed in the control arm. In sharp contrast, the baseline APR of the intervention arm and control arm were both around 81%.

Table 2.3: Summary of cost and effectiveness

	Baseline period		Study period	
	Control (N=79,336)	Intervention (N=116,050)	Control (N=43,805)	Intervention (N=56,519)
Total per visit cost (SD)	**7.84 (1.86)**	**7.20 (4.23)**	**7.63 (5.22)**	**7.82 (4.64)**
Medication & Consultation	7.84 (1.86)	7.20 (4.23)	7.63 (5.22)	6.72 (4.47)
Implementation & Maintenance				0.22 (0.23)
Review meeting & App checking				0.88 (0.64)
APR (%)	**80.59**	**81.14**	**67.93**	**26.29**

Patient and physician characteristics

In order to ensure that the difference in outcomes is not due to patient and physician heterogeneity between the intervention and the control arm, patient and physician characteristics are included as controls in the net benefit regression. Patient age is a categorical variable with 4 levels: 0-19 (reference category), 20-40, 41-64, and $\geq$ 65. Information about sex (female as the reference category) and payment method (self-paying as the reference category) are included as dummy variables. For physician characteristics, covariates include age (0-29 as the reference category, 30-39, 40-49, and ≥ 50), sex (female as the reference category), education level (3 years of medical secondary school as the reference category [5], 3 years of medical college, and 5 years of medical university), and years of experience (0-5 as the reference category, 6-10, and ≥ 11). In addition to patient and physician characteristics, the data are coded to include a intervention dummy variable (equal to 1 if the patient visited a hospital

[5] Vocational education for students who graduated from junior high school.

in the intervention arm, and 0 otherwise), and a study period dummy variable (equal to 1 if the patient visited between March 2020 and February 2021 during which the intervention had been introduced, and 0 otherwise). Panels A and B of Table 2.4, show the characteristics of patients and physicians respectively.

Table 2.4: Patient and physician characteristics

	Baseline period		Study period	
Characteristics	Control (N=79,336)	Intervention (N=116,050)	Control (N=43,805)	Intervention (N=56,519)
Panel A: Patient characteristics				
Age (%)				
≤19	58.59	58.33	53.40	55.77
20-40	10.32	10.28	11.42	11.31
41-64	18.18	18.36	20.53	19.35
≥65	12.90	13.03	14.65	13.58
Sex (%)				
Male	51.94	50.34	50.93	49.51
Payment Method (%)				
Coinsurance	65.05	67.27	70.7	73.37
Panel B: Physician characteristics				
Age (%)				
≤29	12.90	13.78	10.75	13.72
30-40	42.83	37.66	49.29	35.46
40-50	15.13	25.08	14.17	26.78
≥51	29.14	23.47	25.79	24.04
Sex (%)				
Male	60.78	60.03	62.53	57.88
Education Level (%)				
3-year vocational	16.89	14.13	17.76	14.28
3-year college	51.85	57.93	42.62	55.60
5-year university	31.27	27.94	39.62	30.12
Years of Experience (%)				
≤5	12.42	11.22	18.71	12.24
6-10	30.17	20.70	29.14	20.60
≥11	57.41	68.09	52.15	67.17

2.4 Empirical Strategy and Results

2.4.1 The net benefit statistic and net benefit regression

We employ the net-benefit regression approach to estimate cost-effectiveness by defining a net-benefit statistic for each patient following Hoch et al. (2002):

$$NB_i = \lambda \cdot E_i - C_i \tag{2.1}$$

where NB_i is the program's net-benefit for patient i, which is calculated by subtracting the observed costs C_i for patient i from the observed effect E_i for patient i valued in dollars. The maximum willingness to pay (WTP) for a one percentage drop in prescriptions for antibiotics to treat acute respiratory infections (ARIs) is denoted by λ.

To control for the baseline cost or antibiotic prescription rate and to account for patient and physician characteristics, the following linear regression model is estimated once where the outcome is cost and again where the outcome is effectiveness:

$$y_{ijht} = \alpha + \delta Study_t \times I_{ijh} + \boldsymbol{\beta}\mathbf{X_i} + \boldsymbol{\tau}\mathbf{Z_j} + \gamma_h + \gamma_t + \varepsilon_{ijht} \tag{2.2}$$

where:

- y_{ijht} is the outcome variables of interest for patient i, who had outpatient visit attended by physician j in hospital h and month t ($t = 1, \ldots, 24$).
- α is an intercept term.
- $Study_t$ is a dummy variable that takes the value 1 if the visit was between March 2020 and February 2021 (i.e., $13 \leq t \leq 24$) and 0 otherwise.
- The variable I_{ijh} is a dummy variable that takes the value 1 if patient i visited a hospital in the intervention arm and 0 otherwise.

- The vector $\mathbf{X_i}$ consists of the patient characteristics, including age, sex, and payment method (i.e., coinsurance or self-pay).

- The vector $\mathbf{Z_j}$ consists of the physician characteristics including age, sex, education level, and years of experience.

- γ_h capture hospital fixed effects, and γ_t capture period-specific month fixed effects. There are a total of 24 period-specific month. We include 23 of period-month indicators in the regression. Similarly, we include 33 indicators of the 34 hospitals.

- ϵ_{ijht} is an i.i.d. error term.

As noted above, equation (2.2) is estimated once using the cost (C) as the outcome and again using the effect (E) as the outcome. When setting $\lambda = 0$, this implies that $NB =$ -Cost. By taking the absolute value of this NB as the outcome variable, results in a cost regression, and the coefficient $\delta_{\Delta C}$ provides the estimate of the incremental cost $\Delta\bar{C}$ associated with the introduction of the program. Similarly, setting λ to 1 and cost to 0, implies that NB then is interpreted as an effect, and the coefficient $\delta_{\Delta E}$ from the resulting regression provides the estimate of the incremental effectiveness $\Delta\bar{E}$. The conventional incremental cost-effectiveness ratio (ICER) is given by $\Delta\bar{C}/\Delta\bar{E}$.

The results for effect and cost regressions are reported in the left panel and right panel of Table 2.5. The estimated effectiveness of the program is a reduction in the APR of 41.9%. Patients were more likely to be prescribed antibiotics if they were above 19 years old and had insurance coverage. The probability was also higher for male patients to be prescribed antibiotics compared to female patients. Similar patterns hold in the cost regression: those who were more likely to be prescribed with antibiotics were more likely to have higher total visit costs. The estimated incremental cost associated with the introduction of the intervention program is \$0.696. Thus, the ICER of the antibiotics stewardship program is ($\Delta\bar{C}/\Delta\bar{E} = \$0.696/41.9\%$) \$0.017 per percentage point reduction in antibiotic prescriptions for an ARI.

Table 2.5: Effectiveness and cost regressions for ICER

	Effect		Costs	
	Estimate	Std.Error	Estimate	Std.Error
Study $\times$ *I*	-0.419***	-0.045	0.696	0.442
Patient age: ≤19 as reference				
20-40	0.048***	0.014	1.228***	0.194
41-64	0.068***	0.014	1.417***	0.203
≥65	0.054***	0.015	1.544***	0.319
Patient sex: female as reference				
Male	0.012***	0.002	0.162***	0.034
Patient payment-method: self-paying as reference				
Coinsurance	0.049***	0.007	1.461***	0.123
Physician age: ≤29 as reference				
30-40	0.035	0.032	0.109	0.214
41-50	-0.001	0.046	1.037***	0.369
≥51	0.032	0.055	1.457***	0.440
Physician sex: female as reference				
Male	0.008	0.025	0.111	0.231
Physician education level: 3-year vocational as reference				
3-year college	-0.027	0.023	0.408	0.437
5-year university	-0.043	0.027	0.303	0.564
Physician years of experience: ≤5 as reference				
6-10	-0.016	0.034	0.057	0.208
≥11	-0.001	-0.033	-0.322	0.298
Hospital FE	Y		Y	
Period-Month FE	Y		Y	
R^2 (Adjusted)	0.258		0.172	

Notes: Heteroscedastic-robust standard errors in parentheses are clustered at the hospital level. *Significant at 10%,**significant at 5%,***significant at 1%.

Sensitivity analysis

As shown in Equation (2.1), the net-benefit statistic is a function of λ, a value which depends upon the decision maker's willingness to pay (WTP) which is not known from the trial data. Stinnett and Mullahy (1998) suggested that this uncertainty can be addressed through sensitivity analysis of different values of λ that captures the amount of money the decision maker is willing to pay for one extra unit of benefit. Therefore, the sensitivity of cost-effectiveness findings in relation to WTP assumptions can be assessed by estimating net benefit regression equations with a range of WTP values. The range of WTP (λ) values is typically determined using WTP equals to ICER as a reference point somewhere in the middle and includes WTP equals to 0 (Hoch et al. (2019)).

In our case, given the estimated ICER of $ 0.017 for one percentage point reduction in APR, a set of λ values (λ=$0, $0.01, $0.02, $0.03, $0.04, $0.05 and $0.06) are used to generate seven corresponding net-benefit (NB) statistics. For each of the seven NB λ values as the outcome variable, we rerun the regression according to Equation (2.2). The coefficient δ on the variable $Study \times I$ is now an estimate of the incremental net-benefit (INB), $\Delta \bar{N}B = N\bar{B}_1 - N\bar{B}_0$.

A positive INB (δ) indicates that the extra benefits derived from the intervention are of greater value than the extra costs. The INB could also be interpreted as the difference in the average net benefits between the intervention and control (i.e, usual care groups. In other words, a significantly positive δ implies that the intervention is cost-effective under the predetermined WTP value λ. The higher the difference in net benefits between the intervention and the control, the more cost-effective the intervention is. The estimated coefficients are presented in Table 2.6. For λ is $0.04 or higher, the coefficients δ are positive and statistically significant which indicates a high probability of being cost-effective when the WTP is $0.04 or more.

It is important to note that the coefficient δ is a statistical estimate that represents the incremental net benefit with uncertainty. Given a specific λ, the probability of the intervention being cost-effective is essentially the probability of δ being truly positive. To calculate the probability that the intervention is cost-effective, we can use the one-sided significance level (i.e., the one-sided p-value) of the estimated δ. When $\delta < 0$ (as $\lambda = 0$ or $= 0.01$ in Table 2.6), the probability of δ actually being positive equals

Table 2.6: Net-benefit regressions with WTP ranging from \$ 0 to \$ 0.06

	$\lambda = \$0$ (se)	$\lambda = \$0.01$ (se)	$\lambda = \$0.02$ (se)	$\lambda = \$0.03$ (se)	$\lambda = \$0.04$ (se)	$\lambda = \$0.05$ (se)	$\lambda = \$0.06$ (se)
$Study \times I$	-0.696	-0.277	0.142	0.561	0.981**	1.400***	1.820***
	(0.442)	(0.429)	(0.411)	(0.418)	(0.419)	(0.425)	(0.436)
Patient characteristics	Y	Y	Y	Y	Y	Y	Y
Physician characteristics	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y
Period-Month FE	Y	Y	Y	Y	Y	Y	Y
R^2 (Adjusted)	0.172	0.169	0.170	0.171	0.173	0.177	0.180

Notes: Heteroscedastic-robust standard errors in parentheses are clustered at the hospital level. Patient controls include age, sex and payment method. Physician controls include age, sex, education level and years of experiences. *Significant at 10%,**significant at 5%,***significant at 1%.

the one-sided p-value. When $\delta > 0$ (as $\lambda \geq 0.02$ in Table 2.6), the probability of δ actually being positive is equal to one minus the one-sided p-value (Hoch et al. (2006)). It is worth noting that most statistical packages report a two-sided p-value, which needs to be divided by two.

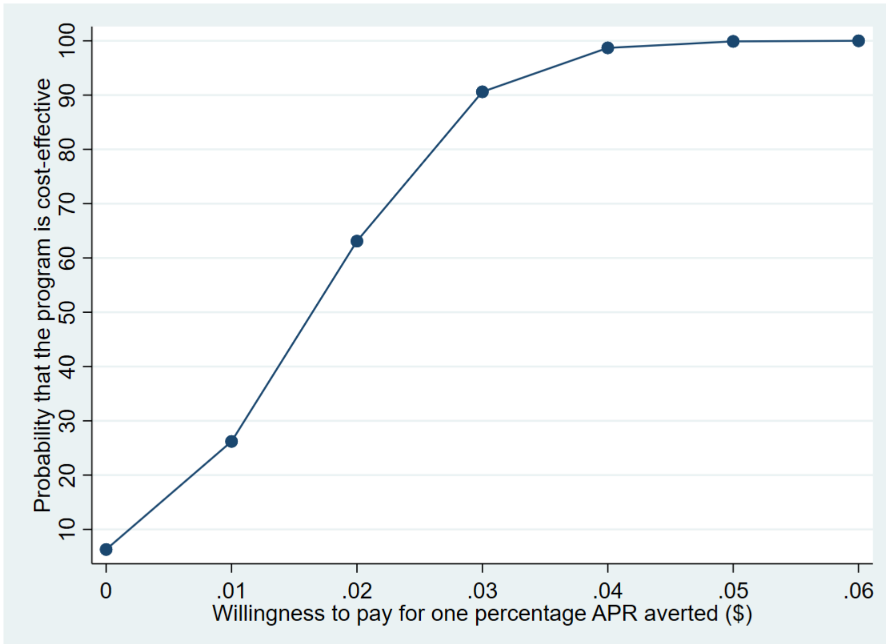
Table 2.7 presents the net benefit regression estimates of δ (i.e, INB) for $\lambda = \$0$ through \$0.06. The table also includes the two-sided p-value, the one-sided p-value, and the corresponding probability of INB being positive, which indicates the probability of the intervention being cost-effective. The results from Table 2.7 can be used to generate the cost-effectiveness acceptability curve (CEAC) which is recommended for highlighting the relationship between the assessment of cost-effectiveness and the unknown value of λ (Van Hout et al. (1994); Briggs and Fenn (1998); Löthgren and Zethraeus (2000); Fenwick et al. (2001)). The horizontal axis of the CEAC displays different values of λ, and the vertical axis represents the statistical uncertainty about the cost-effectiveness. Figure 2.1 illustrates the resulting CEAC.

Table 2.7: Net benefit regression estimates and corresponding probability of being cost-effective

λ(\$)	Estimate δ	p-value	One-sided p-value	Probability of cost-effective
0.00	-0.696	0.125	0.063	6.3%
0.01	-0.277	0.523	0.262	26.2%
0.02	0.142	0.738	0.369	63.1%
0.03	0.561	0.188	0.094	90.6%
0.04	0.981	0.025	0.013	98.7%
0.05	1.400	0.002	0.001	99.9%
0.06	1.820	$<$0.001	$\approx$0	$\approx$100%

When $\lambda = \$0$, there is still a 6.3% chance the intervention program yields a positive INB which indicates the program has a 6.3% probability being cost-saving (Fenwick et al. (2001)). Specifically, for $\lambda = \$0.02$ the probability of the program being cost-effective is higher than 60%; and when λ rise to \$0.04 or higher, the program is almost certain to be cost-effective.

Figure 2.1: CEAC showing the probability that the intervention is cost-effective with WTP range from $0 to $0.06



2.4.2 Scenario analysis: same patient volume in study period and baseline period

The implementation and maintenance costs as well as costs associated with physician time spent on review meetings and App checking as listed in Table 2.3, are dependent on the number of outpatient visits to the intervention hospitals observed over the study period. However, public health restrictions during COVID-19 and patients' choices to forgo seeking care may have led to fewer visits in the study period compared with the baseline period (Chen et al. (2021b); Modesti et al. (2020)). Therefore, the patient volume reduction in the study period may have resulted in an overestimation of the total per visit cost for visits in the intervention arm. The total per visit cost $7.82 (SD=$4.64), as listed in Table 2.3 for the intervention arm in the study period, is based on 56,519 outpatient visits.

Considering a counterfactual scenario where the number of outpatient visits remained the same from the baseline to the study period, the implementation and maintenance costs, as well as the costs associated with physician time spent on review meetings and App checking, would be spread across 116,050 visits. Spreading costs associated with the intervention across a higher number of visits (which is likely the case without the influence of COVID) leads to lower cost per visit. Assuming medication and consultation costs for patients remained the same, the total per visit cost is recalculated at \$7.33 (SD=\$4.57). The total per visit cost for visits in the baseline period and for visits in the control arm during the study period are independent of the number of visits and are assumed to be the same. We re-estimated the net benefit regressions according to Equation (2.2) with the recalculated total per visit cost and WTP (λ) ranging from \$0 to \$0.03. The regression results and the probability of being cost-effective are presented in Table 2.8 and Table 2.9, respectively.

The incremental cost in this scenario analysis is \$0.192, which is the absolute value of the coefficient δ when λ is equal to 0. The ICER is reduced from \$0.017 to \$0.005 per percentage point reduction in APR. The probability of the program being cost saving increases from 6.3% to 33.4% which would result in a positive INB with a WTP of 0. With a WTP greater or equal to \$0.03, the program has a nearly 100% probability of being cost-effective. The CEAC for this scenario analysis is illustrated in Figure 2.2.

2.5 Discussion and Conclusions

We estimated the cost-effectiveness of an antibiotic stewardship program from the perspective of the publicly funded healthcare system. A net-benefit regression framework was used to determine the probability that the program is cost-effective over a range of WTP thresholds in reducing inappropriate antibiotic prescribing among patients with ARIs in a primary care setting in rural China. The framework allows us to estimate incremental cost and incremental effect separately and together (i.e.,

Table 2.8: Net benefit regressions with recalculated cost and WTP ranging from \$ 0 to \$ 0.03

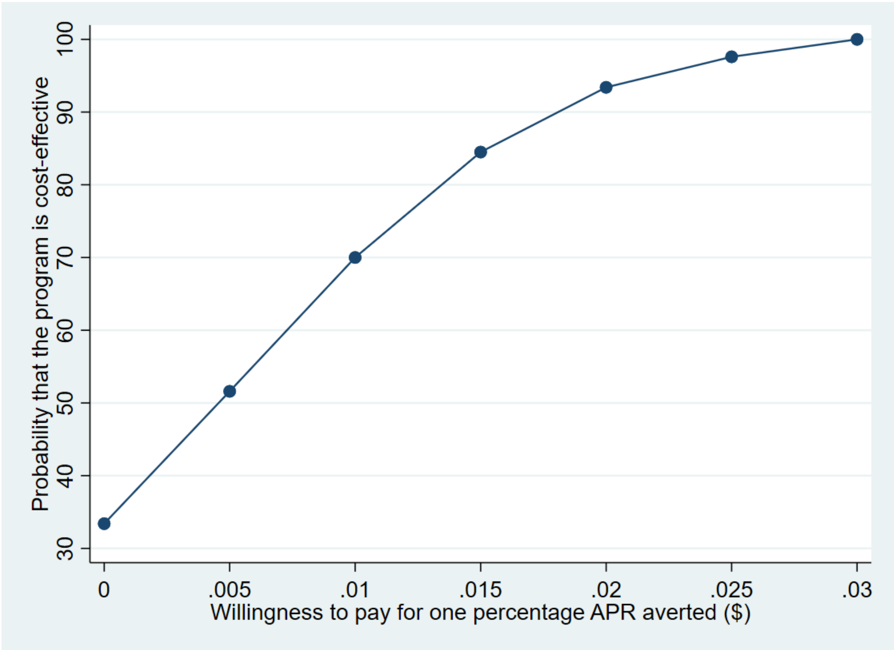
	$\lambda = \$0$ (se)	$\lambda = \$0.005$ (se)	$\lambda = \$0.01$ (se)	$\lambda = \$0.015$ (se)	$\lambda = \$0.02$ (se)	$\lambda = \$0.025$ (se)	$\lambda = \$0.03$ (se)
$Study \times I$	-0.192	0.018	0.227	0.437	0.646	0.856**	1.166***
	(0.444)	(0.436)	(0.429)	(0.423)	(0.418)	(0.414)	(0.411)
Patient characteristics	Y	Y	Y	Y	Y	Y	Y
Physician characteristics	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y
Period-Month FE	Y	Y	Y	Y	Y	Y	Y
R^2 (Adjusted)	0.169	0.170	0.170	0.172	0.173	0.175	0.177

Notes: Heteroscedastic-robust standard errors in parentheses are clustered at the hospital level. Patient controls include age, sex and payment method. Physician controls include age, sex, education level and years of experiences. *Significant at 10%,**significant at 5%,***significant at 1%.

Table 2.9: Net benefit regression estimates and corresponding probability of being cost-effective with recalculated total cost

λ($)	Estimate δ	p-value	One-sided p-value	Probability of cost-effectiveness
0.00	-0.192	0.668	0.334	33.4%
0.005	0.018	0.0.968	0.484	51.6%
0.01	0.227	0.600	0.300	70.0%
0.015	0.437	0.309	0.155	84.5%
0.02	0.646	0.131	0.066	93.4%
0.025	0.846	0.047	0.024	97.6%
0.03	1.166	$<$0.001	$\approx$0	$\approx$100%

Figure 2.2: CEAC showing the probability that the intervention is cost-effective with recaculated cost and a WTP range from $0 to $0.03



using a range of net benefit statistics as dependent variables). A 42% reduction in APR was achieved at an incremental cost of \$0.70 per outpatient visit, resulting in an ICER of \$0.017 per percentage point reduction in APR. Moreover, with a WTP of \$0.05 or higher for one percentage point reduction in APR, the program is almost certain to be cost-effective (i.e., yielding a positive INB).

Furthermore, we explored a counterfactual scenario that assumes patient volume was not affected by the COVID-19 pandemic. In the scenario analysis, the 42% reduction in APR can be achieved with an incremental cost of \$0.19 per visit, resulting an ICER of \$0.005 per percentage point reduction in APR. The probability of the program being cost-effective is nearly 100% with a WTP as low as \$0.03. Our results suggest that this program has the potential to be scaled-up with moderate resources required.

In a previous cost-effectiveness study of a similar program among children aged 2 to 14 years old with URTIs in rural Guangxi province, there was a 29% reduction in APR and an incremental cost of \$1.02 per visit which produced an ICER of \$0.035 per percentage point reduction in APR (Zhang et al. (2018)). Compared with the previous program, there are two notable advantages to the enhanced antibiotic stewardship program that may improve its cost-effectiveness. First, taking advantage of the WeChat app and embedded modules in the EMR system may have resulted in an improvement in effectiveness through better facilitation of physician access to information. Second, the new program targets a much larger cohort of patients across a wider set of age groups. Additionally, besides providing point estimates of the ICER, we also explore the estimates of cost-effectiveness and the associated uncertainty over a range of WTP values and illustrated the results using CEACs.

There are some limitations to our research. First, physician time spent on consultation, review meetings and App checking were not measured objectively. Instead, we retrospectively obtained the time spent by physicians on these activities based on self-reported information. Second, the implementation and maintenance cost per township hospital was the average across the 17 intervention hospitals in the two counties. Cost savings through economies of scale might be achieved if the program were implemented across a larger number of administrative areas. Third, future health costs and potential spill-over effects were not included in the analysis due to limitations in available data. In other words, this study was not conducted from a societal perspective, and there may be consequences resulting from the intervention that were not captured by our dataset. For example, the intervention may increase patients' expenditures on antibiotics purchased from other facilities, such as pharmacies and county hospitals. As another example, some patients may have initially received treatment in township hospitals but were later hospitalized and provided antibiotics in county hospitals. Lastly, our results rely on data collected during a 12-month study period. Hence, conducting future research with data from a more extended follow-up period would be valuable in assessing the durability of the study results over a longer time frame.

Chapter 3

The spillover effects of scientific information on physician prescribing of Traditional Chinese Medicine

3.1 Introduction

Prescribing medicines to patients is a complex decision-making process influenced by factors such as patient morbidity, medicine efficacy evaluated in terms of cost-benefit trade-offs, and subjective factors such as physician educational and training background, the physician work environment and so on (Knight (2013); Davari et al. (2018)). The quality of these prescribing decisions heavily relies on physicians' judgement and medical knowledge (Britten (2001); O'Connor et al. (2012)). To ensure that medical practices align with the ever-growing scientific evidence, physicians need to continuously update their medical knowledge; they typically rely on various sources of scientific and educational information, including pharmaceutical companies, academic literature, and health authorities.

In a systematic literature review, Spurling et al. (2010) concluded that direct information diffusion from pharmaceutical companies to physicians is associated with higher prescribing rates of the promoted medicines, increased cost of prescribing, and lower prescribing quality. On the other hand, information from non-profit oriented entities such as academic journals and health authorities have shown more promise in improving physician prescribing behavior (Lexchin (1998)). When physicians acquire new information about a specific medicine or medicine class, there is evidence that it may influence their prescribing decisions for related medicines or medicines targeting the same condition (Cawley and Rizzo (2008); Collins et al. (2013); Dubois and Tunçel (2021)). Similarly, in the case of Traditional Chinese Medicine (TCM), new information about one indication (e.g., one type of viral infection) of a remedy may spill over to physician prescribing for other related indications (e.g., other types of viral infections) (Ling (2020)). Yet there has been limited research on the spillover effects of information provided to physicians. The understandings of such spillover effects have important policy implications for a comprehensive assessment of the impacts resulting from information dissemination. Furthermore, the existence of spillover effects can offer valuable insights into how physicians incorporate new information when making prescribing decisions.

In this paper, our main research objective is to examine the potential spillover effects of new scientific information on physician prescribing by leveraging two sources of new information encountered by primary care physicians in rural China. The first source of new information is related to the introduction of national treatment guidelines for COVID-19, which were published in January 2020. These guidelines include a section which recommends the use of TCM to improve the cure rate and reduce the motility rate of COVID-19 infection. By exposing physicians to TCM-related information, these guidelines may have spillover effects on prescribing for other indications commonly treated with TCM. Specifically, our hypothesis is that there could be a resultant increase in the prescribing of TCM (positive spillovers) for non-COVID-related acute respiratory infections (ARIs).

The second source of new information is the implementation of an antibiotic stewardship program for reducing inappropriate antibiotic prescribing for ARIs. This program was introduced in February 2020 in 17 randomly selected township hospitals out of a total of 34 hospitals in two counties in Guangdong province. After being exposed to information about the negative effects associated with prescribing antibiotics for ARIs, physicians in the intervention hospitals may respond in several ways: (1) ceasing to prescribe antibiotics for ARIs which could lead to a medicine regimen with fewer medicines, (2) substituting antibiotics with TCMs to treat ARIs, (3) substituting antibiotics with other Western medicines to treat ARIs, and (4) continuing to prescribe antibiotics for ARIs. Considering that the actual situation is likely a combination of these four cases, we hypothesize that patients treated by physicians in the intervention hospitals will exhibit a comparatively higher utilization of TCMs compared to patients treated by physicians in the control group.

To investigate the spillover effects of the new information, we turn to a unique outpatient records data set collected from 34 hospitals from January to December 2019 (pre-COVID period), and from March 2020 to February 2021 (in-COVID period). Employing a difference-in-differences (DID) empirical strategy, we examine the spillover effects of the two aforementioned sources of new information within a single framework. Both sources of new information are expected to have positive spill over effects on TCM prescribing, as indicated by higher proportions of medicines prescribed for non-COVID-related ARIs during the in-COVID period compared to the pre-COVID period, as well as a higher proportion of TCMs prescribed amongst physicians in the intervention group than physicians in the control group. The DID approach enables us to attribute the effects due to each of the two pieces of information.

Additionally, we assess the financial implications of the changes in TCM utilization by estimating their impacts on healthcare expenditures, including total outpatient healthcare expenditures, medicine expenditures, non-medicine expenditures, and out-of-pocket expenditures. However, the estimation of healthcare expenditures poses a challenge due to the skewed nature of the data. To address this, we apply both log-transformed OLS estimation and generalized linear models (GLMs) to accommodate the skewness.

This study contributes to the extant literature in a number of ways. Firstly, it adds to the literature regarding the influence of information from non-profit oriented sources on physician prescribing behavior. Secondly, this paper extends our understanding of the spillover effects on physician prescribing by exploring the impact of previously unexplored information sources, such as the antibiotic stewardship program. Furthermore, this paper expands on prior research by examining the financial consequences of physician response, specifically by comparing health care expenditures among outpatients that were prescribed with varying proportions of TCMs. These expenditures provide valuable quantification of financial impacts on the public health insurance plan and patient welfare, thereby carrying significant implications for public policy.

The rest of the chapter proceeds as follows. Section 2 provides a brief overview of the relevant literature. Section 3 provides some background about treatments for ARIs with antibiotics and TCM, the antibiotic stewardship program, the COVID-19 situation in the study region, and TCM in the COVID-19 context. Section 4 introduces the data and variables used in this study. Section 5 presents the empirical strategy and reports results, and Section 6 concludes.

3.2 Related Literature

There are two strands of empirical literature that have evaluated the intended consequences of scientific information targeted at physicians, but the unintended consequences are rarely examined. The first strand focuses on passive dissemination of information via journal articles, treatment guidelines, and warnings released by health authorities. Many studies have demonstrated that physicians gradually abandon old or adopt new technologies/procedures/medicines based on scientific information published in high-profile journals. However, the promptness of response may vary depending on physician and patient characteristics (e.g., see Duffy and Farley (1992); Howard and Shen (2011); Howard et al. (2012, 2013, 2017); Depalo et al. (2019)). Avdic et al. (2019) investigate physician responses to changes in treatment guidelines using data from drug-eluting stents for treating cardiovascular disease. They find that there are heterogeneous responses to new information among physicians. Their results also suggest that physicians who were slow to respond to new information had better outcomes than those who quickly adopted the new information.

The second strand focuses on actively disseminated information such as recommendations provided through educational interventions like academic detailing (i.e., educational outreach) and performance summaries presented through audit and feedback directly to health care providers, often comparing them to peers or to a desired standard. A substantial body of literature in the United States and Canada suggests that academic detailing has the potential to improve physician prescribing by providing unbiased and evidence-based recommendations (Soumerai and Avorn (1990); Van Hoof et al. (2015); Gale et al. (2019); Kulbokas et al. (2021)).

One key feature of academic detailing is that it is delivered in a customized setting, typically through one-to-one or small group session, with specifically designed packages of educational information (Diwan et al. (1995); van Eijk et al. (2001); Figueiras et al. (2001); Simon et al. (2005)). For instance, results from a randomized controlled trial conducted by Solomon et al. (2001) in a large U.S. teaching hospital shows a 37% reduction of unnecessary use of broad-spectrum antibiotics among physicians who received academic detailing versus the control physicians. Audit and feedback which involves providing clinical performance summaries to health-care providers can also significantly improve physician compliance with desired practice (Brehaut and Eva (2012); Ivers et al. (2012)). Another illustration in the field of antibiotic stewardship, Høgli et al. (2016) show audit and feedback significantly improves appropriate antibiotic prescribing from 61.7% to 83.8%, and reduces the prescribing of broad-spectrum of antibiotics from 48.8% to 38.6% at a Norwegian hospital.

Our study contributes to the above literature by analyzing the spillover effects of both passively (TCM guideline information) and actively (antibiotic stewardship program) disseminated scientific information. The treatment guidelines for COVID-19 promote the use of TCMs, which in turn increases physician exposure to TCM related information. This increased exposure may lead to higher utilization of TCM for treating other respiratory infectious diseases such as non-COVID-related ARIs. Additionally, the antibiotic stewardship program exposes physicians to information about the negative consequences for patients associated with prescribing antibiotics for ARIs. We hypothesize that information from this program has positive spillover effects, resulting in a greater relative usage of TCM for patients with ARIs.

This study is also related to literature on the spillover effects that primarily focuses on medicine warnings, withdrawals or recalls. Cawley and Rizzo (2008) examine the withdrawals of seven medicines from six therapeutic classes and find gross negative spillovers, resulting in decreased utilization of non-withdrawn medicines in the same class. The study does not indicate gross competitive benefits, where the number of patients switching from the withdrawn to the non-withdrawn medicines exceeds those who quit the class altogether. Using the case of Vioxx withdrawal, Collins et al. (2013) show overall positive spill over effects for substitute medicines in direct competitor classes such as increased number of prescriptions and market share for those medicines.

In the case of antidepressant medicines, Dubois and Tunçel (2021) evaluate the effect of an unexpected warning release by health authorities on physicians' prescribing choice. They find that the warning lowered the average prescribing rate of the affected medicine, however, physicians' response to the warning were highly heterogeneous. Specifically, physicians' response to the affected medicine and its substitutes depended on their preference for prescribing these types of medicines before the warning was issued. Moreover, withdrawals and recalls on one product (e.g., medicine, medical device) can even spill over to reduce the use of dissimilar products in the same category (Kerger et al. (2016)). By exploiting information sources that were not explored in previous studies, such as an intervention program, this study aims to extend our understanding of the spillover effects on physician prescribing.

3.3 Background

3.3.1 Antibiotics and TCM treatments for acute respiratory infections

Acute respiratory infections (ARIs) are one of the most common symptomatic reasons for seeking outpatient care in both developed and developing countries, and are a persistent and pervasive worldwide public health threat (World Health Organization (2004); Wang et al. (2016)). It is important to note that most ARIs are caused by viruses and are typically self-limited (Dasaraju and Liu (1996)). However, despite the inappropriate nature of using antibiotics to treat ARIs, antibiotics continue to be widely prescribed for treatment of ARIs in both the U.S. and in China (Rattinger et al. (2012); Fleming-Dutra et al. (2016); Dong et al. (2008)). Good prescribing decisions involve accurately matching patients with medications that are most likely to result in better health outcomes (Currie and MacLeod (2017)). Therefore, prescribing antibiotics to patients diagnosed with ARIs indicates non-adherence to best practice guidelines and increases the risk of antibiotic-resistant infections.

TCM is one of the oldest healing systems, and has been used in treating a variety of diseases (including ARIs) for more than 2,000 years (Tang et al. (2008); Yu et al. (2014)). Rooted in the philosophical and spiritual traditions of Taoism, TCM embraces a holistic approach to health, emphasizing the balance and harmony of the body, mind, and spirit (Keji and Hao (2003); Kaptchuk (2000)). Over the centuries, TCM has been an integral aspect of traditional Chinese culture, evolving and being passed down through generations. In recent times, the Chinese government has shown increased support for TCM, and there has been a growing interest in integrating TCM with Western medicine (Xu and Yang (2009); Ma et al. (2021)).

The ingredients of TCM primarily comes from natural medicines and their derivatives (Zhu (1998)). Modern dosage forms, including decoction pieces and capsules, have made TCM more accessible and standardized in its administration (Ma et al. (2021)). This development has facilitated the acceptance and use of TCM both within and outside of China (Fung et al. (2015)). The efficacy of TCM for the purpose of symptom relief of ARIs is based on the purported antiviral effects of Chinese herbal medicines (Wang and Liu (2014)). According to the TCM theory, using a combination of herbs aligns with the holistic approach, as it is believed that the synergistic effects of combining herbs can enhance the treatment of infections (Wang et al. (2020)). Nevertheless, despite the extensive utilization of TCM for treatment of ARIs, there is a notable absence of rigorous clinical trials of high quality that thoroughly assesses the efficacy of TCM in treating ARIs (Liu and Douglas (1998); Wu et al. (2008); Yang et al. (2020)).

3.3.2 The antibiotic stewardship program and the study region's experience with COVID-19

Inappropriate use of antibiotics is a worldwide issue, but one which is more severe in low-and-middle-income countries (Laxminarayan et al. (2013); Heddini et al. (2009); Okeke et al. (1999); Do et al. (2016); Meeker et al. (2014); Wei et al. (2017)). In China, improper antibiotic use is particularly grave in rural primary care settings, where there is a lack of adequate training and insufficient oversight (Wang et al. (2014); Li (2014)). To address the issue of inappropriate antibiotic prescribing in rural township hospitals, an antibiotic stewardship program was developed; as outlined in the detailed study protocol by Zhuo et al. (2020). In short, the intervention package was customized for primary care physicians working in township hospitals and included several components: (1) a half-day academic detailing session on appropriate antibiotic prescribing, (2) feedback from monthly peer-review meetings assessing the individual physician's antibiotic prescription rates compared to their peers, (3) an improved electronic prescription system with embedded modules that can pop-up recommendations and alerts, and (4) an operational guideline as to how to use antibiotics appropriately.

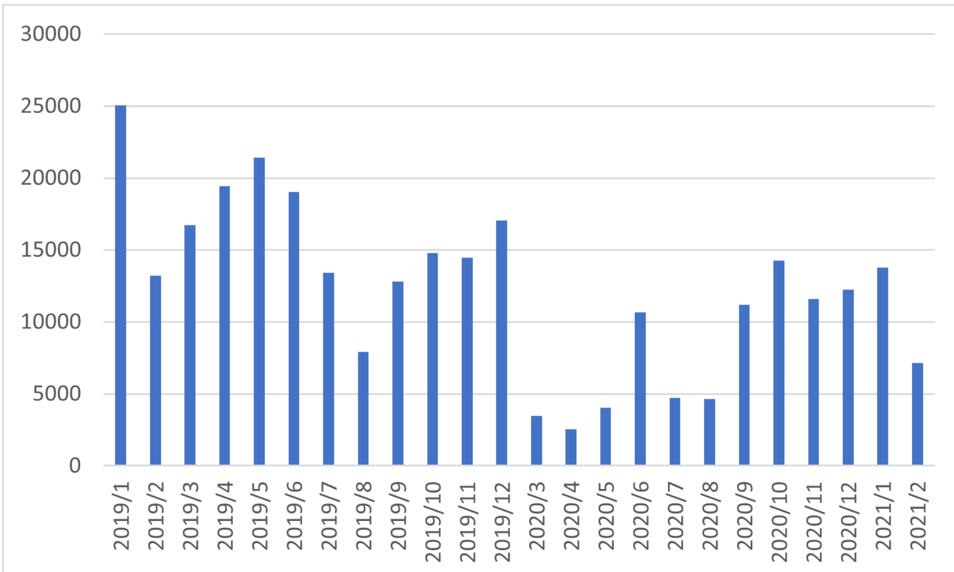
All primary care physicians in the intervention group received the intervention package, and the half day academic training took place at the end of February 2020. The intervention was followed over a 12 month period, from March 2020 to February 2021. A total of 34 township hospitals were randomised into the intervention and control groups at a one to one ratio. These hospitals are located in two counties (17 hospitals in each county) within the Shaoguan city of Guangdong province. According to the National Health Commission, as of March 1, 2021, there were no reported confirmed COVID-19 cases in the two sample counties[1]. Therefore, none of the ARI patient visits to the study township hospitals during the in-COVID period (from March 2020 to February 2021) were related to COVID-19.

From March to June 2020, patients experiencing certain symptoms, such as fever, were restricted to seek care in township hospitals. According to the government guideline to combat COVID-19, patients who were regarded as suspected COVID-19 cases had to seek care only in Fever Clinics located in designated county/city hospitals. Additionally, many patients may have chosen to delay or forgo in-person care during the pandemic due to concerns about contracting the virus within hospital settings (Modesti et al. (2020)). These factors may partially explain the decreased volume of

[1]Data on COVID-19 cases are updated daily at many platforms, for example, see https://www.ipe.org.cn/MapGZBD/GZBDMap.html.

ARI-related patient visits to township hospitals during the COVID pandemic compared to the period prior to the pandemic even when the restrictive public health measures were lifted. Figure 3.1 displays the monthly ARI-related patient visits to the study township hospitals.

Figure 3.1: Monthly ARI patient visits to township hospitals



3.3.3 TCM in the COVID-19 context

In December 2019, COVID-19 was first identified in Wuhan City, Hubei Province, and later spread to other provinces (Zhu et al. (2020)). In an effort to control the spread of the virus, the National Health Commission of China released the 1^{st} Trial Version of "Guidelines for the Diagnosis and Treatment of COVID-19" on January 15, 2020. Later, On January 27, the 3^{rd} edition of the guidelines was updated including the use of TCM as a treatment and prevention measure for COVID-19 (National Health Commission & National Administration of Traditional Chinese Medicine (2020)). The national guideline encouraging the use of TCM has remained essentially unchanged since then (Xu et al. (2020)).

Following the issuance of the national guidelines, most provinces officially released their own TCM-related guidelines, referring to the government guidelines as a reference (Ang et al. (2020)). Additionally, health organizations such as the China Association of Chinese Medicine published their 1st "Guideline for the appropriate use of Traditional Chinese Medicine (TCM)" in February 2020 (Qiu et al. (2020)). About 85% of confirmed COVID-19 patients in China had been treated with TCM (in combination with Western medicines), which demonstrates that TCM had been widely used as part of the effort to contain and treat the virus (Yang et al. (2020)).

As a result of increased exposure to TCM through treatment guidelines and reports from health authorities, it was expected that physicians' knowledge and attitudes towards TCM would change. In a study that surveyed 401 medical professionals working in a province with little spread of COVID-19, about 70% of participants were aware that TCM has been recommended for treatment of COVID-19 by the National Health Commission, and about 90% of participants indicated that they would take TCM for the prevention of COVID-19 (Pu et al. (2021)). As another example, Lianhua-Qingwen capsule, a niche TCM typically used for treating viral infections such the respiratory infectious and influenza, experienced a surge in popularity following its recommendation in the COVID-19 treatment guidelines (Ding et al. (2017); Niu et al. (2017); Chen et al. (2021a); Fan et al. (2022)). With the increased publicity surrounding the Lianhua-Qingwen capsule, physicians may be more inclined to prescribe it to patients with respiratory infections unrelated to COVID-19.

3.4 Data

The main data set for our empirical analysis is drawn from electronic medical records (EMR) for outpatient visits related to ARIs in the 34 township hospitals. The data covers a 24- month period, from January 1, 2019 to December 31, 2019 and from March 1, 2020 to February 28, 2021. Each visit in the data records information including the patient's age, sex, attending physician, diagnosis, medicines prescribed, and payment method (i.e., coinsurance or self-paying). In addition to total expenditures; the data also provide details on medicine expenditures, non-medicine expenditures, the data also show the breakdown of insurance-covered and out-of-pocket expenditures.

To supplement the main data set, we have another data set that contains information on all physicians who worked in the township hospitals during the 24-month period. This includes details such as age, sex, level of education, and years of experience. The physician-level information is linked to the main data set using anonymized physician IDs that match the attending physician's ID in the patient EMR records. As a result, the final data set encompasses information on 295,710 outpatient visits related to ARIs, with 360 primary care physicians involved in attending to these visits.

3.4.1 Proportion of TCM

Our primary dependent variable in the analysis of spillover effects is the proportion of TCMs ($PTCM$), within a given prescription. We construct this measure as follows. First, the total number of medicines prescribed to the patient is tabulated as reported in the EMR record. According to the National Healthcare Security Administration (NHSA), medicines can be classified into chemical and biological medicines (i.e., Western medicines), and TCMs, which includes TCM patent drugs and TCM decoction pieces. Using the detailed information of the names of medicines prescribed, we determine whether a medicine is a TCM by searching the Medicine Directory Query on the NHSA website [2]. We then count the number of TCMs in a given prescription, and divide the number of TCMs by the total number of medicines prescribed to get the variable $PTCM$.

[2] The Medicine directory Query can be accessed through `http://bmfw.www.gov.cn/ybypmlcx/index.html`

Before proceeding to the formal regression analysis, we provide some descriptive evidence to help place our findings in context. In Table 3.1, we report the relative change in proportion of TCM prescribed before and after the COVID-19 outbreak in both control and intervention groups at the outpatient-visit level. There was greater relative use of TCMs in both control and intervention groups during the pandemic. However, the relative change in the intervention group is much greater which suggests the information on the negative consequences of prescribing antibiotics may have had a much larger impact than the information on TCM contained in the release of COVID-19 treatment guidelines.

Table 3.1: Differences in $PTCM$ between the intervention and the control at pre- and in-COVID periods

	12-month-pre-COVID (N=195,386)	12-month-in-COVID (N=100,324)	Difference
Control	0.406	0.428	0.022
Intervention	0.359	0.516	0.157
Difference			0.135

The proportion of TCM ($PTCM$) is a variable restricted between 0 and 1. To further explore the probability changes at the two bounds, we generate two dummy variables: (1) whether a prescription only contains TCMs as $ATCM$ (probability at the upper bound, = 1 if $PTCM = 1$ and 0 otherwise) and (2) whether a prescriptions has no TCM as $NTCM$ (probability at the lower bound, = 1 if $PTCM = 0$ and 0 otherwise). Table 3.2 reports the outpatient-visit level probability change at the upper bound, while Table 3.3 presents the outpatient-visit level probability change at the lower bound.

For visits to intervention hospitals during the pandemic, the probability of receiving a prescription containing only TCMs increased, while the probability of receiving a prescription without any TCM decreased. In contrast, for visits to control hospitals during the pandemic, both the probability of receiving a prescription containing

Table 3.2: Differences in $ATCM$ between the intervention and the control at pre- and in-COVID periods

	12-month-pre-COVID (N=195,386)	12-month-in-COVID (N=100,324)	Difference
Control	3.17%	5.99%	2.72%
Intervention	2.48%	13.66%	11.18%
Difference			8.46%

Table 3.3: Differences in $NTCM$ between the intervention and the control at pre- and in-COVID periods

	12-month-pre-COVID (N=195,386)	12-month-in-COVID (N=100,324)	Difference
Control	8.77%	11.20%	2.42%
Intervention	12.35%	10.04%	-2.31%
Difference			-4.73%

only TCMs and the probability of receiving a prescription without any TCM slightly increased.

3.4.2 Health expenditures

For the analyses of financial consequences associated with the changing proportions of TCMs, we use four measures of health expenditures: total expenditures, medicine expenditures, non-medicine expenditures, and out-of-pocket expenditures. The total expenditures include all payments received by the township hospitals, including insurance payments and patients' out-of-pocket expenditures. The total expenditures are further divided into two mutually exclusive categories, medicine expenditures and non-medicine expenditures, the latter of which include the consultation fee, fees for diagnostic tests and examinations, and fees for medical consumables. Table 3.4 reports the detailed summary statistics for all expenditures measures. As is typical with health expenditure data and as can be seen from the Table, the data are skewed.

Table 3.4: Summary statistics of health expenditures

	Mean	S.D.	Median	1st percentile	99th percentile
Total Exp.(RMB)	50.64	32.18	42.24	11.61	159.79
Med Exp.(RMB)	33.40	28.09	25.82	1.87	131.99
Non-Med Exp.(RMB)	17.24	14.24	12.61	0.40	71.65
Out-of-pocket Exp.(RMB)	29.71	24.91	22.51	4.58	119.50
Obs.			295,710		

3.4.3 Control variables

We include the following patient and physician controls in the model:

Patient Controls We include patient age as a categorical variable with 4 levels (0-19, 20-40, 41-64, and $\geq$ 65), patient sex (male/female) and payment method (coinsurance/self-paying) as dummy variables. We also include the total number of medicines prescribed during each outpatient visit, to account for the fact that physicians prescribed fewer medicines during the pandemic.

Physician Controls For physicians, we include age (0-29, 30-39, 40-49, and $\geq$ 50), sex ((male/female)), education level (3 years of medical secondary school [3], 3 years of medical college, and 5 years of medical university), and years of experience (0-5, 6-10, and $\geq$ 11).

Table 3.5 summarizes the descriptive statistics for all the control variables included in our analysis. It is important to note that the number of medicines prescribed during the in-COVID period was lower compared to the pre-COVID period. Therefore, the number of medicines prescribed serves as an important control variable in the analysis of the study data. The descriptive evidence presented in Table 3.1, Table 3.2 and Table 3.3 illustrate the impact on the number as well as the mix of medicines prescribed pre-COVID versus in-COVID. For instance, in the intervention group, the total number of medicines prescribed decreased from 5.24 pre-COVID to 4.09 in-COVID. Interestingly, the $PTCM$ in the intervention group increased from 0.359

[3] Vocational education for students graduated from junior high school.

pre-COVID to 0.516 in COVID with an increased proportion of 0.157. It is worth pointing out that taking the total number of medicines prescribed into consideration, the number of TCMs prescribed per prescription is 1.88 (i.e., 0.359×5.24) pre-COVID, and increased to 2.11 (i.e., 0.516×4.09) in-COVID. The forthcoming analysis will assess the extent to which these observed changes in physician prescribing can be related to the introduction of new information from the COVID TCM guidelines and the antibiotic stewardship program.

3.5 Empirical strategy and Results

3.5.1 Positive spillovers in prescribing TCM

We follow a standard difference-in-difference (DID) approach to estimate the positive spillover effects for each of the two sources of new information on TCM usage within one framework. To examine the impacts of the release of TCM guideline information, we compare the differences in TCM proportions between the pre-COVID period and the in-COVID period. Additionally, we also assess the effects of new information from the antibiotic stewardship program by comparing the relative changes in the prescribing of TCM among physicians working in intervention hospitals that received the intervention (during the in-COVID period) relative to those working in hospitals that were in the control group. Three equations are estimated, each corresponding to one of the outcomes of interest: (1) proportion of TCM ($PTCM$), (2) whether a prescription only contains TCMs ($ATCM$), and (3) whether a prescription is with no TCM ($NTCM$). Each equation takes the general form:

$$Y_{ijht} = \alpha + \beta COVID_t + \delta COVID_t \times I_{ijh} + \mathbf{X_i} + \mathbf{Z_j} + \gamma_h + \varepsilon_{ijht}, \qquad (3.1)$$

Table 3.5: Summary statistics of patient and physician controls

	Full sample	Control group			Intervention group		
		All	Pre-COVID	In-COVID	All	Pre-COVID	In-COVID
Patient Controls							
# of Med							
Mean	4.94	5.05	5.25	4.69	4.86	5.24	4.09
(S.D.)	(2.25)	(2.21)	(2.26)	(2.09)	(2.27)	(2.31)	(1.97)
Age (%)							
$\leq$19	57.18	56.74	58.59	53.40	57.49	58.33	55.77
20-39	10.66	10.71	10.32	11.42	10.62	10.28	11.31
40-59	18.82	19.02	18.18	20.53	18.69	18.36	19.35
$\geq$60	13.34	13.53	12.90	14.65	13.21	13.03	13.58
Sex (%)							
Male	50.70	51.58	51.94	50.93	50.07	50.34	49.51
Payment Method (%)							
Co-insurance	68.35	67.06	65.05	70.70	69.27	67.27	73.37
Physician Controls							
Age (%)							
$\leq$29	13.09	12.13	12.90	10.75	13.76	13.78	13.72
30-40	40.35	45.13	42.83	49.29	36.94	37.66	35.46
40-50	21.12	14.79	15.13	14.17	25.64	25.08	26.78
$\geq$51	25.45	27.95	29.14	25.79	23.66	23.47	24.04
Sex (%)							
Male	60.19	61.40	60.78	62.53	59.33	60.03	57.88
Education Level (%)							
3-year vocational	15.44	17.20	16.89	17.76	14.18	14.13	14.28
3-year college	53.59	48.57	51.85	42.62	57.17	57.93	55.60
5-year university	30.98	34.24	31.27	39.62	28.65	27.94	30.12
Years of Experience (%)							
$\leq$5	12.85	14.66	12.42	18.71	11.55	11.22	12.24
6-10	24.47	29.80	30.17	29.14	20.66	20.70	20.60
$\geq$11	62.69	55.54	57.41	52.15	67.78	68.09	67.17
Obs.	295,710	123,141	79,336	43,805	172,569	116,050	56,519

Notes: We define the outpatient visits from January 1, 2019 to December 31, 2019 as occurred during pre-COVID period, and the visits from March 1, 2020 to February 28, 2021 as occurred during in-COVID period.

where i indexes patients, j indexes physicians, h indexes hospitals, and t indexes month ($t = 1, \ldots, 24$). The outcome of interest, denoted Y_{ijht} is one of the three outcomes including the $PTCM$, the $ATCM$, and the $NTCM$. $COVID$ is a dummy variable that equals 1 if a visit occurred between February 2020 and March 2021 (($13 \leq t \leq 24$)), and 0 if occurred between January 2019 and December 2019 ($1 \leq t \leq 12$). I is a dummy variable which equals 1 if the visit happened in a hospital that was randomized into the intervention group of the antibiotics stewardship program. $\mathbf{X_i}$ is a vector of patient level controls including number of prescribed medicines, age, sex, and payment method (coinsurance/self-pay). The vector $\mathbf{Z_j}$ consists of the physician level controls including age, sex, education level, and years of experience. The equation also contains controls for hospital fixed effects γ_h.

The first coefficient of interest is β, which represents the estimated spillover effects of TCM related information from COVID-19 treatment guidelines on physicians' prescribing of TCMs for ARIs. The other coefficient of interest is δ, which captures the spill over effects of information about the negative effects related to inappropriate prescribing of antibiotics, provided to physicians practicing in the hospitals that had been randomized to the intervention group, on the prescribing of TCMs. We hypothesize that both coefficients will be significant and positive.

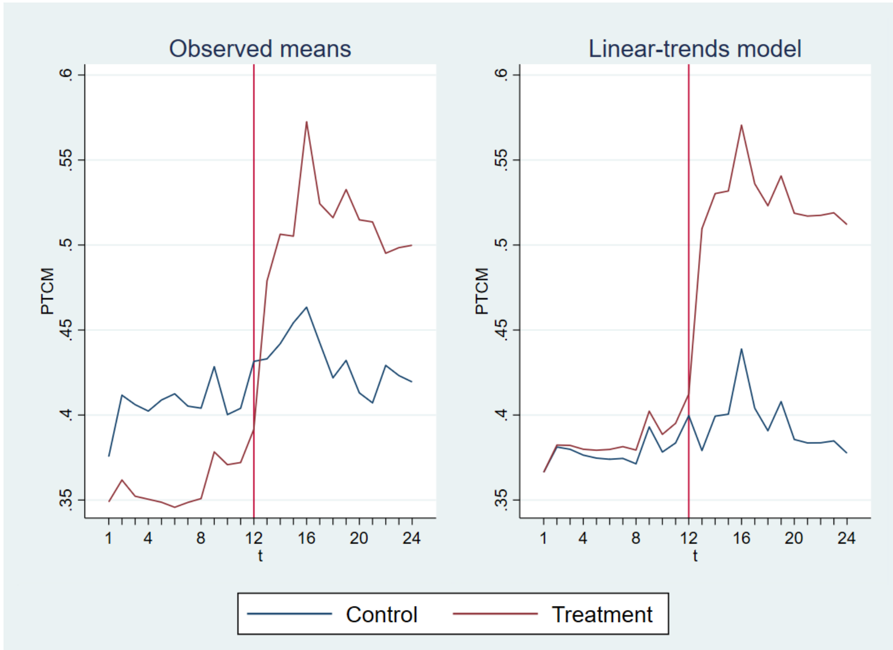
For the DID empirical specification to provide estimates of causal impact, the following four assumptions are required. First, that the assignment of hospitals to the intervention group was not determined by the outcome at baseline (January to December 2019). Because the intervention was randomly assigned in our data, this assumption is most likely met. Second, that the composition of the intervention group and control group is stable. Although it is not a concern at the hospital level, composition does vary over time at the patient and physician level. However, we do not expect this to have a substantive effect on the estimates after controlling for both patient and physician characteristics. Third, that the intervention in the intervention group does not spill over to members of the control group. In China, physicians typically practice in only one hospital (Sun et al. (2016); Fang (2018)). Furthermore, the effectiveness of the intervention (information about the negative effects related to inappropriate prescribing of antibiotics) in our case requires resources such as academic detailing from the research team, new technologies using EMR and smart phone apps. Since hospitals in the control group were not provided with these resources, the intervention is unlikely to have significant effects in reducing inappropriate antibiotic prescribing in the control group. Fourth, that the control and intervention groups exhibit parallel pre-trends (i.e. prior to the introduction of the intervention) in the outcome variables of interest.

To test the parallel pre-trend assumption, we first explore the parallel trends graphically by comparing the trajectories of the dependent variable $PTCM$ for the control and intervention groups prior to the implementation of the intervention. We also check this assumption by visualizing the results of a linear-trends model. Both of the diagnostic checks are shown in Figure 1. The graph seems to indicate that the parallel-trends assumption is satisfied. Prior to the intervention implementation, the proportion of TCMs prescribed in the intervention and control hospitals followed a parallel path. We also performed a Parallel-trends test by estimating a coefficient for the differences in linear trends prior to the introduction of both new sources of information (Pinzón et al. (2021)), and a Wald test was used to determine whether the coefficient was statistically different from 0. Taken together, both the test and the graphical analysis suggest the parallel-trends assumption is satisfied in our case.[4]

We present the estimation results derived from Equation (3.1) in Table 3.6. Both

[4]There is an immediate jump of $PTCM$ in the intervention group which starts in t= 13. It is worth noting that t= 12 (December 2019) and t= 13 (March 2020) are treated as two consecutive months because we don't have data for January and February 2022 in our sample. Both sources of new information from the COVID-19 treatment guideline and the antibiotics stewardship program were introduced between January and February 2020. We do not expect that conducting the analysis without data from January and February 2020 to be a major concern for the validity of the parallel trend assumption or for the interpretation of our main results.

Figure 3.2: Graphical diagnostics for parallel trends



OLS and fractional logit estimation were employed for the outcome variable $PTCM$ since it is restricted to the unit interval of [0,1] (Wooldridge (2010)). For binary outcome variables $ATCM$ and $NTCM$, both OLS and logit estimations were conducted.

As shown in the first row of Table 3.6, we find that increased publicity of TCMs in the COVID treatment guidelines has relatively small spillover effects on physicians prescribing behavior. The effects are limited to an increase of less than 2% in the probability of receiving prescriptions that contain only TCMs. The findings from the second row of Table 3.6 suggest that there were large spillover effects from the information on antibiotics provided by the intervention on the relative use of TCMs. The proportion of TCM prescribed in the intervention group during the in-COVID period increases by 0.127. Meanwhile, the probability of receiving a prescription containing only TCMs increases by about 7% in the intervention group, and the probability of getting a prescription containing no TCM decreases by about 6%.

Table 3.6: Spillovers of TCM prescribing

#Obs. = 295,710	*PTCM*		*ATCM*		*NTCM*	
	OLS	Frac.logit	OLS	logit	OLS	logit
$COVID$	0.015	0.015	0.016**	0.019**	-0.01	-0.005
	(0.017)	(0.016)	(0.006)	(0.008)	(0.014)	(0.013)
$COVID \times I$	0.127***	0.128***	0.072***	0.068***	-0.067***	-0.061***
	(0.024)	(0.024)	(0.018)	(0.011)	(0.018)	(0.011)
Patient Controls	Y	Y	Y	Y	Y	Y
Physician Controls	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
(Pseudo) R^2	0.125	0.114	0.093	0.105	0.100	0.109

Notes: $***$, $**$ and $*$ represent statistical significance at 0.01, 0.05 and 0.1 level, respectively. Robust standard errors in parentheses are clustered at the hospital level for OLS estimates. Average partial effects and Delta method standard errors are reported for fractional logit and logit estimates.

3.5.2 Financial implications of prescribing TCM

For each outpatient visit, we observe total expenditures as well as medicine expenditures, non-medicine expenditures and the out-of-pocket portion of the expenditures. In this study, we are investigating whether there are differences in expenditures between prescriptions containing varying proportions of TCMs. The results help to better understand the potential financial implications for both public health insurance and patients related to the relative usage of TCM. The model in which expenditures is the outcome of interest, is specified as follows:

$$ln(E_{ijht}) = \alpha + \theta PTCM_{ijht} + \mathbf{X_i} + \mathbf{Z_j} + \gamma_h + \gamma_t + \varepsilon_{ijht} \tag{3.2}$$

where $ln(E_{ijht})$ is the natural logarithm of one of the four measures of expenditures for patient i written by physician j at hospital h in month t ($t = 1, \ldots, 24$). $PTCM$ is a variable indicating the proportions of medicines prescribed were TCMs. $\mathbf{X_i}$ and $\mathbf{Z_j}$ are vectors of patient and physician controls, as described previously. γ_h and γ_t are fixed effects of hospital and period-specific month respectively. The hospital fixed effects allow for (time-invariant) unobservable hospital characteristics to affect the outcome variable of interest. The period-specific month fixed effects allow for a flexible specification of the aggregate trend over the 24 month study period in the outcome variable of interest. To further elaborate, a complete set of month fixed effects serves two purposes. Firstly, it helps account for any potential variation in patient illness severity that may be attributed to seasonality. Secondly, it controls for any differences in the mix of patients caused by COVID-related restrictions and the subsequent lessening of those restrictions in certain months. The estimated coefficient θ in Equation (3.2) reflects the relationship between varying proportions of TCM and health expenditures.

Models with $ATCM$ and $NTCM$ that are analogous to the model in (3.2) are estimated as following:

$$ln(E_{ijht}) = \alpha + \tau ATCM_{ijht} + \phi NTCM_{ijht} + \mathbf{X_i} + \mathbf{Z_j} + \gamma_h + \gamma_t + \varepsilon_{ijht}. \tag{3.3}$$

The coefficients τ and ϕ are interpreted as the impact of prescriptions comprised entirely of TCMs or with no TCM on healthcare expenditures in relation to a prescription with a mixture of TCMs and Western medicines (as the reference category).

To address the issue of skewed expenditures in Equation (3.2) and Equation (3.3), we employ both OLS estimation with natural logarithm transformation and GLM using a log link function with variance function of a gamma scale family (Buntin and Zaslavsky (2004)). The results for all four measures of expenditures are presented in Table 3.7 and Table 3.8 respectively. Higher proportions of TCMs are associated with lower total expenditures and lower out-of-pocket expenditures. The decrease in total expenditures is primarily driven by a decrease in non-medicine expenditures. On the other hand, higher proportions of TCMs are associated with higher medicine expenditures. The findings in Table 3.8, which include analysis based on $ATCM$ and $NTCM$, align largely with the results presented in Table 3.7.

Table 3.7: Impact of *PTCM* on health expenditures

	Total Exp.		Med Exp.		Non-Med Exp.		Out-of-pocket Exp.	
	OLS	GLM	OLS	GLM	OLS	GLM	OLS	GLM
PTCM	-0.072**	-0.123***	0.322***	0.126***	-0.511***	-0.489***	-0.086**	-0.148***
	(0.033)	(0.037)	(0.071)	(0.061)	(0.045)	(0.042)	(0.037)	
Patient Controls	Y	Y	Y	Y	Y	Y	Y	Y
Physician Controls	Y	Y	Y	Y	Y	Y	Y	Y
Period-Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	295,710		295,710		295,710		295,710	
R^2	0.404		0.444		0.335		0.465	

Notes: Heteroscedastic-robust standard errors in parentheses are clustered at the hospital level. Patient controls include age, sex and payment method and number of prescribed medicines. Physician controls include age, sex, education level and years of experiences. *Significant at 10%,**significant at 5%,***significant at 1%.

Compared with prescriptions containing a combination of TCMs and Western medicines, prescriptions that contain only TCMs are associated with lower total expenditures, lower non-medicine expenditures and lower out-of-pocket expenditures. In contrast, the prescriptions with no TCMs are associated with higher total expenditures, higher non-medicine expenditures, higher out-of-pocket expenditures as well as lower medicine expenditures, in relation to prescriptions that include a mix of TCMs and Western medicines.

3.6 Discussion and Conclusions

In this paper, we investigate the spillover effects of scientific information diffusion on physician prescribing using a natural experiment of the release of COVID-19 treatment guidelines and an experimental intervention from an antibiotic stewardship program. Our study sheds light as to how the use of scientific information can be expected to alter-physician prescribing and how to address the extent to which information provided about one medicine/indication may have significant spillovers to prescribing of other medicines.

Our findings indicate limited spillover effects from the increased publicity for TCM in COVID-19 treatment guidelines on prescribing of TCM for non-COVID-related ARIs. However, we did observe significant spillover effects of the information from the intervention (academic detailing) on antibiotics from the antibiotic stewardship program. Physicians in the intervention group of the stewardship program prescribed a substantially higher proportion of TCMs compared to other medicines. The spillovers suggest that information about one type of medicine can lead to changes in physician prescribing beyond the intended target, as evidenced by the increased relative use of TCMs due to the information on the negative consequences of prescribing antibiotics for ARIs.

Table 3.8: Impact of $ATCM$ and $NTCM$ on health expenditures

	Total Exp.		Med Exp.		Non-Med Exp.		Out-of-pocket Exp.	
	OLS	GLM	OLS	GLM	OLS	GLM	OLS	GLM
$ATCM$	-0.062**	-0.048**	-0.057	-0.050	-0.051**	-0.065**	-0.096***	-0.080***
	(0.028)	(0.023)	(0.039)	(0.034)	(0.022)	(0.027)	(0.030)	(0.029)
$NTCM$	0.068**	0.113***	-0.283***	-0.085**	0.371***	0.349***	0.047*	0.098***
	(0.033)	(0.029)	(0.055)	(0.042)	(0.027)	(0.026)	(0.021)	(0.036)
Patient Controls	Y	Y	Y	Y	Y	Y	Y	Y
Physician Controls	Y	Y	Y	Y	Y	Y	Y	Y
Period-Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	295,710		295,710		295,710		295,710	
Adj. R^2	0.402		0.424		0.270		0.457	

Notes: Heteroscedastic-robust standard errors in parentheses are clustered at the hospital level. Patient controls include age, sex and payment method and number of prescribed medicines. Physician controls include age, sex, education level and years of experiences. *Significant at 10%,**significant at 5%,***significant at 1%.

Furthermore, we explored the relationship between varying proportions of TCMs and health expenditures. After controlling for physician and patient characteristics such as insurance status and number of medicines prescribed, we find that higher proportions of TCMs are associated with lower total expenditures, lower non-medicine expenditures and lower out-of pocket expenditures. By contrast, higher proportions of TCMs are associated with higher medicine expenditures. These findings suggest that TCMs are not less expensive substitutes for Western medicines to treat patients with ARIs. Moreover, when a high proportion of medicines prescribed to patients are TCMs, physicians may use fewer medical consumables (e.g., injection syringes) which may explain the decreased non-medicine expenditures. An alternative explanation could be that physicians reduce the provision of services (e.g., diagnostic tests) when a high proportion of medicines prescribed to patients were TCMs. The study results suggest that a greater relative use of TCM does not impose an immediate financial burden on either the public health insurance plan or on patients. Nevertheless, more research needs to be done to ensure the clinical effectiveness of using TCMs for ARIs (e.g., does not increase the likelihood of inpatient admission in higher level hospitals), and to understand the longer-term financial implications of the increased relative use of TCMs.

This paper has several shortcomings that results from data availability. Without any quality measures in the data set, we cannot determine whether the increased relative use of TCMs in a given prescription has any impacts on patient health outcomes. Although we have medicine expenditures for each outpatient visit, ideally we would have itemized expenditures on each medicine to better understand the financial implications in greater detail. The TCM proportion is a simple measure constructed using only information on the number of medicines prescribed and were not dose-normalized due to data availability reasons with prescribing TCMs. What is more, our results are based on data collected from outpatient visits to township hospitals.

Medicines purchased from other facilities, such as pharmacies, and higher level hospitals were not included in our analysis. Moreover, our sample only includes the rural patients attended by primary care physicians from 34 township hospitals in two counties. There is likely to be great heterogeneity between the rural and urban settings in terms of the relationship to patient characteristics as well as physician characteristics. Last but not least, apart from the month fixed effects, we lack suitable controls to address the potential shift in systematic patient illness severity levels between the pre-COVID and in-COVID periods, as patients with fever were turned away from township hospitals due to the public health measures implemented in 2020.

Chapter 4

Physician agency in rural China: Evidence from the County Medical Community reform

4.1 Introduction

The rapid growth of total healthcare expenditures has become a common concern in most countries (Ke et al. (2011); Jia et al. (2021)). The problem of rising health care expenditures is partially attributed to physicians, who serve a central role in providing health care (Fuchs (1978)). As physicians direct many resources in the health care system, they have a significant influence on costs and health outcomes for patients. Since the seminal work of Arrow (1963), physicians' motives and their impact on the medical services used by patients have been recognized as the important issue of "physician agency" in health economics (McGuire (2000)). The term "agency" in the physician-patient relationship means that physicians possess the ability to act on behalf of the patient (McGuire (2011)). Therefore, physicians may take advantage of the agency relationship to influence patient demand in their own interests which is known as physician induced demand (PID) (McGuire (2000)). They are able to do this because patients possess little knowledge about the type or the quantity of treatment needed.

In China, total health expenditure has grown considerably since the start of economic reforms in 1978, and it has continued to grow faster than GDP since then (Zhai et al. (2017)). To control rising health expenditure, the Chinese government has implemented a range of provider-side mechanisms such as paying public township hospitals, the main provider of primary health care in rural China, on a capitated global budget (CGB) scheme for outpatient care (Li et al. (2017)). The CGB strategy relies on the idea that costs are controlled by the annual budget fund allocated to the hospital and the quality of care is enforced by the market. The basic rationale for using the market mechanism to ensure quality is the following: the capitated global budget fund hospitals receive gives them an incentive to reduce costs (and quality), while the opportunity to attract more enrollees gives them an incentive to increase quality (and costs) (Frank et al. (2000)).

Another crucial policy reform targeting health care providers is the implementation of a zero markup policy on prescription medicines, which prohibits public hospitals from adding any markup to the procurement price (He et al. (2019); Yip et al. (2019)). Prices of medical services and medical consumables in township hospitals are regulated by the government. In some well-developed provinces, such as Guangdong and Jiangsu, a zero markup policy on medical consumables has been implemented in all public hospitals, similar to the zero markup policy on medicines. Physicians are salaried employees of the township hospital, whose income however, includes a considerable portion in the form of bonuses related to net revenue of the hospital (Ran et al. (2013)). Therefore, the physician's financial incentives largely align with those of the hospital.

There are two types of outpatient visits with respect to the payment method: (1) cost-sharing visits for which patients pay the co-insurance to the hospitals and the rest are covered by the public insurance program through insurance payments; and (2) self-paying visits for which patients pay full price out-of-pocket to the hospitals. The hospitals charge both types of visits under the same government-regulated fee schedule on a fee-for-service (FFS) basis. During a contract year, the CGB fund allocated to the hospital is used to cover all insurance payments associated with cost-sharing visits. At the end of the year, public insurance authorities compare the total insurance payments incurred against the CGB fund allocated to the hospital. The surplus of the budget fund is distributed to the hospital as a bonus, and a major portion of the bonus to the hospital is then distributed as bonuses to its staffed physicians. Although patients for the self-paying visits and cost-sharing visits face the same fee schedule and are both charged on a FFS basis, the physicians' incentives are different between these two types of visits. The self-paying visits are FFS under a fixed fee schedule in nature. Meanwhile, treating the cost-sharing visits in a way that aligns with the CGB scheme meets physician's interest.

Physicians working in rural settings of low-and middle-income countries (LMICs) often face different incentives compared to their counterparts in developed economies. Understanding the issue of physician agency in various contexts is important to inform policy recommendations. Although there is an extensive theoretical and empirical literature on physician agency (see Johnson (2014); McGuire (2000) for reviews), evidence from LMICs is limited. To provide new empirical evidence on physician agency, this paper studies how physicians respond to incentives in rural China. Specifically, we use an exogenous change in financial incentives for hospitals and their staffed physicians, driven by a policy known as the County Medical Community (CMC) reform, to study how physicians alter their prescribing patterns in response to incentives.

To strengthen the primary health-care system and take full advantage of health-care resources, in 2018, China implemented a policy in select counties which aimed to build a more integrated health-care delivery system by combining a county hospital and several subordinate township hospitals to form a CMC.[1]

Although the reform intended to improve service quality and efficiency, the evaluation indicators for this policy provide an opportunity to assess its impacts on changes

[1]The CMC is one form of the medical alliance integrating the health care system in rural China. More information could be found at http://www.nhc.gov.cn/xcs/s3574/202107/ea10acafc7d1493d820f6789c51cf571.shtml.

in financial incentives for hospitals and physicians. Specifically, there are two relevant evaluation indicators of the reform including (1) increasing hospital non-medicine revenue relative to total revenue of the township hospital, and (2) increasing the incomes for physicians working in township hospitals. To examine how physicians respond to incentives imposed by these two evaluation indicators of the reform, a unique micro-level outpatient visit dataset was obtained from 34 township hospitals located in two rural counties of Guangdong province. The dataset includes all outpatient visits for patients with acute respiratory infections (ARIs) between January 2019 and December 2019. During the study time frame, the CMC reform was only implemented in 17 township hospitals from one county. Each outpatient-visit record contains information about the visit date, the attending physician, diagnosis, medicines dispensed, total expenditures, medicine expenditures, and non-medicine service expenditures. It also includes patients' characteristics such as age, sex, and payment method (cost-sharing/self-paying).

We exploit the fact that hospitals from one of the counties underwent the CMC reform while hospitals from the other did not to examine how the reform affects physician prescribing of medicine and medical services, and to examine the heterogeneity of physician inducement behavior with respect to patient payment method. Surplus from the capitated global budget fund could be distributed as additional income to physicians in the form of bonuses. So, one way for physicians working in CMC reform hospitals to increase their income is by reducing insurance payments per visit for cost-sharing visits. Since the insurance payments are positively linked to total expenditures, patients are expected to experience lower health expenditures in comparison with similar visits that happened in hospitals in which the reform was not implemented. In contrast, given the pure fee-for-service nature of self-paying visits, only more non-medicine services increase hospital net revenue under the zero-markup policy on medicines which in turn raises physicians' incomes. Moreover, the

CMC reform promotes higher revenues from non-medicine services relative to total revenues. So we expect that the physicians working in the reform hospitals reduce patient health expenditures mainly by lowering medicine expenditures. There are two main channels through which physicians may lower patient medicine expenditures. Physicians may choose to prescribe fewer medicines, and/or lower the value of each type of medicine (e.g., generic instead of brand-name, substitute smaller for larger package). This paper aims to evaluate to what extent physicians decrease medicine expenditures by using these two channels.

As noted above, physicians working in reform hospitals have an incentive to increase non-medicine expenditure for both cost-sharing and self-paying patients. Treatment by intravenous infusion of antibiotics is widespread in China, partially driven by profit (Reynolds and McKee (2011)). It should be noted that there is no extra charge for outpatient infusion in township hospitals beyond the fixed general consultation fee. However, there are likely other service fees associated with the infusion process, such as a bed occupancy fee.[2] Infusion of antibiotics can not only being used as a measure of physician agency but also as a measure of care quality. This is because ARIs, which are the most common symptomatic reasons to seek outpatient care, are caused by viruses and thus should not be treated with antibiotics (World Health Organization (2004); Dasaraju and Liu (1996)). Over-prescription of unnecessary medications such as antibiotics for ARIs indicates poor quality of care in terms of adherence to best practice guidelines. In addition to infusion of antibiotics, we also include whether any antibiotics were prescribed as another measure of quality of care. Then we examine whether the reform had any impact on prescribing quality while physicians responded to financial incentives.

Consistent with predictions of the agency theory, we find that providers under the CMC reform responded to the financial incentives by decreasing total expenditures,

[2]The bed occupancy fee for outpatient visit in township hospitals is usually 10 RMB/half day.

especially among cost-sharing visits. The reduction in total expenditures was solely caused by lower medicine expenditures, while non-medicine expenditures for both cost-sharing and self-paying visits were higher in hospitals under the CMC reform. We also find that decreased medicine expenditures were due to a lower average value per type of medicine prescribed by physicians working in the reform hospitals, with no significant difference in number of medicines on a prescription. Furthermore, physicians affected by the reform were more likely to prescribe infusion antibiotics, which may also be attributed to incentives to increase non-medicine revenue and physician income. However, the results suggest that the CMC reform did not lead to any improvement in the quality of care, as there was no significant difference in the probability of physicians prescribing antibiotics to patients.

4.1.1 Related Literature

Income shocks and physician induced demand

This paper adds to the empirical literature investigating the extent of physician induced demand (PID). Much of the literature has examined the relationship between physician-to-population ratios and inducement behavior. The concept of PID was first introduced by Evans (1974), and refers to the tendency of physicians to modify their recommendations for care and provision of medical services that have low marginal benefit for their patients in order to enhance their own income.

Fuchs (1978) studies the differences in the supply of surgeons and the demand for operations across metropolitan areas. He finds that a 10% increase in the surgeon-to-population ratio results in a 3% increase in surgeries per capita and argues this is consistent with PID since surgeons who find that they have fewer patients as some have gone to the new surgeons, respond to the fall in their income by increasing the intensity of treatment in the form of surgical treatment to the patients they do treat. Using a similar methodology, Cromwell and Mitchell (1986) and Rossiter and Wilensky (1984) find that a higher surgeon-to-population ratio leads to a higher number of services provided per capita and increased expenses.

Gruber and Owings (1996) provide evidence on PID using more robust instruments for state-level changes in the physician-to-population ratio, specifically the fertility rate decline from 1970 to 1982. They find that physicians respond to this income shock by substituting less profitable vaginal deliveries with more generously reimbursed Cesarean sections. Delattre and Dormont (2003) examine the existence of PID among self-employed physicians in France, using physician level longitudinal data from 1979 to 1993.[3] Their results suggest that the number of consultations declines when there is an increase in the physician-to-population ratio, and physicians respond to the fall in the number of consultations by providing more services in each consultation. In contrast, no evidence of PID was found for Norwegian physicians, who are regulated in a similar way as in France (Grytten et al. (1995)).

J. Sørensen and Grytten (1999) and Carlsen and Grytten (1998) find that a high physician-to population ratio resulted in a decrease in the number of consultations per physician, but physicians in high physician density areas did not counterbalance the fall in patient volume by increasing the volume of care they delivered in each encounter. Grytten and Sørensen (2001) compared self-employed physicians and salaried physicians and found no difference in their response to an increase in physician density. In a recent study, Currie et al. (2023) examine whether family physicians changed their prescribing practice following sharp increases in competition due to revisions in state-level scope-of-practice laws allowing nurse practitioners (NPs) to independently prescribe controlled substances. They find physicians facing greater competition increased prescriptions of controlled substances by a larger extent.

Our paper contributes to the existing literature by analyzing PID with a financial

[3]On a payment scheme of fee-for-service with fixed fees.

scheme that is a mixture of capitated global budget and fee-for-service. Previous studies have relied on geographical level or physician level data, using variation in the number of physicians in a practice area to study PID. In contrast, we take a different approach by utilizing patient level data along with incentives to increase income that were administratively set as part of a policy reform.

Physician agency in the Chinese context

In addition, our paper is related to a small literature on the issue of physician agency in China. Employing a field audit experiment, Lu (2014) finds that physicians write 43% more expensive prescriptions to insured patients than to uninsured patients, when they expect that patients will fill their prescriptions in the hospital pharmacy. In another audit study, simulated patients were able to reduce inappropriate prescription of antibiotics by telling physicians that they would fill the prescription elsewhere other than the hospital pharmacy (Currie et al. (2014)). Their findings suggest that a physician's financial incentives are a significant driver of antibiotics abuse in China. Wu (2019) examines how physicians respond to financial incentives through a policy that penalized tertiary hospitals in China whose medicine sales exceed 45% of total revenue. The results suggest that physicians decreased medicine expenditures and increased non-medicine expenditures, keeping total expenditures at the pre-reform level.

The aforementioned studies focused on physicians working in tertiary hospitals located in major cities, and were conducted using data collected over a period when many public hospitals were still allowed to charge a mark up on medicines [4]. Fang et al. (2021) studied the effect of a zero-markup policy on physician-induced demand in inpatient care using data from one representative county by exploiting the staggered

[4] Tertiary hospitals are the highest level of general acute care hospitals in China. They provide specialist services and take research tasks. They must have a bed capacity exceeding 500, doctor per bed exceeding 1.04 and nurse per bed exceeding 0.4.

rollout of the policy; it was first implemented in township hospitals and later in county hospitals. They find that the policy decreased medicine expenditures by 47%, but that the increases in expenses for non-medicine services almost fully compensated for the decreases in medicine sales. Our paper aims to add to our understanding of physician agency in China by studying physicians in an outpatient primary care setting after the zero-mark up policy has been fully implemented.

The remainder of the Chapter is organized as follows. Section 2 introduces the background. Section 3 outlines the conceptual framework and the hypotheses to be tested. Section 4 describes the data. Section 5 presents the empirical strategy and results. Finally, Section 6 concludes.

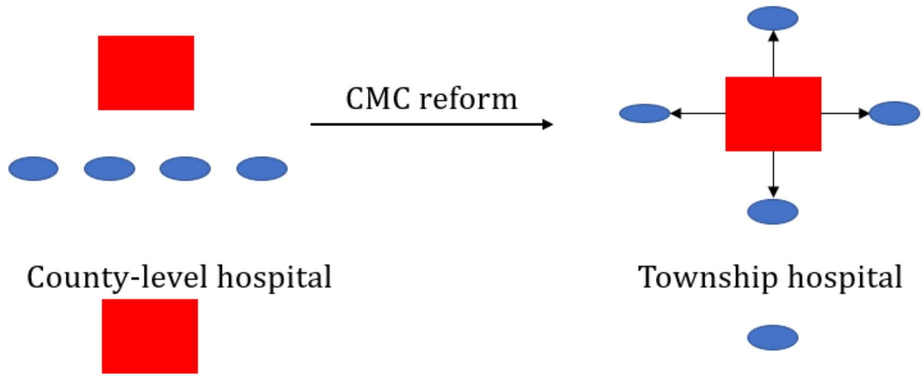
4.2 Background

4.2.1 The County Medical Community reform

In 2018, one of the two study counties was selected to implement a pilot program for the County Medical Community (CMC) reform. The primary objective of the CMC reform is to enhance the quality and efficiency of care provided by township hospitals with guidance from the county-level public general hospitals and advocating that patients receive care within the county (Ye et al. (2022)). Prior to the implementation of the CMC reform, township hospitals had limited connections and received minimal guidance from the county-level hospital. Following the reform, township hospitals and the county-level hospital were vertically integrated to establish a cohesive healthcare delivery system (Wu et al. (2021)). Figure 4.1 demonstrates this change of relationship before and after the CMC reform.

The reform promotes unified management within a CMC, encompassing six aspects including unified medicine procurement, unified rules and regulations, unified quality of care standards, unified human resource management, unified financial man-

Figure 4.1: Structure of the health-care institutions before and after the CMC reform



agement, and a unified information system among hospitals in the same CMC. While the primary objective of the CMC reform is to enhance the provision of quality care in a more efficient manner in rural China, it also introduces financial incentives that are relevant to the physicians with aims to improve physicians' satisfaction in relation to their income. The evaluation indicators for reform implementation includes increasing the proportion of non-medicine revenue in the total revenue for township hospitals, and increasing physician income in township hospitals. The county hospital in a CMC takes primary responsibility for achieving these expected outcomes of the reform.

4.2.2 The incentive scheme for health providers

The incentive scheme for cost-sharing and self-paying visits differ significantly for health providers. For self-paying visits, hospitals receive payments directly from patients on a fee-for-service basis. In the study region, the public health insurance program, Urban and Rural Resident Basic Medical Insurance (URRBMI), pays hospitals based on a capitated global budget model to cover insurance payments for outpatient visits under cost sharing. The annual global budget is determined by a per enrollee base rate (i.e., a simple capitation rate) and the number of contracted enrollees with a specific hospital for a given year.

The public insurance authorities withhold 20% of the annual global budget, while the remaining 80% is distributed to the hospital in monthly payments. At the end of the year, public insurance authorities settle the yearlong insurance payments incurred against the hospital's annual global budget. After settlement, if the surplus is equal to or less than 20% of the annual budget, the surplus is transferred to the hospital in the form of bonuses that can be distributed to physicians. If the surplus exceeds 20%, the hospital would be penalized for not providing sufficient care and the surplus is forfeited by the public insurance authorities. The hospital has to assume the loss when its annual global budget is less than the accumulated insurance payments. As employees of the hospital, physician's financial incentives largely align with the hospital (Eggleston and Yip (2004)).

Physician income consists of a basic salary, benefits and bonuses (Ran et al. (2013); Ding (2014)). While the basic salary level and some of benefits are stipulated by the government, bonuses are positively linked to the hospital's net revenue. The provincial government allows public hospitals to distribute a substantial proportion of net revenues in the form of bonuses to physicians. Though, the details of the compensation scheme for physicians tend to be hospital specific.

4.3 Conceptual Framework

This section presents the conceptual framework for analyzing the impact of the incentives embedded in the CMC reform on physician behavior. There are two mechanisms through which physicians may alter their prescribing patterns in response to the reform's aim of increasing income. First, physicians could enhance the hospital's net revenue by reducing total expenditures for cost-sharing visits, thereby generating a larger surplus in the hospital's capitated global budget fund which later would be distributed to them as bonuses. In other words, within the incentive structure of the capitated global budget model, expenditures related to cost-sharing visits could be seen as costs that deplete the budget fund.

The growing empirical literature on the interaction between physician agency and patient insurance status suggest that physicians prescribe more expensive medicines and provide more services to insured patients compared to uninsured patients (Lundin (2000); Grant (2005); Iizuka (2007); Pan et al. (2009); Iizuka (2012); Lu (2014)). Consequently, cost-sharing visits are likely to result in higher total expenditures compared to self-paying visits, creating a gap in total expenditure between the two visit types. Physicians in the CMC reform hospitals are expected to respond to the incentive by decreasing total expenditures among cost-sharing visits, thereby narrowing the gap in total expenditure between cost-sharing and self-paying visits compared to visits to non-reform hospitals. This expected response allows us to form the following hypothesis.

Hypothesis 1. The difference in total expenditures between cost-sharing visits and self-paying visits would be smaller if treated by physicians working in reform hospitals compared to those working in non-reform hospitals.

Next, we discuss the second mechanism through which physicians could increase their income. After the implementation of the zero-markup policy, prescribing more medicines to patients is no longer a viable means to increase physician income. Instead, for self-paying visits, physicians can benefit financially by prescribing more non-medicine services. Furthermore, the CMC reform also aimed to increase the share of non-medicine revenues as a proportion of the hospital total revenues. Consequently, we anticipate that physicians practicing in the reform hospitals have incentives to increase non-medicine expenditures not only for self-paying visits but also for cost-sharing visits. As a result, we expect the non-medicine expenditures to be higher among visits to the CMC reform hospitals.

Hypothesis 2. Outpatient visits to CMC reform hospitals had higher non-medicine expenditures compared to visits to non-reform hospitals.

To achieve a reduction in total expenditures for cost-sharing visits while simultaneously increasing non-medicine service expenditures, physicians working in CMC reform hospitals need to reduce medicine expenditures by a larger margin. However, due to the fully out-of-pocket nature of self-paying visits, physicians do not have the same incentive to reduce medicine expenditures as they do for cost-sharing visits. Therefore, we anticipate that the gap in medicine expenditures between cost-sharing visits and self-paying patient visits in CMC reform hospitals is going to be smaller compared to visits to non-reform hospitals. Additionally, rural patients are likely to be financially constrained, particularly those who are self-paying. Therefore, physicians in reform hospitals are likely to offset the increased non-medicine expenditures by reducing medicine expenditures, resulting in lower medicine expenditures for visits to reform hospitals compared to visits to non-reform hospitals.

Hypothesis 3. Medicine expenditures are lower on average for patients treated by physicians working in reform hospitals compared to their counterparts treated by physicians practicing in non-reform hospitals, and the difference in medicine expenditures between cost-sharing visits and self-paying visits to be smaller in reform hospitals.

4.4 Data

The primary dataset was derived from 34 township hospitals located in two rural counties of Guangdong province in China. The monthly data covered all outpatient visits for patients with acute respiratory infections (ARIs) from January 2019 to December 2019. The CMC reform was implemented in 17 hospitals from one of the two counties since July 2018, and the reform was not initiated in the 17 hospitals from the other county over our study period. ARIs were the top diagnosis for outpatient visits to township hospitals accounting for about 40% of total patient volume. For each outpatient visit, the visit date, attending physician, diagnosis, prescribed medicines and patient characteristics including age, sex, and payment method (cost-sharing or self-paying) were recorded. The total expenditure, medicine expenditure, and non-medicine expenditure were also recorded. We enrich the existing data set with an additional data source that collected physician characteristics for all attending physicians in the 34 township hospitals including age, sex, educational level, and years of experience which are linked to the main dataset via a de-identified unique physician ID.

For visits determined to be cost-sharing in the hospital records, patients need to present a health insurance card issued by the local government at outpatient registration. All outpatient visits registered without the local health insurance card are assumed to be self-paying in the hospital records and cannot get reimbursement from URRBMI, despite an outpatient's actual insurance status. The policy of URRBMI in the two sample counties remained the same in this regard throughout the study period.

In Table 4.1, we present the characteristics of the patients and their attending physicians for the full sample, and separately for the subsamples of the CMC reform hospitals and non-CMC reform hospitals. For each sample, we also present visit-level statistics separately for the cost-sharing and self-paying visits. Among our full sample of 195,282 outpatient visits, more than 58 percent are aged 19 years or younger, 51 percent are male, about 60 percent were treated by male physicians, about 55.5 percent were treated by physicians with a 3-year college degree, and about 63.8 percent are treated by physicians with 11 years of experience or more. Patients in the CMC reform hospitals tend to be older, more likely to be treated by a relatively young female physician (40 years old or younger), and less likely be treated by a physician with a 5-year university degree. In comparison with cost-sharing visits, there is a higher share of self-paying patients who are male, 19 years old or younger, who were treated by female physicians and physicians with a 5-year university degree.

Table 4.1: Summary statistics of patient and physician controls

	Full	non-CMC hospitals			CMC hospitals		
	Sample	All	Cost-sharing	Self-paying	All	Cost-sharing	Self-paying
Patient Controls							
Age (%)							
≤19	58.43	63.04	56.72	71.72	53.94	50.31	64.61
20-39	10.30	11.80	11.68	11.97	8.83	7.72	12.11
40-59	18.29	15.71	19.62	10.32	20.81	23.06	14.19
≥60	12.98	9.46	11.98	5.99	16.42	18.91	9.09
Sex (%)							
Male	50.99	51.96	50.49	53.99	50.04	49.31	52.19
Physician Controls							
Age (%)							
≤29	13.42	7.61	6.98	8.48	19.10	18.03	22.26
30-40	39.76	37.62	37.68	37.53	41.85	42.75	39.21
40-50	21.04	18.79	18.57	19.10	23.24	23.19	23.38
≥51	25.77	35.98	36.77	34.88	15.81	16.04	15.15
Sex (%)							
Male	60.34	66.92	68.05	65.38	53.91	54.22	52.98
Education Level (%)							
3-year vocational	15.25	14.32	13.60	15.31	16.16	15.92	16.68
3-year college	55.46	49.91	52.50	46.36	60.88	61.39	59.35
5-year university	29.29	35.77	33.90	38.33	22.96	22.68	23.79
Years of Experience (%)							
≤5	11.71	7.38	6.73	8.28	15.93	14.78	19.32
6-10	24.54	21.53	21.99	20.90	27.48	27.75	26.68
≥11	63.75	71.09	71.28	70.82	56.59	57.47	54.00
Obs.	195,282	96,530	55,879	40,651	98,752	73,692	25,060

Notes: Vocational school directly recruits students graduated from junior high school for 3 years medical secondary education.

In Panels A and B of Table 4.2, we describe the basic outpatient statistics including total medical expenditures, medicine expenditures, and non-medicine expenditures, the number of medicines, medicine expenditure per type of medicine, the probability of being prescribed any antibiotics and probability of being prescribed injection or infusion antibiotics, for cost-sharing and self-paying visits respectively. Table 4.2 shows

Table 4.2: Average outpatient experiences in CMC and non-CMC township hospitals

	non-CMC hospitals			CMC hospitals		
	Mean (Std. Dev)	1st PCTL	99th PCTL	Mean (Std. Dev)	1st PCTL	99th PCTL
Panel A: Cost-sharing Visits						
$TotalExp.(RMB)$	63.14 (37.74)	15.18	182.44	47.84 (26.02)	13.2	136.76
$MedExp.(RMB)$	48.26 (34.63)	5.40	160.00	26.23 (19.55)	1.79	94.17
$NonMedExp.(RMB)$	15.13 (10.56)	1.60	54.11	21.87 (15.22)	5.15	80.60
$\#(med)$	5.47 (2.37)	1	12	5.46 (2.30)	1	12
$MedExp./(\#med)$	9.69 (9.12)	1.55	38.55	5.10 (4.81)	0.82	21.06
$Pr(ABX)$	0.811			0.853		
$Pr(Infuse_{ABX})$	0.349			0.494		
Panel B: Self-paying Visits						
$TotalExp.(RMB)$	48.92 (30.85)	10.12	146.74	40.04 (21.55)	11.09	111.07
$MedExp.(RMB)$	35.67 (27.30)	2.08	125.64	21.25 (15.67)	1.14	74.75
$NonMedExp.(RMB)$	13.57 (9.39)	1.18	48.60	18.98 (12.25)	5.70	64.10
$\#(med)$	4.81 (2.16)	1	11	4.83 (2.12)	1	11
$MedExp./(\#med)$	7.91 (7.00)	0.96	29.42	4.57 (3.99)	0.59	18.00
$Pr(ABX)$	0.734			0.797		
$Pr(Infuse_{ABX})$	0.216			0.346		

Notes: PCTL is the abbreviation for percentile. 1 RMB=0.145 US dollars in 2019.

that average total expenditure, medicine expenditure, non-medicine expenditure were all higher for cost-sharing than for self-paying visits, and the differences were smaller for visits to hospitals under the CMC reform.

For example, the difference in average total expenditure between cost-sharing and self-paying visits in non-reform hospitals was RMB 14.22 (63.14-48.92) which is much higher than the difference of RMB 7.80 (47.84-40.04) observed in CMC reform hospitals. The non-medicine expenditures for cost-sharing and self-paying visits in the CMC reform hospitals were RMB 21.87 and RMB 18.98 respectively, which are higher than the corresponding RMB 15.13 and RMB 13.57 in non-reform hospitals. The number of different types of medicine prescribed was similar for visits to the CMC reform hospitals and non-reform hospitals. But the average medicine expenditure per type of medicine was significantly lower for visits to the reform hospitals than visits to the non-reform hospitals. The probability of being prescribed with any antibiotics was slightly higher for visits to the reform hospitals. Meanwhile, the probability of being prescribed infusion antibiotics was elevated by a much larger margin for visits to the reform hospitals, which could be driven by the incentives of increasing income through patient non-medicine expenditures. We explore these relationships further in the regression models outlined below.

4.5 Empirical Analysis and Results

4.5.1 Physician responses to incentives in the CMC reform

In order to examine our hypotheses with regard to physicians altering their prescribing patterns in response to incentives engendered in the CMC reform, the following simple framework is employed:

$$\begin{aligned} Y_{ijht} = & \alpha + \varphi_1 CMC_h + \varphi_2 Insur_{it} + \varphi_3 CMC_h \times Insur_{it} \\ & + \mathbf{x_i} + \mathbf{Z_j} + month_t + \varepsilon_{ijht}. \end{aligned} \tag{4.1}$$

For patient i whose attending physician is j at month t $(1, \ldots, 12)$, the dependent variable Y is one of: the visit's total expenditures, medicine expenditures or non-medicine service expenditures. $Insur_{it}$ is a dummy variable that equals 1 if the outpatient visit was cost-sharing with the public insurance, and equals 0 if the visit was self-paying. $\mathbf{x_i}$ are patient characteristics including age and sex. $\mathbf{Z_j}$ are characteristics of the visit's attending physician including physician age, sex, education level and years of experience. The month fixed effects is captured by $month_t$. We cluster the robust standard errors at the hospital level.

The impacts of the incentives from the CMC reform on physician practice patterns are assessed by φ_1 and φ_3. The difference in healthcare expenditures between visits to reform hospitals and non-reform hospitals is captured in φ_1. Through φ_3, we can gauge how physicians respond to incentives embedded in the CMC reform with cost-sharing visits. The difference in healthcare expenditures between outpatient visits with insurance and those without is measured by φ_2.

As is commonly encountered in modelling health expenditures, our expenditures variables are skewed. As a consequence, in the literature, a generalized linear model (GLM) with a logistic link function and gamma densities is the dominant approach for modelling health expenditures (Deb and Burgess (2003); Buntin and Zaslavsky (2004); Jones et al. (2010)). Table 4.3 reports the estimation results from both OLS and GLM regression models, following Equation(4.1). The coefficients of OLS models represent the change in terms of RMB, and the coefficients of GLM models represent the percent change. The gap in total expenditures for cost-sharing visits and self-paying visits in non-reform hospitals was RMB 12.23. Meanwhile, results from the

GLM model show that total expenditure for cost-sharing visits was 22 log points (25 percent) higher compared to self-paying visits. In CMC reform hospitals, the total expenditures for cost-sharing visits were a much smaller RMB 5.99 or 14 log points (15 percent) higher compared to self-paying visits.

The non-medicine expenditures in the CMC reform hospitals were RMB 6.02 or 36 log points (43 percent) higher than in the non-reform hospitals. In sharp contrast, medicine expenditures in the reform hospitals were about RMB 13 or 47 log points (38 percent) lower than non-reform hospitals. Furthermore, the medicine expenditures for cost-sharing visits to non-reform hospitals were RMB 10.64 higher than the self-paying visits, while the corresponding difference in the reform hospitals was only RMB 3.39. These findings suggest that physicians working in the CMC reform hospitals increased their non-medicine expenditures and decreased their medicine expenditures to a larger extent in term of monetary values, leading to lower total expenditures.

Table 4.3: Regression results of CMC and insurance status on health expenditures

	Total Exp.		*Med Exp.*		*NonMed Exp.*	
	OLS Coef.	GLM Coef.	OLS Coef.	GLM Coef.	OLS Coef.	GLM Coef.
CMC	-6.97***	-0.159***	-12.99***	-0.473***	6.02***	0.362***
	(2.11)	(0.059)	(2.29)	(0.081)	(1.33)	(0.072)
Insur	12.23***	0.220***	10.64***	0.251***	1.60***	0.114***
	(1.99)	(0.026)	(1.72)	(0.027)	(0.37)	(0.022)
$CMC \times Insur$	-6.24***	-0.076**	-7.25***	-0.089**	1.01*	0.031
	(2.26)	(0.032)	(2.03)	(0.038)	(0.593)	(0.031)
Patient Controls	Y	Y	Y	Y	Y	Y
Physician Controls	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Obs.	195,282	195,282	195,282	195,282	195,282	195,282
R^2	0.117		0.189		0.088	

Notes: In all the regressions, we control for patient and physician characteristics for each visit. $***$, $**$ and $*$ represent statistical significance at 0.01, 0.05 and 0.1 level, respectively. Heteroskedasticity-robust standard errors are clustered at the hospital level.

These findings are consistent with our hypotheses and are consistent with the theoretical predictions of physician agency; suggesting that physician may induce medical demand in their own interests. However, an important question arises: If reducing total expenditures by lowering medicine expenditures and increasing non-medicine expenditures could boost physician income, why did physicians wait until the CMC reform went into effect to implement these strategies?

Physician prescribing behaviors tend to be relatively stable and are largely determined by physician-specific factors and environment-level factors (Molitor (2018)). In the absence of exogenous impacts (e.g., new incentives associated with the CMC reform), many physicians who practice in rural areas may not prescribe in a way that aligns with the financial incentive scheme due to their educational backgrounds. With the implementation of CMC reform, the county-level hospital and its subordinate township hospitals were integrated into one entity, with the county-level hospital assuming primary responsibility for successful reform implementation. Therefore, within the same CMC, the county-level hospital shares a lot of common interest with the township hospitals. These shared interests, including achieving evaluation indicators such as increasing physician income in township hospitals, may drive the county-level hospital to provide guidance to physicians practicing in township hospitals with the aim of improving their financial acumen.

4.5.2 Channels of reduced medicine expenditures in the CMC reform hospitals

Physicians under the CMC reform may alter their prescribing behavior through two channels, resulting in lower medicine expenditures. One is by decreasing the number of medicines prescribed. The number of medicines prescribed to a patient in a visit is a count variable that takes on non-negative integer values. For count data, the main shortcoming of the OLS estimators is that the predicted value of the outcome maybe negative. However, linear models can still provide good estimates of average partial effects on the conditional mean (Wooldridge (2010)). We employ a truncated Poisson model to fit our data as shown in Equation (4.1). The results from both OLS and truncated Poisson regressions are given in the left panel of Table 4.4.

The other way physicians can reduce medicine expenditure is by decreasing the medicine expenditure per type of medicine, such as substituting brand-name with generic medicines or using smaller packages instead of larger ones. We then run both OLS and GLM regressions according to Equation (4.1), with medicine expenditures divided by number of medicines as the outcome variable. The results are shown in the right panel of Table 4.4.

Table 4.4: Exploring the channels of reduced medicine expenditures in CMC hospitals

	$\#(med)$		$MedExp./\#(med)$	
	OLS Coef.	TPoisson IRR	OLS Coef.	GLM Coef.
CMC	0.044	1.008	-3.13***	-0.506***
	(0.216)	(0.045)	(0.68)	(0.100)
$Insur$	0.543***	1.112***	1.55***	0.168***
	(0.113)	(0.023)	(0.27)	(0.023)
$CMC \times Insur$	0.062	0.988	-1.14***	-0.081**
	(0.145)	(0.026)	(0.33)	(0.036)
Patient Controls	Y	Y	Y	Y
Physician Controls	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Obs.	195,282	195,282	195,282	195,282
R^2	0.057		0.115	

Notes: In all the regressions, we control for patient and physician characteristics for each visit. $***$, $**$ and $*$ represent statistical significance at 0.01, 0.05 and 0.1 level, respectively. Heteroskedasticity-robust standard errors are clustered at the hospital level. IRR for incidence-rate ratios.

The results indicate that cost-sharing visits were prescribed with 1.11 times the number of medicines prescribed to self-paying visits. The difference in terms of number is approximately 0.54 medicines per prescription. Although physicians in reform hospitals prescribed a similar number of medicines to their patients as physicians in non-reform hospitals, they prescribed medicines with significantly lower value per medicine (RMB 3.13 or 50.6 log points). For cost-sharing visits to non-reform hospitals, patients got more expensive medicines (RMB 1.55 per type of medicine) than those for self-paying visits. By comparison, cost-sharing visits to reform hospitals were associated with prescribed medicines that had a similar value for each type of medicine as those for self-paying visits. Taken together, these findings suggest that physicians in the CMC reform hospitals reduced medicine expenditures by prescribing a similar number of medicines but with lower value per medicine, especially for insured patients.

4.5.3 Prescribing quality

Acute respiratory infections (ARIs) are the most common reason to seek outpatient care, and there is widespread inappropriate prescribing of antibiotics for ARI treatment (Okeke et al. (1999); Heddini et al. (2009); Laxminarayan et al. (2013); Meeker et al. (2014); Do et al. (2016); Wei et al. (2017)). It is useful to examine whether the CMC reform had impacts on physician behavior beyond the financial perspective, particularly in terms of the quality of care. Prescribing antibiotics to patients with ARIs does not provide any benefit since the majority of ARIs are viral and self-limiting (Dasaraju and Liu (1996)). Over-prescription of unnecessary antibiotics not only imposes a financial burden on patients but also contributes to the global crisis of antimicrobial resistance. Thus, prescribing antibiotics for ARIs is considered poor quality of care as it reflects poor adherence by physicians to best practice guidelines. To investigate prescribing quality, two binary outcomes were generated to serve as the dependent variable for two separate regressions: (1) whether a prescription contains any antibiotics and (2) whether a prescription contains any infusion antibiotics. Subsequently, we conducted OLS and logit regressions following Equation (4.1), and the results are presented in Table 4.5.

The left panel of Table 4.5 indicates that there is no significant difference in terms

Table 4.5: Assessing prescribing quality between CMC and non-CMC hospitals

	$Pr(ABX)$		$Pr(Infuse_{ABX})$	
	OLS Coef.	Logit Odds ratio	OLS Coef.	Logit Odds ratio
CMC	0.047	1.287	0.119***	1.695***
	(0.041)	(0.297)	(0.028)	(0.264)
$Insur$	0.066***	1.462***	0.106***	1.749***
	(0.019)	(0.146)	(0.032)	(0.224)
$CMC \times Insur$	-0.019	0.961	0.011	1.040
	(0.021)	(0.113)	(0.035)	(0.133)
Patient Controls	Y	Y	Y	Y
Physician Controls	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Obs.	195,386	195,386	195,386	195,386
(Pseudo) R^2	0.031	0.032	0.085	0.067

Notes: In all the regressions, we control for patient and physician characteristics for each visit. $***$, $**$ and $*$ represent statistical significance at 0.01, 0.05 and 0.1 level, respectively. Heteroskedasticity-robust standard errors are clustered at the hospital level. Pseudo R^2 is reported for logit models.

of the probability of being prescribed antibiotics for visits to reform hospitals versus to non-reform hospitals. For cost-sharing visits, the probability of receiving antibiotics was higher compared to self-paying visits. Patients visiting reform hospitals had a significantly higher likelihood (12 percent in probability or 1.7 times the odds) of being prescribed infusion antibiotics. This phenomenon is likely driven by the financial incentives of increasing physician income through the provision of more non-medicine services.

4.6 Discussion and Conclusions

This paper uses the financial incentives embedded in the CMC reform to examine how physicians responded by changing their prescribing patterns in a rural primary care setting in China. We find that visits to physicians working in reform hospitals had significantly lower total expenditures compared to visits to non-reform hospitals, particularly for cost-sharing visits. We also show that physicians who were affected by the reform increased non-medicine expenditures for both cost-sharing and self-paying visits. Meanwhile, the medicine expenditures were reduced by a larger extent for visits to reform hospitals which yielded reduced total expenditures. There was no significant change in the number of medicines prescribed to patients in reform hospitals. Rather, physicians reduced medicine expenditures by reducing the value of each type of medicine they prescribed.

The CMC reform did not lead to any improvement of care quality which was measured by appropriateness of prescribing. Physicians in the CMC reform hospitals tend to provide antibiotics through infusion which might be driven by the same incentive of increasing net revenues through increasing more non-medicine revenues. Taken together, physician agency has significant impacts on physician prescribing behavior with no change in the likelihood that a patient is inappropriately prescribed an antibiotic for an ARI. Given physicians' unique and central role in providing health care, understanding the issue of physician agency is important for designing policies and achieving the intended goals. The findings of this paper may shed light on policy design in other LMICs where a similar physician income structure exists or is contemplated.

China has long been criticized for having misaligned financial incentives in prescription medicines which led to physician induced demand and over prescribing. The financial incentives in prescription medicines were largely eliminated since the medicine reform (e.g., the zero markup policy) initiated in 2009 and which was fully implemented in 2017. This paper investigates the issue of physician agency in a new era in which township hospitals are not allowed to charge a markup on most of their medicines. Health expenditures are effectively controlled in the rural outpatient setting after the implementation of the medicine reform and managed care component like the capitated global budget model.

However, the current capitation rate in URRBMI may not be generous enough to provide sufficient coverage for rural residents. Given the new financial incentives imposed by the CMC reform, enrollees of URRBMI may face an increased risk of not receiving enough care due to the issue of physician agency. More investments from the government may be needed to continue improving the URRBMI program. Income is one of the areas of lowest satisfaction among the physician workforce in rural China (Luo et al. (2014); Zhang and Fang (2016); Zhao et al. (2021)). The government must consider physician agency and how physicians respond to financial incentives when designing physician remuneration policies in a way that not only improves physician satisfaction but also improves quality of care.

There are several limitations of this paper. First, we do not have data from a period that the CMC was not initiated, so a quasi-experimental design such as the difference-in-difference cannot be employed to obtain an appropriate counterfactual. Therefore, our empirical findings regarding physician agency under the CMC reform are only suggestive. Second, our results are based on data collected from township hospitals located in two counties from a less economically developed area. There is likely great heterogeneity between the rural and urban populations and across areas with different levels of economic development. Third, due to data limitations, several important control variables such as patient family income and the number of contracted enrollees of each township hospital could not be included in our analysis. These omitted variables may introduce bias into our estimates. But we do not expect the biases to be substantive, given the general similarities between the two study counties. Fourth, our data do not contain detailed information on medicine manufacture, package size and the itemized cost of each medicine. This makes it impossible to further disentangle the package price channel (e.g, choose a generic manufacturer) from the package size channel (e.g., substitute lager with smaller packages of the same manufacturer) that may result in the reduced medicine expenditures.

Finally, only short-term response to the reform was captured rather than the long-term effects. This paper takes the first step in exploring the physician response to the CMC reform. Future research is required to generate a more systematic and longer term view on the impacts of the financial incentives of the CMC reform, and the spillover effects on quality of care and patient welfare. The policy implications of this paper are relevant to China and other emerging economies where primary care physicians face a similar financial incentive scheme. It may not be generalized to developed countries where physicians are compensated very differently. More research is needed to generate a more complete view with physicians working in a variety of health care settings under different incentive schemes across geographic areas.

Chapter 5

Conclusion and Summary

Physicians are critical actors in the healthcare system, so understanding their prescribing behaviors is an important aspect of improving health system performance. The primary goal of the medical profession is to service the needs of patients by skillfully using scientific knowledge and technology (Black (1982)). During the advising and treatment process, physicians decide which diagnostic tests to order, what therapies to employ, which medicines to prescribe, if any; they also perform surgery or other procedures, decide whether or not to hospitalize a patient, and decide when to discharge patients.

In order to make appropriate medical decisions, physician constantly update their information about such things as the efficacy of new medicines and best practice guidelines. There are costs associated with production, dissemination and acquisition of scientific information, so physicians may fail to absorb relevant information due to constraints related to time, education background, and practice environment. This, in part, explains the prevalence of non-adherence to best practice guidelines among physicians (Phelps (2000)). A further complication is that information diffusion in relation to one type of medicine or treatment may have spillover effects on the prescribing of other types of medicines or treatments which could result in unintended consequences.

While physicians face issues of incomplete information (e.g. the populations on which existing RCT evidence for a medicine treatment is based may not match the patient population the physician serves), patients face asymmetries in information in relation to prices, quality of care or even the necessary type and quantity of care that they require. These are areas where physicians are likely to have more information relative to patients. Though physicians use their expert knowledge to enhance the health and well-being of their patients, the potential for physician agency can sometimes complicate the relationship between physicians and their patients. Physician agency may provide physicians with power to engage in some activities to shift the patients' demand in ways that advances the physician's self-interest. But the fact that physicians respond to financial incentives or adapt to the release of new information also suggests potential policy tools that can be applied in ways that align physician self-interested behavior with the best health outcomes for patients.

In summary, this dissertation contributes to the economics of physician prescribing behavior in the following ways. First, it highlights the potential for using a carefully designed intervention program, such as the antibiotics stewardship program, to improve physician prescribing behavior in a cost-effective manner by facilitating the dissemination of scientific information. Second, the economic evaluation provides evidence that there may be significant value not only to patients but also to health systems in producing and disseminating scientific information about the efficacy of various medicines and associated prescribing guidelines.

Furthermore, the dissertation demonstrates that the provision of scientific information, in this case, the antibiotics stewardship program may have spill over effects on the prescribing of Traditional Chinese Medicine, leading to unintended financial consequences in the health care system. Thus, when designing interventions to modify physician behavior, planners need to anticipate not only direct effects of the policy but also potential positive and negative spillover effects to achieve overall policy objectives.

Finally, this dissertation adds to the literature that studies the issue of physician agency by examining prescribing behavior changes in response to financial incentives in the current policy context in rural China. Physician agency is an important factor which may drive physician prescribing behavior just like an intervention program and scientific information diffusion. The findings with respect to prescribing behavior that can affect physician income, underscore the importance of designing polices for physician funding models which anticipate their responses in relation to the potential for physician agency.

Although there are numerous strengths with the data used across the three studies in this dissertation, there are also limitations. First, the data only contains outpatient visits to township hospitals, excluding medicines purchased elsewhere and urban populations. The data originates from economically disadvantaged areas and may not represent urban or economically diverse populations. Some potential useful control variables are missing due to data constraints, and detailed medicine information is lacking. The findings may be context-specific to countries with similar physician incentive schemes and may not be generalizable to developed nations with distinct compensation models. More extensive research is needed to provide a comprehensive understanding of physician behavior across various healthcare settings and incentive structures.

More specifically, in the first study, limitations include reliance on self-reported physician time data, the use of averaged implementation costs for township hospitals, and the exclusion of future health costs and potential spill-over effects. The study lacks a societal perspective and may overlook consequences of the intervention not captured in the dataset. In the second study, data limitations hinder the assessment of the impact of TCM on patient health outcomes and lack detailed medicine expenditure breakdowns. Additionally, there are no suitable controls for potential changes in patient mix such as patient illness severity levels due to COVID-19 measures. In the third study, limitations stem from the absence of pre-initiation data for the County Medical Community (CMC) reform, leading to quasi-experimental design challenges.

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Appendix

International classification of Diseases, version 10 (ICD-10) codes used for acute respiratory infections

Acute respiratory infections	ICD-10 codes
Acute nasopharyngitis (common cold)	J00
Acute pharyngitis	J02.8, J02.9
Acute tonsillitis	J03.8, J03.9
Acute URTIs of multiple and unspecified sites	J06
Acute bronchitis	J20
Acute sinusitis	J01.0, J01.1, J01.2, J01.4, J01.9
Acute otitis media	H65, H66, H67
Streptococcal pharyngitis	J02.0
Streptococcal tonsillitis	J03.0

Note: URTIs upper respiratory tract infections