Essays on Pharmaceutical Pricing and Physician Incentives

Jiafeng Wu
Wuhan, China

M.A. Economics, University of Virginia, 2019
B.S. Economics, Arizona State University, 2017
B.A. Mathematics, Arizona State University, 2017

A Dissertation presented to the Graduate Faculty
of the University of Virginia in Candidacy for the Degree of Doctor of Philosophy

Department of Economics

University of Virginia
Apr, 2023

_____

_____

_____

_____

Abstract

The rapid increase in healthcare expenditure is a challenge faced by many countries. Among all factors driving high healthcare costs, the pharmaceutical industry represents a significant and growing share of healthcare spending. The rising cost of pharmaceutical products has become a pressing policy challenge, with governments under pressure to adopt direct or indirect controls on drug prices to ensure access to affordable medicines. In this context, the first chapter of my thesis compares an auction-based drug pricing mechanism used in China with Bertrand competition and reference pricing. Unlike standard auctions where the "prizes" are fixed, in China, auctions are used to determine the sole supplier of the drugs. The winner then faces a downward-sloping demand (prize) in the downstream market. This feature leads to auctions with variable prizes. I develop an empirical framework to estimate the demand for medicine and the manufacturing costs using novel data collected from a province's pharmaceutical procurements. Then, using counterfactual simulations, I find that the auction mechanism leads to lower prices than a laissez-faire Bertrand competition, albeit with a negligible effect on drug expenditures and welfare. However, a reference pricing policy can significantly reduce drug expenditures but also consumer welfare compared to the auction mechanism, leading to lower total welfare.

To address the challenge of rising healthcare costs, it is important to consider not only drug pricing mechanisms but also the behavior of physicians. As pointed out by Arrow (1963), a fundamental characteristic of the healthcare market is the agency relationship between physicians and patients, where physicians may face different incentives than patients. Therefore, in my second chapter, in joint work with Lichen Wang, I study the interaction between physicians and patients and how changes in

the financial incentives of physicians influence treatment choices. Understanding the role of incentives is crucial to identify ways to control healthcare costs. By utilizing a unique exogenous policy change, in which the Chinese government mandated that all public hospitals sell medicines at wholesale prices, and a comprehensive individual-level insurance dataset, I find empirical evidence of physicians' excessive treatment. Furthermore, I document that physicians tend to steer patients away from medicines towards non-medicine based procedures as the latter increases physicians' payoff following the policy change.

JEL Classification: D44, L11, I11, I18

Keywords: Pharmaceutical Pricing, Auction, Physician Financial Incentives

Acknowledgments

First and foremost, I would like to express my sincere gratitude to my advisors, Simon Anderson and Gaurab Aryal for their invaluable guidance and mentorship throughout my academic journey. Without their invaluable advice, exceptional patience, and constant encouragement, this work would not have been possible. I feel incredibly grateful and fortunate to have been their student and to have had the privilege to learn from them.

I am extremely thankful to Federico Ciliberto, Maxim Engers, Amalia Miller, and Leora Friedberg for their constructive feedback on my work and for helping me develop my research skills. Moreover, I would like to express my gratitude to the participants of the UVA IO graduate research group meetings, including Peter Troyan, Andrew Kloosterman, and many others, for their countless valuable comments and suggestions. Additionally, I am grateful to my fellow students, including Nan Liu, Dengli Yang, Lichen Wang, Siqi Yang, Yan Chen, Hasan Toppark, Jaeho Lee, Tyler Ludwig, Ishita Gambhir, and Yooseon Hwang, for their assistance and companionship. I will always cherish the memories of the time we spent together on this journey.

Lastly, I would like to extend my heartfelt gratitude to my parents who have been a constant source of love, support, and encouragement throughout my life. Their unwavering belief in my abilities has been a great motivator for me, and I am deeply indebted to them for everything they have done for me. I would also like to express my sincere appreciation to my wife, Yutong Chen, for being my constant companion and a pillar of strength throughout this journey. Your unwavering faith in me has helped me through the difficult times, and I feel incredibly lucky to have you as my partner in life.

Contents

1 Price and Efficiency in a Market for Generic Drugs in China **1**
1.1 Introduction . . . 1
1.2 Background and Data . . . 7
1.2.1 Institution Background . . . 7
1.2.2 Procurement Process . . . 9
1.2.3 Data . . . 11
1.3 Model . . . 14
1.3.1 Characterization of Equilibrium in the Bidding Stage . . . 15
1.3.2 Characterization of Equilibrium in the Entry Stage . . . 18
1.3.3 Demand . . . 19
1.3.4 Identification in the Model . . . 21
1.4 Structural Estimation . . . 22
1.4.1 Demand Estimation . . . 23
1.4.2 Cost Densities . . . 27
1.4.3 Entry Costs . . . 32
1.5 Counterfactuals . . . 35
1.5.1 Auctions and Bertrand Competition . . . 37
1.5.2 Auctions and Reference Pricing . . . 39
1.6 Conclusion . . . 42
1.7 Appendix . . . 44
1.7.1 Additional Tables and Figures . . . 44
1.7.2 Auctions with Variable Quantity . . . 46
1.7.3 Two-level Nested Logit Model . . . 50

2 Lower Price But Higher Bill? Evidence from the Zero-Markup Policy in China **54**
2.1 Introduction . . . 54
2.2 Institutional Background . . . 60
2.2.1 Public Hospitals in China . . . 60
2.2.2 Hospitals' and Physicians' Incentives . . . 61

2.2.3 Healthcare System Reform . . . 62
2.3 Data and Sample Description . . . 64
2.3.1 Disease Classification . . . 66
2.3.2 Summary Statistics . . . 67
2.4 Empirical Strategy . . . 68
2.5 Results . . . 72
2.5.1 Expenditure . . . 72
2.5.2 Service Utilization . . . 73
2.5.3 Further Evidence on Supplementary Treatment . . . 75
2.5.4 Variation by Diagnosis . . . 77
2.6 Conclusion . . . 80
2.7 Tables . . . 82
2.8 Figures . . . 94
2.9 Appendix . . . 106
2.9.1 Disease Classification . . . 106
2.9.2 Additional Tables . . . 106

Bibliography **110**

Chapter 1

Price and Efficiency in a Market for Generic Drugs in China

1.1 Introduction

Rising healthcare costs have become a significant concern for many countries. Among all factors driving high healthcare costs, the pharmaceutical industry represents a significant and growing share of healthcare spending. The spiraling cost of pharmaceutical products has become an imperative policy challenge, with governments under pressure to adopt direct or indirect controls on drug prices to ensure access to affordable medicines.[1]

The most straightforward approach to addressing drug price issues is to allow the market to determine drug prices and rely on free-market competition to bring the

[1] According to the QuintilesIMS Global Pharma Outlook 2019, worldwide pharmaceutical expenses reached $1.2 trillion in 2018, with an annual growth rate of 6.3% over the past five years, and the figures are predicted to escalate to $1.5 trillion by 2023.

price down. For example, in the United States, drug prices are largely unregulated and determined by (laissez-faire) market competition (Salter, 2014).[2] However, few countries other than the United States allow pharmaceutical firms to set prices without constraints. In fact, most developed countries negotiate or regulate prices. For example, in the European Union, the reference pricing policy (or its variations) is commonly used, which uses the price of the same drug in reference countries as the maximum price in the home country. Another approach is competitive bidding, which is not only used for drug pricing but also health insurance contracting and healthcare service reimbursement. For example, the Chinese government has adopted auctions for drug pricing in the last decade, while the Centers for Medicare and Medicaid Services in the U.S. use auctions to procure durable medical equipment (Song, Landrum, and Chernew 2012; Song, Landrum, and Chernew 2013; Ji 2019; and Ding, Duggan, and Starc 2021).

Despite the prevalence of these drug pricing mechanisms, comparative studies on their effectiveness and impact on welfare are scarce. It remains unclear whether one approach is superior to others in reducing drug expenditures or promoting social welfare. Consequently, in this study, I compare three different pricing methods: Bertrand competition (a laissez-faire approach), a reference pricing policy, and an auction mechanism to study drug prices, expenditures, and welfare under different mechanisms. Specifically, I focus on generic drug procurement in a large province in China with a population of 70 million. The provincial government utilizes a low-bid first-price sealed-bid auction mechanism to determine the price of drugs and allocates

[2]Although the recent Inflation Reduction Act allows the federal government to negotiate prices for some drugs covered under Medicare, most of the drug prices are unregulated and determined by manufacturers

the exclusive rights to sell drugs to public hospitals in the province.

I start by collecting new data on bidding and sales from the province's 2011 procurement for generic drugs. Each drug is considered as a distinct product, defined by a unique combination of active pharmaceutical ingredient(s) (API), formulation, and dose. Accordingly, separate auctions are held for each drug to determine the price and the firm with the exclusive right to sell it. Next, I develop a framework that models both the demand for pharmaceuticals and the bidding process. I model demand side using a discrete choice framework with a nested logit model. On the supply side, I construct a symmetric independent private cost auction model with variable "prizes" and Samuelson (1985) style endogenous entry.

Unlike standard auctions where the prizes are fixed, in China, auctions are used to determine the sole supplier of the drugs. The winner then faces a downward-sloping demand (prize) in the downstream market. This feature leads to auctions with variable prizes. For example, the amount the winner of the acetaminophen-tablet-0.3g auction can sell depends on, among other things, the winning bid for acetaminophen-tablet-0.5g because the two drugs treat the same disease and are substitutes. Under an auction with variable (endogenous) prizes, bidders bid consistently lower than they would bid in a fixed prize auction.[3] To the best of our knowledge, this is the first empirical study that investigates this type of auction.

To connect my model to the data, I first show that the model is identified. To this end, I first combine the "Berry inversion" of Berry (1994) and the "Hausman instrument" to estimate demand parameters. Then, I follow the idea of Guerre, Perrigne,

[3]For some theoretical properties of the auction with endogenous demand, see Hansen (1988). Also see Spulber (1995), who studies Bertrand competition with private information, and Arozamena and Weinschelbaum (2009), who compare sequential and simultaneous moves under Bertrand competition.

and Vuong (2000) and exploit the mapping between the cost and the equilibrium bid to recover the underlying cost distributions. To estimate the entry costs, I leverage the condition that the marginal bidder is indifferent between entering or not at equilibrium. I estimate the model with a focus on analgesic drugs and then use the model estimates to simulate counterfactual results.

The estimated cost distributions suggest that tablet drugs are less expensive than capsule or other forms of drugs (e.g. suppository). This finding is consistent with the industry's production information which indicates that the tablet form is comparatively easier and less expensive to produce than other drug forms. Additionally, drugs in sustained-release form (e.g., sustained-release tablets) tend to be more expensive than their regular counterparts, such as tablets. This can be attributed to the fact that sustained-release drugs require more complex production processes, different equipment, or different excipients (i.e., materials used in drug formulation) in the drug formulation stage as it can reduce the number of times medicine must be taken in a day. Furthermore, the estimates of marginal costs suggest that the average profit margin is about 20%, which is comparable to findings of Du (2012), who reported an average profit margin of 26.1% for non-branded generic drugs in 2011 in China. These findings imply that the generic drug market is competitive.

In auction literature, there are two basic models for entry: the Samuelson (1985) style entry and the Levin and Smith (1994) style entry. The difference between these two models lies in the assumptions made about when bidders learn their costs (or values). Specifically, Samuelson (1985) assumes that potential bidders know their private costs before making entry decisions, while Levin and Smith (1994) assumes that potential bidders learn their costs after entry. In this study, I follow Samuelson (1985)

style entry model since pharmaceutical manufacturers are expected to have a good idea of their production costs before deciding to enter the procurement auction. By leveraging the estimated cost distribution and the condition that the marginal bidder is indifferent between entering or not in equilibrium, I find the entry cost is negligible. Under a Samuelson (1985) style entry model, entry costs are commonly thought of as bid preparation costs such as fees charged to bid or traveling and accommodation expenses associated with submitting bids. However, in China, each province has established a centralized procurement platform, where all activities related to the procurement are conducted online including document submission, bidding, and results announcement. Therefore, there is no need for bidders to be physically present. In addition, there is no fee charged to participate in the auction. As a result, bid preparation costs are expected to be minimal.

Given the demand, the entry cost, and the production cost estimates, I examine drug prices, expenditures, and welfare under Bertrand competition and reference pricing policy. I find that equilibrium prices under variable prize auctions are on average 2% lower than Bertrand competition which aligns with theoretical predictions. To better understand the mechanism, consider a first-price low-bid auction (with fully inelastic demand; standard auction), in which a bidder chooses an optimal bid to balance two effects of raising his bid a little: an increase in profits and a decrease in winning probability. When the demand is downward-sloping, the increase in profits will be smaller as demand decreases with a higher bid. Therefore, to balance the two effects, the optimal bid should be smaller than in a standard auction. Thus, the expected winning price should be lower than the expected second-lowest cost, which is the price under Bertrand competition. However, consumer surplus (CS) and

producer surplus (PS) are almost the same under auctions and Bertrand competition.

In Comparing the auction and the reference pricing policy, I find that the reference pricing policy can reduce drug expenditures by more than 7% on average. However, the reference pricing policy also results in a decrease in consumer surplus compared to the auction mechanism. One important trade-off of the reference pricing policy is that it can lead to a shortage of analgesics due to the low price ceilings, with an average of 14% of products dropping out of the market. As a result, even though drug prices are lower under the reference pricing policy, consumers may not necessarily be better off.

This paper contributes to several strands of literature. Most directly, it contributes to studies on drug pricing regulations by comparing the effectiveness of different pricing mechanisms. While previous studies have focused on examining the impact of specific regulations, such as the reference pricing policy (Danzon, Wang, and Wang 2005; Maini and Pammolli 2021) or Medicaid drug procurement rule (Scott Morton 1996; Duggan and Scott Morton 2006; Feng, Hwang, and Maini 2021), few have compared different pricing mechanisms. The only notable exceptions are the studies by Dubois. Dubois and Lasio (2018) compared the impact of price regulation in France with Bertrand competition and reference pricing policy, while Dubois, Gandhi, and Vasserman (2019) examined the potential consequences of the U.S. adopting a reference pricing policy. Therefore, this study complements existing research by evaluating commonly used competitive bidding with Bertrand competition and reference pricing policy.

This paper contributes to the literature on competitive bidding in healthcare by exploring a new auction mechanism with variable auction prizes. Previous studies

have investigated competitive bidding in Medicare Advantage (Song, Landrum, and Chernew 2012; Song, Landrum, and Chernew 2013; Cabral, Geruso, and Mahoney 2018; Curto et al. 2021) and for durable medical equipment utilized by Medicare beneficiaries (Ji 2019; Ding, Duggan, and Starc 2021). This work studies a new auction mechanism with variable auction prizes for pharmaceutical pricing.

The rest of the paper is structured as follows. Section 2 provides the institutional background and describes the data used in the analysis. Section 3 presents the model of firms' entry and bidding decisions, and Section 4 presents the estimation results. In Section 5, counterfactual analyses are conducted to investigate the impact of different pricing mechanisms on drug prices, expenditures, and welfare. Finally, Section 6 concludes.

1.2 Background and Data

1.2.1 Institution Background

Public hospitals are the primary healthcare service providers in China, delivering over 90% of the country's inpatient and outpatient services (Yip, Hsiao, Chen, et al., 2012). In addition to providing medical care, these hospitals also have a critical role in the distribution of medicines, with an average market share of 80% in all retail drug sales (National Medical Products Administration, 2014).

The dominant market coverage of public hospitals in medicine sales is related to how the healthcare insurance system operates in China. In 2007, the Chinese government launched a universal health insurance program with the aim of providing comprehensive coverage to all citizens. As of 2011, the public health insurance system

had achieved an impressive coverage rate of over 95% of the population. However, to receive insurance reimbursement for medications, individuals must purchase from locations authorized in the government's health insurance network. In most cases, public hospitals are the only authorized locations, and as a result, they have become the primary choice for most citizens. Retail pharmacies, which offer another option for customers to obtain medications, are usually not qualified for reimbursement and are preferred mainly for convenience reasons.

Despite the name implying government ownership, public hospitals in China do not rely solely on government funding. The reality is that government funding only makes up a small fraction of a hospital's total revenue, with an average of less than 10% (as reported by the China Health Statistic Yearbook). To make up for hospitals' budgets, public hospitals were allowed to charge patients up to 15% markup over the drug procurement price. Although this policy initially helped fund public hospitals' operations, it gradually became a way for hospitals to reap profits. This has led to a series of issues, including over-prescribing, the use of unnecessary high-priced medicines, and unaffordable healthcare expenditures.[4]

To contain the high drug expenses, the Chinese government launched the largest healthcare system reform over the past decade in 2009. A key aspect of this overhaul was the establishment of a centralized pharmaceutical procurement platform at the provincial level. Under this new framework, public hospitals are mandated to purchase drugs through the platform, with prices determined via a competitive bidding system.[5] The hope was that the new centralized procurement system can drive drug

[4]Over the past decade, China's healthcare expenditures have outpaced its GDP growth by 3%.

[5]Before the reform, different regions utilized varying procurement methods such as forming GPO (group purchasing organization) to negotiate drug prices with pharmaceutical firms.

prices down.

1.2.2 Procurement Process

In this paper, I focus on a province's (more than 70 million population) 2011 drug procurement, where the drug procurement can be divided into 5 stages.

1. The government releases a procurement list of drugs, each of which is defined by its active pharmaceutical ingredient (API), formulation, and dosage.

2. Companies determine which drug procurements they wish to participate in and submit the necessary information and documentation to the procurement office.

3. After the companies submit their information and documents, the government verifies them and announces the participants for each drug's procurement.[6]

4. For each auction, entrants submit bids. All auctions happen on the same day.

5. For each auction, the lowest bid from qualified bidders wins. The results of all auctions are revealed on another day.

In each drug procurement, the winning bidder becomes the exclusive supplier of that drug to all hospitals within the province. The drug's price is uniform across all hospitals and remains fixed until the next procurement period, which typically occurs every two years. Figure 1.1 provides an illustration of the drug procurement process. This auction format is not a dynamic game in which firms make decisions

[6]If a drug procurement only has one participant, the government negotiates the price directly with the manufacturer. However, for the purposes of this study, only drugs that were being auctioned off were considered.

based on previous auction results. This is due to the fact that firms must register for auctions at the beginning of the procurement process, and all auctions take place on the same day with results being revealed simultaneously on another day, precluding the possibility of a dynamic auction game. [7]

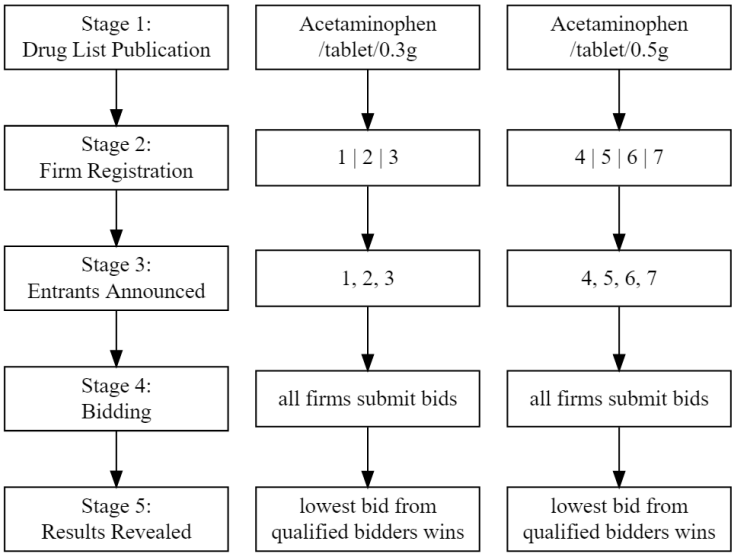

Figure 1.1: Drug Procurement Example

Note: This figure shows an example of the procurement. Assume there are two drugs on the procurement list (stage 1). In the 2nd stage, firms decide which drugs' procurement to participate in (numbers are made up to represent firms). Since they do not know who else participates, there are vertical bars in between firms. In stage 3, the government announces the participants in each auction, so entrants know their competitors. Finally, entrants submit bids and the lowest bid bidder wins the auction.

There is a qualification process, where the winner is chosen from the qualified firms. The qualified firms are selected according to pre-determined rules that are published alongside the drug list. The government first calculates a score for each entrant in the auction and selects entrants to be qualified based on the ranking of their scores. In total, there are 100 points available, with 75 points being allocated based

[7] Jofre-Bonet and Pesendorfer (2003) has previously described such a dynamic auction game in the presence of capacity constraints.

on objective criteria (referred to as the objective score component) such as industry ranking, annual sales, and historical records of drug quality tests. The remaining 25 points are determined by a group of experts, primarily physicians, who evaluate criteria such as clinical efficacy and safety. Details of the evaluation criteria can be found in Table 1.10 in the Appendix. Only a fixed number of firms can be qualified for each auction, depending on the number of entrants. For instance, if an auction has two entrants, both of them are qualified. For auctions with three to four entrants, the two highest-scoring firms are qualified, and for auctions with five to six entrants, the three highest-scoring firms are qualified, and so on. The number of qualified firms according to the number of entrants is shown in Table 1.11 in the Appendix.[8]

It is important to note that the qualification process is independent of the bidding process. Firms are qualified based on pre-determined rules, regardless of the bid they submit. Therefore, the bidding behavior of firms is not influenced by their qualification status. In other words, the game can be viewed as firms first deciding which auctions to participate in. After entering the auctions, firms are notified of their qualification status, and only qualified firms submit bids.

1.2.3 Data

The data used in this study was collected from a large province's 2011 procurement of Non-Steroidal Anti-Inflammatory drugs, which are commonly known as analgesics. There are 17 auctioned analgesics that vary in their active pharmaceutical ingredients (API), forms, or doses. The names of the 17 analgesics are listed in Table 1.1.

For each auction, I collect data on the entrants, their characteristics, qualification

[8] In the event of a tie, where several firms have the same scores, they can all be qualified.

Table 1.1: Sample of Studied Drugs

Analgesics
Acetaminophen/Suppository/0.15g
Acetaminophen/Tablet/0.3g
Acetaminophen/Tablet/0.5g
Diclofenac/Sustained Tablet/0.1g
Diclofenac/Sustained Capsule/0.05g
Diclofenac/Tablet/0.025g
Ibuprofen/Tablet/0.1g
Ibuprofen/Tablet/0.2g
Ibuprofen/Capsule/0.2g
Indometacin/Tablet/0.1g
Naproxen/Tablet/0.1g
Naproxen/Sustained Tablet/0.25g
Naproxen/Cap/0.125g
Naproxen/Cap/0.2g
Nimesulide/Tablet/0.1g
Nimesulide/Capsule/0.1g
Nimesulide/Granules/0.05g

Notes: This figure shows drugs studied in this work.

status, and the bids of the qualified firms. The firm characteristics observed can be used to calculate the objective score component of the firms. I also collect data on product-level sales information at a monthly frequency during the entire contract period in the province. Furthermore, I collect monthly sales of the same drugs from another province after its 2011 procurement for the whole contract period. This additional sales data provides more variations for demand estimation in the studied province and helps to better estimate demand.

To compare sales and prices across drugs that differ by forms or doses, I use the World Health Organization's (WHO) defined daily dose (DDD) as a measure of the unit of consumption. The DDD represents the assumed average maintenance

dose per day for a drug used for its main indication in adults. As such, drug prices (bids) are measured in yuan per DDD, which can be interpreted as the average daily drug expenditures needed for the drug to be effective, and sales are measured by the number of DDDs sold. Table 1.2 presents summary statistics for the studied analgesics. Notably, the average bid of all qualified firms is lower than the average of winning bids, due to the fact that drugs with relatively low prices tend to have more bidders than drugs drug with high prices.

Table 1.2: Data Summary Statistics

NB of Auctions	Analgesics 17	
	Mean	Std.Dev.
NB of Potential Entrants	106.47	134.9
NB of Entrants	11.23	12.95
NB of Qualified Bidders	3.71	1.9
75% Scores (all entrants)	47.83	5.12
qualified bidders	52.57	6.23
Bids (all qualified)	0.986	1.54
winning bids	1.1	1.6
Monthly Sales (ddd)	109,872	152,022

Notes: This table shows summary statistics for studied drugs. The unit of bid is yuan per ddd and monthly sales are measured in the amount of ddd sold.

Firms are allowed to participate in multiple auctions, with 76% of firms bidding in only one auction, 19% bidding in two auctions, and 5% bidding in three auctions. It's possible that firms with multiple bids have different incentives than single-bidding

firms.[9] However, this paper's focus is not on multi-bidding, so we assume that firms treat auctions independently.

Prior to presenting the model, I consider whether large pharmaceutical manufacturers differ systematically in their production cost distributions from small manufacturers. I argue this is not likely because all of the drugs that I study are generic drugs whose formulations were discovered well before the start of the data period. The production technologies of those generics are mature, and marginal production costs are small. Therefore, it is unlikely that large firms possess superior production technologies that result in significantly lower production costs. Consequently, the model that I develop assumes that the bidders are symmetric.

1.3 Model

In this section, I present the models of the firms' entry and bidding decisions. The procurement process is modeled as a two-stage game. In the first stage, potential firms decide whether to pay the entry fee and participate in the auction. In the second stage, qualified firms bid in a sealed-bid first-price auction, in which the firm with the lowest bid wins the contract for the entire period's demand. If a firm fails to win the auction, it sells nothing.

Consider an auctioned drug j that has N_j potential entrants. A potential firm i with privately known cost c_{ij} drawn independently from a distribution $F_j(c)$ with density $f_j(c)$ continuous and strictly positive on its support $[\underline{c}, \bar{c}]$. By incurring the entry cost k_j, firm i becomes an entrant and learns the number of entrants, number

[9] For example, for a firm that bids in auctions for two substitute drugs, it has to consider the situation in which it wins two drugs which do not occur for a single bidding firm.

of qualified firms n_j, and whether it is qualified. If it is qualified, it submits bid b_{ij}, and the contract for the entire period's demand for drug j is awarded to the firm with the lowest bid. Since entry is not free and firms know their cost before making entry decisions, it can be shown only firms with costs below a threshold choose to enter. Therefore, the cost distribution of entrants is a truncated distribution $F_j^*(c)$ with density function $f_j^*(c)$ and support $[\underline{c}, c_j^*]$. Different from fixed prize auctions, bidders face a downward-sloping demand in the auction as there are competing drugs. Let $D_j(b_j, b_{-j})$ be the demand function for the auctioned drug j, which decreases in the price of product j and increases in prices of other competing products b_{-j}.

1.3.1 Characterization of Equilibrium in the Bidding Stage

Under a symmetric private value auction model, the expected profits of a qualified firm i with cost c_{ij} and bid b_{ij} in auction for drug j is

$$\pi(b_{ij}) = (b_{ij} - c_{ij}) \times \mathbb{E}[D_{ij}(\mathbf{b})] \times \Pr[\text{i wins}],$$

where $\mathbb{E}[D_{ij}(\mathbf{b})] = D_{ij}(b_{ij}, \mathbb{E}(b_{-j}))$. Assuming all bidders employ a common strictly increasing bidding strategy $\beta_j(\cdot)$, the probability that firm i wins is $\left(1 - F_j^*(\beta_j^{-1}(b_i))\right)^{n_j - 1}$.

The first-order condition of firm i's bidding problem is

$$\begin{aligned}\frac{\partial \pi_{ij}}{\partial b_{ij}} &= \underbrace{\mathbb{E}[D_{ij}(\mathbf{b})]\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big)^{n_j-1}}_{\text{direct change in profit from bid change}} \\ &+ \underbrace{\Big(b_{ij} - c_{ij}\Big)\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}}\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big)^{n_j-1}}_{\text{change in profit from demand change}} \\ &+ \underbrace{\Big(b_{ij} - c_{ij}\Big)\mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big)^{n_j-2}\Big(-f_j^*(\beta_j^{-1}(b_{ij}))\Big)\frac{d\beta_j^{-1}}{db_{ij}}}_{\text{change in profit from change in winning probability}} \\ &= 0.\end{aligned} \tag{1.1}$$

The second line of the first-order condition (Equation 1.1) shows the difference between auctions with variable prizes and auctions with fixed prizes. If the prize (demand) is fixed, $\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}} = 0$ and we have the first-order condition for auctions with fixed prizes.

At a symmetric equilibrium, $\beta_j(c_{ij}) = b_{ij}$. Making the substitution and rewriting the first order condition, then

$$\frac{d\beta_j}{dc_{ij}} = \frac{\Big(\beta_j(c_{ij}) - c_{ij}\Big)\mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)\Big(1 - F_j^*(c_{ij})\Big)^{n_j-2} f_j^*(c_{ij})}{\Big(1 - F_j^*(c_{ij})\Big)^{n_j-1}\Big[\mathbb{E}[D_{ij}(\cdot)] + \frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial \beta_j}(\beta_j(c_{ij}) - c_{ij})\Big]}. \tag{1.2}$$

The numerator in Equation (1.2) is positive, and the second parenthetical factor of the denominator is the derivative of profit with respect to the price.[10] Due to the conditions placed on demand and cost, firms always want to increase bids to increase

[10]The second term in the denominator is the derivative of the winner's profit $(\beta(\cdot) - c)\mathbb{E}[D_{ij}(\cdot)]$ w.r.t the price.

profits, so this factor is positive.[11] Thus, $\frac{d\beta_j}{dc_{ij}} \geq 0$, and bids are increases in cost.

It will not be necessary to solve the differential equation above to determine how firms' bids are affected by the number of competitors. Equation (1.1) can be rewritten as

$$b_{ij} = c_{ij} - \frac{\mathbb{E}[D_{ij}(\mathbf{b})]\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big)}{\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}}\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big) - \mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)f_j^*(\beta_j^{-1}(b_{ij}))\frac{d\beta_j^{-1}}{db_{ij}}}. \quad (1.3)$$

Because the quantity demanded decreases with price, $\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}} < 0$ and $\frac{d\beta_j^{-1}}{db_{ij}} > 0$ as $\beta_j(c)$ increases in c, the denominator of Equation (1.3) is negative. Thus, firms bid higher than their actual cost c_{ij}. As n_j increases, the denominator gets larger and b_{ij} gets smaller; consequently, firms bid more aggressively when there are more competitors.

By endogenizing the quantity, the auction mechanism can effectively generate lower winning prices than a fixed-quantity auction. In a low-bid first-price auction with a fixed-quantity, a bidder strategically selects an optimal bid, denoted as b^*, to weigh the gains (profits) from increasing their bid against the losses from reducing their probability of winning. However, if the fixed quantity is replaced with a downward-sloping demand function, the increase in profits is smaller than before at b^* due to the corresponding decline in demand. Consequently, the balance between the two effects is disrupted, and to balance the two effects, the new optimal bid must be revised downwards from b^*.[12]

[11] To avoid the situation in which the winning firm would like to charge a price lower than the winning price, I assume that given b_{-j}, $\bar{c}_j < p^*$, where p^* is the price at which the marginal revenue equals $\underline{c}$. Then over the interval $\Big[D_j(\bar{c}_j, b_{-j}), D_j(\underline{c}_j, b_{-j})\Big]$, marginal revenue is below $\underline{c}_j$. Thus, firms always want to increase their prices.

[12] See Appendix for the proof. When it comes to second-price auctions, shifting from a fixed-

1.3.2 Characterization of Equilibrium in the Entry Stage

In auction literature, there are two basic models for entry, both of which assume that bidders must pay a fee in order two submit a bid.[13] In the model proposed by Samuelson (1985), potential bidders are assumed to know their private costs before making entry decisions. In this model, the entry cost is commonly thought of as bid preparation costs, such as expenses associated with document preparation. On the other hand, the model proposed by Levin and Smith (1994) assumes that potential bidders do not know their private costs until after entry. Thus, the entry costs in this model includes fees associated with learning private costs in addition to bid preparation costs. Despite the only difference being the timing of learning costs, the two models have significant different implications. Under the Samuelson (1985) model, entry equilibrium is characterized by a pure strategy, where firms only enter if their costs are lower than a threshold. Conversely, under Levin and Smith (1994), entry equilibrium is characterized by a mixed strategy where potential bidders enter an auction with an endogenous probability.

When pharmaceutical manufacturers decide whether to enter an auction for a particular drug, they should have a good idea of their production costs. I use the entry model proposed by Samuelson (1985) to model this situation. Each firm has a privately known production cost drawn from $F_j(c)$. They then consider whether to

quantity to a variable-quantity arrangement does not alter bidding behavior. A bidder's dominant strategy remains to continue bidding until the price drops below his cost, resulting in the lowest bid being the second lowest of all costs. Consequently, regardless if the quantity is fixed or variable, the auction outcome remains the same for second-price auctions. Since bidders bid lower in a low-bid first-price auction with a variable-quantity than with a fixed-quantity, therefore, the revenue equivalence theorem does not hold between a low-bid first-price auction and a low-bid second-price auction if the quantity is variable.

[13] Auction studies with entry include Li and Zheng (2009), Athey, Levin, and Seira (2011), Li and Zheng (2012), Gentry and Li (2014).

pay an entry fee k_j to participate in the auction for drug j. If they decide to pay the fee, they learn the number of other bidders who have also entered the auction. In equilibrium, there exists a unique threshold c^* such that firms with costs below c^* choose to pay the entry fee, while firms with costs above c^* choose to not bid. A firm with cost c^* is the marginal bidder who is indifferent between entering an auction or not. Thus,

$$(\beta_j(c^*) - c^*) \times \mathbb{E}[D_{ij}(\cdot)] \times (1 - F_j(c^*))^{(N_j - 1)} - k_j = 0, \tag{1.4}$$

where $\beta(\cdot)$ is the equilibrium bid function and N is the number of potential bidders. Since bidders with costs higher than c^* do not enter and all entrants employ a common bidding function that is strictly increasing in cost, the optimal bid for the marginal bidder is the highest bid he can bid, which is the reserve price r_j. Thus, given the entry cost k and the reserve price r_j, the equilibrium cutoff point c^* is determined by

$$(r_j - c^*) \times \mathbb{E}[D_{ij}(\cdot)] \times (1 - F_j(c^*))^{(N_j - 1)} - k_j = 0. \tag{1.5}$$

1.3.3 Demand

I follow Berry (1994) and model demand for drugs using a nested logit model. Assuming there are L_m consumers located in market m. Each consumer chooses one out of $J_m + 1$ differentiated products where $j = 0, 1, ..., J_m$ and good 0 is the outside good such as not purchasing. For a one-level nested logit model, the set of products are partitioned into $G_m + 1$ groups where $g = 0, 1, ..., G_m$, group 0 is reserved for the outside good, and $\sum_{g=1}^{G_m} J_{gm} = J_m$.

The indirect utility of consumer i purchasing drug j in market m is

$$\begin{aligned} u_{ijm} &= X_{jm}\beta + \gamma ln(J_m) + \alpha(y_{im} - p_{jm}) + \xi_{jm} + \zeta_{igm} + (1-\sigma)\epsilon_{ijm} \\ &= \delta_{jm} + \zeta_{igm} + (1-\sigma)\epsilon_{ijm}, \end{aligned}$$

where X_{jm} are observed product characteristics of product j, J_m is the number of products on the market that captures "congestion" in unobserved product characteristic space, y_{im} is income of individual i, p_{jm} is price of product j, ξ_{jm} captures impacts of unobserved product characteristic.[14]. ζ_{igm} is a variable common to all products for individual i in group g, and ϵ_{ijm} is an extreme value random variable such that $\zeta_{igm} + (1-\sigma)\epsilon_{ijm}$ is distributed type-I extreme value.

If product j is in group g, the well known formula for the market share of product j at market m as a fraction of the total group share is (the notation m is suppressed for clarity)

$$s_{j/g}(\delta, \sigma) = \frac{e^{\delta_j/(1-\sigma)}}{D_g},$$

where the denominator of this expression for a product in group g is

$$D_g \equiv \sum_{j \in G_g} e^{\delta_j/(1-\sigma)}.$$

Similarly, the probability of choosing one of the group g products (the group share) is

$$s_g(\delta, \sigma) = \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}}.$$

[14] Ackerberg and Rysman (2005) shows that the logit error assumption puts a strong restriction between unobserved product characteristic space and the number of products. The $ln(J_m)$ is included to capture the "congestion" effect in unobserved product characteristic space.

Then the market share of product j is

$$s_j = s_{j/g} * s_g = \frac{e^{\delta_j/(1-\sigma)}}{D_g^{\sigma}\Big[\sum_g D_g^{(1-\sigma)}\Big]}.$$

The goal is to estimate the parameters (α, β, σ) entering the demand system. By inverting the system of market shares to solve for the mean utilities δ_j, we can obtain an analytical solution for the inverted market share system

$$\ln(s_j) - \ln(s_0) = \delta_j + \sigma \ln(s_{j/g}),$$

which can be estimated by IV regression where endogenous variables are price and within group market share.

1.3.4 Identification in the Model

First, consider the identification of the cost distribution $F_j^*(\cdot)$. Guerre, Perrigne, and Vuong (2000) show how the unobserved value distribution can be recovered from the observed bid distribution, and they provide necessary and sufficient conditions on the bid distribution such that it can be used to recover the unobserved cost distribution.[15] Rearranging Equation (1.3), we have

$$c_{ij} = b_{ij} + \frac{\mathbb{E}[D_{ij}(\mathbf{b})]\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big)}{\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}}\Big(1 - F_j^*(\beta_j^{-1}(b_{ij}))\Big) - \mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)f_j^*(\beta_j^{-1}(b_{ij}))\frac{d\beta_j^{-1}(b_{ij})}{db_{ij}}}. \tag{1.6}$$

[15] Guerre, Perrigne, and Vuong (2000) show that for an auction with a binding reserve price, the value distribution is identified starting from the reserve price.

Let $G_j(\cdot)$ be the distribution of bids in auction j and $g_j(\cdot)$ be the density. Because the bid increases in cost, for every $b_j \in [\underline{b}_j, r_j]$, where $[\underline{b}_j, r_j]$ is the support of bids and r_j is the reserve price of drug j, we have $G_j(b_{ij}) = Pr(b \leq b_{ij}) = Pr(c \leq \beta_j^{-1}(b_{ij})) = F_j^*(\beta_j^{-1}(b_{ij}))$. Then $g_j(b_{ij}) = f_j^*(\beta_j^{-1}(b_{ij}))\frac{d\beta_j^{-1}}{db_{ij}}$. Thus, Equation (1.5) can be written as

$$c_{ij} = b_{ij} + \frac{\mathbb{E}[D_{ij}(\mathbf{b})]\Big(1 - G_j(b_{ij})\Big)}{\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}}\Big(1 - G_j(b_{ij})\Big) - \mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)g_j(b_{ij})}. \tag{1.7}$$

Equation (1.6) expresses the individual cost c_{ij} as a function of the individual's equilibrium bid b_{ij}, bid distribution $G_j(\cdot)$, its density $g_j(\cdot)$, the number of qualified bidders n_j, and the expected demand $\mathbb{E}[D_{ij}(\mathbf{b})]$. The bid b_{ij} and the number of qualified bidders n_j are observed in the data. The distribution $G_j(\cdot)$ and density $g_j(\cdot)$ can be empirically estimated from observed bids. The demand function $D_{ij}(\dot{)}$ can be estimated using the sales data. To estimate the expected demand, the expected winning price in other auctions needs to be known and I use the estimated bid distribution to randomly draw bids and estimate the expected winning price. Then the production cost c_{ij} is identified.

1.4 Structural Estimation

In this section, I describe the estimation strategy and results for the cost distributions and entry costs. The estimation starts from the drug demand estimation and is then followed by production cost estimation and finally the estimation of the entry costs.

1.4.1 Demand Estimation

As discussed in the model section, the indirect utility of patient i in province m and month t from product j and API g follows a nested logit specification:

$$\begin{aligned} u_{ijmt} &= X_{jmt}\beta + \gamma ln(J_{mt}) + \alpha(y_{imt} - p_{jmt}) + \xi_{jmt} + \zeta_{igmt} + (1-\sigma)\epsilon_{ijmt} \\ &= \delta_{jmt} + \zeta_{igmt} + (1-\sigma)\epsilon_{ijmt}. \end{aligned} \tag{1.8}$$

As shown in Berry (1994), the model implies the following demand equation where estimates of the parameters can be obtained from a linear instrumental variables regression:

$$\ln(s_{jmt}) - \ln(s_{0mt}) = \delta_{jmt} + \sigma \ln(s_{j/gmt}). \tag{1.9}$$

The 17 auctioned analgesic drugs can be viewed as differentiated competing products, and I define each API (or the outside option) as a nest, where the outside option ($j = 0$) includes all other analgesics not included in my data and the option for not obtaining any treatment. A market is defined as province m in month t, and I include API, drug form, quality scores of producers, log of the number of products which is used to capture "congestion" effects (Ackerberg and Rysman, 2005), and province dummy variable to capture province fixed effects as determinants of mean utility. I estimate the above equation with two years of drug sales data at the product-province-month level. Since drug prices were fixed until the next procurement, I rely on across-product variations to estimate the price coefficient.

In order to estimate the demand for analgesic drugs using market-level data, it is necessary to measure the size of the potential market. To this end, I begin by computing the number of potential patients, the average quantity of drugs prescribed

per visit, and the average number of visits per year. Then, multiply them to get a measure of the potential market size.[16] For instance, in 2013, approximately 0.97% of the population in a given province was diagnosed with rheumatism, which is typically treated with analgesic drugs. Multiplying this figure by the total population of the province yields an estimate of the potential number of patients taking analgesics in the province. To determine the amount of drugs prescribed per visit, I divide the average annual sales of analgesics by the average annual total number of rheumatism visits. Finally, data on the average number of medical institution visits per person per year is sourced from the provincial Health Statistics Yearbook. On average, the observed annual sales of analgesics amount to about 20% of the size of the estimated potential drug market.[17] However, using the diagnosis rate of rheumatism can underestimate the size of the potential market because it fails to account for short-term pain. Therefore, to address this issue, I conduct a sensitivity analysis in which annual sales are set at 5%, 10%, and 15% of the potential market size. The results of this analysis are similar to those obtained from the original estimation.[18]

In addition to the size of the potential market, it is necessary to specify instruments for the drug price p_{jmt} and the within-group market share $s_{j/gmt}$. Prices are likely to be correlated with unobserved demand shocks that firms observe before setting prices. The within-group market share is also likely to be correlated with unobserved demand shocks as demand shocks that increase a product's market share also increase its within-nest market share. The ideal price instruments are cost shifters because they affect the demand through the price. I propose to use the average prices of

[16] Data are collected from the national or the provincial Health Statistics Yearbook.
[17] In other words, the outside goods' market shares were approximately 80%.
[18] Refer to Table 1.12 for detailed results.

the same drugs in other provinces as price instruments ("Hausman Instruments"). The idea is that the prices of a drug in other provinces can serve as proxies for the production cost; thus the prices satisfy the correlation restriction. The validity of Hausman instruments relies on no common demand shocks across markets such as national campaigns or unobserved seasonality variations. Due to the unique structure of the market, I argue Hausman instruments are valid under my setting. Auctions are held before the realization of demand and also the realization of demand shocks. Even instrumental prices are correlated with demand shocks in their provinces, these demand shocks are not likely to be correlated with unrealized future demand shocks in the studied province. For the within-group share $s_{j/gmt}$, I use the number of drugs within groups as instruments, and variations come from the different numbers of drugs across nests.

Table 1.3 presents the estimated demand coefficients. First, the price coefficient has an expected negative sign. Consistent with the random utility theory, the group parameter σ is between 0 and 1, and it is significant which suggests that consumers prefer drugs with the same molecule. The coefficient for the quality score is not significant which makes sense as all sellers are selected from qualified bidders; thus, quality should not be a concern in decision-making. As expected, the coefficient of the log of the number of products is between 0 and -1.

Drug characteristics are estimated to have coefficients with intuitive signs. The omitted API is Ibuprofen and the omitted formulation is suppository form. The results suggest that Acetaminophen, Nimesulide, and Naproxen are less preferred than Ibuprofen. This is consistent with a 2015 market survey published by the Southern Medicine Economic Research Institute that shows Diclofenac and Ibuprofen are the

two best-selling anti-inflammatory and anti-rheumatic drugs in China. With regards to formulation, the suppository form is less preferred than all other formulations.

Table 1.3: Demand Coefficients

Variables	Coeff	Variables	Coeff	Variables	Coeff
price (α)	-0.060***	Diclofenac	0.201***	Tablet	1.509***
	(-0.007)		(-0.066)		(-0.283)
group (σ)	0.440***	Indometacin	-0.398	SR Tablet	1.783***
	(-0.056)		(-0.355)		(-0.322)
quality scores	0.005	Acetaminophen	-0.781***	SR Capsule	1.763***
	(-0.004)		(-0.104)		(-0.323)
log(nb of products)	-0.174	Nimesulide	-0.563***	Capsule	0.815***
	(-0.114)		(-0.122)		(-0.235)
		Naproxen	-1.274***	Granule	0.987***
			(-0.112)		(-0.288)
				Constant	-4.704***
					(-0.503)
N	1,250				
R-squared	0.78				

*** p < 0.01, ** p < 0.05, * p < 0.1

Notes: This table reports demand estimates from a Berry (1994) logit model for analgesics, where standard errors are reported in the parentheses. The omitted API is ibuprofen and the omitted formulation is suppository form.

The one-level nest structure estimate suggests that consumers are more likely to switch to another product of the same API than to a product with a different API. However, since the nest structure (correlations of preferences) is imposed by the researcher, different nest structures may yield different results. Therefore, I considered two alternative structures: (1) API as the upper nest and forms as the lower nest, and (2) forms as the upper nest and API as the lower nest. However, the estimates for both (1) and (2) do not satisfy the requirements for the model to be consistent with random utility maximization.[19] Following common practice (Goldberg 1995;

[19]For a two-level nested logit model where σ_1 measures correlation of individuals' preferences over products within the same subgroup and σ_2 measures correlation of individuals' preferences over products within the same group. The nested logit model is consistent with random utility maximization if $0 \leq \sigma_2 \leq \sigma_1 \leq 1$, which is a sufficient condition. It is an undesirable result if the condition doesn't hold in terms of McFadden's random utility maximization. Thus, the common practice is to rule out such model specifications.

Bjornerstedt and Verboven 2016), I rule out the alternative nest structures.

1.4.2 Cost Densities

Guerre, Perrigne, and Vuong (2000) propose a two-step procedure to recover distributions of bidders' values from observed bids. They first estimate the bid distributions and density functions nonparametrically and use them to construct a sample of "pseudo" values. Then the sample of pseudo values is used to estimate the density of bidders' values non-parametrically. However, because I have a small sample size, I follow Athey, Levin, and Seira (2011) to recover distributions of costs by making a parametric assumption on the bid distribution.[20] Then I construct the sample of costs and estimate cost densities non-parametrically.

Let $G(\cdot \mid Z, N_2, N_1)$ denote the conditional distribution of bids in a given auction, where Z are observed sales characteristics, N_2 is the number of potential entrants, and N_1 is the number of entrants. The bid distribution is assumed to follow the Weibull distribution; thus

$$G(b \mid Z, N_2, N_1) = 1 - \exp\left(- \left(\frac{b}{\lambda(Z, N_2, N_1)} \right)^{\rho(N_1)} \right) \tag{1.10}$$

[20]The literature on the parametric estimation of auction models has usually used distributions such as Weibull and exponential distributions (Paarsch 1992; Donald and Paarsch 1993; Donald and Paarsch 1996; Paarsch 1997; Li and Zheng 2009; Li and Zheng 2012). Researchers often justify the use of those distributions by performing specification tests (White 1982; Andrews 1997) or testing the sensitivity of results to different assumed distributions. However, a recent paper by Anderson and Palma (2021) reveals the connections between model primitive distributions, demand, and various economic distributions such as price and sales under monopolistic competition. For example, the authors link logit demand structures to log-normal and Pareto profit distributions which have been found to match well with empirical profit distributions. Given the assumption of logit demand and Weibull bid distribution, similar connections are likely to present, which can be used to justify the parametric bid assumption. Such connections may also exist in other parametric estimations of auction models, making Anderson and Palma (2021)'s finding important for future exploration in the auction literature.

where $\lambda(\cdot)$ is the scale parameter and $\rho(\cdot)$ is the shape parameter of the Weibull distribution. They are parameterized as $\ln \lambda(Z, N_2, N_1) = Z\beta_Z + N_2\beta_{N_2} + N_1\beta_{N_1} + \beta_0$ and $\ln \rho(N_1) = N_1\gamma_{N_1} + \gamma_0$. These parameters of the model (β, γ) are estimated by maximum likelihood and reported in Table 1.4.

Table 1.4: Bid Distribution Parameters

	Bid distribution (Weibull)	
	Coeff	S.E.
	$ln(\lambda)$	
Diclofenac	-0.402	0.59
Indometacin	-0.432	2.36
Acetaminophen	-0.048	4.81
Nimesulide	0.949	1.35
Ibuprofen	0.430	1.69
Naproxen	-0.763	1.25
Tablet	-0.531	0.41
SR Tablet	0.950	0.40
SR Capsule	-0.410	0.40
Capsule	0.177	0.39
Granule	0.156	0.43
Suppository	-0.609	0.43
NB Entrants	-0.061	0.01
NB Potential Entrants	0.028	0.10
Constant	-0.271	2.38
	$ln(\rho)$	
NB Entrants	0.007	0.007
Constant	0.587	0.087
N	62	

Notes: This table shows the maximum likelihood estimated bid distribution parameters for analgesics. Standard errors are reported in parentheses.

To test if the Weibull functional form provides a good fit to the observed bids, I plot the observed bid b_i against $\hat{b_i}$ where $\hat{b_i}$ is solved from pseudo cost c_i that is

recovered using the estimated bid distribution. If the Weibull function form fits the data well, $\hat{b_i}$ should be close to b_i. Figure 1.2 shows the Weibull distribution appears to provide a good fit as most of the points are close to the 45-degree line.

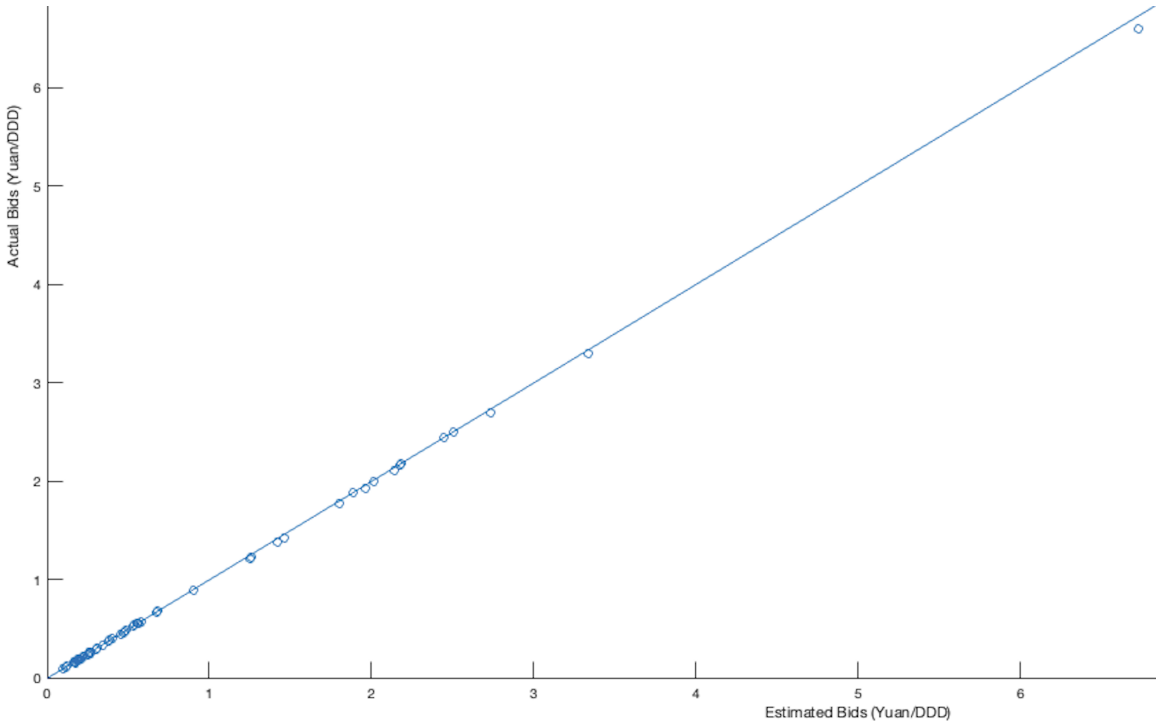

Figure 1.2: Observed Bids Against Estimated Bids

Note: This figure plots observed bids against estimated bids solved from pseudo costs that are recovered using the estimated Weibull bid distribution. The observed bids are plotted along the y-axis and estimated bids are plotted along the x-axis. The blue line is the 45-degree line.

Given the estimated bid distribution, a firm's marginal cost c_{ij} of producing drug j can be recovered through its first-order condition for optimal bidding,

$$c_{ij} = b_{ij} + \frac{\mathbb{E}[D_{ij}(\mathbf{b})]\Big(1 - G_j(b_i \mid Z, N_2, N_1)\Big)}{\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}}\big(1 - G_j(b_i \mid Z, N_2, N_1)\big) - \mathbb{E}[D_{ij}(\mathbf{b})](n_j - 1)g_j(b_i \mid Z, N_2, N_1)}, \tag{1.11}$$

where bids are observed, demand function is known from demand estimation, and bid

distributions and densities are known from the estimation of bid distributions. Then a sample of pseudo production costs is constructed for each auctioned analgesic drug, and Figure 1.3 illustrates the cost distribution for each drug. The cost distributions show that production costs vary significantly across drugs, while median costs per DDD remain consistently low, at less than 3 Yuan for all drugs. These estimates of marginal production costs appear plausible, given most of these drugs are "old" and generic, with many invented in the 70s and 80s. Furthermore, the estimates of marginal costs suggest that the average profit margin is 20%, which is comparable to findings by Du (2012), who found an average profit margin of 26.1% for non-branded generic drugs in 2011 in China. These findings imply that the generic drug market is competitive, which aligns with the common understanding of this market.

Notably, cost samples demonstrate considerable variation between drugs with the same molecule but different forms, while drugs with the same molecule and forms exhibit similar cost samples.[21] To gain a better understanding of the relationship between drug form and cost, I plot cost densities for drugs with average covariates.[22] Figure 1.4 suggests that drugs in tablet form exhibited lower costs than their suppository and capsule counterparts, a finding that could be explained by the ease of production associated with tablets.[23] Additionally, sustained-release-form drugs, such as sustained-release tablets, are found to be more expensive than regular-form

[21] Ibuprofen-Capsule has a higher cost than other drugs, which could be attributed to the large bids observed for this drug.

[22] For analgesics with the same API, I first calculate the average number of potential bidders N_2 and the average number of entrants N_1. Then I construct a sample of pseudo costs, and cost densities are plotted accordingly.

[23] In general, the production of generic drugs can be divided into three stages: API production, drug formulation, and packaging. In the drug formulation stage, different equipment and technology are required for different formulations, and this can cause costs to be different for drugs that have the same API.

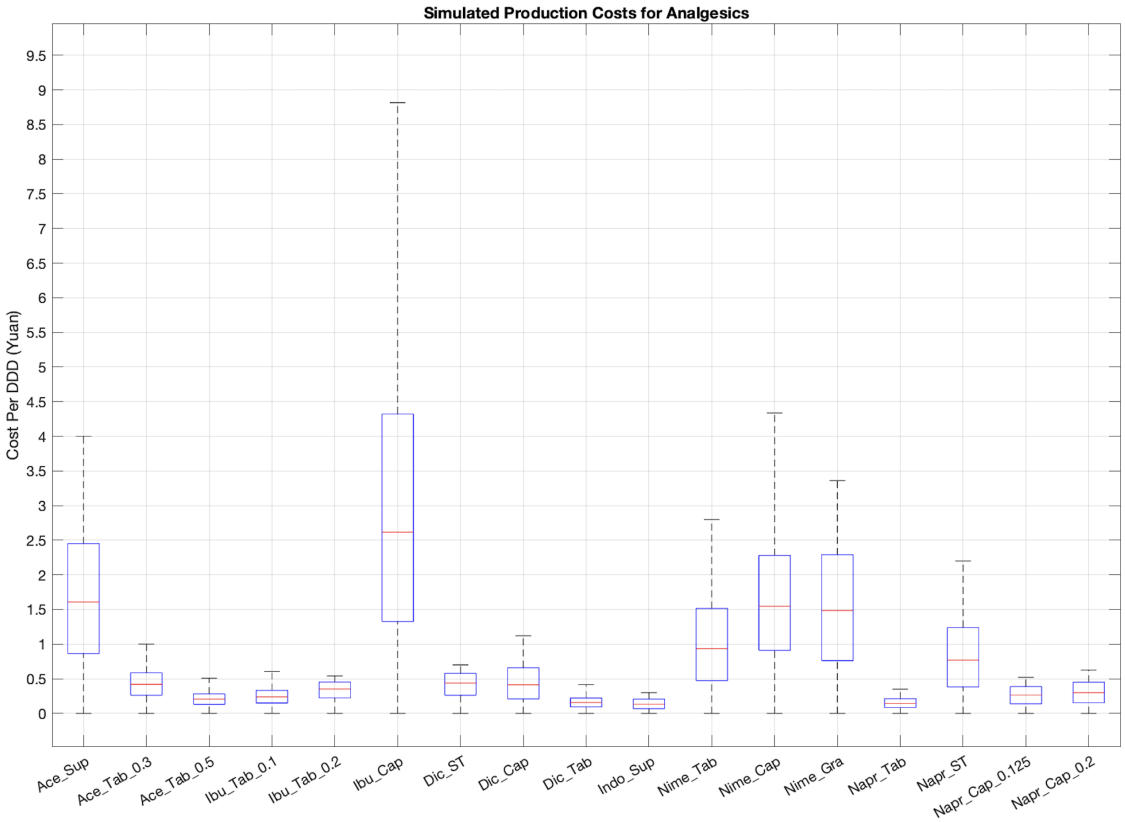

Figure 1.3: Simulated Production Costs for Analgesics

Note: Notes: The simulated production costs of 6 types of auctioned analgesics drugs: acetaminophen (Ace), ibuprofen (Ibu), diclofenac (Dic), indometacin (Indo), nimesulide (Nime), and naproxen (Napr). There are 4 types of formulations: suppository (Sup), tablet (Tab), capsule (Cap), and sustained release tablet (ST). Numbers after formulations represent a difference in dosage.

drugs, which is consistent with previous research indicating that sustained-release drugs require more production processes, different equipment, and excipients in the drug formulation stage.[24] Specifically, one study finds that the production time for sustained-release tablets can increase by as much as 30% more than for regular tablets.

[24]Excipients are materials used in the drug formulation process.

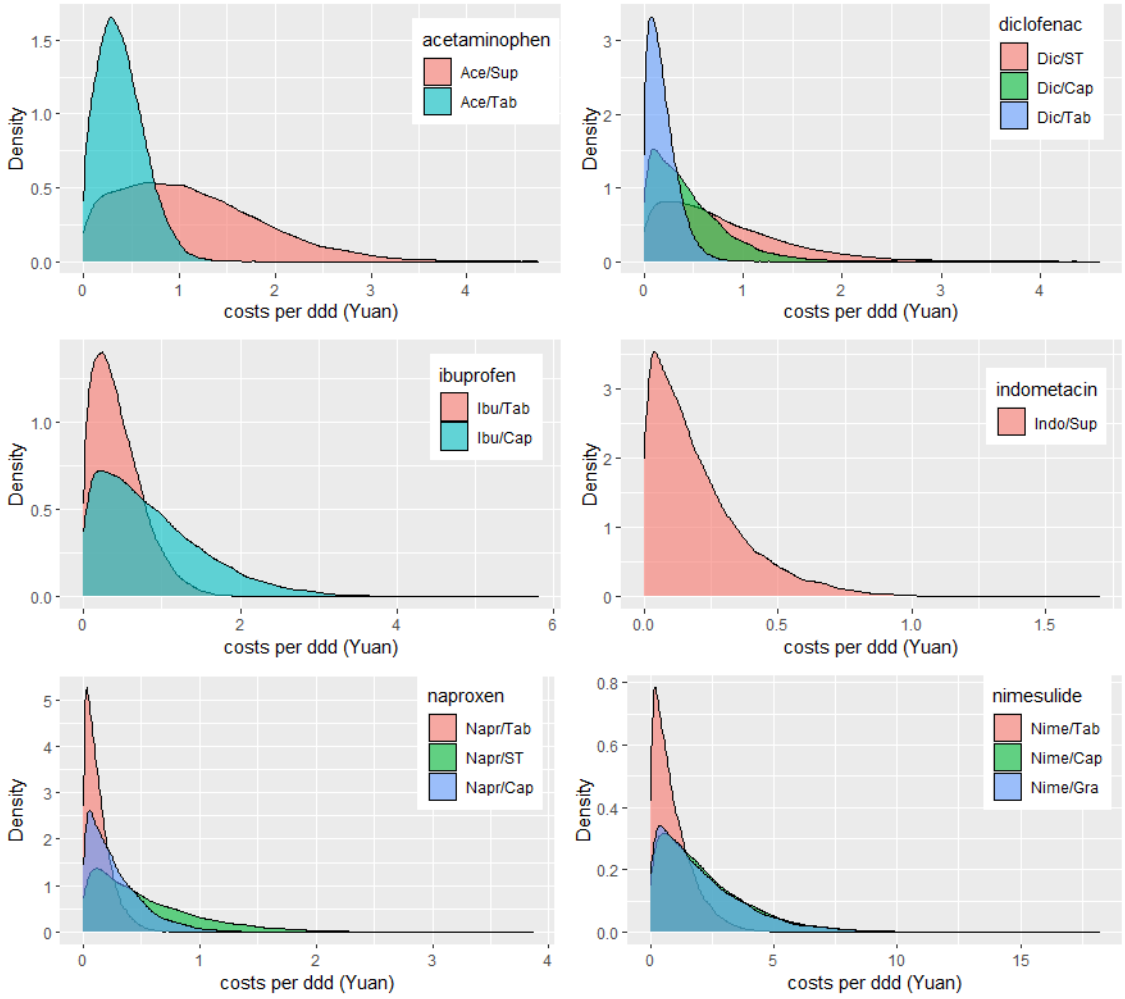

Figure 1.4: Estimated Production Cost Densities for Analgesics

Note: Notes: This figure shows estimated densities of production cost for analgesics with average covariates. Densities of drugs that have the same API appear in the same graph.

1.4.3 Entry Costs

After estimating the distribution of production costs, the subsequent step is to determine the entry cost. This cost is characterized by that the marginal bidder is indifferent between entering or not (equation 1.4), where the only unknown in the equation is the production cost of the marginal bidder. Under the equilibrium, the

marginal bidder bids the reserve price, thus, the production cost can be recovered through the inverse bidding function $\beta^{-1}(r) = c^*$. Using a spline to fit random bids and estimate pseudo costs, the bidding function is determined, and the marginal cost c^* is recovered. Figure 1.5 illustrates the fitted bidding function for acetaminophen-suppository. The spline appears to provide a good fit to the bidding function, where Figure 1.6 shows density of random drawn bids from Weibull estimated bid distribution, as well as the bid density estimated from the fitted bidding function.

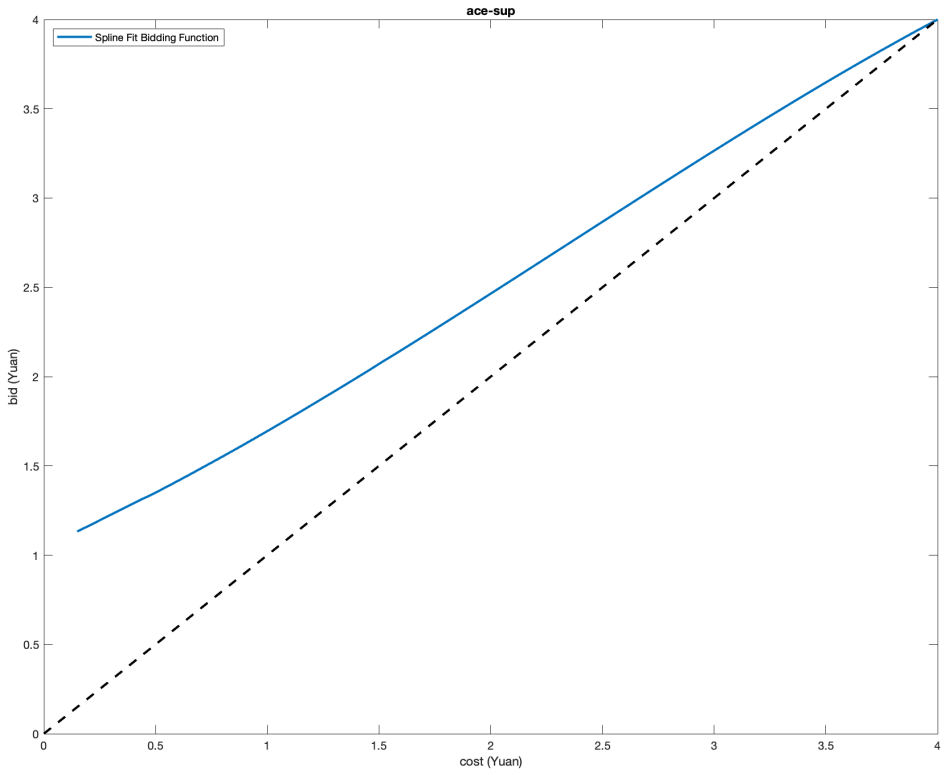

Figure 1.5: Spline Fitted Bidding Function For Acetaminophen-Suppository
Note: Notes: This figure shows spline fitted bidding function for Acetaminophen-Suppository. The black dashed line is the 45 degree line.

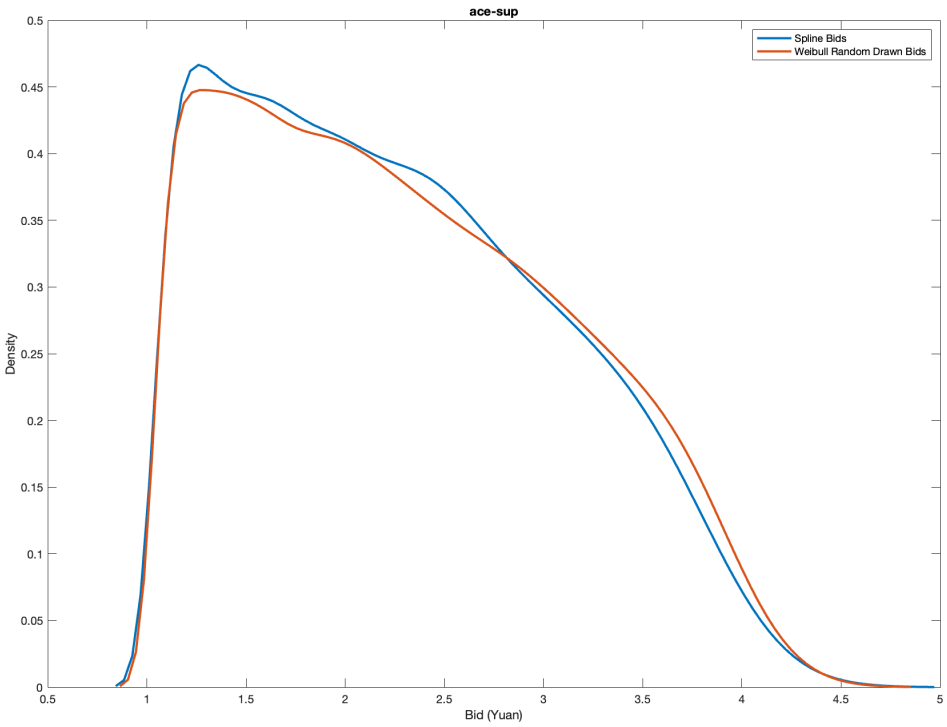

Figure 1.6: Bid Densities from Weibull Random Drawn Bids and Spline Predicted Bids

Note: Notes: This figure shows the bid density of Weibull random drawn bids and bid density of spline predicted bids. The two densities are very close to each other which suggests the spline provides a good fit to the bidding function.

Given estimated marginal costs c^*, I calculate the expected payoff of the marginal bidder, and find that the resulting entry cost is negligible. In the context of pharmaceutical procurement in China, pharmaceutical manufacturers are aware of their production costs prior to making entry decisions. Therefore, the entry costs should not include any expenses related to cost discovering (information acquisition). In a study of timber auctions in the United States, Athey, Levin, and Seira (2011) find significant entry costs, which they attribute to the costs of gathering information. In

the case of timber auctions, loggers and mills do not know the values of the timber ahead of time and need to conduct field surveys to learn their values, which is a costly process.

Other potential entry costs may include bid preparation costs, such as fees paid by firms to participate in the auction, travel expenses, and accommodation costs. However, since the implementation of the healthcare reform in China in 2009, each province has established a centralized procurement platform for drug procurement. Participating in the procurement is free, and all activities related to the procurement process are conducted online, eliminating the need for bidders to be physically present. For instance, bidders can submit documents, place bids, and receive the announcement of results on the centralized procurement platform. Therefore, potential bidders are not required to travel to the procurement location, and associated travel and accommodation costs are avoided.

If the estimated entry costs are considered to be minimal, it is reasonable to question why not all potential firms participated in the auction. Nevertheless, it is important to note that entry costs only capture the costs associated with bid preparation. The drug procurement process involves a qualifying stage, where only qualified firms can bid in the auction. Consequently, it is probable that some firms opt out of participation due to their belief that they are not likely to be qualified.

1.5 Counterfactuals

In this section, I use the model estimates to simulate the counterfactual equilibrium under two alternative pricing mechanisms. The first mechanism I consider is a classic

Bertrand competition model, which represents a market without any pharmaceutical price regulations. The second mechanism is a reference pricing rule that prohibits firms from setting higher drug prices than reference prices. For each counterfactual, I analyze the effects on equilibrium prices, as well as the impacts on total expenditures, consumer welfare, and profits for firms.

Under Bertrand competition, drug prices are set in equilibrium through each firm's profit maximizing strategy. Since the same drug (e.g., Acet/Tab/0.3g) from different producers are homogeneous, the price of each drug cannot exceed the second-lowest production cost ($c_j^{\text{2nd lowest}}$) of the drug. In addition, each drug has only one seller at the Bertrand-Nash equilibrium. However, there are other differentiated drugs, thus, I solve the following Bertrand-Nash equilibrium

$$\begin{aligned} \max_{\{p_j\}} \pi_j &= (p_j - c_j) \times D_j(p_j, p_{-j}) \\ s.t.\ p_j &\leq c_j^{\text{2nd lowest}}. \end{aligned} \tag{1.12}$$

Under a reference pricing rule, pharmaceutical firms are restricted from setting prices higher than a set of reference prices (p_j^{ref}). In this study, I adopt the lowest price for each drug in 2010 in China as the reference price. Thus, the optimization problem to be solved is as follows

$$\begin{aligned} \max_{\{p_j\}} \pi_j &= (p_j - c_j) \times D_j(p_j, p_{-j}) \\ s.t.\ p_j &\leq \min\{c_j^{\text{2nd lowest}}, p_j^{ref}\}. \end{aligned} \tag{1.13}$$

To conduct the counterfactual analysis, I draw a sample of costs from the estimated cost distributions and simulate the prices, expenditures, and welfare under the

auction, Bertrand competition, and reference pricing policies. The simulation is repeated 10,000 times to calculate the average differences in drug prices, expenditures, and welfare.

1.5.1 Auctions and Bertrand Competition

Theoretical predictions suggest that bidders are likely to bid lower in a low-bid first-price auction with variable prizes compared to a low-bid first-price auction with fixed prizes (standard auction). Furthermore, it is known that the expected prices are equivalent under Bertrand competition and standard auctions. As a result, drug prices are expected to be lower under an auction with variable prizes compared to Bertrand competition.

Consistent with the theoretical prediction that drug prices tend to be lower under the auction mechanism than Bertrand competition. Table 1.5 shows drug prices under auction and Bertrand competition. On average, the Bertrand price is 2% higher than the auction price, and the price difference between auctions and Bertrand is determined by the estimated cost densities. If the cost density is tight, such as in the cases of Acet/Tab and Ibup/Tab, the price difference is small. If the cost density is spread, such as in the cases of Acet/Sup and Ibup/Cap, the price difference is large.

However, the difference in sales of each drug is very minimal due to the inelastic demand, resulting in total sales being very close under auction and Bertrand competition. As a result, total expenditures are about 0.24% higher under Bertrand competition, and producer surplus (PS) is about 0.84% higher under Bertrand competition. Despite the higher prices, consumer surplus (CS) is only 0.11% lower under Bertrand competition due to the low price sensitivity of consumers. The results of

Table 1.5: Drug Prices under Auctions and Bertrand Competition

Unit: Yuan	Auction	Bertrand	% Change
Acet/Sup	1.60	1.66	3.93%
Acet/Tab/0.3g	0.28	0.28	0.84%
Acet/Tab/0.5g	0.14	0.14	0.45%
Ibup/Tab/0.1g	0.16	0.16	0.73%
Ibup/Tab/0.2g	0.23	0.23	0.66%
Ibup/Cap/0.2g	3.84	4.16	9.54%
Dic/ST	0.42	0.42	0.64%
Dic/SC	0.61	0.62	1.71%
Dic/Tab	0.10	0.10	0.41%
Indo/Sup	0.19	0.19	0.86%
Nime/Tab	1.40	1.43	2.50%
Nime/Cap	0.97	0.98	1.75%
Nime/Gra	2.02	2.08	3.28%
Napr/Tab	0.10	0.10	0.83%
Napr/ST	1.13	1.16	2.59%
Napr/Cap/0.125g	0.34	0.35	0.91%
Napr/Cap/0.2g	0.40	0.40	0.93%

Notes: This table shows drug prices under auctions and Bertrand competition.

all welfare calculations are presented in Table 1.6, where the minimal differences in welfare between the two mechanisms may explain the limited use of auctions with variable prizes in the real world, despite their potential to generate lower prices.

Table 1.6: Welfare under Auctions and Bertrand Competition

Unit: Million Yuan	Auction	Bertrand	% Change
Total Exp	53.61	53.74	0.24%
PS	26.94	27.16	0.84%
CS	345.94	345.56	-0.11%
TS	372.88	372.72	-0.04%

Notes: This table shows welfare and expenditures under auctions and Bertrand competition.

1.5.2 Auctions and Reference Pricing

Under a reference pricing policy, drug prices are subject to a constraint where they cannot be higher than the minimum of the second-lowest production cost and the reference price. For this study, I consider the reference prices to be exogenously given and do not account for any general equilibrium effects that may occur[25] Table 1.7 shows the impact of reference pricing on the price of each analgesic. The results indicate that the reference pricing rule imposes a binding price constraint for most drugs, resulting in moderate price decreases with an average of 10% across all analgesics. Under reference pricing, the optimal price for a drug is either the second-lowest cost or the reference price, depending on which one is smaller. If the reference price is larger than the second-lowest cost, the reference price is not binding, and the drug price under reference pricing will be the second-lowest cost, which is higher than the price under auction.

While the change in medicine prices does demonstrate the direct effect of reference pricing, it falls short of explaining the impact on expenditures or firm profits. This is because the quantity sales, which are endogenously determined by counterfactual prices, also play a crucial role. Table 1.8 shows changes in price and sales. Generally, a price drop is associated with an increase in demand (e.g., Acet/Tab/0.5g). However, some drugs with a significant drop in price also experience a decrease in sales, such as Acet/Tab/0.3g, Ibup/Tab/0.2g, Dic/Tab, Nime/Gra, and Napr/Cap/0.2g. This is because their reserve prices are quite low, and if the reserve price is binding and lower

[25] A reference pricing policy connects price setting in two areas (countries). For example, if area A uses area B as a reference, firms should consider this connection when setting prices in area B. Ideally, a counterfactual analysis should capture such a connection. However, due to the lack of data on the reference area, I cannot account for this connection. Dubois, Gandhi, and Vasserman (2019) explicitly consider this connection in their study of the reference pricing policy.

Table 1.7: Drug Prices under Auctions and Reference Pricing

Unit: Yuan	Auction	Reference Pricing	% Change
Acet/Sup	1.60	1.24	-14.27%
Acet/Tab/0.3g	0.28	0.19	-19.49%
Acet/Tab/0.5g	0.14	0.12	-5.16%
Ibup/Tab/0.1g	0.16	0.14	-6.24%
Ibup/Tab/0.2g	0.23	0.20	-9.01%
Ibup/Cap/0.2g	3.84	3.80	2.02%
Dic/ST	0.42	0.40	-2.61%
Dic/SC	0.61	0.61	0.84%
Dic/Tab	0.10	0.02	-67.73%
Indo/Sup	0.19	0.18	-2.18%
Nime/Tab	1.40	1.43	2.48%
Nime/Cap	0.97	0.98	1.61%
Nime/Gra	2.02	1.01	-41.55%
Napr/Tab	0.10	0.10	0.34%
Napr/ST	1.13	1.16	2.32%
Napr/Cap/0.125g	0.34	0.33	-3.26%
Napr/Cap/0.2g	0.40	0.25	-30.65%

Notes: This table shows drug prices under auctions and reference pricing.

than the production cost, firms exit from the market, as shown by their probability of exit in Table 1.8. [26] Conversely, a higher price can lead to higher sales, as in Ibup/Cap/0.2g and Nime/Tab, due to the substitution effect, where consumers switch to these drugs when other drugs exit the market. In general, a higher probability of exit is associated with lower sales, where the probability of exit is determined by the estimated cost distributions and the exogenously given price ceilings. Over the 10,000 simulations, 14% of drugs exit the market under reference pricing on average, leading to a 7% drop in drug sales.

[26] An exception is Acet/Sup where the probability of exit is high but sales still increased. This is because that Acet/Sup has relatively small sales so its sales loss when it is not on the market are outweighed by sales gains from substitution when it is on the market but some other drugs exit.

Table 1.8: Prices, Sales and Exit under Reference Pricing

	% Change in Price	% Change in Sales	Probability of Exit
Acet/Sup	-14.27%	4.75%	14.92%
Acet/Tab/0.3g	-19.49%	-24.20%	28.07%
Acet/Tab/0.5g	-5.16%	1.34%	7.29%
Ibup/Tab/0.1g	-6.24%	0.01%	8.76%
Ibup/Tab/0.2g	-9.01%	-10.34%	12.66%
Ibup/Cap/0.2g	2.02%	10.60%	1.71%
Dic/ST	-2.61%	8.40%	4.00%
Dic/SC	0.84%	13.15%	0.20%
Dic/Tab	-67.73%	-76.43%	76.87%
Indo/Sup	-2.18%	0.19%	1.48%
Nime/Tab	2.48%	7.52%	0.01%
Nime/Cap	1.61%	7.61%	0.04%
Nime/Gra	-41.55%	-34.82%	40.03%
Napr/Tab	0.34%	2.78%	0.21%
Napr/ST	2.32%	2.87%	0.05%
Napr/Cap/0.125g	-3.26%	-0.64%	3.60%
Napr/Cap/0.2g	-30.65%	-26.51%	28.72%

Notes: This table shows the probability of exit which is computed by counting the number of exits of a drug during the 10,000 simulations.

Under reference pricing, both drug prices and sales decrease, resulting in total expenditures and PS being lower by about 7%. However, the effect on CS is more nuanced. While lower prices benefit consumers, the negative impact of drug exits on consumers outweighs the positive effect of lower prices. As a result, the average CS decreases by 8%. Although consumers can switch to other similar drugs in the market, total sales still decrease by 7%, leading total CS to be 14% lower under reference pricing. Table 1.9 reports welfare results.

Table 1.9: Welfare under Auctions and Reference Pricing

Unit: Million Yuan	Auction	Reference	% Change
Total Exp	53.61	49.5	-7.63%
PS	26.94	25.11	-6.99%
CS	345.94	296.91	-14.19%
TS	372.88	322.02	-13.67%

Notes: This table shows welfare and expenditures under auctions and reference pricing.

1.6 Conclusion

This paper investigates an innovative auction-based drug procurement system and compares it with a free market mechanism (Bertrand competition) and a reference pricing policy. In contrast to standard auctions where the prizes are fixed, the auction mechanism examined in this study involves variable prizes. Consistent with the theoretical prediction, I find that drug prices are 2% lower on average under the auction mechanism than Bertrand competition. However, the difference in expenditures and welfare is marginal, which may explain why such an auction mechanism is not widely adopted. Furthermore, the study discovers that both the auction and Bertrand competition outperform a price-ceiling policy in terms of consumer and producer surpluses. While a price-ceiling policy may significantly reduce drug expenditures, it may lead to supply shortages, adversely affecting consumers.

There are several caveats to keep in mind when interpreting the results of this study. First, it should be noted that the counterfactual analysis of the reference pricing policy assumes that the reference prices are exogenously determined and not endogenously determined. However, research from Dubois, Gandhi, and Vasserman (2019) suggests that in response to the policy, pharmaceutical companies may adjust

their pricing strategies in reference areas. Secondly, it is worth noting that some firms may participate in multiple auctions, which may give rise to different incentives compared to firms that engage in a single bidding. However, this issue is outside the scope of this study, and future research may benefit from incorporating this feature into the analysis.

1.7 Appendix

1.7.1 Additional Tables and Figures

Table 1.10: Qualification Criteria

Indicators (75 percent)	Max (Min) Points	Indicators (25 percent)	Max (Min) Points
Annual sales	10 (3)	Brand awareness	6 (1)
Industry ranking	10 (0)	Clinical efficacy	8 (0)
Historical record of drug quality test	10 (0)	Drug safeness	5 (0)
Online procurement record	3 (0)	Drug package	3 (0)
Firm quality type	32 (28)	Supply reliability	3 (0)
Source of drug raw materials	4 (0)		
Refrigerated requirement	2 (0)		
Period of validity	2 (0)		
Type of injection form	2 (0)		

Notes: This table shows how 75 percent and 25 percent of scores are evaluated. It only shows the maximum and minimum points for each indicator, and does not breakdown them into more details. For example, for annual sales, if sales are above 1 billion Yuan, firms get 10 points. For 800 million Yuan to 1 billion Yuan, 9 points. For 600 million to 800 million, 8 points.

Table 1.11: Number of Qualified Firms

NB of Entrants	NB of Qualified Firms
2	2
3 to 4	2
5 to 6	3
7 to 8	4
9 to 10	5
above 10	6

Notes: This table shows number of firms can be qualified within each auction according to number of entrants.

Table 1.12: Demand Model Sensitivity Tests

share of observed demand	5%	10%	15%
price (ddd)	-0.0602***	-0.0601***	-0.0600***
	(0.0071)	(0.0071)	(0.0072)
within group share	0.4360***	0.4378***	0.4398***
	(0.0552)	(0.0554)	(0.0557)
quality score	0.0052	0.0053	0.0053
	(0.0039)	(0.0039)	(0.0040)
number of products	-0.1663	-0.1726	-0.1795
	(0.1115)	(0.1120)	(0.1126)
Acetaminophen	-0.7760***	-0.7781***	-0.7805***
	(0.1016)	(0.1021)	(0.1026)
Diclofenac	0.1991***	0.1998***	0.2007***
	(0.0644)	(0.0647)	(0.0650)
Indometacin	-0.3769	-0.3859	-0.3959
	(0.3474)	(0.3490)	(0.3509)
Naproxen	-1.2762***	-1.2749***	-1.2736***
	(0.1095)	(0.1100)	(0.1106)
Nimesulide	-0.5621***	-0.5622***	-0.5623***
	(0.1199)	(0.1205)	(0.1211)
Capsule	0.8248***	0.8205***	0.8158***
	(0.2296)	(0.2307)	(0.2319)
Granule	1.0010***	0.9950***	0.9884***
	(0.2817)	(0.2829)	(0.2845)
ST_Capsule	1.7815***	1.7738***	1.7653***
	(0.3162)	(0.3177)	(0.3194)
ST_Tablet	1.8024***	1.7944***	1.7855***
	(0.3150)	(0.3164)	(0.3182)
Tablet	1.5258***	1.5187***	1.5109***
	(0.2767)	(0.2780)	(0.2795)
Constant	-6.5918***	-5.8163***	-5.3230***
	(0.4924)	(0.4947)	(0.4974)
Observations	1250	1250	1250

Notes: This table shows estimated demand parameters under different size of potential market measured by the share of observed demand to potential market size.

1.7.2 Auctions with Variable Quantity

This section shows bidders bid lower in a low-bid first price auction with variable quantity than in a low-bid first price auction with fixed quantity. Consider a low-bid first price sealed bid auction j with n bidders. A bidder i draws his privately known cost c_i independently from a distribution $F_j(c)$ with density $f_j(c)$ continuous and strictly positive on its support $[\underline{c}, \bar{c}]$. Let $D_j(b_j, b_{-j})$ be the demand function for the auctioned drug j, which decreases in price of product j and increases in prices of other competing products b_{-j}. To avoid the situation in which the winning firm would like to charge a price lower than the winning price, I assume that given b_{-j}, $\bar{c}_j < p^*$, where p^* is the price at which the marginal revenue equals $\underline{c}$. Then over the interval $\Big[D_j(\bar{c}_j, b_{-j}), D_j(\underline{c}_j, b_{-j})\Big]$, marginal revenue is below $\underline{c}_j$. Thus, firms always want to increase their prices.

Bidder i's objective is to maximize

$$\pi(b_{ij}) = (b_{ij} - c_{ij}) \times \mathbb{E}[D_{ij}(\mathbf{b})] \times \Pr[\text{i wins}],$$

where $\mathbb{E}[D_{ij}(\mathbf{b})] = D_{ij}(b_{ij}, \mathbb{E}(b_{-j}))$. Assuming all bidders employ a common strictly increasing bidding strategy $\beta_j(\cdot)$, the probability that firm i wins is $\Big(1 - F_j(\beta_j^{-1}(b_i))\Big)^{n_j - 1}$. The first-order condition of firm i's bidding problem is

$$\frac{\partial \pi_{ij}}{\partial b_{ij}} = \underbrace{\mathbb{E}[D_{ij}(\mathbf{b})]\Big(1 - F_j(\beta_j^{-1}(b_{ij}))\Big)^{n_j-1}}_{\text{direct change in profit from bid change}}$$
$$+ \underbrace{\Big(b_{ij} - c_{ij}\Big)\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}}\Big(1 - F_j(\beta_j^{-1}(b_{ij}))\Big)^{n_j-1}}_{\text{change in profit from demand change}}$$
$$+ \underbrace{\Big(b_{ij} - c_{ij}\Big)\mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)\Big(1 - F_j(\beta_j^{-1}(b_{ij}))\Big)^{n_j-2}\Big(-f_j(\beta_j^{-1}(b_{ij}))\Big)\frac{d\beta_j^{-1}}{db_{ij}}}_{\text{change in profit from change in winning probability}} = 0.$$

The second line of the above first-order condition shows the difference between auctions with variable quantity and auctions with fixed quantity. If the quantity is fixed, $\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial b_{ij}} = 0$ and we have the first-order condition for auctions with fixed quantity.

At a symmetric equilibrium, $\beta_j(c_{ij}) = b_{ij}$. Making the substitution and rewriting the first order condition, then

$$\frac{d\beta_j}{dc_{ij}} = \frac{\Big(\beta_j(c_{ij}) - c_{ij}\Big)\mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)\Big(1 - F_j(c_{ij})\Big)^{n_j-2} f_j(c_{ij})}{\Big(1 - F_j(c_{ij})\Big)^{n_j-1}\Big[\mathbb{E}[D_{ij}(\cdot)] + \frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial \beta_j}(\beta_j(c_{ij}) - c_{ij})\Big]}$$
$$= \frac{\Big(\beta_j(c_{ij}) - c_{ij}\Big)\mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big) f_j(c_{ij})}{\Big(1 - F_j(c_{ij})\Big)\Big[\mathbb{E}[D_{ij}(\cdot)] + \frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial \beta_j}(\beta_j(c_{ij}) - c_{ij})\Big]}.$$

The numerator in the above equation is positive, and the second parenthetical factor of the denominator is the derivative of profit with respect to the price. Due to the conditions placed on demand and cost, firms always want to increase bids to increase profits, so this factor is positive. Thus, $\frac{d\beta_j}{dc_{ij}} \geq 0$, and bids are increases in cost.

Suppose that quantity demanded is fixed at one. Then bidders' objective is to

maximize

$$\pi(b_{ij}) = (b_{ij} - c_{ij}) \times \Pr[\text{i wins}],$$

and the first order condition can be written as

$$\frac{d\beta_j^F}{dc_{ij}} = \frac{(\beta_j^F(c_{ij}) - c_{ij})(n_j - 1)f_j(c_{ij})}{1 - F_j(c_{ij})}.$$

Notice that

$$\begin{aligned}\frac{d\beta_j^V}{dc_{ij}} &= \frac{\Big(\beta_j^V(c_{ij}) - c_{ij}\Big)\mathbb{E}[D_{ij}(\cdot)]\Big(n_j - 1\Big)f_j(c_{ij})}{\Big(1 - F_j(c_{ij})\Big)\Big[\mathbb{E}[D_{ij}(\cdot)] + \frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial \beta_j}(\beta_j^V(c_{ij}) - c_{ij})\Big]} \\ &> \frac{(\beta_j^V(c_{ij}) - c_{ij})(n_j - 1)f_j(c_{ij})}{1 - F_j(c_{ij})}\end{aligned}$$

because $\frac{\partial \mathbb{E}[D_{ij}(\cdot)]}{\partial \beta_j} < 0$. Then,

$$\begin{aligned}\frac{d\beta_j^V}{dc_{ij}} &> \frac{(\beta_j^V(c_{ij}) - c_{ij})(n_j - 1)f_j(c_{ij})}{1 - F_j(c_{ij})} \\ &\geq \frac{(\beta_j^F(c_{ij}) - c_{ij})(n_j - 1)f_j(c_{ij})}{1 - F_j(c_{ij})} \\ &= \frac{d\beta_j^F}{dc_{ij}}\end{aligned}$$

if $\beta_j^V(c_{ij}) \geq \beta_j^F(c_{ij})$.

To prove $\beta_j^V(c_{ij}) < \beta_j^F(c_{ij})$ for $c < \bar{c}$, first notice that the bidder with highest cost has zero probability of winning, so $\beta(\bar{c}) = \bar{c}$ and this is true for both the variable and fixed quantity auctions. Then we can use proof by contradiction. Suppose that $\beta_j^V(c') \geq \beta_j^F(c')$ for some $c' < \bar{c}$. Then by the mean value theorem, there should exist

a c'' in $(c', \bar{c})$ such that

$$\frac{d\beta^V(c'')}{dc} = \frac{\beta_V(\bar{c}) - \beta_V(c')}{\bar{c} - c'},$$
$$\frac{d\beta^F(c'')}{dc} = \frac{\beta_F(\bar{c}) - \beta_F(c')}{\bar{c} - c'}.$$

Thus, $\frac{d\beta^V(c'')}{dc} \leq \frac{d\beta^F(c'')}{dc}$. However, this is contradicting with $\frac{d\beta^V}{dc} > \frac{d\beta^F}{dc}$ if $\beta^V(c) \geq \beta^F(c)$. Thus, $\beta^V(c) < \beta^F(c)$ for $c < \bar{c}$. In other words, bidders bid consistently lower in auctions with variable quantity.

1.7.3 Two-level Nested Logit Model

Assuming there are L_m potential consumers located in the market m. Each consumer chooses one out of $J_m + 1$ differentiated products where $j = 0, ..., J_m$ and good 0 is the outside good such as not purchasing. The set of products are partitioned into $G_m + 1$ groups where $g = 0, ..., G_m$ and group 0 is reserved for the outside good. Each group $g = 1, ..., G_m$ is further partitioned into H_{gm} subgroups where $h = 1, ..., H_{gm}$. Each subgroup h of group g contains J_{hg} products, so that $\sum_{g=1}^{G_m} \sum_{h=1}^{H_{gm}} J_{hg} = J_m$.

The indirect utility of consumer i purchasing drug j in market m is

$$\begin{aligned} u_{ijm} &= X_{jm}\beta + \gamma ln(J_m) + \alpha(y_{im} - p_{jm}) + \xi_{jm} + v_{ijm} \\ &= \alpha y_{im} + \delta_{jm} + v_{ijm}, \end{aligned}$$

where X_{ij} is a vector of observed product characteristics of product j, J_m is the number of products on the market, y_{im} is income of individual i, p_{jm} is price, and ξ_{jm} captures unobserved product characteristics influencing δ_{jm}. Specify the individual-specific part of utility for drug j in market m, v_{ijm} as

$$v_{ijm} = \epsilon_{igm} + (1 - \sigma_2)\epsilon_{ihgm} + (1 - \sigma_1)\epsilon_{ijm}.$$

The ϵ_{igm}, ϵ_{ihgm}, and ϵ_{ijm} have the unique distribution such that ϵ_{igm}, $(1 - \sigma_2)\epsilon_{ihgm} + (1-\sigma_1)\epsilon_{ijm}$, and $\epsilon_{igm}+(1-\sigma_2)\epsilon_{ihgm}+(1-\sigma_1)\epsilon_{ijm}$ have the extreme value distribution. In addition, $(1 - \sigma_2)$ can be interpreted as measuring preference heterogeneity across products of the same group, and $(1 - \sigma_1)$ can be interpreted as measuring preference heterogeneity across products of the same subgroup.

Then the probability that a consumer i chooses product $j = 1, ..., J_m$ takes the

following well-known form:

$$s_{jm} = \frac{exp(\delta_{jm}/(1-\sigma_1))}{exp(I_{hgm}/(1-\sigma_1))} \frac{exp(I_{hgm}/(1-\sigma_2))}{exp(I_{gm}/(1-\sigma_2))} \frac{exp(I_{gm})}{\sum_{g=0}^{G_m} exp(I_{gm})}.$$

where I_{hgm} and I_{gm} are inclusive values defined as

$$I_{hgm} = (1-\sigma_1) ln \sum_{l \in V_{hgm}} e^{\delta_{lm}/(1-\sigma_1)}$$

$$I_{gm} = (1-\sigma_2) ln \sum_{h \in V_{gm}} e^{I_{hgm}/(1-\sigma_2)}.$$

The V_{hgm} is the set of drugs in subgroup h of group g in market m, and V_{gm} is the set of subgroups in group g of market m. The nesting parameters capture the preference correlation across products of the same subgroup (σ_1) or group (σ_2), and should satisfy $1 \geq \sigma_1 \geq \sigma_2 \geq 0$. When σ_1 is high, preferences are strongly correlated across products of the same subgroup, and when σ_2 is high, preferences show additional correlation across products of the same group.

Same as one-level nested logit model, we can invert the system of choice probabilities s_{jm}, $j = 1, ..., J_m$ to solve for the mean utilities δ_{jm}. Then we can obtain a analytical solution for the inverted choice probability system:

$$ln(s_{jm}/s_{0m}) = \sigma_1 ln(s_{j|hgm}) + \sigma_2 ln(s_{h|gm}) + \delta_{jm}$$

For the two-level nested logit model, I tried two specifications. I first tried to use the substance as the upper nest and form as the lower nest. This implies consumers are most likely to substitute to another product of the same substance and

form and would substitute more to another form than to another substance. The second specification uses the form as the upper nest and substance as the lower nest which implies the substitution is strongest between products with the same form and substance followed by drugs with the same form. Table 1.13 shows estimation results for both specifications but the estimated nesting parameters are inconsistent with random utility theory. Thus, they are ruled out.

Table 1.13: Two-Level Nested Logit Model

	subs form	form subs
pricePerDDD	-0.0619***	-0.2069***
	(0.0079)	(0.0462)
ln_S_hg	0.4548***	
	(0.0628)	
ln_S_jh	0.3184***	
	(0.0696)	
qualityS	0.0029	-0.0216*
	(0.0044)	(0.0113)
ln_nbProducts	-0.1838	-0.6690*
	(0.1242)	(0.3494)
Acetaminophen	-0.6997***	-0.4567**
	(0.1134)	(0.2285)
Diclofenac	0.2261***	0.5285**
	(0.0728)	(0.2487)
Indometacin	-0.4695	3.0746***
	(0.3927)	(0.6870)
Naproxen	-1.1136***	-2.2354***
	(0.1321)	(0.5560)
Nimesulide	-0.4708***	-0.3166
	(0.1343)	(0.3079)
Capsule	0.7948***	2.3345***
	(0.2573)	(0.5385)
Granule	0.9990***	4.6773***
	(0.3140)	(1.0118)
ST_Capsule	1.7713***	5.0731***
	(0.3528)	(0.7495)
ST_Tablet	1.6655***	3.7961***
	(0.3604)	(0.5273)
Tablet	1.3652***	1.9186***
	(0.3202)	(0.6964)
ln_S_hg		-1.3521***
		(0.4916)
ln_S_jh		-0.9902**
		(0.3921)
Constant	-4.5363***	-6.1948***
	(0.5572)	(1.2866)
Observations	1250	1250

Notes: This table shows estimated demand parameters for analgesics using a two-level nested logit model. The first specification has substance as the upper nest and form as the lower nest. The second specification has form as the upper nest and substance as the lower nest.

Chapter 2

Lower Price But Higher Bill? Evidence from the Zero-Markup Policy in China

joint work with Lichen Wang (UVA)

2.1 Introduction

The financial burdens of high medical spending are a challenge faced by many countries. Among all factors driving high healthcare costs, increasing expenditure on prescription drugs plays a key role. The United States spent 369.7 billion dollars on retail prescription drugs or 1.7% of the GDP in 2019. The situation is even more daunting for some other countries. In China, for example, the total pharmaceutical expenditure reached 2.4% of the GDP.

China's high costs of medications have drawn significant attention from media, researchers, and policymakers. Several studies (e.g., Li, Xu, et al., 2012; Currie, Lin, and Meng, 2014; Chen et al., 2014) have found that the way how hospitals operated in China contributed to high retail prices. In addition to providing healthcare services, public hospitals in China have played a significant role in dispensing medicines. They purchased medications at a fixed price set at the provincial level and were permitted to dispense these prescriptions to patients at a higher price, up to a 15% cap. This profit-generating tool has been believed to create strong financial incentives for hospitals to sell drugs that can bring high profits to patients. As direct employees of hospitals, physicians play an important role in this process since part of their total income was coming from the bonus, which depended on the revenue that they brought in, including medicine prescription (Yip and Hsiao 2008; Yip, Hsiao, Meng, et al. 2010). Furthermore, despite the availability of local pharmacies, public hospitals remain significant providers of medications to the general public. In fact, public hospitals in China, which relied heavily on drug sales, charged relatively low diagnostic fees. The drug sale, on average, accounted for more than 40% of a hospital's outpatient and inpatient revenue before the healthcare reform (Fu, Li, and Yip, 2018).

In realization of the tight linkages between pharmacies and physicians and the resulting patients' burdens, the Chinese government launched a national reform in 2009, commonly known as the "Zero-Markup Policy" (ZMP), which aimed to alleviate patients' financial burdens resulting from high retail prices and potential over-prescriptions. The policy targeted almost all medicines sold at public hospitals, requiring that they be sold at their procurement costs.[1] The program was gradually

[1] All medication dispensed at public hospitals should be sold at their procurement costs. The only exception is a category of liquid (or liquid extracts) Chinese herbal medicine.

implemented across cities, beginning with test trials at primary clinics in local townships and extending to all city hospitals. By 2017, the policy was fully implemented in all public hospitals throughout China.

While it might be attractive to conclude that removing medication markups relieves patients' burdens of high bill payments, evaluating the overall effectiveness of such reform needs more careful empirical analysis. It is because physicians' behaviors could be affected by the two opposing forces brought by a lower medication price. On the one hand, the lack of profits may reduce the incentives for over-prescribing medication, leading to decreased medical expenses for patients. A cheaper alternative, a lower dosage, or a combination of both could result in lower medical costs for patients, assuming no other changes exist. On the other hand, lost profits from price controls may incentivize physicians to increase the intensity of non-medicine treatments, particularly when they have more sayings in the diagnosis process. These incentives may be further amplified when other services have higher profit margins. Previous studies have documented the financial incentives and behavior of healthcare providers (e.g., Yip, 1998; Gruber, Kim, and Mayzlin, 1999; Dafny, 2005; Ho and Pakes, 2014; Fang and Gong, 2017; Alexander, 2020). In these contexts, changes in reimbursement rates, whether higher or lower, led physicians to prescribe more services to compensate for revenue loss or extract more profits.

In this paper, we exploit a unique individual-level administrative database from the Healthcare Security Administration (HSA) of a representative city in China. The city has a population of around 1 million urban residents and a per-capita income level slightly higher than the average prefecture city in China, making it generally comparable to many prefecture cities in terms of demographics and economic char-

acteristics. Additionally, the broad coverage of China's health insurance ensures that the HSA system covers nearly all inpatient visits to the city's public hospitals for recent periods, enabling us to examine the specifics of a person's hospital visits, including the reasons for visits and the associated costs for a detailed set of diagnoses and treatments received.

We leverage a Difference-in-Differences strategy to address the question of if and how physicians responded to the removal of medication markups under the ZMP. Specifically, we estimate the impacts of the ZMP by comparing changes in medicine expenditure, medical service expenditure, and utilization between the post-ZMP months in 2017 and the earlier months of the year with the relative differences between the corresponding months in the previous year 2016. Following the ZMP, we find a significant decrease of 18% to 20% of the average spending on medication for the two general-purpose hospitals. However, this decrease was entirely offset by a corresponding increase in non-drug services, resulting in no change in the average patient's medical bill. We also estimate the utilization change of specific medical services such as exams, surgeries, or the days for inpatient care and find no strong evidence that physicians directed patients towards increased service utilization. However, we find that physicians implicitly prescribed more expensive supplementary materials in their treatment process or personal care, resulting in a significant increase in an average patient's consumables spending, unrelated to any price changes in the comprehensive hospitals. The expense increase for specific disease groups was substantial enough to completely offset the benefits of reduced medication prices. We also document a heterogeneous response across hospital types. In particular, the integrated hospital, the only hospital in the city that offers traditional Chinese treatment, followed

a different strategy to compensate for the lost medicine revenue. While we also observed a significant decline in medicine revenue of 32%, there were no substantial rises in consumable expenses. Instead, the physicians in this hospital attempted to prescribe more supplementary herbal therapies or traditional physical treatment to extract extra surplus.

Extensive literature has been trying to explain the high level of and the continuing increase in healthcare expenditures. For example, a change in demographics, including the growth of the aging population and chronic diseases, and income growth, could contribute to a higher demand for healthcare services (e.g., Newhouse, Group, and Staff, 1993; Hall and Jones, 2007). While part of the healthcare costs is demand-driven, the institution-induced rising healthcare system usage is another unavoidable determinant. The fundamental feature of the agency-principal relationship between physicians and patients in the healthcare market explains why physicians would provide excessive treatments (Arrow, 1965). The literature has also established evidence of physicians' responses to financial incentives using experimental design (Currie, Lin, and Zhang, 2011; Currie, Lin, and Meng, 2014; Lu, 2014; Alexander, 2020) or through quasi-experiment settings (Gruber and Owings, 1994; Yip, 1998; Dafny, 2005; Fang and Gong, 2017). Moreover, recent discussions started to center on how broader access to healthcare services could increase overall utilization and, at the same time, result in higher prices (e.g., Finkelstein, Taubman, Wright, et al., 2012; Taubman et al., 2014; Finkelstein, Taubman, Allen, et al., 2016).

Our work first directly contributes to the literature on how medical providers adjust their behaviors in response to financial incentives. By exploring a unique policy experiment and novel and rich individual-level insurance dataset, we show how

physicians could behave when the government removed the profit margins of drug prescriptions and provide empirical new evidence of physicians' excessive treatment as suggested by a principal-agent relationship between physicians and patients (Arrow, 1965). More importantly, we discover a new and more implicit channel that has not been documented by previous research through which physicians compensate for their profit loss. We also find suggestive evidence that beyond just more charges in medical services, there is a shift of financial burdens across diagnosis groups, with patients with specific diseases paying much more than others. We shed light on the welfare consequences across patient groups in this aspect.

Additionally, our paper contributes to the strand of literature studying the healthcare reform in China or other similar contexts with a top-down policy design. The recent decades have seen a series of healthcare reforms in China, with the primary objective being a reduction of medical burdens for individuals. Particularly, the reforms in the drug sector have been in the spotlight because of the high presentation of pharmaceutical spending in total health expenditure.[2] However, formal evaluations of these policies are limited, probably because of the data challenges. The few existing works (e.g., Xiang, 2021; Fang, Lei, et al., 2021) on the impacts of ZMP have been focused either on township or county hospitals whose facilities are usually not qualified for more complicated treatment, such as surgeries or on for certain diseases. We instead conduct analysis using inpatient services from the comprehensive city hospitals, which cover a wide range of diseases and allow us to examine physicians' responses to different types of medical services.

[2]For example, to ensure the need for certain essential medicines are satisfied due to disease prevalence, China has been updating its reimbursement drug list and the national essential drug list. The ZMP targets reducing drug prices and hospitals' reliance on drug-selling revenue.

The rest of the paper is organized as follows. Section 2 introduces the institutional background of China's healthcare system and the medical reform. Section 3 discusses data and summarizes our sample. Section 4 outlines the framework of our research design. The presentation and interpretation of results are in Section 5. Section 6 concludes.

2.2 Institutional Background

2.2.1 Public Hospitals in China

Public hospitals in China are the primary providers of healthcare services, delivering more than 90% of the country's inpatient and outpatient services (Yip, Hsiao, Chen, et al., 2012). In addition to providing diagnosis and treatment, they have played a critical role in distributing medicines, representing an average market share of 80% of all retail drug sales (National Medical Products Administration, 2014).

The dominant market coverage of public hospitals in medicine sales is related to how the healthcare insurance system operates in China. The Chinese central government launched a universal health insurance program in 2007 to provide comprehensive coverage for all residents. By 2011, the public health insurance system had covered more than 95% of the population.[3] Each local government (usually the provincial administration) designs and provides guidance, including details on individual co-payment and reimbursement rates for each type of healthcare service. Participants

[3]The plan designated the residents into three main classifications: Urban Employer Sponsored, Urban Non-Employer Sponsored, and Rural Group. The two urban groups cover only city residents, with the first group consisting of people whose employers sponsor the insurance through the Social Security Administration. The HSA data covers all hospital visits of people in this group.

who locate in the same city and are registered under the same insurance group share the same insurance plan and thus have the same policy reimbursement rates.

Like many other countries, an individual must show an official prescription issued at hospitals to purchase the corresponding prescription medicines. However, to receive insurance reimbursement for medications, individuals need to buy from places authorized in the government's health insurance network, which in most cases are public hospitals. Retail pharmacies, another option for customers to obtain medications, usually are not qualified for reimbursement and are preferred chiefly for convenience reasons.

2.2.2 Hospitals' and Physicians' Incentives

Although the name suggests government ownership, the government does not fully fund public hospitals in China. In fact, on average, government funding only accounted for less than 10% of a hospital's total revenue (China Health Statistic Yearbook), rendering medicine sales and other services their primary income sources. Like health insurance plans, the government actively regulates the prices of medication and services. Specifically, public hospitals were allowed to charge up to 15% markup over the drug procurement price when selling drugs to patients. Besides, the government sets a price ceiling for each type of healthcare service. It is commonly known that labor-related services were heavily under-priced which creates strong incentives for hospitals to rely on its medicine sales.[4] In 2011, for example, the national pharmaceu-

[4]According to a 2009 statement from the National Health Commission of China, one of the healthcare system issues is that prices of some medical services had been lower than their costs for a long time. For example, in the public hospitals of our city, the consultation fee could be as low as2 - 3 Yuan ($0.3 - $0.46) each time.

tical revenue, on average, accounted for about 40% of total health expenditure. The average ratio of medicine to the total medical spending of the three comprehensive hospitals in this study ranged from 27% to 35% before the medical reform. As employees of hospitals, physicians were also aligned with the hospitals in prescribing more profitable medicines since they were rewarded with bonus payments and promotions on the basis of the revenue they generated (Yip, Hsiao, Meng, et al. 2010).

2.2.3 Healthcare System Reform

To cut the linkages between physicians and medicines, the central government launched a nationwide healthcare system reform, commonly known as the Zero Markup Policy (ZMP), in 2009. The reform prohibited any markup profits made by public hospitals for dispensing medications. As a result, the retail prices of all medicines sold at public hospitals must be set just as their procurement cost, a cost fixed at the province level through a centralized procurement process. Nevertheless, the policy allowed public hospitals to adjust the medical service prices subject to a regulated price cap for each category.

In the same spirit as the Chinese regional experiment regime, the policy was initially piloted at a smaller scale and later rolled out sequentially to cover a broader population base. Figure 2.1 demonstrates the policy's guided timeline from the Central government. The first phase (between 2009 and 2012) launched a pilot program targeting primary healthcare institutions (e.g., township clinics). In the second phase (2012 to 2015), all county-level hospitals were required to implement the policy. The program was then rolled out to different cities across the county so that by the end of September 2017, all city-level hospitals had removed their markup from medicine

Figure 2.1: General Policy Timeline

Note: This figure shows the general implementation timeline of the ZMP policy.

sales.

Complying with this planned national schedule, the provincial governments then determined the exact timing of policy implementation for each city under its administration. For instance, the ZMP implementation date in our sample city was July 31, 2017. Following the reform, all public hospitals in the city must sell medications at the procurement price determined in the provincial centralized drug procurement system.[5] Apart from the medicine price change under the ZMP, the city government issued price adjustment guidance for all medical services. The guidance updated a list of cap prices that each public hospital is allowed to charge for each type of service, including inpatient and post-surgery care, examination, surgical treatment, and all other supplementary treatment. Hospitals are allowed to set prices of medical ser-

[5]To lower prices, each provincial government established a central bidding platform to which pharmaceutical companies bid for the wholesale price for each designated drug category. Once the winning bids are finalized, the local (provincial) centralized procurement requires all public hospitals to purchase medicines from the winning producers at the bid price. Wu (2022) studies the efficiency of the auction-based drug pricing system established at the provincial level. This centralized procurement process was launched nationally in 2009 and renewed every two years.The most recent medicine procurement in our sample province happened in December 2015, and the new wholesale price was issued in Oct 2016. We do not observe a visually obvious change in the average medicine expenditure from our data since Oct 2016 to the official ZMP implementation date.

vices as long as they do not exceed the cap prices set by the government. We refer to the official document published by the city government for the ZMP in 2017 when aggregating the granular service items. Generally, the guidance allowed an upward price adjustment for the diagnosis, inpatient care services, and surgery treatment and required a downward price adjustment for exams.[6] Unlike these service groups, there were no price changes in the medical consumables during our sample period.[7]

2.3 Data and Sample Description

Our primary data is from the Healthcare Security Administration (HSA) of a prefecture city[8] in a central Chinese province. The city is generally representative of a median Chinese prefecture city – it has a population of around 1 million urban residents and an annual GDP per capita of roughly USD $8,000, both of are slightly higher than a median and average prefecture city in China, according to the 2010 Chinese Population Census.

We use the daily-individual-level patient healthcare claims data from HSA, which covers the city's urban residents' healthcare expenditure. Patients visiting public hospitals are identified using their government-sponsored medical insurance IDs and are

[6]Each broader category of medical services in the document contains tens or hundreds of service items, and each may vary by unit. For example, during the entire hospitalization experience, there could be multiple times of nursery services provided, whereas there is generally at most one surgery conducted. The document also exhibits a variety of price cap changes across service types. The adjustments range from -6% to -15% for medical examination services and are from 20% to 30% for surgical treatments.

[7]Medical consumables may include general medical equipment such as syringes, needles, tubing, sealants for wounding, etc., or high-value medical supplies such as vascular catheters or artificial joints typically used in surgeries. The medical consumables were also procured through a centralized procurement system.

[8]An administrative division in China is ranked as Province - Prefecture City - County.

digitally recorded in the healthcare system. The broad coverage of such government insurance means that almost all urban residents are included in the design, minimizing a sample selection risk commonly seen in survey data.[9] We conduct the analysis using the city's three public comprehensive hospitals. These hospitals provide both inpatient and outpatient medical services and have licensed health professionals to offer consultative, diagnostic, and therapeutic services to almost all types of disease categories.[10] Specifically, three city-level comprehensive hospitals form the basis of our sample. Among them are the general types of comprehensive hospitals: The City No.1 People's Hospital and The City No.2 People's Hospital. We refer to them as Hospital A and Hospital B in the following sections. There is also an integrated hospital that provides traditional Chinese physical and herbal treatment as an additional option, with the official name being the City's Hospital of Traditional Chinese Medicine. We denote it as Hospital C in the following sections.

The HSA data provides rich expenditure information on each patient's visits to these comprehensive hospitals. For each patient visit, we observe the visit date, the person's characteristics such as age, gender, if the visit is for an inpatient service, and the duration of stay in the hospital. We focus on inpatient records for the completeness of disease information.[11] Pairing with each individual-daily level visit

[9]China's government medical insurance covered more than 95% of the population as of 2013. https://web.archive.org/web/20150328095843/http://www.mckinsey.com/insights/health_systems_and_services/health_care_in_china_entering_uncharted_waters

[10]The comprehensive hospitals are different from specialty hospitals in that the latter only offer medical services to a particular disease group. For example, the city has nine public hospitals, out of which three are city-level comprehensive hospitals, four are specialty hospitals (A Stomatology, a Maternity, a Dermatology, and a Rehabilitation hospital), and two district hospitals for clinics.

[11]Since inpatient services are eligible for insurance reimbursement, the disease name is well-recorded by physicians. In contrast, many outpatient services may not qualify for insurance coverage and are only vaguely reported as "general" in the claim item "reason of visit." Therefore, we observe the massive missing value of the disease types for outpatient observations.

record, we observe a rich vector of prescription spending and service expenditures covering from consultation to therapies. Together, we can examine the behavioral responses of physicians in prescribing non-medicine services when there is a drop in the profit margin of medical prescriptions.

2.3.1 Disease Classification

Before moving to investigate the summary statistics of our sample, we first aggregate the granular disease names up to a consistent broader category based on the tenth revision of the International Classification of Diseases (ICD-10) from the National Clinical Disease Classification Code.[12] Grouping granular diseases into broader categories allows us to control for the common factors of diseases that lead to systematically higher (or lower) expenditures. Without grouping, the system contains thousands of unique disease names, some of which could have been treated as different diseases simply because one includes a few more words of description. By recognizing that certain groups of diseases are fundamentally related under an independent classification system, we can use the fixed effect to control for all disease-related time-invariant factors affecting the outcome levels. We describe in Appendix A how we match diseases recorded in the local health administrative system with the diseases from ICD-10 according to the number of matched Chinese characters.

[12]China has adopted the ICD-10 standard since 2003. We obtained the ICD-10 mapping file from the National Clinical Disease Classification Code 2.0 published by the National Health Commission of the People's Republic of China in 2019

2.3.2 Summary Statistics

Patients in our city sample have three choices when deciding which type of facilities they utilize among the comprehensive facility list. While they are all general-purpose hospitals and are classified by the provincial government as the top tier group[13], each hospital differs in the number and the types of patients. For example, a hospital with an integrated traditional Chinese and Western treatment (Hospital C) is believed to attract patients who at least value parts of the conventional treatment. Probably due to a more extended establishment history, Hospital A received more inpatient visits than the other two. Our sample covers all inpatient visits to these three hospitals on daily-person levels from 2016-01-01 to 2017-12-31. We focus on relatively common disease types that receive at least 300 visits annually to avoid measurement biases related to a small set of uncommon diseases.

Tables 2.1, 2.2, and 2.3 show the annual distribution of diseases diagnosed by each hospital. Among all the inpatient services provided by the three hospitals during the two sample years, the most common disease groups are "Circulatory system" or "Neoplasms" -related. We see from Table 2.1 that Hospital A received more than double the number of patients than Hospital B as Hospital A is the largest hospital in the city. In terms of disease distribution, more than a quarter of the inpatient services were diagnosed as related to "Circulatory system" for both Hospital A and B. While "Neoplasm" diseases were also a common visit reason in Hospital A. We can see that the proportion of Tumor-related diseases is much higher in Hospital B

[13]Each public hospital is evaluated by the government with a grade based on their service and facility quality. The grading scale includes three groups: primary (bottom-tier), secondary (middle-tier), and tertiary (top-tier). Within each group, there are letter grades from A to C, with A being the best subdivision. The three hospitals in our sample are classified as a tertiary A group, indicating that they can serve more than 500 beds and are considered the best city-level general hospitals.

than in Hospital A.

Table 2.4 provides further details of patients' demographics in each hospital. We observe a relatively stable distribution of disease groups across hospitals. We divide our sample into four age groups. The sample similarity in terms of the disease types and demographic distribution indicates no evidence of a changing patient composition across the years within the same hospital.

Figures 2.2, 2.4, and 2.6 demonstrate the basic patterns of the average medicine expenditure per patient in the two years. The average medicine expenditure was comparable across these two years from January through July. However, a sharp contrasting pattern had followed since August, when the ZMP started to be effective. After August 2017, the average medicine expenditure per patient experienced a noticeable visual decline relative to the 2016 levels. The trends of a patient's total medical spending are shown in Figures 2.3, 2.5, and 2.7. In contrast to a declining trend of medicine expenditure, there is not much disparity in the total medical bill an average person received between the two years. The decreasing medicine price and a similar medical bill lead us to formally examine the channels through which the expenditures are altered.[14]

2.4 Empirical Strategy

To study the impacts of the ZMP on an individual's medical spending, we leverage a Difference-in-Differences (DID) strategy that compares a patient's bill between the post- and pre-ZMP period in the same hospital. Our empirical strategy is partially

[14] Additional summary statistics such as expenditures by category and Service Utilization by category are also reported in the Table section.

illustrated in Figures 2.2 - 2.7. Since all city hospitals implemented the ZMP simultaneously, we cannot rely on a conventional approach in which we compare the outcomes of the treated group to those of the control group unaffected by the hospital.

In light of these empirical complications, we compute the counterfactual outcomes following Miller, Segal, and Spencer (2022). We use the most comparable outcomes from the year just before the ZMP to construct the outcomes that would have been observed for each hospital had the policy not occurred.[15] Specifically, our general DID strategy takes the following form:

$$Exp_{iwt} = \beta_1 ZMP_{iwt} + m_t + dow_t + wave_t + \delta X_{iwt} + \epsilon_{iwt}, \tag{2.1}$$

where Exp_{iwt} is an individual patient's expense on a particular medical service or medication, measured at the individual-wave-day level. The two waves are the years 2016 and 2017, respectively. The primary explanatory variable is ZMP_{iwt} for which an individual observed is assigned with value 0 if the patient is admitted before 2017-07-31 and is of 1 afterward. $wave_t$ represents the wave fixed effect and control for systematic time-invariant factors at the year level. Differences in expenditures could also occur in the timing of hospital visits. For example, people are expected to be less likely to visit hospitals during the lunar new year holidays unless necessary, so the average medical during the new year is typically different from the rest of the year. The fluctuations in hospital visits could also be observed for days within a week. To account for seasonal and weekday variation, we control for month-fixed effects m_t, and

[15] While we could observe partial visit records before 2016, we chose the sample period from the first month of 2016. The city hospitals did not adopt complete digitization until late 2015, and there exists a strong selection bias of the observations in earlier periods. Moreover, the procurement costs of medical consumables were fixed during the sample period from 2016 Jan to 2017 Dec.

day-of-week fixed effects. Moreover, we also include a vector of individuals' observed characteristics such as gender, age, and a categorical variable covering the diagnosis groups. We follow the same practice as Eqn. 2.1 and separately repeat the analysis for each comprehensive hospital.

In addition to expense changes, we also examine the effects of ZMP on medical service utilization. As described in Section 2, a ZMP policy is linked to a corresponding price adjustment in other service categories.[16] To exclude the possibility that an expense change of service categories merely reflects price change, we estimate a second model that studies the effects on service utilization rate. The specification is:

$$\mathbb{1}(\text{Service Utilization})_{iwt} = \beta_1 ZMP_{iwt} + m_t + dow_t + wave_t + \delta X_{iwt} + \epsilon_{iwt}. \quad (2.2)$$

The second model is shown in Equation 2.2. Here, the dependent variable is a binary indicator that takes a value of 1 if an individual was observed taking an exam or surgery during the diagnosis process. We impute the service utilization through a positive service charge for any exam or surgery-related categories. Therefore, a positive value of β_1 means that an individual is more likely to be charged with these services between the months after ZMP and December compared to a similar individual who visited the hospital between these months when ZMP was not effective.

The identification of the causal impacts of ZMP hinges on several assumptions. First, all prices were exogenously determined so that no changes within the hospital were associated with the reform's timing and medical service provisions. The top-down implementation nature of such reform creates a plausibly exogenous variation

[16] For example, there is a systematic price decrease of 15% in MRI and CT exam fees, a 6% reduction of blood test fees, and a 20 or a 30 % increase of surgery fees.

in physicians' compensations. The central government initiated the ZMP reform, and the provincial government then planned and carried out county and city rollouts. Therefore, local bureaucrats (the city government in this paper) were not allowed discretion in the process. We also assume that the counterfactual average medical service utilization would have been the same as in the past year without any reform. Since all patients in the city were affected by the policy at a clear-cut time, we rely on the prior year to serve as a control wave, and the calendar days of admission before (after) Jul-31 are the typical "pre" ("post") for each wave.

While one cannot verify such an assumption, we formally compare the differences in the outcomes of interests during the periods before the ZMP in the two years through a visual examination and an event-study framework. The event-study analysis is of the following form:

$$Y_{iwt} = \alpha + \sum_{\tau \neq 7} \beta_\tau \times \mathbb{1}(ZMP_i) \times \mathbb{1}(t = \tau) + m_t + dow_t + wave_t + \delta X_{iwt} + \epsilon_{iwt}, \quad (2.3)$$

where $1(t = \tau)$ is a group of indicator variables for each calendar month from January to December, except for July. It is the month since the ZMP started to take effect and is the baseline group we compare our coefficients. The framework incorporates a set of monthly indicators interacting with the ZMP year. Thus, these coefficients β_1 to β_6 capture the differences in outcome variables between the year 2016 and 2017 for months when ZMP was not effective, and the coefficients β_8 to β_{12} measure the outcome differences relative to July for the months since ZMP. Our outcome variables include expenses, utilization of service categories, and the length of stay at the hospital. The rest of the variables are the same as those in Equations 2.1 and

2.2. We show in section 5 that the control (wave 2016) and treatment (2017) groups exhibit parallel pre-trends on the outcome variables.

2.5 Results

2.5.1 Expenditure

Tables 2.7 and 2.8 present the main findings on aggregate medical spending for two comprehensive hospitals, Hospital A and Hospital B. The outcome variables are presented as the average per-person medical bills in local currency (Chinese Yuan, CNY), and the coefficients in the table indicate the relative change in spending for medicine, non-medicine, and total expenditure. Column 1 shows that following the ZMP enforcement, there were noticeable decreases in medicine expenditure, with an average reduction ranging from ¥599 (17.8%) to ¥669 (19.9%) for the two general-purpose hospitals. Although we cannot observe the price and quantity changes separately, the significant decline in medicine prescriptions suggests that the price reduction percentage outweighed demand responses, leading to an overall decrease in drug expense. Furthermore, the average percentage drop of more than 15% indicates that over-prescription for drugs could be a problem in these city hospitals before the ZMP. However, there was a large and significant increase in the sum of non-medicine categories, as shown by Column 2. While the absolute amounts of these increases were not as large as the medicine expense drop, the changes were still statistically significant. As a result, we only observed a slight decrease in the final bill amount, but the magnitudes were statistically insignificant (Column 3). The ZMP also changed the relative reliance of hospitals' revenue on drug sales. The ratio of medicine expense to

a patient's total spending decreased from 33 - 35% to 27% for these two hospitals.

2.5.2 Service Utilization

Since our results show a large adjustment of non-medicine expenditure in both hospitals, it's worth examining if the increased bill was due to more physician-induced services. However, our findings on medical service utilization exclude such a possibility. We categorize the granular diagnosis and treatment services into the following main categories: (1) Inpatient and Post-Surgery Care, (2) Exam, (3) Surgical Treatment, and (4) Medical Consumables, each varying in terms of costs and utilization across patients. For example, consultation services included in the first category are mandatory for every patient. Additionally, the usages of exams or medical consumables, although not necessarily 100%, are almost seen for all patients in this inpatient sample. Therefore, the utilization was already extensive for these groups, and any changes could only occur at the intensive margins. In contrast, we can exploit the differences in service utilization in the other categories to examine the effects of the ZMP on physician-induced demand.

We present the expenditure changes in Tables 2.10 and 2.11 for Hospitals A and B. To begin with, there were significant changes in the average expenditure for all categories. Take Hospital A as an example, relative to the pre-ZMP months, there was an average increase of ¥350 in the Inpatient and Post-Surgery Care expenditure (Column 1), an average drop of ¥310 in exam expenditure (Column 2), and a small increase in surgery expenditure of ¥95 (Column 3), respectively. Moreover, medical consumables increased by ¥332, or more than 30% of the pre-ZMP level.

While there was an expense rise in specific categories, one cannot conclude if

this was due to a price adjustment or a change in service utilization. Recall from section 2 that hospitals were *required* to reduce exam fees whereas were *allowed* to increase prices charged for medical services subject to a cap. Does the increase in bills associated with Inpatient and Post-Surgery Care mean that physicians in our sample hospitals keep patients longer at the hospital, or was it purely a reflection of price changes? To answer this question, we need to look at the utilization rates of the service, as mentioned earlier.

Tables 2.13 and 2.14 present the coefficient estimates for Equation 2.2 for Inpatient and Post-Surgery Care and Surgical Treatment for the two general-purpose hospitals, A and B, respectively. Regarding the Inpatient and Post-surgery Care services, we use the admission and discharge dates to calculate the length of hospital stay and refer to it as the duration of inpatient care. None of these services experienced a significant increase in utilization rate after the ZMP. If anything, we observed a slight decrease of 0.5 days in Hospital A's average length of stay post the ZMP. Our estimates show a different finding from the few studies that examined clinics at a more primary level. For example, Fang, Lei, et al. (2021) found that physicians in township health centers increased their charges on bed and exam fees.[17]

In Column 1 of Table 2.13, we find there was an increase in the average surgery rates for Hospital A. We show in the later subsection that the surges in surgery rates in Hospital A were primarily driven by a specific group of diseases in "Musculoskeletal system and connective tissue" and "Endocrine and metabolic diseases" (E). While the evidence may be suggestive given the relatively small sample size, the result is

[17]However, we do not know if there was a price change in the township clinics for the bed or exam fees. If those clinics were allowed to raise exam fees, the conclusion of a shift towards more nights in the hospital or more exams should have been reflected in a change in the usage rates rather than the fees.

consistent with Xiang (2021) in which the patients with Spondylosis were seen with a higher surgery rate.

Our findings from the two hospitals suggest that physicians in these two city hospitals tried to maximize surplus to compensate for their earnings losses from lower medicine profits. However, they did not necessarily have the power to induce more service utilization, such as extended hospital stays, exams, or surgeries. Surgical treatment often requires more discretion from both sides, and higher prices may lead to reduced demand. Moreover, since the exam rates for inpatient services in our sample were already sufficiently high, and the even lower prices for the already under-priced exam fees leave no incentives for physicians to direct towards them. On the other hand, the physicians have much more discretion in charging medical consumables, which were procured through a centralized system at a fixed cost during our sample period. Specifically, the estimates in Columns 4 of Tables 2.10 and 2.11 show that the average spending increase of medical consumables were so large that it significantly weakened the markup reduction of the retail drugs. Consequently, an average patient's medical bill was barely lowered. Unlike exams or surgeries, since there was no cost adjustment in the medical consumables, all expenditure changes were caused by an increased prescription of the corresponding items or a substitution towards more expensive materials.

2.5.3 Further Evidence on Supplementary Treatment

Our study of two general-purpose comprehensive hospitals has revealed that physicians in the sample city tend to compensate for revenue loss by charging more for medical consumables, the item over which they have complete discretion. To gain

further insights into how physicians could leverage the additional treatment options, we analyze a third comprehensive hospital (Hospital C) – the only hospital in the city that provides traditional Chinese treatment options. Our analysis concludes a second finding, where physicians may adopt different approaches to increase their charges on treatment fees depending on their hospital type,. For example, the coefficient estimates in Table 2.12 show that patients at Hospital C spent significantly more on the unique service option provided by the integrated hospital rather than on other categories.

After ZMP, the average spending on medicines declined by 33% in Hospital C. Different from the two previous hospitals, Column 2 of Table 2.9 does not show a sizable increase in spending in a few medical service categories, which resulted in only a partial offset to decreases in medicine expenditure. A further examination of service utilization also did not suggest strong evidence of a systematic increase in service utilization, except for one category. Similar to Hospital B, the coefficient estimates on the utilization rates in Table 2.15 illustrate that there were no significant changes in the probability of a patient getting surgery. We also observe that the average length of stay decreased by an average of 1.3 days, possibly due to higher prices for personal care during hospitalization. Interestingly, this hospital does not see a systematic expense increase in medical consumables. However, we find consistent evidence that physicians in Hospital C attempted to increase surplus from other services to break even the lost revenue. Specifically, the utilization rate of traditional Chinese physical treatment significantly increased for Hospital C after the ZMP. The coefficient in Column 3 of Table 2.15 shows an increase of 8.5 percentage points relative to an average utilization rate before the ZMP. This finding is also consistent

with our previous interpretation that physicians are likely to induce patients to spend more on items over which they have more discretion in the treatment procedure.

2.5.4 Variation by Diagnosis

The findings indicate that physicians may pass their financial pressures onto patients by overcharging for other services, and the significant increase in additional charges following the ZMP almost offsets the spending decreases from medicine prescriptions. A related question is whether all patients are affected similarly and whether there is a shift in burdens from diagnosis groups with higher medicine expenditure to those who spent less before the ZMP.

To answer this question, we provide suggestive evidence on how the average expenditure of individuals diagnosed with different disease groups varies after the implementation of ZMP. Table 2.16 presents the ZMP impacts on medical expenses for Hospital A, and we observe that the policy impacts varied across disease groups. Specifically, the estimates reveal that most disease groups experienced significant decreases in medicine spending, although the estimates for some groups were less precisely estimated. While it is possible that the average prices of the drugs prescribed for specific diseases were already at the price ceilings set by the government, leaving little room for additional markup. Our results show that the average medicine expenditure decreased by at least 15%. Similarly, we find significant decreases in an average patient's medicine spending across diagnoses at Hospital B, as shown in Table 2.17. Among these groups, patients diagnosed with digestive system diseases (K) had the most considerable dollar (percentage) decrease in spending compared to the pre-ZMP period mean spending.

We then report separate estimates for the ZMP impacts on other service expenditures for each disease group. Tables in Appendix A show the corresponding estimates for medicine changes for Hospital A. To summarize, relative to the pre-ZMP period, the policy led to a consistent increase (decrease) in inpatient care and diagnosis (exam) expenditure. In contrast, the impact on surgery expenditure was insignificant for most disease groups.[18]

It's interesting to see variations in the ZMP impacts on different disease groups' expenditures. Increases in other services' expenditures might have offset the decrease in drug expenses for some disease groups. For example, there is an increase in the average surgery expenditure for three disease groups, "Neoplasm (CD)", "Endocrine and metabolic diseases (E)", and "Genitourinary System (N)" in Hospital A. For the medical consumables, we find that six disease groups in Hospital A experienced significant increases in their expenditure. It's also noteworthy that some disease groups, such as those with "Musculoskeletal system and connective tissue (M)" diseases, ended up paying more for medical consumables, which could have imposed additional financial burdens on them.

To examine whether the spending increases are due to higher service utilization rates, we analyze the average utilization rates after the ZMP. The results in Table 2.27, Columns 4 and 7 show that there was an increase of surgical rates by 10% and 8%, respectively, for disease groups "Musculoskeletal system and connective tissue (M)" and "Endocrine and metabolic diseases (E)" in Hospital A.[19] Additionally, we do not

[18] As the service prices were not recorded in the HSA data, we could not directly observe if the surgical prices were adjusted.

[19] While we attempted to mitigate the effects of small-sample bias by targeting relatively common disease groups, the estimates presented here may still be vulnerable to such bias, and should therefore be interpreted with care.

find significant changes in the length of stay at Hospital A across disease groups. If anything, the average hospital stay decreased by 1.2 days for "Genitourinary System (N)", possibly due to a higher price and the resulting lower demand.

Similarly, for Hospital B, while the changes in service utilization are not substantial, there are significant increases in the average medical consumables expenditure across almost all disease groups. Moreover, for the diagnosis group "Injury, poisoning and certain other consequences of external causes (S)", the spending increase on this category is so high that it results in an even greater overall cost. Many patients in this group were diagnosed with "Bone Fracture", which was commonly reported for charging high prices for fixation plates.

Similar to Hospital A and B, the ZMP impacts on medical expenses for Hospital C varied across diseases (Table 2.18). Given that the compensation mechanism for Hospital C was different from the previous two, we would expect a different expense distribution. Other than the "Digestive System (K)" group, there was no significant change in the expenses on medical consumables. A breakdown of the disease groups based on the traditional Chinese treatment category reveals a rise in the average spending for many disease groups. Furthermore, at least part of the higher average expenditure was due to the high usage rate of this supplementary treatment. Columns 2 and 3 of Table 2.26 show that after the ZMP, the average utilization rate increased by 22 and 12.5 percentage points for the disease groups "Circulatory system (I)" and "Digestive System (K)," respectively. These are substantial usage rate increases compared to the pre-ZMP sample mean of 75 and 65 percentage points, resulting in almost a universal treatment plan for almost all patients.

Taken together with the estimates for all hospitals, our results suggest that the

reduced medicine expenditure may benefit certain patients more than others. However, the increases in spending on other services partly or entirely offset the potential benefits of the ZMP, resulting in disproportionate impacts across different diagnosis groups.

2.6 Conclusion

The high cost of pharmaceuticals has raised concerns in China, with many pointing to public hospitals and the financial incentives tied to physicians' prescribing behavior as crucial contributing factors. In response, the Chinese government implemented a nationwide program to reduce the over-prescription of medications and alleviate the financial burden of healthcare expenses. This program eliminated the previously permitted 15% profit margin on drug sales at all public hospitals, and by the end of 2017, all public hospitals throughout the country had adopted this change.

This paper examines the effectiveness of government-led healthcare reform in reducing healthcare expenditure for individuals. We use novel admission-level healthcare claims data from a representative city to investigate this question. We study the question by exploiting the plausibly exogenous change in the retail medicine prices caused by ZMP. Our estimates suggest that while the policy led to a decrease in medical expenses, it did not result in a reduction in the final medical bill.

The evidence presented in this study leads to several main conclusions. First, we find that hospitals may use various methods to compensate for their drug revenue loss resulting from the ZMP, including physicians' leveraging their information advantage to prescribe more expensive materials for treatment, which may be buried in the final

medical bills. For example, the patients at the two general-purpose hospitals in our sample paid more for medical consumables. In contrast, the patients in the integrated hospital were prescribed more traditional supplementary treatment. Second, physicians may be unable to persuade patients into surgeries requiring discretion from both sides. We observe a slight rise in surgery rates in Hospital-1, mainly driven by "Musculoskeletal system and connective tissue (M)" related diseases. Still, we do not see strong evidence in the other two hospitals. In addition, our study highlights the need to monitor unintended outcomes, such as medical resource utilization across diagnosis groups, in addition to targeted medicine expenditure. Depending on the severity of the illness, some patients may be more prone to unnecessary medical resource usage than others, leading to an even higher financial burden than before ZMP.

From a policy perspective, the findings of this study suggest that price controls for drugs and services alone may not be effective in controlling total healthcare expenditure. As long as physicians' remuneration remains dependent on hospital revenue, the distorted principal-agent incentives in the Chinese healthcare system cannot be eliminated by programs that aim to remove partial profits from medicine prescription. An open question that requires further research is whether a lump sum compensation for profit loss or a change in physicians' compensation tied to the service revenue they generate could minimize unintended costs.

2.7 Tables

Table 2.1: Disease Distributions in Hospital A

NB Obs	Hospital A	
Disease Groups	2016	2017
I (Circulatory system)	3,323 (29%)	3,161 (27%)
CD (Neoplasms)	1,532 (13%)	1,712 (15%)
K (Digestive system)	1,679 (15%)	1,556 (13%)
J (Respiratory system)	1,015 (8.8%)	1,111 (9.5%)
N (Genitourinary System)	943 (8.2%)	1,071 (9.1%)
R (Abdominal Pain)	953 (8.3%)	1,048 (8.9%)
E (Endocrine and metabolic diseases)	693 (6.0%)	775 (6.6%)
H (Ear and Mastoid Process)	762 (6.6%)	633 (5.4%)
M (Musculoskeletal system and connective tissue)	649 (5.6%)	647 (5.5%)
Total	11549	11714

Table 2.2: Disease Distributions in Hospital B

NB Obs	Hospital B	
Disease Groups	2016	2017
CD (Neoplasms)	1,457 (31%)	1,863 (32%)
I (Circulatory system)	1,336 (28%)	1,797 (31%)
K (Digestive System)	862 (18%)	1,007 (18%)
N (Genitourinary System)	541 (11%)	544 (9.5%)
S (Injury, poisoning and more)	524 (11%)	543 (9.4%)
Total	4720	5754

Table 2.3: Disease Distributions in Hospital C

NB Obs	Hospital C	
Disease Groups	2016	2017
M (Musculoskeletal system and connective tissue)	873 (34%)	1,198 (39%)
I (Circulatory system)	748 (29%)	830 (27%)
K (Digestive system)	600 (23%)	680 (22%)
CD (Neoplasms)	352 (14%)	356 (12%)
Total	2573	3064

Table 2.4: Patient Demographics

	Hospital A			Hospital B			Hospital C		
	All	Before	After	All	Before	After	All	Before	After
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age (%)									
group1	0.25	0.26	0.24	0.28	0.29	0.25	0.31	0.32	0.28
group2	0.28	0.29	0.28	0.25	0.25	0.25	0.32	0.32	0.33
group3	0.25	0.24	0.26	0.24	0.23	0.24	0.21	0.21	0.23
group4	0.22	0.22	0.23	0.23	0.22	0.26	0.15	0.15	0.16
Gender (%)									
Male	0.55	0.56	0.55	0.58	0.58	0.6	0.53	0.52	0.55
Obs	23263	18155	5108	10474	8001	2473	5637	4320	1317

Table 2.5: Expenditure By Category

	All		Before		After	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Hospital A						
Total Exp (CNY)	9088	99302	9035	9233	9278	9541
Medicine Exp (CNY)	3230	4417	3348	4576	2809	3772
General Treatments (CNY)	1367	2392	1269	2117	1713	3161
Surgery Exp (CNY)	675	1911	627	1925	843	1852
Examination Exp (CNY)	2940	1887	2965	1908	2848	1805
Medical Consumables Exp (CNY)	878	2752	825	2622	1065	3163
Hospital B						
Total Exp (CNY)	8574	7669	8598	7273	8493	8829
Medicine Exp (CNY)	3156	3792	3361	3914	2494	3282
General Treatments (CNY)	1420	2513	1317	1884	1753	3889
Surgery Exp (CNY)	538	1238	532	1231	560	1259
Examination Exp (CNY)	2724	1605	2738	1642	2680	1475
Medical Consumables Exp (CNY)	735	2168	651	1859	1006	2939
Hospital C						
Total Exp (CNY)	7373	5663	7442	5979	7148	4450
Medicine Exp (CNY)	2227	3336	2388	3600	1698	2179
Traditional Chinese Treatments (CNY)	850	1065	803	980	1007	1292
General Treatments (CNY)	1272	1267	1265	1266	1296	1272
Surgery Exp (CNY)	412	922	370	897	551	988
Examination Exp (CNY)	2177	1324	2179	1332	2171	1298
Medical Consumables Exp (CNY)	434	1459	437	1610	426	782

Table 2.6: Service Utilization By Category

Variables	All Mean (1)	Before Mean (2)	After Mean (3)
Hospital A			
Exam Rates (%)	0.99	0.99	1
Surgery Rates (%)	0.39	0.39	0.42
Medical Consumable Rates (%)	1	1	1
Duration (days)	12.3	12.4	11.7
Hospital B			
Exam Rates (%)	1	1	1
Surgery Rates (%)	0.37	0.38	0.34
Medical Consumable Rates (%)	1	1	1
Duration (nb days)	12.6	12.7	12.1
Hospital C			
Exam Rates (%)	0.99	0.99	0.99
Traditional Chinese Treat Rates (%)	0.84	0.82	0.92
Surgery Rates (%)	0.41	0.41	0.43
Medical Consumable Rates (%)	0.99	1	0.99
Duration (nb days)	16.5	16.7	15.9

Table 2.7: ZMP Impacts on Medicine and Total Expenditure in Hospital A

Hospital A	(1) Medicine Expenditure	(2) Non-Medicine Expenditure	(3) Total Expenditure
ZMP	-598.988***	446.899***	-152.089
	(114.080)	(155.441)	(243.146)
month FE	Y	Y	Y
day-of-week FE	Y	Y	Y
wave FE	Y	Y	Y
Demographics	Y	Y	Y
Mean	3348	5687	9035
N	23263	23263	23263

Table 2.8: ZMP Impacts on Medicine and Total Expenditure in Hospital B

Hospital B	(1) Medicine Expenditure	(2) Non-Medicine Expenditure	(3) Total Expenditure
ZMP	-668.920***	518.583***	-150.337
	(146.636)	(189.364)	(300.551)
month FE	Y	Y	Y
day-of-week FE	Y	Y	Y
wave FE	Y	Y	Y
Demographics	Y	Y	Y
Mean	3361	5237	8598
N	10474	10474	10474

Table 2.9: ZMP Impacts on Medicine and Total Expenditure in Hospital C

Hospital C	(1) Medicine Expenditure	(2) Non-Medicine Expenditure	(3) Total Expenditure
ZMP	-788.487***	135.141	-653.346**
	(168.159)	(176.075)	(301.417)
month FE	Y	Y	Y
day-of-week FE	Y	Y	Y
wave FE	Y	Y	Y
Demographics	Y	Y	Y
Mean	2388	5054	7442
N	5637	5637	5637

Table 2.10: ZMP Impacts on Service Expenditure in Hospital A

Hospital A	(1) Inpatient and Post-Surgery Care	(2) examination	(3) surgery	(4) consumable
ZMP	350.368***	-310.832***	95.353*	312.010***
	(62.244)	(48.676)	(49.778)	(72.352)
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Mean	1269	2965	627	825
N	23263	23263	23263	23263

Table 2.11: ZMP Impacts on Service Expenditure in Hospital B

Hospital B	(1) Inpatient and Post-Surgery Care	(2) examination	(3) surgery	(4) consumable
ZMP	385.188***	-289.170***	2.348	420.216***
	(98.288)	(59.916)	(46.079)	(85.455)
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y
Mean	1317	2738	532	651
N	10474	10474	10474	10474

Table 2.12: ZMP Impacts on Service Expenditure in Hospital C

Hospital C	(1) Inpatient and Post-Surgery Care	(2) examination	(3) surgery	(4) consumable	(5) Chinese Treatment
ZMP	106.009	-307.069***	105.920**	51.562	178.719***
	(66.620)	(68.957)	(47.907)	(77.722)	(49.008)
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y
Mean	1265	2179	370	437	803
N	5637	5637	5637	5637	5637

Table 2.13: ZMP Impacts on Service Utilization in Hospital A

Hospital A	(1) duration	(2) surgery rates
ZMP	-0.537**	0.030**
	(0.25)	(0.01)
Mean	11.4	0.39
month FE	Y	Y
day-of-week FE	Y	Y
wave FE	Y	Y
Demographics	Y	Y
N	23263	23263

Table 2.14: ZMP Impacts on Service Utilization in Hospital B

Hospital B	(1) duration	(2) surgery rates
ZMP	-0.242	-0.024
	(0.34)	(0.02)
Mean	11.7	0.38
month FE	Y	Y
day-of-week FE	Y	Y
wave FE	Y	Y
Demographics	Y	Y
N	10474	10474

Table 2.15: ZMP Impacts on Service Utilization in Hospital C

Hospital C	(1) Surgery Rate	(2) Duration	(3) Chinese Treatment rate
ZMP	-0.016	-1.267**	0.085***
	(0.025)	(0.589)	(0.018)
Mean	0.41	15.7	0.81
month FE	Y	Y	Y
day-of-week FE	Y	Y	Y
wave FE	Y	Y	Y
Demographics	Y	Y	Y
N	5637	5637	5637

Table 2.16: ZMP Impacts on Medicine Expense by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	-1287.086***	-466.845*	-384.097	-586.847**	-671.583*
	(422.984)	(247.262)	(287.332)	(262.125)	(347.819)
N	3244	6484	3235	1296	2001
Mean	4711.05	3249.8	3653.8	2175.7	2983.9
	(6) J	(7) E	(8) H	(9) N	
ZMP	-741.465**	-361.797	-281.279	-501.170*	
	(363.121)	(223.071)	(213.375)	(297.772)	
N	2126	1468	1395	2014	
Mean	3865.2	2418.22	1878.216	3261.9	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

Table 2.17: ZMP Impacts on Medicine Expense by Disease Groups, Hospital B

Hospital B	(1) CD	(2) I	(3) K	(4) N	(5) S
ZMP	-658.595*	-646.827***	-859.104***	-513.803**	-547.846**
	(338.818)	(249.951)	(323.998)	(260.149)	(254.501)
N	3320	3133	1869	1085	1067
Mean	3948.7	3124.1	3561.4	2557.3	2702.3
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y

Table 2.18: ZMP Impacts on Medicine Expense by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	-1846.938	-776.191***	-677.499***	-548.155***
	(1135.050)	(238.991)	(249.177)	(103.895)
N	708	1578	1280	2071
Mean	4811.1	2611.9	2592	1208.5
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.19: ZMP Impacts on Consumable Expense by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	255.342*	391.436*	401.261***	973.985***	244.735
	(138.567)	(226.457)	(104.285)	(232.709)	(152.948)
N	3244	6484	3235	1296	2001
Mean	631.1	1276.97	690.6	601.7	561.9
	(6) J	(7) E	(8) H	(9) N	
ZMP	-35.211	392.196***	-68.085	311.048**	
	(113.403)	(117.197)	(101.441)	(134.115)	
N	2126	1468	1395	2014	
Mean	622.9	672.1	538.2	807.2	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

Table 2.20: ZMP Impacts on Consumable Expense by Disease Groups, Hospital B

Hospital B	(1) CD	(2) I	(3) K	(4) N	(5) S
ZMP	373.242***	209.584	298.090**	277.452**	1769.625***
	(118.607)	(206.764)	(116.129)	(131.498)	(378.976)
N	3320	3133	1869	1085	1067
Mean	498.7	706.1	675.5	720	847.8
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y

Table 2.21: ZMP Impacts on Consumable Expense by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	-65.702	-60.553	242.776*	11.451
	(137.420)	(241.622)	(138.835)	(34.459)
N	708	1578	1280	2071
Mean	476.4	613.5	613.8	183
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.22: ZMP Impacts on Chinese Treatment Expense by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	239.052**	180.735*	122.657**	170.414*
	(114.337)	(103.896)	(53.873)	(95.505)
N	708	1578	1280	2071
Mean	308.6	581.3	239.6	1490.2
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.23: ZMP Impacts on Length of Stay by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	-0.532	-0.591	0.056	-1.661	0.095
	(0.802)	(0.553)	(0.689)	(1.053)	(0.684)
N	3244	6484	3235	1296	2001
Mean	11.9	11.5	11.2	12.2	9.9
	(6) J	(7) E	(8) H	(9) N	
ZMP	0.182	-0.577	-0.860	-1.208*	
	(0.961)	(0.750)	(0.694)	(0.704)	
N	2126	1468	1395	2014	
Mean	13.2	11.5	10	10.8	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

Table 2.24: ZMP Impacts on Length of Stay by Disease Groups, Hospital B

Hospital B	(1) CD	(2) I	(3) K	(4) N	(5) S
ZMP	-0.669	0.277	-0.914	0.359	0.426
	(0.734)	(0.625)	(0.688)	(0.781)	(0.893)
N	3320	3133	1869	1085	1067
Mean	12.1	12.2	11.3	9.6	12.1
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y

Table 2.25: ZMP Impacts on Length of Stay by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	-5.514*	0.453	-1.466	-0.852
	(2.863)	(0.991)	(1.113)	(0.781)
N	708	1578	1280	2071
Mean	17.2	14.7	13.4	17.3
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.26: ZMP Impacts on Chinese Treatment Rates by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	0.003	0.220***	0.125**	-0.002
	(0.062)	(0.040)	(0.052)	(0.009)
N	708	1578	1280	2071
Mean	0.74	0.75	0..65	0.99
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.27: ZMP Impacts on Surgery Rate by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	0.046	0.004	0.052	0.101*	0.033
	(0.035)	(0.023)	(0.035)	(0.054)	(0.045)
N	3244	6484	3235	1296	2001
Mean	0.46	0.3	0.55	0.33	0.41
	(6) J	(7) E	(8) H	(9) N	
ZMP	0.026	0.084*	-0.016	0.014	
	(0.040)	(0.050)	(0.052)	(0.044)	
N	2126	1468	1395	2014	
Mean	0.34	0.35	0.35	0.44	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

2.8 Figures

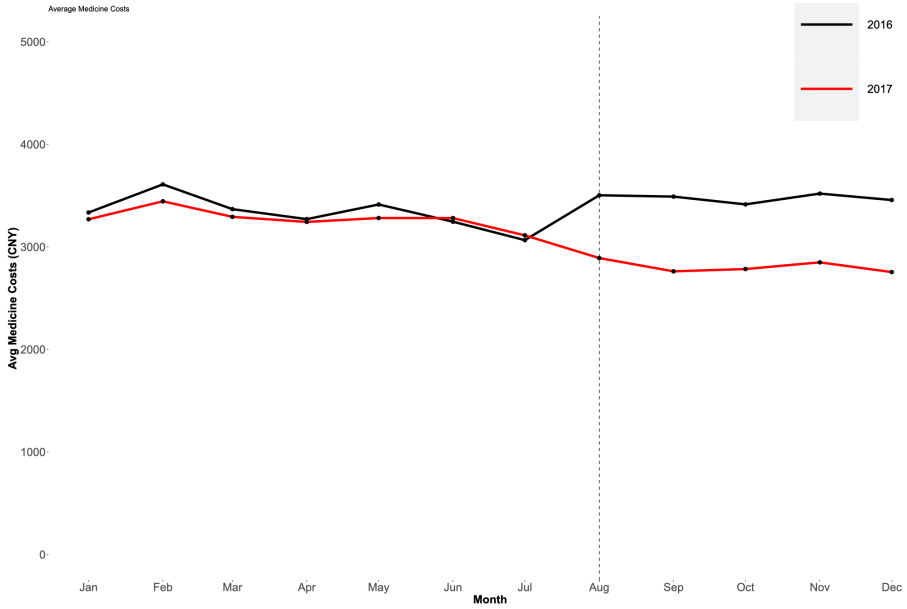

Figure 2.2: Average Medicine Expenditure in Local Currency, Hospital A

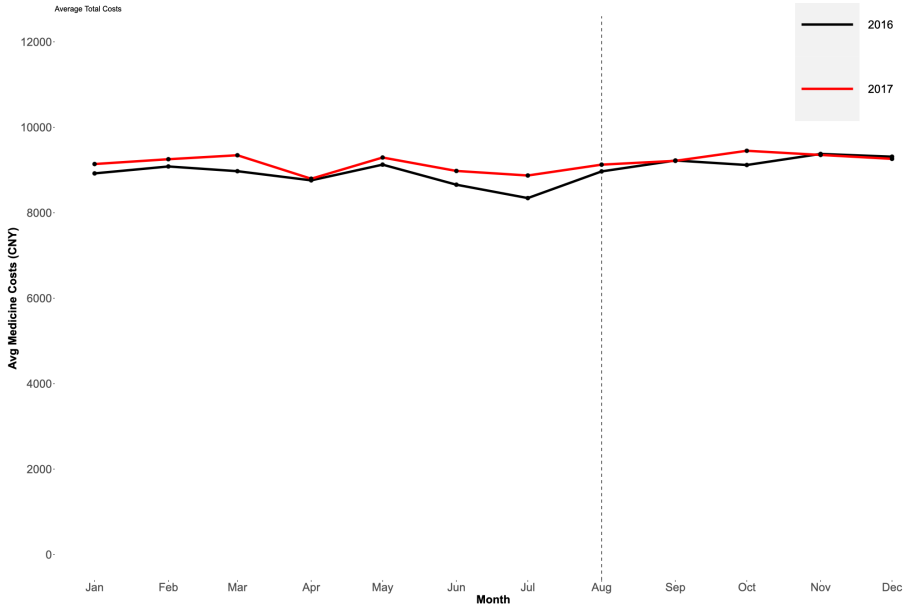

Figure 2.3: Total Medical Expenditure in Local Currency, Hospital A

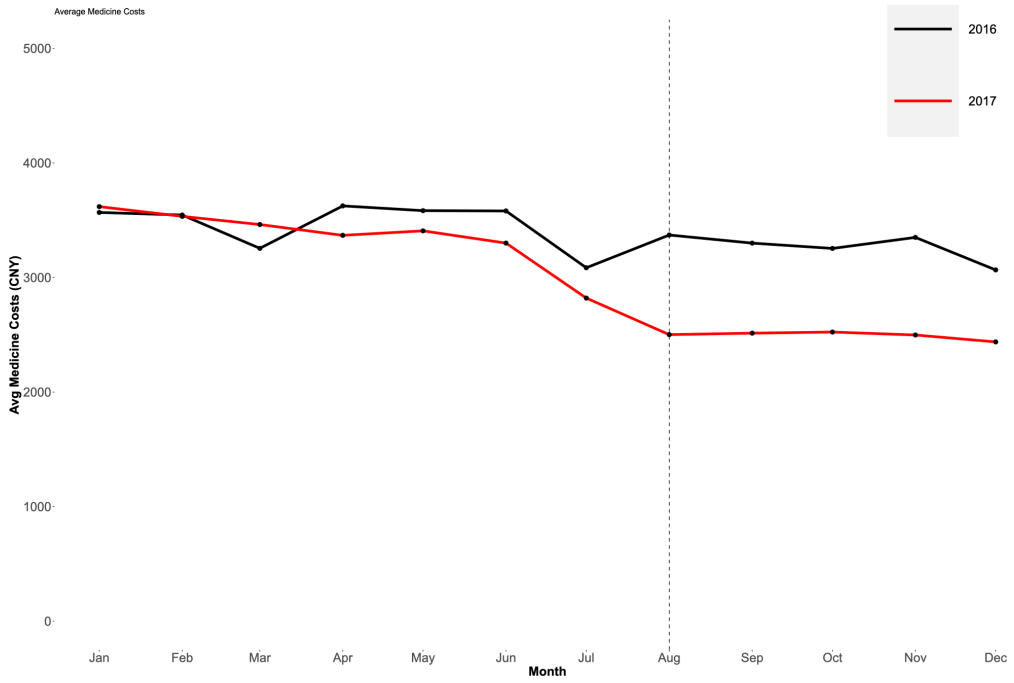

Figure 2.4: Average Medicine Expenditure in Local Currency, Hospital B

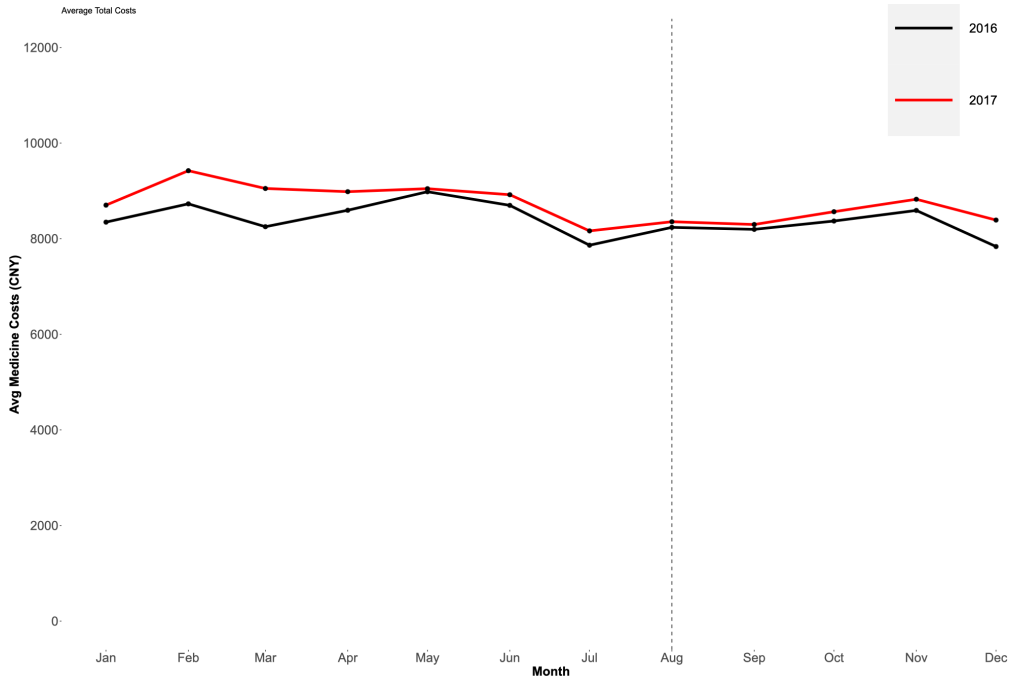

Figure 2.5: Total Medical Expenditure in Local Currency, Hospital B

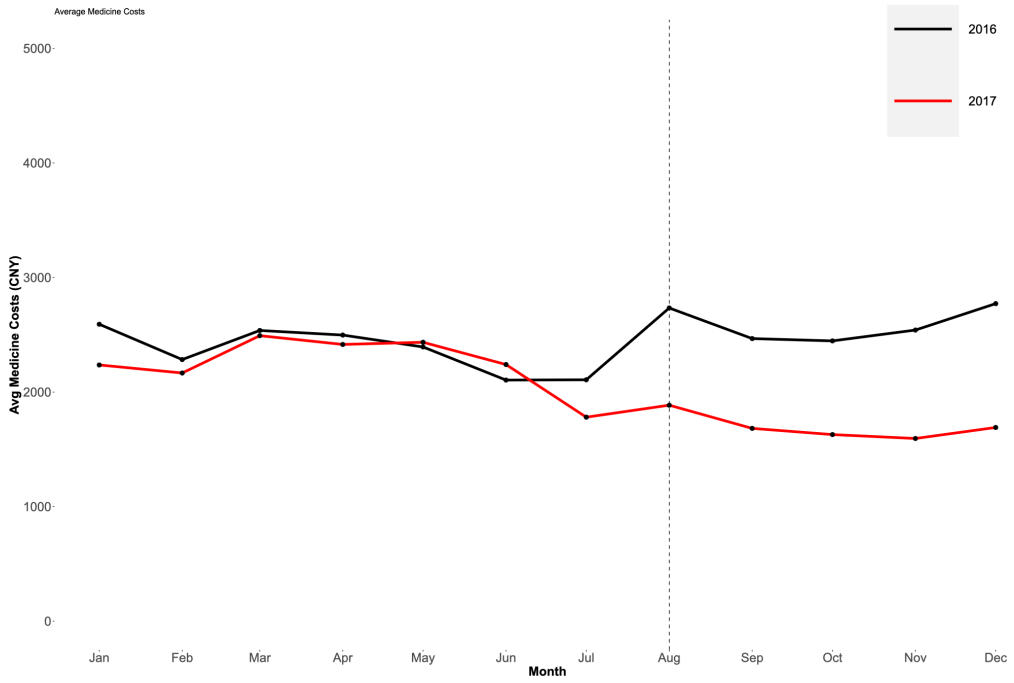

Figure 2.6: Average Medicine Expenditure in Local Currency, Hospital C

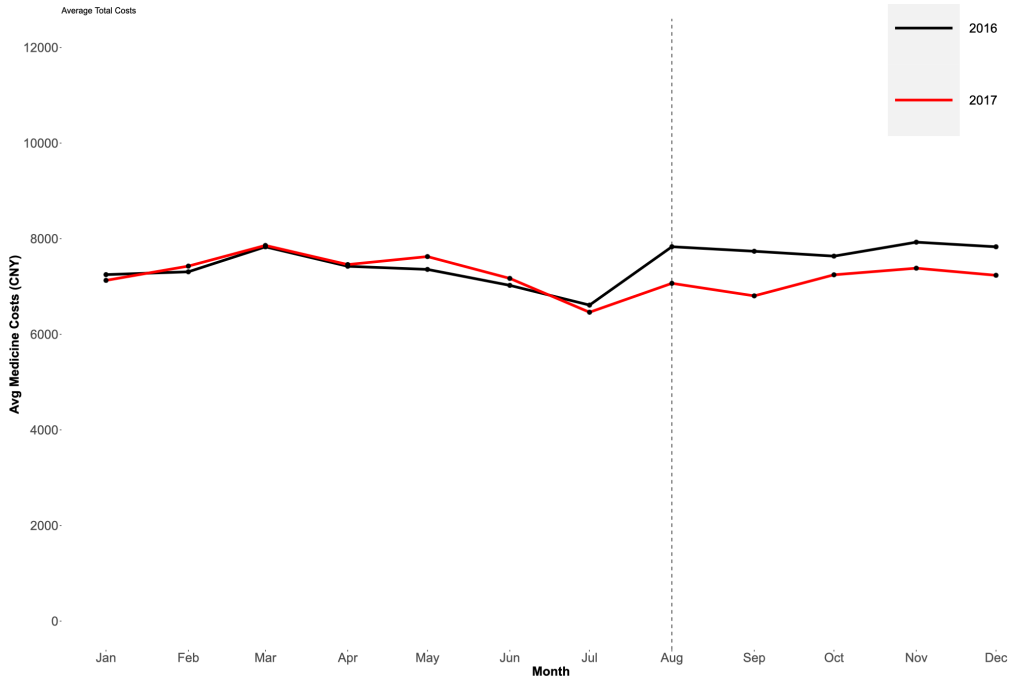

Figure 2.7: Total Medical Expenditure in Local Currency, Hospital C

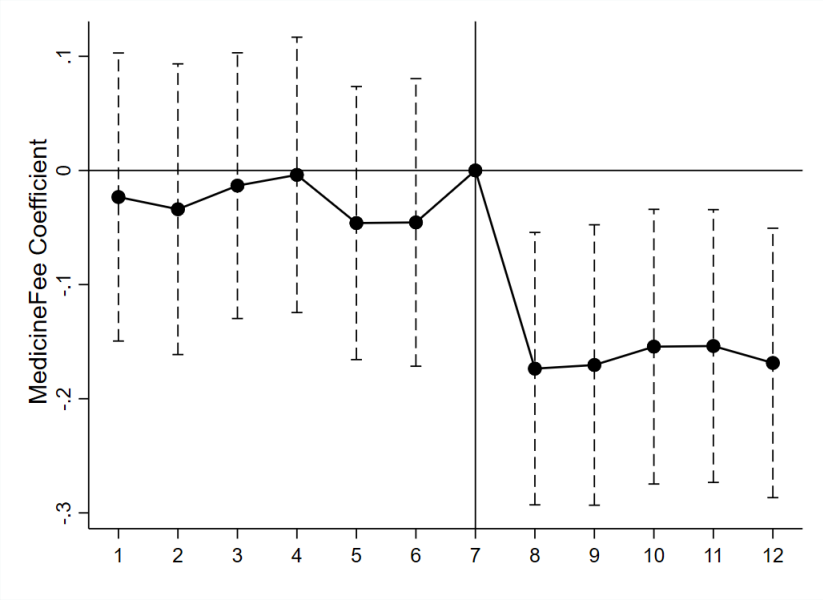

Figure 2.8: Event Study Analysis of Hospital A, ZMP Impacts on Medicine Expenditure

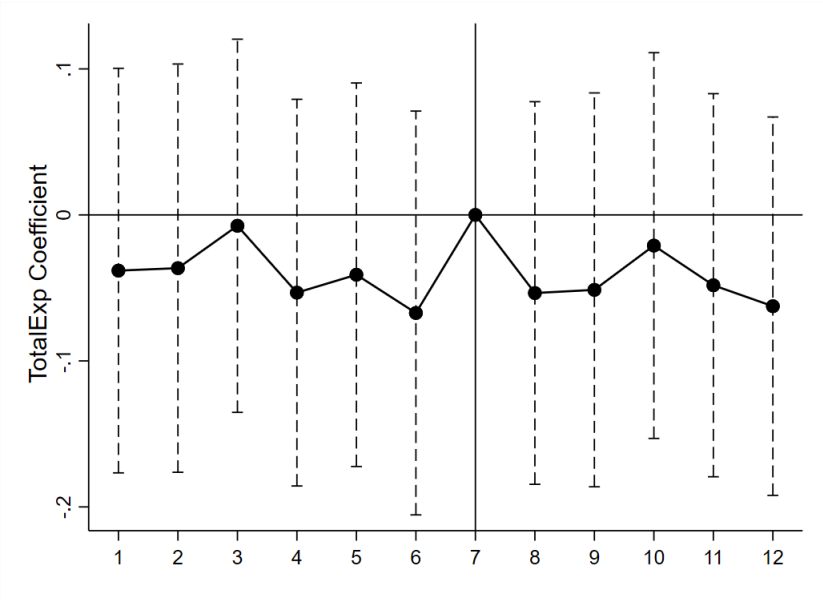

Figure 2.9: Event Study Analysis of Hospital A, ZMP Impacts on Total Expenditure

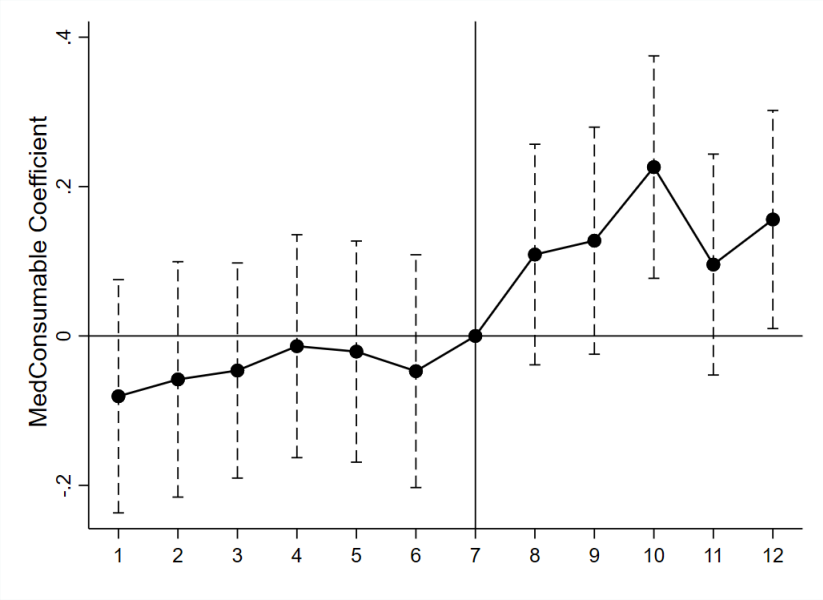

Figure 2.10: Event Study Analysis of Hospital A, ZMP Impacts on Consumable Expenditure

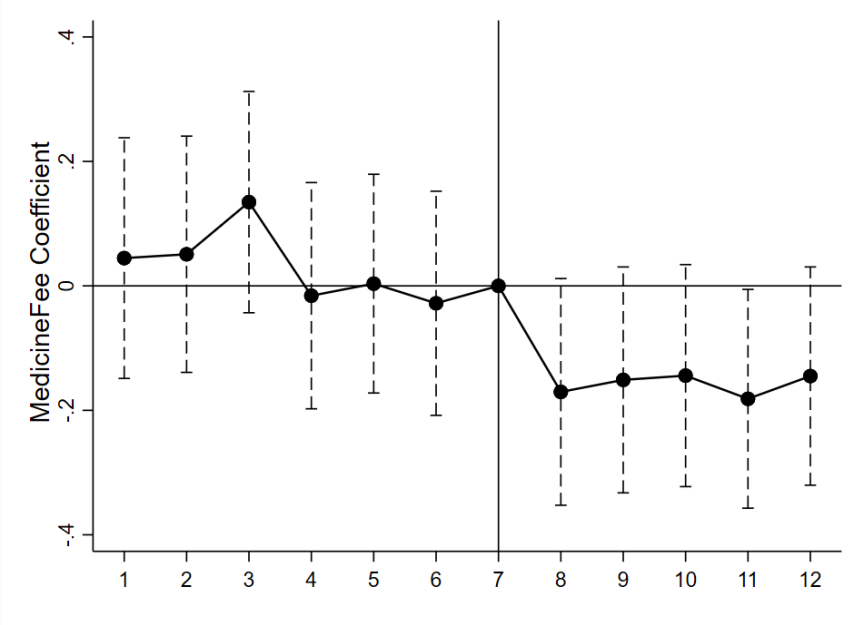

Figure 2.11: Event Study Analysis of Hospital B, ZMP Impacts on Medicine Expenditure

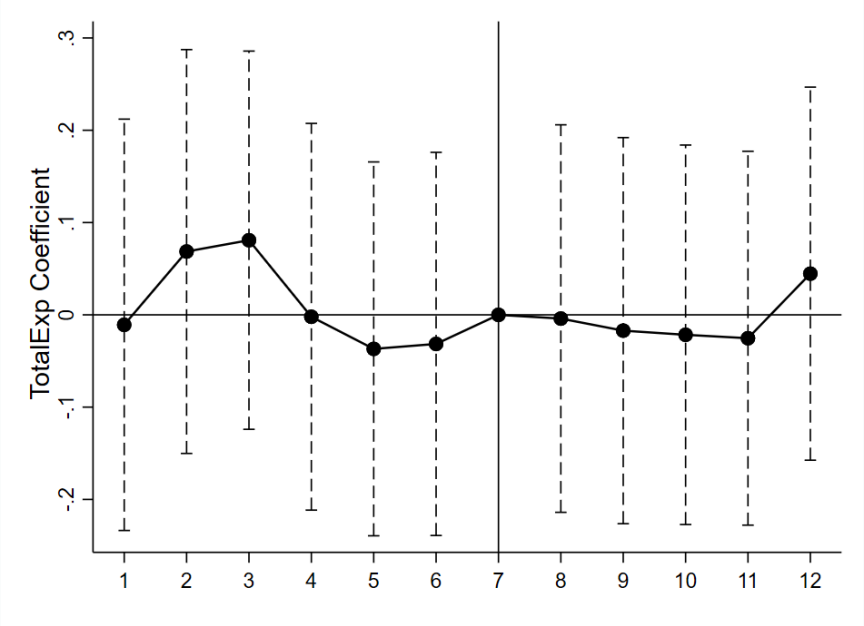

Figure 2.12: Event Study Analysis of Hospital B, ZMP Impacts on Total Expenditure

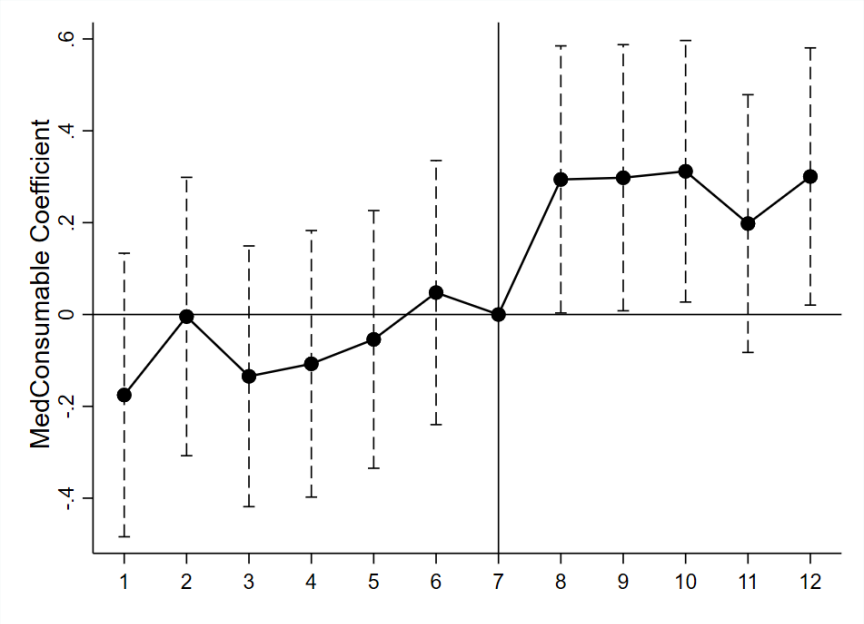

Figure 2.13: Event Study Analysis of Hospital B, ZMP Impacts on Consumable Expenditure

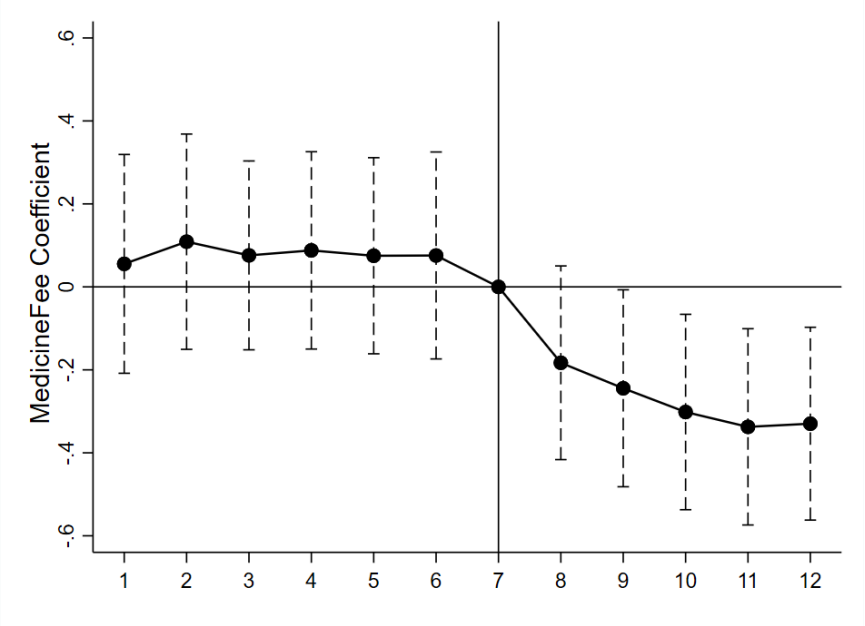

Figure 2.14: Event Study Analysis of Hospital C, ZMP Impacts on Medicine Expenditure

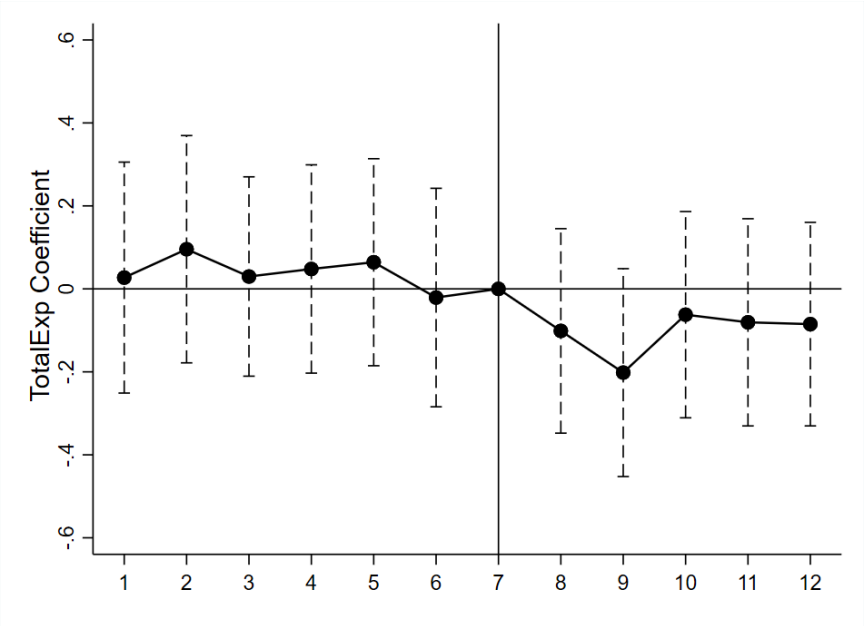

Figure 2.15: Event Study Analysis of Hospital C, ZMP Impacts on Total Expenditure

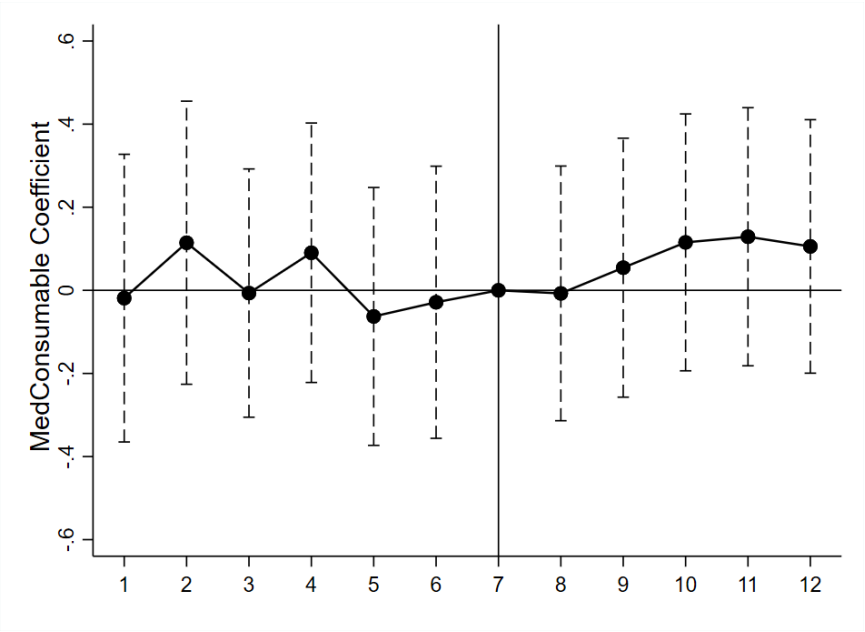

Figure 2.16: Event Study Analysis of Hospital C, ZMP Impacts on Consumable Expenditure

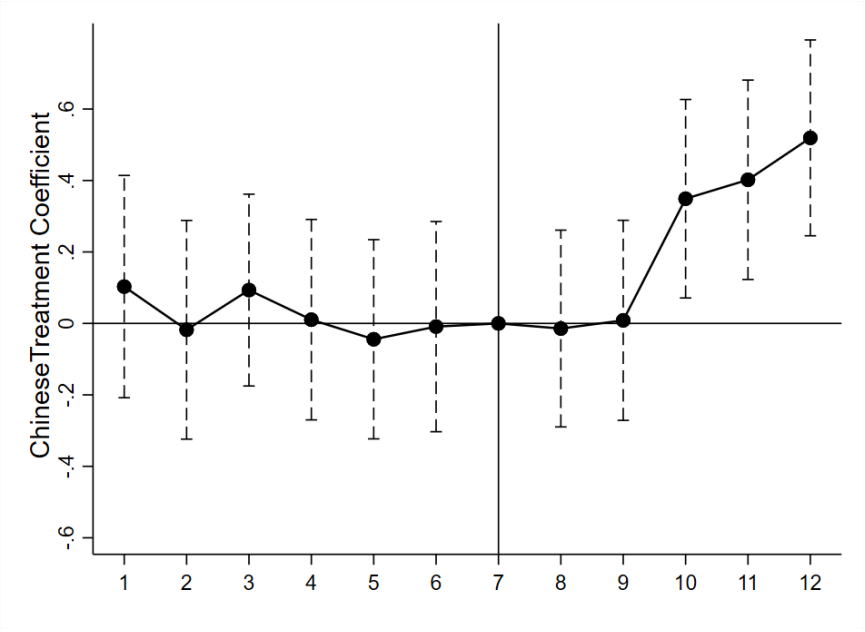

Figure 2.17: Event Study Analysis of Hospital C, ZMP Impacts on Traditional Chinese Treatment Expenditure

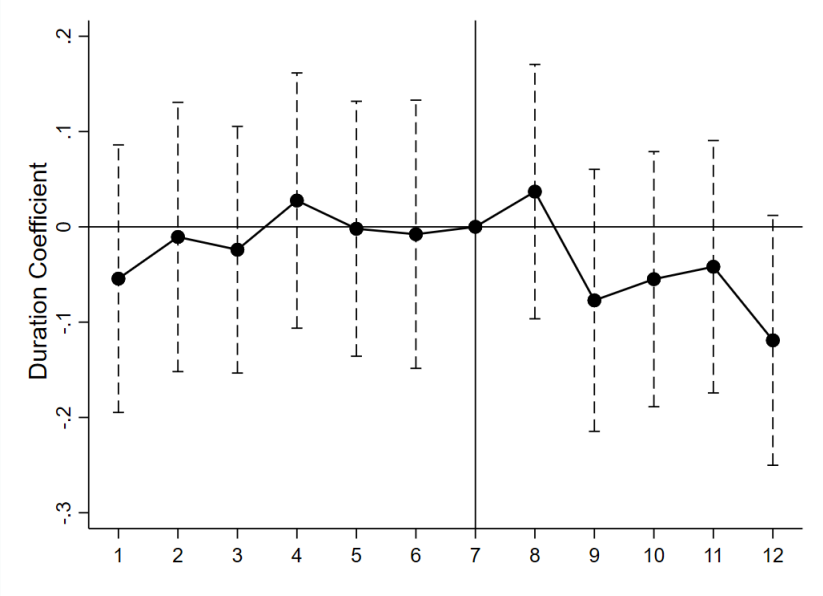

Figure 2.18: Event Study Analysis of Hospital A, ZMP Impacts on the Average Length of Stay

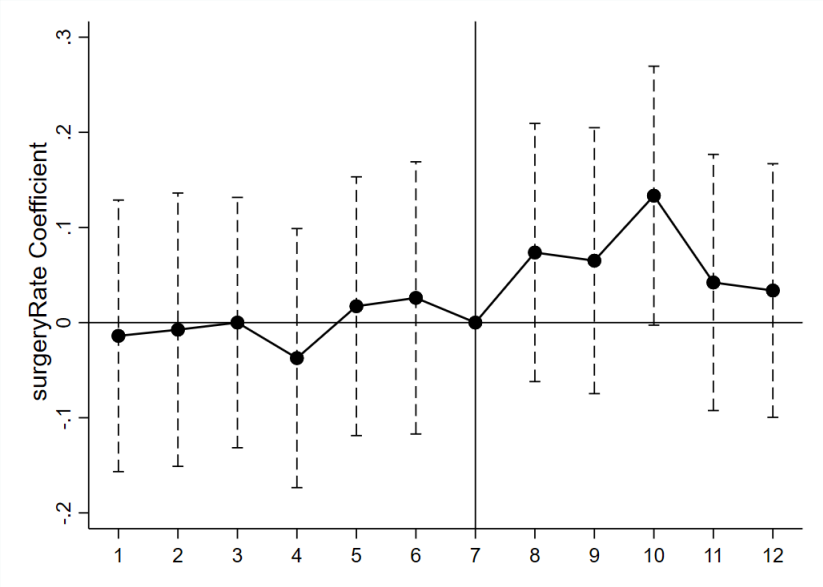

Figure 2.19: Event Study Analysis of Hospital A, ZMP Impacts on the Average Surgery Rate

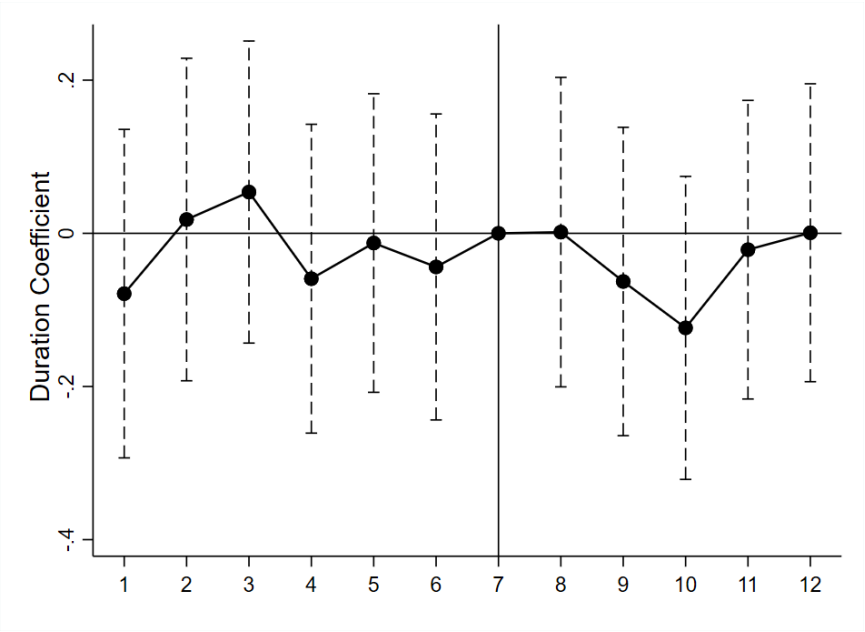

Figure 2.20: Event Study Analysis of Hospital B, ZMP Impacts on the Average Length of Stay

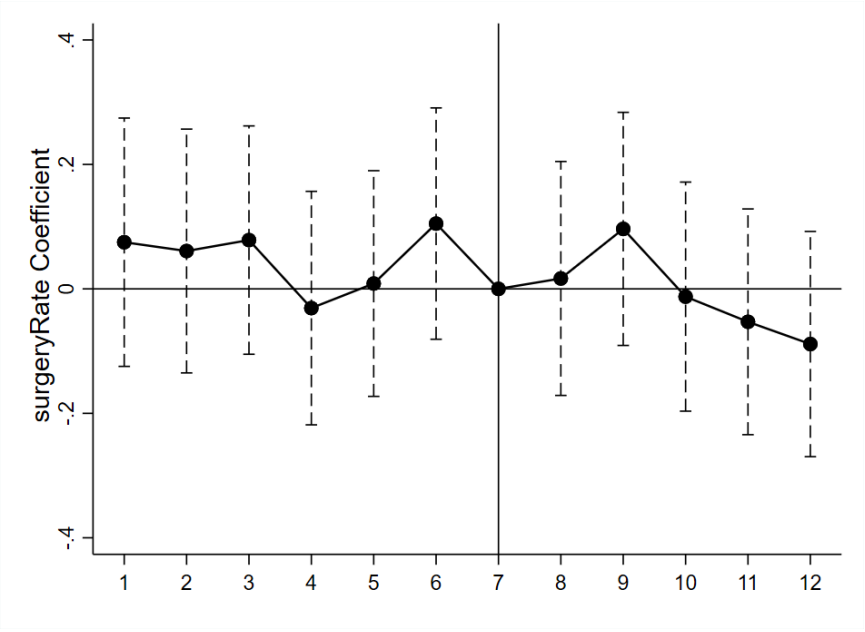

Figure 2.21: Event Study Analysis of Hospital B, ZMP Impacts on the Average Surgery Rate

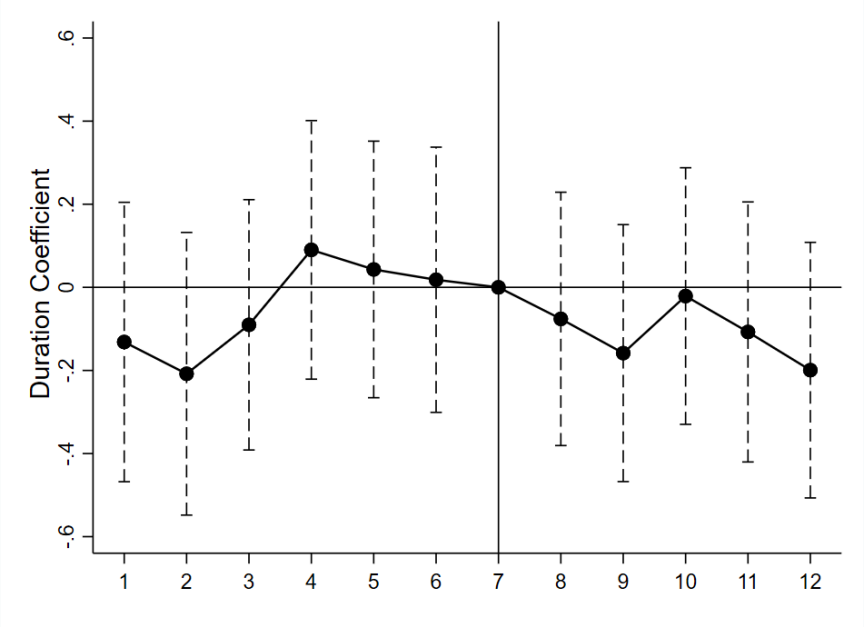

Figure 2.22: Event Study Analysis of Hospital C, ZMP Impacts on the Average Length of Stay

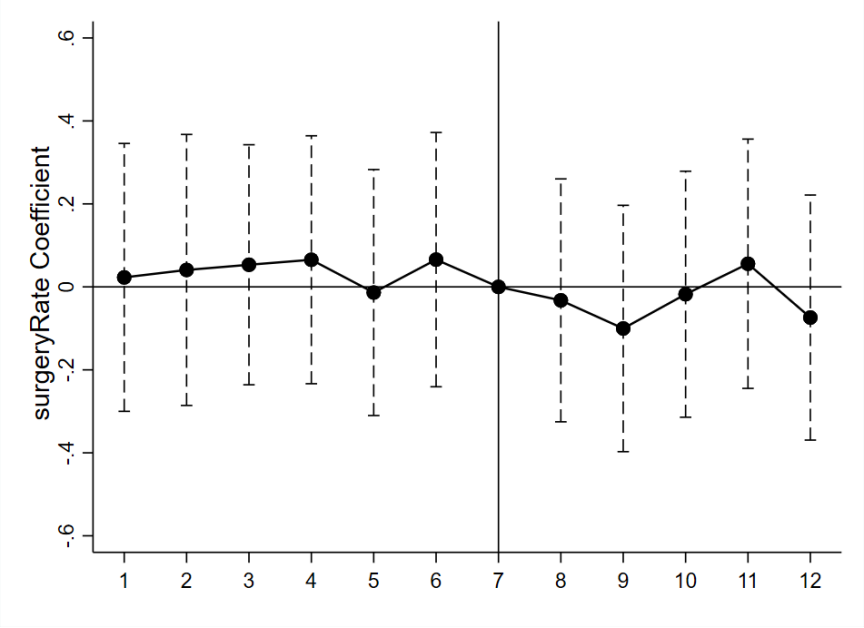

Figure 2.23: Event Study Analysis of Hospital C, ZMP Impacts on the Average Surgery Rate

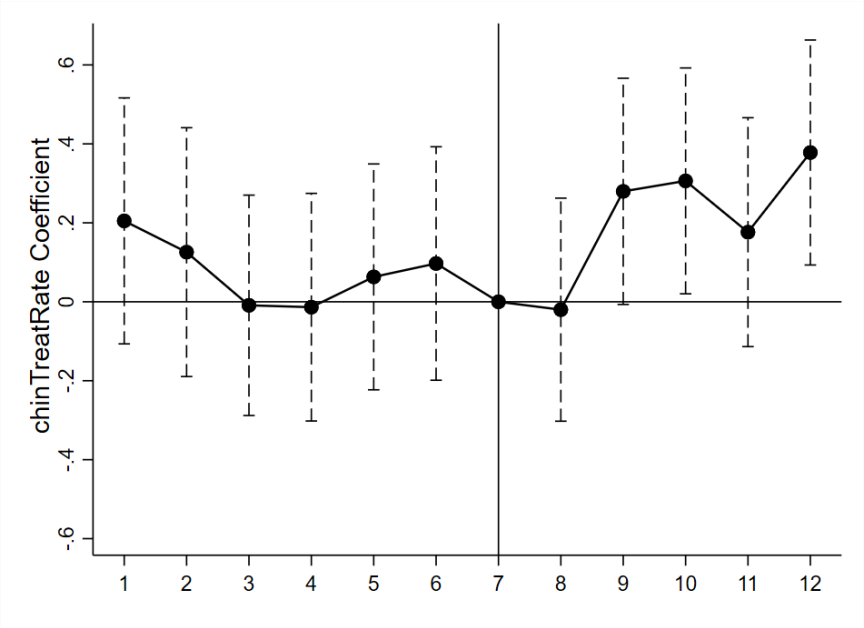

Figure 2.24: Event Study Analysis of Hospital C, ZMP Impacts on the Average Usage Rate of Traditional Chinese Treatment

2.9 Appendix

2.9.1 Disease Classification

We map each granular disease name to an ICD-10 sample which contains detailed disease names and their ICD codes consisting of letters and numbers. A code always starts with a letter followed by five digits (e.g., S01.001, S01.101). The first three characters designate the category of the diagnosis. For example, all diseases with an "S" initial represent a diagnosis related to "Injuries, poisoning and certain other consequences of external causes related to single body regions." If the second character is number 6, it indicates that the diagnosis falls into the category of "Injuries to the wrist, hand, and fingers".

Our method of classification is to first match the disease names from our data with the disease names from the ICD-10 sample. We then group the matched diseases to letter codes of ICD-10. For each disease (variable "disease sample") from our sample, we loop over the disease names in the ICD-10 sample (variable "disease ICD") and locate the ones with the most matches of Chinese characters. We choose the disease name with the most number of matched characters to be the matched disease and then link its ICD code to the matched words.

The algorithm, particularly for Chinese characters, enables groupings of the diseases into a harmonized category that can be applied systematically for the related analysis covering the local healthcare system, which information is usually too granular to be compared.

2.9.2 Additional Tables

Table 2.28: ZMP Impacts on Exam Expense by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	-247.138	-397.096***	-375.530***	-186.268	-370.841**
	(154.200)	(90.388)	(133.415)	(167.225)	(173.285)
N	3244	6484	3235	1296	2001
Mean	3072.1	3465	2679.6	2579.2	2831.4
	(6) J	(7) E	(8) H	(9) N	
ZMP	-343.077**	-632.819***	-232.039	225.805	
	(153.500)	(167.160)	(188.847)	(157.675)	
N	2126	1468	1395	2014	
Mean	2443.5	3332	2486.2	2637.1	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

Table 2.29: ZMP Impacts on Exam Expense by Disease Groups, Hospital B

Hospital B	(1) CD	(2) I	(3) K	(4) N	(5) S
ZMP	-228.936**	-558.167***	-204.935	-166.536	6.252
	(106.490)	(113.871)	(169.774)	(130.365)	(147.322)
N	3320	3133	1869	1085	1067
Mean	2546.5	3406.8	2856.1	1928.3	2069.5
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y

Table 2.30: ZMP Impacts on Exam Expense by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	-66.544	-93.780	-284.483**	-590.259***
	(262.210)	(131.805)	(136.907)	(101.413)
N	708	1578	1280	2071
Mean	2073.6	2610.1	2038.1	1976.2
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.31: ZMP Impacts on Inpatient and Post-Surgery Care Expense by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	132.209	588.561***	541.789***	252.581**	299.836**
	(142.563)	(167.330)	(122.884)	(99.743)	(133.834)
N	3244	6484	3235	1296	2001
Mean	1272.1	1356.4	1319.5	992.2	1050.4
	(6) J	(7) E	(8) H	(9) N	
ZMP	258.812	234.338**	205.313**	113.374	
	(278.317)	(101.856)	(86.610)	(129.719)	
N	2126	1468	1395	2014	
Mean	1849.8	1012.99	834.1	1182.2	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

Table 2.32: ZMP Impacts on Inpatient and Post-Surgery Care Expense by Disease Groups, Hospital B

Hospital B	(1) CD	(2) I	(3) K	(4) N	(5) S
ZMP	308.326*	736.294***	161.160	201.863*	377.921***
	(162.084)	(263.155)	(134.766)	(120.424)	(120.701)
N	3320	3133	1869	1085	1067
Mean	1387	1339.4	1319.4	1094.2	1269.6
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y

Table 2.33: ZMP Impacts on Inpatient and Post-Surgery Care Expense by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	-125.893	404.369***	66.122	-26.042
	(351.139)	(140.431)	(101.243)	(61.174)
N	708	1578	1280	2071
Mean	1855	1209.4	1124.8	1175.9
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Table 2.34: ZMP Impacts on Surgery Expense by Disease Groups, Hospital A

Hospital A	(1) CD	(2) I	(3) K	(4) M	(5) R
ZMP	288.297**	-153.537	219.908	155.838	42.168
	(146.754)	(93.867)	(137.153)	(361.468)	(136.852)
N	3244	6484	3235	1296	2001
Mean	730.3	283.4	1018.7	1125.8	593.1
	(6) J	(7) E	(8) H	(9) N	
ZMP	1.754	334.624*	37.193	357.399**	
	(116.102)	(174.443)	(140.918)	(147.639)	
N	2126	1468	1395	2014	
Mean	449.5	729.6	463.6	870.5	
month FE	Y	Y	Y	Y	
day-of-week FE	Y	Y	Y	Y	
wave FE	Y	Y	Y	Y	
Demographics	Y	Y	Y	Y	

Table 2.35: ZMP Impacts on Surgery Expense by Disease Groups, Hospital B

Hospital B	(1) CD	(2) I	(3) K	(4) N	(5) S
ZMP	-10.607	46.908	-26.451	313.804*	4.535
	(75.031)	(31.785)	(137.251)	(186.084)	(220.756)
N	3320	3133	1869	1085	1067
Mean	846.7	1156.5	1077.2	498.7	706.1
month FE	Y	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y	Y
wave FE	Y	Y	Y	Y	Y
Demographics	Y	Y	Y	Y	Y

Table 2.36: ZMP Impacts on Surgery Expense by Disease Groups, Hospital C

Hospital C	(1) CD	(2) I	(3) K	(4) M
ZMP	121.080	63.510	272.274***	-13.268
	(132.583)	(51.932)	(92.050)	(102.269)
N	708	1578	1280	2071
Mean	480	126.8	716.9	305.1
month FE	Y	Y	Y	Y
day-of-week FE	Y	Y	Y	Y
wave FE	Y	Y	Y	Y
Demographics	Y	Y	Y	Y

Bibliography

Ackerberg, Daniel A. and Marc Rysman (2005). "Unobserved Product Differentiation in Discrete-Choice Models: Estimating Price Elasticities and Welfare Effects". In: *RAND Journal of Economics* 36.4, pp. 771–788.

Alexander, Diane (2020). "How do doctors respond to incentives? unintended consequences of paying doctors to reduce costs". In: *Journal of Political Economy* 128.11, pp. 4046–4096.

Anderson, Simon P and André de Palma (2021). "Economic distributions, primitive distributions, and demand recovery in monopolistic competition". In.

Andrews, Donald WK (1997). "A conditional Kolmogorov test". In: *Econometrica: Journal of the Econometric Society*, pp. 1097–1128.

Arozamena, Leandro and Federico Weinschelbaum (2009). "Simultaneous vs. sequential price competition with incomplete information". In: *Economics Letters* 104.1, pp. 23–26.

Arrow, Kenneth J (1965). "Uncertainty and the welfare economics of medical care: reply (the implications of transaction costs and adjustment lags)". In: *The American economic review* 55.1/2, pp. 154–158.

Athey, Susan, Jonathan Levin, and Enrique Seira (2011). "Comparing open and sealed bid auctions: Evidence from timber auctions". In: *The Quarterly Journal of Economics* 126.1, pp. 207–257.

Berry, Steven T (1994). "Estimating discrete-choice models of product differentiation". In: *The RAND Journal of Economics*, pp. 242–262.

Bjornerstedt, Jonas and Frank Verboven (2016). "Does merger simulation work? Evidence from the Swedish analgesics market". In: *American Economic Journal: Applied Economics* 8.3, pp. 125–64.

Cabral, Marika, Michael Geruso, and Neale Mahoney (2018). "Do larger health insurance subsidies benefit patients or producers? Evidence from Medicare Advantage". In: *American Economic Review* 108.8, pp. 2048–87.

Chen, Chun et al. (2014). "Is the prescribing behavior of Chinese physicians driven by financial incentives?" In: *Social Science & Medicine* 120, pp. 40–48.

Currie, Janet, Wanchuan Lin, and Juanjuan Meng (2014). "Addressing antibiotic abuse in China: an experimental audit study". In: *Journal of development economics* 110, pp. 39–51.

Currie, Janet, Wanchuan Lin, and Wei Zhang (2011). "Patient knowledge and antibiotic abuse: Evidence from an audit study in China". In: *Journal of health economics* 30.5, pp. 933–949.

Curto, Vilsa et al. (2021). "Can health insurance competition work? evidence from medicare advantage". In: *Journal of Political Economy* 129.2, pp. 570–606.

Dafny, Leemore S (2005). "How do hospitals respond to price changes?" In: *American Economic Review* 95.5, pp. 1525–1547.

Danzon, Patricia M, Y Richard Wang, and Liang Wang (2005). "The impact of price regulation on the launch delay of new drugs—evidence from twenty-five major markets in the 1990s". In: *Health economics* 14.3, pp. 269–292.

Ding, Hui, Mark Duggan, and Amanda Starc (2021). *Getting the Price Right? The Impact of Competitive Bidding in the Medicare Program*. Tech. rep. National Bureau of Economic Research.

Donald, Stephen G and Harry J Paarsch (1993). "Piecewise pseudo-maximum likelihood estimation in empirical models of auctions". In: *International Economic Review*, pp. 121–148.

— (1996). "Identification, estimation, and testing in parametric empirical models of auctions within the independent private values paradigm". In: *Econometric Theory* 12.3, pp. 517–567.

Du, Wei (2012). *Zhuanxingzhongguo: fangzhiyao fazhan jiangchongsu shichang geju*.

Dubois, Pierre, Ashvin Gandhi, and Shoshana Vasserman (2019). *Bargaining and international reference pricing in the pharmaceutical industry*. Tech. rep. Technical report.

Dubois, Pierre and Laura Lasio (2018). "Identifying Industry Margins with Price Constraints: Structural Estimation on Pharmaceuticals". In: *American Economic Review* 108.12, pp. 3685–3724.

Duggan, Mark and Fiona M Scott Morton (2006). "The distortionary effects of government procurement: evidence from Medicaid prescription drug purchasing". In: *The Quarterly Journal of Economics* 121.1, pp. 1–30.

Fang, Hanming and Qing Gong (2017). "Detecting potential overbilling in medicare reimbursement via hours worked". In: *American Economic Review* 107.2, pp. 562–591.

Fang, Hanming, Xiaoyan Lei, et al. (2021). *Physician-induced demand: Evidence from China's drug price zero-markup policy*. Tech. rep. National Bureau of Economic Research.

Feng, Josh, Thomas Hwang, and Luca Maini (2021). "Profiting from most-favored customer procurement rules: Evidence from medicaid". In: *American Economic Journal: Economic Policy, forthcoming*.

Finkelstein, Amy, Sarah Taubman, Bill Wright, et al. (2012). "The Oregon health insurance experiment: evidence from the first year". In: *The Quarterly journal of economics* 127.3, pp. 1057–1106.

Finkelstein, Amy N, Sarah L Taubman, Heidi L Allen, et al. (2016). "Effect of Medicaid coverage on ED use—further evidence from Oregon's experiment". In.

Fu, Hongqiao, Ling Li, and Winnie Yip (2018). "Intended and unintended impacts of price changes for drugs and medical services: evidence from China". In: *Social science & medicine* 211, pp. 114–122.

Gentry, Matthew and Tong Li (2014). "Identification in auctions with selective entry". In: *Econometrica* 82.1, pp. 315–344.

Goldberg, Pinelopi Koujianou (1995). "Product differentiation and oligopoly in international markets: The case of the US automobile industry". In: *Econometrica: Journal of the Econometric Society*, pp. 891–951.

Gruber, Jon, John Kim, and Dina Mayzlin (1999). "Physician fees and procedure intensity: the case of cesarean delivery". In: *Journal of health economics* 18.4, pp. 473–490.

Gruber, Jonathan and Maria Owings (1994). *Physician financial incentives and cesarean section delivery*.

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong (2000). "Optimal nonparametric estimation of first-price auctions". In: *Econometrica* 68.3, pp. 525–574.

Hall, Robert E and Charles I Jones (2007). "The value of life and the rise in health spending". In: *The quarterly journal of economics* 122.1, pp. 39–72.

Hansen, Robert G (1988). "Auctions with endogenous quantity". In: *The RAND Journal of Economics*, pp. 44–58.

Ho, Kate and Ariel Pakes (2014). "Hospital choices, hospital prices, and financial incentives to physicians". In: *American Economic Review* 104.12, pp. 3841–3884.

Ji, Yunan (2019). *The Impact of Competitive Bidding in Health Care: The Case of Medicare Durable Medical Equipment*.

Jofre-Bonet, Mireia and Martin Pesendorfer (2003). "Estimation of a dynamic auction game". In: *Econometrica* 71.5, pp. 1443–1489.

Levin, Dan and James L Smith (1994). "Equilibrium in auctions with entry". In: *The American Economic Review*, pp. 585–599.

Li, Tong and Xiaoyong Zheng (2009). "Entry and competition effects in first-price auctions: Theory and evidence from procurement auctions". In: *The Review of Economic Studies* 76.4, pp. 1397–1429.

Li, Tong and Xiaoyong Zheng (2012). "Information acquisition and/or bid preparation: A structural analysis of entry and bidding in timber sale auctions". In: *Journal of Econometrics* 168.1, pp. 29–46.

Li, Yongbin, Jing Xu, et al. (2012). "Overprescribing in China, driven by financial incentives, results in very high use of antibiotics, injections, and corticosteroids". In: *Health affairs* 31.5, pp. 1075–1082.

Lu, Fangwen (2014). "Insurance coverage and agency problems in doctor prescriptions: evidence from a field experiment in China". In: *Journal of Development Economics* 106, pp. 156–167.

Maini, Luca and Fabio Pammolli (2021). "Reference pricing as a deterrent to entry: Evidence from the European pharmaceutical market". In: *AMERICAN ECONOMIC JOURNAL: MICROECONOMICS (FORTHCOMING)*.

Miller, Amalia R, Carmit Segal, and Melissa K Spencer (2022). "Effects of COVID-19 shutdowns on domestic violence in US cities". In: *Journal of urban economics* 131, p. 103476.

Newhouse, Joseph P., Rand Corporation. Insurance Experiment Group, and Insurance Experiment Group Staff (1993). *Free for all?: lessons from the RAND health insurance experiment*. Harvard University Press.

Paarsch, Harry J (1992). "Deciding between the common and private value paradigms in empirical models of auctions". In: *Journal of econometrics* 51.1-2, pp. 191–215.

— (1997). "Deriving an estimate of the optimal reserve price: an application to British Columbian timber sales". In: *Journal of Econometrics* 78.2, pp. 333–357.

Salter, Marie (2014). "Reference pricing: an effective model for the US pharmaceutical industry". In: *Nw. J. Int'l L. & Bus.* 35, p. 413.

Samuelson, William F (1985). "Competitive bidding with entry costs". In: *Economics letters* 17.1-2, pp. 53–57.

Scott Morton, Fiona (1996). *The strategic response by pharmaceutical firms to the Medicaid most-favored-customer rules*.

Song, Zirui, Mary Beth Landrum, and Michael E Chernew (2012). "Competitive bidding in Medicare: who benefits from competition?" In: *The American journal of managed care* 18.9, p. 546.

— (2013). "Competitive bidding in Medicare Advantage: Effect of benchmark changes on plan bids". In: *Journal of health economics* 32.6, pp. 1301–1312.

Spulber, Daniel F (1995). "Bertrand competition when rivals' costs are unknown". In: *The Journal of Industrial Economics*, pp. 1–11.

Taubman, Sarah L et al. (2014). "Medicaid increases emergency-department use: evidence from Oregon's Health Insurance Experiment". In: *Science* 343.6168, pp. 263–268.

White, Halbert (1982). "Maximum likelihood estimation of misspecified models". In: *Econometrica: Journal of the econometric society*, pp. 1–25.

Wu, Jiafeng (2022). "Price and Efficiency in a Market for Generic Drugs in China". In.

Xiang, Jia (2021). "Physicians as Persuaders: Evidence from Hospitals in China". In: *Available at SSRN 3906909*.

Yip, Winnie (1998). "Physician response to Medicare fee reductions: changes in the volume of coronary artery bypass graft (CABG) surgeries in the Medicare and private sectors". In: *Journal of health economics* 17.6, pp. 675–699.

Yip, Winnie and William C Hsiao (2008). "The Chinese health system at a crossroads". In: *Health affairs* 27.2, pp. 460–468.

Yip, Winnie Chi-Man, William Hsiao, Qingyue Meng, et al. (2010). "Realignment of incentives for health-care providers in China". In: *The Lancet* 375.9720, pp. 1120–1130.

Yip, Winnie Chi-Man, William C Hsiao, Wen Chen, et al. (2012). "Early appraisal of China's huge and complex health-care reforms". In: *The Lancet* 379.9818, pp. 833–842.