Examining the Zero-Markup Drug Policy in China: A Structural Approach

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Abstract

This paper estimates a structural model of China's prescription drug market and quantifies the impact of the "Zero-Markup Drug Policy" on the profitability of hospital drugs and patient welfare. Results suggest that: physicians' prescription choices are sensitive to both patients' out-of-pocket costs and hospitals' drug markups; drug pricing is largely dominated by provincial governments; branded drugs are more preferable and less price elastic than generic ones; the policy accounts for more than half of the decrease in average wholesale price; overall the policy improves patient welfare, and decreases the sales and profits of hospital drugs.

JEL Classification: I11, I18, L11, L13, L22, L51, L65.

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1 Introduction

Policymakers around the world have been regulating their pharmaceutical industries for decades to keep drugs and health care affordable, and China is not an exception. In the past decade, there have been a series of important regulatory changes in China's pharmaceutical industry, affecting pricing decisions of firms and drug choices of hospitals, physicians, and patients. One influential reform is the "Zero-Markup Drug Policy" (ZMDP), which requires that hospitals (and therefore physicians) cannot profit from dispensing drugs. Physician prescribing and dispensing is common in Asia and is a standard practice in the United States for infused drugs, including cancer and dialysis drugs. For example, Medicare pays physicians a markup of 6 percent for infused drugs. Also, according to IQVIA's report, China is the second largest in sales across the globe, making it an important market for drugs.[1] Thus, investigating the impact of ZMDP has important implications for policy discussions both in China and other countries.

Previous work has documented some aggregate effects of the policy on equilibrium outcomes such as drug prices and quantities (see the literature review at the end of this section), but little is known about its underlying mechanisms and distributional effects, e.g., how it changes physician choices, firm profitability, and consumer welfare. This paper tries to fill the void by estimating a structural model of China's pharmaceutical industry and quantifying the impacts on different parties in the market using counterfactual simulations.

One important feature of the demand for drugs is that there is an "expert-client" relationship such that a physician acts as a patient's agent. This naturally generates agency problems as physicians concern both hospitals' profit from selling drugs and patients' welfare.[2] Since the 1950s, due to the lack of funding, the Chinese govern-

[1] For more details, visit https://www.iqvia.com/insights/the-iqvia-institute/reports/the-global-use-of-medicines-2023.

[2] The integration between drug prescription and dispensation has a long history in China, dating back to the Eastern Han Dynasty. Inspired by Zhang Zhongjing (A.D. 150–219), Chinese physicians started to "sit" in the pharmacies to provide services as *zuotangyi* (on-site physicians). It cultivated the partnership of physicians and drug sellers. Sometimes, physicians may even open pharmacies themselves, known as *langzhong*. With the rapid transformation of the pharmaceutical

ment explicitly allowed public hospitals to add a 15 percent markup to the wholesale prices of drugs when selling them to patients. Part of hospitals' profit became physicians' income. Consequently, physicians had been taking drug markups into account when making drug choices for or with patients by deliberately prescribing more and expensive drugs. Although agency problems were somewhat restricted by the 15 percent markup itself and a price upper limit regulation, these pricing constraints are not stringent enough to eliminate "distortions" in physicians' prescription decisions. To mitigate this incentive problem, in July 2012, China started the ZMDP in urban (prefecture-level) public hospitals. This policy was then implemented nationwide in 2017.[3]

Eliminating hospitals' drug markups may affect drug retail prices either positively or negatively. If wholesale prices are fixed, it would directly lower retail prices. But it also alters relative prices and physicians' incentives. On the one hand, it makes the relatively less expensive (e.g., generic drugs) more attractive than before, which might increase the market power of generic drugs relative to branded ones and boost their prices. On the other hand, removing markups also makes physicians less likely to prescribe in general (such as encouraging patients to go on a healthy diet instead), so the overall market power of prescription drugs decreases, which might lead to lower prices. Through these mechanisms, the ZMDP is likely to affect branded and generic drugs differently, which leads to an ambiguous total effect. The policy effects on prices translate into those on manufactures' profitability, patient welfare, etc., and quantifying these different aspects is the main goal of this paper.

To single out the effect of ZMDP from those of other policy changes that happen around the same time, we develop a structural model of demand and supply of China's pharmaceutical market and use it to quantify the impact of ZMDP. We estimate the model using nationwide data on drug sales and observed binding constraints on the prices of lipid-lowering drugs, an important market that can potentially affect every household in China. Lipid-lowering drugs has a huge market not only in China but also in the world. According to WHO, the global prevalence of raised total

and healthcare systems in Mao Era, on-site physicians flooded in public hospitals as employees.

[3]The pilot reform was launched earlier for county-level or township hospitals. But due to the lack of detailed nationwide data, in this research, we focus on urban (prefecture-level) public hospitals. For the effects of pilot reform within a sample county, see Fang et al. (2021).

cholesterol among adults was 39 percent.[4] IQVIA suggests that the global revenue of lipid regulators can reach 23 billion US dollars by 2026, which is one of the top 20 therapy areas in 2026 in terms of global spending.[5] After estimating the structural parameters in the model, we simulate the counterfactual equilibrium outcome in the absence of ZMDP. The comparison between the actual and counterfactual market outcomes gives us a quantitative account of the impact of ZMDP.

Our first step is to estimate the demand system for differentiated lipid-lowering drugs. Following the standard approach in empirical IO (Berry, 1994; Berry et al., 1995; Iizuka, 2007; Berry and Jia, 2010), we set up a two-type mixed nested logit model of the joint preference of a physician-patient pair, where the mixture captures the unobserved heterogeneity due to our partial observation on whether a hospital is subject to the ZMDP. We find that physicians care about both patient welfare and hospitals' profits from drugs, and put more weight on the former for commonly implemented coinsurance rates for drugs.

Once we have obtained demand estimates and the substitution patterns among drugs, we estimate a supply side model in which competing drug manufacturers simultaneously negotiate with the provincial government about wholesale prices in a Nash bargaining game (Horn and Wolinsky, 1988; Crawford and Yurukoglu, 2012; Grennan, 2013; Gowrisankaran et al., 2015; Ho and Lee, 2017; Dubois et al., 2022) given the observed price constraints imposed by regulation. The model allows us to separately identify costs and bargaining parameters, the latter of which captures how the provincial policymakers in China trade off between firm profits and patients' welfare at province level.

Finally, given the estimated parameters of preference, production cost, and bargaining power, we can quantify how much the observed decline in China's prescription drug prices can be explained by ZMDP using counterfactual simulations. In particular, we calculate the new equilibrium prices in a hypothetical scenario in which ZMDP was not implemented. Then the market shares, revenues, profits and social welfare under our counterfactual scenario are compared to those under the actual situation.

[4]See https://www.who.int/data/gho/indicator-metadata-registry/imr-details/3236.

[5]For more details, visit https://www.iqvia.com/insights/the-iqvia-institute/reports/the-global-use-of-medicines-2022.

We find that, 54 percent of the price drop from 2012 to 2018 can be attributed to the ZMDP.

Our results have a few implications. First, given that physicians' prescription choices might be influenced by drug markups, medical burden of patients might be lowered if policymakers reduce either coinsurance rate or drug markup or both. Second, pricing is mostly dominated by provincial governments based on our estimated bargaining power, and thus profitability of firms could be impacted greatly when the main policy goal is reducing drug prices. Third, branded drugs are more preferred than generic drugs in China, and the demand elasticity for generic drugs is about 23 percent more elastic than branded drugs on average, suggesting a higher market power of the latter. Fourth, the ZMDP makes popular generic drugs relatively more favorable, and increases their market concentration. Last, overall drug demand are weakened by the ZMDP (mainly due to the reduction of physician-induced demand), but due to the reduced prices, overall patient welfare is improved by a sizable amount.

1.1 Related Literature

Our work is related to several strands of literature. First, it builds upon the broad research agenda on estimating demand for pharmaceuticals using various methods to estimate preferences for drugs and substitution patterns, from the log-log models (Berndt et al., 1995) to the discrete choice models such as logit (Berndt et al., 2003), nested logit (Iizuka, 2007; Donohue and Berndt, 2013; Song et al., 2017), and random coefficient logit (Björnerstedt and Verboven, 2016; Dubois and Lasio, 2018; Dubois et al., 2022).

Second, it relates to the research on physicians' financial incentives and physician-induced demand (Dranove, 1988; Gruber et al., 1999; Dafny, 2005; Clemens and Gottlieb, 2014; Dickstein, 2017; Fang et al., 2021). It is shown that physicians play an important role in prescription (Hellerstein, 1998). Agency problems arise such as over-prescription behaviors (Lu, 2014). The demand model in our paper is similar to that of Iizuka (2007), who models the role of physician in a reduced-form way and shows that Japanese physicians' prescription decisions respond to drug markups when diagnoses and drug sales are integrated. Besides these papers, there are several

studies on physicians' behavior beyond prescription, such as referral decisions (Ho and Pakes, 2014), and the substitution between drugs and other types of medical care, e.g., inpatient care (Yi et al., 2015) and tests and examinations (Fang et al., 2021). We shall discuss how our results connect to these studies in the conclusion.

Third, our paper belongs to the literature on the program evaluation of China's healthcare reforms such as the ZMDP (Zhou et al., 2015; Yi et al., 2015; Fu et al., 2018; Fang et al., 2021), Sanming model and "two invoices" system (Meng et al., 2019), and Shenzhen's experiment with group purchasing organizations (Yang et al., 2020). These existing studies are either case studies using data from only a sample city or are based on county-level hospitals. Case studies may fail to distinguish the effects of different components of a systemic reform, while studies that focus on county-level hospitals leave the effects in the cities unanswered. Our work evaluates the broader impact of ZMDP on urban public hospitals in China using a nationally representative sample.

The remainder of the paper is organized as follows. Section 2 describes the empirical setting, including the prescription drug market in China, the incentive problem, the regulatory efforts to solve the problem, the recent policy changes, the data used, and a reduced-form evidence of price drop. In Section 3, we present the structural model of the demand and supply for each market, as well as the identification and estimation strategy. Section 4 presents the estimation results of the structural model. In Section 5, we then provide the counterfactual price equilibrium and profitability calculations in the absence ZMDP in 2018, and then calculate the welfare change for patients. Finally, we conclude in Section 6.

2 Background and Data

2.1 Drug procurement reform in China

In 2009, the Chinese government formally initiated a nationwide centralized drug procurement (henceforth CDP) scheme after 9 years of development and experiment in four provinces since 2000. The scheme is outlined in two documents released in

2010, namely *Notice on the Issuance of the Centralized Drug Procurement in Health Facilities* (Ministry of Health, 2010) and *State Council Office's Notice on Establishing and Standardizing Essential Drug Procurement in Government-sponsored Primary Health Facilities* (State Council's General Office, 2010). The new policy required that all public healthcare institutions could procure drugs only via their provincial governments' CDP platforms.

The procurement procedure can be described as follows. First, each hospital takes physicians' advice into account and submits a proposal of drug demand. Then, the provincial government evaluates the proposal and approves a list of drugs to enter the next step in the procurement process. Finally, drug suppliers (e.g., manufacturers, domestic agencies of foreign pharmaceutical companies) compete on the drugs they would like to provide via a rather complicated bidding process.[6] The bidding process is not a standard scoring auction and the specific rules are different across provinces. Without detailed information, it's hard to exactly model this process. So in our empirical analysis, we proceed with a parsimonious model of bargaining between the governments and drug suppliers on drug prices a la Dubois et al. (2022, 2019). After December 2018, the procurement process is changed/enhanced,[7] and so the data in 2019 are only used to generate summary statistics but not for estimating the structural model.

The major players in the CDP scheme, i.e., the main subjects of our research, are included in Figure 1. Note that we do not explicitly incorporate strategic advertising (e.g., via sales representatives) in our model, but advertisement costs are implicitly incorporated in a reduced-form way, and we shall discuss potential consequences and limitations at the end of the paper. As mentioned in Ministry of Health (2010), the

[6]For example, one popular bidding framework is the so-called "two envelope" bidding, in which drug suppliers are required to submit prices in one envelope (termed a price envelope) and the information of their drugs (such as indications) and suppliers (such as reputation) in another envelope (termed a quality envelope). The government then groups suppliers according to their proposals. Next, for each group, the government does a quality screening and chooses qualified candidates based on the quality envelope. Within each group, if there are only a few candidates (e.g., two), the government would directly negotiate with them, otherwise the government may simply choose several low bids (not necessarily the lowest one) as the winning suppliers.

[7]Joint procurement was carried out by "4+7" large cities in December 2018 and then by 27 provinces in September 2019.

bargaining should be between pharmaceutical companies and provincial governments; Renegotiation is prohibited.

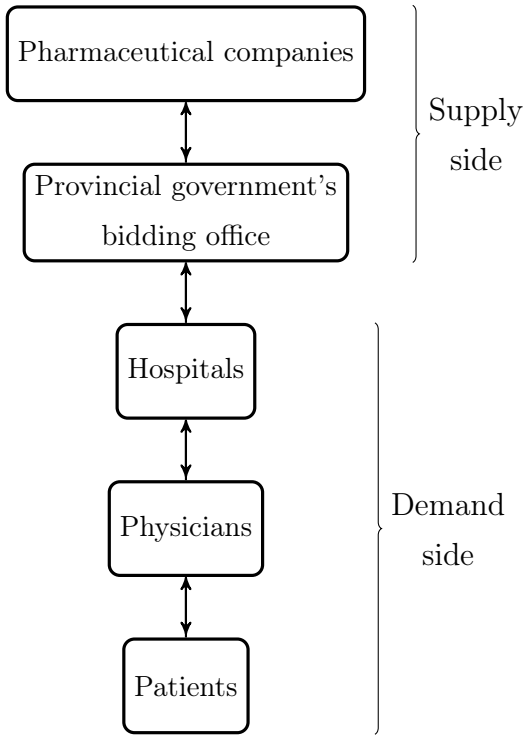

Figure 1: Basic structure of China's drug market (at provincial level)

2.2 The ZMDP and price regulations

We briefly summarize the major regulatory policy changes that may affect drug prices during 2012–2018 in Table 1. The key policy change during this period is the ZMDP, which was first implemented among urban (prefecture-level) public hospitals in July 2012 and later extended to all public hospitals nationwide in September 2017.

To understand the implications of the price regulations on the retail price of a drug, let us denote p^W as a wholesale price, which is the same for all hospitals in the same province and is decided by the bargain between the firm and the provincial government. Let p^R denote the retail price of the drug at the hospital. Before July 2012, the regulations require that:

$$\frac{p^R - p^W}{p^W} \leq 15\% \text{ and } p^R \leq p^{Highest}, \tag{1}$$

Table 1: Major policy changes between 2012 and 2018

Time	Description
Jul 2012*	Shenzhen became the first city to initiate the ZMDP among urban prefecture-level public hospitals (start of the trial period).
Apr 2014$^\diamond$	Retail price caps for Lovastatin, Fenofibrate, Gemfibrozil, Xuezhiang, and Zhibituo were removed.
May 2015*	The ZMDP was encouraged among all urban (prefecture-level) public hospitals (start of the expansion period).
Jun 2015$^\diamond$	Retail price caps for all other lipid-lowering drugs were removed.
2015–2017	Based on State Council's General Office (2015), the revenue from drugs should be no more than 30% of the total medical revenues in the urban public hospitals by 2017.
2016–2018	Local governments were encouraged to experiment with "joint procurement". For example, Shanghai and Shenzhen experimented with some Group Purchasing Organizations (GPOs) in 2016; Beijing, Tianjin, and Hebei united in the procurement of medical supplies in 2017.
Mar 2016	The Generic Consistency Evaluation (GCE) program was launched to test the quality and efficacy of generic drugs. The deadline for chemical drugs that entered before October 2007 was set to December 2018 but then it was canceled/extended.
2017–2018	Based on State Council's Healthcare Reform Committee (2016), a "two invoices" system should be phased in among publicly owned medical institutions and implemented nationwide by 2018.
Sep 2017*	The ZMDP was implemented in all public hospitals.
Dec 2018	"4+7" large cities joint procurement of Atorvastatin and Rosuvastatin. Winners take 60%–70% public hospital market shares in those cities.

Notes: $^\diamond$ denotes shocks from the removal of retail price caps; * denotes shocks from the ZMDP. ZMDP = Zero-Markup Drug Policy.

where $p^{Highest}$ is the price cap imposed by the provincial government (may be different across provinces). We can rewrite (1) as

$$p^R \leq \min\{p^{Highest}, 1.15p^W\}. \tag{2}$$

After June 2015, the price cap is removed, so we simply have $p^R \leq 1.15p^W$. Finally, it is replaced by $p^R = p^W$ since 2017Q4.

2.3 Data and descriptive statistics

We obtain quarterly data between 2012Q1 and 2019Q3 from the Pharmaceutical DataBase (PDB) on revenues and quantities of the prescription drugs in China's "national drug catalog"[8] treating hyperlipidemia in the sample hospitals. The data cover around seven hundred hospitals in 21 provinces of China, as illustrated by Figure 2. Among these hospitals, about 80 percent are tertiary and about 20 percent are secondary.[9]

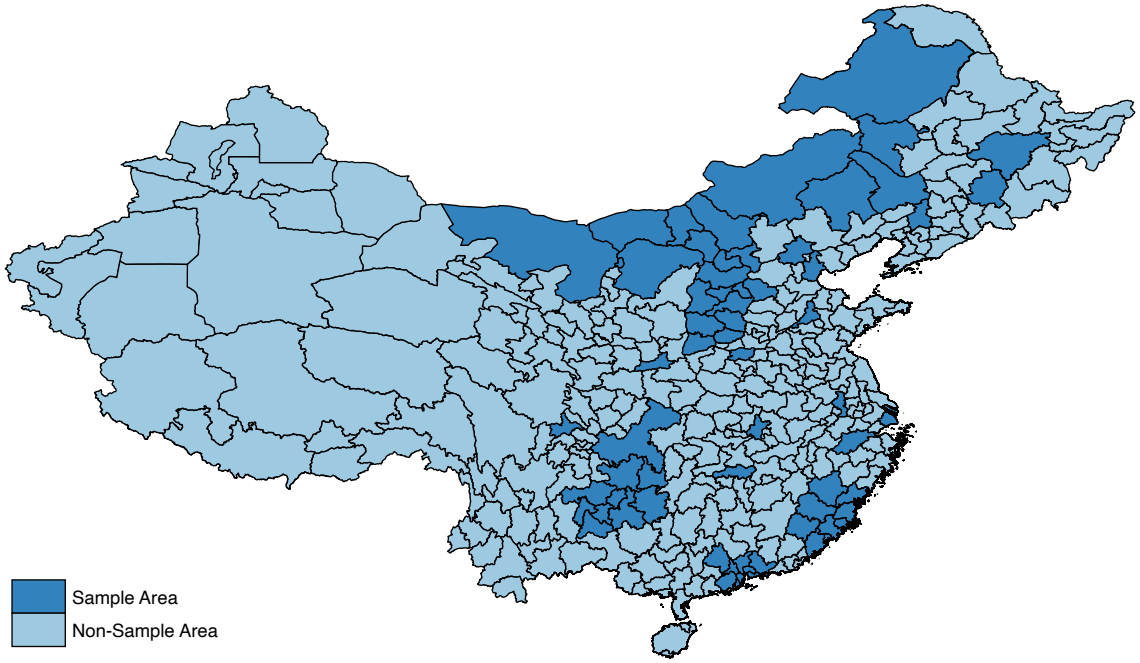

Figure 2: Sample Areas in Mainland China

In the raw data, the same drug can come with different forms (e.g., tablets and capsules) and sizes (e.g., 5mg and 10mg). We aggregate drug products (defined by a molecule-firm pair) with the same name but with multiple forms and sizes by the "standard unit", the recommended daily dose of a given molecule produced by a given firm.[10] We obtain aggregate sales of different drug products at the province-quarter

[8]The "national drug catalog" is designed for the basic medical insurance, work-related injury insurance, and maternity insurance.

[9]Very few hospitals are either lower-level or not classed and thus are negligible. For more details, visit http://pdb.pharmadl.com.

[10]We treat firms that share the same parent company as one firm.

Table 2: Definitions of main variables

Variable	Definition
Drug characteristics	
Dose	Amount (mg) of drug taken at one time
Frequency	How often each drug is taken every day
Standard unit	Daily dose = dose × frequency
# of indications	Number of indications
# of contraindications	Number of situations in which the drug should not be used with another drug (termed a drug contraindication) or by a patient (termed a patient contraindication)
Chinese	Dummy = 1 if the drug contains Chinese herbal medicine ingredients
Old Statins	Dummy = 1 for the first / second generation of Statins
New Statins	Dummy = 1 for the third generation of Statins
Fibrates	Dummy = 1 if the drug belongs to Fibrates
Niacin	Dummy = 1 if the drug belongs to Niacin
# of forms	Number of drug forms by each firm
# of sizes	Number of drug sizes by each firm
Firm characteristics	
First generic drug	Dummy = 1 if the drug is the first generic drug available in China
Branded	Dummy = 1 if the drug is branded
Time from entry	Number of quarters from entry in Chinese market
Foreign	Dummy = 1 if the firm is foreign-invested
Cost shifters	
Min wage	Minimum hourly wage of the county in which the manufacturer is located
Imported	Dummy = 1 if the drug is imported
GSP	Dummy = 1 if the firm has the Good Supply Practice certification for distribution
Policy shocks	
Pilot rate	The proportion of cities in a province that pilot the systemic public hospital reform
Start GCE	Dummy = 1 if the firm has started the Generic Consistency Evaluation
Market performance	
Retail price	Price charged by each hospital per standard unit
Wholesale price	Procurement price per standard unit
Hospital markup	Difference between retail price and wholesale price
Market share	The ratio of the sales volume of a firm/drug to the total market sales volume

(defined as a "market" later) level, and then compute quarterly wholesale prices as the ratio of total revenue to total quantity (in standard unit). Retail prices are not directly observed from the data. We calculate them by assuming that the price constraint (2) is binding.[11]

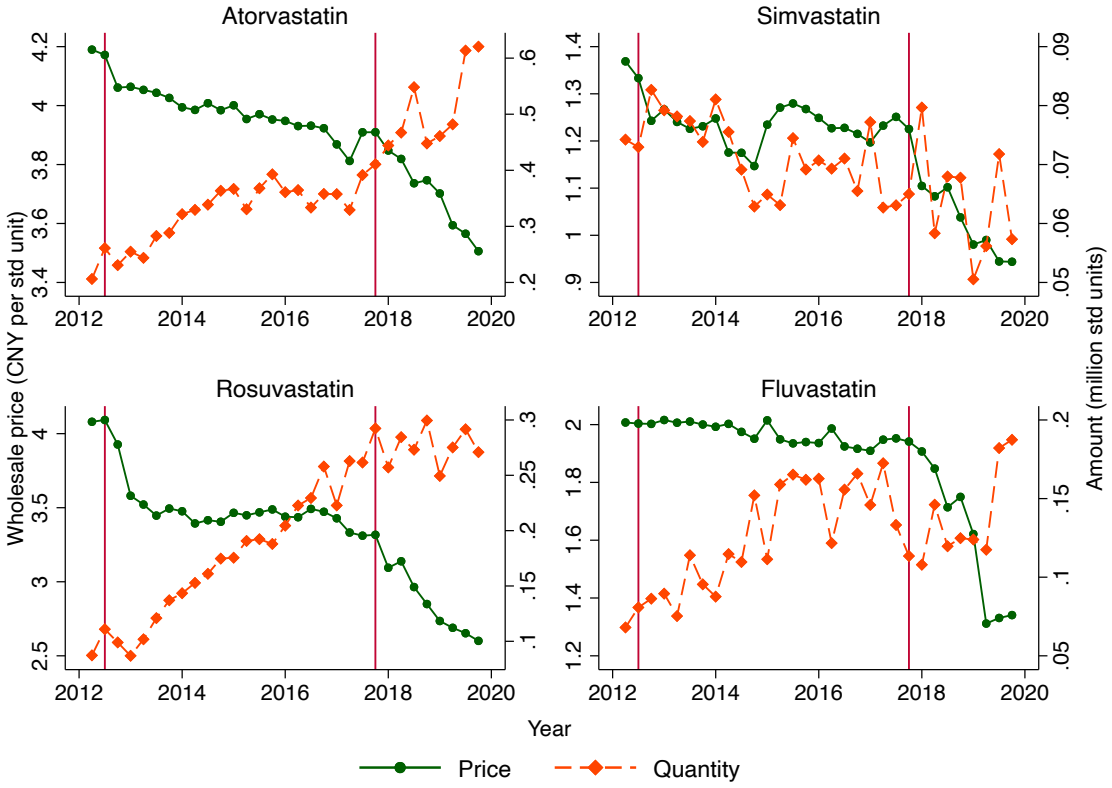

Figure 3: Average prices and quantities of top-selling lipid-lowering drugs in China

Drug characteristics (including standard units, indications, contraindications, and side effects) are manually collected from the package inserts provided by *Yaozh*, one of the major health industry big data service platforms in China,[12] and various sources (most of which are publicly available). Information on price caps are from *Yaozh* as well. Firm characteristics (such as the time a firm was first allowed to produce each drug in China, and the time each firm was certified by GSP for distribution)

[11] That is, we assume that the hospitals set the highest possible retail prices, as hospitals typically add a 15% drug markup when they can. Anecdotal evidence suggests that this assumption almost certainly hold in reality.

[12] For more information, please visit https://data.yaozh.com/.

Table 3: Summary statistics

	Obs.	Mean	St. Dev.	Min	Max
Price and markup (CNY)					
(2012Q1–2012Q2)					
Retail price	1,740	3.65	2.75	0.06	13.95
Hospital markup	1,740	0.45	0.39	-3.90	1.82
(2012Q3–2017Q3)					
Non-pilot retail price	17,382	3.75	2.77	0.04	19.47
Non-pilot hospital markup	17,382	0.47	0.36	-5.07	2.54
Pilot retail price	17,382	3.28	2.43	0.03	16.93
Pilot hospital markup	17,382	0	0	0	0
(2017Q4–2018Q4)					
Retail price	4,025	3.28	2.49	0.12	14.40
Hospital markup	4,025	0	0	0	0
Product and firm features					
# of indications	23,147	3.05	0.97	1	4
# of contraindications	23,147	5.31	1.71	2	7
First generic drug	23,147	0.22	0.42	0	1
Branded	23,147	0.25	0.43	0	1
Time from entry	23,147	48.97	20.16	4	138
Foreign	23,147	0.28	0.45	0	1
Chinese	23,147	0.06	0.24	0	1
Old Statins	23,147	0.43	0.49	0	1
New Statins	23,147	0.28	0.45	0	1
Fibrates	23,147	0.19	0.39	0	1
Niacin	23,147	0.04	0.19	0	1
Cost shifters					
Min wage	23,147	18.71	13.61	6	80.39
Imported	23,147	0.22	0.42	0	1
GSP	23,147	0.72	0.45	0	1
Policy shocks					
Pilot rate	23,147	0.41	0.40	0	1
Start GCE	23,147	0.02	0.15	0	1

Note: Please refer to Table 2 for variable definitions.

are obtained from *MENET*, a leading healthcare and pharmaceutical information service platform in China.[13] We also manually collect the county-level minimum wages facing each manufacturer each quarter from the policy documents posted by local governments. Table 2 lists all of these variables.

We present the average wholesale prices in CNY per standard unit and quantities in standard unit in Figure 3 for some best-selling drugs, i.e., Atorvastatin, followed by Simvastatin, Rosuvastatin, and Fluvastatin since 2012. Most of the best-selling prescription drugs treating hyperlipidemia experienced a drastic drop in price within a few quarters following the two cutoffs—i.e., the first trial and the nationwide implementation of the ZMDP—and a relatively stable period in between; the quantities are mostly increasing except Simvastatin.

The summary statistics of drug characteristics and other variables used in this paper are shown in Table 3. Patient-day unit retail prices vary across molecules, but it is 3.65 CNY on average before the ZMDP pilot started. Physicians/hospitals in turn earned 0.45 CNY on average per patient-day (or 168 CNY per patient-year) by prescribing a lipid-lowering drug. Starting from 2017Q4, physicians could not earn such profits directly from dispensing drugs anymore. Note that, before June 2015, the regulated price cap $p^{Highest}$ may be lower than the wholesale price p^W, which leads to (a small number of) negative sales markups, as shown by the last but one column.[14] According to the number of quarters from first entry, we learn that some drugs are relatively new while some are quite old. And most of the drugs entered the Chinese market before our sample period.

Finally, as shown by Table 4, the revenue of all drugs was initially increasing but then started to decrease after 2015. Revenues were also more and more concentrated among the top 10% firms over the years, especially for the generics. Are they due to the ZMDP? How much can the policy explain these trends? How to quantify the policy effect? To answer these questions, we need to set up a pricing model.

[13] For more information, please visit https://www.menet.com.cn/.

[14] Hospitals were able to finance their losses in selling these drugs from other products and services, however, due to lack of data, this is beyond the scope of our current paper.

Table 4: Revenue per market in 2012–2018 (China)

Year		All firms	Bottom 90%	Top 10 %
2012	All drugs	24.62	6.17	18.45
	Branded	18.11	2.48	15.63
	Generic	6.51	3.69	2.82
2013	All drugs	25.20	6.02	19.18
	Branded	18.44	2.43	16.01
	Generic	6.76	3.59	3.17
2014	All drugs	25.42	5.72	19.70
	Branded	18.55	2.24	16.31
	Generic	6.87	3.48	3.39
2015	All drugs	25.31	5.89	19.42
	Branded	17.60	2.17	15.43
	Generic	8.05	4.06	3.99
2016	All drugs	25.33	6.18	19.15
	Branded	17.28	2.28	15.00
	Generic	8.05	3.9	4.15
2017	All drugs	25.03	5.87	19.16
	Branded	17.09	2.28	14.81
	Generic	7.94	3.59	4.35
2018	All drugs	24.59	5.70	18.89
	Branded	16.67	2.25	14.41
	Generic	7.92	3.44	4.48

Notes: (1) Market is defined by a specific quarter of a year in a province in China. (2) Revenue is sample estimation, which is just 20-30% of the real-world values. (3) Revenue is in 100 million CNY.

2.4 Reduced-form analysis of price and quantity

Before presenting our structural model, we would like to show some reduced-form results regarding aggregate wholesale price and quantity. As Table 1 shows, there are several regulatory changes that might affect demand or supply of lipid-lowering drugs in China during the period of study. Nevertheless, we consider four implementation phases of the ZMDP: pre-reform (2012Q1–Q2), trial (2012Q3–2015Q2), expansion

(2015Q3–2017Q3), and post-reform (2017Q4–2018Q4) periods.[15] Admittedly, we do not intend to explore any causal relationship with the reduced-form regressions as we cannot completely rule out the effects of the "two invoices" system, GCE program, local joint procurement attempts, restricted revenue composition (e.g., revenues from drugs should account for less than 30 percent of total hospital revenues), and other regulations that were phased in during the same period of time. Nevertheless, the reduce-form regressions are still informative as they portray the general trends of price and quantity over the three policy periods.

To make comparisons of price and quantity across different phases of the ZMDP meaningful, we control for the firm and drug fixed effects, and other characteristics of the drug products in the regressions. We also try our best to control for measures of policy shocks that are uneven to different markets and firms in each quarter. Table 5 reports the results of the fixed-effect regression of the log wholesale price and quantity of drugs on the reform phase dummies and drug characteristics. When we control for the fixed effects, we see an evident price drop coinciding with the implementation of the ZMDP. In the first column, we can also see that branded drugs and those with more indications are more expensive; drugs with more contraindications are cheaper; older generic drugs tend to have lower prices. Other policy shocks are also associated with lower wholesale prices. In the second column, we notice that the expansion and nationwide implementation of the ZMDP was associated with lower quantity as well, suggesting that patients substitute away from hospital drugs.[16]

3 Model

In this section, we set up an empirical model of demand, supply and market equilibrium in the Chinese lipid-lowering drug market (focusing on hospital pharmacies). Given our data, we define a market as a province-quarter pair and label it

[15] Due to the data availability, we have a relatively short pre-policy period that may raise concerns regarding the control of pre-trend in the estimation. This issue should be partially addressed by our structural model in Section 3, where variations used for identification are also from the cross-sectional differences in price regulations (induced by the highest price caps for different drugs).

[16] The results are similar when we jointly estimate both equations.

Table 5: Fixed-effect regressions of log wholesale price and quantity

	(1) log price	(2) log quantity
2012Q1–2012Q2 (pre-reform)	(reference group)	
2012Q3–2015Q2 (trial)	-0.053***	0.107**
	(0.008)	(0.043)
2015Q3–2017Q3 (expansion)	-0.086***	-0.126***
	(0.009)	(0.047)
2017Q4–2018 (post-reform)	-0.115***	-0.139***
	(0.010)	(0.052)
# of indications	0.461***	1.834***
	(0.090)	(0.466)
# of patient contraindications	-0.238***	0.690***
	(0.034)	(0.178)
# of drug contraindications	-0.684***	-0.452
	(0.054)	(0.278)
First generic drug	-0.083***	0.676***
	(0.020)	(0.103)
Branded	0.076**	3.205***
	(0.035)	(0.182)
Pilot rate	-0.033***	0.945***
	(0.006)	(0.033)
Start GCE	-0.220***	0.516***
	(0.016)	(0.083)
Firm fixed effect	Yes	Yes
Molecule fixed effect	Yes	Yes
Observations	23,147	23,147
R^2	0.551	0.395

Notes: (1) Standard errors in parentheses under each coefficient. (2) Dependent variables are the natural log of wholesale price in CNY, and the natural log of quantity in "standard unit". (3) Data for China in 2012–2018. (4) ***, **, * denote significance level at 1%, 5%, and 10%, respectively.

by $t = 1, ..., T$. Each market t consists a set of competing products, labeled by $j = 1, ..., J_t$, which are defined as molecule-firm pairs.

3.1 Demand side

A patient and her physician jointly decide on which drug product to buy and use. So we model the joint preference of a patient-physician pair, labeled by i, using a standard nested-logit random utility model, i.e., the utility that i obtains from choosing product j is

$$U_{ijt} = \underbrace{X_{jt}\theta_1 + \xi_{jt}}_{\equiv \delta_{jt}} - \alpha P_{ijt} + \gamma M_{ijt} + \zeta_{igt}(\lambda) + (1-\lambda)\varepsilon_{ijt}, \tag{3}$$

where

- δ_{jt} represents the mean utility, in which X_{jt} is a vector of observed product or market characteristics, including molecule dummies, the proportion of public hospital reform pilot cities in market t (to control for reform intensity), the indicator for the start of GCE process, and a constant term, and ξ_{jt} is an unobserved product-market level demand shock;

- P_{ijt} and M_{ijt} are the retail price and (hospital) markup that patient-physician i faces for drug product j in market t, and α is the dis-utility of price and γ measures the severity of the expert agency problem (Iizuka, 2007);

- Depending on whether the hospital associated with i is subject to the ZMDP, P_{ijt} and M_{ijt} differ across i's: $P_{ijt} = p^W_{jt}$ and $M_{ijt} = 0$ if i is subject to the ZMDP and $P_{ijt} = p^R_{jt}$ and $M_{ijt} = m_{jt}$ otherwise;[17] also, for the partial ZMDP periods, we do not observe whether i is subject to the ZMDP, so P_{ijt} and M_{ijt} become unobserved heterogeneity and we shall estimate the fraction of i's that are not subject to the ZMDP as a parameter $\phi \in [0,1]$;[18]

- ζ_{igt} is a random variable that is common to all products in nest g, whose distribution depends on λ. $\lambda \in [0,1)$ is the "nesting parameter" capturing the

[17] The variation in $p^{Highest}$ across markets will ensure non-colinearity between p^R and the markup m, which will help us identify how the retail price and hospital drug markup affect the utility of consumers separately.

[18] We test for robustness by defining the partial ZMDP period as 2015Q1–2017Q3. See Appendix E for details.

within-group correlation between choices. Larger λ means nests matter more. ε_{ijt} is an i.i.d. idiosyncratic preference shock following the standard Type I extreme value distribution. In our empirical analysis, a group g is defined by a molecule and there are 17 of them (0 for outside goods, and 1–16 for the 16 molecules in Table A1 except Jiaogulan). One can interpret the nesting as a two-step procedure: choosing a molecular class first and then a product within this class.

Each decision maker i in market t maximizes her utility by choosing the best option in $\mathcal{J}_t$. Given nested-specification, the choice probability that i chooses j in t can be written as

$$\sigma_j\left(\delta_t, P_{it}, M_{it}\right) = \underbrace{\frac{\exp\left(\frac{\delta_{jt}-\alpha P_{ijt}+\gamma M_{ijt}}{1-\lambda}\right)}{\sum_{j\in g}\exp\left(\frac{\delta_{jt}-\alpha P_{ijt}+\gamma M_{ijt}}{1-\lambda}\right)}}_{\text{within-group share}} \underbrace{\frac{\left(\sum_{j\in g}\exp\left(\frac{\delta_{jt}-\alpha P_{ijt}+\gamma M_{ijt}}{1-\lambda}\right)\right)^{1-\lambda}}{\sum_{g\in\mathcal{G}_t}\left(\sum_{j\in g}\exp\left(\frac{\delta_{jt}-\alpha P_{ijt}+\gamma M_{ijt}}{1-\lambda}\right)\right)^{1-\lambda}}}_{\text{group share}}. \tag{4}$$

Thus we can obtain the aggregate market share $E\left[\sigma_j\left(\delta_t, P_{it}, M_{it}\right)\right]$ by integrating out the heterogeneous P_{it} and M_{it}. For the pre-2012Q3 periods, all the i's are not subject to ZMDP and thus

$$E\left[\sigma_j\left(\delta_t, P_{it}, M_{it}\right)\right] = \sigma_j\left(\delta_t, p_t^R, M_{ijt}\right). \tag{5}$$

Also, between 2012Q3 and 2017Q3 (partial implementation of ZMDP), whether each i is subject to the ZMDP is an unobserved heterogeneity and thus[19]

$$E\left[\sigma_j\left(\delta_t, P_{it}, M_{it}\right)\right] = \phi\sigma_j\left(\delta_t, p_t^R, M_{ijt}\right) + (1-\phi)\,\sigma_j\left(\delta_t, p_t^W, 0\right). \tag{6}$$

Finally, after 2017Q3 (full implementation of ZMDP), the market share equation is

$$E\left[\sigma_j\left(\delta_t, P_{it}, M_{it}\right)\right] = \sigma_j\left(\delta_t, p_t^W, 0\right). \tag{7}$$

With the above specified market share function, we can write the demand system as

$$s_{jt} = \bar{\sigma}_{jt}\left(\delta_t; \theta_2\right), \ \forall j, t \tag{8}$$

[19] One extension is to let $E\left[\sigma_j\left(\delta_t, P_{it}, M_{it}\right)\right] = \phi_t\sigma_j\left(\delta_t, p_t^R, M_{ijt}\right) + (1-\phi_t)\,\sigma_j\left(\delta_t, p_t^W, 0\right)$ where ϕ_t is time varying. In this way, we allow an expansion of the ZMDP during the partial implementation period (also see Appendix E).

where s_{jt} is the observed market share of j in t, $\bar{\sigma}_{jt}(\delta_t;\theta_2) \equiv E[\sigma_j(\delta_t, P_{it}, M_{it})]$, and $\theta_2 = (\theta_1, \alpha, \gamma, \lambda, \phi)$.

To estimate the model, we invert the demand systems[20], (5), (6) and (7), to obtain

$$X_{jt}\theta_1 + \xi_{jt} = \bar{\sigma}_{jt}^{-1}(s_t;\theta_2) \tag{9}$$

and assume the following identification condition

$$\mathbb{E}\left[Z_{jt}^d \xi_{jt}\right] = 0, \tag{10}$$

where Z_{jt}^d is a vector of exogenous variables, including exogenous product characteristics, cost shifters ("Min wage" and "Imported" in Table 2) and BLP-type IVs: (1) the number of drugs and the sum of characteristics for other drugs sharing the same molecular class at market t (the crowdedness of the product space), and (2) the number of drugs and the sum of characteristics for other drugs sold by the same firm at market t (the ownership pattern).

Based on the moment condition (10), We estimate the demand model using GMM. Standard errors of the estimates are calculated according to the formulas provided in Appendix A.

3.2 Supply side

As discussed earlier, the wholesale price of a drug is determined jointly by its pharmaceutical company and the local government, which typically have distinct objective functions. In particular, we assume that pharmaceutical firms try to maximize their profits while governments concern the welfare of patients and physicians, following the literrature convention (Crawford and Yurukoglu, 2012; Grennan, 2013; Gowrisankaran et al., 2015; Ho and Lee, 2017; Dubois et al., 2022). This is a parsimonious characterization of the trade-offs facing policymakers, who should balance producer profits against consumer welfare.

[20] We solve the following contraction mapping and obtain ξ_{jt}, whose validity has been proved by Iizuka (2007) and Berry and Jia (2010):

$$\delta_{jt}^M = \delta_{jt}^{M-1} + (1-\lambda)\left\{\ln s_{jt} - \ln s_{jt}(\delta_{jt}^{M-1}, \theta_2)\right\}$$

where M is the iteration number.

To capture the obvious conflict of interests between firms and governments, we model the determination of wholesale prices of drugs using a simultaneous "Nash-in-Nash" bargaining model (Dubois et al., 2022), in which each drug's wholesale price is negotiated bilaterally between its firm and a local government given the equilibrium prices of other bargain pairs. Following Dubois et al. (2022), we assume that bargaining takes place at product-by-product level.

In each market t, the profit function of a firm supplying a set of products $\mathcal{F}_t$ is

$$\Pi_{\mathcal{F}_t,t}\left(\mathbf{p}_t^W\right) = N_t \sum_{j\in\mathcal{F}_t}\left(p_{jt}^W - c_{jt}\right)\bar{\sigma}_{jt}\left(\delta_t;\theta_2\right) \tag{11}$$

where N_t is the market size of t. Note that we can write the profit function as a function of wholesale price only (given everything else) because the retail price is a fixed function of wholesale price (recall the discussion in Section 2.2).

For a given market t, the welfare is defined as the sum of the expected patient-physician joint utility produced by each drug available in market (Small and Rosen, 1981),

$$\Lambda_t\left(\mathbf{p}_t^W\right) = N_t E\left[\ln\left(\sum_{g\in\mathcal{G}_t}\left(\sum_{j\in g}\exp\left\{\frac{\delta_{jt}-\alpha P_{ijt}+\gamma M_{ijt}}{1-\lambda}\right\}\right)^{1-\lambda}\right)\right] \tag{12}$$

where the expectation is taken with respect to the heterogeneity in P_{it} and M_{it}.

In each market t, the equilibrium prices solve the Nash-in-Nash bargaining problem

$$\max_{p_{jt}^W}\left\{\left[\Pi_{\mathcal{F}_t,t}\left(\mathbf{p}_t^W\right) - \Pi_{\mathcal{F}_t\setminus\{j\},t}\left(\mathbf{p}_t^W\right)\right]^{\rho_j}\left[\Lambda_{\mathcal{J}_t,t}\left(\mathbf{p}_t^W\right) - \Lambda_{\mathcal{J}_t\setminus\{j\},t}\left(\mathbf{p}_t^W\right)\right]^{1-\rho_j}\right\},\ \forall j \tag{13}$$

where $\rho_j \in [0,1]$ represents the relative bargaining power of the firm in the bargaining of product j's price. The firm's objective is the change in profit generated by offering drug j in market t. The government's objective is the change in consumer welfare generated by the presence of drug j in market t.

The first order condition of product j in market t is

$$c_{jt} = p_{jt}^W + \frac{1}{\underbrace{\frac{\partial \ln \bar{\sigma}_{jt}\left(\delta_t;\theta_2\right)}{\partial p_{jt}^W}}_{\text{Demand semi-elasticity}} + \frac{1-\rho_j}{\rho_j}\underbrace{\frac{\partial \ln \Lambda_{\mathcal{J},t}\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W}}_{\text{Welfare semi-elasticity}}}. \tag{14}$$

Note that (14) collapses to the first order condition of standard Bertrand-Nash equilibrium when ρ_j equals to 1, i.e., when government's preference is not taken into account.

Next, we parameterize the marginal cost as follows:

$$c_{jt} = \left(Z_{jt}^s\right)' \beta + \omega_{jt}, \tag{15}$$

where Z_{jt}^s includes a constant, the three cost shifters from Table 2, duration since entry, molecule and province-year dummies. Combining (14) and (15), we estimate the β and $(\rho_1, ..., \rho_J)$ based on the least square criteria, i.e.,

$$\min_{\beta \in R^{k_\beta}, (\rho_1,...,\rho_J) \in [0,1]^J} \sum_{j,t} \omega_{jt}^2. \tag{16}$$

Given that β enters the first order condition linearly, We simplify the optimization problem by concentrating out β in close-form

$$\tilde{\omega}_{jt}(\rho_j) = \left[1 - \left(Z_{jt}^s\right)' \left[Z_{jt}^s \left(Z_{jt}^s\right)'\right]^{-1} Z_{jt}^s\right] \tilde{c}_{jt}(\rho_j), \tag{17}$$

where

$$\tilde{c}_{jt}(\rho_j) \equiv p_{jt}^W + \frac{1}{\frac{\partial \ln \bar{\sigma}_{jt}(\delta_t;\theta_2)}{\partial p_{jt}^W} + \frac{1-\rho_j}{\rho_j} \frac{\partial \ln \Lambda_{\mathcal{J},t}\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W}}. \tag{18}$$

Then we solve the simplified optimization problem

$$\min_{(\rho_1,...,\rho_J) \in [0,1]^J} \sum_{j,t} \left[\tilde{\omega}_{jt}(\rho_j)\right]^2. \tag{19}$$

4 Estimation Results

4.1 Demand estimation results

Demand estimation results are reported in Table 6. We can see that the physicians care both patients' and hospitals' interests, since the coefficients on retail price and hospital markup are significant. To make sense of the estimated coefficients, we illustrate how physicians trade off the markup and patients' out-of-pocket cost via a simple numeric example. Suppose that patients on average pay 20 percent of the cost

of medication.Since the coefficient of hospital drug markup is approximately three times of that (absolute value) of retail price, a patient-physician pair is willing to give up one dollar of markup for a reduction of drug price (to a patient) by 60 cents ($\approx 3 \times 0.2$). That is, a patient-physician puts a greater weight on patient welfare than hospital profit (derived from drug) under the assumption that the coinsurance rate is lower than 33 percent. This finding resembles Iizuka (2007)'s results on Japanese market, where Japanese physicians are willing to give up 1 dollar if patient's cost is reduced by 28 cents (under the assumption that the coinsurance rate is 20 percent), suggesting that the agency problem of physicians in Japan might be less severe than China.[21]

Other estimated parameters in Table 6 also provide some interesting insights. For example, the number of indications significantly increases the demand, and branded drugs are also favored over generic ones. First mover advantage appears to exist in China's prescription drug market as the first generic drug marketed in China in its molecular class has a significantly higher demand. There is an upward trend in the demand for lipid-lowering drugs after entry, but the growth rate drops a little over time. Molecule dummies suggest that the demand for Statins is usually larger than drugs of other therapeutic class, except for Probucol. Public hospital reform seems to negatively impact the market share, while the generic consistency evaluation program may increase the market share (although not significant, probably due to a small sample issue because it's relatively new).

From the estimated demand model, we calculate the price elasticities and summarize the top 10 popular lipid-lowering drugs, in terms of the number of markets covered, in Table 7 and Table 8. Branded drugs and generic drugs are sorted by their market share separately. First, the tables show that branded drugs are typically less price elastic than generic drugs, as their elasticities are typically below 5 in 2012, while generics typically have an elasticity that is close to 10 in 2012. This suggests that branded drugs have higher market power than generics do. According to our back-of-the-envelope calculations, the mean own-price elasticity across products and markets in China in 2018 is -2.86 and ranges from -3.44 to -1.69 across markets. As

[21] This numeric example can be extended to incorporate richer, auxiliary information on heterogeneous coinsurance rates for different provinces, insurances, hospitals, and drugs.

expected, generics are more elastic than branded drugs (-2.99 versus -2.43), suggesting that even in 2018, after ZMDP is fully implemented, the branded drugs generally have higher market power in China. Second, average cross-price elasticities across

Table 6: Demand estimation results

	Coef.	St. Err.
# of indications	5.092***	0.487
# of patient contraindications	-0.181*	0.106
# of drug contraindications	-2.298***	0.241
First generic drug	0.156***	0.085
Branded	0.970***	0.099
Time from entry	0.034***	0.007
(Time from entry)^2	-0.000***	0.000
Pilot rate	-0.030**	0.015
Start GCE	0.209	0.166
α	0.455***	0.087
γ	1.371**	0.561
λ	0.653***	0.007
ϕ	0.973*	0.555
Constant	-14.712***	1.171
Molecule dummies (Reference: Acipimox, Rosuvastatin, Simvastatin, Xuezhikang)		
Atorvastatin	0.191	0.146
Bezafibrate	-5.626***	0.412
Ezetimibe	-0.136	0.213
Fenofibrate	-7.218***	0.640
Fluvastatin	0.669***	0.209
Gemfibrozil	-13.481***	0.954
Inositol Nicotinate	-2.593	1.847
Lovastatin	-1.879***	0.304
Pitavastatin	1.595***	0.327
Pravastatin	2.824***	0.280
Probucol	6.474***	0.582
Zhibituo	-0.858***	0.285
Year dummies (Reference: 2012)		
2013	0.000	0.048
2014	-0.001	0.052
2015	0.002	0.059
2016	-0.001	0.070
2017	0.001	0.096
2018	-0.001	0.263
Observations	23,147	
Objective function value	0.081	

Notes: (1) ***, **, * denote significance level at 1%, 5%, and 10%, respectively. (2) See Table 2 for variable definitions. (3) α measures the disutility of price, γ measures physician's marginal utility from drug markup (or the severity of expert agency problem) if there is any, λ is the nesting parameter, and ϕ measures the average proportion of type 1 consumers between 2012Q3 and 2017Q3.

Table 7: Own-price elasticities for main lipid-lowering drugs, 2012–2018 (China)

	Branded							Generic		
Subclass	Statin	Statin	Statin	Statin	Statin	Fibrate	CAI	Statin	Statin	Niacin
Company	Pfizer	AstraZ	MSD	Novartis	Luye	Fournier	SGP	Jialin	Lunan	Lunan
Molecule	Atorva.	Rosuva.	Simva.	Fluva.	Xuezhikang	Feno.	Ezetimibe	Atorva.	Rosuva.	Acipimox
Drug name	Lipitor	Crestor	Zocor	Lescol	Xuezhikang	Tcicor	Zetia	–	–	–
Year	Estimate									
2012	-7.755	-4.458	-3.345	-2.601	-3.404	-10.350	-7.974	-10.905	-9.308	-6.724
2013	-7.400	-6.774	-3.120	-2.491	-3.620	-10.160	-11.134	-10.023	-11.072	-5.202
2014	-7.385	-5.737	-3.008	-2.196	-3.296	-8.778	-10.549	-9.258	-9.178	-5.405
2015	-5.915	-5.988	-2.599	-2.070	-3.586	-7.179	-8.277	-7.628	-9.268	-5.077
2016	-5.129	-5.210	-2.253	-2.084	-3.200	-6.424	-7.024	-5.752	-8.236	-4.643
2017	-4.752	-4.963	-1.787	-1.709	-3.276	-4.946	-6.038	-5.618	-7.009	-4.141
2018	-2.837	-2.994	-1.163	-0.722	-2.094	-3.622	-3.386	-3.246	-3.688	-2.345

Notes: (1) Each number is the estimated own-price elasticity of demand for the drug defined in the first few rows. (2) Company names: Luye stands for Luye Pharma Group, AstraZ is AstraZeneca, SGP is Schering-Plough, and MSD is Merck Sharp & Dohme. (3) Molecules: Feno. is Fenofibrate, Fluva. is Fluvastatin, Atorva. is Atorvastatin, Rosuva. is Rosuvastatin, and Simva. is Simvastatin. (4) Subclass: CAI stands for Cholesterol absorption inhibitors. (5) Drugs are sorted by market share (decending order) within branded and generic categories separately.

Table 8: Average cross-price elasticities among main lipid-lowering drugs, 2012–2018 (China)

	Branded							Generic		
Subclass	Statin	Statin	Statin	Statin	Statin	Fibrate	CAI	Statin	Statin	Niacin
Company	Pfizer	AstraZ	MSD	Novartis	Luye	Fournier	SGP	Jialin	Lunan	Lunan
Molecule	Atorva.	Rosuva.	Simva.	Fluva.	Xuezhikang	Feno.	Ezetimibe	Atorva.	Rosuva.	Acipimox
Drug name	Lipitor	Crestor	Zocor	Lescol	Xuezhikang	Tcicor	Zetia	–	–	–
Year	Estimate									
2012	1.392	0.727	0.086	0.051	0.022	0.029	0.010	0.350	0.080	0.014
2013	1.465	0.936	0.067	0.054	0.024	0.029	0.018	0.322	0.120	0.019
2014	1.330	0.834	0.054	0.045	0.019	0.024	0.012	0.323	0.114	0.010
2015	1.113	0.763	0.041	0.038	0.017	0.020	0.013	0.287	0.134	0.009
2016	0.895	0.641	0.030	0.025	0.015	0.016	0.017	0.265	0.145	0.008
2017	0.853	0.545	0.021	0.013	0.013	0.013	0.016	0.248	0.162	0.006
2018	0.494	0.277	0.009	0.007	0.008	0.007	0.011	0.154	0.112	0.004

Notes: (1) Each number is the average of the estimated cross-price elasticities of demand for the drug defined in the first few rows with respect to (the price changes) of the other drugs. (2) Company names: Luye stands for Luye Pharma Group, AstraZ is AstraZeneca, SGP is Schering-Plough, and MSD is Merck Sharp & Dohme. (3) Molecules: Feno. is Fenofibrate, Fluva. is Fluvastatin, Atorva. is Atorvastatin, Rosuva. is Rosuvastatin, and Simva. is Simvastatin. (4) Subclass: CAI stands for Cholesterol absorption inhibitors. (5) Drugs are sorted by market share (decending order) within branded and generic categories separately.

molecular classes are quite low, typically 0.01 or less in 2018, suggesting a substantial degree of product differentiation. Third, to see how the price elasticities change over time, the tables also report own- and cross-price elasticities for the main lipid-lowering drugs in China from 2012 to 2018. Point estimates of own-price elasticity declined for both branded and generic drugs over the years, which could be due to that patients became less price sensitive when facing lower prices and at the same time their income or purchasing power became higher. Also, lipid-lowering drugs became less substitutable as indicated by lowering magnitudes of cross-price elasticities. In general, these drugs are more substitutable within a molecular class (e.g., Atorvastatin produced by Pfizer versus Jialin, or Rosuvastatin produced by AstraZeneca versus Lunan) than between branded and generic groups.

The decreasing price sensitivity might seem a bit surprising given that retail prices are also decreasing, because standard oligopoly theory tells us that they should be inversely related. However, recall that the overall demand becomes much weaker (less prescriptions from physicians) after ZMDP so the market become more competitive, which (at least partially) explains the decreasing prices.

4.2 Supply side estimation

We first present our estimates of bargaining power parameters ρ_j in Figure 4. It's not surprising to see that most firms/products have lower bargaining power than the provincial governments (indicated by $\rho_j < 0.5$), and only a small fraction of firms/products show higher bargaining power than the government.

To show the goodness of fit of the bargaining model, we predict the wholesale prices using our estimated marginal cost function $c_{jpt}(\rho_j)$, following Pakes (2017) and Wollmann (2018). The predicted prices and actual prices are largely centering around a 45-degree line, as shown by Figure 5. The linear regression of actual prices on predicted prices without a constant gives a coefficient of 1.006.

We also look at the predicted price index and compare it with the actual one. The price index is calculated by a weighted average in which the weights are the projected market sizes (using sample weights and quantities sold). As shown by Figure 6, the

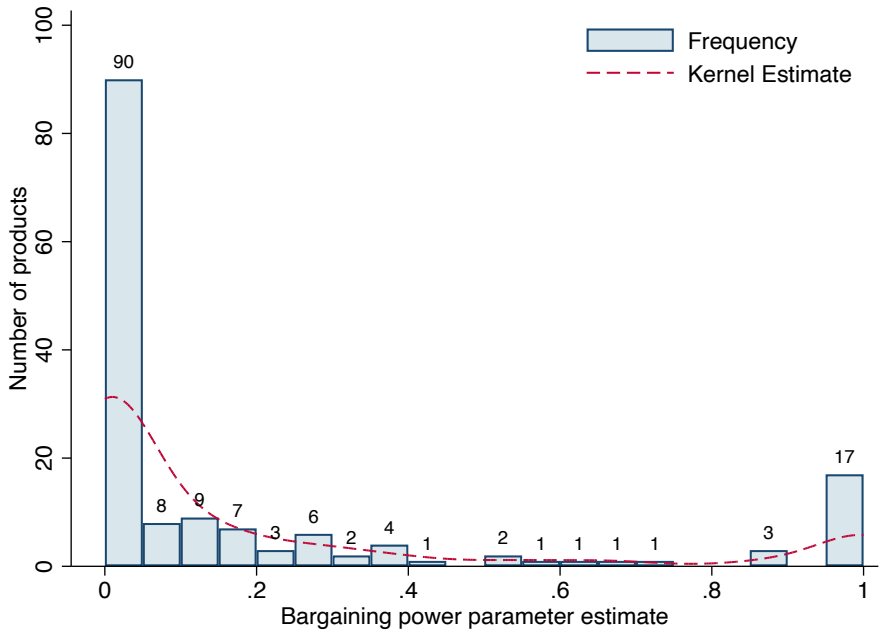

Figure 4: Distribution of bargaining parameters

Notes: There are 156 products (molecule-firm pairs). For the kernel estimate, Gaussian kernel with optimal width is used. The numbers above the bars are the number of products within each 0.05-wide bin.

predicted price index is rather close to (although slightly lower than) the actual one and captures the general declining trend over time.

Using our estimated demand parameters, bargaining power parameters, and pricing equilibrium, we can then estimate total revenue and profit of each market. Before showing the total revenues and total profits, we provide the distribution of estimated margins of each product in 2018 in Figure 7 and Figure 8. The average profit per each standard unit across products and markets (i.e., each observation is weighted by the corresponding amount of standard units sold) in 2018 is 0.44 CNY, ranging from nearly zero to 2.21 CNY. Profit margin, or price-cost margin (also known as the Lerner index), is 0.14 on average, and most products exhibit a relatively low market power.

We noticed that branded drugs typically have a slightly higher price-cost margin than generic drugs.[22] As pointed out by Dubois and Lasio (2018), it is known in

[22]Price-cost margin is defined as the difference between wholesale price and marginal cost as a

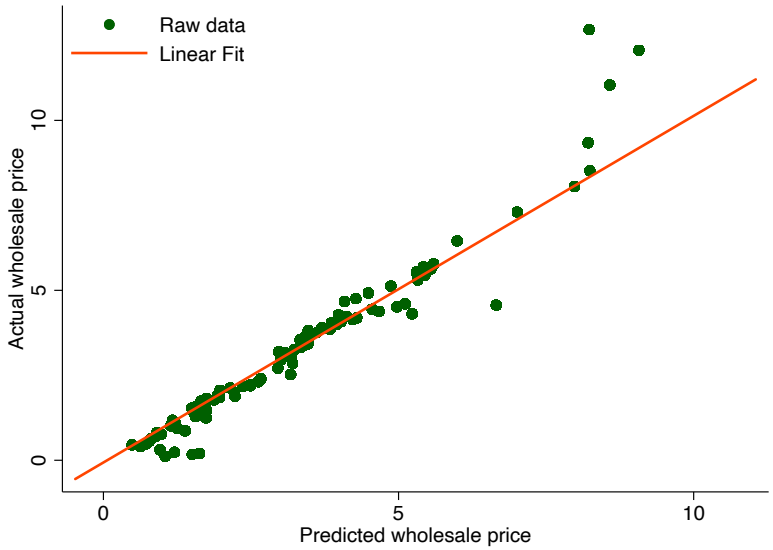

Figure 5: Predicted versus actual prices

Notes: The slope of the fitted line without a constant is 1.006. The original scatters are sorted based on the actual wholesale prices and then binned into 100 groups; then, the averages are calculated for each group and plotted on the figure. Unit: CNY per standard unit.

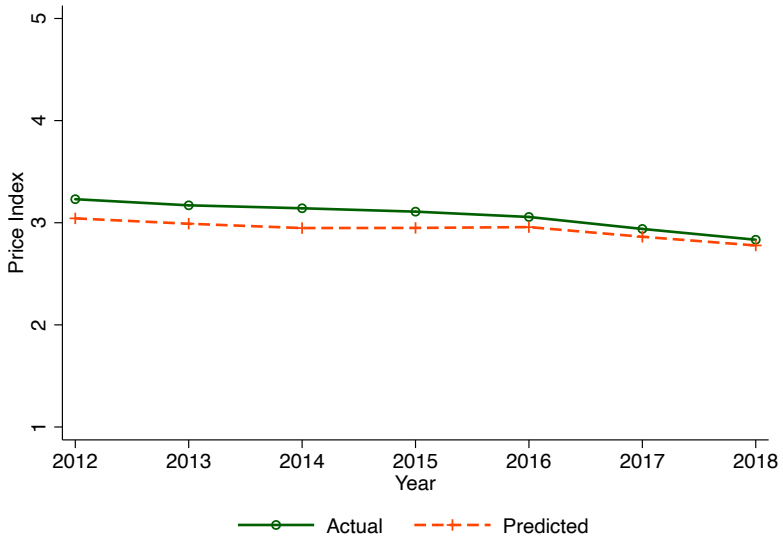

Figure 6: Predicted versus actual price index

fraction of wholesale price. Weighted averages are 0.14 versus 0.13.

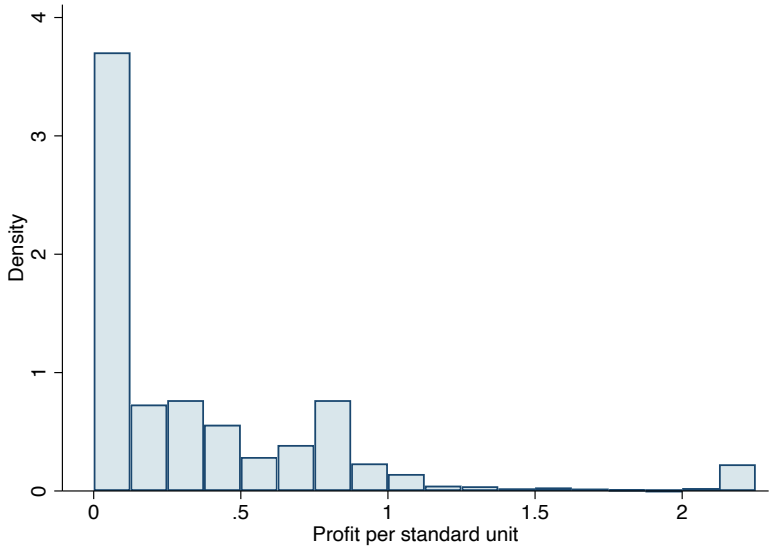

Figure 7: Estimated profit per standard unit in 2018

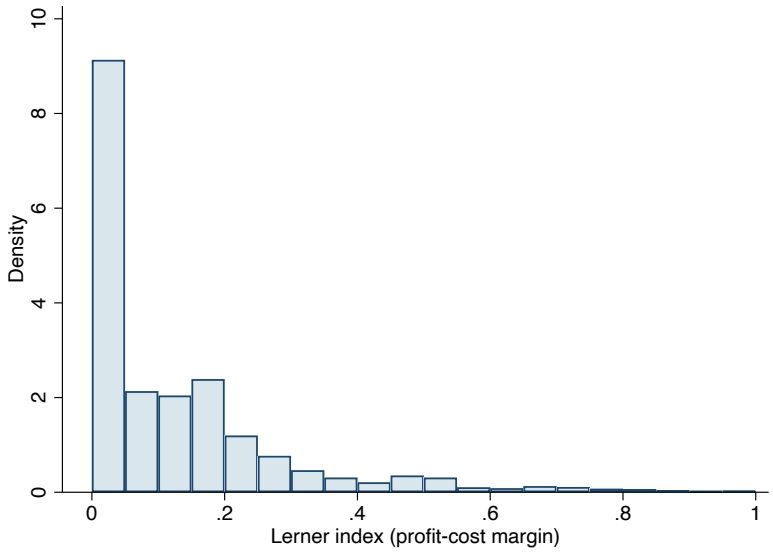

Figure 8: Lerner index in 2018

the industry that generic firms have lower marginal costs. Our back-of-the-envelope calculations suggest that, in 2018, the (weighted) average cost of a standard unit of generic drugs is 2.43 CNY, compared to 3.01 CNY for branded drugs. The prices of generic drugs, however, are much lower than branded drugs (2.80 versus 3.50), suggesting lower margins of generic drugs.

Table 9: Market share, revenue and profit per market in 2018 (China)

		All firms	Bottom 90%	Top 10 %
Market share (%)	All drugs	38.99	11.97	27.02
	Branded	23.73	3.93	19.80
	Generic	15.26	8.04	7.22
Revenue	All drugs	24.59	5.70	18.89
	Branded	16.67	2.25	14.41
	Generic	7.92	3.44	4.48
Profit	All drugs	2.64	0.30	2.34
	Branded	1.80	0.09	1.71
	Generic	0.84	0.21	0.63

Notes: (1) Market is defined by a specific quarter of a year in a province in China. (2) Revenue and profit are in 100 million CNY.

We summarize the average revenue and profit per market in Table 9. In an average market, branded drugs take up the majority (61 percent) of the market share, and the top 10 percent best selling branded products account for 83 percent of the branded market share, indicating high market concentration. The total manufacture revenue of an average market (defined by a season-province pair) in 2018 is 2.46 billion CNY, and the total manufacture profit of a market is 0.26 billion CNY. Due to higher market shares and higher prices, branded drugs are more lucrative. The total revenue and profit in an average market of 2018 of all branded drugs are more than two times those of all generic drugs.

5 Counterfactual: Quantifying the Effects of ZMDP

In this section, we examine how profit and consumer surplus were affected by ZMDP that "breaks" the integration between prescribing and dispensing drugs (Iizuka, 2007). To avoid the complication of price caps that were in place during the transition periods, we conduct the counterfactual simulation based on on the data of the post-reform era, i.e., 2018. Specifically, we assume the absence of ZMDP such that pre-reform hospital markup, i.e., 15 percent of wholesale price, is restored. Then, we calculate counterfactual equilibrium prices, market shares, profits, etc., using the estimates and data of 2018.[23]

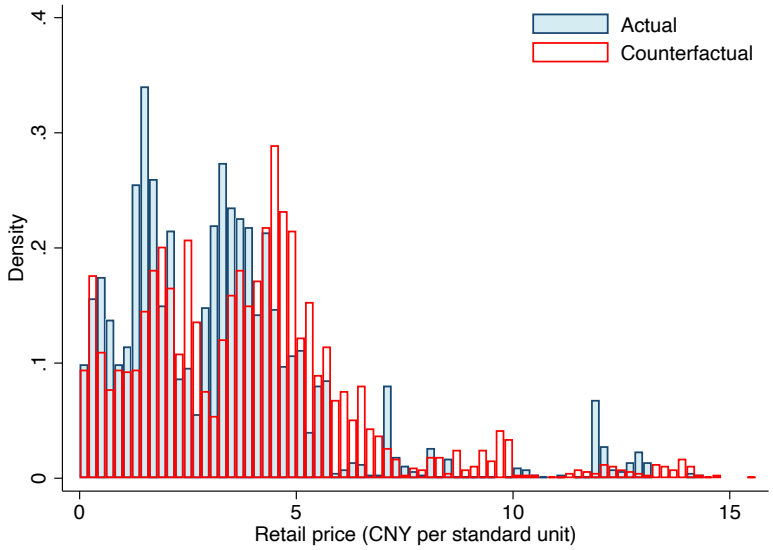

Figure 9: Counterfactual versus actual retail prices in 2018

Figure 9 compares the counterfactual retail prices to the actual prices, showing that the distribution of counterfactual prices shifts to the right, i.e., if the 15% hospital drug markup still existed, the average retail price would be higher. The wholesale prices would also be slightly higher on average (3.07 versus 2.85), according to our calculations. We calculate the average prices of a "basket" of products that appear in every year, weighting by their market shares in 2012. This average wholesale price difference explains 54% of the average wholesale price change from 2012 (3.25) to 2018

[23] We solve for new equilibrium prices using firms' first-order conditions. A fixed point algorithm was used to solve the system with a numerical tolerance level smaller than 10^{-6}.

(2.85), as suggested by Table A2. This could be due to the substitution back to drugs (i.e., a higher demand). The profit from selling a standard unit of lipid lowering drug (defined by the difference between the retail price and the marginal cost) is shown in Figure 10. Again, it is clear that hospital drug markup would generate higher profits for both hospitals and manufacturers.

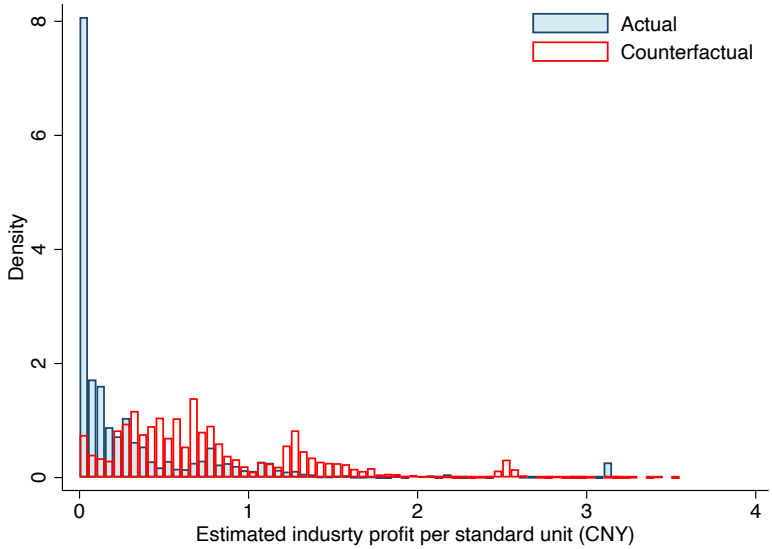

Figure 10: Counterfactual versus actual industry profit per unit in 2018

Based on the counterfactual market equilibrium, we calculate the implied market shares, revenues, and profits that are summarized in Table 10. The share of an average market could expand to nearly half of the hyperlipidemia population with the hypothetical 15 percent hospital drug markup in 2018. Compared to the estimates in Table 9, branded drugs could experience a much larger increase in market share, and become even more concentrated; this again suggests that, without the ZMDP, top selling branded drugs are more preferred by physicians (due to their financial considerations).

Comparing to actual data, the total revenue under the counterfactual scenario goes up by 49 percent, and the total profit increases by 48 percent. Generic drugs would have more profit gains on average than branded drugs do if the ZMDP were removed in 2018. This could be due to the fact that generics typically have lower costs, and thus the almost same increases in wholesale prices (as we verified) would lead

Table 10: Counterfactual share, profit, revenue, and surplus per market (2018)

		All firms	Bottom 90%	Top 10 %
Market share (%)	All drugs	49.56	13.59	35.97
	Branded	32.82	4.69	28.13
	Generic	16.74	8.90	7.84
Revenue	All drugs	36.65	8.35	28.30
	Branded	24.78	3.39	21.39
	Generic	11.87	4.96	6.91
Profit	All drugs	3.90	0.48	3.42
	Branded	2.26	0.19	2.07
	Generic	1.64	0.29	1.35
Patient surplus change			-22.54%	

Notes: (1) We use 2018 product attributes for all counterfactual exercises. The counterfactuals assume that there is a 15% drug markup just like 2012-2014. (2) Other cautions are in Table 9. (3) Revenue and profit are in 100 million CNY.

to higher increases in profits.[24] Note also that, the top selling generics also have slightly higher revenue gains on average—this does not conflict with Table 4 as in the counterfactual analysis the elasticities are held constant, while for the time trend the underlying elasticities are decreasing. Concerning profit, the loss caused by the policy is potentially large: from 390 million in Table 10 to 264 million in Table 9, per province per quarter, which is a 32.3% drop.

Finally, we measure the changes in patients' welfare due to the counterfactual drug markup. This is done by assuming that the utility function fully represents patients' preference (so γ is fixed at 0). Our calculation suggests that, patient's welfare would drop by 22.5 percent if there were a 15 percent hospital drug markup. This result suggests that the ZMDP is overall beneficial to patients.

Note that the effects we focus on in this counterfactual experiment are immediate or short-term effects. In the long term, we hypothesize that any additional profits would be competed away by the entry of competing firms, while any additional losses would be gone by the exit of firms, unless there are substantial forces preventing

[24] That is, the ZMDP might lead to a higher profit loss of generics due to their already low markups (and also due to the substitution between drugs and non-drug services), holding elasticities constant.

free entry/exit of drug manufacturers.[25] Also, we are holding physician behaviors in providing non-drug services unchanged in the counterfactual analysis. While confirming the direct (intended) effect of the policy being beneficial to patients, studies have shown that physicians could increase patients' spending on inpatient care or non-drug services, leading to ambiguous overall welfare effects for patients (Yi et al., 2015; Fang et al., 2021).

6 Concluding remarks

In this paper, we develop a structural model of China's prescription drug market to investigate the impact of the ZMDP. Using the data from PDB and various sources (e.g., *MENET*, *Yaozh*, etc.) on wholesale transactions of lipid-lowering drugs in a sample of hospitals during 2012–2018, we first estimate a mixed nested-logit demand model that accommodates the consumer heterogeneity due to zero-markup drug policy pilot programs. The demand estimation suggests that lipid-lowering drugs are highly differentiated. Brand-name drugs are preferred to their generic versions, which is in line with the literature. Moreover, physicians' prescription decisions are affected by the hospital markups, although they care more about patient welfare and choose drugs that have less out-of-pocket costs, unless coinsurance rate is high.

Under the assumption that prices are set according to Nash bargaining between each firm and the corresponding provincial government in China, we separately identify costs and bargaining parameters, the latter of which can be interpreted as the degree to which the government leaders choose to balance firm profits and the immediate consumer welfare. Results suggest that most policymakers value immediate consumer welfare more, and thus firms typically have a bargaining power parameter that is less than 0.5.

We perform a counterfactual analysis by removing the ZMDP in 2018 and quantify its impact on firms' profitability and patients' welfare. Our calculations indicate that, the ZMDP could lead to an increase in patients' welfare by about 22 percent.

[25] It is, however, likely that the effects we present here can persist for an extended period of time, given that pharmaceutical markets are highly regulated in China. Investigating the persistence of the effect is an interesting direction for future research.

Moreover, the ZMDP leads to lower (wholesale and retail) prices of both generic and branded drugs and makes the branded drugs less concentrated, which implies a 32 percent drop in firm profits. Overall, this counterfactual exercise confirms that the ZMDP largely achieves its policy goal of reducing drug prices, but the welfare impacts on the market depend on the weights we put on demand and supply sides, as well as the time frame we use to evaluate its effects (i.e., long term versus short term). Taking into account the unintended effects on non-drug services, the overall welfare effect of the policy is still an open question.

Finally, we close our paper by discussing some caveats and limitations of our current work. First, our results are based on a static model and does not include dynamic considerations, such as investment, entry and exit, etc., and so they can only evaluate the short-term effects of the policy. This also means that we do not consider physicians' strategic substitution between drugs and non-drug services, and thus ignore the potential longer-term, indirect, and likely "unintended" negative impacts on consumers. Second, we only focus on lipid-lowering drugs in a selected sample of urban hospitals (although across the country) in this paper, and a more comprehensive investigation that covers more hospitals, provinces and types of drugs would be helpful to understand the broader impact of ZMDP. Third, by controlling strategic advertising and other interactions between consumers/physicians and sales representatives (from manufacturers) in a reduced-form way in our model, we may not be able to evaluate the effects of the ZMDP through other channels. In fact, advertising may be a more relevant topic for investigating the "joint procurement" after late 2018, which intend to further lower drug prices that manufacturers are willing to accept (willing to sell) by reducing advertisement costs. These directions are potentially interesting and warrant future studies.

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Appendices

A Standard error

To calculate the standard errors of our estimated demand parameters, we need the derivatives of the unobserved drug quality with respect to the parameters, $\partial\xi_t/\partial\theta_2$. According to the implicit function theorem, we have

$$\frac{\partial \xi_t}{\partial \theta_2} = -\left(\frac{\partial s_t}{\partial \xi_t}\right)^{-1} \frac{\partial s_t}{\partial \theta_2}.$$

Let's denote

$$\sigma^r_{j|g}\left(P_t, M_t, \delta_t, \theta_2\right) = \frac{\exp\left\{\frac{\delta_{jt}-\alpha^r P_{jt}+\gamma^r M_{jt}}{1-\lambda}\right\}}{\sum_{j\in g}\exp\left\{\frac{\delta_{jt}-\alpha^r P_{jt}+\gamma^r M_{jt}}{1-\lambda}\right\}},$$

$$\sigma^r_{g}\left(p^R_t, M_t, \delta_t, \theta_2\right) = \frac{\left(\sum_{j\in g}\exp\left\{\frac{\delta_{jt}-\alpha^r P_{jt}+\gamma^r M_{jt}}{1-\lambda}\right\}\right)^{1-\lambda}}{\sum_{g\in G}\left(\sum_{j\in g}\exp\left\{\frac{\delta_{jt}-\alpha^r P_{jt}+\gamma^r M_{jt}}{1-\lambda}\right\}\right)^{1-\lambda}},$$

and

$$\kappa_t = \begin{cases} 1 & \text{before 2012Q3} \\ \phi & \text{between 2012Q3 and 2017Q3} \\ 0 & \text{after 2017Q3} \end{cases}.$$

If we denote $\kappa^1_t = \kappa_t$ and $\kappa^2_t = 1-\kappa_t$, then

$$\frac{\partial s_{jt}}{\partial \xi_{jt}} = \sum_{r=1}^{2}\kappa^r_t\left(\frac{1-\sigma^r_{j|g}}{1-\lambda}+\sigma^r_{j|g}(1-\sigma^r_g)\right)\sigma^r_{j|g}\sigma^r_g,$$

$$\frac{\partial s_{jt}}{\partial \xi_{j't}} = \begin{cases} \sum_{r=1}^{2}\kappa^r_t\left(-\frac{\sigma^r_{j'|g}}{1-\lambda}+\sigma^r_{j'|g}(1-\sigma^r_g)\right)\sigma^r_{j|g}\sigma^r_g & \text{if } j'\in g(j) \\ -\sum_{r=1}^{2}\kappa^r_t\sigma^r_{j'|g(j')}\sigma^r_{g(j')}\sigma^r_{j|g}\sigma^r_g & \text{if } j'\notin g(j) \end{cases},$$

$$\frac{\partial s_{jt}}{\partial \theta_{1,k}} = \sum_{r=1}^{2}\kappa^r_t\left(\frac{1-\sigma^r_{j|g}}{1-\lambda}+\sigma^r_{j|g}(1-\sigma^r_g)\right)\sigma^r_{j|g}\sigma^r_g x^k_t \text{ for } k=1,...,22,$$

$$\begin{aligned}\frac{\partial s_{jt}}{\partial \alpha} =& \kappa_t\left(\frac{1-\sigma^1_{j|g}}{1-\lambda}+\sigma^1_{j|g}(1-\sigma^1_g)\right)\sigma^1_{j|g}\sigma^1_g(-p^R_{jpt}) \\ &+(1-\kappa_t)\left(\frac{1-\sigma^2_{j|g}}{1-\lambda}+\sigma^2_{j|g}(1-\sigma^2_g)\right)\sigma^2_{j|g}\sigma^2_g(-p^W_{jpt}),\end{aligned}$$

$$\frac{\partial s_{jt}}{\partial \gamma} = \kappa_t \left(\frac{1-\sigma^1_{j|g}}{1-\lambda} + \sigma^1_{j|g}(1-\sigma^1_g) \right) \sigma^1_{j|g}\sigma^1_g m_{jpt},$$

$$\frac{\partial s_{jt}}{\partial \lambda} = \sum_{r=1}^{2} \kappa^r_t \left(\frac{1-\sigma^r_{j|g}}{1-\lambda} + \sigma^r_{j|g}(1-\sigma^r_g) \right) \sigma^r_{j|g}\sigma^r_g \frac{\delta_{jt} - \alpha^r P_{jt} + \gamma^r m_{jt}}{(1-\lambda)^2},$$

and

$$\frac{\partial s_{jt}}{\partial \phi} = \frac{\partial \kappa_t}{\partial \phi} \left(\sigma^1_{j|g}\sigma^1_g - \sigma^2_{j|g}\sigma^2_g \right)$$

where

$$\frac{\partial \kappa_t}{\partial \phi} = \begin{cases} 1 & \text{2012Q3} \leq t \leq \text{2017Q3} \\ 0 & \text{otherwise} \end{cases}.$$

Given $\partial \xi_t / \partial \theta_2$, the standard errors of our parameters are

$$\text{Std. Err.}(\theta_2) = \sqrt{\frac{1}{n} \left(\hat{Q}' \hat{W} \hat{Q} \right)^{-1} \hat{Q}' \hat{W} \hat{\Omega} \hat{W}' \hat{Q} \left(\hat{Q}' \hat{W} \hat{Q} \right)^{-1'}}$$

where

$$\hat{Q} = \frac{1}{n} \sum_{j,p,t} h(z^d_{jpt}) \left. \frac{\partial \xi_{jpt}}{\partial \theta_2} \right|_{\hat{\theta}_d},$$

$$\hat{\Omega} = \frac{1}{n} \sum_{j,p,t} \left(h(z^d_{jpt}) \xi_{jpt} - \bar{g} \right) \left(h(z^d_{jpt}) \xi_{jpt} - \bar{g} \right)'$$

in which $\bar{g} = \frac{1}{n} \sum_{j,p,t} h(z^d_{jpt}) \xi_{jpt}$; note that, $\hat{W} = \mathbb{I}$, and n is the full sample size.

B Elasticity

Demand semi-elasticity is given by

$$\begin{aligned}
\frac{\partial \ln s_{jt}\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W} &= \frac{\partial \ln\left(\kappa_t s_{jt}^1 + (1-\kappa_t)s_{jt}^2\right)}{\partial p_{jt}^W} \\
&= \frac{1}{s_{jt}}\sum_{r=1}^{2}\kappa_t^r \frac{\partial s_{jt}^r}{\partial p_{jt}^W} \\
&= \frac{1}{s_{jt}}\sum_{r=1}^{2}\kappa_t^r \left(\frac{\partial \sigma_{j|g}^r}{\partial p_{jt}^W}\sigma_g^r + \sigma_{j|g}^r \frac{\partial \sigma_g^r}{\partial p_{jt}^W}\right) \\
&= \frac{1}{s_{jt}}\sum_{r=1}^{2}\kappa_t^r \left(\frac{\sigma_{j|g}^r\left(1-\sigma_{j|g}^r\right)}{1-\lambda}\sigma_g^r + \sigma_g^r(1-\sigma_g^r)(\sigma_{j|g}^r)^2\right)\eta^r \\
&= \frac{1}{s_{jt}}\sum_{r=1}^{2}\kappa_t^r \left(\frac{1-\sigma_{j|g}^r}{1-\lambda} + \sigma_{j|g}^r(1-\sigma_g^r)\right)\sigma_{j|g}^r\sigma_g^r\eta^r
\end{aligned}$$

where

$$\eta^1 = \begin{cases} -1.15\alpha + 0.15\gamma & p_{jt}^{Highest} \geq 1.15 p_{jt}^W \\ -\gamma & p_{jt}^{Highest} < 1.15 p_{jt}^W \end{cases}, \; \eta^2 = \begin{cases} -\alpha & p_{jt}^{Highest} \geq p_{jt}^W \\ 0 & p_{jt}^{Highest} < p_{jt}^W \end{cases}$$

and welfare semi-elasticity is

$$\begin{aligned}
\frac{\partial \ln \Delta_j w_t\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W} &= \frac{1}{\Delta_j w_t\left(\mathbf{p}_t^W\right)}\frac{\partial w_t\left(p_{jt}^W, \mathbf{p}_{-jt}^W\right)}{\partial p_{jt}^W} \\
&= \frac{1}{\Delta_j w_t\left(\mathbf{p}_t^W\right)}\sum_{r=1}^{2}\kappa_t^r \frac{\partial\left[\delta_{jt} - \alpha^r P_{jt} + \gamma^r m_{jt} - (1-\lambda)\ln\sigma_{j|g}^r - \ln\sigma_g^r\right]}{\partial p_{jt}^W} \\
&= \frac{1}{\Delta_j w_t\left(\mathbf{p}_t^W\right)}\sum_{r=1}^{2}\kappa_t^r\eta^r\left[1 - \left(1-\sigma_{j|g}^r\right) - \sigma_{j|g}^r(1-\sigma_g^r)\right] \\
&= \frac{1}{\Delta_j w_t\left(\mathbf{p}_t^W\right)}\sum_{r=1}^{2}\kappa_t^r\eta^r\sigma_{j|g}^r\sigma_g^r
\end{aligned}$$

Note that, the (wholesale) price elasticity of demand is

$$p_{jt}^W \frac{\partial \ln s_{jt}\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W},$$

and the cross-price elasticity of demand is

$$
\begin{aligned}
& p_{j't}^W \frac{\partial \ln s_{jt}\left(\mathbf{p}_t^W\right)}{\partial p_{j't}^W} \\
&= \frac{\partial \ln\left(\kappa_t s_{jt}^1 + (1-\kappa_t) s_{jt}^2\right)}{\partial p_{j't}^W} \\
&= \frac{p_{j't}^W}{s_{jt}} \sum_{r=1}^{2} \kappa_t^r \frac{\partial s_{jt}^r}{\partial p_{j't}^W} \\
&= \frac{p_{j't}^W}{s_{jt}} \sum_{r=1}^{2} \kappa_t^r \left(\frac{\partial \sigma_{j|g}^r}{\partial p_{j't}^W} \sigma_g^r + \sigma_{j|g}^r \frac{\partial \sigma_g^r}{\partial p_{j't}^W} \right) \\
&= \begin{cases} \frac{p_{j't}^W}{s_{jt}} \sum_{r=1}^{2} \kappa_t^r \left(-\frac{\sigma_{j'|g}^r}{1-\lambda} + \sigma_{j'|g}^r (1-\sigma_g^r) \right) \sigma_{j|g}^r \sigma_g^r \eta^r & \text{if } j' \in g(j) \\ -\frac{p_{j't}^W}{s_{jt}} \sum_{r=1}^{2} \kappa_t^r \sigma_{j'|g(j')}^r \sigma_{g(j')}^r \sigma_{j|g}^r \sigma_g^r \eta^r & \text{if } j' \notin g(j) \end{cases}
\end{aligned}
$$

C Dealing with unobserved package sizes

The highest price regulation varies by package size (i.e, the number of units in each package, such as 12 tablets versus 14 tablets per package), which are not observed from our data.

Table A1: Rate at which retail price equals highest price (2012–2014)

	Lower bound (%)			Upper bound (%)		
	2012	2013	2014	2012	2013	2014
Molecule:						
Ezetimibe	82.61	98.78	92.77	82.61	98.78	92.77
Atorvastatin	85.23	76.33	75.31	86.91	81.00	78.75
Inositol Nicotinate	66.67	66.67	66.67	66.67	66.67	66.67
Probucol	73.81	70.68	67.16	73.81	70.68	67.16
Fluvastatin	69.83	73.41	72.02	80.45	80.35	79.17
Fenofibrate	56.83	53.19	51.84	60.43	57.60	55.81
Pravastatin	66.06	59.57	57.30	82.48	80.14	73.03
Simvastatin	56.33	55.20	60.51	58.77	58.28	64.23
Bezafibrate	45.55	46.11	40.31	63.35	62.69	54.08
Acipimox	61.38	49.60	45.38	66.90	59.20	58.46
Lovastatin	48.91	49.58	53.23	77.37	75.63	72.58
Rosuvastatin	56.82	67.95	56.59	59.09	81.79	72.20
Gemfibrozil	50.57	38.27	37.93	75.86	67.90	65.52
Pitavastatin	65.17	56.44	55.65	96.63	87.13	86.96
Jiaogulan	49.40	58.90	58.70	77.11	84.93	71.74
Zhibituo	50.00	35.71	50.00	53.85	53.57	50.00
Xuezhikang	48.96	52.17	48.94	84.38	83.70	89.36
Overall	60.66	59.86	59.35	70.20	70.62	68.81

Notes: (1) These rates are conditional frequencies calculated using the sub-sample with highest price regulations. (2) The highest price regulations can vary by drug form and size, and in our data only about 0.1% of the cases aggregate the forms and/or sizes without highest prices and the ones with highest prices, and we assume that those standardized drugs are under highest price regulations. (3) The highest price regulation also varies by package size, which is not observed from the data, and so we use the highest per unit price cap to calculate the lower bounds of the binding rates and the lowest per unit price cap to calculate the upper bounds of the binding rates.

To deal with this issue, for each aggregated drug product (a molecule-firm pair), we calculate the price caps based on several package sizes, and use the highest per unit

price cap to calculate the highest possible retail price (upper bound), and the lowest to calculate the lower bound. Our calculations suggest that they are very close to each other, compared to the magnitude of the prices themselves. Although the lower bound and upper bound are fairly close to each other, it creates a small problem in defining a "binding constraint" because in some cases $1.15p^W$ falls in the middle of the range created by the lower bound and upper bound of $p^{Highest}$. Table A1 illustrates this potential issue by calculating the portion of observations that encounter a binding highest price (i.e., $p^{Highest} \leq 1.15p^W$) between 2012 and 2014. The binding rates calculated based on the lower bounds and upper bounds are different but in general they are fairly close to each other. Our main results will be based on the lower bound (highest per unit price cap and thus highest retail price or markup). The analysis based on the upper bound is similar. One more takeaway from Table A1 is that the binding rates are fairly high and vary a lot by molecule, which suggests that there should be a good variation in retail price and hospital markup, although the retail price and markup are likely correlated.

D Market structure at the national level

Table A2 illustrates the structure of the lipid-lowering prescription drug market in China between 2012 and 2019, where we regard the whole country as a market and weight each province by the number of actual hospitals versus that of sampling hospitals. The market shares are relative to the total potential sales of lipid-lowering drugs and we assume that the treatment rate is 39 percent, based on Gao et al. (2013), for every year (so outside goods account for 69 percent of the market shares). We leave the question of the consequences of having time-varying (and later market-varying) treatment rates for future research. We also do not assume any variation in how each drug is used in each hospital.

As we can see from Table A2, the average wholesale price of each standard unit (weighted based on a fixed "basket" of firms in 2012) is declining over time. We include the firms that appear in each year at least once in the "basket" and weight the simple average wholesale price across different quarters and provinces for each firm by its corresponding yearly market share. While the decline was modest before 2016, it became quite significant after 2017 as the ZMDP kicked in and the CDP was enhanced. Entry was observed in Atorvastatin and Rosuvastatin, the top two most popular molecules in recent years.

Table A2: Lipid-lowering prescription drug market structure in China (2012–2019)

	2012	2013	2014	2015	2016	2017	2018	2019
Wholesale price (CNY)/std unit	3.25	3.19	3.16	3.13	3.08	2.96	2.85	2.63
Market shares of top brands								
Lipitor (Pfizer)	11.17%	11.99%	12.47%	11.79%	11.95%	12.77%	13.40%	13.21%
Zocor (MSD)	5.73%	4.31%	3.62%	3.00%	2.70%	2.16%	1.46%	0.90%
Crestor (AstraZeneca)	4.00%	4.97%	6.43%	7.03%	7.36%	8.14%	8.07%	5.90%
A Le (Jialin)	2.56%	2.81%	3.16%	3.72%	4.02%	3.99%	3.96%	5.39%
Lescol (Novartis)	2.30%	2.21%	1.96%	2.04%	1.77%	1.12%	1.03%	0.90%
Jing Bi Shu Xin (Jingxin)	1.36%	0.94%	0.69%	0.46%	0.44%	0.27%	0.21%	0.19%
You Jia (Topfond/Sinopharm)	1.08%	1.20%	1.11%	1.10%	0.81%	0.68%	0.48%	0.30%
Market shares of selected molecules								
Atorvastatin	14.82%	16.09%	16.86%	16.82%	17.39%	18.13%	18.85%	20.22%
Simvastatin	11.06%	8.86%	7.21%	6.29%	5.29%	4.47%	3.24%	2.44%
Rosuvastatin	5.59%	7.35%	9.01%	9.95%	10.77%	11.85%	12.44%	11.46%
Fluvastatin	2.66%	2.51%	2.18%	2.23%	2.01%	1.24%	1.10%	0.96%
Xuezhikang	0.53%	0.46%	0.35%	0.37%	0.34%	0.29%	0.24%	0.24%
Acipimox	0.32%	0.28%	0.18%	0.18%	0.17%	0.18%	0.17%	0.25%
Probucol	0.22%	0.18%	0.17%	0.18%	0.20%	0.19%	0.16%	0.17%
# firms of selected molecules								
Atorvastatin	4	6*	6	6	6	6	6	7
Simvastatin	42	39	42	39	35	38	37	36
Rosuvastatin	5	5	5	7	7	7	7	7
Fluvastatin	2	2	2	2	2	2	2	2
Xuezhikang	1	1	1	1	1	1	1	1
Acipimox	3	3	3	4	4	4	4	3
Probucol	2	2	2	2	2	2	2	2

Notes: (1) Wholesale price per standard unit is calculated using the "basket" of firms that appear in every year, weighted by their market shares in 2012. (2) Market shares are relative to the total potential sales of lipid-lowering drugs (the treatment rate is 39%). (3) The reported mean values of prices and market shares are weighted according to the hospital distribution in China versus in the sample. * In 2003, Topfond merged into Sinopharm, so we merge them into one firm here.

E Additional results

We present the estimation results under the assumption that the partial ZMDP period was 2015Q1–2017Q3 in Table A3.[26] With this alternative timeline, we can see that ϕ becomes lower (although less precisely estimated), which is reasonable because the average pilot rate increases as time goes by. Other parameter estimates are basically unchanged, showing the robustness of our estimation results.

Additionally, we allow the partial implementation parameter ϕ to be time varying and see if it affects our estimation results greatly. In particular, we assume that

$$\kappa_t = \begin{cases} 1 & \text{before 2012Q3} \\ \phi_1 & \text{between 2012Q3 and 2015Q2} \\ \phi_2 & \text{between 2015Q3 and 2017Q3} \\ 0 & \text{after 2017Q3} \end{cases}.$$

We do not restrict ϕ_1 to be larger than ϕ_2, although in reality we should have $\phi_1 \geq \phi_2$. If our estimation procedure gives the estimates $\hat{\phi}_1 \geq \hat{\phi}_2$ without any additional parameter constraints, we are surely more confident that our partial implementation parameter in the main model (see Table 6) identifies the proportion of type 1 consumer in our sample areas at least partially. Indeed, Table A4 shows that ϕ_t is decreasing over time, although it is more precisely estimated in the early period than the later period. When checking other parameters, we see that the magnitudes are almost identical with the main ones. Similar to the previous case when we use an alternative timeline, the estimation precision for γ declines.

[26] Policy documents about the ZMDP among urban hospitals are vague between 2013 and 2014. Also, Shenzhen only accounts for a very small portion of our sample, and is arguably negligible.

Table A3: Demand estimation results with alternative timeline

	Coef.	St. Err.
# of indications	5.095***	0.500
# of patient contraindications	-0.190*	0.100
# of drug contraindications	-2.229***	0.241
First generic drug	0.253***	0.080
Branded	1.111***	0.101
Time from entry	0.033***	0.008
(Time from entry)^2	-0.000***	0.000
Pilot rate	-0.035**	0.014
Start GCE	0.197*	0.103
α	0.438***	0.126
γ	1.249*	0.724
λ	0.668***	0.007
ϕ (for 2015Q1–2017Q3)	0.872	1.653
Constant	-14.719***	1.194
Molecule dummies (Reference: Acipimox, Rosuvastatin, Simvastatin, Xuezhikang)		
Atorvastatin	0.174	0.139
Bezafibrate	-5.356***	0.454
Ezetimibe	-0.179	0.199
Fenofibrate	-7.558***	0.669
Fluvastatin	0.283	0.213
Gemfibrozil	-12.572***	1.033
Inositol Nicotinate	-2.664	1.877
Lovastatin	-1.720***	0.287
Pitavastatin	1.846***	0.329
Pravastatin	2.225***	0.304
Probucol	6.588***	0.636
Zhibituo	-1.355***	0.223
Year dummies (Reference: 2012)		
2013	0.001	0.016
2014	-0.001	0.023
2015	0.001	0.178
2016	-0.001	0.193
2017	-0.000	0.137
2018	-0.001	0.291
Observations	23,147	
Objective function value	0.061	

Notes: (1) ***, **, * denote significance level at 1%, 5%, and 10%, respectively. (2) See Table 2 for variable definitions. (3) α measures the disutility of price, γ measures physician's marginal utility from drug markup (or the severity of expert agency problem) if there is any, λ is the nesting parameter, and ϕ measures the average proportion of type 1 consumers between 2015Q1 and 2017Q3.

Table A4: Demand estimation results with ZMDP expansion

	Coef.	St. Err.
# of indications	5.116***	0.427
# of patient contraindications	-0.168*	0.093
# of drug contraindications	-2.259***	0.214
First generic drug	0.316***	0.063
Branded	1.077***	0.092
Time from entry	0.034***	0.008
(Time from entry)^2	-0.000***	0.000
Pilot rate	-0.044***	0.015
Start GCE	0.213*	0.127
α	0.457***	0.127
γ	1.423	1.016
λ	0.714***	0.004
ϕ_1 (for 2012Q3–2015Q2)	0.862	0.613
ϕ_2 (for 2015Q3–2017Q3)	0.834	1.499
Constant	-14.719***	1.194
Molecule dummies (Reference: Acipimox, Rosuvastatin, Simvastatin, Xuezhikang)		
Atorvastatin	0.212	0.129
Bezafibrate	-5.598***	0.347
Ezetimibe	-0.176	0.186
Fenofibrate	-7.822***	0.551
Fluvastatin	0.552***	0.179
Gemfibrozil	-10.901***	0.838
Inositol Nicotinate	-2.232*	1.164
Lovastatin	-2.015***	0.259
Pitavastatin	2.221***	0.287
Pravastatin	2.413***	0.230
Probucol	5.715***	0.480
Zhibituo	-0.858***	0.210
Year dummies (Reference: 2012)		
2013	0.000	0.059
2014	-0.001	0.061
2015	0.000	0.076
2016	-0.001	0.190
2017	-0.000	0.114
2018	-0.001	0.376
Observations	23,147	
Objective function value	0.152	

Notes: (1) ***, **, * denote significance level at 1%, 5%, and 10%, respectively. (2) See Table 2 for variable definitions. (3) α measures the disutility of price, γ measures physician's marginal utility from drug markup (or the severity of expert agency problem) if there is any, λ is the nesting parameter, and ϕ measures the average proportion of type 1 consumers between 2015Q1 and 2017Q3.