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

Previously circulated as "Vertical Separation and Price Negotiation: A Case Study of China's Lipid-lowering Drug Industry"

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[2] The views expressed are ours and do not reflect those of the Bank of Canada.

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Introduction: Research Backgrounds
Institutional Background

- Since the Eastern Han Dynasty (25 - 220 A.D.), physicians and pharmacies had been “working together” in China—“integration” between prescribing and dispensing drugs.
- Patients and physicians are in an “expert-client” relationship, and an incentive problem can arise.

Figure 1: Zuotangyi (on-site physician)

Introduction: Research Backgrounds

Institutional Background (continued)

- Since 1950s, under financial distress, public hospitals were allowed to make profits from dispensing drugs (up to a 15% markup).
- Income source switches from financial subsidies to drug sales. Agency problem: tend to prescribe more and expensive drugs. Drug prices became too high.
- In 2010, China initiated a centralized drug procurement scheme to cut drug prices (bargain between firms and governments).
- A series of reforms were carried out in the past decade to further cut drug prices, including the zero-markup drug policy (ZMDP).
- It ended the 2,000 years long history of drug profit consideration by physicians.

Lipid-Lowering Drugs

- Market size is fast growing from 2014 to 2018 (20.3 to 30.2 billion CNY), and is expected to reach 50 billion CNY in 2023—this is an important market in China, so what's going on?

Introduction: Research Backgrounds

Key Time Frame

- 2012–2015Q1: non ZMDP period
- 2015Q2–2017Q3: partial ZMDP period
- 2017Q4–2018Q4: full ZMDP period

Table 1: Important policy changes between 2014 and 2018

Time	Description
Apr 2014	Removed highest retail price constraints $p^R \leq p^{Highest}$ for Lova., Feno., Gemfibrozil, Xuezhiang, and Zhibituo.
May 2015	**Initiated the ZMDP among some pilot prefecture-level hospitals (phase-in period).**
Jun 2015	Removed $p^R \leq p^{Highest}$ for all lipid-lowering drugs.
2015–2017	Drug revenue should account for $\leq$ 30% of all medical revenues in urban public hospitals by 2017.
Mar 2016	Launched the Generic Consistency Evaluation (GCE) program.
Sep 2017	**Drug markup m $=$ 0 for all public hospitals.**
Dec 2018	"4+7" large cities' joint procurement of two drugs (Atorva. and Rosuva.). Winning bidders (firms) shared 60–70% of the markets in those cities. (Since then, the CDP scheme has been changed largely. For the purpose of this paper, we narrow our focus to before 2019.)

Introduction: Research Questions & Literature

- Research Questions:
  1. Is the agency problem severe?
  2. What's the general equilibrium effect of ZMDP?
     2.1 How would physicians change their prescribing behavior?
     2.2 Would it decrease drug prices?
     2.3 How would it affect consumer welfare, firm profitability and market structure?
- Literature:
  1. Structural estimation of physicians' "agency problem": Izuka (2007), Jia Xiang (2021)
  2. Structural estimation of price negotiation: Horn and Wolinsky (1988), Crawford and Yurukoglu (2012), Grennan (2013), Gowrisankaran et al. (2015), Ho and Lee (2017), Dubois et al. (2019)

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Data: Sources

Sales and Prices

- Quarterly revenues *R* and quantities *q* of drugs treating hyperlipidemia included in China's "national drug catalog" between 2012Q1 and 2019Q3 in sample hospitals (700 across 24 provinces, 79% tertiary and 20% secondary) from **Pharmaceutical DataBase (PDB)**
- Regulatory highest retail prices from **YAOZH**
- Illness and treatment rates from **Annual Report on Cardiovascular Health and Diseases in China (2019)**

Drug and Firm Characteristics

- Product characteristics from various **package inserts**
- Firm characteristics from **MENET**
- Minimum wages (cost shifters) and systemic public hospital reform details (pilot rates) from various **policy documents**

Data: Cleaning

- Observations are at the manufacturer-molecule-form-size level in each province-quarter pair (defined as a market, t).
- Aggregate drugs across forms (e.g., tablets and capsules) and sizes (e.g., 5mg and 10mg per tablet) using "standard units" (dose $\times$ frequency).
- Aggregate sales to the company-molecule-market level, and then calculate standardized p^W in each market.
- Calculate pre-reform retail prices based on
  $\frac{p^R - p^W}{p^W} = 15\%$ and $p^R \leq p^{Highest} \Rightarrow p^R = \min\{p^{Highest}, 1.15p^W\}$
  and post-reform prices $p^R = p^W$.
- Obtain 23,147 data points in 2012–2018 (we dropped 2019 data in estimation due to a major change of procurement procedure).

Summary Statistics

Summary statistics

	Obs.	Mean	St. Dev.
Product and firm features			
# of indications	23,147	3.05	0.97
# of contraindications	23,147	5.31	1.71
First generic drug	23,147	0.22	0.42
Branded	23,147	0.25	0.43
Time from entry	23,147	48.97	20.16
Foreign	23,147	0.28	0.45
Chinese	23,147	0.06	0.24
Old Statins	23,147	0.43	0.49
New Statins	23,147	0.28	0.45
Fibrates	23,147	0.19	0.39
Niacin	23,147	0.04	0.19
Cost shifters			
Min wage	23,147	18.71	13.61
Imported	23,147	0.22	0.42
GSP	23,147	0.72	0.45
Policy shocks			
Pilot rate	23,147	0.41	0.40
Start GCE	23,147	0.02	0.15

Data: Reduced-form Trends of Price and Quantity

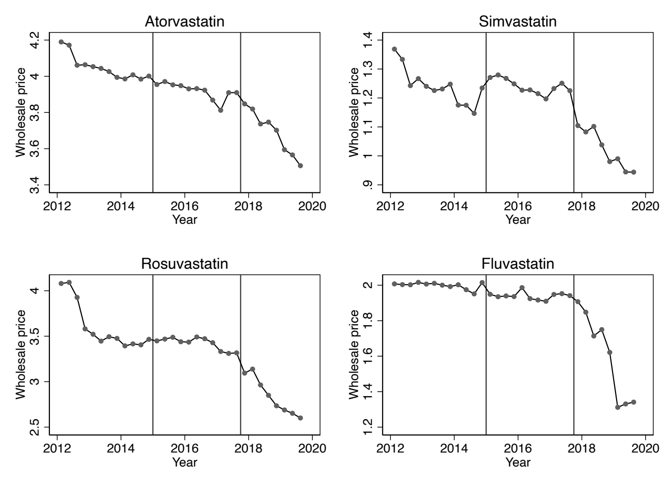

Figure 2: Average prices of top-selling lipid-lowering drugs in China

Fixed-effect regressions of log wholesale price and quantity

	(1) log price	(2) log quantity
2012–2014 (pre-reform)	(reference group)	
2015–2017Q3 (partial reform)	-0.042***	-0.197***
	(0.005)	(0.027)
2017Q4–2018 (post-reform)	-0.074***	-0.246***
	(0.007)	(0.037)
# of indications	0.461***	1.848***
	(0.090)	(0.466)
# of patient contraindications	-0.239***	0.685***
	(0.035)	(0.178)
# of drug contraindications	-0.684***	-0.460*
	(0.054)	(0.278)
First generic drug	-0.083***	0.681***
	(0.020)	(0.103)
Branded	0.075**	3.209***
	(0.035)	(0.182)
Pilot rate[3]	-0.033***	0.936***
	(0.006)	(0.033)
Start GCE	-0.220***	0.512***
	(0.016)	(0.083)
Firm fixed effect	Yes	Yes
Molecule fixed effect	Yes	Yes
Observations	23,147	23,147
R^2	0.551	0.394

[3] The proportion of cities with systemic public hospital reforms in each province.

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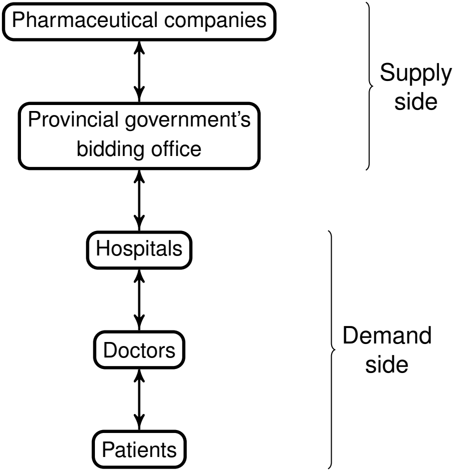
Model: Industry Compositions



Modeled participants of the lipid-lowering drug industry

Model: Demand

Utility from Drug

The joint utility of a patient-physician pair i from a standard unit of drug j in market t is:

$$\begin{aligned} U_{ijt} &= (1+\gamma)\log\left(\left(\exp\{\delta_{jt} - \alpha p^R_{jt} + \tilde{\varepsilon}_{ijt}\}\right)^{\frac{1}{1+\gamma}} \cdot \left(\exp\{m_{jt}\}\right)^{\frac{\gamma}{1+\gamma}}\right) \\ &= \delta_{jt} - \alpha p^R_{jt} + \gamma m_{jt} + \tilde{\varepsilon}_{ijt} \end{aligned}$$

where

- $\delta_{jt} = X'_{jt}\theta_1 + \xi_{jt}$ represents the mean utility, in which X_{jt} is a vector of observed product or market characteristics, ξ_{jt} is unobservable demand shock.
- Group g is defined by molecule and there are 17 of them.
- $\tilde{\varepsilon}_{ijt} = \zeta_{igt} + (1-\lambda)\varepsilon_{ijt}$ follows type 1 extreme value distribuition. ζ_{igt} is a random variable that is common to all products in nest g. λ is a "nesting parameter" capturing the within-group correlation between choices. Larger λ means nests matter more.

Model: Demand

Market Share of Drug

A physician represents the patient to (or they jointly) choose a drug j^* to maximize:

$$\max_{j \in 0, \mathcal{J}_t} U^r_{ijt}.$$

The market share of drug j in market t amongst type r consumers is

$$\begin{aligned} s^r_{jt} &= \sigma^r_j \left(p^R_t, m_t, \delta_t, \theta_2 \right) \\ &= \sigma^r_{j|g} \left(p^R_t, m_t, \delta_t, \theta_2 \right) \cdot \sigma^r_g \left(p^R_t, m_t, \delta_t, \theta_2 \right) \\ &= \frac{\exp\left\{ \frac{\delta_{jt} - \alpha^r p^R_{jt} + \gamma^r m_{jt}}{1-\lambda} \right\}}{\sum_{j \in g} \exp\left\{ \frac{\delta_{jt} - \alpha^r p^R_{jt} + \gamma^r m_{jt}}{1-\lambda} \right\}} \cdot \frac{\left(\sum_{j \in g} \exp\left\{ \frac{\delta_{jt} - \alpha^r p^R_{jt} + \gamma^r m_{jt}}{1-\lambda} \right\} \right)^{1-\lambda}}{\sum_{g \in \mathcal{G}_t} \left(\sum_{j \in g} \exp\left\{ \frac{\delta_{jt} - \alpha^r p^R_{jt} + \gamma^r m_{jt}}{1-\lambda} \right\} \right)^{1-\lambda}}, \forall j \in 0, \mathcal{J}_t \end{aligned}$$

and $s_{jt}(\delta_t, \theta_2) = \kappa_t s^1_{jt} + (1 - \kappa_t) s^2_{jt}$ where θ_2 (including θ_1, α, γ, λ, and κ_t) is to be estimated.

Assume $\kappa_t = \phi$ in 2015Q1–2017Q3, 1 before that and 0 afterwards.

Demand

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Demand Estimation

Discrete type random coefficient logit model (Berry and Jia, 2010)
Inner loop: The unobserved demand shock ξ_{jt} is obtained by a contraction mapping:

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

where M is the iteration number. And we have:

$$\xi_{jt}(\theta) = \delta_{jt} - X_{jt}'\theta$$

Outer loop: Our GMM identification conditions are

$$\mathbb{E}\left[Z_{jt}^{d}\xi_{jt}(\theta)\right] = 0$$

where Z_{jt}^{d} includes cost shifters and BLP-type IVs.

Demand

Demand Estimation

- BLP-type IVs:
  - The crowdedness of the product space: the number of drugs and the sum of characteristics for other drugs sharing the same molecular class at market t.
  - The ownership pattern: the number of drugs and the sum of characteristics for other drugs sold by the same firm at market t.
  - Although the assumption is commonly made in the literature, it may be strong in general. However, we believe our case is less severe than others due to the nature of the drug discovery process.
- Cost shifters: minimum wage, import or not, Good Supply Practice (GSP) certification.

Model: Supply

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Company Profit

Competing companies in each market choose their own prices (given prices of rival companies, so their decisions are interrelated) in order to maximize profits as follows:

$$\begin{aligned}\Pi_{ft}\left(\mathbf{p}_t^W\right) &= N_t\left(\sum_{j\in\mathcal{J}_{ft}}\left(p_{jt}^W - c_{jt}\right) s_{jt}(\delta_t, \theta_2)\right) \\ &= N_t \pi_{\mathcal{J}_{ft},t}\left(\mathbf{p}_t^W\right)\end{aligned}$$

where $\mathcal{J}_{ft}$ is the set of products produced by company f in market t, and N_t is its market size, i.e., the population of hyperlipidemia patients.

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Consumer Welfare

Regulators maximize aggregate consumer welfare in their provinces. For a given market t, the welfare is defined as the sum of the expected patient-doctor joint utility (rationalization: hospital representative during bargain) produced by each drug available in market (Small and Rosen, 1981):

$$
\begin{aligned}
W_t\left(\mathbf{p}_t^W\right) =& N_t w_t\left(\mathbf{p}_t^W\right) \\
=& N_t \sum_{r=1}^{2} \kappa_t^r \ln\left(\sum_{g\in\mathcal{G}_t}\left(\sum_{j\in g}\exp\left\{\frac{\delta_{jt}-\alpha^r p_{jt}^R+\gamma^r m_{jt}}{1-\lambda}\right\}\right)^{1-\lambda}\right)
\end{aligned}
$$

where $\kappa_t^1 = \kappa_t$ and $\kappa_t^2 = 1-\kappa_t$.

Model: Supply

Bargaining

- Bilateral Nash bargaining between firms and regulators.
- Bargaining takes place product-by-product, so that neither firms nor regulators are able to bargain jointly over their portfolio of pharmaceutical drugs.

$$\text{Nash product} = \underbrace{\left(N_t \Delta_j \pi_{\mathcal{J}_{ft},t}\left(\mathbf{p}_t^W\right)\right)^{\rho_j}}_{\text{Profit from j in t}} \underbrace{\left(N_t \Delta_j w_t\left(\mathbf{p}_t^W\right)\right)^{1-\rho_j}}_{\text{Welfare gain from j in t}}$$

$$= N_t \left(\Delta_j \pi_{\mathcal{J}_{ft},t}\left(\mathbf{p}_t^W\right)\right)^{\rho_j} \left(\Delta_j w_t\left(\mathbf{p}_t^W\right)\right)^{1-\rho_j}$$

where $\rho_j \in [0, 1]$ represents the relative bargaining power of the company in the bargaining of product j's price.

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Model: Supply

Bargaining (continued)

Company f cares about the equilibrium profit generated by offering drug j at price p_{jt}^W:

$$\Delta_j \pi_{\mathcal{J}_{ft}t}\left(\mathbf{p}_t^W\right) \equiv \pi_{\mathcal{J}_{ft},t}\left(\mathbf{p}_t^W\right) - \pi_{\mathcal{J}_{ft}\setminus\{j\},t}\left(\mathbf{p}_t^W\right) = \pi_{\{j\},t}\left(\mathbf{p}_t^W\right)$$

On the other hand, the government cares about the extra consumer welfare generated by the presence of drug j in market t:

$$\Delta_j w_t\left(\mathbf{p}_t^W\right) \equiv w_t\left(p_{jt}^W, \mathbf{p}_{-jt}^W\right) - w_t\left(\infty, \mathbf{p}_{-jt}^W\right)$$

The first order condition (FOC) is then given by:

$$c_{jt} - \frac{1}{\underbrace{\frac{\partial \ln s_{jt}\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W}}_{\text{Demand semi-elasticity}} + \frac{1-\rho_j}{\rho_j}\underbrace{\frac{\partial \ln \Delta_j w_t\left(\mathbf{p}_t^W\right)}{\partial p_{jt}^W}}_{\text{Welfare semi-elasticity}}} = p_{jt}^W$$

Note that when $\rho_j = 1$, pricing is set according to an unrestricted Bertrand-Nash equilibrium in prices where firms maximize profits.

Model: Supply

Supply Estimation

We parameterize the marginal cost function as follows:

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

And our identification condition is:

$$\mathbb{E}\left[Z_{jt}^{s}\omega_{jt}\right] = 0$$

where Z_{jt}^{s} includes cost shifters (min wage, import or not, and GSP[4] certification), time from entry, the molecule dummies and the province-year fixed effects. Given that β enters the FOC linearly, we simplify the optimization problem by concentrating out β in close-form

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

where $\tilde{c}_{jt}\left(\rho_j\right)$ is based on the FOC. We therefore have

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

[4]GSP = Good Supply Practice.

Results: Demand Parameters

The coefficient of hospital drug markup is approximately 2.89 times that of retail price in magnitude. This means that a physician is willing to give up 1 dollar of markup for a reduction of patient cost by 58 cents assuming a coinsurance rate of 20% (in reality it is 10%–30%, Zhang et al., 2020). Physicians would put a greater weight on patient welfare than hospital profit (derived from drug) unless the coinsurance rate is higher than 35%.

Demand parameter estimates

	Coef.	St. Err.
# indications	5.085***	0.519
# patient contradications	-0.188*	0.102
# drug contradications	-2.266***	0.260
First generic drug	0.251***	0.057
Branded	1.148***	0.063
Time from entry	0.034***	0.007
(Time from entry)^2	-0.000***	0.000
Pilot rate	-0.042***	0.012
Start GCE	0.176	0.240
α	0.439***	0.080
γ	1.268***	0.264
λ	0.668***	0.005
ϕ	0.796*	0.440
Constant	-14.63***	1.100
Molecule dummies	Yes	
Observations	23,147	
Objective function value	0.140	

Results: Demand Parameters

This finding is similar to Iizuka (2007)'s results in Japan, where Japanese physicians were willing to give up 1 dollar if patient's cost is reduced by 28 cents (assuming 20% coinsurance rate as well), suggesting that the agency problem of physicians in Japan was smaller in magnitude than that in China.

Results: Demand Parameters

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Other parameters also provide some interesting insights.

- The number of indications significantly increases the demand.
- Branded drugs are also favored over generic drugs.
- First mover advantage appears to exist.
- Time from entry indicates that there is a learning effect and/or a reputation accumulation effect.
- Molecule dummies suggest that the demand for Statins is usually larger than drugs of other therapeutic class.
- Public hospital reform seems to negatively impact the market share.
- The effect of generic consistency evaluation program insignificant, probably because it's too new.

Results: Demand Elasticities

The following table reports own-price elasticities for major drugs in China from 2012 to 2018. Overall, branded drugs are more inelastic (potentially showing higher market power). Both branded and generic drugs, nevertheless, became more inelastic over time, which suggests that patients became less price sensitive when facing lower prices (or higher purchasing power).

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

	Branded							Generic		
Subclass	Fibrate	Statin	Statin	Statin	Statin	CAI	Statin	Statin	Niacin	Statin
Company	Fournier	Luye	Novartis	Pfizer	AstraZ	SGP	MSD	Jialin	Lunan	Lunan
Molecule	Feno.	Xuezhikang	Fluva.	Atorva.	Rosuva.	Ezetimibe	Simva.	Atorva.	Acipimox	Rosuva.
Drug name	Tcicor	Xuezhikang	Lescol	Lipitor	Crestor	Zetia	Zocor	–	–	–
Year	Estimate									
2012	-9.918	-3.206	-2.478	-7.414	-4.305	-7.473	-3.119	-10.713	-6.373	-9.149
2013	-9.772	-3.419	-2.396	-7.118	-6.506	-10.413	-3.040	-9.850	-4.956	-10.870
2014	-8.450	-3.119	-2.111	-7.114	-5.538	-9.878	-2.932	-9.100	-5.187	-9.038
2015	-6.442	-3.155	-1.790	-5.307	-5.310	-7.290	-2.261	-6.838	-4.598	-8.351
2016	-5.834	-2.855	-1.817	-4.690	-4.740	-6.319	-1.997	-5.315	-4.190	-7.485
2017	-4.612	-2.926	-1.517	-4.372	-4.536	-5.479	-1.638	-5.152	-3.735	-6.447
2018	-3.570	-2.020	-0.704	-2.818	-2.987	-3.267	-1.159	-3.261	-2.268	-3.708

Results: Demand Elasticities

The following table presents cross-price elasticities among major drugs in China from 2012 to 2018. 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.

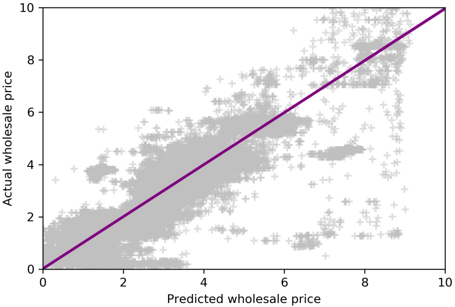
Most lipid-lowering agents are highly differentiated, as cross-price elasticities are much lower in magnitude than own-price elasticities. They tend to be more substitutable within the same molecular class (e.g., Atorvastatin produced by Pfizer versus Jialin, or Rosuvastatin produced by AstraZeneca versus Lunan).

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

	Branded							Generic		
Subclass	Fibrate	Statin	Statin	Statin	Statin	CAI	Statin	Statin	Niacin	Statin
Company	Fournier	Luye	Novartis	Pfizer	AstraZ	SGP	MSD	Jialin	Lunan	Lunan
Molecule	Feno.	Xuezhikang	Fluva.	Atorva.	Rosuva.	Ezetimibe	Simva.	Atorva.	Acipimox	Rosuva.
Drug name	Tcicor	Xuezhikang	Lescol	Lipitor	Crestor	Zetia	Zocor	–	–	–
Year	Estimate									
2012	0.027	0.021	0.048	1.363	0.718	0.009	0.080	0.342	0.013	0.080
2013	0.027	0.023	0.051	1.429	0.924	0.017	0.063	0.314	0.018	0.119
2014	0.022	0.018	0.042	1.300	0.823	0.011	0.051	0.316	0.010	0.112
2015	0.019	0.015	0.033	1.019	0.702	0.012	0.036	0.261	0.008	0.123
2016	0.015	0.014	0.022	0.836	0.597	0.015	0.026	0.244	0.007	0.136
2017	0.012	0.012	0.012	0.796	0.512	0.015	0.019	0.230	0.006	0.152
2018	0.007	0.007	0.007	0.494	0.279	0.011	0.009	0.154	0.004	0.113

Results: Supply Estimation

To show the fitness of our pricing equilibrium, we predict the wholesale prices using our estimated marginal cost function by following Pakes (2017) and Wollmann (2018). The predicted prices and actual prices are basically centering around a 45-degree line, with few outliers. The linear regression of actual prices on predicted prices without a constant gives a coefficient of 0.998, which is nearly 1.

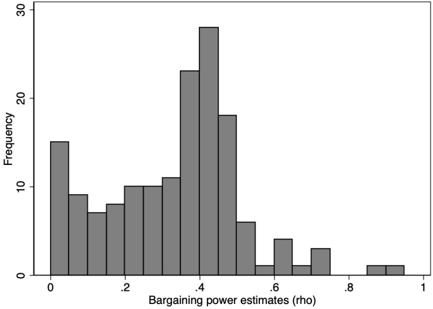


Predicted prices versus actual prices

Results: Supply Parameters

It's not surprising to see that most firms/products have $\rho_j < 0.5$, while only few show higher bargaining power over the government. A significant amount of firms have low bargaining power (< 0.1).

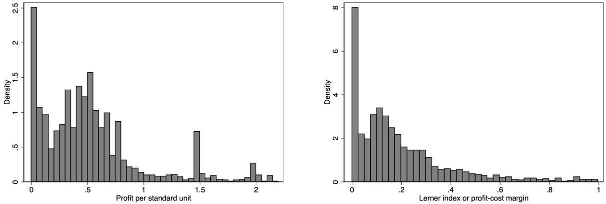
Our results are very different from Dubios et al. (2019). They studied US, Canada, France, Germany, UK, Italy and Spain. They found most firms with > 0.5 bargaining power parameters.



Distribution of bargaining parameters

Results: Estimated Margins in 2018

- 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 0.63 yuan (about 0.1 dollars). Range: near 0 to 2.15.
- Lerner index is 0.27 on average, and most products exhibit a relatively low market power.



(a) Estimated profit per standard unit in 2018

(b) Lerner index in 2018

- Further calculations suggest that most branded drugs have a higher average marginal cost, a much higher average price, and thus a higher average price-cost margin (0.28 versus 0.19).

Results: Market Concentration

Branded drugs take up 61% of the total market share, and the top 10% (in terms of market share) take up 83% of the branded drug market share, indicating high market concentration.

Revenue of all branded drugs is 110% higher than that of all generic drugs, while profit is 321% higher. The top 10% branded drugs have way higher price-cost margins than the rest.

Share, profit, and revenue 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 (in 100m yuan)	All drugs	24.59	5.70	18.89
	Branded	16.67	2.25	14.41
	Generic	7.92	3.44	4.48
Profit (in 100m yuan)	All drugs	4.47	0.87	3.60
	Branded	3.61	0.27	3.34
	Generic	0.86	0.60	0.26

Counterfactuals: Equilibrium

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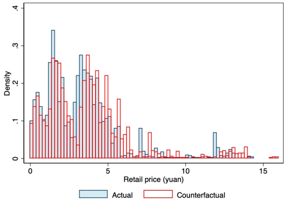
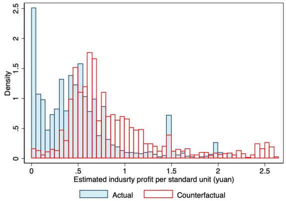
- We perform a counterfactual analysis by withdrawing the ZMDP in 2018 by adding back a 15% hospital drug markup.
- There are 3 mechanisms that ZMDP would affect retail price:
  - Direct effect: if wholesale prices are fixed, it would directly lower retail prices;
  - Dethronement (substitution) effect: it makes the expensive branded drugs less attractive than the cheap generic drugs, which leads to lower prices (either wholesale or retail) of branded drugs and higher prices of generic drugs;
  - Push-out effect: removing markup also makes physicians less likely to prescribe in general (such as encouraging patients to go on a diet instead), which leads to lower prices of prescription drugs.

Counterfactuals: Equilibrium

- With a counterfactual drug markup, prices paid by consumers would be higher, and the industry profit per unit would also be higher (although manufacture profit per unit would be lower due to a lower average wholesale price).



(a) Counterfactual versus actual retail prices in 2018



(b) Counterfactual versus actual industry profit per unit in 2018

Counterfactuals: Shares, Revenues, and Profits

Branded drugs experience a large increase in share, and become more concentrated, while generic drugs would lose some profits. Under a drug markup top-selling branded drugs are more preferred by physicians.

A 15% hospital drug markup could lower the consumer surplus (only consider patient) of patients by 12% in 2018.

		All firms	Bottom 90%	Top 10 %
Market share (%)	All drugs	50.58	13.52	37.06
		(38.99)	(11.97)	(27.02)
	Branded	34.57	4.69	29.88
		(23.73)	(3.93)	(19.80)
	Generic	16.01	8.83	7.18
		(15.26)	(8.04)	(7.22)
Revenue (in 100m yuan)	All drugs	33.81	7.53	26.28
		(24.59)	(5.70)	(18.89)
	Branded	24.29	2.93	21.36
		(16.67)	(2.25)	(14.41)
	Generic	9.52	4.61	4.92
		(7.92)	(3.44)	(4.48)
Profit (in 100m yuan)	All drugs	4.83	0.82	4.01
		(4.47)	(0.87)	(3.60)
	Branded	4.09	0.26	3.83
		(3.61)	(0.27)	(3.34)
	Generic	0.74	0.56	0.18
		(0.86)	(0.60)	(0.26)
Patient surplus change			-12.24%	

Counterfactuals: Shares, Revenues, and Profits

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 yuan.

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- We present a structural model of China's prescription drug market, and estimate the impact of hospital drug markup on profitability and patient welfare. This may help us understand better how a policy works.
- Our results suggest that, in China:
  - Prescription choices are influenced by drug markup, but are more sensitive to patient's out-of-pocket costs, unless the coinsurance rate is $\geq 35\%$.
  - Pricing is mostly dominated by provincial governments.
  - Branded drugs were favored and more concentrated than generics, and the demand for generics is 23% more price sensitive than branded drugs on average.
  - The ZMDP is pro-generics.
  - Although market shares could be lowered by the ZMDP, patient welfare could be improved by $> 12\%$.

Thank You!

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