Online Appendix for

"Competitive Bidding in Drug Procurement: Evidence from China"

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A Proofs and Derivations

In this section, we provide details of the proofs and derivations for the stylized model outlined in Section III.

Consider a molecule with one firm selling a branded product B and another firm selling a bioequivalent generic product G. Both products offer an identical clinical value of 1 to a unit mass of consumers. Consumers have heterogeneous brand preferences for product B that are drawn independently from a continuously differentiable distribution $\mathscr{F}$ with non-negative support. We further assume $\mathscr{F}$ has no mass at 0. The marginal costs of both products are the same at c. Prior to competitive bidding, firms set prices to maximize profits simultaneously in a Bertrand game with differentiated products. We use p_B^* and p_G^* to denote equilibrium prices under the Bertrand competition.

The government introduces competitive bidding with sales guarantee $\tau \in (0,1]$. The format is a first-price sealed-bid auction, and we assume firms have complete information on $\mathscr{F}$ and marginal costs. The winner commits to selling at the winning bid and is guaranteed a quantity of τ, or all consumers who value the winning product no less than the winning bid if there are fewer than τ such consumers. Then the losing firm sets a price to maximize profits taking the winner's price and quantity guarantee as given. If it sets a price such that its unconstrained quantity exceeds $1-\tau$, the losing firm will only sell to $1-\tau$ of consumers who value its product (relatively) the most. We use p'_B and p'_G to denote equilibrium prices under competitive bidding.

A.1 The Generic Drug Always Wins

We prove this result for a general $\mathscr{F}$ with non-negative support by contradiction. Let F denote its cumulative distribution function. Suppose there exists an equilibrium where the branded drug submits a bid $p_1 < 1$ and the generic drug submits a bid $p_1' \geq p_1$, and the branded drug wins the auction. The generic drug chooses a price p_2 to maximize profits after losing the auction. We must have $p_2 < p_1$, otherwise, the generic drug will have a market share of 0.

The generic drug's profit is $(p_2 - c)\min\{1-\tau, F(p_1 - p_2)\}$. Note that the generic drug always chooses p_2 such that $F(p_1 - p_2) \leq 1-\tau$ because its market share is at most $1-\tau$. Its profit thus simplifies to $(p_2 - c)F(p_1 - p_2)$, subject to $F(p_1 - p_2) \leq 1-\tau$.

Now consider a unilateral deviation by the generic drug: the generic drug cuts its bid to $p_1 - \varepsilon > 0$ and wins the auction. Let $p^B(\varepsilon)$ represent the best response by the branded drug. We must have $p^B(\varepsilon) > p_1 - \varepsilon$. Otherwise, the branded drug will have an unconstrained market share of 1. That contradicts to the fact that the loser can only receive a maximum quantity of $1-\alpha$ due to the quantity guarantee. Therefore, the branded drug could be better off by increasing the price, thus it should always choose $p^B(\varepsilon)$ such that $1 - F(p^B(\varepsilon) - p_1 + \varepsilon) \leq 1-\tau$. The generic drug's profit under this deviation is $(p_1 - \varepsilon - c)\max\{\tau, F(p^B(\varepsilon) - p_1 + \varepsilon)\}$, which can be simplified to $(p_1 - \varepsilon - c)F(p^B(\varepsilon) - p_1 + \varepsilon)$ subject to $F(p^B(\varepsilon) - p_1 + \varepsilon) \geq \tau$, or $p^B(\varepsilon) \geq p_1 + F^{-1}(\tau) - \varepsilon$.

For this deviation to be unprofitable, we need:

$$\text{(A.1)} \qquad \underbrace{(p_2 - c)F(p_1 - p_2)}_{\text{Generic losing the auction}} \geq \underbrace{(p_1 - \varepsilon - c)F(p^B(\varepsilon) - p_1 + \varepsilon)}_{\text{Generic winning the auction}}.$$

By continuity, this inequality holds for $\varepsilon \to 0^+$, which is

$$\text{(A.2)} \qquad (p_2 - c)F(p_1 - p_2) \geq (p_1 - c)F(p_3 - p_1),$$

where $p_3 = p^B(0) \geq p_1 + F^{-1}(\tau) > p_1$. The fact that $F^{-1}(\tau) > 0$ for any $\tau > 0$ comes from the assumption that $\mathscr{F}$ has no mass at 0.

Next, consider a unilateral deviation by the branded drug: the branded drug increases its bid above p_1' and loses the auction. Let p_3' represent its optimal price after losing the auction. Similarly, for this deviation to be unprofitable, we need:

$$\begin{aligned}
\underbrace{(p_1-c)(1-F(p_1-p_2))}_{\text{Branded winning the auction}} &\geq \underbrace{(p_3'-c)(1-F(p_3'-p_1'))}_{\text{Branded losing the auction}} \\
&\geq (p_3-c)\min\{1-\tau, 1-F(p_3-p_1')\} \\
&\geq (p_3-c)\min\{1-\tau, 1-F(p_3-p_1)\} \\
&= (p_3-c)(1-F(p_3-p_1)). \qquad \text{(A.3)}
\end{aligned}$$

The second line comes from the fact that p_3' is the best response to p_1' and is weakly more profitable than p_3. The third line comes from $p_1' \geq p_1$. The last line comes from $F(p_3-p_1) \geq \alpha$.

As $p_2 < p_1$, inequality A.2 implies $F(p_1-p_2) \geq F(p_3-p_1)$. As $p_3 > p_1$, inequality A.3 implies $F(p_3-p_1) \geq F(p_1-p_2)$. It follows that $F(p_3-p_1) = F(p_1-p_2) > 0$. Then equation A.2 holds only if $p_2 \geq p_1$, which contradicts the fact that $p_2 < p_1$. So there does not exist an equilibrium where the branded drug wins the auction.

A.2 Derivations of Equilibrium Prices

To analytically solve the equilibrium prices, we assume $\mathscr{F}$ follows a uniform distribution $\mathbb{U}(0,1)$. For simplicity, we also assume the marginal costs of both firms are 0. Then firms' profits under the Bertrand competition are given by:

$$\begin{aligned}
\pi_B &= p_B(1-p_B+p_G) \\
\pi_G &= p_G(p_B-p_G)
\end{aligned}$$

The best response functions are $p_B = \frac{1+p_G}{2}$, and $p_G = \frac{p_B}{2}$. Equilibrium prices are $p_B^* = \frac{2}{3}$, and $p_G^* = \frac{1}{3}$. Equilibrium market shares are $s_B^* = \frac{2}{3}$, and $s_G^* = \frac{1}{3}$.

Now consider a competitive bidding with a quantity guarantee τ between $\frac{1}{3}$ and 1. From Appendix A.1, the generic product always wins the auction. We solve the equilibrium prices.

Let $p_G' \leq 1$ denote the winning bid of the generic drug G. When $p_G' < 1$, in equilibrium, this bid must make the firm B exactly indifferent between undercutting and conceding to the bid. Otherwise, if the bid is higher, firm B has the incentive to undercut; if the bid is lower, firm G has the incentive to raise the bid and still win the auction. When $p_G' = 1$, this bid must make firm B weakly prefer conceding to the bid than undercutting, because firm G cannot further increase the bid, otherwise, it will receive zero market share despite the guarantee, as no consumers value the product more than 1.

We hope to write p'_G as a function of τ and proceed case by case. When $p'_G < 1$, the indifference condition is

$$p'_G \times \max\{1 - \frac{p'_G}{2}, \tau\} = (1-\tau)(p'_G + \tau) \tag{A.4}$$

The left-hand side of Equation (A.4) is the profit of firm B from undercutting the bid by $\varepsilon \to 0^+$. When it undercuts the bid, firm B will win the auction. In response, firm G will either set a price of $p'_G - (1-\tau)$ so that it has a market share of exactly $1-\tau$, or a price of $\frac{p'_G}{2}$ and has a market share of $\frac{p'_G}{2}$. It will choose the former if $1-\tau \geq \frac{p'_G}{2}$ and the latter otherwise.

The right-hand side of Equation (A.4) is the profit of firm B from conceding to the bid. It's easy to see that firm B's best response is to target the remaining consumers, set a price of $p'_G + \tau$, and capture all the remaining $1-\tau$ consumers.

Case I: $1 - \frac{p'_G}{2} < \tau$. Equation (A.4) reduces to $p'_G\tau = (1-\tau)(p'_G+\tau)$, which gives us

$$p'_G = \frac{\tau(1-\tau)}{2\tau - 1}.$$

For this to hold, we need $2(1-\tau) < p'_G < 1$, or $\tau \in (\frac{\sqrt{5}-1}{2}, \frac{2}{3})$.

Case II: $1 - \frac{p'_G}{2} \geq \tau$. Equation (A.4) reduces to $p'_G(1 - \frac{p'_G}{2}) = (1-\tau)(p'_G+\tau)$, which gives us

$$p'_G = \tau - \sqrt{3\tau^2 - 2\tau}.$$

For this to hold, we need $3\tau^2 - 2\tau \geq 0$ and $p'_G \leq 2(1-\tau)$, or $\tau \in [\frac{2}{3}, 1]$.

Case III: $p'_G = 1$. Firm B must weakly prefer conceding to the bid than undercutting. Similarly, we need

$$1 \times \max\{0.5, \tau\} \leq (1-\tau)(1+\tau).$$

It follows that $\tau \leq \frac{\sqrt{5}-1}{2}$. We also need to impose the incentive compatibility constraint, i.e., firm G must be weakly better off participating in the auction than the Bertrand competition. Its profit under the Bertrand competition is $\frac{1}{3}$, so this implies $\tau \geq \frac{1}{3}$. No equilibrium would exist if $\tau < \frac{1}{3}$.

Collecting the cases, we have:

$$p'_G = \begin{cases} 1, & \frac{1}{3} \leq \tau < \frac{\sqrt{5}-1}{2} \\ \frac{\tau(1-\tau)}{2\tau-1}, & \frac{\sqrt{5}-1}{2} \leq \tau < \frac{2}{3} \\ \tau - \sqrt{3\tau^2 - 2\tau}, & \frac{2}{3} \leq \tau \leq 1 \end{cases}.$$

The branded product always sets $p'_B = p'_G + \tau$ to target the remaining $1-\tau$ consumers:

$$p'_B = \begin{cases} 1+\tau, & \frac{1}{3} \leq \tau < \frac{\sqrt{5}-1}{2} \\ \frac{\tau^2}{2\tau-1}, & \frac{\sqrt{5}-1}{2} \leq \tau < \frac{2}{3} \\ 2\tau - \sqrt{3\tau^2 - 2\tau}, & \frac{2}{3} \leq \tau \leq 1 \end{cases}.$$

The results are plotted in Figure 1.

A.3 The Winning Bid Weakly Decreases in Quantity Guarantee τ

We show that the winning bid weakly decreases in the level of quantity guarantee τ. Start with a quantity guarantee τ_1 and let the winning bid be p_B^1. If $p_B^1 = 1$, the bid cannot increase as τ increases because the bid cannot exceed the value of the generic drug. If $p_B^1 < 1$, firm B is exactly indifferent between undercutting and conceding to the bid at τ_1. Suppose the quantity guarantee increases to $\tau_2 > \tau_1$, while the winning bid remains at p_B^1. For firm B, profits from undercutting the bid increase because of the larger quantity guarantee to the winner, while profits from conceding to the bid decrease because of a smaller residual market. Firm B will undercut p_B^1, which forces firm G to reduce its bid to $p_B^2 < p_B^1$.

B A Model with Heterogeneous Brand Preferences

We extend our demand model to allow heterogeneous brand preferences. We assume that each patient chooses a drug product j to maximize utility under the supervision of physicians. A market is defined as province m in year t. The indirect utility of patient i in province m and year t from product j and molecule g follows a nested-logit specification with a random coefficient:

$$(B.5)\, u_{ijmt} = \underbrace{\alpha\phi_i p_{jmt} + \beta BE_{jt} + \lambda_{jm} + \lambda_{mt} + \xi_{jmt}}_{\delta_{jmt}} + \sigma_\nu \nu_i branded_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}.$$

Here, $\phi_i p_{jmt}$ is patient i's out-of-pocket expenditures equal to the listed price p_{jmt} multiplied by the coinsurance rate ϕ_i (1 minus the reimbursement rate), where $\phi_i = 0.28$ for insured patients $\phi_i = 1$ for uninsured ones. Variable $branded_j$ takes the value 1 if j is a branded product. Preference draw ν_i follows a standard normal distribution, and parameter σ_ν is the standard deviation of the brand preferences. We define each molecule (or the outside option) as a nest. ζ_{igmt} is consumer i's preference shock common to all products in molecule g. Both ε_{ijmt} and $\zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$ follow a type-I extreme value distribution, and σ determines the degree of the within-nest correlation in preference shocks.

To estimate this model, we leveraged microdata from hospitals in one large administrative district in Beijing in 2018. We observe the insurance status of each patient who visited the hospitals and the drugs they purchased (if any). We highlight two useful moments in the microdata. First, the fraction of uninsured patients is 24% among all patients, but only 3% conditional on buying any antihypertensive medication. While we do not directly target the 3% as a moment, we will use it as an over-identification test for our price elasticity estimate.

Second, conditional on purchasing any drug, 40.6% of uninsured patients bought the branded drugs, compared to 71.1% of insured patients. In other words, insured patients are 75% more likely to buy branded drugs than uninsured patients. This moment helps us estimate σ_b. When we restrict σ_b to 0, our model predicts 77.5% of the insured patients would buy branded drugs, more than four times the 17.5% among the uninsured patients. A larger variance in brand preferences implies that more uninsured patients would get a large enough draw of brand preference to make them prefer the branded drugs despite the higher out-of-pocket prices. We target this moment and the orthogonality conditions of our instruments using the simulated method of moments (SMM). We calculate the standard errors using 50 bootstrapped samples at the province level.

Appendix Table A.2 shows the estimation results. Column (1) shows the results of our baseline nested-logit model, where we assume all consumers are insured. In Column (2), we replicate the baseline model but assume 24% of consumers are uninsured. The results are very close between the two columns. The estimated price elasticity in Column (2) implies that 5.1% of patients who bought antihypertensive drugs are uninsured, similar to the 3% observed in the data. Column (3) shows the results of the random coefficient model. The estimated price elasticity becomes slightly larger. We also find a sizable variance in brand preferences among consumers. One-standard deviation increase in brand preference is worth about 1.13 CNY in the out-of-pocket drug price (the average out-of-pocket branded price is 1.59 CNY).

Appendix Figure A.21 plots the distribution of estimates of markups using the random coefficient nested logit model, separately for branded and generic drugs. The estimates are similar to what we found in the nested-logit model because of two countervailing changes: slightly more elastic demand (which reduces markups) and sizable variation in brand preferences across consumers (which increases markups).

C Imputation of Policy Demand Shifters

As in Section V.E, the estimated demand shifter for drug j in province m in 2019 is denoted as $\hat{\gamma}_{jm,2019}$ in Equation (7). Since drugs might enter or exit the market across years, our sample is not a balanced panel of product-year-province combinations. As discussed in Section V.E, we exclude products that were new to some provinces in 2019, as we do not have marginal cost estimates for these products. For a few losing drugs that were only sold in 2018 but not in 2019 in some provinces, we impute $\hat{\gamma}_{jm,2019}$ using the estimated demand shifters of the same product or products in the same molecule in other provinces. There are a total of 38 such observations.

More specifically, in the first step, if the product is missing in an enacting province in 2019, we impute its policy demand shifter using the average estimated policy effect of the same product across all other enacting provinces. If it is missing in an non-enacting province, we use the average estimated policy effect of the same product across all other non-enacting provinces.

$$\hat{\gamma}_{jm\in M,2019} = \frac{\sum\limits_{k\in M, j\in \mathscr{J}_{k,2019}} \hat{\gamma}_{jk,2019}}{|\{k : k \in M, j \in \mathscr{J}_{k,2019}\}|}, \quad \text{where } M \in \{E, NE\},$$

where $\mathscr{J}_{m,2019}$ is the set of available drugs in province m in 2019, E is the set of enacting provinces, and NE is the set of non-enacting provinces. In this way, we can impute the policy demand shifters for 32 out of the 38 product-province observations.

We impute the rest 6 drug-province pairs using the average estimated policy demand shifters across all products of the same molecule, excluding the auction winner.[34] Specifically,

$$\hat{\gamma}_{j\in g,m\in M,2019} = \frac{\sum_{k\in M}\sum_{l\in g,l\in \mathscr{J}^{loser}_{k,2019}} \hat{\gamma}_{lk,2019}}{\sum_{k\in M}\{|l : l\in g, l\in \mathscr{J}^{loser}_{k,2019}\}|}, \quad \text{where } M\in\{E,NE\},$$

where g is the molecule that drug j belongs to and $\mathscr{J}^{loser}_{m,2019}$ is the set of available drugs in province m in 2019, excluding the auction winner if the province is an enacting province.

D Welfare When Decision Utility and Actual Utility Differ

As discussed in Sections V.E and VI.A, in our setting, a consumer's decision utility can differ from her actual utility in two ways. First, under the quantity guarantee, consumers' decision utility for drug j is shifted by $\tilde{\gamma}_{jm,2019}$. Second, consumers' brand preferences could be a misperception and welfare irrelevant, which might only contribute to decision utility but not actual utility. In this section, we describe the calculation of consumer surplus when the decision utility differs from the actual utility.

Our method builds on Train (2015)'s example where the consumers' anticipated and experienced attributes differ. Similar exercises can be found in Allcott (2013) and Cao and Chatterjee (2022). Suppose the decision utility is given by u_{ijmt} and the actual utility is given by $\tilde{u}_{ijmt} = u_{ijmt} + \Delta u_{jmt}$. The true consumer surplus is given by

$$CS = \frac{1}{\alpha}E(\tilde{u}_{ijmt}) = \frac{1}{\alpha}E(u_{ijmt}) + \frac{1}{\alpha}\sum s_{jmt}\times\Delta u_{jmt}, \tag{D.6}$$

where s_{jmt} is the market share of drug j chosen under the decision utility u_{ijmt}.

Now we apply this method to different utility functions in Section VI.A. First, we consider the case without the policy demand shifters, but we assume consumers' brand preferences are welfare irrelevant, thus does not affect the actual utility. Consumer i's decision utility is given by:

$$\tilde{u}^{D}_{ijm,2019} = v^{perceived}_{jm,2019} + \alpha\phi p_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$$

while her actual utility is

$$\tilde{u}^{A0}_{ijm,2019} = v^{true}_{jm,2019} + \alpha\phi p_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$$

[34] All auction winners are not missing in 2019. So these products are all losing products or products in the non-enacting provinces.

The consumer surplus is given by

$$CS = \frac{1}{\alpha}E(\tilde{u}^{D}_{ijm,2019}) + \frac{1}{\alpha}\sum s_{jmt} \times (v^{true}_{jm,2019} - v^{perceived}_{jm,2019}),$$

where s_{jmt} is the market share of drug j chosen under the decision utility $\tilde{u}^{D}_{ijm,2019}$.

Second, we consider the case with the policy demand shifters, but assume consumers' brand preferences are welfare relevant. Consumer i's decision utility is given by:

$$\tilde{u}^{D}_{ijm,2019} = v^{perceived}_{jm,2019} + \alpha\phi p_{jm,2019} + \tilde{\gamma}_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt},$$

while her actual utility is given by:

$$\tilde{u}^{A0}_{ijm,2019} = v^{perceived}_{jm,2019} + \alpha\phi p_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}.$$

The consumer surplus is given by

$$CS = \frac{1}{\alpha}E(\tilde{u}^{D}_{ijm,2019}) - \frac{1}{\alpha}\sum s_{jmt} \times \tilde{\gamma}_{jm,2019},$$

where s_{jmt} is the market share of drug j chosen under the choice utility $\tilde{u}^{D}_{ijm,2019}$.

Last, we consider the case with the policy demand shifters, and assume consumers' brand preferences are welfare irrelevant. Consumer i's decision utility is given by:

$$\tilde{u}^{D}_{ijm,2019} = v^{perceived}_{jm,2019} + \alpha\phi p_{jm,2019} + \tilde{\gamma}_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$$

while her actual utility is

$$\tilde{u}^{A0}_{ijm,2019} = v^{true}_{jm,2019} + \alpha\phi p_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$$

The consumer surplus is given by

$$CS = \frac{1}{\alpha}E(\tilde{u}^{D}_{ijm,2019}) + \frac{1}{\alpha}\sum s_{jmt} \times (v^{true}_{jm,2019} - v^{perceived}_{jm,2019} - \tilde{\gamma}_{jm,2019}),$$

where s_{jmt} is the market share of drug j chosen under the decision utility $\tilde{u}^{D}_{ijm,2019}$.

E Supplemental Tables and Figures

Table A.1: Demand Estimation Using Alternative Instruments

	(1) NLogit IV1	(2) NLogit IV2	(3) NLogit IV3
Price	-1.415	-1.712	-1.699
	(0.561)	(0.411)	(0.337)
Passed BE	0.0586	0.0135	-0.0315
	(0.110)	(0.0789)	(0.0888)
Cond. Mkt Share	0.419	0.474	0.796
	(0.294)	(0.312)	(0.482)
N	3191	2623	2623
Province-Drug FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Kleibergen-Paap Wald rk F-statistic	9.5	5.4	2.5
Stock-Yogo Weak ID Test 5% Critical Value	7.0	7.0	7.0

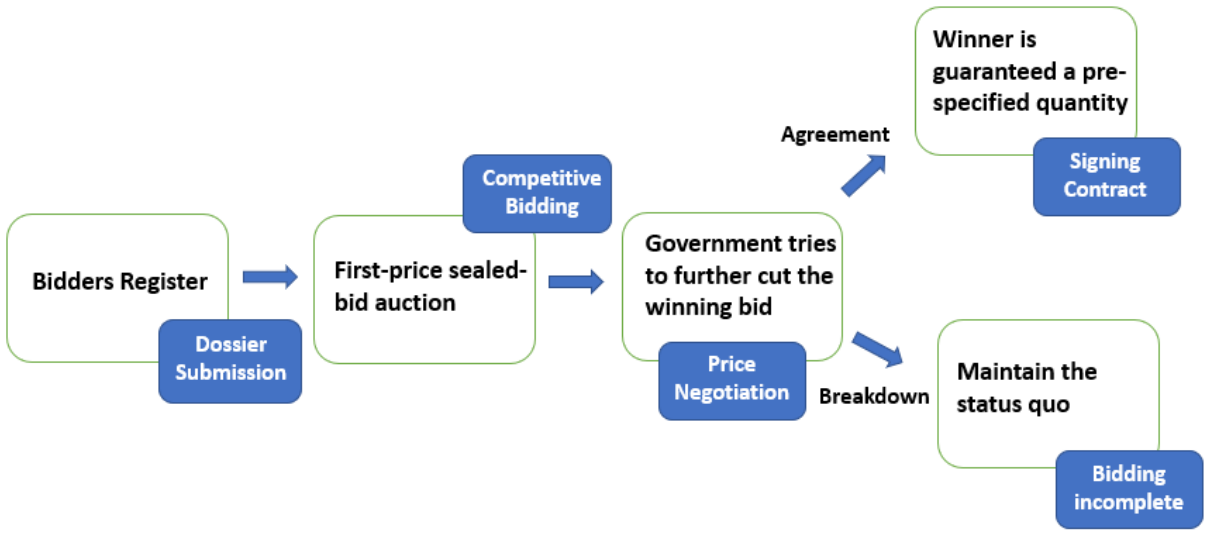
Notes: This table shows the estimation results of the demand system in Equation (3) using alternative instruments. Column (1) reports results from our main specification with the Hausman instrument and the BLP instruments. Column (2) uses the same set of instruments as in Column (1) but uses a smaller sample as in Column (3), where we exclude the first year in our data from the regression. Column (3) uses the same Hausman instrument and redefines the BLP instruments as the total number of drugs for each molecule in each market in the previous year. We perform a weak identification test using the Kleibergen-Paap Wald rk F-statistic. The Stock-Yogo weak ID test critical value is for a 5% Wald test using the 10% maximal IV size.

Table A.2: Estimation Results from the Random-Coefficient Nested Logit Model

	(1) Main	(2) Insured	(3) RC
Price	-1.415	-1.275	-1.436
	(0.561)	(0.626)	(0.737)
Pass BE	0.059	0.032	0.035
	(0.110)	(0.093)	(0.083)
Cond. Mkt Share	0.419	0.415	0.449
	(0.294)	(0.254)	(0.259)
RC			1.629
			(0.944)
N	3191	3191	3191
Province-Drug FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes

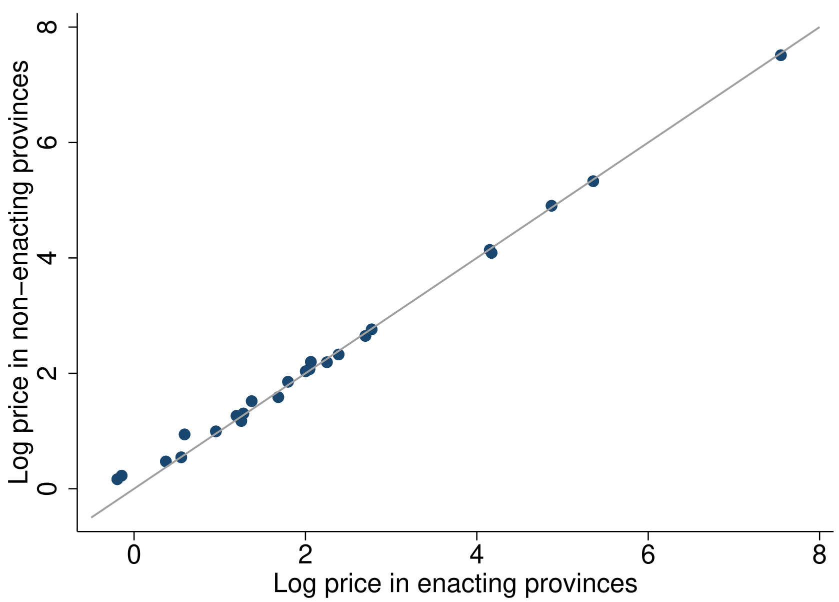
Notes: This table shows the estimation results of the random-coefficient model. Price is the out-of-pocket price paid by patients. Column (1) shows the results of our baseline nested-logit model as in Column (4) of Table 2, where we assume all consumers are insured. In Column (2), we replicate the baseline model but assume 24% of consumers are uninsured. Column (3) shows the results of the random coefficient model. Standard errors are clustered at the province level.

Figure A.1: Bidding and Negotiation Process



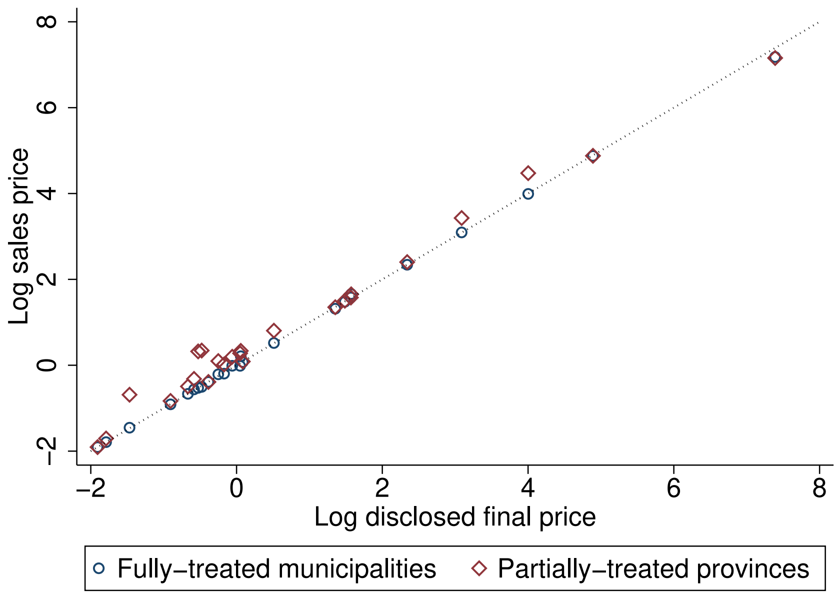
Notes: This figure shows the detailed bidding and negotiation process. The drug producers first register for competitive bidding and submit their dossiers. Then they participate in a first-price sealed-bid auction. The bidder with the lowest bidding price is selected as the auction winner. In some scenarios, the government would initiate a negotiation process with the auction winner in an attempt to further cut down the price. If a deal is not reached at this stage, the status quo would be maintained. Otherwise, the auction winner would be guaranteed a pre-specified quantity and sell their drugs at the final negotiated price.

Figure A.2: Drug Pricing in Enacting and Nonenacting Provinces in 2018



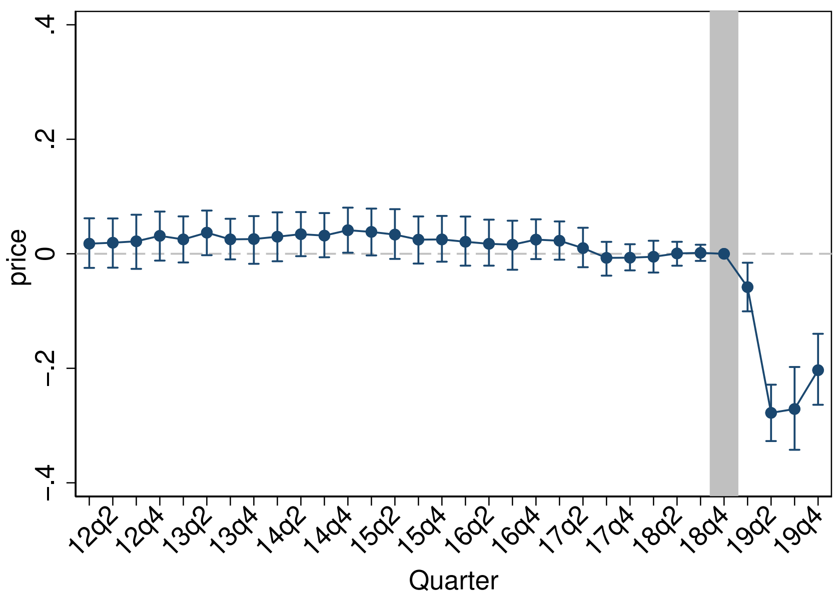
Notes: This figure compares average prices for each drug product in enacting provinces and nonenacting provinces in 2018.

Figure A.3: Compare Sales Price and Disclosed Final Price



Notes: This figure compares the final negotiated prices disclosed by the government and the sales prices observed in the data. The x-axis represents the log of final prices disclosed by the government, and the y-axis represents the log of sales prices of the winning products in enacting provinces observed in our data. We categorize provinces by whether they are fully treated (i.e., four municipalities including Beijing, Shanghai, Chongqing, and Tianjin) or partially treated with only one or two large cities covered by the competitive bidding. The gray dotted line represents the 45-degree line.

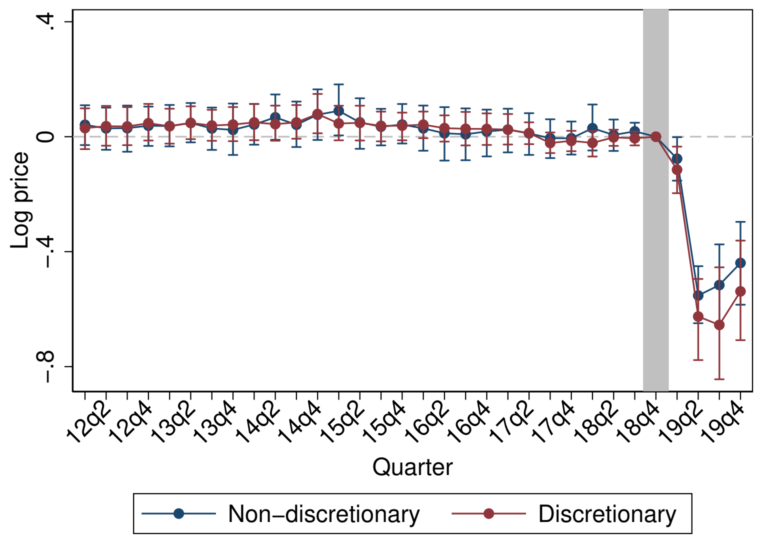
Figure A.4: Policy Effects on Drug Price Levels



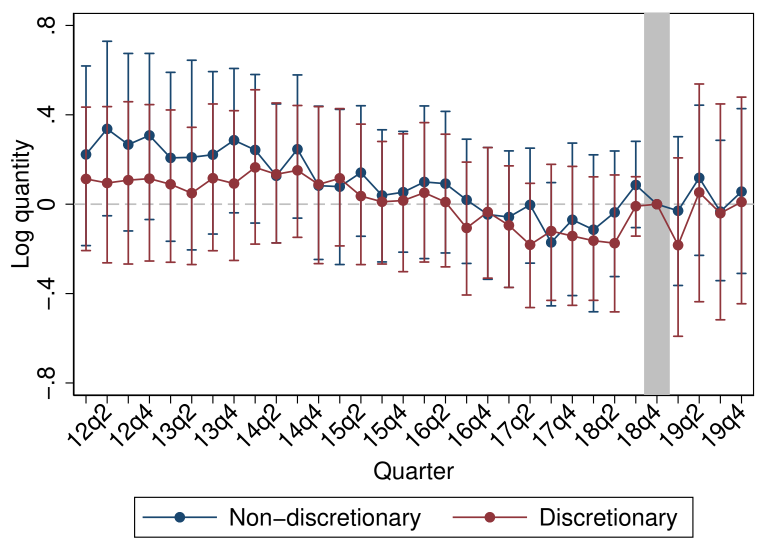
Notes: This figure shows the effects of competitive bidding on the level of drug prices, estimated using the specification shown in Equation (1). The outcome variable is the price of each drug product in each province-quarter pair, normalized by its price in the first quarter of 2012. Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval with standard errors clustered at the province level. The coefficient for the fourth quarter of 2018 is normalized to zero.

Figure A.5: Heterogeneous Policy Effects by Discretionary and Non-discretionary Drugs

A. Price



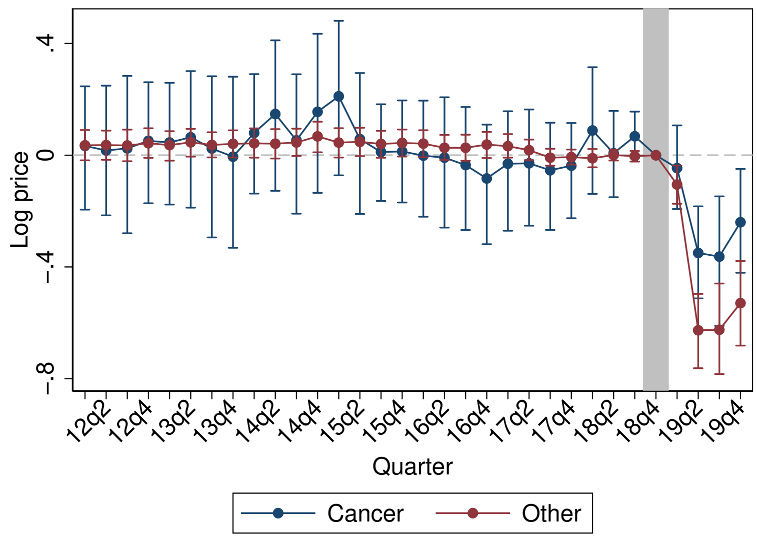
B. Quantity



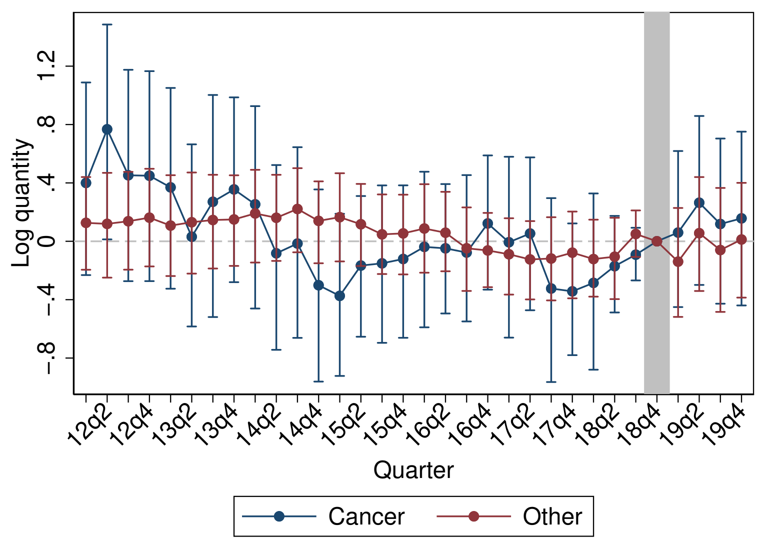
Notes: This figure shows the effects of competitive bidding on drug prices and sales separately for drugs in discretionary and non-discretionary categories. Disease categories that we consider discretionary include arteriosclerosis, high cholesterol, epilepsy, hypertension, and mental illness. Disease categories that we consider non-discretionary include asthma, cancer, diarrhea, HIV, hepatitis B, infection, and painkillers.

Figure A.6: Heterogeneous Policy Effects by Out-of-pocket Costs

A. Price



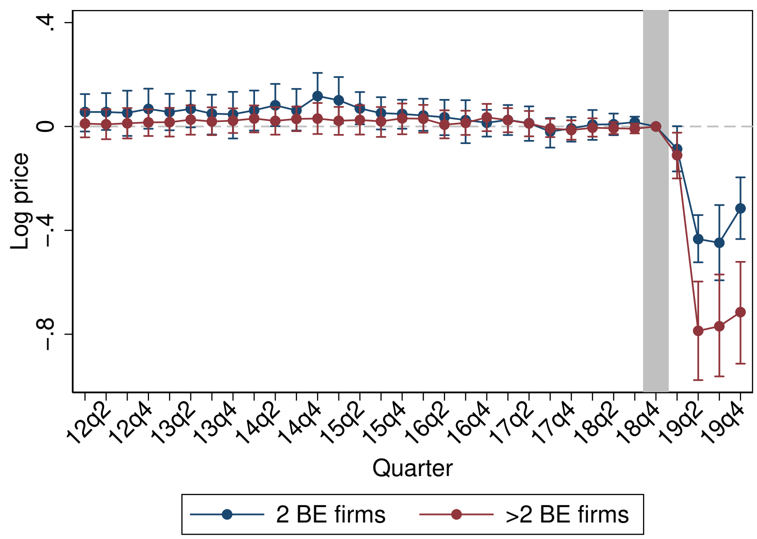
B. Quantity



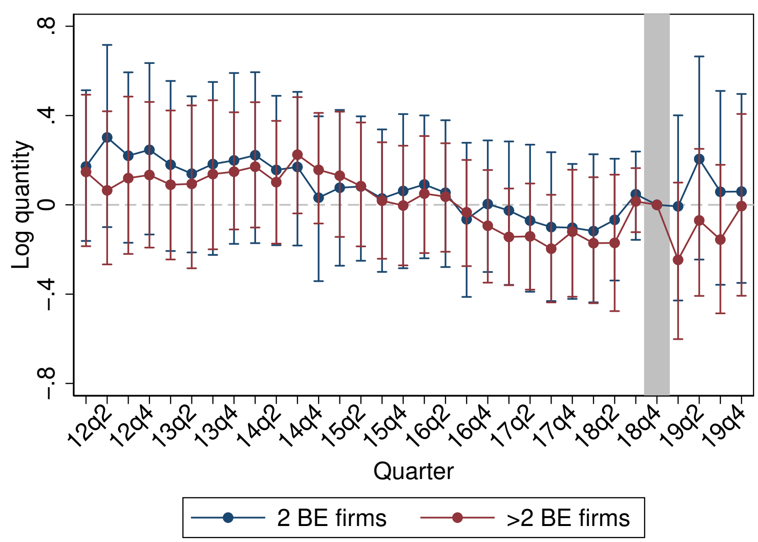
Notes: This figure shows the effects of competitive bidding on drug prices and sales separately for drugs with high and low out-of-pocket costs. We consider out-of-pocket costs to be high for drugs that treat cancer (gefitinib, imatinib mesylate, and pemetrexed disodium) and low for other drugs.

Figure A.7: Heterogeneous Policy Effects by the Number of Bidders

A. Price



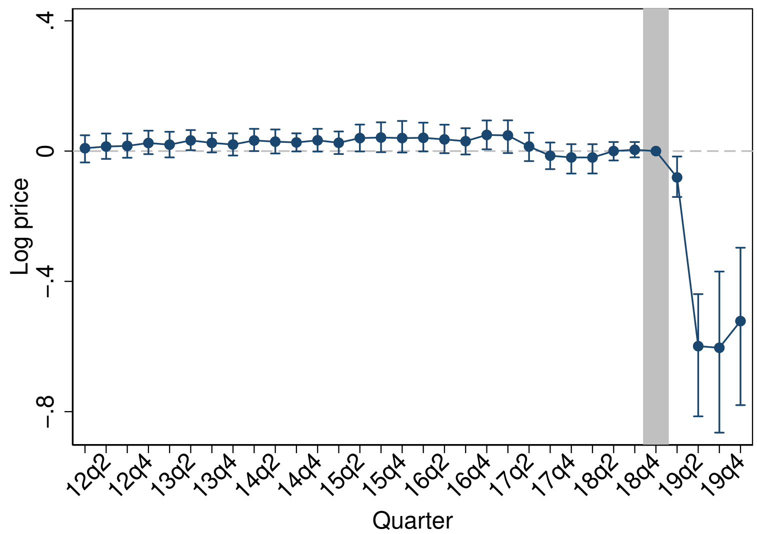
B. Quantity



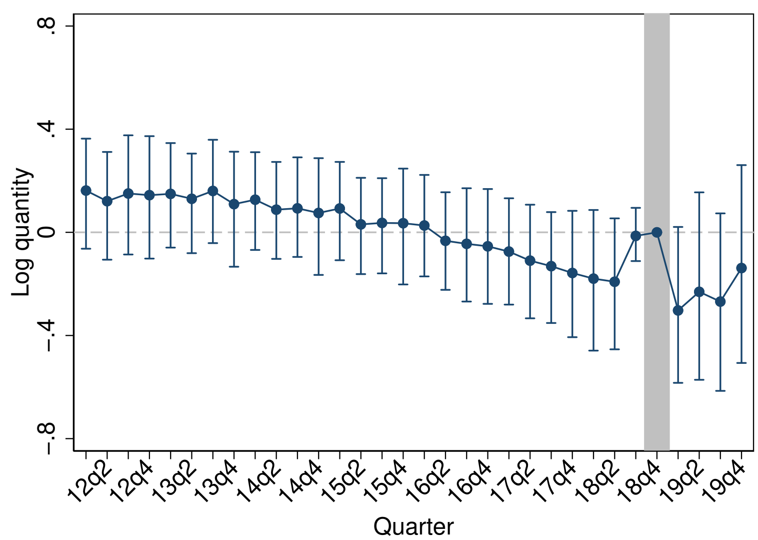
Notes: This figure shows the effects of competitive bidding on drug prices and sales separately for molecules with two bioequivalent firms (14 molecules) and drugs with more than 2 bioequivalent firms (11 molecules). Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval with standard errors clustered at the province level. The coefficient for the fourth quarter of 2018 is normalized to zero.

Figure A.8: Policy Effects on Drug Prices and Sales, Sales Weighted

A. Price

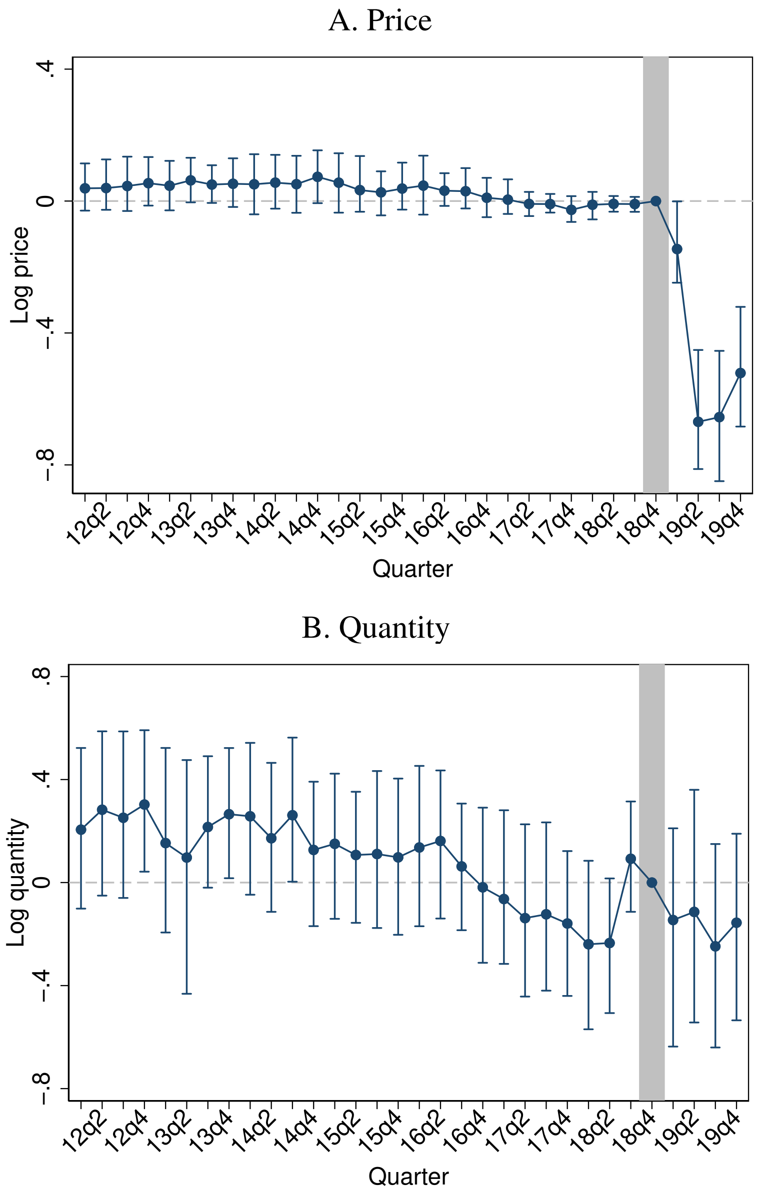


B. Quantity



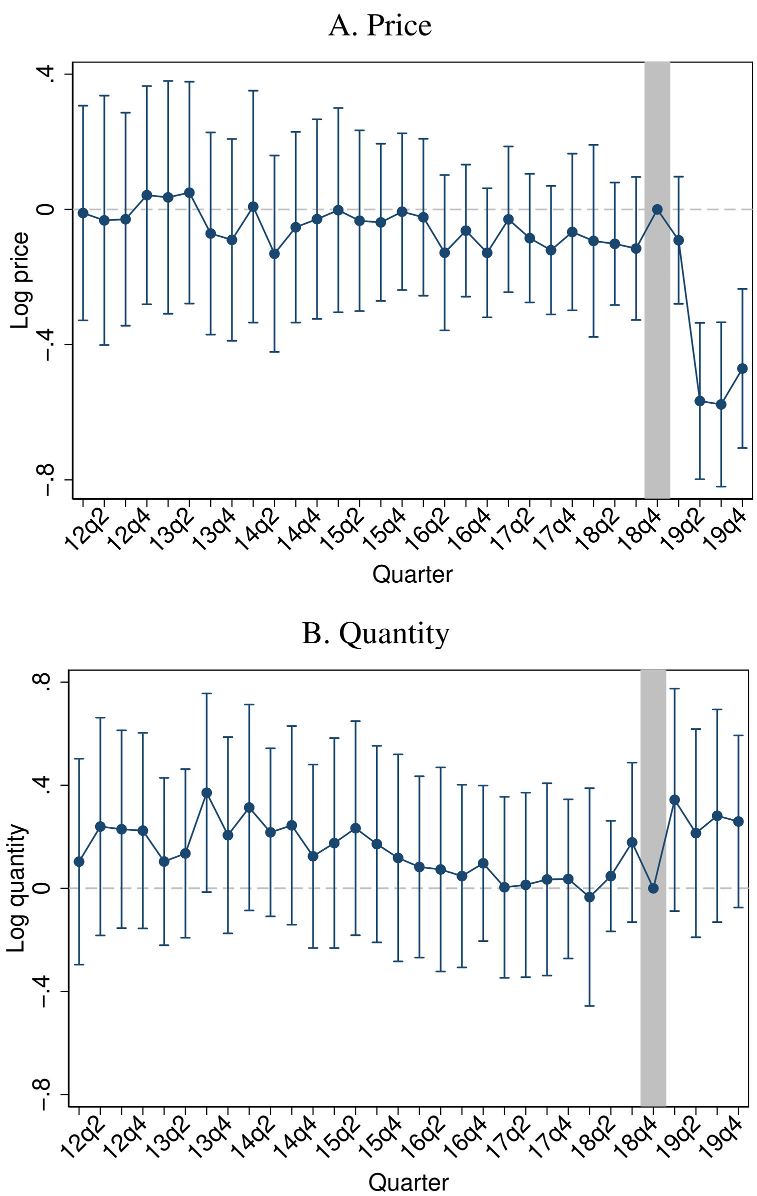
Notes: This figure shows the effects of competitive bidding on drug prices and sales, similar to Figure 6. The only difference is that each observation is weighted by the total sales quantity at the province-molecule level during 2012-2018 in this figure.

Figure A.9: Policy Effects on Drug Prices and Sales, Excluding Partially Treated Provinces



Notes: This figure shows the effects of competitive bidding on drug prices and sales, similar to Figure 6. The only difference is that only four municipalities, Beijing, Tianjin, Shanghai, and Chongqing, are included as enacting provinces in this figure. We drop provinces where seven other enacting cities are located, as these provinces are only partially treated.

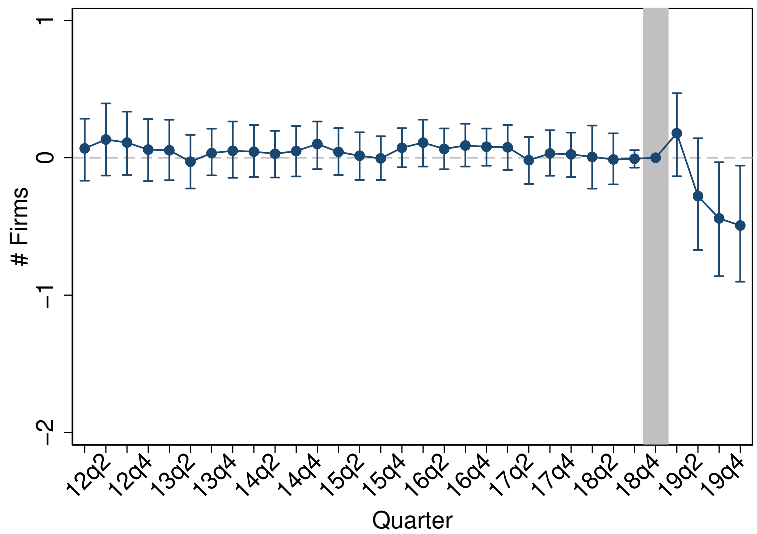
Figure A.10: Policy Effects on Drug Prices and Sales, DDD Specification



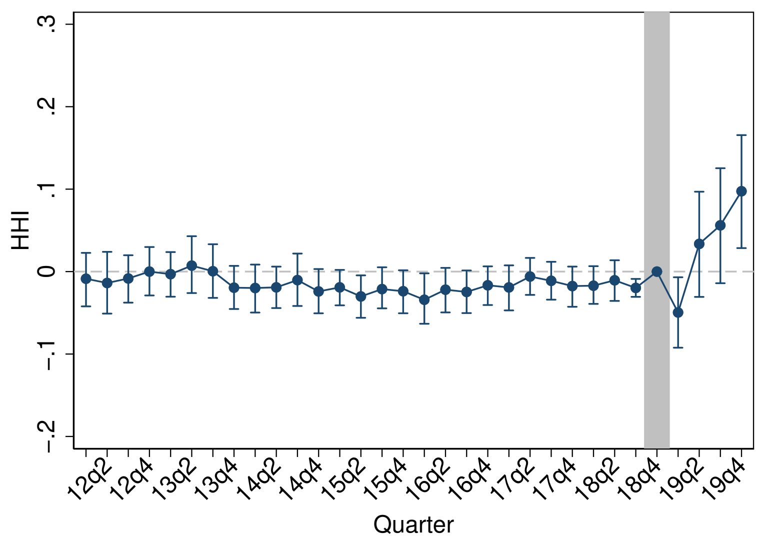
Notes: This figure shows the effects of the competitive bidding on drug prices and sales, estimated using the DDD specification described in Section IV.C. Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval with standard errors clustered at the province level.

Figure A.11: Policy Effects on Market Concentration

A. Number of Firms

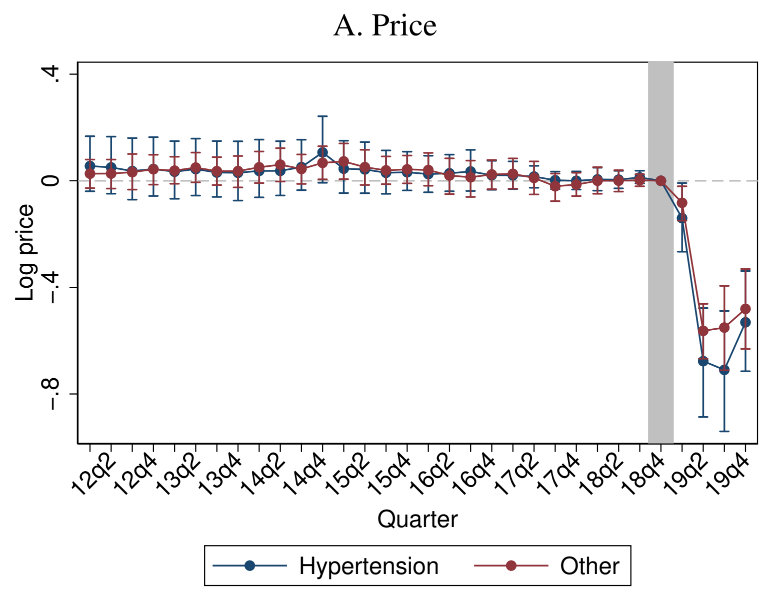


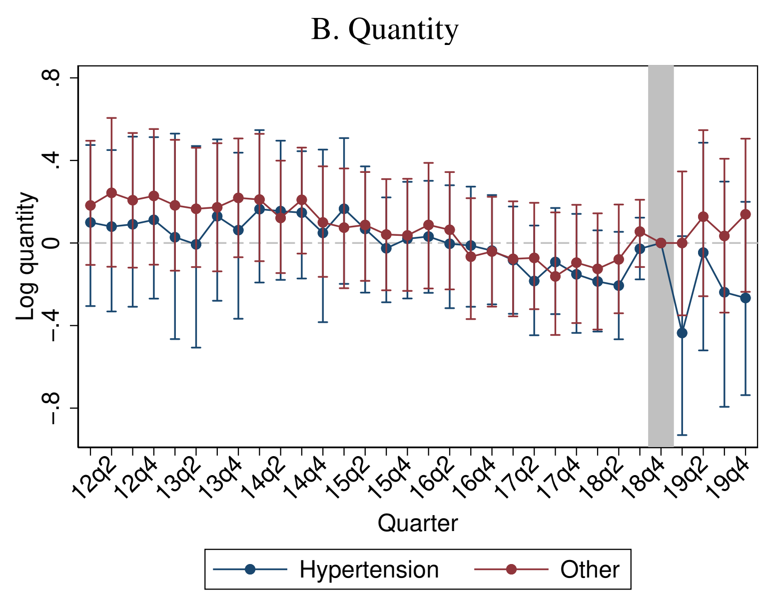
B. HHI



Notes: This figure shows the effects of the competitive bidding on the number of active firms and Herfindahl-Hirschman Index (HHI), estimated using the specification shown in Equation (1). Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval using standard errors clustered at the province level. The coefficient of the fourth quarter of 2018 is normalized to zero.

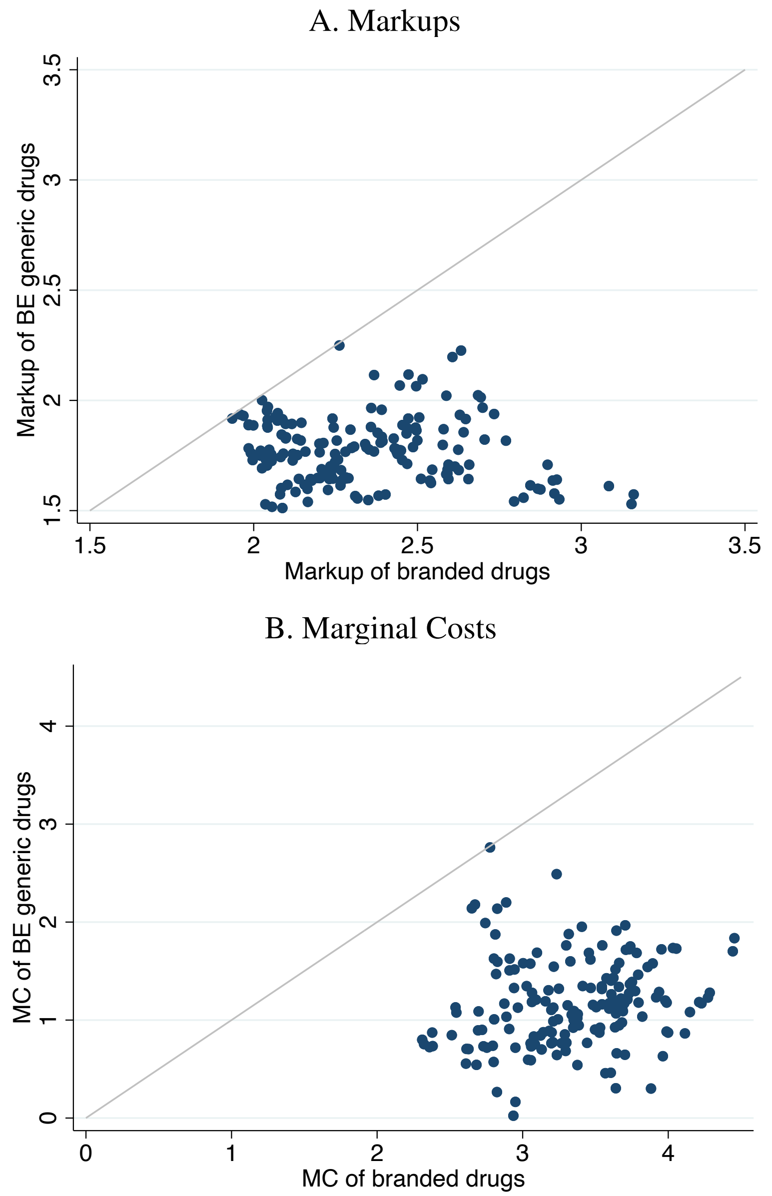
Figure A.12: Heterogeneous Policy Effects: Antihypertensive Drugs vs. Other Drugs





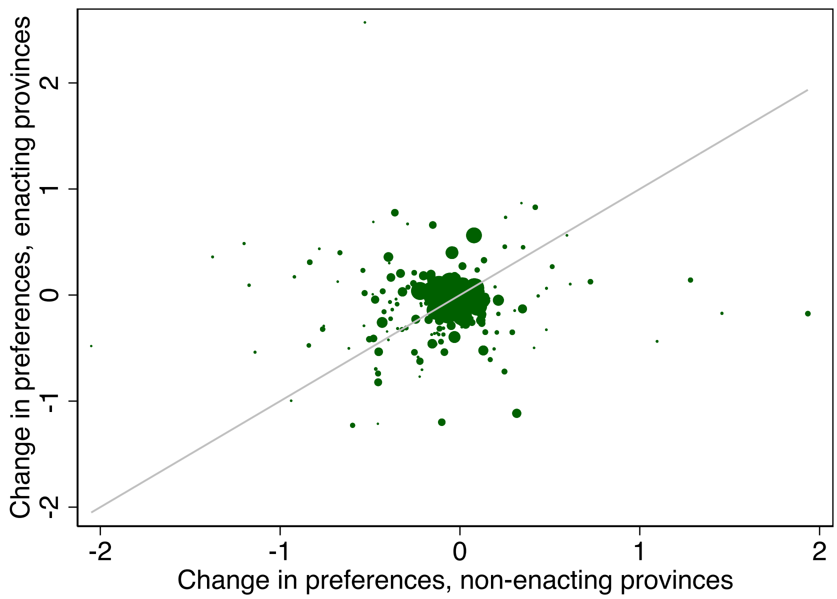
Notes: This figure shows the effects of competitive bidding on drug prices and sales separately for hypertension drugs and other drugs. Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval using standard errors clustered at the province level. The coefficient of the fourth quarter of 2018 is normalized to zero.

Figure A.13: Markup and Marginal Cost Estimates for Branded and Generic Drugs



Notes: This figure compares the estimated average markup and marginal costs between branded and BE generic products. Each point is a province-year. We show the average markup and marginal costs of all branded and bioequivalent generic products in each market. Markups are calculated from Equation (6) as the differences between prices and marginal costs.

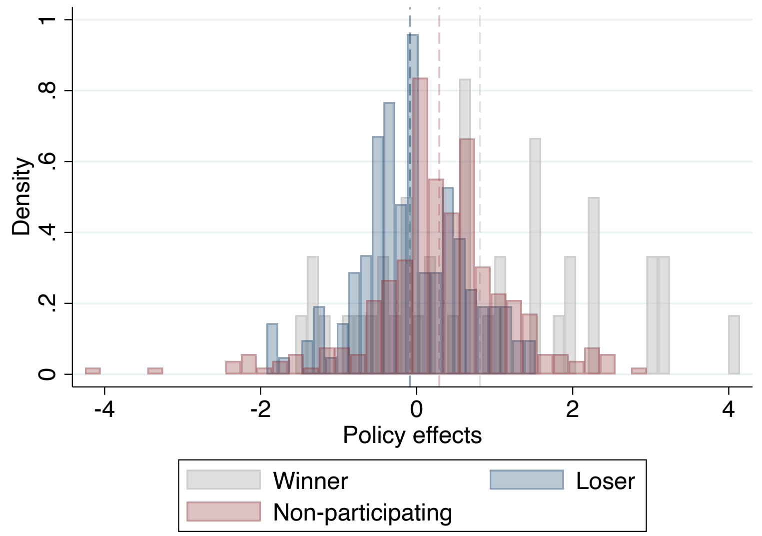
Figure A.14: Demand Shifters in Enacting and Nonenacting Provinces before 2019



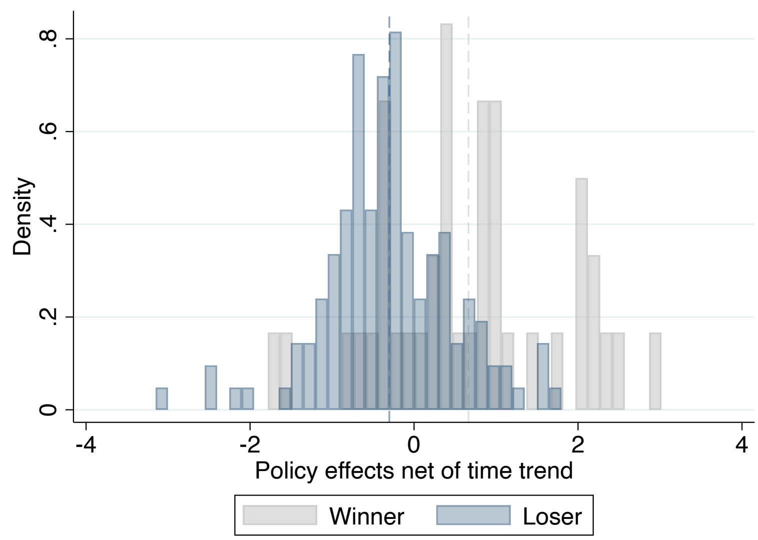
Notes: This figure compares the average demand shifters between enacting and nonenacting provinces between 2012 and 2018. The unit of observation is at the drug-product-by-year level (e.g., branded atorvastatin calcium in 2013). The size of each point is proportional to the total sale revenue of the drug product in that year.

Figure A.15: Distribution of Policy Demand Shifters

A. Policy Shifters

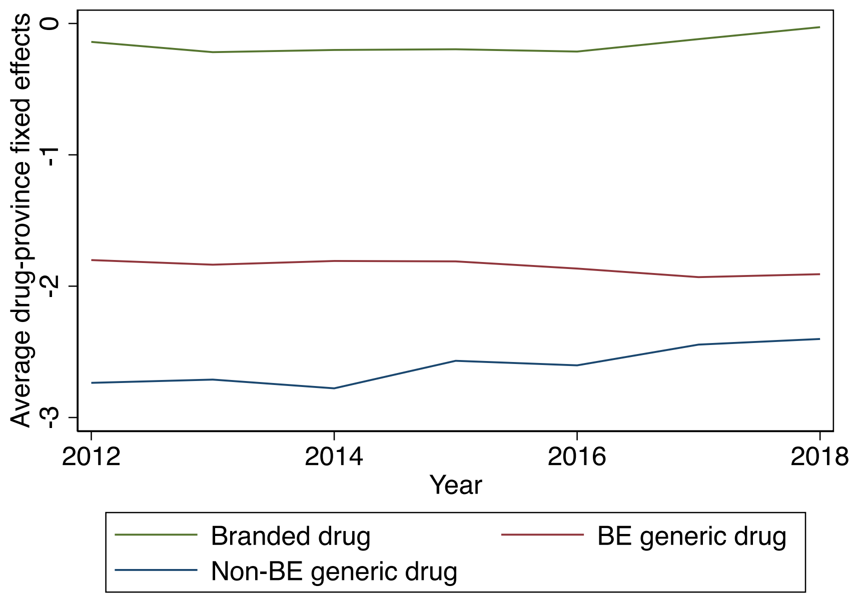


B. Policy Shifters Net of Time Trend



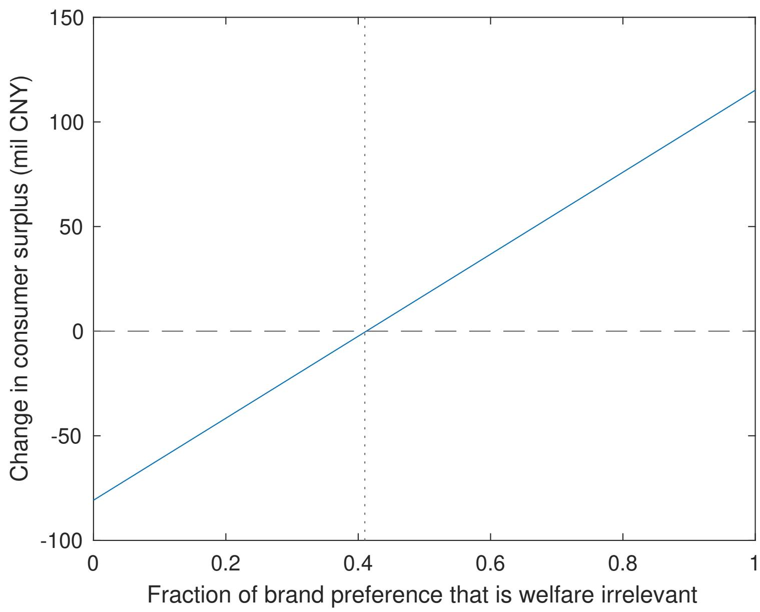
Notes: This figure shows the effects of the policy on drug demand. We assume there exists a policy demand shifter for each available product in each market during the post-auction period, and consumers' price sensitivity and the within-nest preference correlation remain unchanged after the auction. We estimate policy demand shifters at the province-product level such that the observed and predicted market shares during the post-auction period are perfectly matched. Panel A plots the distribution of the policy demand shifters for auction winners and losers in enacting provinces and products in non-enacting provinces separately. The policy effects for products in non-enacting provinces can reflect the time trend, so we normalize all policy demand shifters such that the mean for these products is 0. In Panel B, we plot the net policy shifters for auction winners and losers in enacting provinces by subtracting the corresponding average policy shifters in non-enacting provinces for the same product. The dashed lines represent the average value of each group separately.

Figure A.16: Time Trend in Brand Preferences



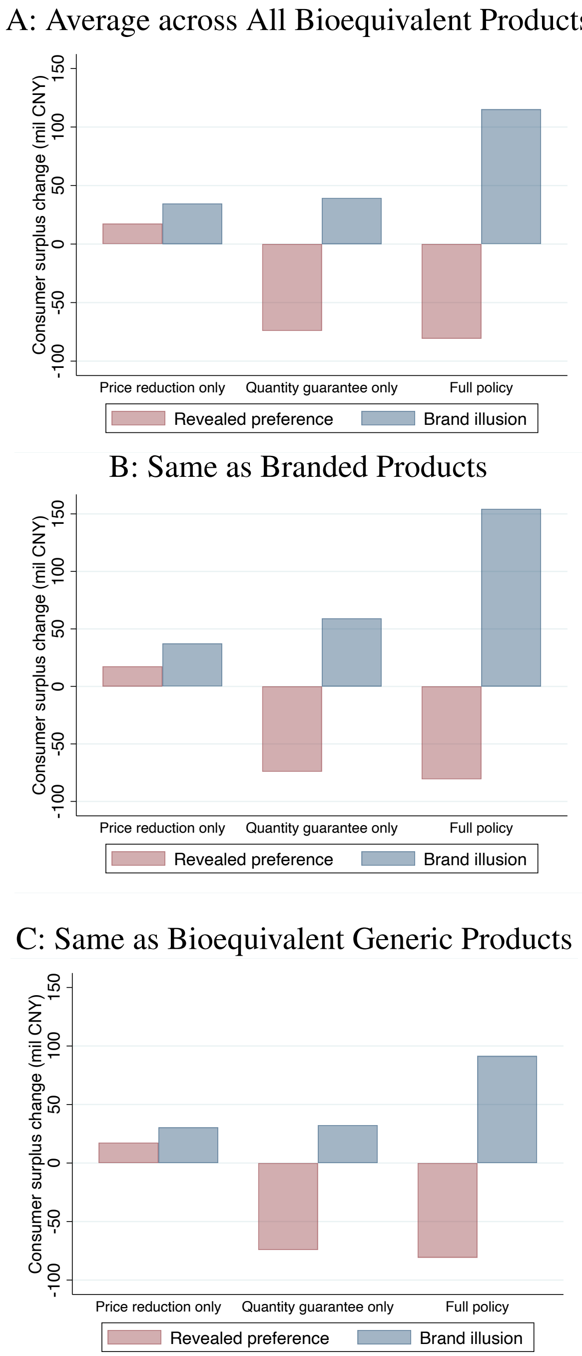
Notes: This figure shows the time trend in consumers' valuations of branded products, bioequivalent generic products, and other generic products. We measure valuation using the average drug-province fixed effects across all drug-province pairs in each year.

Figure A.17: Welfare Effects under Different Assumptions of Brand Preferences



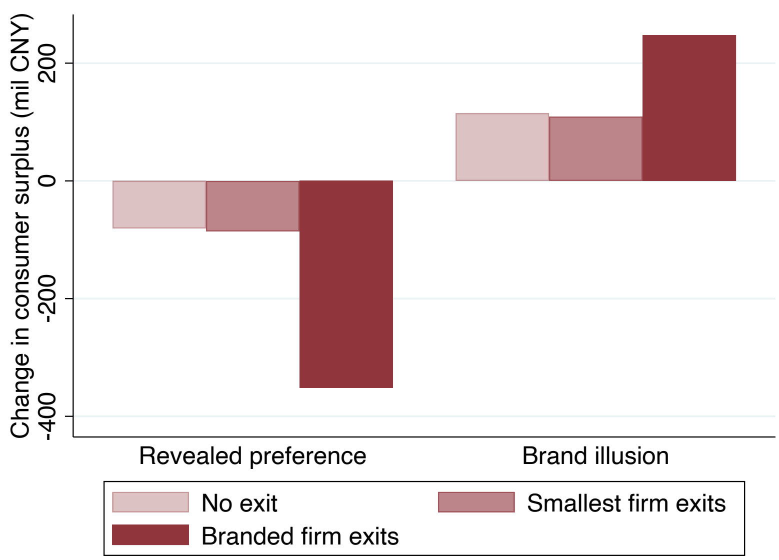
Notes: This figure shows changes in the welfare effects of the competitive bidding program as we vary the fraction of brand preferences that is welfare irrelevant.

Figure A.18: Changes in Consumer Surplus, Different Welfare Measures



Notes: This figure shows the change in consumer surplus with different assumptions on the intrinsic utility under the scenario of brand illusion. In all cases, we assume bioequivalent generic products have the same intrinsic value as branded drugs under the scenario of brand illusion. In Panel A, we assume the intrinsic as the average perceived value among all bioequivalent products of the same molecule. In Panel B, we assume the intrinsic as the perceived value of the branded product in the same molecule. In Panel C, we assume the intrinsic as the average perceived value of the bioequivalent generic product in the same molecule.

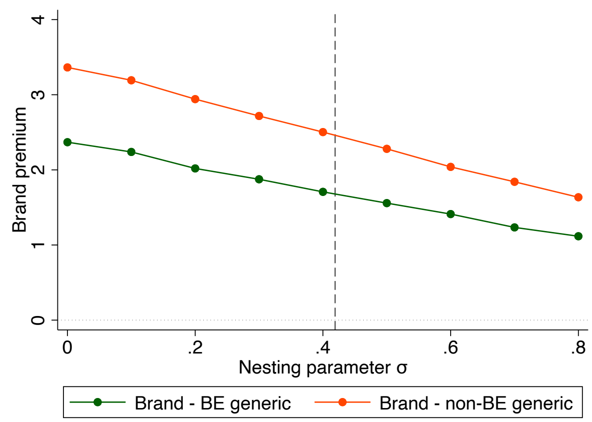
Figure A.19: Effects of Firm Exits on Consumer Surplus



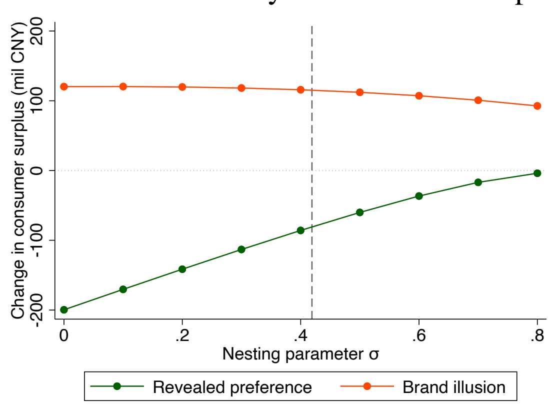
Notes: This figure shows the effect of firm exits on consumer surplus. The left three bars show the results if we measure consumer surplus based on consumers' revealed preferences. The right three bars show the results if we assume brand preference is welfare irrelevant. "No exit" measures consumer surplus in the observed equilibrium. "Smallest firm exits" measures consumer surplus when the product with the lowest market share for each molecule exits. "Branded firm exits" measures consumer surplus when all branded products exit.

Figure A.20: Sensitivity Analysis at Different Values of the Nesting Parameter σ

A: Brand Premium over BE and non-BE Generics

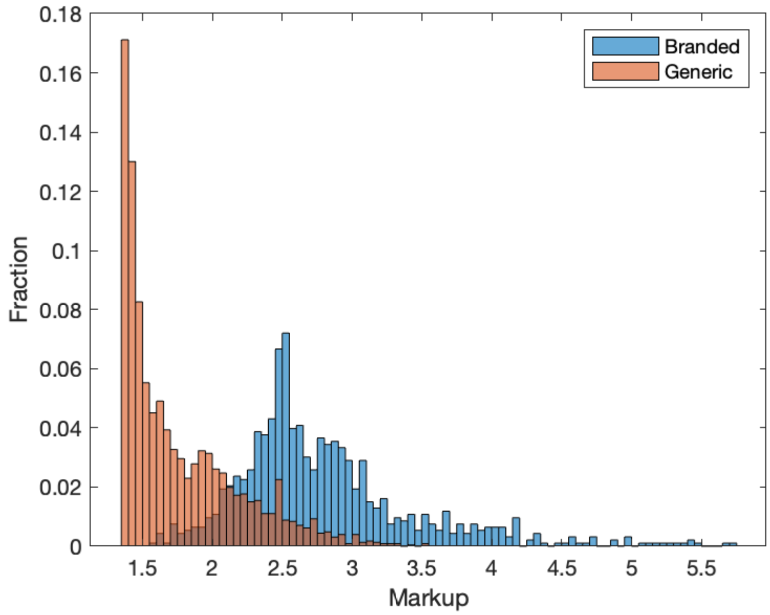


B: Effects of the Policy on Consumer Surplus



Notes: This figure shows the change in consumer surplus and the estimated brand premium under different values of the coefficient on conditional market shares σ. We re-estimate the model fixing σ at different values. The dashed line marked the value of σ in our baseline result.

Figure A.21: Markup for Branded and Generic Drugs, Random-Coefficient Nested Logit Model



Notes: This figure plots the distribution of markups using the random-coefficient nested logit model described in Appendix B. The markups are calculated from Equation (6) as the differences between prices and marginal costs.