# Competitive Bidding in Drug Procurement: Evidence from China

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**Abstract**

We study the impact of competitive bidding in the procurement of off-patent drugs. In 2019, China introduced competitive bidding with a quantity guarantee for thirty-one molecules in nine provinces. Using a difference-in-difference design, we show that the program reduced drug prices by 47.4%. Generic drug companies won the majority of the bids and on average cut prices by 59.4%. Losing branded drug companies cut prices by 7.5%. We develop a model of demand and supply to quantify the trade-off between lower prices and choice distortions. We find that competitive bidding increases consumer welfare if policymakers consider brand preferences welfare irrelevant.

**Keywords:** competitive bidding, procurement auctions, drug prices, consumer welfare
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# 1 Introduction

Drug prices have remained high in many pharmaceutical markets after patent expiration and generic entry. Branded off-patent drugs continue to sell at high prices because consumers prefer them to their generic counterparts (Caves et al. 1991; Grabowski and Vernon 1992; Bronnenberg et al. 2015).[1] Prices of many generic drugs also far exceed their production costs. (Dubois and Lasio 2018; Cuddy 2020). These high prices have significantly contributed to high health care expenditures in many countries, imposing a burden on patients and governments.

In an effort to reduce prices of off-patent drugs, the Chinese government launched a pilot competitive bidding program for a prespecified quantity of drugs to procure for hospitals. In theory, competitive bidding has ambiguous effects on drug prices. And even if it leads to price reductions, the quantity guarantee might distort consumer choices. The welfare implications of the program are thus ambiguous ex ante. In this paper, we evaluate, both theoretically and empirically, the effects of the competitive bidding program on drug prices and consumer welfare.

Before the competitive bidding program, hospitals in China made their own drug-procurement decisions. Manufacturers set wholesale prices at the provincial level. Each hospital decided which drugs to procure and then sold them to patients at the same price.[2] Despite generic competition in most molecules, drug prices have been high. Consumers' preferences for branded drugs and their generous insurance coverage make branded drugs popular choices for hospitals despite their higher prices. In addition, sales costs and detailing costs add to the prices of all drugs.

The Chinese government implemented the competitive bidding program for thirty-one molecules in nine provinces in 2019. For each molecule, the branded drug company and all bio-equivalent (BE) generic drug companies were eligible to participate in the bidding.[3] The program took place in two rounds. The first round was a first-price sealed-bid auction to select a winner with the lowest bid. In the second round, the winner of the first round negotiated with government officials, who could

[1] A branded drug, also known as an innovator drug, is the first drug created containing specific active ingredients to receive approval for use.

[2] Hospitals in China cannot charge a markup when selling drugs to consumers, as stipulated by the zero-markup policy (Fang et al. 2021). The policy has been implemented in a staggered fashion across provinces since 2009.

[3] China started certifying the bio-equivalence of generic drugs and branded drugs in 2016. Bio-equivalence certification requires rigorous laboratory evidence that the generic drug has the same clinical effectiveness and safety profile as the branded drug.

attempt to further reduce the bid.[4] If an agreement was reached, the winner committed to selling at the agreed price for the year between March 2019 and February 2020 and was guaranteed a prespecified procurement quantity.[5] Agreements were reached for twenty-five of the thirty-one molecules, while negotiations stalled for the remaining ones.

We analyze the impact of competitive bidding on drug prices and consumer welfare in three main steps. First, we consider a stylized model with a branded product and a generic product to illustrate the potential price effects. Both products have the same real value and zero marginal costs, but all consumers weakly prefer the branded product. The two firms first participate in an auction. The winner commits to the winning bid and is guaranteed a specified sales quantity. Faced with the residual demand, the loser sets its price to maximize profits.

We derive three main predictions from the model. First, the generic drug company always wins the bidding. The intuition is that it will undercut any bid submitted by the branded drug company, because it can only sell at a price below the winning bid should it lose the auction. Second, competitive bidding has an ambiguous effect on the price set by the winner. On the one hand, since the winner is determined only by the submitted bids and not by brand preferences, there is less product differentiation and stronger competition. On the other hand, as the winner commits to the winning bid, the bidding turns a Bertrand game into a Stackelberg game, thereby reducing competition. Finally, the price change of the losing (branded) product is also ambiguous. It depends on the price change of the winning product and the distribution of brand preferences among consumers not covered by the quantity guarantee.

Next, we turn to our empirical setting and estimate the price impact of the competitive bidding program in China. We leverage quarterly price and sales data at the product-province level for the twenty-five molecules for which agreements were reached. We use a difference-in-difference (DID) design in which we compare market outcomes in provinces that introduced competitive bidding with outcomes in provinces that did not.

We highlight three main empirical findings. First, generic drug companies win the bidding for

[4] If government officials did not attempt to reduce the winning bid, an agreement was automatically reached. The winner could not renege in this case.

[5] The prespecified quantity was usually between 60% and 70% of the procurement quantity in the nine provinces in the previous year. The central government split the quantity target among hospitals. A hospital that fell short of its target was subject to punishments such as reduced government funding, lower ratings, and demotion of hospital management.

twenty-two of the twenty-five molecules.[6] Second, winners on average reduce prices by 59.4% and gain 68.4% in sales. The large price drop provides direct evidence that profit margins on generic drugs were high before the competitive bidding. Third, for the twenty-two molecules for which generic drug companies win the bidding, losing branded drug companies on average reduce prices by 7.5%. Overall, competitive bidding reduces average drug prices by 47.4%. Our results show that moving from decentralized procurement to competitive bidding can significantly reduce drug prices.

Our final step is to quantify the effects of the competitive bidding program on consumer welfare in the context of hypertension treatment.[7] We focus on a key welfare trade-off: consumers benefit from lower prices, but some consumers experience a welfare loss because they are forced to substitute generic drugs for branded drugs because of the quantity guarantee.

A key empirical challenge is to disentangle the roles of price changes and the quantity guarantee in changing consumers' drug choices in 2019. We decompose the two effects in three steps. First, we estimate a model of consumer demand for hypertension drugs between 2012 to 2018, with a focus on recovering consumers' price elasticity and substitution patterns. Second, we estimate the time trend in consumer preferences for each product between 2018 and 2019 using data in provinces that did not participate in the competitive bidding. Finally, we attribute residual sales changes in provinces that participated in the competitive bidding to the quantity guarantee. Our estimates imply that the time trend in preferences, the price reductions, and the quantity guarantee explain 15.5%, 17.8%, and 66.7% of sales gains by the winners of the competitive bidding, respectively.

Our results suggest that the net welfare effects of the competitive bidding program depend on whether consumers' brand preferences are welfare relevant. If policymakers only focus on the clinical values of the drugs, the program increases consumer welfare by 39.2% because it significantly reduces out-of-pocket expenditures and because the clinical values of branded products and BE generic ones are identical. In addition, the program greatly reduces government expenditures on insurance payments by 24.3%. If policymakers also care about consumers' brand preferences, though, the program reduces consumer welfare by 9.8% by distorting choices.

[6] This result is broadly, but not completely, consistent with the prediction of our stylized model. Branded drug companies may win the auction for reasons not captured by the model, such as capacity constraints or differences in marginal costs.

[7] The competitive bidding program covered eight molecules that treat hypertension. We choose hypertension because it has the largest number of treatment molecules that were covered by the program.

We end by highlighting one key caveat in interpreting our results. We focus on the short-term effects of the policy experiment and abstract from several important long-run dynamic considerations. One consideration is that firms that lose the bidding may gradually exit the market, and the policy may become less effective as the market becomes more concentrated. Still, we consider this paper an important first step toward understanding the potential of competitive bidding to reduce prices of off-patent drugs.

This paper contributes to a long line of research on the pricing of off-patent drugs. An extensive literature investigates the effects of generic entry after innovator brands go off-patent in developed countries (Caves et al. 1991; Grabowski and Vernon 1992; Frank and Salkever 1997; Saha et al. 2006; Huckfeldt and Knittel 2011; Branstetter et al. 2016). Several recent studies investigate the nature of brand preferences (Colgan et al. 2015; Bronnenberg et al. 2015; Bairoliya et al. 2017) and their implications for the pricing and regulation of off-patent drugs (Atal et al. 2019). Some studies evaluate other price-control policies, such as price caps (Mohapatra and Chatterjee 2016) and mandatory generic substitution (Song and Barthold 2018). We show that competitive bidding has been effective in reducing off-patent drug prices in China's pharmaceutical industry, though its welfare implications depend on the welfare interpretation of consumers' brand preferences. Our results point to a policy tool to promote generic substitution and reduce prices of off-patent drugs.

This paper is closely connected to a small literature on competitive bidding in health care. Dubois et al. (2021) use cross-country variation to study centralized drug procurement in developing countries. And a number of studies have investigated competitive bidding in Medicare Advantage (Song et al. 2013; Duggan et al. 2016; Cabral et al. 2018; Curto et al. 2021). The two papers that are closest to ours are Ji (2019) and Ding et al. (2021), which leverage the staggered roll-out of competitive bidding to supply durable medical equipment in the US to study its impact on equipment prices and sales. Our study uses a similar quasi-experimental design but focuses on a policy setting in an emerging economy. Our results show that competitive bidding can reduce drug prices in a setting with market frictions such as sticky brand preferences. We also contribute to the literature by quantifying the welfare effects of competitive bidding on consumers.

This paper also relates to the literature on auction theory (see Klemperer 1999 for a review). We study a novel auction format that guarantees a prespecified quantity to the winner but requires the winner to sell products at the winning bid. We show in theory that this auction format has ambiguous

price effects and empirically that it can address market frictions by inducing substitution to generic drugs and reducing prices. Our results could inform the design of similar auctions in other settings.

The remainder of the paper is organized as follows. Section 2 describes the policy background. Section 3 outlines a simple model that illustrates the potential effects of centralized competitive bidding on drug prices. In Section 4, we describe the data and provide our main estimates of the effects of the program on market outcomes. In Section 5, we develop and estimate a model of demand and supply for hypertension drugs. Section 6 uses the model to quantify the welfare effects of the policy. Section 7 concludes with a discussion of our findings and their policy implications.

# 2 Background

As of 2015, pharmaceutical expenditures accounted for more than 40% of health care spending in China, while the OECD average was less than 20% (OECD 2018, 2019). Hospitals account for around 70%–80% of all pharmaceutical sales in China and a majority of them go to public hospitals (Mossialos et al. 2016). Therefore, we focus on drugs prescribed in public hospitals, where physicians specify the drug molecule and recommend their preferred brands to patients. In this section, we discuss the main frictions in China's pharmaceutical market prior to 2019 and describe the competitive bidding program in more detail.

## 2.1 Prior to Competitive Bidding

Historically, public hospitals in China made their own drug-procurement decisions. Pharmaceutical firms set wholesale prices for their drug products at the provincial level. Each hospital decided which products to procure and then sold the drugs to patients for inpatient use or through hospital pharmacies. The zero-markup policy, first implemented in 2009, mandated that hospitals sell drugs to consumers at the cost of procurement (Fang et al. 2021). Most off-patent drugs have multiple generic competitors. Since 2016, China has been testing the bio-equivalence of generic drugs and branded drugs. The testing consists of rigorous laboratory and clinical studies on whether the generic drug has an identical therapeutic efficacy and safety profile to the branded drug. On average, the molecules covered by the competitive bidding program have seven generic products, including two BE generic ones. Fourteen out of the twenty-five molecules studied here have only one BE generic product.

Prices of these off-patent drugs have been high because of several market features. First, despite

the availability of BE generic drugs, many consumers have strong preferences for branded drugs. As a result, branded drugs remain popular choices for hospitals despite their higher prices.

Second, generous public health insurance has reduced consumers' price sensitivity and removed an important check on drug prices. According to the 6th National Health Services Survey in China, by the end of 2018, around 96.8% of the population in China was covered by basic medical insurance.[8] Public insurance covers around 72% of the costs for a list of drugs that the government considers essential for public health.

Finally, sales costs and detailing costs further add to drug prices. Pharmaceutical companies have been engaging in aggressive sales activities to promote their products. Sales commissions typically account for 20% to 30% of drug prices (Yang and Fan 2012; Zhang et al. 2014).

## 2.2 The Competitive Bidding Program

To mitigate market frictions and reduce drug prices, the Chinese government implemented a pilot competitive bidding program for thirty-one molecules at the end of 2018. According to the China National Health Development Research Center, the program covers eleven major cities in nine provinces.[9] These eleven cities accounted for around one-third of drug procurement in China.[10] For each molecule, the branded drug company and all BE generic drug companies are eligible to participate in the bidding. The number of participating firms for each molecule ranges from two to six and is on average three.

The program consisted of two rounds. The first round was a first-price sealed-bid auction in which the firm with the lowest bid for each molecule was selected as the winner. In the second round, the winner negotiated with government officials, who sometimes attempted to cut the bid. If an agreement was reached, the winner committed to selling the drug at the agreed price for the year between March 2019 and February 2020 and was guaranteed a prespecified sales quantity ranging

[8] See http://www.nhc.gov.cn/mohwsbwstjxxzx/qgdlcws/lcdc.shtml. Accessed September 9, 2021.

[9] In China's administrative system, the first level is province and municipality, and the second level is city. Each province usually consists of around ten cities, while each municipality is built around one large city. The program covers four municipalities (Beijing, Tianjin, Shanghai, Chongqing) and seven cities (Shenyang, Dalian, Xiamen, Guangzhou, Shenzhen, Chengdu, Xian) located in five different provinces.

[10] See https://www.cgdev.org/sites/default/files/CGD-procurement-background-china-case.pdf. Accessed September 9, 2021.

from 60% to 70% of the previous year's sales volume in public-hospital procurement. Otherwise, the winner could quit the negotiation without facing punishment, and no quantity guarantee would be given. The stated goal of the policy was to bring about a large price reduction by the auction winner and to induce follow-on price reductions by losing firms. An agreement was reached on twenty-five out of the thirty-one molecules, while negotiations stalled on the remaining ones. Appendix Figure A.1 illustrates the policy process.

To enforce the quantity guarantee, the central government imposed a quantity target on each hospital during the specified period. For hospitals that fell short of the target, punishments included reduced government funding, lower government ratings, and demotion of hospital management. Therefore, hospital management made it a priority to get physicians to persuade patients to switch to the winning products to meet the target.

# 3 A Stylized Model

In this section, we develop a stylized model to illustrate the potential impact of the competitive bidding on the prices of off-patent drugs.

## 3.1 Model Setup

Consider a molecule for which one firm sells the branded product $B$ and another firm sells a BE generic product $G$.[11] Both products provide an identical clinical value of 1 to a unit mass of consumers. Consumers have brand preferences for product $B$ concerning how much more they are willing to pay for $B$ relative to $G$. We assume brand preferences are heterogeneous in the population and are drawn independently from a continuously differentiable distribution $\mathscr{F}$ with non-negative support. We further assume $\mathscr{F}$ has no mass at 0. Marginal costs of both products are assumed to be 0 for simplicity. Prior to the competitive bidding, firms set prices to maximize profits simultaneously in a Bertrand game with differentiated products.

Under competitive bidding with a quantity guarantee of $\tau \in (0,1]$,[12] firms bid and set prices

[11] We consider a two-product case for simplicity of exposition. Empirically, fourteen out of the twenty-five molecules that completed the bidding had two eligible bidders, while the remaining eleven had three to six.

[12] In all equilibria we consider in this section, all consumers purchase one product. So the quantity guarantee is equivalent to a market-share guarantee.

in a two-stage game. In the second stage, the losing firm sets a price to maximize profits, taking the winner's price and the quantity guarantee as given. If it sets a price such that its unconstrained quantity exceeds $1-\tau$, it will only sell to the $1-\tau$ consumers who value its product the most.[13] Foreseeing the results of the second stage, both firms bid in a first-price sealed-bid auction with complete information in the first stage.[14] The winner commits to selling at the winning bid and is guaranteed a quantity of either $\tau$ or all consumers who value the winning product no less than the winning bid if there are fewer than $\tau$ such consumers.[15]

### 3.2 Effects of Competitive Bidding on Drug Prices

We use the model to illustrate potential effects of the competitive bidding on drug prices. For illustration, we consider an example in which $\mathscr{F}$ follows a uniform distribution $\mathbb{U}[0,1]$. Additional details on proofs and derivations of the results are provided in Appendix A.

**Who Wins the Auction.** Generic product $G$ always wins. A formal proof of this result for a general $\mathscr{F}$ is provided in Appendix A. The intuition is that if the generic drug company were to lose the bidding in the first stage, then in the second stage, it would have to set a price below the winning bid in order to sell any positive quantity, as all consumers weakly prefer the branded product. Therefore, the generic drug company prefers to win the bid in the first stage for the guaranteed quantity. As a result, the generic drug company will undercut any positive bid above its cost by the branded drug company.

[13] For example, if the branded product $B$ loses the bidding and sets a price such that its unconstrained quantity exceeds $1-\tau$, it can only sell to the $1-\tau$ consumers with the strongest brand preferences. Some consumers, even if they prefer the branded product, would have to purchase the generic product under the quantity guarantee.

[14] We consider a simple auction and abstract from post-auction price negotiation. Under complete information, the equilibrium winning bid is the one in which the losing firm is indifferent between conceding and undercutting. The actual auction takes the nonstandard form of a first-price sealed-bid auction followed by potential negotiation with the government. Since the winner must commit to the bid unless the government officials try to reduce it, the post-bidding negotiation does not have a major impact on firms' bidding strategies but can ensure that the winner will not increase the price.

[15] This implies that there does not exist an equilibrium in which the generic drug wins with a bid larger than 1, as no consumers value the generic drug at more than 1. Despite the quantity guarantee, the generic drug would have no sales in this case.

**Price Change by the Winning Firm.** Figure 1 shows the prices of the generic product $G$ under Bertrand competition and under competitive bidding. Competitive bidding reduces the price of the winning drug only when $\tau$ is above a certain threshold.

The intuition for the price increase of the winner at lower values of $\tau$ is that competitive bidding turns the Bertrand game into a Stackelberg game. The bidding allows firm $G$ to first commit to a price, thereby reducing price competition. At a lower value of $\tau$, for any bid by firm $G$, firm $B$ prefers targeting the remaining $1-\tau$ consumers over undercutting the bid; thus, with complete information, firm $G$ wins with a maximum bid of 1, which is three times the price in the original Bertrand game.

As $\tau$ increases, the branded drug company $B$ has a greater incentive to undercut the bid, and as a result, the winning bid gradually decreases. Competitive bidding intensifies competition by decoupling brand preferences from drug choices for $\tau$ consumers. When $\tau = 1$, the auction completely eliminates vertical product differentiation and drives prices down to marginal costs.

**Price Change by the Losing Firm.** Conditional on a price reduction by the winner, the price response by the losing firm is again ambiguous. On the one hand, it has an incentive to reduce the price given strategic complementarity in prices. On the other hand, it has the opposite incentive to increase prices to target the remaining $1-\tau$ consumers who have stronger brand preferences. In the example we consider, the second force dominates, so the branded drug $B$ increases in price relative to that under Bertrand competition.

# 4 The Market Impact of Competitive Bidding

## 4.1 Data

The main data set for our empirical analysis contains quarterly product-level quantities and revenues for the thirty-one molecules covered by the competitive bidding program in each province. A product is defined as a molecule-firm combination.[16] The data were collected by China's Food and Drug Administration based on its audits of major public hospitals in twenty-four provinces in

[16]The raw data are recorded at the product-dosage level, where the same product could be represented in different dosages. We convert quantity to the most common dosage of each molecule, and we aggregate quantities and revenues to the product level. For example, if we observe 1,400 units of 10 mg Lisinopril tablets and 2,000 units of 20 mg Lisinopril tablets, we convert the former to 700 units of 20 mg Lisinopril tablets.

mainland China. We divide revenue by quantity to derive the average price of each product at the province-quarter level. This is the average price that hospitals pay to procure the drugs and in principle is equal to how much they charge patients under the zero-markup policy, as described in Section 2.1.

The eleven cities covered by the competitive bidding program are located in nine provinces. We refer to them as *enacting provinces* and consider them directly affected by the policy. The other fifteen provinces in our data are considered *non-enacting provinces* and not affected by the policy.[17] Both enacting and non-enacting provinces lie in the western, eastern, and middle parts of China. The enacting provinces include highly developed regions such as Shanghai and Guangdong, and the non-enacting ones include similarly developed regions such as Zhejiang and Jiangsu. Therefore, the two groups are comparable with each other. We refer to the twenty-five molecules that reached an agreement as *bidding molecules* and the six that did not as *nonbidding molecules*.

We complement our main data set with two auxiliary ones. First, we collected data on the set of generic products that passed the bio-equivalence test for each of the thirty-one molecules by the end of 2018 and the exact time when they passed the test. This identifies the participants eligible for the competitive bidding. Second, we observe the identity of the auction winners and the final prices after the negotiation stage for the twenty-five bidding molecules. We verify that the prices inferred from our quarterly sales data at the provincial level are aligned reasonably well with the disclosed final prices, as shown in Appendix Figure A.2.[18] This also suggests that including those partially treated provinces as enacting provinces is a reasonable approximation.

Table 1 reports the summary statistics for all thirty-one molecules in our sample. These molecules treat a wide range of common health conditions, including diabetes, cardiovascular diseases, depression, and viral infection. We highlight three main takeaways from the table. First, compared with

[17]This definition is not perfectly precise, as each province usually has around ten cities and the policy only covers one or two cities in each province. But we believe this is a reasonable approximation for two reasons. First, treated cities are the largest ones in each province and account for a large fraction of population and drug prescriptions. Second, hospitals sampled by the data provider are mainly in large cities. As we show in section 4.3, our results are robust to only including the four municipalities and excluding partially treated provinces.

[18]In Appendix Figure A.2, the x-axis represents the log of final prices disclosed by the government and the y-axis represents the log of sale prices of the winning product in enacting provinces observed in our data. We categorize provinces by whether they are fully treated (four municipalities) or partially treated (with only one or two large cities covered by the competitive bidding). Both sets of dots are located close to the forty-five-degree line.

the bidding molecules, the nonbidding molecules on average bring in much smaller revenues (24.4 million versus 142.7 million RMB per quarter prior to 2019) and are sold by a significantly larger number of competing firms (45.7 versus 10.1 in 2018). This result suggests that the bidding and non-bidding molecules are not directly comparable. Therefore, in our main analysis, we focus on bidding molecules and use the variation between enacting and non-enacting provinces to estimate the impacts of competitive bidding. Second, the average bidding molecule is sold as three BE products, and some sell only as two. The BE requirement ensures the quality of products that participate in the competitive bidding but makes the bidding less competitive. Finally, for most molecules, the branded product was significantly more expensive than the average BE generic product prior to 2019. The median ratio of branded to BE generic price is 1.7. As discussed in Section 2, consumers' brand preferences are a key contributor to high drug prices and a main motivation for the competitive bidding program. In the following analysis, we focus on medium and large firms with cumulative market share of over 95%.

In Figure 2, we plot the market shares for auction winners in enacting provinces prior to the competitive bidding (2018) and after (2019). Each dot is a molecule-province pair for all bidding molecules and enacting provinces. Since the quantity guarantee of the competitive bidding went into effect in March 2019, we drop the first quarter when we compute market shares in 2019. For most molecule-province pairs, the market shares of the auction winners increased in 2019, which could be driven by both the quantity guarantee and the large price reductions. Even if a winner already had a market share over 70% in 2018 and might not have directly benefited from the guarantee, the price drop would still have boosted its market share. Winners' market shares were on average 74.9% in 2019. In a few cases, winners' market shares fell short of 60% for a number of possible reasons, including partial treatment of some provinces, inaccurate projection of the quantity guarantee, or unsuccessful enforcement by the government.

Appendix Figure A.3 shows the market shares for branded and BE generic drugs in enacting provinces before and after the competitive bidding, regardless of whether they won the auction. The main takeaway is that this program induced large-scale generic substitution. Branded products, despite their significantly higher prices, commanded large market shares in 2018. Their market shares fell significantly in 2019, while market shares of BE generic drugs increased from an average of 35.6% to 64.7%.

## 4.2 Empirical Strategy

In this section, we describe our empirical strategy for evaluating the effects of the competitive bidding on various market outcomes. Let $j$ denote molecules, $m$ denote provinces, and $t$ denote quarters. We estimate the effects of the policy experiment on drug prices, quantities, and market structure using a DID framework. We focus on bidding molecules and compare enacting and non-enacting provinces using the following event-study specification:

$$y_{jmt} = \alpha_0 + \sum_{q=4}^{-27} \beta_q Enact_m \mathbb{1}(t = q) + \lambda_{jm} + \lambda_{jt} + \varepsilon_{jmt}. \tag{1}$$

Each observation is a molecule($j$)-province($m$)-quarter($t$) combination. Our primary outcome of interest $y_{jmt}$ refers to the log of the average price and the log of total quantities of molecule $j$ in province $m$ and quarter $t$. Note that these variables are aggregated across all drugs for each molecule. In addition, we examine the effects of the policy on the level of market concentration, using the Herfindahl-Hirschman index (HHI) and the number of firms selling the molecule as the outcome variables. $Enact_m$ is a dummy variable that is equal to 1 for enacting provinces and 0 for non-enacting provinces.

$\beta_q$ captures how the outcome of interest moves differently in enacting provinces and non-enacting provinces $q$ quarters before or after the policy is implemented. We normalize $\beta_{-1} = 0$ for the last quarter of 2018 as the baseline period. $\beta_q$ with $q > 0$ captures the effect of the policy on the outcome variable. We include molecule-province fixed effects $\lambda_{jm}$ to control for the time-invariant popularity of each molecule in each province, reflecting local preference heterogeneity. We also include molecule-quarter fixed effects $\lambda_{jt}$ to control for molecule-specific time trends common to all provinces. The standard errors are clustered at the year-province level.

Three conditions are needed for the estimates to capture the causal effects of the policy on the outcome variable. First, we need $\beta_q = 0$ for $q < 0$. In other words, there should be no differential time trends for a molecule between enacting and non-enacting provinces prior to the policy experiment. This condition can be tested empirically. Second, there should be no shocks concurrent with the policy and differently affecting enacting and non-enacting provinces. A hypothetical example is a surge in diabetes cases (and thus demand for a bidding molecule) in Beijing (an enacting province) in 2019. While we cannot rule out such confounders, we are not aware of any major shocks of this type, and we believe that this condition is likely to be satisfied. The third condition is that bidding

molecules in non-enacting provinces are not affected by the policy. This condition is the least likely to hold because the policy could have caused significant spillover effects. For example, firms that lost the bid might have shifted their focus to non-enacting provinces and behaved differently there than they would have in a counterfactual world without the bidding. To the extent that the potential spillovers occur, our DID estimates pick up the difference between the policy effects in enacting and non-enacting provinces.

### 4.3 Effects of the Competitive Bidding

Figure 3 shows our main results from the DID specification in Equation (1). It compares drug prices and total quantities of bidding molecules at the provincial level between enacting and non-enacting provinces before and after 2019. Each dot represents the regression coefficient $\beta_q$ for the corresponding quarter. For 2012 to 2017, we plot only the estimates for the first quarter to conserve space. Panel A shows that the average price drops by around 47.4% (58.5% after the first quarter) in enacting provinces relative to non-enacting provinces. Estimates prior to 2019 are mostly precise zeros, suggesting that province-specific time trends are not a major threat to identification. Panel B shows that the policy has no appreciable effects on total quantities at the provincial level. With insurance coverage, most consumers could afford some drugs they need, and aggregate drug demand is relatively inelastic to price changes. The competitive bidding program in a large part results in substitutions between different drug products and has small impacts on total drug sales.

Appendix Figure A.4 shows the effects of the policy on measures of market concentration, where the outcomes are the HHI and the number of firms selling the molecule. The point estimates suggest that the policy slightly increases the HHI and reduces the number of firms by around 0.3. These results provide some tentative evidence that the policy may lead to firm exits and an increase in market concentration. We only have data for one year after the policy, and we expect larger changes in the market structure in the long run.

Our results are robust to a number of alternative specifications. In Appendix Figure A.5, we estimate Equation (1) with each observation weighted by its quantity. The results are almost identical to our baseline results. This confirms that these results are not driven by molecules or provinces with low sales. The sales-weighted regressions are harder to interpret by themselves since quantity is also an outcome variable.

As discussed in Section 2.2, the competitive bidding was first implemented in four municipalities and seven cities in nine provinces. As a robustness check, we include as enacting provinces only the four fully treated municipalities and exclude the five partially treated provinces from the analysis. Figure A.6 shows the results of our baseline regressions using this new sample. We find a slightly larger reduction in drug prices (52.7% versus 47.4%). It may suggest that including partially treated provinces leads to an underestimate of the effects of the policy in our main specification, but the difference is small and we consider our baseline definition of an enacting province to be a reasonable approximation.

### 4.4 Heterogeneous Effects across Firms

In Section 4.3, we present the aggregate effects of the competitive bidding at the molecular level. In this section, we investigate the heterogeneous effects on each molecule for auction winners versus losers and for branded versus generic drugs.

For auction winners, their prices fall a lot. However, the price responses are less clear for losing drug companies and non-BE generic drug companies that are not eligible to participate in the bidding. For simplicity, we refer to both types of drugs as auction losers. As illustrated in our simple model in Section 3, two competing forces can drive the response of auction losers. On the one hand, since prices are strategic complements, the policy may induce those firms to cut prices in response and achieve price reductions across the board. That was part of the government's stated policy rationale. On the other hand, branded auction losers can target the remaining consumers with stronger brand preferences, which might increase their prices. Therefore, the price response by losing firms is ambiguous ex ante and needs to be tested empirically.

We examine price responses in enacting provinces separately for drugs that won the auction and those that lost, using all firms in the non-enacting provinces as the control group. Specifically, we run two versions of Equation (1), one in which we exclude all auction *losers* in enacting provinces when constructing the molecule-level prices and quantities and one in which we exclude all auction *winners*. Everything else remains the same. The estimates correspond to the effects on auction winners and losers, respectively. Note that winners and losers are endogenously determined, so the results should be interpreted with caution.

Figure 4 shows the results. We find winners on average reduce prices by 59.4% and see an

increase in sales of around 68.4%. In contrast, losing drugs do not adjust prices much in response, and they cede market share to the auction winners. Therefore, consistent with model predictions, the competitive bidding is successful in achieving a steep price reduction by auction winners but falls short of inducing follow-up price reductions across the board.

We further decompose auction losers into branded losers and generic ones and check their responses separately. The setting is the same as before. We use all products in non-enacting provinces as the control group and estimate two versions of Equation (1). In the first regression, we keep branded losers in enacting provinces as the treatment group; in the second one, we keep generic losers in enacting provinces as the treatment group. Figure 5 shows the results. We find that the price drop of branded losers is 7.5%, while the price decrease of generic losers is insignificant. The drop in quantity is 42.1% for branded losers and 93.9% for generic losers.

To summarize, our descriptive analysis shows that the competitive bidding program significantly reduces drug prices and induces large-scale substitutions from branded drugs to BE generic ones. Price reductions benefit consumers, while (forced) generic substitutions under the quantity guarantee may reduce consumer welfare. Therefore, the impact of the program on consumer welfare is ex ante unclear. In the next section, we develop and estimate a structural model of drug demand and supply to quantify the welfare impact of the program.

# 5 Model and Estimation

In this section, we develop and estimate a structural model of drug demand and supply to quantify the welfare impact of the bidding program. We focus on the market for hypertension treatments since the set of bidding molecules includes seven major anti-hypertension drugs.

A key empirical challenge is to disentangle the roles of price changes and the quantity guarantee in driving consumers' drug choices in 2019. To do so, we first use the pre-bidding-program data to estimate a model of drug demand and supply. The estimated price elastities allow us to infer the part of the sales change in 2019 that is driven by price reductions. Second, we attribute the remaining sales changes in enacting provinces relative to those in non-enacting provinces to the quantity guarantee. We discuss each step in detail in this section.

## 5.1 Demand

We assume that each patient chooses 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:

$$u_{ijmt} = \underbrace{\alpha\phi p_{jmt} + BE_{jt}\beta + \lambda_{jm} + \lambda_{mt} + \xi_{jmt}}_{\delta_{jmt}} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}. \tag{2}$$

Here, $\phi p_{jmt}$ is patient $i$'s out-of-pocket expenditure and is equal to the listed price $p_{jmt}$ multiplied by $\phi = 0.28$, or 1 minus the reimbursement rate. We consider a molecule as a nest. $\zeta_{igmt}$ is consumer $i$'s preference shock that is common to all products of molecule $g$. Both $\varepsilon_{ijmt}$ and $\zeta_{imt} + (1-\sigma)\varepsilon_{ijmt}$ follow a type-I extreme value distribution, and $\sigma$ determines the degree of the within-nest correlation in preference shocks.

$BE_{jt}$ takes the value of 1 if product $j$ has passed the bio-equivalence test by year $t$. $\lambda_{jm}$ and $\lambda_{mt}$ are product-province and province-year fixed effects. $\xi_{jmt}$ represents demand shocks observed by consumers but not by econometricians. The outside option ($j = 0$) includes all other hypertension treatments not included in our sample and the option of not getting any treatment. The utility of the outside option is normalized to 0.

As shown in Berry (1994), our model implies the following demand equation:

$$\ln(s_{jmt}) - \ln(s_{0mt}) = \alpha\phi p_{jmt} + BE_{jt}\beta + \lambda_{jm} + \lambda_{mt} + \sigma\ln(s_{j/g,mt}) + \xi_{jmt}. \tag{3}$$

Here, $s_{j/g,mt}$ is the conditional market share of product $j$ within the molecule $g$. The unobserved demand shock $\xi_{jmt}$ is likely to be correlated with both the price $p_{jmt}$ and the conditional market share $\ln(s_{j/g,mt})$. We use instruments to consistently estimate $\alpha$ and $\sigma$ as discussed in Section 5.3.

## 5.2 Supply

Firms set prices in each market to maximize profits under standard Bertrand-Nash competition. Let $\mathcal{J}_{ft}$ denote the set of products sold by firm $f$ in year $t$. Let $mc_{jmt}$ denote the marginal cost of product $j$ in province $m$ and year $t$. Then firm $f$'s profit-maximization problem in province $m$ and year $t$ is the following:

$$\max_{\{p_{jmt}\}_{j\in\mathcal{J}_{ft}}} \pi_{fmt}(\boldsymbol{p}) = \sum_{j\in\mathcal{J}_{ft}} s_{jmt}(p_{jmt} - mc_{jmt}).$$

Let $J_{mt}$ be the total number of products in province $m$ and year $t$, and let $\Delta_{mt}$ be a $J_{mt}$-by-$J_{mt}$ matrix whose $(k,r)$-th term is $-\frac{\partial s_{rmt}}{\partial p_{kmt}}$ if products $k$ and $r$ are produced by the same firm and 0 otherwise. Let $\vec{s}_{mt}$, $\vec{p}_{mt}$, and $\overrightarrow{mc}_{mt}$ represent $J_{mt}$-by-1 vectors of market shares, prices, and marginal costs for all products in market $mt$. The first-order conditions in the firms' profit-maximization problem can be written in vector notation as follows:

$$\vec{s}_{mt} - \Delta_{mt}(\vec{p}_{mt} - \overrightarrow{mc}_{mt}) = 0.$$

This implies

$$\overrightarrow{mc}_{mt} = \vec{p}_{mt} - \Delta_{mt}^{-1}\vec{s}_{mt}. \tag{4}$$

We derive elements of $\Delta_{mt}$ from the demand system and use Equation (4) to compute the marginal cost of each product.

### 5.3 Identification

We estimate Equation (3) using data at the product-province-year level. To convert sales to market shares, we assume the market size to be 1.2 times total quantity sold in each market. Since we include province-year fixed effects, our demand estimates stay the same under alternative assumptions about market size.

With product-province fixed effects, the identification of demand-side parameters relies on the time-series variation in drug prices and sales. Year-on-year changes in prices are likely to be correlated with unobserved demand shocks that firms observe before setting prices. The within-nest conditional market share is also endogenous, as any demand shock that increases a product's market share also increases its within-nest market share. So OLS regressions overestimate both parameters. We use instruments to consistently estimate $\alpha$ and $\sigma$.

The first instrument is the average price of the focal product in all other provinces in the same year, which is the classic Hausman instrument (Hausman 1996). The identifying assumption is that conditional on the fixed effects, demand shocks are uncorrelated across markets, while common cost shocks pass through to prices in all markets. The second instrument is the total number of drugs of each molecule in each market, also known as the BLP instrument (Berry et al. 1995). The identifying assumption is that product entry and exit are not correlated with contemporaneous unobserved demand shocks. This assumption is likely to be valid since approval of new drugs takes time. Our

preferred specification is the nested logit model estimated using two instruments. We also estimate a simple logit model without a nest structure.

### 5.4 Estimation Results

Column (1) in Table 2 presents results from an OLS estimation of a simple logit model. The estimate implies an average own-price elasticity of around 0.61. Column (2) presents results from an instrumental variables (IV) regression with the Hausman instrument. The estimated average own-price elasticity is 1.46. Note that in the logit model, we do not allow drugs within the same molecule to substitute more strongly with each other than drugs across different molecules do, which could bias our estimates.

Columns (3) and (4) in Table 2 show the results under the nested logit model, estimated using OLS and IV regressions, respectively. The estimated own-price elasticities are similar to the estimates under the simple logit model for both the OLS and IV regressions. In Column (4), the coefficient of 0.41 on conditional market share suggests that consumers are indeed more likely to substitute between different products of the same molecule than between products of different molecules. In addition, our estimates suggest that passing the BE test does not have an appreciable impact on drug sales. Possible reasons include that consumers are not aware of the BE test results and that they do not fully understand what BE is.

Appendix Table A.1 shows the results of the first-stage regressions. The first column summarizes the first stage of the logit model, and the last two columns summarize the nested logit model. Comparing the three columns, we can see that the Hausman instrument is highly predictive of the average price, while the BLP instrument mainly helps identify the coefficient of the conditional market share. The $F$-statistics are reasonably large.

The drug-province fixed effects represent province-specific drug preferences. We plot the distributions of the drug-province fixed effects separately for branded drugs, BE generic drugs, and other generic drugs in Figure 6. The branded drugs on average have higher values of fixed effects than both types of generic drugs. This is direct evidence of the existence of brand preferences; that is, consumers derive more utility from consuming branded drugs. However, the difference between generic drugs with and without a bio-equivalence certificate is not significant. Combined with the small and insignificant effect of passing the bio-equivalence test in Table 2, this implies that patients may lack

the information needed to choose generic drugs with higher quality in the pre-auction period.

With the demand estimates at hand, we derive cross-price elasticities and recover marginal costs of each product using Equation (4). Figure 7 presents the distribution of markups for branded and generic drugs separately. Compared with generic drugs, branded drugs sell with higher markups. In addition, we find that the distribution of markups for BE generic drugs is almost the same as that for non-BE generic ones.

### 5.5 Effects of the Quantity Guarantee

So far, we have estimated the price coefficient and the within-nest preference correlation using data prior to 2019. Under the assumption that these parameters remain the same in 2019, we can recover the effects of price changes after competitive bidding on drug sales in 2019. We estimate demand shifters at the product-province level that explain changes in sales in 2019 that are not driven by the price change.

Define consumer $i$'s utility from product $j$ in market $m$ in 2019 as follows:

$$\tilde{u}_{ijm,2019} = \tilde{\delta}_{jm,2019} + \zeta_{igm,2019} + (1-\sigma)\varepsilon_{ijm,2019}. \tag{5}$$

Here, $\tilde{\delta}_{jm,2019} = \delta_{jm,2019} + \gamma_{jm,2019}$, and $\gamma_{jm,2019}$ is the demand shifter. We calculate $\delta_{jm,2019}$ using the estimated values in 2018, adjusting for price changes in 2019. We then estimate $\gamma_{jm,2019}$ for each product-province pair by matching the observed market shares and the predicted market shares in 2019.[19]

A part of the demand shifter may capture changes in consumer preferences across time instead of impacts of the quantity guarantee. We use the average demand shifter in non-enacting provinces as an estimate for the time trend from 2018 to 2019 in consumers' preferences for each drug product:

$$\hat{\tau}_j = \frac{1}{|NE|}\sum_{k\in NE}\hat{\gamma}_{jk,2019}.$$

[19] One minor issue is that the set of products is not identical in 2018 and 2019 because products entered or exited in some provinces. We exclude products that were new to some provinces in 2019, as we do not have marginal-cost estimates for these products. We calculate the demand shifter for the set of product-province pairs in 2018. 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. Appendix B provides more details on the imputation.

Here, $NE$ is the set of non-enacting provinces. We then subtract it from the estimated $\hat{\gamma}_{jm,2019}$ in enacting provinces to recover the net policy demand shifter:

$$\tilde{\gamma}_{jm,2019} = \hat{\gamma}_{jm,2019} - \hat{\tau}_j.$$

We assume that absent the competitive bidding program, consumers' preferences for each drug product would have trended similarly in enacting and non-enacting provinces.

These policy demand shifters provide a reduced-form description of the effects of the quantity guarantee on consumer demand. Appendix Figure A.7 shows the distribution of the policy demand shifters. We see that the quantity guarantee significantly shifts consumer demand from the losing products to the auction winners. Such choice distortions may potentially reduce consumer surplus and offset welfare gains from price cuts. In the next section, we quantify the welfare effects of the competitive bidding program.

# 6 The Welfare Effects of Competitive Bidding

In this section, we use the model described in Section 5 to quantify the welfare effects of the competitive bidding program in the market for hypertension treatments. The standard measure of consumer welfare, which is based on the revealed-preference paradigm, does not capture the possibility that consumers' preferences for specific drug products may be driven by misinformation rather than true utility. We first introduce an alternative welfare measure and then quantify the welfare effects of the competitive bidding program under the standard and alternative welfare measures.

## 6.1 Welfare Measures

We follow Train (2015) and make a distinction between consumers' "decision utility" and "actual utility." Decision utility determines consumer choices, while actual utility determines consumer welfare. In our setting, the decision utility includes both the policy demand shifter (that is, the effects of the quantity guarantee) and consumers' brand preferences. The actual utility does not include the policy demand shifter and may or may not include brand preferences depending on whether one believes the brand preferences to be welfare relevant.

Formally, let $\delta'_{jm,2019}$ denote the intrinsic therapeutic value of product $j$ in market $m$ in 2019. For a non-BE generic product, we define $\delta'_{jm,2019}$ to be equal to the perceived value $\delta_{jm,2019}$. For a branded

or BE generic product, we define $\delta'_{jm,2019}$ to be the average perceived value of all branded and BE generic products of the same molecule $g$ in market $m$ (excluding the price component $\alpha\phi p_{jmt}$). This definition uses the fact that all BE generic products are certified to have the same therapeutic value as the branded product. Specifically,

$$\delta'_{jm,2019} = \alpha\phi p_{jm,2019} + \frac{1}{|\{k \in g, k \in BE_{m,2019}\}|} \sum_{k \in g, k \in BE_{m,2019}} (\delta_{km,2019} - \alpha\phi p_{km,2019}),$$

where $BE_{m,2019}$ is the set of branded and BE generic drugs available in province $m$ in 2019.

Consumer $i$'s decision utility in 2019 is as follows:

$$\tilde{u}^{D}_{ijm,2019} = \delta_{jm,2019} + \hat{\tau}_j + \tilde{\gamma}_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}. \tag{6}$$

Her actual utility is as follows:

$$\begin{cases} \tilde{u}^{A1}_{ijm,2019} = \delta_{jm,2019} + \hat{\tau}_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt} & \text{if brand preference is relevant;} \\ \tilde{u}^{A0}_{ijm,2019} = \delta'_{jm,2019} + \hat{\tau}_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt} & \text{if brand preference is irrelevant.} \end{cases} \tag{7}$$

Welfare loss occurs when consumers' choice utility is misaligned with their actual utility. We discuss additional details on the calculation of consumer surplus in Appendix C.

## 6.2 Welfare Analysis

We quantify consumer surplus under four scenarios to assess the trade-off between price reductions and potential choice distortions. The baseline scenario is the market equilibrium without any policy intervention. In the first scenario, we force the auction winners to commit to the winning bid but do not impose the quantity guarantee. In the second scenario, we impose the quantity guarantee by adding the policy demand shifter to consumers' decision utility but allow all firms to set prices freely. In the last scenario, we consider the full policy, which combines both effects.

- **Baseline (status quo):** Consumers' decision utility follows Equation (6) but without the $\tilde{\gamma}_{jm,2019}$ term. All firms set prices freely in Bertrand-Nash competition.
- **Case 1 (price constraint only):** Consumers' decision utility follows equation (6) but without the $\tilde{\gamma}_{jm,2019}$ term. Auction winners' prices are set at the observed negotiated prices. Other producers adjust prices strategically.

- **Case 2 (quantity guarantee only):** Consumers' decision utility follows Equation (6). All firms set prices freely in Bertrand-Nash competition. In particular, auction winners' prices are not constrained by the observed negotiated prices.

- **Case 3 (full policy):** Consumers' decision utility follows Equation (6). Auction winners' prices are set at the observed negotiated prices, and other producers can respond strategically. This essentially replicates the actual policy.

We first check the price changes relative to the baseline under the three scenarios. The results are shown in Figure 8. In panel A, the first set of bars shows the price changes for auction winners and losers in Case 1, in which we only impose the winners' price constraints. The auction winners reduce their prices, and auction losers' prices also decrease slightly because prices are strategic complements. The second set of bars shows price changes under Case 2, in which we only impose the quantity guarantee. Auction winners increase prices because they have additional market power, while losers reduce their prices slightly. The price changes under the full policy are similar to those under Case 1. In panel B, we further explore the heterogeneous impacts on branded losers, BE generic losers, and other generic losers. Consistent with our reduced-form evidence shown in Section 4.4, under the full policy, the price drop is larger for branded losers, while it is very limited for generic ones.

Figure 9 summarizes the effects of the competitive bidding program on consumer surplus under the two different welfare measures in Section 6.1. Compared with the baseline case, the results for Case 1 show that price reductions following the competitive bidding benefit consumers under both welfare measures. For Case 2, when consumers' brand preferences are welfare relevant, the quantity guarantee distorts consumer choices and significantly reduces consumer welfare. When consumers' brand preference is welfare irrelevant, however, the quantity guarantee helps offset choice distortions caused by brand preferences, and overall it significantly improves consumer welfare. Taken together, under Case 3, we see that when brand preference is welfare relevant, the choice-distortion effect looms large and the full policy reduces consumer welfare by 9.8%. When brand preference is welfare irrelevant, price reductions and generic substitutions both improve consumer welfare and add up to a total increase in consumer surplus of 39.2%.

Apart from consumers, producers and government expenditures are also affected by this policy. Figure 10 summarizes the percentage changes of consumer surplus, producer surplus, and government surplus, where the government surplus is measured as the negative of the government's expenditures,

as it needs to reimburse patients for 72% of drug expenditures. We again report the results under the two welfare measure. The choice of welfare measure affects consumer surplus and total surplus but leaves firms' profits and government expenditures unchanged. We find that producer surplus decreases by 24.4% and the government reduces expenditures by 24.3%. The first set of bars shows that total surplus decreases by 14.5% under revealed preferences, and the second set shows that total surplus increases by 7.8% if we assume the brand premium away in the welfare calculation.

Overall, our analysis shows that the competitive bidding program was highly effective in reducing drug prices. The quantity guarantee, which is usually distortionary in ordinary market settings, may also improve consumer welfare by correcting choice distortions due to mistaken brand preferences. Competitive bidding is an appealing tool to reduce the prices of off-patent drugs and to guide consumers to switch toward generic drugs if policymakers believe consumers' brand preferences to be welfare irrelevant.

# 7 Conclusion

In this paper, we evaluated a novel policy experiment run by the Chinese government to limit the prices of off-patent drugs: competitive bidding with a quantity guarantee. We first built a simple model to predict the moving forces behind this competitive bidding. Our model predicts that the generic drug company always wins the bidding; however, the price changes are ambiguous ex ante.

Our empirical analysis yielded three main findings consistent with the model predictions. First, competitive bidding was effective in reducing drug prices: auction winners on average cut prices by 59.4%, and the average drug price fell by 47.4%. However, the losing firms did not cut prices significantly in response, and the policy fell short of achieving price reductions across the board. Second, the bidding program led to large-scale generic substitution. We built a simple model to quantify the welfare impacts for hypertension drugs that participated in the bidding. Under the assumption that consumers' choices of branded drugs over cheaper BE generic ones are driven by misinformation or misperception, we found that this policy increased consumer surplus in China's pharmaceutical market by 39.2%. In addition, government expenditures decreased by 24.3%. Finally, the policy resulted in heavy losses for drug firms and has led firms that lost auctions to exit. Over time, it may increase market concentration and become less effective at limiting drug prices.

Overall, our results show that competitive bidding with a quantity guarantee is a useful addition to

the toolkit of policy instruments for limiting drug prices. A unique advantage of competitive bidding, compared to common policies such as cost-plus price regulations and reference pricing, is that it leverages market forces to identify a price level that is still profitable for the winner. This ensures that the product remains available to consumers after the price restriction is imposed, and it therefore allows all patients to benefit from cheaper drugs. This could be a useful approach for policymakers to consider, especially in countries in which public hospitals and pharmacies constitute a large part of the pharmaceutical market. That said, policymakers should be mindful of its negative impact on firms' surplus and its long-term effects on market structure.

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**Table 1:** List of Molecules and Summary Statistics

| | Disease Category | Revenues (Million) | Price (RMB) | Sales (Million) | Brand-BE Price Ratio | # Firms | # BE Firms |
|---|---|---|---|---|---|---|---|
| **Bidding Molecules** | | | | | | | |
| Clopidogrel bisulfate | Arteriosclerosis | 561.2 | 4.6 | 124.9 | 1.6 | 3 | 3 |
| Montelukast sodium | Asthma | 108.2 | 9.2 | 12.0 | 2.4 | 5 | 2 |
| Gefitinib | Cancer | 102.0 | 391.0 | 0.3 | 2.2 | 3 | 2 |
| Imatinib mesylate | Cancer | 152.0 | 122.2 | 1.7 | 9.5 | 4 | 2 |
| Pemetrexed disodium | Cancer | 320.5 | 2275.4 | 0.1 | 3.6 | 16 | 2 |
| Atorvastatin calcium | Cholesterol | 462.3 | 8.3 | 56.5 | 1.3 | 8 | 3 |
| Rosuvastatin calcium | Cholesterol | 218.1 | 7.1 | 31.7 | 1.4 | 7 | 6 |
| Diosmectite | Diarrhea | 10.3 | 1.6 | 6.6 | 1.8 | 20 | 5 |
| Levetiracetam | Epilepsy | 58.2 | 8.3 | 7.1 | 1.5 | 6 | 2 |
| Tenofovir | HIV | 30.6 | 35.1 | 1.6 | 1.7 | 7 | 4 |
| Entecavir | Hepatitis B | 412.4 | 22.2 | 20.4 | 1.8 | 10 | 5 |
| Amlodipine besylate | Hypertension | 184.3 | 3.4 | 53.5 | 3.4 | 47 | 6 |
| Enalapril maleate | Hypertension | 4.1 | 1.0 | 4.2 | 1.2 | 16 | 2 |
| Fosinopril sodium | Hypertension | 16.0 | 2.8 | 5.7 | 1.4 | 3 | 2 |
| Irbesartan | Hypertension | 98.0 | 3.6 | 27.2 | 2.6 | 17 | 4 |
| Irbesartan-Hydrochlorothiazide | Hypertension | 62.1 | 3.8 | 16.6 | 1.6 | 7 | 3 |
| Lisinopril | Hypertension | 0.9 | 1.4 | 0.6 | 1.4 | 14 | 2 |
| Losartan potassium | Hypertension | 89.5 | 4.1 | 22.1 | 1.6 | 11 | 2 |
| Cefuroxime axetil | Infection | 31.9 | 2.5 | 12.5 | 1.4 | 11 | 4 |
| Escitalopram | Mental Illness | 74.4 | 11.9 | 6.5 | 1.7 | 6 | 4 |
| Olanzapine | Mental Illness | 147.8 | 10.6 | 14.3 | 2.8 | 7 | 2 |
| Paroxetine HCL | Mental Illness | 60.7 | 6.4 | 9.6 | 2.2 | 6 | 2 |
| Risperidone | Mental Illness | 30.3 | 1.9 | 16.1 | 2.3 | 10 | 2 |
| Dexmedetomidine HCL | Painkiller | 150.2 | 158.7 | 1.0 | 1.3 | 6 | 2 |
| Flurbiprofen axetil | Painkiller | 181.9 | 68.1 | 2.7 | 1.1 | 3 | 2 |
| **Non-Bidding Molecules** | | | | | | | |
| Captopril | Hypertension | 1.9 | 0.5 | 3.9 | 19.5 | 49 | 3 |
| Amoxicillin | Infection | 8.9 | 0.4 | 22.9 | 2.9 | 59 | 4 |
| Azithromycin, injection | Infection | 61.0 | 35.4 | 1.7 | 1.2 | 44 | 2 |
| Azithromycin, tablet | Infection | 23.6 | 6.4 | 3.7 | 5.0 | 85 | 2 |
| Alfacalcidol | Osteoporosis | 41.0 | 1.7 | 24.5 | 1.8 | 13 | 2 |
| Tramadol HCL | Painkiller | 10.1 | 3.8 | 2.7 | 1.8 | 24 | 2 |

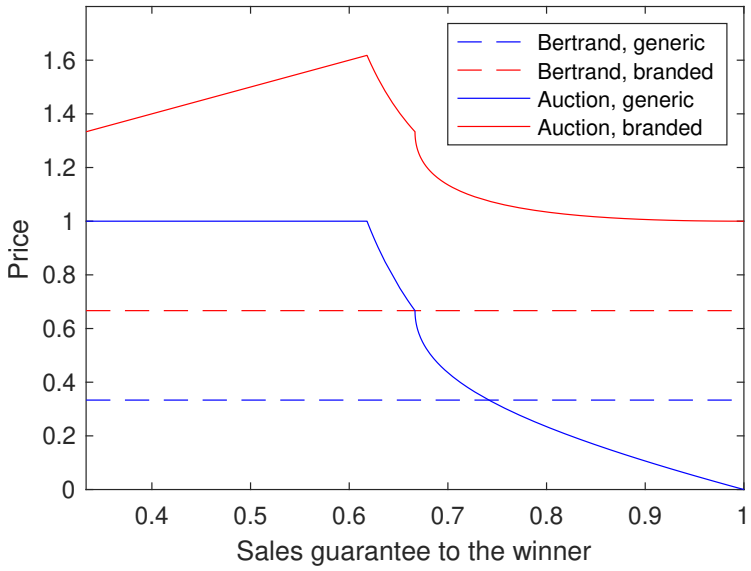
*Notes*: This table shows 25 bidding and 6 non-bidding molecules in our sample. Quantities for each molecule are measured in the unit of the same dosage for the molecule (e.g., 10 mg Lisinopril tablet). B-G price ratio measures the ratio between the price of the branded drug and the average price of generic drugs in the same molecule. The number of firms lists the number of active firms selling the molecule in 2018. The number of BE firms includes both generic drugs that have passed the bio-equivalence test by 2018 and the branded drug.

**Table 2:** Demand Estimation

| | (1) Logit OLS | (2) Logit IV | (3) NLogit OLS | (4) NLogit IV |
|---|---|---|---|---|
| Price | -0.587 | -1.414 | -0.681 | -1.362 |
| | (0.230) | (0.486) | (0.0856) | (0.388) |
| Passed BE | 0.175 | 0.141 | -0.0210 | 0.0601 |
| | (0.0733) | (0.0756) | (0.0219) | (0.0618) |
| Cond. Mkt Share | | | 0.939 | 0.412 |
| | | | (0.0176) | (0.188) |
| *N* | 3205 | 3191 | 3205 | 3191 |
| Province-Drug FE | Yes | Yes | Yes | Yes |
| Province-Year FE | Yes | Yes | Yes | Yes |

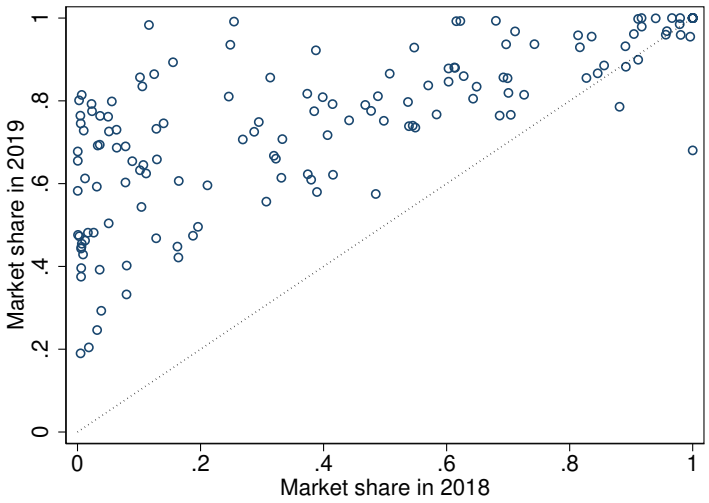
*Notes*: This table shows the estimation results of the demand system in Equation (3). Price is the out-of-pocket price paid by the patients. Columns (1)-(2) use the logit specification and columns (3)-(4) use the nested logit specification. We use data in 2012-2018, prior to the competitive bidding. We control for province-drug fixed effects and province-year fixed effects. Columns (1) and (3) show the OLS estimates without using any instruments. Columns (2) and (4) show the IV estimates using instruments described in Section 5.3. Appendix Table A.1 shows the first-stage regressions. Standard errors are clustered at the province-year level and are reported in the parentheses.

**Figure 1:** Equilibrium Prices under the Bertrand Competition and Competitive Bidding



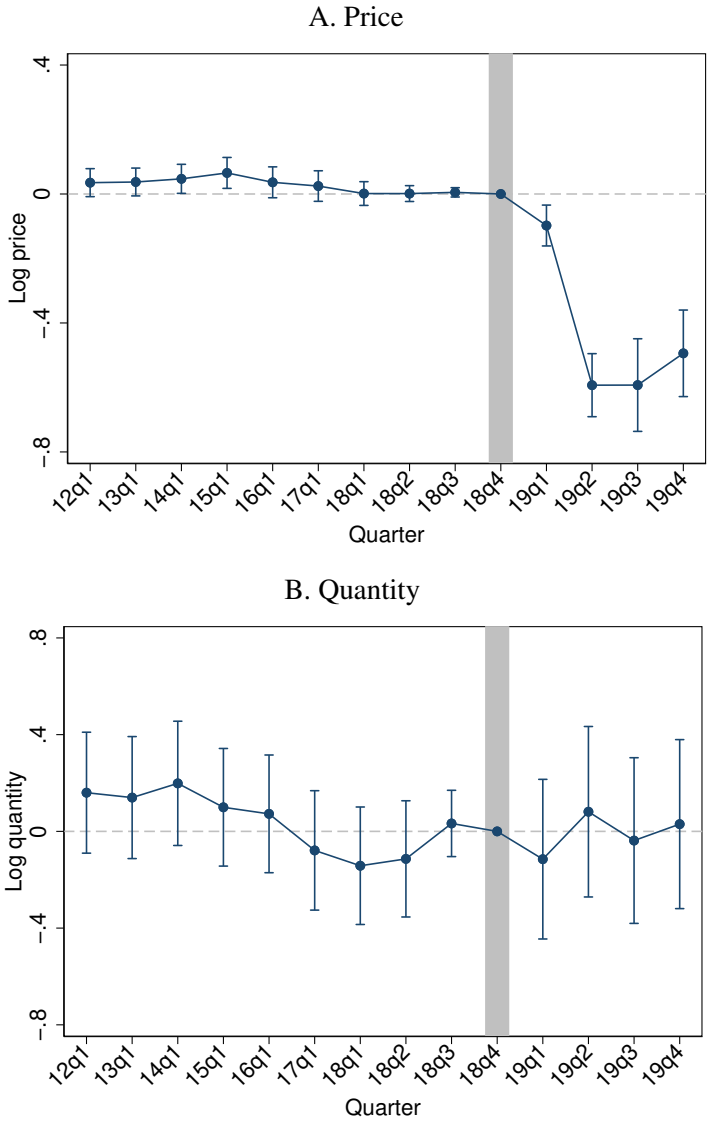

*Notes*: This figure shows equilibrium prices under both the Bertrand competition and competitive bidding in the model of Section 3. See Appendix A for the derivations.

**Figure 2:** Market Shares of Auction Winners in Enacting Provinces



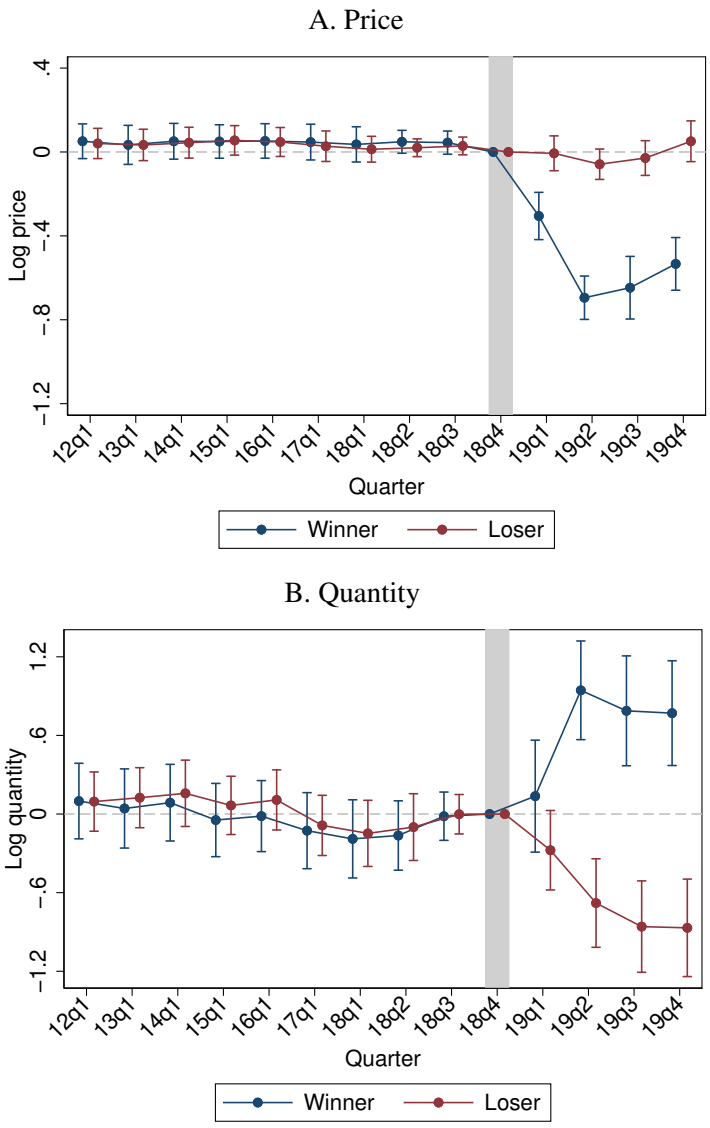

*Notes*: This figure plots the market shares for auction winners in enacting provinces prior to the competitive bidding (2018) and after (2019). Since the quantity guarantee of the competitive bidding went into effect in March 2019, we drop the first quarter when computing market shares in 2019. Each dot is a molecule-province pair for all bidding molecules and enacting provinces.

**Figure 3:** Effects of the Competitive Bidding on Drug Prices and Sales



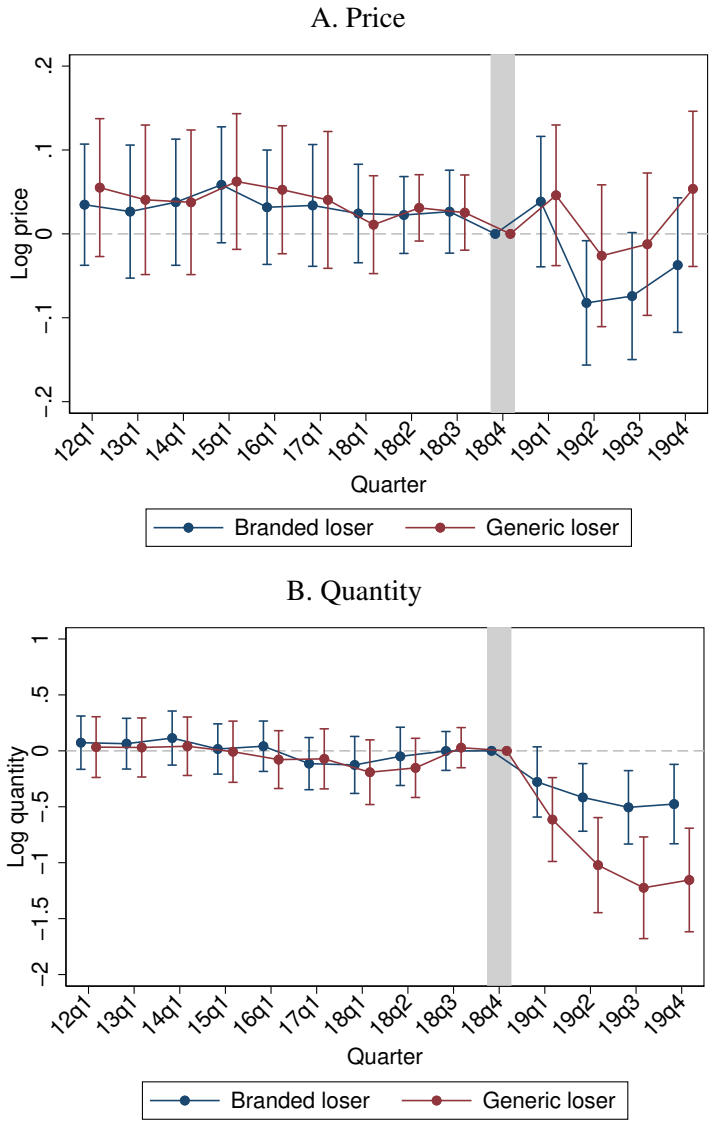

*Notes*: This figure shows the effects of the competitive bidding on drug prices and sales, estimated using the specification shown in Equation (1). Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval using standard errors clustered at the province-year level. The coefficient of the fourth quarter in 2018 is normalized to zero. From 2012 to 2017, we only show coefficients for the first quarter of each year to conserve space.

**Figure 4:** Heterogeneous Effects on Auction Winners and Losers



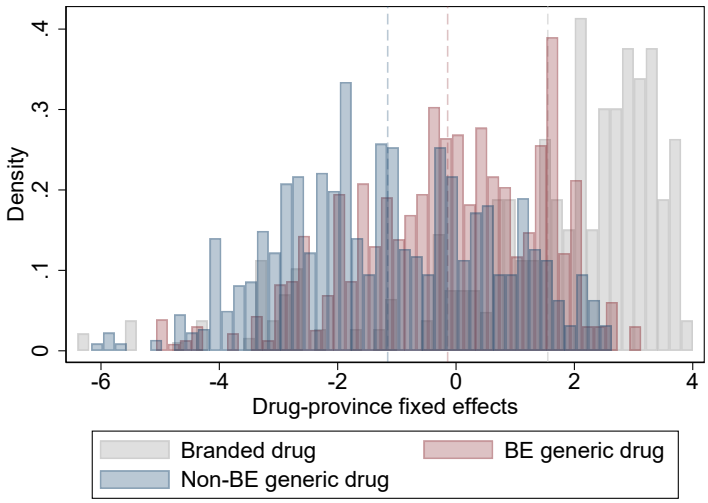

*Notes*: This figure pools the results from two regressions similar to Figure 3, where we estimate the effects of the competitive bidding on drug prices and sales using the specification shown in Equation (1), separately for firms that won (in blue) and lost (in red) the auction. Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval using standard errors clustered at the province-year level. The coefficient of the fourth quarter in 2018 is normalized to zero. From 2012 to 2017, we only show coefficients for the first quarter of each year to conserve space.

**Figure 5:** Heterogeneous Effects on Branded and Generic Auction Losers



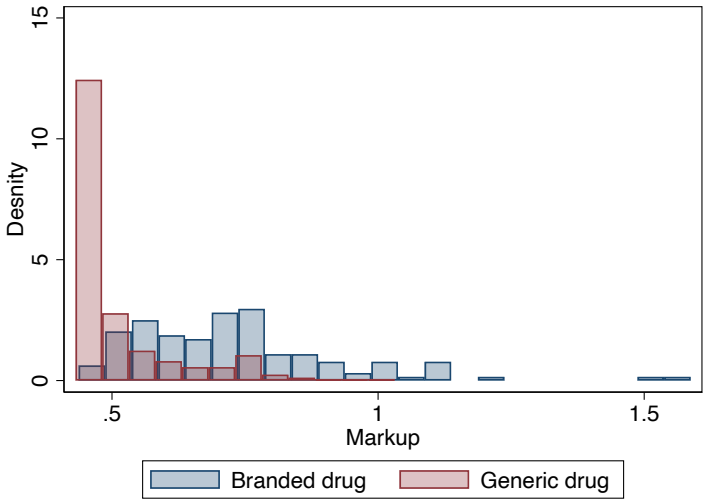

*Notes*: This figure pools results from two separate regressions similar to Figure 3, where we estimate the effects of the competitive bidding on drug prices and sales using the specification shown in Equation (1), separately for branded (in blue) and generic drugs (in red) that lost the auction. Each 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-year level. The coefficient of the fourth quarter in 2018 is normalized to zero. From 2012 to 2017, we only show coefficients for the first quarter of each year to conserve space.

**Figure 6:** Illustration of Brand Preferences



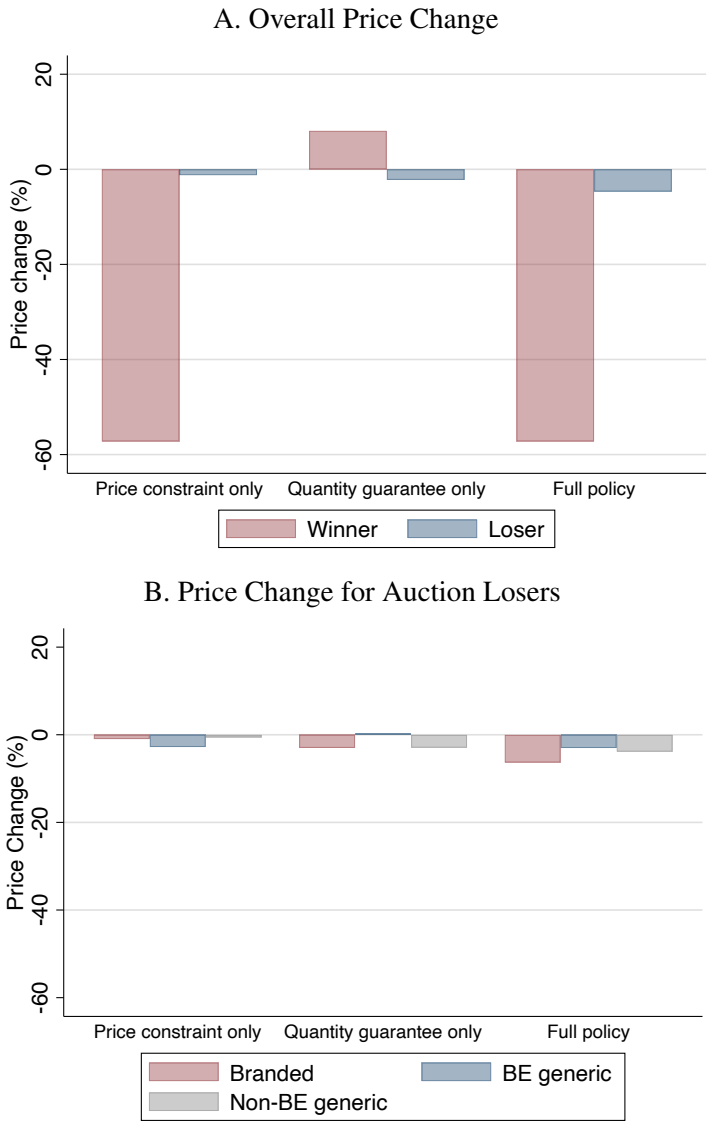

*Notes*: This figure illustrate the brand preferences. We treat estimated drug-province fixed effects in Equation (1) as the province-specific drug preferences, and plot the distribution of the drug-province fixed effects for branded drugs, BE generic drugs, and non-BE generic drugs separately. The dash lines represent the average drug-province fixed effects for the three types of products.

**Figure 7:** Markup for Branded and Generic Drugs



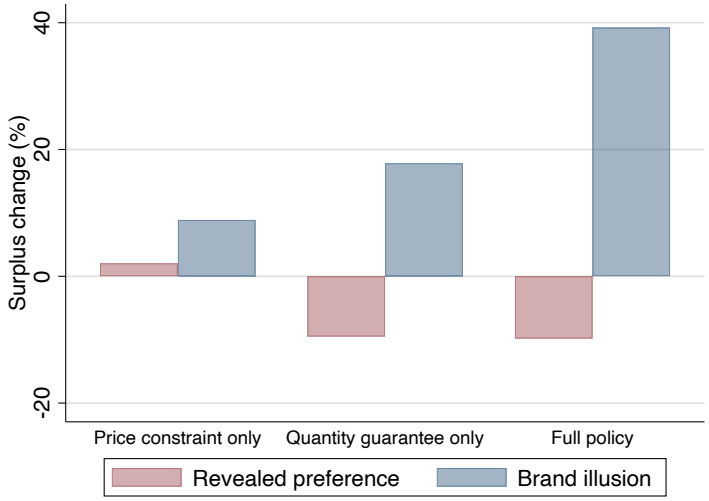

*Notes*: This figure plots the distribution of markups in 2018 for branded and generic drugs separately. The markups are calculated from Equation (4) as the differences between prices and marginal costs.

**Figure 8:** Price Changes under Counterfactual Scenarios



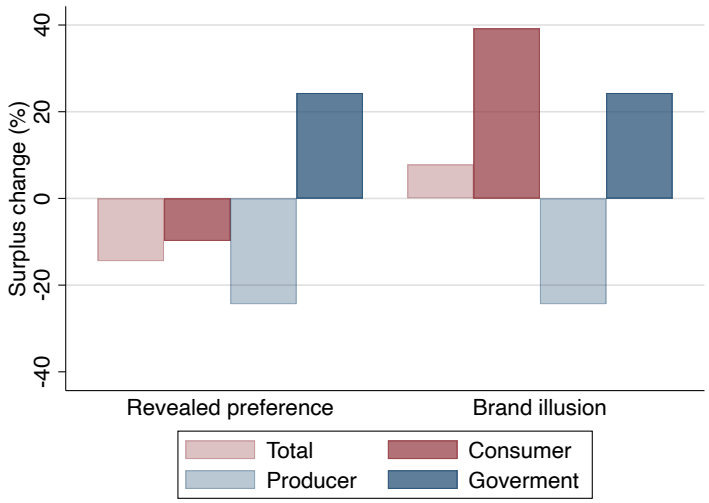

*Notes*: This figure shows price changes under three counterfactual scenarios. The status quo is the pre-auction period in 2018. In the first scenario, consumer demand remains fixed, prices of auction winners are fixed at the post-auction prices, and other firms can freely adjust their prices. In the second scenario, consumer demand is distorted by the quantity guarantee and all firms can freely adjust their prices. In the third scenario, consumer demand is distorted by the quantity guarantee, prices of auction winners are fixed at the post-auction prices, and other firms can freely adjust their prices. The third scenario corresponds to the actual competitive bidding that took place. We calculate price changes for auction winners and losers separately. Panel A shows the price changes for winners and losers separately. Panel B shows the price changes for branded and generic losers separately. See Section 6 for more details.

**Figure 9:** Changes in Consumer Surplus




*Notes*: This figure shows the change in consumer surplus under three counterfactual scenarios, the same as Figure 8. We measure consumer surplus in two ways. In red bars, we measure consumer surplus using consumers' revealed preferences. In blue bars, we assume brand preference is an illusion and welfare irrelevant, as discussed in Section 6.1.

**Figure 10:** Changes in Total Surplus




*Notes*: This figure shows the change in total surplus from the full competitive bidding and decomposes the change in total surplus into changes in consumer, producer, and government surplus. The left four bars show results if we measure consumer surplus using consumers' revealed preferences. The right four bars show results if we assume brand preference is an illusion and welfare irrelevant. See Section 6.2 for more details.

# Online Appendix, Not for Publication

# A Proofs and Derivations

In this section, we provide details of the proofs and derivations for the stylized model outlined in Section 3.

Consider a molecule with one firm selling a branded product $B$ and another firm selling a BE 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. Marginal costs of both products are the same at $c$. Prior to the 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 a competitive bidding with sales guarantee $\tau \in (0,1]$. The format is 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 $\tau$, or all consumers who value the winning product no less than the winning bid if there are fewer than $\tau$ 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 the 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:

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

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

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

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:

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

The second line comes from the fact that $p_3'$ is a best response to $p_1'$ and 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 to 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:

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

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 $\tau$ 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 wins 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 $\tau$ 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 $1-\tau$ 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 $G$'s best response is to target the remaining consumers, set a price of $p'_G + \tau$, and captures 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.

# B Imputation of Policy Demand Shifters

As in Section 5.5, the estimated demand shifter for drug $j$ in province $m$ in 2019 is denoted as $\hat{\gamma}_{jm,2019}$ in Equation (5). 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 5.5, 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.

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

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.[20] Specifically,

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

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.

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

# C Welfare when Decision Utility and Actual Utility Differ

As discussed in Sections 5.5 and 6.1, 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. 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

$$CS = \frac{1}{\alpha} E(\tilde{u}_{ijmt}) = \frac{1}{\alpha} E(u_{ijmt}) + \frac{1}{\alpha} \sum s_{jmt} \times \Delta u_{jmt}, \tag{C.5}$$

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 6.1. 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:

$$\tilde{u}^{A1}_{ijm,2019} = \delta_{jm,2019} + \hat{\tau}_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt},$$

while her actual utility is

$$\tilde{u}^{A0}_{ijm,2019} = \delta'_{jm,2019} + \hat{\tau}_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$$

The consumer surplus is given by

$$CS = \frac{1}{\alpha} E(\tilde{u}^{A1}_{ijm,2019}) + \frac{1}{\alpha} \sum s_{jmt} \times (\delta'_{jm,2019} - \delta_{jm,2019}),$$

where $s_{jmt}$ is the market share of drug $j$ chosen under the choice utility $\tilde{u}^{A1}_{ijm,2019}$.

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:

$$\tilde{u}^{D}_{ijm,2019} = \delta_{jm,2019} + \hat{\tau}_j + \tilde{\gamma}_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt},$$

while her actual utility is given by:

$$\tilde{u}^{A1}_{ijm,2019} = \delta_{jm,2019} + \hat{\tau}_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}.$$

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:

$$\tilde{u}^D_{ijm,2019} = \delta_{jm,2019} + \hat{\tau}_j + \tilde{\gamma}_{jm,2019} + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt},$$

while her actual utility is given by:

$$\tilde{u}^{A0}_{ijm,2019} = \delta'_{jm,2019} + \hat{\tau}_j + \zeta_{igmt} + (1-\sigma)\varepsilon_{ijmt}$$

The consumer surplus is given by

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

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

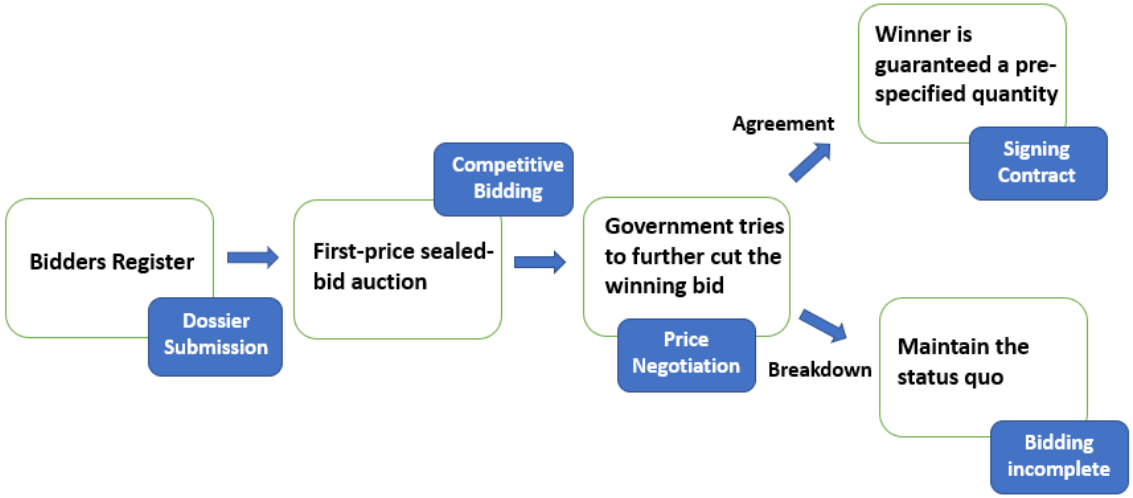
# D Supplemental Tables and Figures

**Table A.1:** First Stage of Demand Estimation

| | Logit IV | Nested Logit IV | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Price | Price | Cond. Mkt Share |
| Hausman IV | 0.126 | 0.126 | -0.0106 |
| | (0.0113) | (0.0112) | (0.0514) |
| BLP IV | | -0.00722 | -0.173 |
| | | (0.00347) | (0.0288) |
| Passed BE | -0.0238 | -0.0239 | 0.197 |
| | (0.00848) | (0.00852) | (0.0679) |
| *N* | 3191 | 3191 | 3191 |
| *F* | 67.20 | 48.33 | 14.55 |
| Province-Drug FE | Yes | Yes | Yes |
| Province-Year FE | Yes | Yes | Yes |

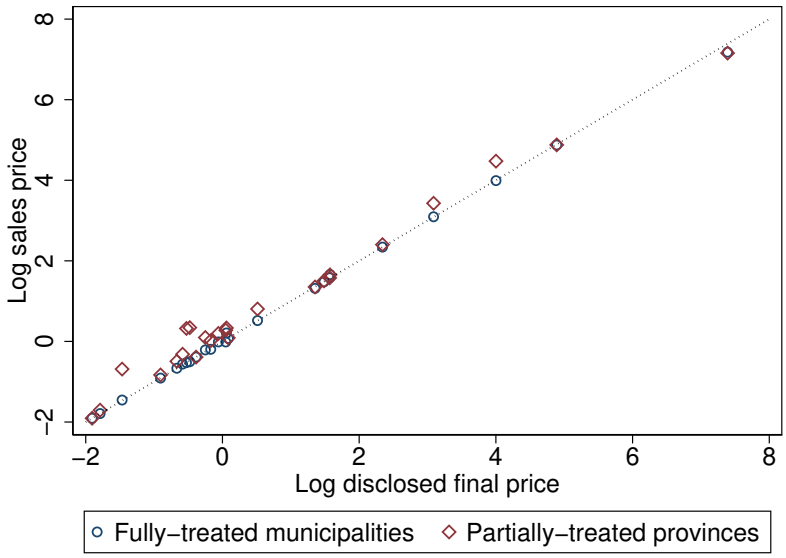
*Notes*: This table shows the first-stage regressions of the demand estimation using instrumental variables, corresponding to columns (2) and (4) in Table 2. Hausman price IV is defined as the average price of the same product sold in other provinces in the same year. BLP IV is defined as the total number of drugs in each molecule in the market. Standard errors are clustered at the province-year level and are reported in the parentheses.

**Figure A.1:** Bidding and Negotiation Process



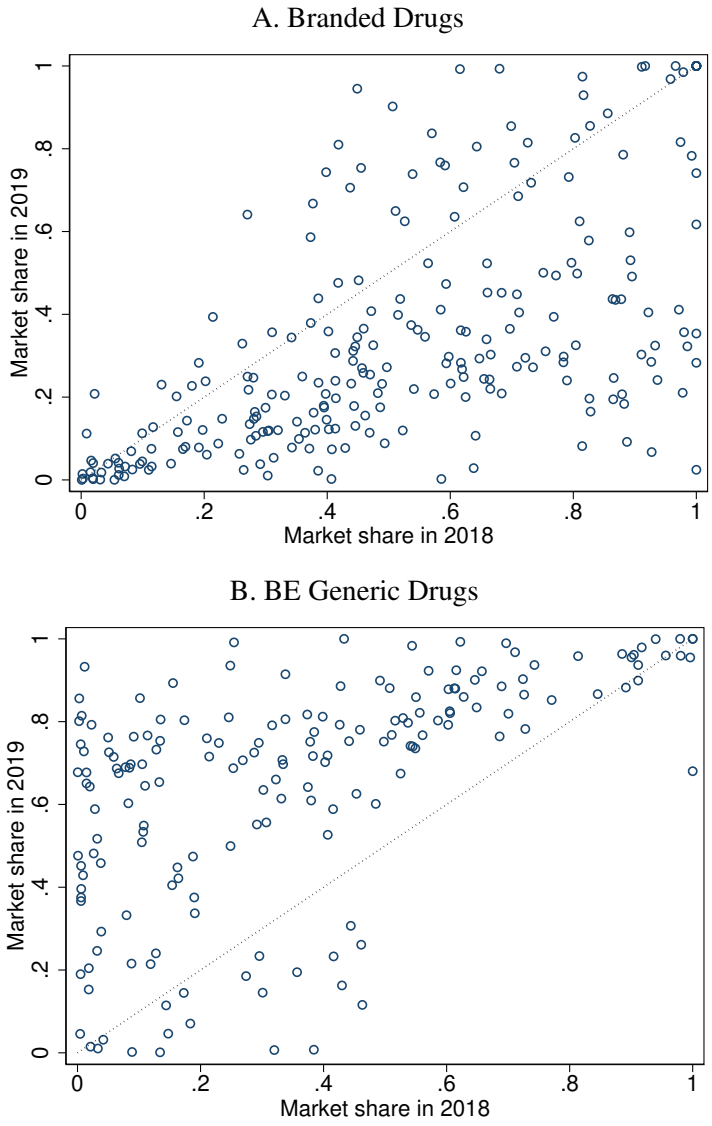

*Notes*: This figure shows the detailed bidding and negotiation process. The drug producers first register for the competitive bidding and submit their dossiers. Then they participate in a first-price sealed-bid auction. The bidder with the lowest bidding price is selected as the auction winner. In some 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:** 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 y-axis represents the log of sale prices of the winning product 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.

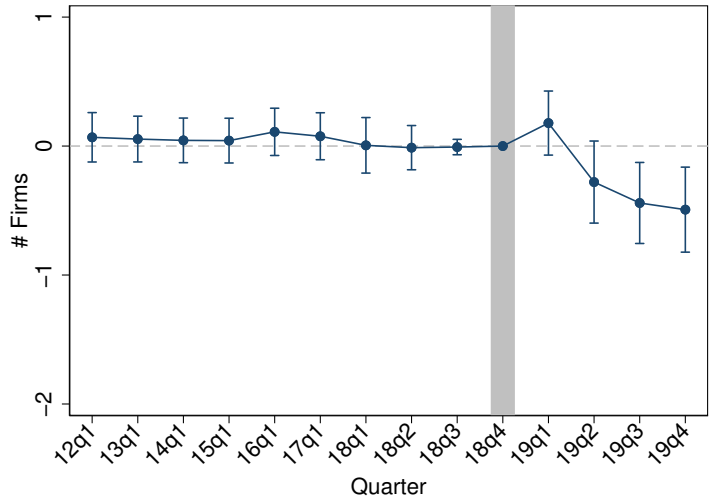
**Figure A.3:** Market Shares of Branded and Generic Drugs in Enacting Provinces



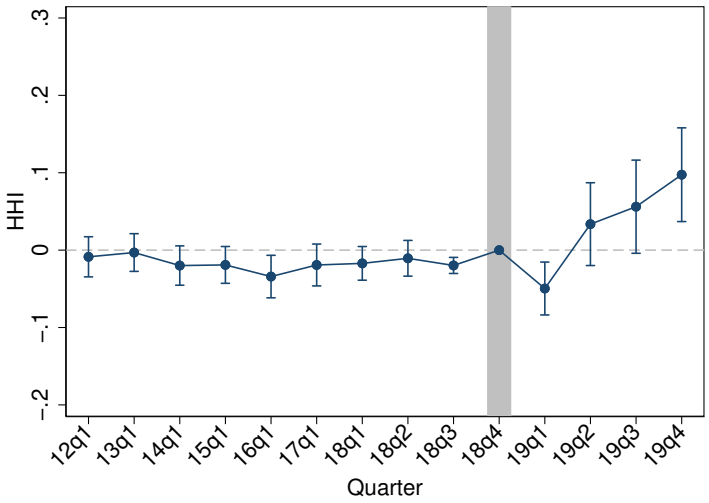

*Notes*: This figure plots the market shares for branded drugs (Panel A) and BE generic drugs (Panel B) in enacting provinces prior to the competitive bidding (2018) and after (2019). Since the market guarantee of the competitive bidding went into effect in March 2019, we drop the first quarter when computing market shares in 2019. Each dot is a molecule-province pair for all bidding molecules and enacting provinces.

**Figure A.4:** Effects of the Competitive Bidding on Market Concentration

A. Number of Firms

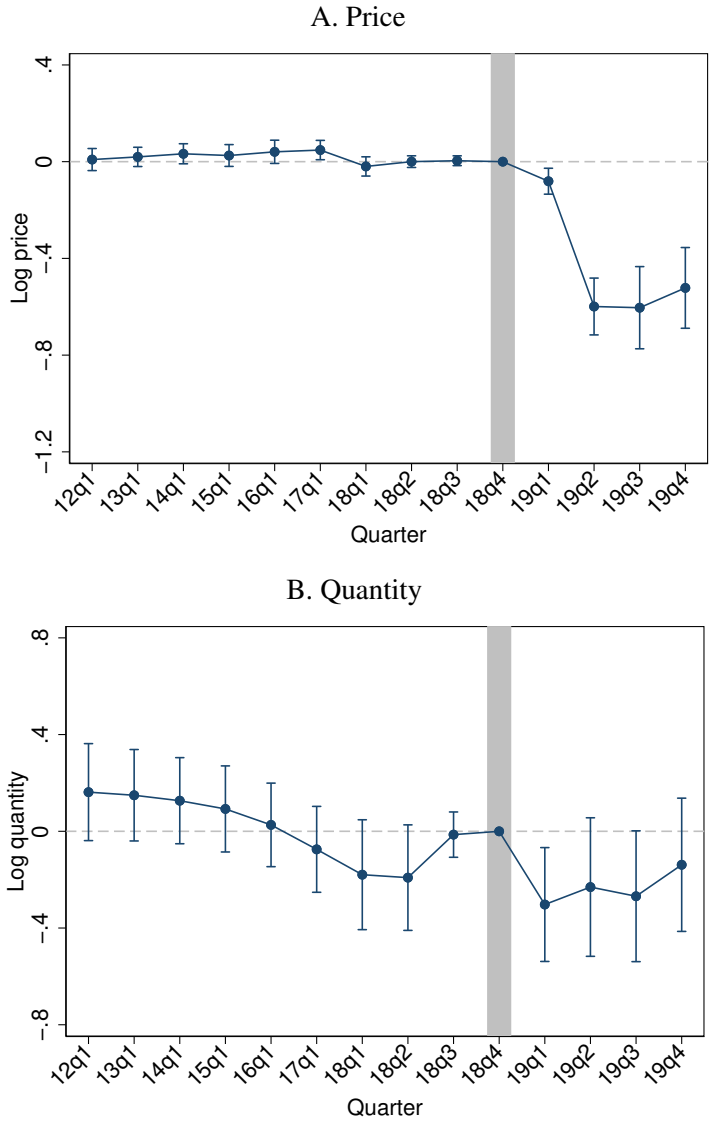



B. HHI



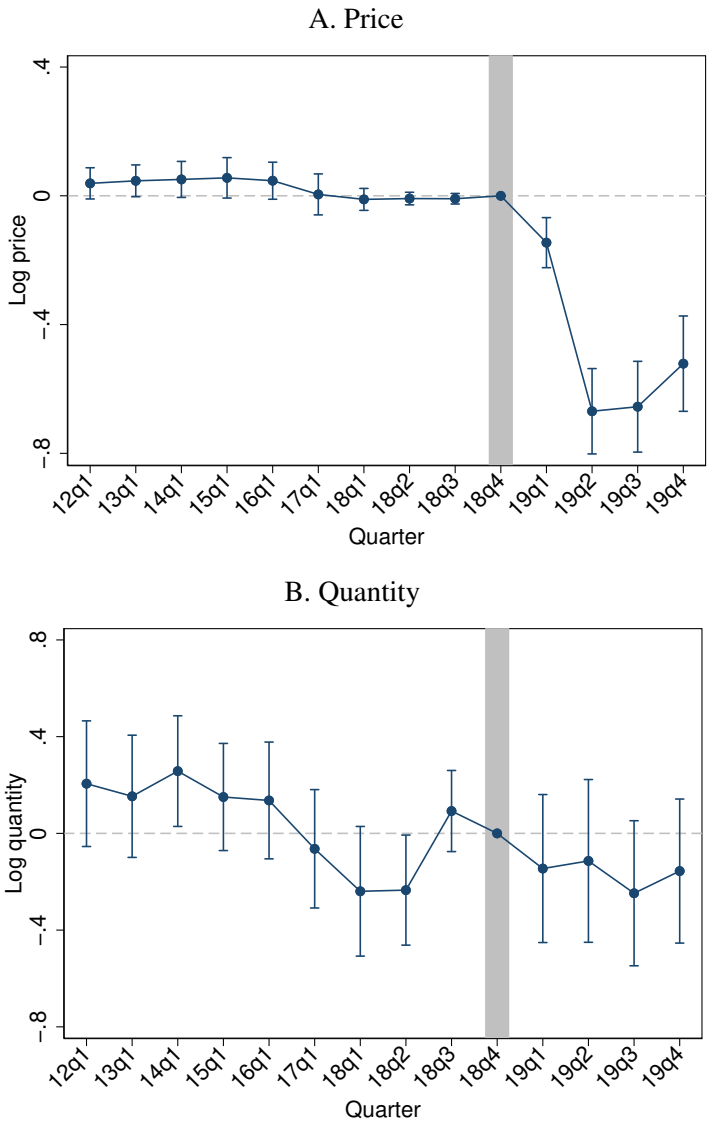

*Notes*: This figure shows the effects of the competitive bidding on the number of active firms and Herfindahl-Hirschman Index (HHI), estimated using the specification shown in Equation (1). Each dot represents the regression coefficient for the corresponding quarter, and each line segment represents the 95% confidence interval using standard errors clustered at the province-year level. The coefficient of the fourth quarter in 2018 is normalized to zero. From 2012 to 2017, we only show coefficients for the first quarter of each year to conserve space.

**Figure A.5:** Effects of the Competitive Bidding on Drug Prices and Sales, Sales Weighted




*Notes*: This figure shows the effects of the competitive bidding on drug prices and sales, similar to Figure 3. The only difference is that each observation is weighted by sales quantity in this figure.

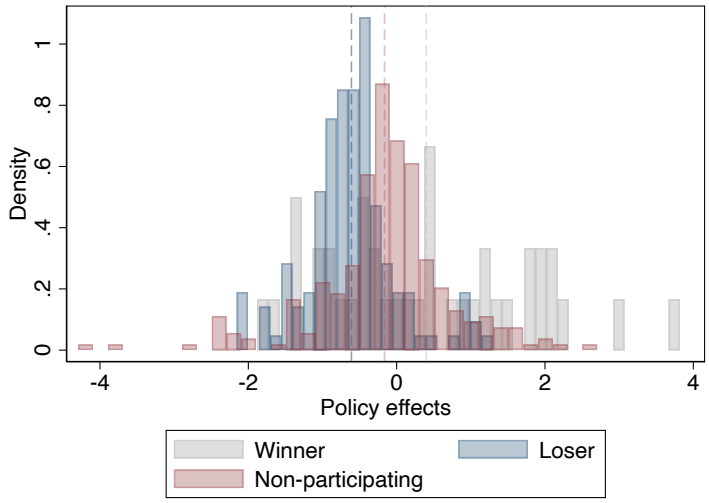
**Figure A.6:** Effects of the Competitive Bidding on Drug Prices and Sales, Excluding Partially Treated Provinces



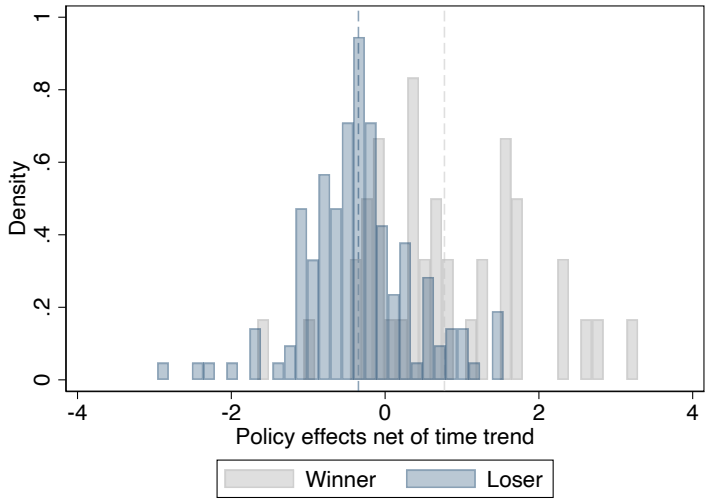

*Notes*: This figure shows the effects of the competitive bidding on drug prices and sales, similar to Figure 3. The only difference is that only four municipalities, Beijing, Tianjin, Shanghai, and Chongqing, are included as enacting provinces in this figure. We drop provinces where seven other enacting cities are located, as these provinces are only partially treated.

**Figure A.7:** 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 dash lines represent the average value of each group separately.