# Excessive Pharmaceutical Marketing Expenditure: Policy Remedies from China

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November 2025

**Abstract**

Many developing countries face high pharmaceutical prices, even though multiple producers of generic versions of drugs often exist. One reason is that drug firms spend excessively on sales and marketing efforts. In this paper, we explore the effect of centralized procurement of drugs on limiting firms' excessive marketing efforts and reducing drug prices by leveraging a policy experiment in China. Under the policy, certain generic drugs are procured via centralized auctions in pilot cities. The winning firms can directly capture large market shares without incurring high marketing costs. We find that the centralized auction effectively reduces the sales costs and prices, and the winning firms' sales costs and marketing-related labor demand decrease significantly. *JEL Codes:* I11, L40.

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# 1 Introduction

High drug prices have become a major concern for public insurance programs and create high financial costs for low-income households, especially in developing countries (Danzon, Mulcahy and Towse, 2015). Theoretically, the availability of generic drugs should intensify competition and drive down drug prices. In many developing countries, however, even though there are generic producers, drug prices are still high relative to the international reference point and exhibit a large variation across regions (Dubois, Lefouili and Straub, 2021).

One potential reason for the high drug prices is excessive drug promotion activities, especially the payments from pharmaceutical firms to physicians. Theoretically, detailing activities may increase drug prices directly via higher operating costs and indirectly via higher monopolistic power (Brekke and Kuhn, 2006; Dave, 2013). Empirically, a growing literature studies how drug promotion activities affect prescribing behavior, price elasticity, drug costs, etc.[1] The existing literature on the issue mostly focuses on pharmaceutical detailing of drugs under patent in developed countries, but the phenomenon may well happen in developing countries. For example, anecdotal court reports from China suggest that many pharmaceutical firms pay hidden kickbacks to physicians, and a large portion of the retail prices of generics is due to sales expenditure.[2] There is an open question on what policy may reduce wasteful marketing efforts in these markets.

In this paper, we examine how centralized procurement policies for drugs can limit firms' excessive marketing efforts and reduce drug prices. Many developed and developing countries have implemented centralized procurement of drugs and medical equipment for their public health insurance programs. The procurement often uses competitive bidding to determine the eligible products and prices.[3] The existing literature documents its impact on drug prices through

[1] See Kremer et al. (2008) and Spurling et al. (2010) for a review.

[2] According to the statistics published by China's Court Judgements Document website, there are more than 3000 cases related to bribery in the pharmaceutical industry between 2013 and 2019. Many of them involve local producers of generic drugs.

[3] For example, centralized procurement is used in the procurement of durable medical equipment in Medicare (Ding, Duggan and Starc, 2024) and essential medicines in some Sub-Saharan

strengthened bargaining power and intensified competition (Dubois, Lefouili and Straub, 2021; Cao, Yi and Yu, 2024). We focus on an under-explored mechanism: the decline of firms' marketing expenditure.

We study the question by leveraging a recent policy reform in China, which provides a good context to examine the impacts of centralized procurement. Before the policy experiment, Chinese pharmaceutical firms needed to approach public hospitals and physicians individually to sell generic versions of essential medicines. The process often involved illicit hidden kickbacks to hospitals and physicians, driving up drug prices and pharmaceutical expenditure. In August 2018, the central government announced a pilot program to implement a national-level central procurement of drugs for public insurance programs. The policy targeted 25 commonly used molecules and was first implemented in 11 cities and regions in 2019. The procurement allowed all firms producing branded drugs or generics passing certain quality standards to compete in a first-price auction. The winning firm for each molecule would get a guaranteed quantity of 50%-70% of the previous market size in these 11 cities.

We begin with a stylized model to illustrate how centralized procurement can alter firms' pricing and marketing strategies. The model features two firms producing a drug, where patients can only purchase the drug prescribed by their physician. Physician choices are influenced by patients' heterogeneous preferences—shaped by tastes and prices—and by firms' marketing efforts, modeled as per-unit kickbacks. Firms simultaneously choose prices and kickbacks to maximize profits. Without centralized procurement, both firms offer positive kickbacks, which raise prices. These marketing expenditures are socially wasteful, as banning kickbacks yields the same allocation at lower prices.

Under centralized procurement, we model the policy as a first-price sealed-bid auction in which the winning firm is guaranteed a market share of size $t$ without needing to pay kickbacks. We show that the winning firm's price is lower than in the no-auction case and decreases with $t$, while its marketing expenditure falls to zero when $t$ is sufficiently large. These price reductions

African countries (Arney and Yadav, 2014). More broadly, centralized procurement has been used in government procurement of other commodities outside of health care. Lenhart and Sullivan (2012) discusses examples in China.

are driven by the lowered kickbacks and intensified price competition. In contrast, the losing firm sees a smaller price decline, as it must continue offering kickbacks to compete for the remaining market and maintains its kickbacks at pre-auction levels.

In our empirical analysis, we examine the price effects of the centralized procurement policy using data on quarterly sales revenues and quantities from over 500 representative public hospitals in 20 cities spanning from 2013 to 2019. We employ a difference-in-differences design to compare prices and sales of molecules subject to the pilot procurement program with those not selected for the pilot program but selected in the second national procurement round. Our findings indicate that centralized procurement leads to sharp price cuts but only modest increases in the total quantities sold. On average, the sales revenues of molecules covered by the procurement decrease by 43%. We observe limited spillover effects from pilot to non-pilot cities.

Next, we examine how the centralized procurement policy changes firms' marketing strategies. We measure marketing strategies in two ways. First, we extract listed pharmaceutical firms' sales and marketing expenditures from their financial reports. Second, we compile a dataset of online job postings and identify marketing-related job posts based on keywords. We find that firms winning the auction in the pilot program and having large pre-policy revenue shares for the pilot molecules experience significant declines in sales and marketing expenditure compared to their competitors. They also have fewer marketing-related online job posts. Both findings suggest that the centralized procurement policy reduces the marketing efforts of winning firms. On the contrary, we find insignificant changes in non-winning firms.

Our paper contributes to the literature studying the role of marketing and advertising in pharmaceutical markets. Previous literature explores how drug promotion activities affect physicians' prescribing behaviors, costs and quality of care, and social welfare.[4] Most of these works predominantly focus on detailing practices for new and branded drugs in developed countries. Instead, our research focuses on the marketing of pharmaceuticals in developing countries. Our

[4]See, for example, David, Markowitz and Richards-Shubik (2010), Grennan et al. (2018), Shapiro (2018), Carey, Lieber and Miller (2020), Agha and Zeltzer (2022), and Dubois and Majewska (2022).

study highlights the unique challenge in these markets: many of the drug products are widely used generics, which implies that the marketing practices are largely wasteful. Moreover, policies that are proven to be effective in reducing wasteful marketing efforts in developed countries may not be as effective in developing countries. For example, literature has shown that policies like bans on commissions and mandatory disclosure of kickbacks and caps are effective in changing prescribing behaviors in developed countries (Pham-Kanter, Alexander and Nair, 2012; Guo, Sriram and Manchanda, 2020, 2021). In contrast, our research reveals that these regulations alone fail to effectively curb physician kickbacks in China, where weak state capacity hinders enforcement. In response to these challenges, we propose and demonstrate how centralized procurement, coupled with guaranteed quantity provisions, can effectively address the hidden physician kickback issue in developing countries like China.

Our paper also contributes to the growing literature studying the effects and mechanisms of centralized pharmaceutical procurement on drug prices. The literature documents that centralized or pooled procurement has been effective in reducing prices for generic drugs.[5] Many of these works find that the price change is mainly driven by intensified competition and shifts in bargaining power. In alignment with the literature, we find a similar pattern that centralized procurement leads to decreases in drug prices. However, we emphasize a different mechanism driving this price reduction: the decline of marketing and sales expenditure. The study closest to our setting is Cao, Yi and Yu (2024), which also studies China's centralized procurement policy using different data and drugs. Their focus is on the competition between generic and branded drugs, while our focus is on the reduction of wasteful detailing for generic drugs.

The rest of the article is organized as follows: Section 2 introduces the institutional background of volume-based drug procurement reform in China; Section 3 shows the conceptual

[5]See, for example, Wirtz et al. (2009), Danzon, Mulcahy and Towse (2015), Kim and Skordis-Worrall (2017), and Dubois, Lefouili and Straub (2021). In particular, medical and health policy literature documents that the "4+7" pilot program is associated with lowered drug prices and patient expenditure, e.g., Chen et al. (2020), Yuan et al. (2021), and Zhang et al. (2022). These works use data covering specific drugs or pilot cities only or use different statistical methods from ours.

framework; Section 4 outlines the data; Section 5 presents the empirical analysis; Section 6 concludes the paper.

# 2 Institutional Background

In China, rising pharmaceutical expenditure has become a great challenge. During the period of 1990–1999, the total pharmaceutical expenditure grew year by year from 41.83 to 197.64 billion CNY[6], making up around 2% of the Gross Domestic Product (GDP) stably (National Health Commission, 2018).

Since 2000, provincial governments in China started to carry out drug procurement programs for the public medical insurance program to mitigate the high increase in drug expenditure. These programs involved procurement auctions conducted by provincial governments or regional alliances for essential medicines. However, due to weak state capacity, the auctions were not well organized and enforced. The procurement programs typically selected multiple eligible products and set a price ceiling. Public hospitals were granted considerable autonomy in choosing which products to purchase and prescribe. This decentralized approach led pharmaceutical firms to engage with public hospitals individually to negotiate prices and sell products, resulting in substantial sales and distribution costs. Despite regulations prohibiting physician kickbacks, anecdotal evidence indicates that such practices were widespread and contributed to high drug prices.[7]

To address the high drug expenditure trend and enhance the efficiency of drug procurement, the General Office of the State Council of the People's Republic of China launched a nationally centralized drug procurement (NCDP) program in mid-2018. This initiative marked a significant shift towards a more centralized approach to drug procurement in China. Different from

[6] The exchange rate between the Chinese currency (CNY) and US dollar increased dramatically from 4.73 in January 1990 to 8.28 in December 1999.

[7] Zhu (2007) estimates that the sales and distribution costs constitute 30%-70% of the retail price for new drugs. Additionally, there are many news reports and government notices documenting instances of illegal physician kickbacks, for example, `https://www.ccdi.gov.cn/ywjt/202403/t20240313_334015.html` (in Chinese).

the previous self-formed alliance, the NCDP program was organized at the national level by the national public medical insurance program, the primary payer of medical expenditures to public hospitals. The NCDP program was piloted in December 2018. 11 cities and regions were selected to participate based on criteria such as market share, procurement capacity, and past reform experience. These areas include four municipalities (Beijing, Chongqing, Shanghai, and Tianjin) and seven sub-provincial cities (Chengdu, Dalian, Guangzhou, Shenyang, Shenzhen, Xiamen, and Xi'an). Therefore, this pilot program is also known as the "4+7" pilot. The pilot planned to procure 31 molecules, which were selected from those with large sales volumes in the fields of cardiovascular, anti-tumor, antibiotics, and psychology.

There are two main features that distinguish the pilot program from previous procurement practices. First, the program only allowed products that met specific quality standards to participate in the procurement process. Eligible drug products for procurement included original products, generic products that had passed the bioequivalence tests conducted by the State Drug Administration, and products used as reference preparations for the bioequivalence testing.[8] Second, the procurement was volume-based. Public medical institutions in the pilot cities, as the main purchasing entities, estimated their planned purchase amount of each molecule as 50%-70% of the total purchase volume in the previous year. The program guaranteed selected winners a pre-specified quantity for the molecule won. To enforce this guarantee, the government established direct distribution channels from pharmaceutical firms to public hospitals. Hospitals' and physicians' refusal to purchase the winning products may trigger penalties such as delays or denials of public medical insurance payments.

The NCDP was implemented via competitive bidding, with one bidding session held for each molecule for all participating cities. All bidding sessions were held at the same time. The winning firm for each molecule would supply the pre-specified volume to all participating cities. There were two stages in the bidding process. In the first stage, for each molecule, all

[8] The bioequivalence testing has been conducted since 2012 with the aim of ensuring that the qualities of generic drug products are equivalent to that of the corresponding original branded drug product. The firms were permitted to and indeed did participate in the procurement of multiple molecules if all their corresponding products met the eligibility requirements.

participating firms submitted a tender, and the lowest bidder would become the preliminary candidate.[9] The firm offering the second lowest price would become the backup candidate in case the preliminary candidate could not fulfill the quantity requirement.[10] In the second stage, the JPO determined the final winner and price. If there were three or more firms participating in the bidding for a molecule, the Joint Procurement Office (JPO) would accept the lowest offering price, and the preliminary candidate would be awarded the contract for one year. If only one or two firms participated, the JPO would rank the reductions in the offering prices across the 31 molecules and accept the price for the top molecules. For the remaining molecules, the JPO would negotiate the price with the preliminary candidate and reject it if the negotiation failed. All molecules were tendered simultaneously to streamline the procurement process and ensure consistency across the bidding sessions.

The pilot program successfully tendered 25 out of 31 molecules in December 2018. Among these molecules, 23 were generic drugs, and two were branded ones. Winning firms signed one-year (i.e., 12-month) contracts with the local government in each city sequentially. Starting in the first quarter of 2019, the pilot cities began implementing the volume-based procurement.[11] The program resulted in an average price reduction of 52%, with the maximum reduction reaching 96%, compared to the lowest prices observed in the pilot cities in 2017 (Xiao, 2019). No-

[9] In cases where more than one firm offered the lowest price, the Joint Procurement Office (JPO) at the National Healthcare Security Administration (NHSA) would select the firm with a stronger capacity to meet the minimum quantity requirement based on past production and sales.

[10] In the "4+7" pilot programs, all winning firms successfully delivered the specified quantity in the 11 pilot cities, and no backup candidates were used.

[11] Before the pilot procurement implementation, cities needed to make arrangements for drug transport and storage, as well as establish penalty guidelines for potential issues, such as hospitals failing to purchase the guaranteed quantity or firms failing to meet the guaranteed quantity. As a result, the implementation timings varied slightly across cities, but all pilot cities initiated the procurement by April 2018. Additionally, in June and July 2019, Fujian and Hebei provinces voluntarily followed suit and implemented the procurement of the same set of molecules based on the bidding prices of the pilot program.

tably, there are six molecules with the final retail price much lower than that in the US market. Entecavir (30 tablets, 0.5mg) used for hepatitis B had the largest per unit price gap (0.09 US dollars per tablet compared to 10.93 US dollars in the US and 15.84 US dollars in the UK).

After the one-year contracts for the pilot molecules and cities were completed, the procurement auction was repeated and expanded to cover the entire country and additional molecules. In December 2019, the remaining cities and regions of the country conducted centralized procurement for the same molecules included in the pilot round. Subsequently, in January 2020, the government implemented the second round of national-level volume-based drug procurement, which included an additional 33 molecules. In the following years, seven more rounds were carried out sequentially. The National Healthcare Security Administration (NHSA) estimated that the first three rounds of the centralized drug procurement program resulted in an average price reduction of over 50% (Xinhua, 2020).

# 3 Conceptual Framework

In this section, we present a stylized model of two firms competing via marketing efforts to reach consumers. The model illustrates how a centralized procurement policy can reduce wasteful marketing expenditures, lower drug prices, and improve consumer welfare. We collect the model details and proofs in Appendix A.

**Model Setup** There is a continuum of patients of measure one in the market. Each patient has a unit demand for a drug. Two firms, $A$ and $B$, are producing the drug, with marginal production costs $c_A = c_B = 0$.[12] Let $u_{ij}$ denote patient $i$'s utility from consuming product $j$. We assume that $u_{ij} = -mp_j + v_{ij}$, with $p_j$ denoting the price of product $j$, $m \in (0, 1)$ is the coinsurance rate paid by the patient, and the rest $(1 - m)$ share is paid by the public insurance program. We also assume $v_{iA} = v$, and $v_{iB} = v + \varepsilon_i$. The term $\varepsilon_i$ represents consumers' idiosyncratic tastes

[12]The marginal costs of manufacturing another tablet of a developed drug are considered close to zero in the literature (Berndt, 2002; Dave, 2013).

for $B$ and is uniformly distributed on $[-0.5, 0.5]$.[13]

In this market, patients get access to drugs through physician prescriptions. Physicians act as imperfect agents whose decisions are affected by patient utility and firms' marketing strategies. Let $k$ denote firms' marketing expenditure per unit of sale, e.g., kickbacks to physicians. Physicians prescribe drug $A$ to patient $i$ if

$$\underbrace{u_{iA} - u_{iB}}_{\Delta \text{ patient utility}} + \lambda \underbrace{(h(k_A) - h(k_B))}_{\Delta \text{ physician payoffs}} > 0,$$

where $h(k)$ represents physician payoffs as a function of $k$, and $\lambda > 0$ captures physicians' relative preferences of their own payoffs over patient utility. We assume $h'(\cdot) > 0$ and $h''(\cdot) < 0$, so kickbacks have diminishing returns in expanding market shares. For illustration, we further parameterize $h(k) = \sqrt{k}$. Physicians' kickbacks are irrelevant to patient welfare.

**Wasteful marketing expenditure under no centralized procurement** When there is no centralized procurement, the timeline proceeds as follows: in the first stage, firms simultaneously determine their kickbacks and prices to maximize profits in a Bertrand-Nash competition: $\pi_j = (p_j - c_j)s_j - k_j s_j$, where $s_j$ is the market share of product $j$. Subsequently, physicians prescribe the product, and patients follow their advice to make a purchase. In equilibrium, both firms set the kickback level as $k^* = \frac{\lambda^2}{4m^2}$ and prices are set at $p^* = \frac{1}{2m} + k^*$. If marketing expenditures are prohibited and both firms are forced to set $k^* = 0$, then the price will be lower by exactly $k^*$, and the market allocation will remain unchanged. Thus, payments to physicians have no impact on matching patients to suitable products. However, these payments increase the price that patients face. The marketing expenditure is, hence, socially wasteful. In reality, prohibiting kickbacks might be challenging due to weak state capacity and high enforcement costs. Instead, the government may implement a centralized procurement auction to mitigate the wasteful marketing expenditure, which we discuss next.

[13] We assume the two products have the same expected quality (e.g., $A$ and $B$ are two generics). Whether $\varepsilon_i$ matters for welfare depends on the context.

**Centralized procurement policy with guaranteed quantity** Now, suppose the government implements a centralized procurement policy. In the first stage, the government announces $t$ and a reservation price, $r$, which is set at the lowest price observed in the market without the procurement policy. Both firms submit bids in a first-price sealed-bid auction, and the government announces the winner and the winning bid. In the second stage, both firms compete for the remaining $(1-t)$ market by simultaneously determining the kickback level, and the losing firm sets its price, given the winning bid and the guaranteed quantity. The winning firm needs to sell at the bidding price in the remaining market. In the final stage, physicians prescribe a product subject to the quantity guarantee. If the guaranteed quantity is binding, the $(1-t)$ patients with the highest willingness to pay for the losing product would purchase the losing product.

We highlight the following insights from the model. First, the equilibrium bid is lower than the no-auction level and decreases with $t$, but the losing firm's price does not change monotonically with $t$. As $t$ increases, winning the auction yields greater savings from marketing expenditures because the winning firm does not need to pay kickbacks to sell up to the guaranteed share. This provides extra incentives to win the auction. The equilibrium bid is determined such that firms are indifferent between undercutting the bid further and losing the auction. As $t$ approaches one, the losing firm's profit approaches zero. This implies that the equilibrium bid will approach 0. The losing firm's price initially decreases as $t$ increases and is lower than the no-auction level due to intensified price competition in the auction. However, when the guaranteed share is binding, the losing firm targets only patients with the highest $(1-t)$ willingness to pay for its product and may charge a higher price as $t$ increases.

Second, the winning firm's marketing expenditure decreases with $t$ and eventually becomes zero, whereas the losing firm's kickback level remains unchanged. The winning firm receives the guaranteed market share without paying the marketing expenditure. When $t$ is sufficiently large, the winning firm only sells to the guaranteed market and incurs zero marketing expenditure in equilibrium. In contrast, the losing firm still needs to pay physicians to compete for the remaining market share, and, in the case of binding $t$, prevent the winning firm from selling beyond the guaranteed share. In equilibrium, we show that the losing firms maintain a kickback level equal to that when there is no centralized procurement auction.

Third, the procurement policy reduces public insurance expenditure and firm profits, and likely increases consumer surplus. If patients' idiosyncratic taste for the product, $\varepsilon$, is welfare irrelevant, then the procurement policy increases consumer surplus because of lowered drug prices. Otherwise, the impact on consumer surplus also depends on the loss from the reduction in the product variety when $t$ increases. In the case where the two products are generics, the welfare loss due to product variety is likely to be small. The lower drug price also implies a reduction in both firms' profits and the public insurance expenditure.

The above predictions—namely, that the centralized procurement auction lowers market prices and drug expenditure, increases consumer welfare, reduces the marketing expenditure of the winning firm, and does not change the kickback level of the losing firm—are robust under alternative assumptions. First, in the baseline model, we assume that both firms have zero marginal production costs. Allowing one firm to have a higher marginal production cost does not change the model predictions: the only difference is that when $t$ approaches one, the bid is at the higher marginal cost level. Second, in the baseline model, we assume that all patients have the same trade-off between price and drug quality. We also assume physicians are equally likely to be affected by kickbacks (i.e., represented by the same $\lambda$). Introducing heterogeneity in patient price sensitivity or heterogeneity in physicians' $\lambda$ yields similar model predictions. Third, we consider the competition between two firms. Allowing more firms to enter the market gives similar predictions. We discuss the model's generality concerning alternative assumptions in Appendix A.

# 4 Data and Variables

## 4.1 Drug Sales Data

Our analysis focuses on the "4+7" pilot program, in which we have clean pre-program periods with no anticipation and sufficient post-program periods without other confounding policies. The primary data source is the drug sales dataset from a consulting firm. The dataset records the quarterly sales revenues and quantities in the smallest unit of measurement in 20 cities from 2013 to 2021.[14] The dataset is collected from more than 500 representative public hospitals[15], so the ratio of sales revenue and quantity of a product represents the retail price. In addition, we also observe detailed information about each product, including product name, production firm, main ingredients, route of administration, dosage form, strength, and package size.

In our main reduced-form analysis, we aggregate the raw data at the following two levels. First, we define a drug product, $j$, as a unique combination of molecule $m$ produced by firm $f$. We then aggregate different package sizes and strength levels of the same product sold in city $c$ at year and quarter $t$ into one observation. The unit price is calculated as the average price for one milligram of the product. We use the product by city by the year-quarter-level of observations to compare the market outcomes of winning and non-winning products.

Second, we construct molecule-level sales revenue and quantity by aggregating the products of the same molecule $m$ produced by different firms $f$ in city $c$ and year-quarter $t$. We construct a variable log price at the molecule-by-city-by-year-quarter level. Let $F(m)$ denote the set of firms producing products of molecule $m$. We calculate the price as the ratio of sales revenue to quantity in molecule-city-quarter level and then take natural logarithm:[16]

$$Log\ Price_{mct} = log\{\frac{\sum_{f \in F(m)} Sales\ Revenue_{mfct}}{\sum_{f \in F(m)} Sales\ Quantity_{mfct}}\}. \tag{1}$$

[14]The included cities are Beijing, Changchun, Changsha, Chengdu, Chongqing, Fuzhou, Guangzhou, Harbin, Hangzhou, Jinan, Nanjing, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Taiyuan, Tianjin, Wuhan, Xi’an, and Zhengzhou.

[15]According to industry reports, public hospitals have always been the main channel for drug sales in China, with their market share remaining between 61% and 68% during the period from 2016 to 2023.

[16]Moreover, following Atal, Cuesta and Sæthre (2022) and Chevalier, Kashyap and Rossi (2003), we calculate the weighted average of log prices across products for each molecule, city, and quarter, using sales revenue shares as weights, that is, $Weighted\ Log\ Price_{mct} = \sum_{f \in F(m)} \{log(\frac{Sales\ Revenue_{mfct}}{Sales\ Quantity_{mfct}}) \frac{Sales\ Revenue_{mfct}}{\sum_{f \in F(m)} Sales\ Revenue_{mfct}}\}$. The results for this alternative measure are presented in Appendix Table C7, and Appendix Figures C1, C2, C3 and C4.

Finally, we make two sample restrictions. First, we exclude the cities Fuzhou and Shijiazhuang from our analysis (about 5% of total revenue) because these two cities followed and implemented the pilot procurement voluntarily one quarter later than the pilot cities. Including these cities makes few changes to our baseline estimates (see Panel A in Appendix Table C2). Second, we exclude products with missing price or quantity information (less than 1% of the sample).

## 4.2 Procurement Information

We combine the sales data with information about the centralized procurement program. We collect information about the pilot procurement and later rounds, including the planned molecules, successfully procured molecules, winning firm and product of each procured molecule, provinces and cities to supply, procurement period, and guaranteed procurement volumes from official government reports. In cases where the information is incomplete, we try our best to collect and double-check it using consulting reports. This procurement information provides extra confirmation that the sales dataset is accurate.

## 4.3 Pharmaceutical Firms' Financial Reports

In addition, we employ the China Stock Market & Accounting Research (CSMAR) dataset to explore how the pilot procurement affects firms' cost structures. The CSMAR dataset contains financial reports of listed firms. We extract yearly financial statistics for all listed pharmaceutical firms, including the total revenues, total costs, sales and marketing costs, etc., from 2013 to 2019. To delve deeper into sales and marketing costs, we extract item-level information under the "Sales and Marketing Expense" category and categorize them into three groups: advertising-related items, entertainment, travel, and conferences (ETC)-related items, and all other items, following the literature (Shi and Zhao, 2021).[17] The second category is often associ-

[17]Advertising-related costs encompass expenses for promoting products or services to the general public or specific groups through various media and activities, aiming to enhance brand awareness and market influence. In contrast, ETC-related costs cover expenses for organizing academic conferences, maintaining customer relationships, and conducting market research or

ated with corporate corruption in the Chinese context (Cai, Fang and Xu, 2011). Subsequently, we aggregate the revenues and costs at the firm-year level and merge the financial report data with the drug sales data. The merged data covers 297 pharmaceutical firms during the period of 2013 to 2019.

## 4.4 Online Job Posting Data

To further examine how the pilot procurement changes firms' marketing strategy, we use an online job posting dataset collected from several major job recruitment websites in China from 2017 to 2019. The dataset contains detailed information for each job post, including the recruiting firm, job description, and the number of job vacancies. We categorize job posts into marketing-related and others by utilizing keywords present in job titles and descriptions.[18] We drop duplicate job posts (e.g., posts appearing multiple times or cross-posted on several websites) if they originate from the same recruiting firm, are published in the same month, and feature identical job titles and descriptions.

We construct a firm-by-year-quarter-level dataset for the analysis. We match firm names with the sales dataset and "4+7" procurement policy reports to identify the firms producing the pilot molecules and those winning at least one molecule auction. The merged sample covers 368 pharmaceutical firms during the period of 2017 to 2019. For each observation and for each job category, we generate variables for the number of job posts and job vacancies.[19]

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consultation, targeting a narrower audience such as hospitals and physicians to foster business relationships and support product development and market promotion. While some direct-to-physician expenses are categorized under advertising-related costs, the majority fall under ETC-related costs.

[18]Given that our analysis primarily focuses on white-collar positions, we do not include production-related positions. Refer to Appendix Table C1 for a list of keywords used to identify marketing-related jobs.

[19]We handle observations with missing number of job vacancies by imputing the median value within the same year and job category.

# 5 Empirical Analysis

In this section, we present empirical evidence showing the impacts of the pilot procurement program on market equilibrium prices, sales quantities, and sales revenues. We illustrate the heterogeneous effects for different cities and firms: the direct effects in pilot cities and for winning firms and indirect spillovers in non-pilot cities and for non-wining firms. We also highlight how the procurement program changes the cost structures of the firms.

## 5.1 Molecule-Level Analysis

To examine the impacts of the "4+7" pilot on the sales revenue, sales quantity, and price, we employ a difference-in-differences (DD) framework. Specifically, the treatment molecules are the 20 molecules with ordinary tablet dosage formats that were successfully procured in the pilot programs. We drop five molecules in powder or injection dosage format. Most of these molecules are essential medicines, with a sufficient number of generic firms passing the bioequivalence tests. To ensure that the control molecules are comparable to the treated ones, we choose molecules that were selected for the second national procurement carried out in January 2020. For these drugs, we restrict them to ordinary tablet dosage formats. Since there might be spillover effects to similar molecules due to cross-molecule substitution, we drop, from the control group, molecules that are in the same Anatomical Therapeutic Chemical (ATC) classification 4 level as the treatment molecules.[20] This trimming step results in 22 control molecules. In total, our main sample covers quarterly observations on 536 drug products of 42 molecules, produced by 387 pharmaceutical firms, and sold in 18 cities.[21]

[20]The ATC classification system is a widely used way to classify drugs, which has five levels, where higher levels are more disaggregated classifications, and class five indicates the molecular level. Previous literature suggests that cross-molecule substitution often happens at class four (Dubois and Lasio, 2018).

[21]The included cities are nine pilot cities—Beijing, Chengdu, Chongqing, Guangzhou, Shanghai, Shenyang, Shenzhen, Tianjin, and Xi'an—and nine non-pilot cities—Changchun, Changsha, Hangzhou, Harbin, Jinan, Nanjing, Taiyuan, Wuhan, and Zhengzhou. Though many cities do not implement the pilot procurement program, the non-pilot cities in our sample are

We focus on the periods before the expansion of the NCDP reform to the whole country; that is, the period of 2013Q1–2019Q3. Specifically, the pre-treatment period is from 2013Q1 to 2018Q4 before the pilot program was rolled out, whereas the post-treatment period is from 2019Q1 to 2019Q3.[22]

A glance at the raw data suggests that the pilot procurement program has significant impacts on market prices and sales. Table 1 presents the summary statistics at the molecule by city by year and quarter level. The table shows that treatment molecules experience large reductions in prices after the procurement, while the prices decrease slightly for control molecules. There are also noticeable differences in the sales revenues and quantities for the treated and control molecules.

[Insert Table 1 Here]

To pin down the impacts of the pilot procurement program, we estimate the following DD regression equation in the pilot city sample:

$$y_{mct} = \beta Treat_m \times Post_t + \zeta_{mc} + \lambda_t + \epsilon_{mct}, \tag{2}$$

where $y_{mct}$ denotes either the sales revenue, sales quantity, or price for molecule $m$ in city $c$ and quarter $t$, all in log scale. $Treat_m \times Post_t$ is the interaction term between the indicator for treatment molecules and the indicator for the post-policy period, i.e., 2019Q1–2019Q3. $\zeta_{mc}$ and $\lambda_t$ denote the molecule by city fixed effects and year-quarter fixed effects, respectively. Standard errors are two-way clustered at the molecule and city level.[23]

Panel A in Table 2 summarizes the baseline results. As shown in the table, compared with

all large cities similar to the pilot cities.

[22]Since the pilot cities implemented the procurement sequentially from 15th March to 1st April, we conduct a robustness check by setting the quarters after the first quarter of 2019 as the post-pilot period. Results are presented in Panel B of Appendix Table C2.

[23]We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and detrend the coefficients accordingly. We do this for all regressions and event studies.

the control group, treatment molecules experience a significant price reduction of 40% after the pilot procurement. At the same time, there is a slight and statistically insignificant reduction in sales quantity. As a result, the sales revenue decreases significantly by around 43%. One potential explanation for the insignificant change in sales quantity is that before the pilot, the market size was almost full for treatment molecules with limited potential effects in extensive margins. Hence, the winning firms earn market shares at the expense of the failing firms.

[Insert Table 2 Here]

We further investigate whether there are spillover effects across cities by estimating equation (2) for the non-pilot city sample. Panel B in Table 2 displays the results. Different from the pattern in pilot cities, the relative price of treatment molecules to control molecules does not change much in non-pilot cities after the pilot program. In addition, non-pilot cities experience a similar modest decrease in sales quantity, leading to a slight and insignificant reduction in sales revenue.

The underlying assumption of the DD approach is that the variables of interest in the treatment and control groups evolve similarly before the treatment. To examine this assumption and to explore how the price changes after the pilot program in pilot and non-pilot cities, we estimate the following event-study regression separately for the pilot cities and non-pilot cities:

$$y_{mct} = \sum_{k=2013Q1}^{2019Q3} \beta_k I[t = k] \times Treat_m + \zeta_{mc} + \lambda_t + \epsilon_{mct}, \tag{3}$$

where $I[t = k]$ denotes the indicator of quarter $k$. We set 2018Q4 as the baseline period. Standard errors are estimated by using 200 bootstrapped samples.

Figure 1 shows the event study results for sales revenue, sales quantity, and price, respectively. The time trends before the reform are quite parallel for all variables in pilot and non-pilot cities. These results imply the satisfaction of the parallel pre-treatment trend condition for the DD approach, lending support to our identification. In addition, comparing the trends after the reform, we find that treatment molecules experience a sharp decrease in price in pilot cities after the implementation of the pilot, whereas the sales quantity shows no significant change.

As a result, the sales revenue declines substantially. On the contrary, in non-pilot cities, the relative sales revenue and quantity decrease modestly after the pilot program, and prices remain relatively constant.

Overall, our molecule-level analyses demonstrate significant effects of the "4+7" pilot on the price and sales revenue in the pilot cities, implying that the reform achieves its intended targets. However, we do not find evidence of spillover effects of the procurement from pilot cities to non-pilot cities. One potential explanation for the missing spillover effects is that pharmaceutical markets in different cities in China are segmented. On the supply side, firms often conduct independent pharmaceutical promotions in each city. Hence, the sales performance in one city does not affect the sales strategy in another city. On the demand side, as all the pilot molecules are prescription medicines, arbitrage across cities is not common. Given there are no spillover effects across pilot and non-pilot cities, we exploit the policy variation across molecules, cities, and quarters, and employ a triple difference design to conduct a causal analysis.[24] Appendix Table C3 shows the regression results, and Appendix Figure C2 plots the event study results, both of which are consistent with our baseline findings.

[Insert Figures 1 Here]

## 5.2 Product-Level Analysis

We then explore whether the pilot procurement affects winning and non-winning firms' pricing strategies. Specifically, we use product-by-city-by-year-quarter-level data and estimate the direct effects of the pilot programs on the winning products and the indirect spillovers on non-winning products. The control group includes all products of the above-defined control molecules produced by firms producing products neither of pilot molecules nor of the molecules in the same ATC class 4 level as the pilot molecules. We separately estimate the DD equation for winning products and other products of pilot molecules using the pilot city sample.[25]

[24] See Appendix B for the detailed illustration of the triple difference regression setting.

[25] Since we do not have a full list of firms participating in the pilot procurement auctions, we cannot identify non-winning products that participated and failed the pilot bidding. Hence, we

Specifically, in the first regression, the treatment group includes the winning products of the molecules selected in the pilot procurement program. In the second regression, the treatment group includes other products of the pilot molecules.

The product-level DD regression equation is as follows:

$$y_{jct} = \beta Treat_j \times Post_t + \zeta_{jc} + \lambda_t + \epsilon_{jct}, \tag{4}$$

where $y_{jct}$ denotes the variable of interest for the product $j$ sold in city $c$ and year-quarter $t$. $Treat_j$ is the indicator for treatment products. $Post_t$ is defined the same as in equation (2). $\zeta_{jc}$ and $\lambda_t$ denote the product-city fixed effects and year-quarter fixed effects, respectively. Standard errors are two-way clustered at the product and city level.

Table 3 shows the results for pilot cities.[26] Panel A presents the results using winning products as the treatment group, and Panel B presents the results using other products of pilot molecules as the treatment group. Compared with control products, the treatment products produced by winning firms experience a significant decrease in price by around 52% after the pilot program. They also experience a 290% increase in sales quantity and hence a significant increase in total sales revenue. Similarly, under the pressure of competition, the treatment products produced by non-winning firms also experience a decrease in price, though the reduction is much smaller. In addition, non-winning products have a significant decrease in sales quantity. This result is as expected, given that the procurement program guarantees quantities for the products of the winning firms. Therefore, the sales revenue declines significantly by 47% for non-winning products.

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define non-winning products as those of pilot molecules but not winning the auction. Similarly, we define non-winning firms as those not winning the auction. Appendix Table C4 compares the product-level summary statistics of winning products with those of non-winning products. Note that most winning products were not the market leaders within the molecule before procurement; only 4 out of 20 winning products had the largest pre-pilot revenue share within their respective molecules in pilot cities.

[26]Appendix Table C6 shows the results for non-pilot cities. Appendix Figures C3 and C4 plot the event study results.

The product-level analyses confirm the spillover effects across winning and non-winning firms due to the market competition. That is, to retain the remaining market share, non-winning firms also reduce the prices of products after the “4+7” pilot reform.

[Insert Table 3 Here]

To further explore the heterogeneity effects, we categorize the treatment group products into different groups based on whether the winning products are branded and whether they were sold in the pilot cities during the first half of the pre-pilot period, i.e., in 2013-2015. The definition of control group products remains unchanged. Consistent with the past literature (Cooper and Hoffman, 2002; Sah and Fugh-Berman, 2013; Marquardt and Ryan, 2024), the regression results show that without informational values generated from extensive marketing, the branded or newer winning products experienced a smaller increase in sales quantity despite a larger price reduction (see the Appendix Table C5).

## 5.3 Firm-Level Analysis

As suggested by the stylized model, since the procurement guarantees a fixed and large sales volume, winning firms could spend less on advertising and marketing. To examine this prediction, we explore listed firm data and job posting data to study the effects on sales costs and marketing-related labor demand by comparing winning firms with other firms.[27] For the sales cost analysis, since we do not have product-level cost information, we rely on firm-year-level financial reports. For the job posting analysis, we employ firm-quarter-level data.

We explore the differential impacts of the pilot program on winning and other firms by using a triple difference design. The treatment variable, $Revenue\_Share_{f,t_0}$, is continuous and denotes the firm’s sales revenue share from the pilot molecules during 2013-2018. We interact this variable with a post-treatment dummy and a dummy indicating whether the firm won at

[27] See Appendix Table C8 for firm-level summary statistics.

least one molecule in the pilot auction. The regression equation is as follows:

$$\begin{aligned} y_{ft} = {} & \alpha Revenue\_Share_{f,t_0} \times Post_t \times Winning\_Firm_f + \beta Revenue\_Share_{f,t_0} \times Post_t \\ & + \gamma Revenue\_Share_{f,t_0} \times Winning\_Firm_f + \eta Post_t \times Winning\_Firm_f \\ & + \zeta_f + \lambda_t + \epsilon_{ft}, \end{aligned} \tag{5}$$

where $y_{ft}$ denotes the cost variables, number of job posts, and number of marketing-related job posts for firm $f$ in year $t$. $Post_t$ is the indicator for the post-policy period, i.e., the year 2019. $Winning\_Firm_f$ is the indicator of firms winning at least one molecule in the pilot bidding. $\zeta_f$ and $\lambda_t$ denote the firm fixed effects and year fixed effects, respectively. Standard errors are clustered at the firm level.

We are interested in two parameters. The parameter $\beta$ represents the effect of pilot procurement on the outcome variables of other firms, whereas the coefficient $\alpha$ estimates whether the effects are different for winning firms.

Table 4 presents the results for the sales costs analysis and marketing-related labor demand analysis. Columns (1) and (2) show the regression results for outcome variables—inverse hyperbolic sine of sales costs and total costs, respectively. Columns (3) and (4) show the results for two sub-categories of sales costs—advertising costs and ETC costs, respectively.[28] As shown in the table, sales costs and total costs do not change much across non-winning firms with different previous sales revenue shares of treatment molecules. Compared with other firms, a one percentage point increase in the previous sales revenue share from treatment molecules leads to around a 2% greater decrease in sales costs for winning firms, while the total costs are al-

[28]As discussed in Chen and Roth (2024), the interpretation of the average treatment effect estimate for the inverse hyperbolic sine transformation depends on the units of the outcome and may not be approximate percentage effects. To address this issue, we rescale the units of variables Sales Costs, Total Costs, Advertising Costs, and ETC Costs by 0.001 and reapply the inverse hyperbolic sine transformation. The regression results are consistent with our baseline findings (see Appendix Table C9). Additionally, Poisson regression robustness checks confirm these results (see Appendix Table C10).

most unchanged. In addition, both advertising costs and ETC costs show significant decreases for winning firms when the previous sales revenue share increases. These results support our expectation that the pilot program decreases the sales costs for winning firms.

Columns (5) and (6) in Table 4 present the results for the total number of job posts and the number of marketing-related job posts. As shown in the table, non-winning firms with higher previous sales revenue shares of treatment molecules post slightly fewer job ads after the pilot for both marketing-related and other positions. Compared with other firms, winning firms experience a larger reduction: a one percentage increase in the previous sales revenue share of treatment molecules leads to a decrease of 1.3 total job posts and 0.6 marketing-related job posts. Consistent with the sales cost analysis, these results imply that firms reduce their marketing efforts after winning the pilot procurement auction.[29] Since the sales revenues of pilot products constitute only a portion of firms' total revenues, the above firm-level analysis reflects a lower bound for the impacts of the pilot procurement on firms' marketing costs and efforts.

[Insert Table 4 Here]

To validate the robustness of the above results, we conduct the following robustness checks. First, we use the firm-level revenue share of molecules for which the firm actually won the auction during 2013-2018 to measure the intensity of treatment of the pilot program. The results are consistent with the baseline findings and suggest that if a firm wins the procurement auction for 10% of its product portfolio, its sales costs would decrease by approximately 26% (see Appendix Table C11).[30] Second, some firms in our molecule-level analysis are not publicly listed and thus lack financial reports, which could introduce sample attrition bias, as listed firms may

[29]Appendix Table C14 displays consistent supplementary results on more outcome variables—share of sales costs in total costs, share of sales costs in total revenues, number of total job vacancies posted, and number of marketing-related job vacancies posted. Appendix Figures C5 and C7 plot the by-firm-group parameterized event study coefficients for baseline and supplementary firm-level results, respectively.

[30]Appendix Figure C6 plots the coefficients of the event study.

differ from unlisted ones. To mitigate this concern, we apply the inverse-probability-weighted (IPW) method (Wooldridge, 2002, 2007). Specifically, we estimate each firm's propensity to be listed based on its pre-pilot sales revenue and use the inverse of this propensity as a weighting factor. The weighted results align with our baseline findings, alleviating concerns over sample attrition bias (see Appendix Table C12).

With unchanged total costs and reduced sales costs, firms' sales costs should be reallocated. Appendix Table C13 explores the reallocation of costs and the estimation results show that the saved marketing costs were reallocated to financial costs and administration costs. One potential explanation is that firms winning the procurement experienced a sharp decline in price, a significant increase in sales quantity and a moderate increase in sales revenue, resulting in binding production capacity and tight cash flow. Hence, firms need to spend more on financing and administration to maintain sound operations.

# 6 Conclusion

In this paper, we study a centralized drug procurement policy. We show a few stylized facts that, compared to the pre-policy Bertrand competition case, centralized procurement significantly reduces prices. We further explore that one mechanism is the decrease in sales and distribution costs. We find that winning firms significantly reduce the sales and marketing expenditure relative to non-winning and other unaffected firms. They also post fewer marketing-related job ads after winning the pilot program.

The policy likely generates large social benefits. The pilot molecules are mostly basic medicines, and most participating firms are generic producers. The informational content of the marketing efforts is low, so the sales costs saved by the centralized procurement are likely to be socially wasteful. A complete welfare analysis requires more research on the quality of the winning products, especially in the long run. Some existing research finds no statistical differences in clinical outcomes and occurrence of adverse drug reactions between the branded drugs and the winning generic drugs in the two years after the "4+7" pilot programs (National Healthcare Security Administration, 2021). More research is needed to further explore the health outcome for the affected population along longer time horizons.

Our results suggest that in other developing countries with weak state capacity, implementing centralized drug procurement might be an effective way to lower drug prices because such a policy reduces wasteful marketing expenditure. One limitation of our research is that we focus on the short-term effects on prices and marketing expenditure. However, the policy may exert long-run and broader impacts. For example, the centralized procurement policy may potentially curtail excessive firm entry and encourage some firms to change strategies and invest more in research and development. More research is needed in this area.

## Figures and Tables

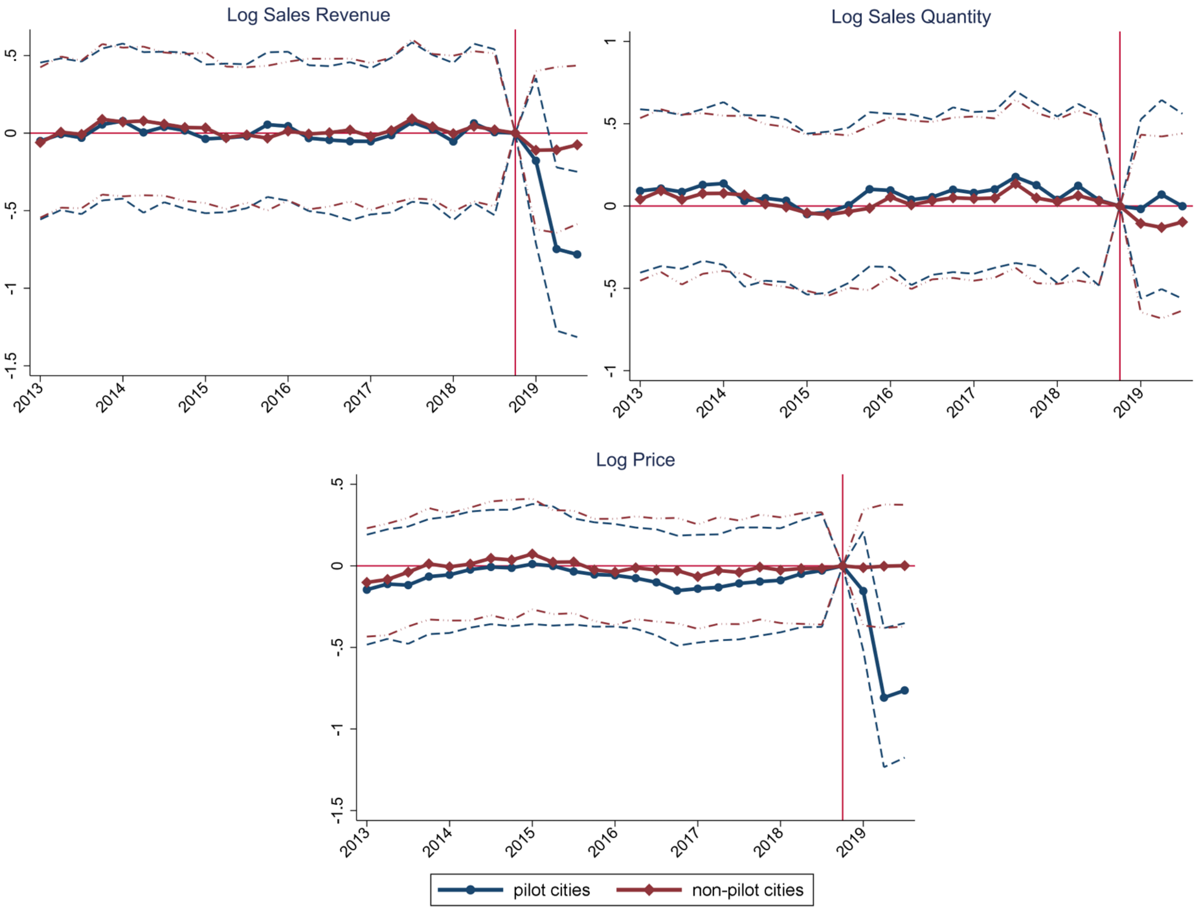


Figure 1: Impacts of Pilot on Sales Revenue, Sales Quantity, and Price, by Pilot and Non-Pilot Cities

Notes: This figure compares the sales revenues, sales quantities, and prices of treatment and control molecules before and after the pilot in pilot and non-pilot cities. Each dot on the blue curve with dot markers (red curve with diamond markers) represents the estimated coefficient of the interaction between the quarter-to-policy dummy and treatment molecule dummy in pilot cities (non-pilot cities) after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and detrending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

Table 1: Summary Statistics for Molecules

| | Before | | After | |
|---|---|---|---|---|
| | mean | std dev | mean | std dev |
| Variables | (1) | (2) | (3) | (4) |
| Panel A. Treatment Molecules in Pilot Cities | | | | |
| Log Sales Revenue | 14.71 | 1.92 | 14.32 | 2.23 |
| Log Sales Quantity | 12.73 | 2.01 | 13.16 | 1.76 |
| Log Price | -1.11 | 1.94 | -1.95 | 1.89 |
| Panel B. Treatment Molecules in Non-Pilot Cities | | | | |
| Log Sales Revenue | 13.95 | 2.01 | 14.22 | 2.16 |
| Log Sales Quantity | 11.90 | 1.96 | 12.36 | 1.86 |
| Log Price | -1.03 | 1.89 | -1.27 | 1.84 |
| Panel C. Control Molecules in Pilot Cities | | | | |
| Log Sales Revenue | 12.59 | 2.51 | 12.96 | 2.44 |
| Log Sales Quantity | 11.89 | 2.27 | 11.98 | 2.28 |
| Log Price | -2.71 | 3.06 | -2.49 | 2.86 |
| Panel D. Control Molecules in Non-Pilot Cities | | | | |
| Log Sales Revenue | 11.79 | 2.47 | 12.19 | 2.48 |
| Log Sales Quantity | 11.09 | 2.11 | 11.16 | 2.15 |
| Log Price | -2.74 | 3.14 | -2.50 | 3.00 |

*Notes*: This table displays the summary statistics for the main sample. Panels A and B show the results for molecules selected in the "4+7" pilot in pilot and non-pilot cities, respectively. Panels C and D show those for molecules selected in the second national round and in a different ATC 4 with the treatment molecules in pilot and non-pilot cities, respectively.

Table 2: Molecule-Level Results

| | Log Sales Revenue | Log Sales Quantity | Log Price |
|---|---|---|---|
| Variables | (1) | (2) | (3) |
| Panel A. Pilot Cities (Baseline Results) | | | |
| Treat_Molecule × Post | -0.57** | -0.05 | -0.51*** |
| | (0.17) | (0.21) | (0.13) |
| N | 9,392 | 9,392 | 9,392 |
| Panel B. Non-Pilot Cities | | | |
| Treat_Molecule × Post | -0.12 | -0.14 | 0.01 |
| | (0.14) | (0.18) | (0.09) |
| N | 9,198 | 9,198 | 9,198 |
| Molecule-City Fixed Effects | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes |

*Notes*: Each observation is a molecule by city by year-quarter. Panel A presents baseline results for pilot cities, and Panel B presents results for other cities. Each column presents one regression result for the outcome variable specified in the column title. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and detrend the coefficients accordingly. Standard errors are two-way clustered at the molecule and city level. * p <0.1, ** p <0.05, *** p <0.01.

Table 3: Product-Level Results

| Variables | Log Sales Revenue (1) | Log Sales Quantity (2) | Log Price (3) |
|---|---|---|---|
| Panel A. Treatment: Products of Pilot Molecules and Produced by Winning Firms | | | |
| Treat_Product × Post | 0.63* | 1.36*** | -0.74*** |
| | (0.28) | (0.29) | (0.16) |
| N | 14,411 | 14,411 | 14,411 |
| Panel B. Treatment: Products of Pilot Molecules and Produced by Non-Winning Firms | | | |
| Treat_Product × Post | -0.63*** | -0.56*** | -0.07* |
| | (0.11) | (0.12) | (0.03) |
| N | 23,978 | 23,978 | 23,978 |
| Product-City Fixed Effects | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes |

*Notes*: This table displays the product-level results for pilot cities. The treatment group is specified in the title of each panel. The control group is defined as products of the molecules for the second national round and produced by firms producing products neither of pilot molecules nor of the molecules in the same ATC 4 as pilot molecules. Each column presents one regression result for the outcome variable specified in the column title. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and detrend the coefficients accordingly. Standard errors are two-way clustered at the product and city level. * p <0.1, ** p <0.05, *** p <0.01.

Table 4: Firm-Level Results

| | | | Sales Costs | | | No. of |
|---|---|---|---|---|---|---|
| | | | $sinh^{-1}$(Advertising Costs) | $sinh^{-1}$(ETC Costs) | No. of Job Posts | Marketing-Related Job Posts |
| | $sinh^{-1}$(Sales Costs) | $sinh^{-1}$(Total Costs) | | | | |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Revenue_Share × Post | -0.0246*** | -0.0071 | -0.0238*** | -0.0230*** | -1.3652*** | -0.5630*** |
| × Winning_Firm | (0.0053) | (0.0055) | (0.0057) | (0.0057) | (0.0891) | (0.0575) |
| Revenue_Share × Post | 0.0009 | 0.0014 | -0.0026 | -0.0031 | -0.1351 | -0.0615 |
| | (0.0013) | (0.0011) | (0.0034) | (0.0033) | (0.0891) | (0.0575) |
| N | 1,751 | 1,751 | 1,751 | 1,751 | 3,571 | 3,571 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | No | No |
| Quarter Fixed Effects | No | No | No | No | Yes | Yes |

*Notes*: This table displays the firm-level results. Variable Revenue_Share denotes the firm's sales revenue share from the pilot molecules during 2013-2018 and is expressed as percentages. The variable Winning_Firm is a dummy indicating whether the firm won at least one molecule in the pilot procurement. Each column presents one regression result for the outcome variable specified in the column title. Columns (3) and (4) present results for two of three subgroups of sales costs—advertising-related costs, and entertainment, travel, and conferences (ETC)-related costs. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and detrend the coefficients accordingly. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

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# Excessive Pharmaceutical Marketing Expenditure: Policy Remedies from China

# Online Appendix

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## Appendix A. Model Details

In this appendix, we provide details on how the model is derived.

### 1.1 No Centralized Procurement Policy

Let $s_j$ denote the market share for product $j$. We consider the case where $v$ is large enough such that all patients make a purchase.[1] To simplify the derivation below, we change the notation from the main text and let $k^2$ denote firms' marketing expenditure per unit of sale. Hence, given $h(k^2) = \sqrt{k^2} = k$, physicians prescribe drug $A$ to patient $i$ if $u_{iA} - u_{iB} + \lambda(k_A - k_B) > 0$. The equation implies that the market share of product $A$ as $s_A = -m(p_A - p_B) + \lambda(k_A - k_B) + \frac{1}{2}$, subject to $s_A \in [0, 1]$, and $s_B = 1 - s_A$. The profit function for firm $j$ is $\pi_j = p_j s_j - k_j^2 s_j$.

In our baseline model, two firms are homogeneous, and we focus on a symmetric equilibrium under which the two firms follow the same strategy. We omit the subscript $j$ for simplicity. The first-order conditions are $\frac{\partial \pi}{\partial p} = s - m(p - k^2) = 0$ and $\frac{\partial \pi}{\partial k} = -2sk + \lambda(p - k^2) = 0$, which imply that $k^* = \frac{\lambda}{2m}$, and $p^* = \frac{s^*}{m} + (k^*)^2$. In equilibrium, $s_A^* = s_B^* = \frac{1}{2}$, thus $p^*$ is $\frac{1}{2m}$ plus the kickback. Note that if both firms are forced to set $k = 0$, then $p^* = \frac{1}{2m}$, and the market allocation remains the same. Thus, payments to physicians are socially wasteful.

### 1.2 Centralized Procurement Policy

Under centralized procurement, the government sets a guaranteed market share $t$ for the winner. The winner is determined in a first-price, sealed-bid auction. We assume that the government sets a reservation price of $r$ at the lowest observed price when there is no centralized procurement, which is known to both firms before the auction.[2] We also assume firms have complete information about the cost distribution. Let $w$ denote the winning firm, and $l$ denote the losing firm.

We solve the model backward. In the second stage, both firms take the winning bid, $b$, and the guaranteed market share, $t$, as given. Let $\pi_w$ denote the winning firm's profit and $\pi_l$ denote the losing firm's profit. Let $s_w = \frac{1}{2} - m(b - p_l) + \lambda(k_w - k_l)$. If $s_w > t$ and is between 0 and 1, $s_w$ presents the winning firm's market share, and then the profit functions are:

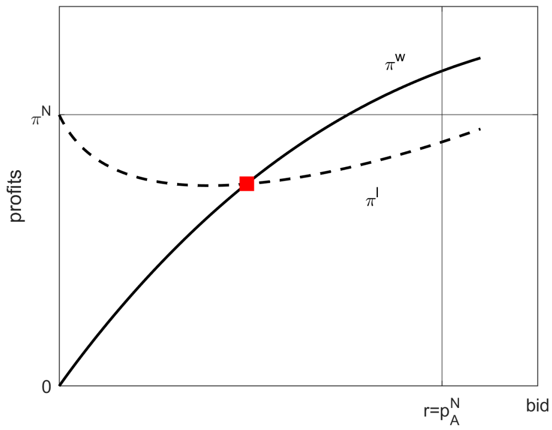
$$\pi_w = s_w b - (s_w - t)k_w^2,$$
$$\pi_l = (1 - s_w)p_l - (1 - s_w)k_l^2.$$

Note that the winning firm gets a guaranteed market share of $t$. Thus, it does not need to pay physicians for the share up to $t$. The winning firm sets $k_w$ given $b$ and $t$ to maximize $\pi_w$. For the losing firm, the first-order conditions for $k_l$ and $p_l$ are the same

[1] Our analysis focuses on prescription drugs, so patients can only purchase the drug prescribed by the physician. Patients prefer product $A$ over the outside option of not purchasing any product if $mp_A < v$. Patients prefer product $B$ over the outside option if $mp_B - \varepsilon_i < v$. As we will show next, the equilibrium prices do not depend on $v$. Thus, as long as $v$ is sufficiently large, patients will always make a purchase. This condition makes sure that following physicians' advice is incentive-compatible for patients.

[2] In reality, the government sets $r$ according to the lowest observed Bertrand prices with a discount, and firms often have a good sense of what $r$ is, especially for later rounds of procurement.

Figure A1: Bidding Strategy Illustration




*Notes*: We set $t = 0.1, m = 0.5$ and $\lambda = 1$. The red square denotes the equilibrium.

as the scenario when there is no centralized auction, so $k_l^* = \frac{\lambda}{2m}$, the same as the Bertrand competition case. Similarly, we have $p_l^* = \frac{1-s_w}{m} + \frac{\lambda^2}{4m^2}$.

When $t$ is sufficiently large and $s_w \leq t$, the guaranteed share requires that the winning share must bind at $t$. In this case, the winning firm pays no marketing expenditure but still optimally sets $k_w$ given $b$ and the opponent's strategy (though not paid in equilibrium). Since all patients in the $(1-t)$ remaining market purchase the losing firm's product, the winning firm and the losing firm set $p_l$, $k_l$, and $k_w$ at levels where the losing firm's market share is precisely $(1-t)$ (i.e., $s_w = t$). Hence, for the losing firm, optimization requires that $k_l^* = \frac{\lambda}{2m}$. In equilibrium, $\pi_w = bt$ and $\pi_l = (1-t)p_l^* - (1-t)(k_l^*)^2$. From the above derivation, the losing firm always sets $k$ at the same level regardless of whether there is a centralized procurement auction and regardless of the value of $t$.

In the first stage, we then solve for the equilibrium bid $b$ given the profits of the losing and winning firms with their optimal strategies, including the losing prices and kickbacks. Appendix Figure A1 illustrates the value of $\pi_w$ and $\pi_l$ as a function of $b$ when $t = 0.1, m = 0.5$ and $\lambda = 1$. The vertical and horizontal lines indicate the price and profit under no centralized procurement, respectively. If the opponent chooses not to participate in the auction, the best response is to participate in the auction and set the bid at the reservation price (which is the price under no centralized procurement), because the firm earns more profits than not participating in the auction ($\pi_w(r) > \pi_l(r)$). However, given the opponent participating in the auction, the firm has incentives to undercut the bid until losing the auction results in the same profits as winning. Thus, the equilibrium bid will be at the level where $\pi_w$ and $\pi_l$ cross each other.

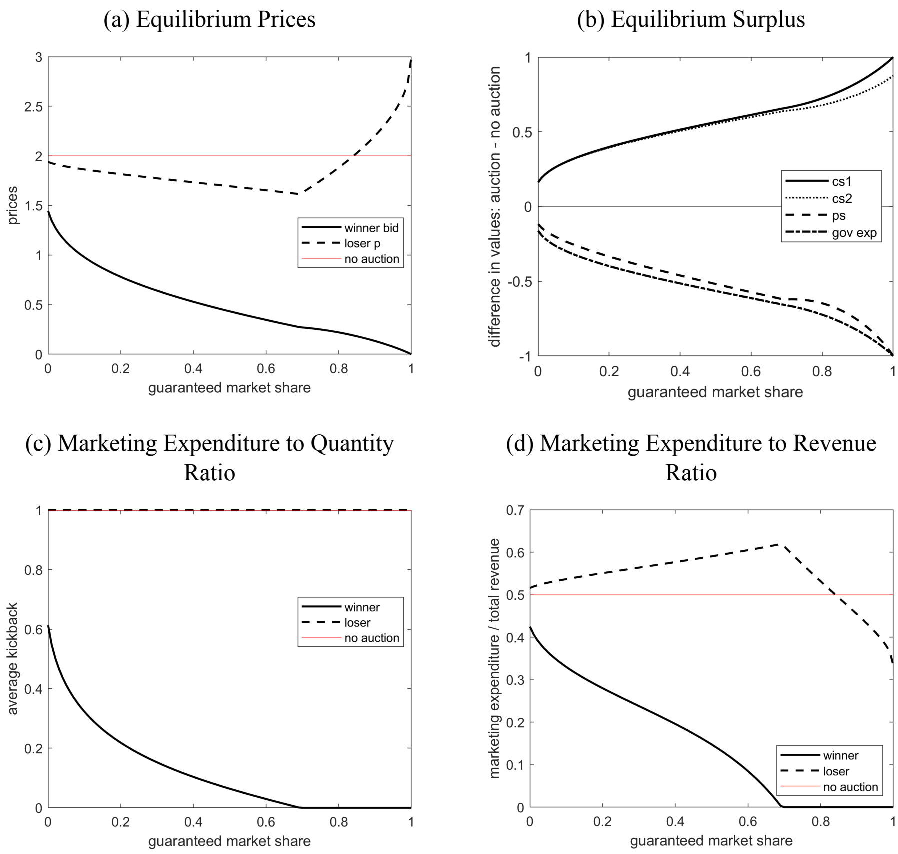
We illustrate the model predictions with varying guaranteed market shares using a numerical example with $m = 0.5$ and $\lambda = 1$. Appendix Figure A2 panel (a) summarizes how the equilibrium price changes when the guaranteed share increases. When $t$ increases from 0 to 1, the winning bid decreases and approaches zero. This occurs because the losing firm has an incentive to undercut the current bid unless the profit of winning is less than the profit of losing. As $t$ approaches one, the losing firm's profit approaches zero, and consequently, the its profit of winning also approaches zero. This implies that the equilibrium bid will approach zero as $t$ approaches one.

Appendix Figure A2 panel (a) also shows that the losing firm's price decreases with $t$ first, but then increases with regard to $t$ when the guaranteed share is binding, i.e., $s_w \leq t$. The reason is that, as $t$ is sufficiently large and binding, the losing firm targets only patients with a higher willingness to pay for their products. Thus, the equilibrium price for the losing product may increase, sometimes even surpassing the no-procurement auction level. As we will illustrate in robustness checks, this pattern disappears when there are multiple losing firms because competition among them will make the losing price decrease when the guaranteed share is binding and approaches one. In addition, in this numerical example, the losing prices are lower than the no-auction level when $t < 0.8$.

The decrease in prices implies that there is a decrease in public insurance expenditure and an increase in consumer surplus (see the "cs1" curve in Appendix Figure A2 panel (b)) when $\varepsilon_i$ is not relevant for welfare. In this numeric example, the loss of variety due to an increased guaranteed share is secondary, thus even when $\varepsilon_i$ is relevant for welfare, we find the procurement policy increases consumer surplus (see the "cs2" curve in Appendix Figure A2 panel (b)). We also find that there is a decrease in firm profits of a similar magnitude to the decrease in insurance expenditure. Thus, the total surplus of the market increases.

A driving force of the change in social surplus is the marketing expenditure: we find that the average kickbacks per unit of sales decrease largely for the winning firm (goes to zero when $t$ is around 0.7). At the same time, it stays at the no-auction level for the losing firm (Appendix Figure A2 panel (c)).[3] This implies that the total marketing expenditure decreases for both winning and losing firms, but on a much larger scale for the winning firm. We also find that the marketing expenditure-to-revenue ratio decreases substantially for the winning firm relative to the no-auction level, but is larger than the no-auction level when $t$ is small and lower for large $t$ for the losing firm (Appendix Figure A2 panel (d)).

Figure A2: Illustration of Equilibrium




*Notes*: These figures display the model predictions with $m = 0.5$, $\lambda = 1$, and $v = 2$. In Panel (b), values indicate the difference between scenarios of auction and no auction. "cs1" is the consumer surplus assuming $\varepsilon_i$ is not relevant for welfare, and "cs2" is the consumer surplus assuming $\varepsilon_i$ is relevant for welfare. "ps" is the total profits for both firms and "gov exp" is the total government expenditure (i.e., public insurance expenditure).

[3] We empirically test the relationship between the marketing expenditure and market share for losing firms, and the estimated positive and statistically significant coefficient lends support to the prediction of the model. Detailed results are available upon request.

## 1.3 Model Robustness

The baseline model makes several simplifying assumptions for ease of presentation. We now demonstrate that the predictions remain robust even when we relax certain assumptions.

**Firms with different marginal production costs.** In the baseline model, we assume that both firms have zero marginal production costs, motivated by the fact that most generic firms have almost zero production costs (Berndt, 2002; Dave, 2013). The assumption simplifies the presentation because the two firms are homogeneous, and we consider the equilibrium where both firms have symmetric strategies. Allowing one firm to have a higher marginal production does not change the key model predictions. Consider the case where $0 \leq c_A < c_B$. The firms' profit function is $\pi_j = s_j(p_j - c_j) - s_j k_j^2$ under no auction, and $\pi_j^w = s_j(b - c_j) - (s_j - t)k_j^2$ if the firm wins the auction. Now, the firm with a lower marginal cost, i.e., firm $A$, wins the auction, and the winning bid approaches $c_B$ when $t$ approaches 1. The intuition is as follows: firm B has no incentive to bid below $c_B$. As $t$ approaches one, the losing firm's profit approaches zero. Equilibrium requires that the losing firm earns the same profits, losing or winning the auction, implying the bid approaches $c_B$. The derivation of kickbacks is similar to the baseline case.

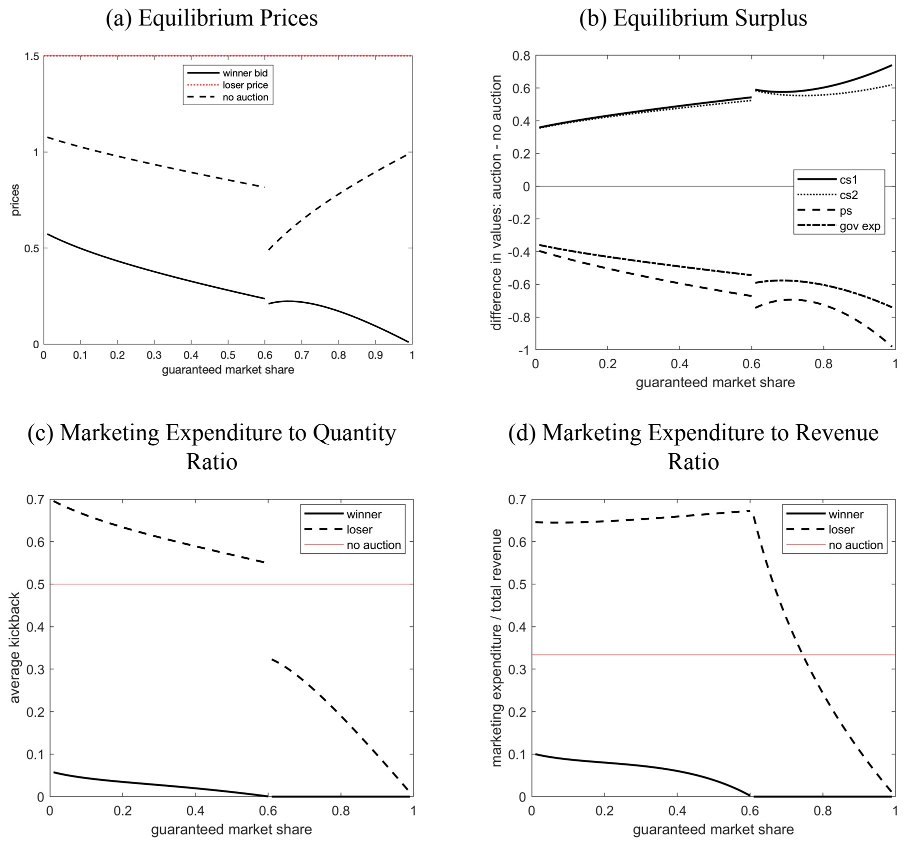
**Patients with varying price coefficient.** The baseline model can be easily extended to cases where patients have heterogeneous valuations of drugs relative to prices. Let $\alpha_i$ denote patient $i$'s price coefficient. Hence, patient utility function is $u_{ij} = -\alpha_i m p_j + v_{ij}$ In the baseline model, we implicitly assume that $\alpha_i = 1, \forall i$. The model predictions are similar if we allow patient heterogeneity in $\alpha_i$. Consider a case where half of the patients have $\alpha_i = a_1 > 1$ and the other half have $\alpha_i = a_2 < 1$, and the average of $a_1$ and $a_2$ is 1. We further assume that patients are randomly assigned to physicians. As a result, market share of product $A$ is: $s_j = \frac{1}{2} - \frac{\alpha_1 + \alpha_2}{2} m(p_A - p_B) + \lambda(k_A - k_B) = \frac{1}{2} - m(p_A - p_B) + \lambda(k_A - k_B)$, the same as the baseline case. This fact implies that equilibrium outcomes are the same as the baseline model. The only subtle difference from the baseline occurs when $t$ is large enough such that the market share for the more price-sensitive patients reaches one. When this happens, it slightly changes the profit functions but still predicts that the bid goes to zero when $t = 1$.

**Physicians with varying $\lambda$.** In reality, the market might consist of physicians with different responses to kickbacks and hence different impacts on market shares (Nair, Manchanda and Bhatia, 2010). We extend the baseline model by allowing two types of physicians $f$, one with $\lambda_f = 1$ and the other with $\lambda_f = 0.1$, with equal shares. Patients are randomly matched to physicians. We assume that firms set kickbacks to different physicians as a function of their $\lambda$. Specifically, the kickbacks are linear in $\lambda$: $k = d\lambda$, where $d$ is a parameter that the firm sets. Thus, the market share of product $A$ is $s_A = \frac{1}{2} - m(p_A - p_B) + (\lambda_1^2 + \lambda_2^2)(d_A - d_B)$. We further assume that the kickbacks enter the profit functions linearly: $\pi_j = (p_j - k_j)s_j$. These specifications ensure the model has analytical solutions. When there is no auction, each firm simultaneously decides on prices and $d$. Under auction, firms first compete in a first-price sealed bid auction, and then compete in $d$ and the price of the losing product.

We present a numerical example of the equilibrium when $m = 0.5$ and $v = 2$. There are two legs in the solution: when the guaranteed share is not binding, and when the guaranteed market share is binding. The cutoff point is when the share is binding for at least one physician, creating discontinuity in the equilibrium solutions. Appendix Figure A3 shows that the model predictions are similar to the baseline model.

**More than two firms.** In the baseline model, we assume that there are two symmetric firms. The model can be extended to multiple firms with similar predictions. To illustrate the intuition, we consider a model of the circular city with three firms, each of which takes on one of the three equal points on a unit circle. Patients are evenly distributed on the circle, whose utility function is $u_{ij} = -mp_j + v - d_{ij}$, where $d_{ij}$ is the distance between the patient and the firm. The other setups are identical to those of the baseline model. Again, we focus on solving for the equilibrium where the three firms play symmetric strategies.

Figure A3: Robustness Check: Physicians with Varying $\lambda$




*Notes*: These figures display the model predictions with $m = 0.5$, $v = 2$, $\lambda_1 = 1$ and $\lambda_2 = 0.1$. In Panel (b), values indicate the difference between auction and no auction. "cs1" is the consumer surplus assuming $\varepsilon_i$ is not relevant for welfare, while "cs2" is the consumer surplus assuming $\varepsilon_i$ is relevant for welfare. "ps" is the total profits for both firms and "gov exp" is the total government expenditure (public insurance expenditure).

The key difference between the three-firm model and the baseline two-firm model is that there are two losing firms, which compete with each other, resulting in a lower losing price than the baseline model. In Appendix Figure A4 panel (a), we show how the prices change with $t$. When $t$ is small, the losing price decreases first and then increases with $t$, following a similar pattern as the baseline model. However, up to $t = 2/3$, the competition in the remaining market becomes increasingly intense, resulting in a decreasing price for the losing firm as $t$ increases. The other patterns are similar to the baseline model.

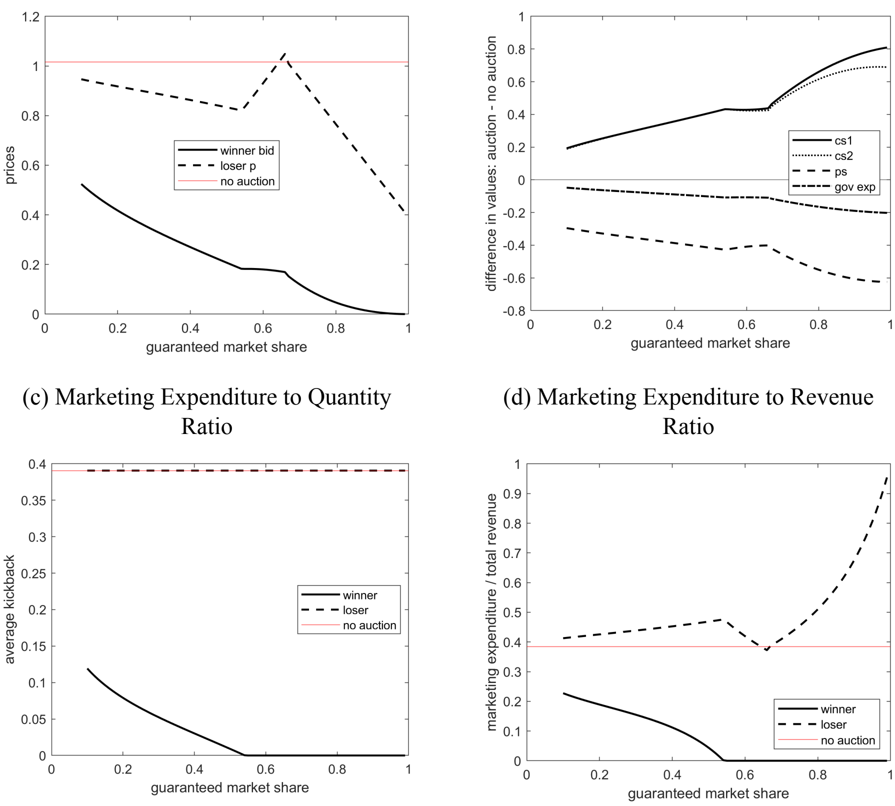
## 1.4 Model Caveat

The stylized model abstracts away from certain procurement policy details. We explain our modeling assumptions and model caveats in this section.

First, we abstract away from the fact that multi-product firms may participate in and win multiple auctions. In fact, among the 25 molecules successfully procured, four winners won multiple molecules. Theoretically, firms may coordinate bids across the auctions of different molecules, making the bidding strategy more complicated. In reality, all auctions were held simultaneously, so firms may not be able to observe the bidding outcomes of other auctions when submitting bids, thereby limiting the scope of coordination.

Second, we model the competitive bidding process as a first-price sealed-bid auction. In reality, as explained in Section 2, the auction format varied by the number of participating firms. When there were fewer than three participants, the government might negotiate the prices further. Though we do not have complete information on the number of participants for all molecules, we collect data on firms' eligibility in the auctions. We find that, among the 31 molecules, there are 12 molecules with fewer than

Figure A4: Robustness Check: Three Firms




(a) Equilibrium Prices

(b) Equilibrium Surplus

(c) Marketing Expenditure to Quantity Ratio

(d) Marketing Expenditure to Revenue Ratio

*Notes*: These figures display the model predictions with $m = 0.5$, $\lambda = 1$, and $v = 2$. In Panel (b), values indicate the difference between auction and no auction. "cs1" is the consumer surplus assuming $\varepsilon_i$ is not relevant for welfare, while "cs2" is the consumer surplus assuming $\varepsilon_i$ is relevant for welfare. "ps" is the total profits for both firms and "gov exp" is the total government expenditure (public insurance expenditure).

three firms eligible to participate. Besides, the second-lowest-bid firm served as a backup candidate if the winning firm failed to deliver the quantity. If both firms failed to deliver, the remaining firms would compete freely for the rest of the market (though in the "4+7" pilot procurement, all winning firms delivered the guaranteed quantity). Modeling the bidding strategy given these details is beyond the scope of this paper and is left for future work.

Third, we model the procurement as a static game. In reality, winning firms signed contracts for one year, and there were more rounds in the pilot cities and the rest of the country in the following years. Winning firms may be forward-looking when they participate in the auction; for example, their uncertainty about whether the guaranteed quantity is real might decrease once the pilot program is successfully delivered. They might also enjoy future profits by enhancing their reputation through winning the pilot program. However, our interviews with the firms suggest that the direct benefits of winning are the major concern when they bid. Thus, we abstract from the dynamic incentives of firms and leave it for future research.

Fourth, we assume that the marginal production cost, denoted as $c$, remains constant both before and after the implementation of the procurement policy for both the winning and losing firms. This assumption is made based on the fact that marginal production costs typically exhibit stability within the pharmaceutical industry (Dave, 2013). To further substantiate this assumption, we conducted interviews with several pharmaceutical firms engaging in centralized procurement, and none of them reported any significant changes in production costs in the short term. Additionally, we collect monthly API prices at the national level for four pilot molecules in our sample and find no significant fluctuations around the time of the "4+7" pilot program. Based on these findings, we infer that marginal production prices remain stable in the short term. It is acknowledged that in the long run, there may be alterations to marginal production costs, such as firms upgrading their production lines. We leave this issue for potential exploration in future research endeavors.

Finally, our model highlights how the procurement policy may change firms' kickbacks and advertising strategies. The procurement policy may affect firms' other behaviors, for example, fixed-cost investment (Ganapati and McKibbin, 2023) or entry decisions (Berry and Waldfogel, 1999; Iizuka, 2012), thereby yielding different policy implications. Due to data limitations, we cannot fully explore these channels in the current paper and leave them for future research.

# Appendix B. Triple Difference Regression Model

Given there are no spillover effects across pilot and non-pilot cities (presented in Table 2 and Figure 1), we exploit the policy variation across molecules, cities, and quarters and employ a triple difference design to conduct a causal analysis. We estimate the following triple difference regression equation in the full sample:

$$y_{mct} = \beta Treat_m \times Pilot\_Cities_c \times Post_t + \zeta_{mc} + \gamma_{mt} + \delta_{ct} + \epsilon_{mct}, \tag{1}$$

where $y_{mct}$ denotes either the sales revenue, sales quantity, or price for molecule $m$ in city $c$ and quarter $t$, all in log scale. $Treat_m \times Pilot\_Cities_c \times Post_t$ is the interaction term between the indicator for treatment molecules, indicator for pilot cities, and indicator for the post-policy period, i.e., 2019Q1–2019Q3. $\zeta_{mc}$, $\gamma_{mt}$, and $\delta_{ct}$ denote the molecule by city fixed effects, molecule by year-quarter fixed effects, and city by year-quarter fixed effects, respectively. Standard errors are two-way clustered at the molecule and city level.

To test the underlying assumption of the triple difference approach, we estimate the following event-study regression:

$$y_{mct} = \sum_{k=2016Q1}^{2019Q3} \beta_k I[t=k] \times Treat_m \times Pilot\_Cities_c + \zeta_{mc} + \gamma_{mt} + \delta_{ct} + \epsilon_{mct}, \tag{2}$$

where $I[t=k]$ denotes the indicator of quarter $k$. In both equations, we follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and detrend all the coefficients accordingly. Standard errors are estimated using 200 bootstrapped samples.

# Appendix C. Supplementary Analysis

Table C1: Keywords to Identify Marketing-Related Job Posts

| | | | |
|---|---|---|---|
| 销售 | (sales) | BD | (business development) |
| 营销 | (marketing) | 客户代表 | (client representative) |
| 推广 | (promotion) | 客户经理 | (client manager) |
| 分销 | (distribution) | 商务代表 | (business representative) |
| 医药代表 | (pharmaceutical sales representative) | 服务专员 | (service agent) |

*Notes*: We use the above Chinese keywords in job titles and job descriptions to identify marketing-related job posts. English translations are in parenthesis.

Table C2: Robustness Results with Alternative Sample or Alternative Post-Pilot Period

| | Log Sales Revenue | Log Sales Quantity | Log Price |
|---|---|---|---|
| Variables | (1) | (2) | (3) |
| Panel A. Alternative Sample: Including Fuzhou and Shijiazhuang Cities | | | |
| Treat_Molecule × Post | -0.55*** | -0.07 | -0.47*** |
| | (0.17) | (0.20) | (0.12) |
| N | 11,392 | 11,392 | 11,392 |
| Panel B. Alternative Post-Pilot Period: 2nd to 3rd Quarters of 2019 | | | |
| Treat_Molecule × Post | -0.77*** | -0.04 | -0.72*** |
| | (0.19) | (0.23) | (0.15) |
| N | 9,038 | 9,038 | 9,038 |
| Molecule-City Fixed Effects | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes |

*Notes*: This table displays the robustness results for pilot cities using an alternative sample—including Fuzhou and Shijiazhuang cities—in Panel A and an alternative post-pilot period between the second and third quarters of 2019 in Panel B. Each column presents one regression result for the outcome variable specified in the column title. Standard errors are two-way clustered at the molecule and city level. * p <0.1, ** p <0.05, *** p <0.01.

Table C3: Robustness Results for Triple Difference Analysis

| | Log Sales Revenue | Log Sales Quantity | Log Price |
|---|---|---|---|
| Variables | (1) | (2) | (3) |
| Treat_Molecule × Pilot_Cities | -0.40*** | 0.13 | -0.49*** |
| × Post | (0.08) | (0.09) | (0.08) |
| N | 18,580 | 18,580 | 18,580 |
| Molecule-City Fixed Effects | Yes | Yes | Yes |
| Molecule-Quarter Fixed Effects | Yes | Yes | Yes |
| City-Quarter Fixed Effects | Yes | Yes | Yes |

*Notes*: This table displays the robustness results in all cities using an alternative triple difference model. Each column presents one regression result for the outcome variable specified in the column title. Standard errors are two-way clustered at the molecule and city level. * p <0.1, ** p <0.05, *** p <0.01.

Table C4: Summary Statistics for Products

| Variables | Winning Products mean (1) | Winning Products std dev (2) | Other Products mean (3) | Other Products std dev (4) |
|---|---|---|---|---|
| Panel A. Quality of Products before the Pilot Procurement | | | | |
| Branded Products | 0.10 | 0.31 | 0.12 | 0.32 |
| Passing Bioequivalence Tests | 0.90 | 0.31 | 0.14 | 0.35 |
| Sales Revenue Share in Pilot Molecules, Pilot Cities | 22.14 | 29.96 | 7.84 | 18.98 |
| Sales Revenue Share in ATC 4, Pilot Cities | 9.40 | 15.81 | 3.21 | 9.67 |
| Panel B. Sales in Pilot Cities before the Pilot Procurement | | | | |
| Log Sales Revenue | 11.52 | 3.64 | 10.24 | 3.14 |
| Log Sales Quantity | 10.19 | 3.03 | 9.52 | 2.61 |
| Log Price | -1.55 | 2.03 | -1.76 | 2.06 |
| Panel C. Sales in Pilot Cities after the Pilot Procurement | | | | |
| Log Sales Revenue | 12.92 | 1.90 | 8.34 | 4.98 |
| Log Sales Quantity | 12.49 | 1.41 | 7.71 | 4.45 |
| Log Price | -2.64 | 1.95 | -1.39 | 1.97 |
| Panel D. Sales in Non-Pilot Cities before the Pilot Procurement | | | | |
| Log Sales Revenue | 11.05 | 3.47 | 7.93 | 4.94 |
| Log Sales Quantity | 9.72 | 2.77 | 7.09 | 4.31 |
| Log Price | -1.54 | 2.01 | -1.16 | 1.94 |
| Panel E. Sales in Non-Pilot Cities after the Pilot Procurement | | | | |
| Log Sales Revenue | 11.73 | 2.54 | 6.89 | 5.69 |
| Log Sales Quantity | 10.37 | 1.85 | 6.20 | 5.03 |
| Log Price | -1.69 | 1.88 | -1.01 | 1.83 |

*Notes*: This table displays the summary statistics for the product-level analysis sample. Columns (1) and (2) show the results for products of pilot molecules produced by winning firms; columns (3) and (4) show the results for products of pilot molecules produced by other firms. Panel A shows the results for the quality of products before the pilot program. The variable "Sales Revenue Share in Pilot Molecules, Pilot Cities" is calculated as the pre-pilot average of the ratio of a product's quarterly sales revenue to the corresponding molecule's quarterly sales revenue in pilot cities. The variable "Sales Revenue Share in ATC 4, Pilot Cities" is calculated as the pre-pilot average of the ratio of a product's quarterly sales revenue to the quarterly sales revenue of molecules of the same ATC class 4 in pilot cities. Panels B to E show the results for sales revenue, sales quantity, and price in pilot or non-pilot cities before or after the pilot procurement.

Table C5: Heterogeneity Results for Product-Level Analysis

| Variables | Log Sales Revenue (1) | Log Sales Quantity (2) | Log Price (3) |
|---|---|---|---|
| Panel A. Treatment: Branded Products of Pilot Molecules Produced by Winning Firms | | | |
| Treat_Product × Post | 0.01 | 0.84 | -0.82*** |
| | (0.34) | (0.53) | (0.19) |
| N | 11,567 | 11,567 | 11,567 |
| Panel B. Treatment: Generic Products of Pilot Molecules Produced by Non-Winning Firms | | | |
| Treat_Product × Post | 0.71** | 1.43*** | -0.73*** |
| | (0.29) | (0.31) | (0.18) |
| N | 13,925 | 13,925 | 13,925 |
| Panel C. Treatment: Newer Products of Pilot Molecules Produced by Winning Firms | | | |
| Treat_Product × Post | -2.23*** | 0.26 | -2.44*** |
| | (0.48) | (0.63) | (0.08) |
| N | 11,194 | 11,194 | 11,194 |
| Panel D. Treatment: Older Products of Pilot Molecules Produced by Non-Winning Firms | | | |
| Treat_Product × Post | 0.64* | 1.31*** | -0.67*** |
| | (0.29) | (0.29) | (0.16) |
| N | 14,298 | 14,298 | 14,298 |
| Product-City Fixed Effects | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes |

*Notes*: This table displays the heterogeneity of product-level results in pilot cities. The treatment group is specified in the title of each panel. Newer products are defined as the products having been sold in the pilot cities during the first half of the pre-pilot period, i.e., in 2013–2015. The control group is defined as products of the molecules for the second national round and produced by firms producing products neither of pilot molecules nor of the molecules in the same ATC 4 level as pilot molecules. Each column presents one regression result for the outcome variable specified in the column title. Standard errors are two-way clustered at the product and city level. * p <0.1, ** p <0.05, *** p <0.01.

Table C6: Robustness Results for Product-Level Analysis in Non-Pilot Cities

| Variables | Log Sales Revenue (1) | Log Sales Quantity (2) | Log Price (3) |
|---|---|---|---|
| Panel A. Treatment: Products of Pilot Molecules Produced by Winning Firms | | | |
| Treat_Product × Post | -0.0552 | -0.1110 | 0.0383 |
| | (0.1767) | (0.2005) | (0.0600) |
| N | 10,983 | 10,983 | 10,983 |
| Panel B. Treatment: Products of Pilot Molecules Produced by Non-Winning Firms | | | |
| Treat_Product × Post | 0.0042 | 0.0295 | -0.0232 |
| | (0.1038) | (0.1202) | (0.0397) |
| N | 18,447 | 18,447 | 18,447 |
| Product-City Fixed Effects | Yes | Yes | Yes |
| Quarter Fixed Effects | Yes | Yes | Yes |

*Notes*: This table displays the robustness checks for product-level results in non-pilot cities. The treatment group is specified in the title of each panel. The control group is defined as products of the molecules for the second national round and produced by firms producing products neither of pilot molecules nor of the molecules in the same ATC 4 level as pilot molecules. Each column presents one regression result for the outcome variable specified in the column title. Standard errors are two-way clustered at the product and city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C7: Robustness Results Using Alternative Price Measure: Weighted Log Price

| | | Product-Level Analysis | |
|---|---|---|---|
| | Molecule-Level Analysis | Winning Products | Non-Winning Products |
| Variables | (1) | (2) | (3) |
| Treat_Molecule × Post | -0.39*** | | |
| | (0.11) | | |
| Treat_Product × Post | | -0.72*** | -0.07* |
| | | (0.16) | (0.03) |
| N | 9,392 | 14,411 | 23,978 |
| Molecule-City FE | Yes | No | No |
| Product-City FE | No | Yes | Yes |
| Quarter FE | Yes | Yes | Yes |

*Notes*: This table displays the robustness results using an alternative price measure—weighted log price. For molecule-level price, we calculate the weighted average of log prices across products for each molecule, city, and quarter, using sales revenue shares as weights. For product-level price, we calculate the weighted average of log prices across different package sizes and strength levels for each product, city, and quarter, using sales revenue shares as weights. Each column presents one regression result for pilot cities with the model and sample specified in the column title. Standard errors are two-way clustered at the molecule and city level in column (1) and at the product and city level in columns (2) and (3), respectively. * p <0.1, ** p <0.05, *** p <0.01.

Table C8: Summary Statistics for Firms

| | Winning Firms | | Other Firms | |
|---|---|---|---|---|
| | mean | std dev | mean | std dev |
| Variables | (1) | (2) | (3) | (4) |
| Panel A. Product Quality and Sales Revenue Share before the Pilot Procurement (in 2013-2018) | | | | |
| No. of Products | 24.69 | 20.09 | 18.39 | 20.26 |
| No. of Products of Pilot Molecules | 1.75 | 1.65 | 0.88 | 0.68 |
| No. of Branded Products of Pilot Molecules | 0.31 | 0.87 | 0.07 | 0.34 |
| No. of Bioequivalent Products of Pilot Molecule | 1.19 | 1.60 | 0.11 | 0.34 |
| Pilot Products' Sales Revenue Share in Pilot Molecules, Pilot Cities | 18.34 | 29.47 | 7.17 | 19.27 |
| Pilot Products' Sales Revenue Share in ATC 4, Pilot Cities | 11.24 | 27.95 | 3.58 | 12.12 |
| Pilot Products' Sales Revenue Share in Firms' Total Revenue | 56.71 | 33.74 | 4.17 | 17.85 |
| Panel B. Revenues and Costs | | | | |
| Average Annual Total Revenues in 2013-2018 | 28.38 | 21.08 | 19.00 | 51.53 |
| Average Annual Total Revenues in 2019 | 7.79 | 6.61 | 5.61 | 14.59 |
| Average Annual Total Costs in 2013-2018 | 24.16 | 20.48 | 17.63 | 49.85 |
| Average Annual Total Costs in 2019 | 7.02 | 6.42 | 5.18 | 14.06 |
| Average Annual Sales Costs in 2013-2018 | 6.39 | 4.69 | 2.56 | 4.73 |
| Average Annual Sales Costs in 2019 | 2.61 | 2.64 | 0.87 | 1.51 |
| Average Annual Advertising Costs in 2013-2018 | 3.88 | 4.56 | 1.42 | 2.72 |
| Average Annual Advertising Costs in 2019 | 2.07 | 2.83 | 0.47 | 0.92 |
| Average Annual ETC Costs in 2013-2018 | 3.86 | 4.45 | 1.74 | 3.34 |
| Average Annual ETC Costs in 2019 | 2.05 | 2.76 | 0.59 | 1.33 |
| Annual Financial Costs in 2013-2018 | 0.64 | 1.13 | 0.20 | 0.56 |
| Annual Financial Costs in 2019 | 0.19 | 0.27 | 0.07 | 0.22 |
| Annual Tax Costs in 2013-2018 | 0.36 | 0.27 | 0.13 | 0.22 |
| Annual Tax Costs in 2019 | 0.10 | 0.09 | 0.04 | 0.06 |
| Annual Administration Costs in 2013-2018 | 3.36 | 2.32 | 1.19 | 1.95 |
| Annual Administration Costs in 2019 | 0.59 | 0.38 | 0.28 | 0.43 |
| Panel C. Job Posts | | | | |
| Average Quarterly No of Job Posts in 2017-2018 | 60.60 | 44.30 | 17.76 | 33.23 |
| Average Quarterly No of Job Posts in 2019 | 58.08 | 55.08 | 11.94 | 26.40 |
| Average Quarterly No of Marketing-Related Job Posts in 2017-2018 | 6.43 | 5.40 | 4.86 | 13.83 |
| Average Quarterly No of Marketing-Related Job Posts in 2019 | 5.89 | 6.69 | 3.16 | 9.72 |
| Average Quarterly No of Job Vacancies Posted in 2017-2018 | 1,808.28 | 3,943.60 | 77.92 | 217.11 |
| Average Quarterly No of Job Vacancies Posted in 2019 | 78.08 | 83.28 | 22.21 | 68.56 |
| Average Quarterly No of Marketing-Related Job Vacancies Posted in 2017-2018 | 161.50 | 363.31 | 22.45 | 92.99 |
| Average Quarterly No of Marketing-Related Job Vacancies Posted in 2019 | 7.31 | 9.07 | 6.08 | 24.63 |

*Notes*: This table displays the summary statistics for the firm-level analysis sample. Columns (1) and (2) show the results for winning firms; columns (3) and (4) show the results for other firms. Panel A shows the results for the product quality and sales revenue share before the pilot procurement. The variable "Pilot Products' Sales Revenue Share in Pilot Molecules, Pilot Cities" is calculated as a firm's pre-pilot cross-product average of the ratio of a pilot product's quarterly sales revenue to the corresponding molecule's quarterly sales revenue in pilot cities. The variable "Pilot Products' Sales Revenue Share in ATC 4, Pilot Cities" is calculated as a firm's pre-pilot cross-product average of the ratio of a pilot product's quarterly sales revenue to the quarterly sales revenue of all molecules of the same ATC class 4, in pilot cities. The variable "Pilot Products' Sales Revenue Share in Firms' Total Revenue" is calculated as a firm's pre-pilot ratio of the sum of pilot products' quarterly sales revenues to the firm's total sales revenue from all products. Panel B shows the results for firms' revenues and costs including conferences, entertainment, travel-related (ETC) costs. Panel C shows the results for the firms' job posts.

Table C9: Robustness Results for the Inverse Hyperbolic Sine Transformation

| | | | Sales Costs | |
|---|---|---|---|---|
| | | | $sinh^{-1}$(Advertising Costs) | $sinh^{-1}$(ETC Costs) |
| | $sinh^{-1}$(Sales Costs) | $sinh^{-1}$(Total Costs) | | |
| Variables | (1) | (2) | (3) | (4) |
| Revenue_Share × Post | -0.0248*** | -0.0071 | -0.0242*** | -0.0234*** |
| × Winning_Firm | (0.0053) | (0.0055) | (0.0057) | (0.0057) |
| Revenue_Share × Post | 0.0009 | 0.0014 | -0.0025 | -0.0030 |
| | (0.0013) | (0.0011) | (0.0034) | (0.0033) |
| N | 1,751 | 1,751 | 1,751 | 1,751 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |

*Notes*: This table displays the robustness results for firm-level sales costs analysis using the inverse hyperbolic sine transformation. The outcome variables are rescaled by 0.001 and then transformed. Variable Winning_Revenue_Share denotes the firm's sales revenue share from the pilot molecules for which it won the auction during 2013-2018 and is expressed as percentages. Each column presents one regression result for the outcome variable specified in the column title. Columns (3) and (4) present results for two of three subgroups of sales costs—advertising-related costs, and entertainment, travel, and conferences (ETC)-related costs. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

Table C10: Robustness Results with Poisson Regression

| | | | Sales Costs | |
|---|---|---|---|---|
| | Sales Costs | Total Costs | Advertising Costs | ETC Costs |
| Variables | (1) | (2) | (3) | (4) |
| Revenue_Share × Post | -0.0221*** | -0.0067 | -0.0180** | -0.0175** |
| × Winning_Firm | (0.0063) | (0.0042) | (0.0078) | (0.0072) |
| Revenue_Share × Post | 0.0014* | 0.0008 | -0.0048 | -0.0051 |
| | (0.0008) | (0.0013) | (0.0053) | (0.0050) |
| N | 1,751 | 1,751 | 1,751 | 1,751 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |

*Notes*: This table displays the robustness results for firm-level sales costs analysis using the Poisson regression. Variable Winning_Revenue_Share denotes the firm's sales revenue share from the pilot molecules for which it won the auction during 2013-2018 and is expressed as percentages. Each column presents one regression result for the outcome variable specified in the column title. Columns (3) and (4) present results for two of three subgroups of sales costs—advertising-related costs, and entertainment, travel, and conferences (ETC)-related costs. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

Table C11: Robustness Results for Firm-Level Analysis

| Variables | $sinh^{-1}$(Sales Costs) (1) | $sinh^{-1}$(Total Costs) (2) | Sales Costs: $sinh^{-1}$(Advertising Costs) (3) | Sales Costs: $sinh^{-1}$(ETC Costs) (4) | No. of Job Posts (5) | No. of Marketing-Related Job Posts (6) |
|---|---|---|---|---|---|---|
| Winning_Revenue_Share | -0.0259** | -0.0023 | -0.0306*** | -0.0309*** | -1.1992*** | -0.4992*** |
| × Post | (0.0106) | (0.0062) | (0.0083) | (0.0074) | (0.2041) | (0.0847) |
| N | 1,751 | 1,751 | 1,751 | 1,751 | 3,571 | 3,571 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | No | No |
| Quarter Fixed Effects | No | No | No | No | Yes | Yes |

*Notes*: This table displays the robustness results for firm-level analysis. Variable Winning_Revenue_Share denotes the firm's sales revenue share from the pilot molecules for which it won the auction during 2013-2018 and is expressed as percentages. Each column presents one regression result for the outcome variable specified in the column title. Columns (3) and (4) present results for two of three subgroups of sales costs—advertising-related costs, and entertainment, travel, and conferences (ETC)-related costs. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

Table C12: Robustness Results for Sample Attrition Issue of Firm-Level Analysis

| Variables | $sinh^{-1}$(Sales Costs) (1) | $sinh^{-1}$(Total Costs) (2) | Sales Costs: $sinh^{-1}$(Advertising Costs) (3) | Sales Costs: $sinh^{-1}$(ETC Costs) (4) | No. of Job Posts (5) | No. of Marketing-Related Job Posts (6) |
|---|---|---|---|---|---|---|
| Revenue_Share × Post | -0.0246*** | -0.0091* | -0.0256*** | -0.0241*** | -1.3679*** | -0.5639*** |
| × Winning_Firm | (0.0055) | (0.0055) | (0.0060) | (0.0060) | (0.0887) | (0.0576) |
| Revenue_Share × Post | 0.0004 | 0.0021* | -0.0023 | -0.0031 | -0.1325 | -0.0607 |
| | (0.0013) | (0.0011) | (0.0035) | (0.0033) | (0.0887) | (0.0576) |
| N | 1,751 | 1,751 | 1,751 | 1,751 | 3,571 | 3,571 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | No | No |
| Quarter Fixed Effects | No | No | No | No | Yes | Yes |

*Notes*: This table displays the robustness checks for firm-level analysis employing the inverse of the estimated propensity of a firm to have financial reports as the sample weight. Variable Revenue_Share denotes the firm's sales revenue share from the pilot molecules during 2013-2018 and is expressed as percentages. The variable Winning_Firm is a dummy indicating whether the firm won at least one molecule in the pilot procurement. Each column presents one regression result for the outcome variable specified in the column title. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

Table C13: More Results on Costs

| Variables | $sinh^{-1}$(Total Costs) (1) | $sinh^{-1}$(Sales Costs) (2) | $sinh^{-1}$(Financial Costs) (3) | $sinh^{-1}$(Tax Costs) (4) | $sinh^{-1}$(Administration Costs) (5) |
|---|---|---|---|---|---|
| Revenue_Share × Post | -0.0071 | -0.0246*** | 0.5725*** | -0.0059 | 0.0159*** |
| × Winning_Firm | (0.0055) | (0.0053) | (0.1101) | (0.0077) | (0.0022) |
| Revenue_Share × Post | 0.0014 | 0.0009 | -0.0120 | 0.0005 | -0.0018** |
| | (0.0011) | (0.0013) | (0.0650) | (0.0012) | (0.0009) |
| N | 1,751 | 1,751 | 1,751 | 1,751 | 1,751 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table displays more results on firms' costs. Variable Revenue_Share denotes the firm's sales revenue share from the pilot molecules during 2013-2018 and is expressed as percentages. The variable Winning_Firm is a dummy indicating whether the firm won at least one molecule in the pilot procurement. Each column presents one regression result for the outcome variable specified in the column title. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

Table C14: Supplementary Firm-Level Results

| Variables | Share of Sales Costs in Total Costs (1) | Share of Sales Costs in Total Revenues (2) | No. of Job Vacancies Posted (3) | No. of Marketing-Related Job Vacancies Posted (4) |
|---|---|---|---|---|
| Revenue_Share × Post | -0.6293*** | -0.5730*** | -2.8282*** | -2.4922*** |
| × Winning_Firm | (0.0720) | (0.1170) | (0.8992) | (0.5040) |
| Revenue_Share × Post | 0.0226 | 0.0147 | -1.9373** | -0.6709 |
| | (0.0233) | (0.0293) | (0.8549) | (0.5040) |
| N | 1,751 | 1,751 | 3,571 | 3,571 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | No | No |
| Quarter Fixed Effects | No | No | Yes | Yes |

*Notes*: This table displays the robustness checks for sales costs analysis and marketing-related labor demand analysis. Variable Revenue_Share denotes the firm's sales revenue share from the pilot molecules during 2013-2018 and is expressed as percentages. The variable Winning_Firm is a dummy indicating whether the firm won at least one molecule in the pilot procurement. Each column presents one regression result for the outcome variable specified in the column title in firm-by-year-level data. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.


Figure C1: Impacts of Pilot on Weighted Price, by Pilot and Non-Pilot Cities

Notes: This figure compares the weighted log prices of treatment and control molecules before and after the pilot in pilot and non-pilot cities. Each dot on the blue curve with dot markers (red curve with diamond markers) represents the estimated coefficient of the interaction between the quarter-to-policy dummy and treatment molecule dummy in pilot cities (non-pilot cities) after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and detrending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

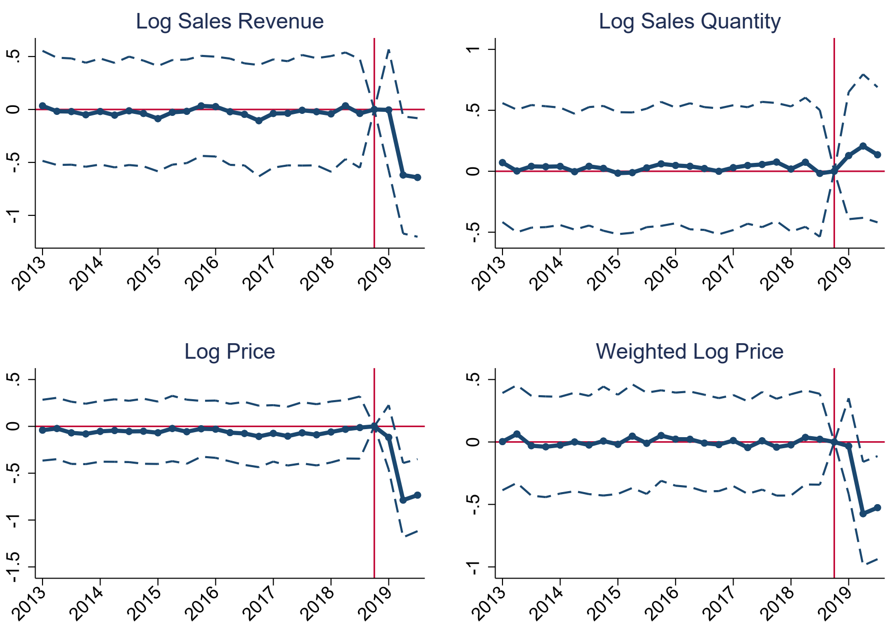



Figure C2: Impacts of Pilot on Sales Revenue, Sales Quantity, and Price, for Triple Difference Analysis

Notes: This figure compares the sales revenues, sales quantities, prices, and weighted prices of treatment and control molecules before and after the pilot in pilot and non-pilot cities. Each dot represents the estimated coefficient of the interaction between the quarter-to-policy dummy, treatment molecule dummy, and pilot city dummy after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and detrending all the coefficients accordingly, following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

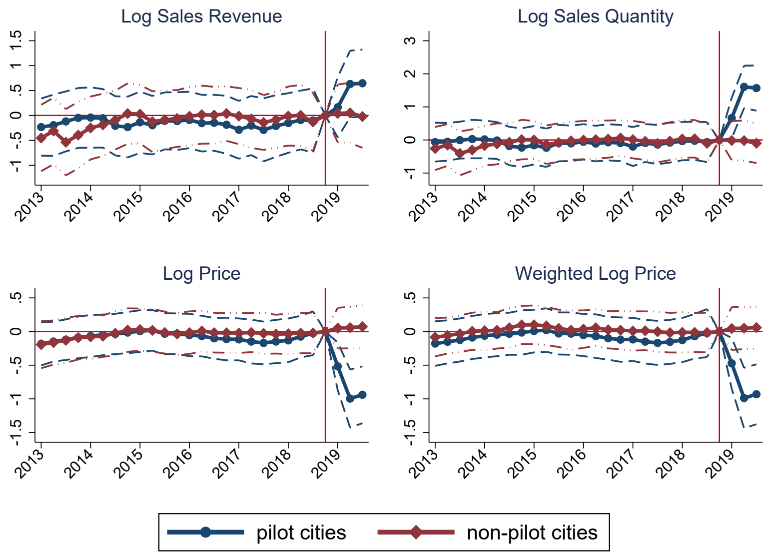



Figure C3: Impacts of Pilot on Winning Products, by Pilot and Non-Pilot Cities

Notes: This figure compares the sales revenues, sales quantities, prices, and weighted prices of treatment and control products in pilot and non-pilot cities. Treatment products are defined as the ones of pilot molecules produced by winning firms in the pilot bidding. Control products are defined as the ones of the molecules for the second national round and in different ATC 4 with pilot molecules produced by firms producing products neither of pilot molecules nor of the molecules in the same ATC 4 level as pilot molecules.

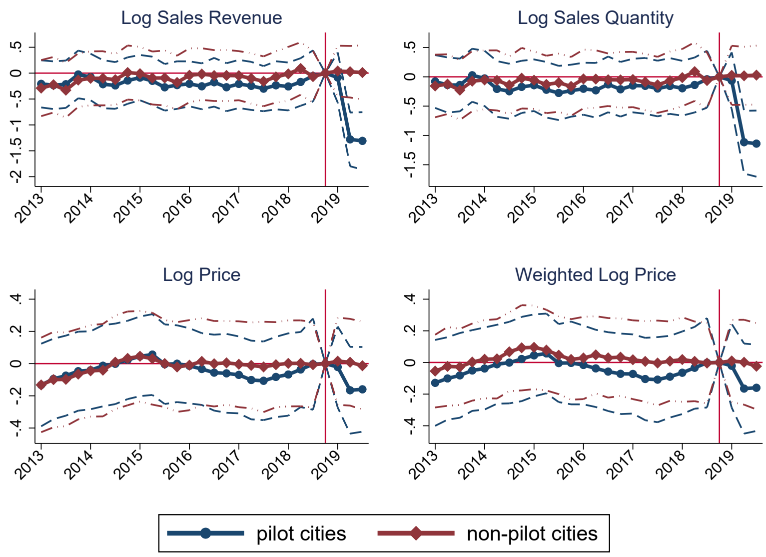



Figure C4: Impacts of Pilot on Non-winning Products, by Pilot and Non-Pilot Cities

Notes: This figure compares the sales revenues, sales quantities, prices, and weighted prices of treatment and control products in pilot and non-pilot cities. Treatment products are pilot molecules produced by firms not winning the auction in the pilot bidding. Control products are molecules procured in the second national round, in different ATC 4 levels than pilot molecules, and produced by firms producing products neither of pilot molecules nor of the molecules in the same ATC 4 level as pilot molecules.

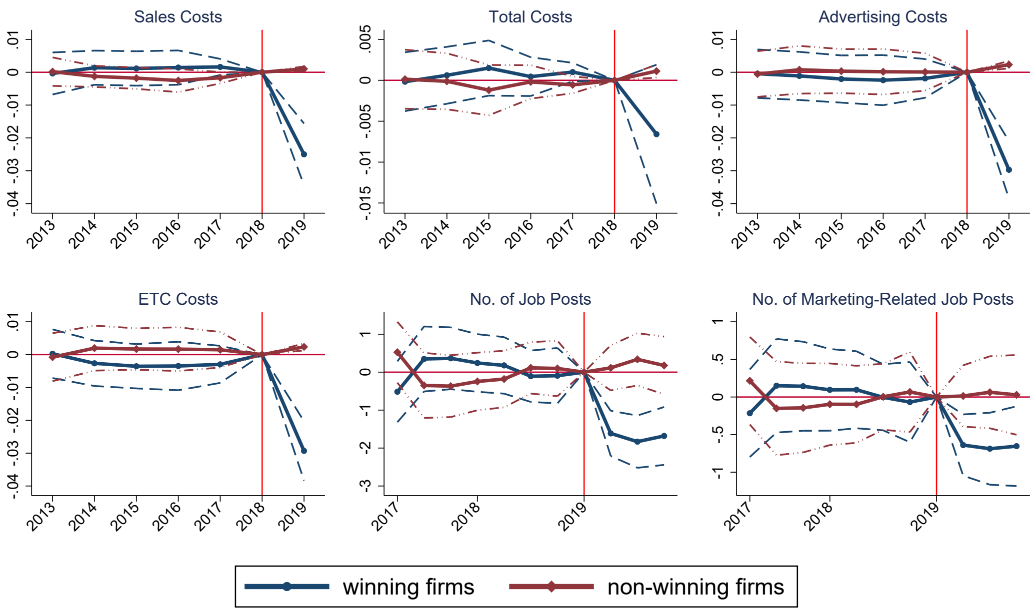



Figure C5: Impacts of Pilot on Costs and Labor Demand of Firms

Notes: This figure compares the sales costs, total costs, advertising-related sales costs, entertainment, travel, and conferences (ETC)-related sales costs, number of job posts, and number of marketing-relate job posts among winning and other firms with different 2013-2018 sales revenue shares from pilot molecules.


Figure C6: Impacts of Pilot on Costs and Labor Demand of Firms, Robustness Results

Notes: This figure compares the sales costs, total costs, advertising-related sales costs, entertainment, travel, and conferences (ETC)-related sales costs, number of job posts, and number of marketing-related job posts among firms with different 2013-2018 sales revenue shares from the pilot molecules for which the firms actually won the auction.

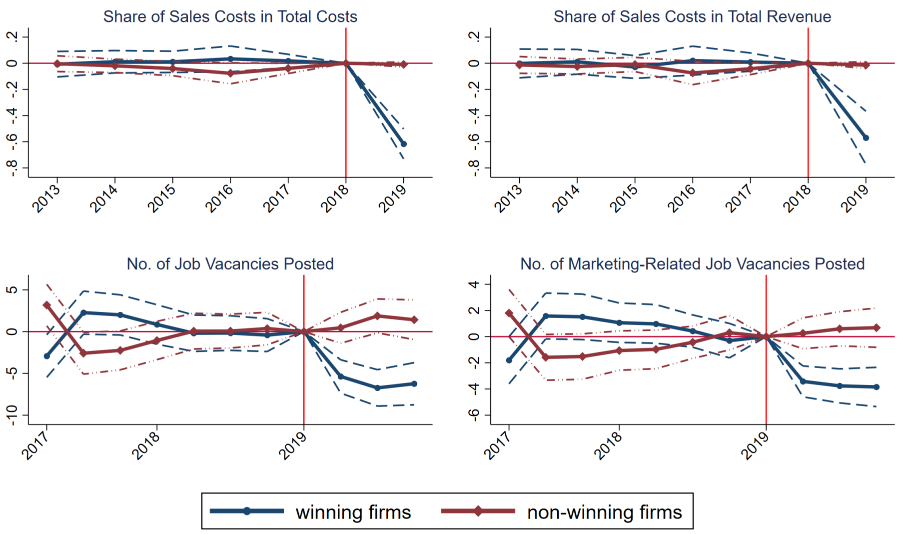



Figure C7: Impacts of Pilot on Costs and Labor Demand of Firms, Supplementary Results

Notes: This figure compares the share of sales costs in total costs, share of sales costs in total revenues, number of job vacancies posted, and number of marketing-related job vacancies posted among winning and other firms with different 2013-2018 sales revenue shares from pilot molecules.