# Excessive Pharmaceutical Marketing Expenditure: Policy Remedies from China

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**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 first develop a stylized model to illustrate how the centralized procurement may change firms' pricing and marketing strategies. We consider a market with two firms producing the drug, differing in production costs. Patients can only purchase the drug prescribed by the physician, whose decision is affected by both patients' preferences for the products and the kickbacks offered by firms. Firms compete in both marketing and pricing decisions. In the absence of the policy, our model shows that both firms will pay kickbacks to physicians if physicians prioritize their financial interests over patients' utility. These decisions result in socially wasteful marketing efforts, as both firms paying kickbacks leads to the same market allocation as if none of them pay, but with higher prices for patients. Under centralized procurement, we model firms as bidding in a first-price sealed-bid auction where the winning firm is guaranteed a market share of $t$ without the need for payments to physicians. We demonstrate that with a sufficiently large guaranteed market share $t$, both firms would lower prices below the Bertrand competition

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.

level. This price reduction is driven by the winning firm's lowered marketing expenditure and intensified price competition due to the auction.

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 study highlights the unique challenge in these markets: many of the drug products are widely

[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).

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

[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.

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 the previous self-formed alliance, the NCDP program was organized at the national level by

[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 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, Tianjin, Shanghai, Chongqing) and seven sub-provincial cities (Shenyang, Dalian, Xiamen, Guangzhou, Shenzhen, Chengdu, 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 participating firms submitted a tender, and the lowest bidder would become the preliminary

[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.

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). Notably, there are six molecules with the final retail price much lower than that in the US market.

[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.

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 shows how a centralized procurement policy may reduce wasteful marketing expenditures, cut drug prices, and enhance 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. There are two firms producing the drug, $A$ and $B$, with the marginal production costs being $c_A < c_B$. Let $u_{ij}$ denote patient $i$'s utility from consuming product $j$. We assume that $u_{ij} = -p_j + v_{ij}$, with $p_j$ denoting the price of product $j$, $v_{iA} = v$, and $v_{iB} = v + \varepsilon_i$. The term $\varepsilon_i$ represents consumers' idiosyncratic tastes for $B$ and is uniformly distributed on $[e-1, e]$.[12]

[12]The positive number $e$ captures the relative quality of the two products. $e = 0.5$ indicates the case where the two products have the same expected quality (e.g., $A$ and $B$ are two generics); $e = 1$ indicates the case where product $B$ has higher quality than $A$ for all patients (e.g., $B$ is the branded drug). Whether $\varepsilon_i$ matters for welfare depends on the context.

In this market, patients get access to the drugs through physician's prescriptions. Physicians act as imperfect agencies whose prescriptions are affected by firms' marketing strategies. Specifically, firms may choose to pay an exogenously determined kickback $k > 0$ to physicians if their products are prescribed. Let $a_j = 1$ or $0$ denote the firm's marketing strategy. Physicians prescribe drug $A$ to patient $i$ if

$$\underbrace{(u_{iA} - u_{iB})}_{\Delta \text{ patient utility}} + \lambda \underbrace{(a_A - a_B)k}_{\substack{\Delta \text{ physician} \\ \text{kickbacks}}} > 0,$$

where $\lambda > 0$ captures physicians' relative preferences of their own financial interests over patient utility. Physicians' kickbacks are irrelevant to patient welfare.

The timeline goes as follows: in the first stage, firms make marketing decisions simultaneously by choosing $a_j = 1$ or $0$; in the second stage, after observing the marketing decisions, firms set prices simultaneously to maximize profits in a Bertrand-Nash competition; finally, physicians prescribe the product, and patients follow the advice to make a purchase.

**Wasteful marketing expenditure under no centralized procurement** In the first stage, firms decide whether to pay kickbacks to physicians. There are four potential scenarios: both, neither, or either one of them pays the kickback. We find that paying kickbacks is a (weakly) dominant strategy for both firms if $\lambda > 1$, i.e., physicians prioritize their financial interests over patient utility. In the two scenarios where both firms pay the kickbacks and where neither firm pays them, the patients who purchase $A$ (and also $B$) are the same. Thus, payments to physicians have no impact on matching patients to suitable products. However, in the scenario where both firms pay the kickbacks, patients face higher prices because of the extra payments to physicians. The marketing expenditure is, hence, socially wasteful.

**Centralized procurement policy with guaranteed quantity** Now, suppose the government implements a centralized procurement policy. Firms compete in a first-price sealed-bid auction. The winning product is guaranteed a market share of $t$. Thus, the winning firm does not need to pay physicians for selling up to the guaranteed quantity. The remaining market is free of competition but with the winning firm selling its product at the bidding price. 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.

The timeline goes as follows. 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 (or refuse to participate) in a first-price sealed-bid auction, and the government announces the winner and the winning bid. In the second stage, both firms decide their marketing strategies.[13] In the third stage, the losing firm decides its price, given the winning bid, guaranteed quantity, and observed marketing strategies. In the final stage, physicians prescribe a product subject to the quantity guarantee.

We illustrate several insights of the model using a numeric example with $\lambda > 1$ and $\varepsilon_i \sim U(-0.5, 0.5)$. First, the equilibrium bid decreases with $t$. When $t$ is close to zero, firm $B$ prefers losing the auction, and firm $A$ wins with the reservation price. The equilibrium prices coincide with the case when there is no procurement policy. When $t$ gets larger, winning the auction means more savings from the marketing expenditure for the guaranteed share. This provides extra incentives to win the auction. We show that with a sufficiently large $t$, both firms have incentives to bid below the reservation price and above their marginal production costs. Firm $A$ wins the auction with the winning bid, $b$, making firm $B$ indifferent between undercutting the bid further and losing the auction. With $t$ getting close to one, the bid gets lower and eventually equals $c_B$ when $t = 1$. The losing firm's price first decreases with $t$ because of intensified price competition in the auction. However, when the guaranteed share is binding, the losing firm only targets the patients with the highest (1-$t$) willingness to pay for its product and charges a higher price when $t$ increases.

Second, firms' marketing expenditure decreases with $t$. We show that with $\lambda > 1$, paying physician kickbacks is a (weakly) dominant strategy for the losing firm. When $t$ increases, the losing firm's market share decreases, and thus its total physician payments decrease. The

[13] The winning firm may still choose to pay physician kickbacks for selling beyond the guaranteed quantity. When the guaranteed quantity is binding, we assume that the winning firm still sets $a = 1$ (though not paid in equilibrium) to rule out the possibility that the losing firm sets a high price for the remaining market. More details are in Appendix A.

winning firm sets $a = 1$ when $t$ is small and stops paying physicians when $t$ is large enough and binds. Thus, the market-wide total payments to physicians decrease when $t$ gets larger and eventually go to zero when $t = 1$.

Third, how the procurement policy affects consumer surplus depends on the savings from drug expenditure against the welfare loss from the reduction in the product variety. In the case where the two products are generics, the former is likely to dominate.

# 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 for 4,909 drug products produced by 2,647 pharmaceutical firms in 20 cities from 2013 to 2021.[14] The dataset is collected from more than 500 representative public hospitals, 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

[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.

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:[15]

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

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.

[15]Moreover, following Atal, Cuesta and Sæthre (2022) and Chevalier, Kashyap and Rossi (2003), we construct another measure of the log price to conduct robustness checks. Specifically, 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 C6, and Appendix Figures C1, C2, C3 and C4.

## 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). The second category is often associated 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.[16] 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. The firms included are pharmaceutical firms, identified using industry codes. We match firm names with the sales dataset and "4+7" procurement policy reports to identify the firms producing the pilot molecules

[16]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.

and those winning at least one molecule auction. For each observation and for each job category, we generate variables for the number of job posts and job vacancies.[17] The merged sample covers 6,651 pharmaceutical firms during the period of 2017 to 2019.

# 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.[18] This trimming step results in 22 control

[17] We handle observations with missing job vacancy information by imputing the median value within the same year and job category.

[18] 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

molecules. In total, our main sample covers quarterly observations on 516 drug products of 42 molecules in 18 cities.

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.[19]

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.[20]

four (Dubois and Lasio, 2018).

[19]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.

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

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

and event studies.

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.[21] 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 equa-

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

tion for winning products and other products of pilot molecules using the pilot city sample.[22] 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.[23] 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.

[22] 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 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.

[23] Appendix Table C5 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]

## 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.[24] 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 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.

[24] See Appendix Table C7 for firm-level summary statistics.

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. 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 2% more decrease in sales costs for winning firms, while the total costs are almost 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.[25]

[Insert Table 4 Here]

[25] Appendix Table C8 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 C6 plot the by-firm-group parameterized event study coefficients for baseline and supplementary firm-level results, respectively.

# 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

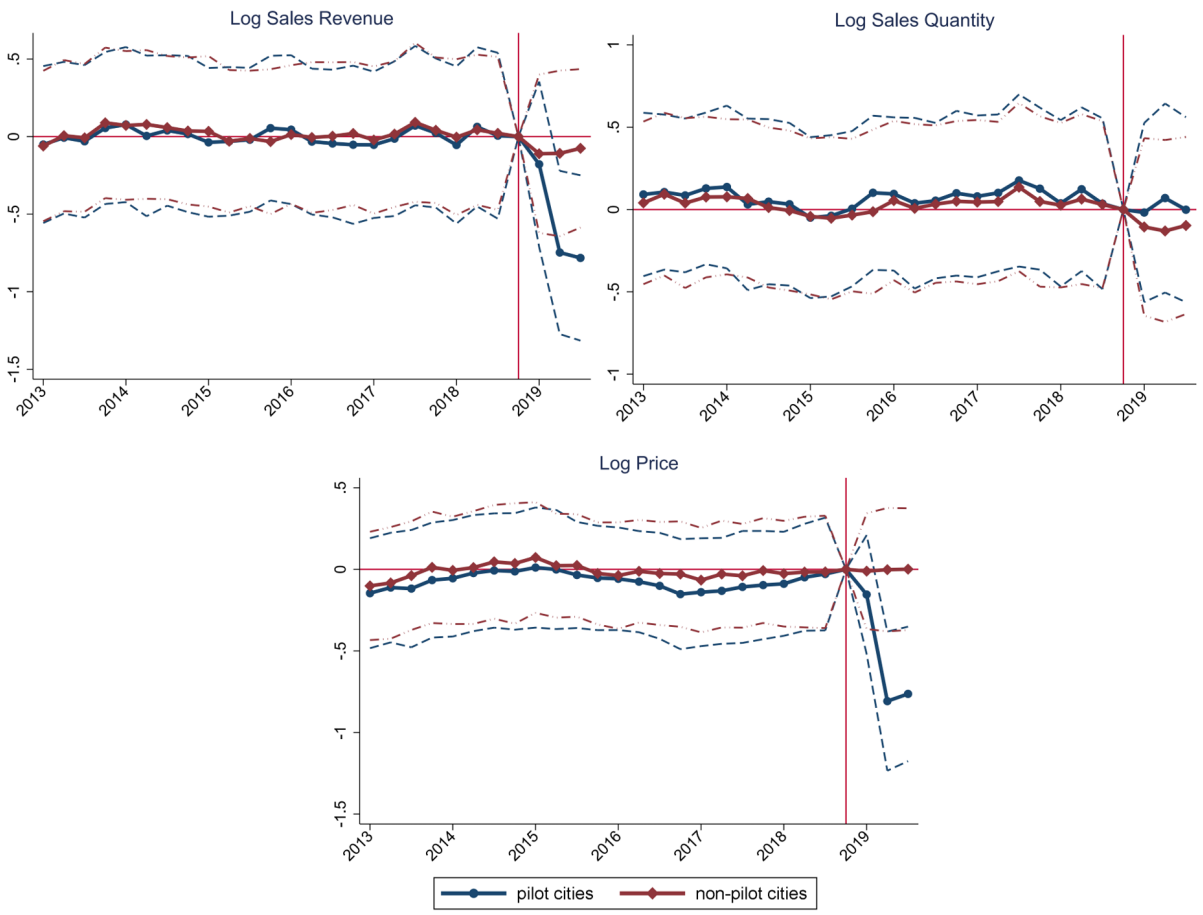


Figure 1: Impacts of Pilot on Sales Revenue, Sales Quantity, and Price, by Pilot and Non-Pilot Cities

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 de-trending 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 de-trend 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

| | Log Sales Revenue | Log Sales Quantity | Log Price |
|---|---|---|---|
| Variables | (1) | (2) | (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 de-trend 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 |
|---|---|---|---|---|---|---|
| | $sinh^{-1}$(Sales Costs) | $sinh^{-1}$(Total Costs) | $sinh^{-1}$(Advertising Costs) | $sinh^{-1}$(ETC Costs) | No. of Job Posts | Marketing-Related Job Posts |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| Revenue_Share × Post | -0.0246*** | -0.0071 | -0.0238*** | -0.0230*** | -1.3348*** | -0.5539*** |
| × Winning_Firm | (0.0053) | (0.0055) | (0.0057) | (0.0057) | (0.1630) | (0.0800) |
| Revenue_Share × Post | 0.0009 | 0.0014 | -0.0026 | -0.0031 | -0.1631* | -0.0701 |
| | (0.0013) | (0.0011) | (0.0034) | (0.0033) | (0.0872) | (0.0560) |
| N | 1,751 | 1,751 | 1,751 | 1,751 | 52,317 | 52,317 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: This table displays the firm-level results 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. 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 de-trend the coefficients accordingly. Standard errors are clustered at the firm level. * p <0.1, ** p <0.05, *** p <0.01.

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# (For Online Publication Only)

# Appendix A. Model Details

In this appendix, we provide details on how we derive the equilibrium and proof of the propositions.

## 1.1 No Centralized Procurement Policy

When there is no centralized procurement, we solve the model backward. In the second stage, firms take the marketing strategies as given. There are four scenarios: $a_A = a_B = 1$, $a_A = a_B = 0$, $a_A = 1, a_B = 0$, and $a_A = 0, a_B = 1$. Let $s_j(p_A, p_B; a_A, a_B)$ denote the market share for product $j$ in each scenario. We consider the case where $v$ is large enough such that all patients make a purchase, then $s_A(p_A, p_B; a_A, a_B) = -p_A + p_B + \lambda(a_A - a_B)k - e + 1$, subject to $s_A \in [0, 1]$, and $s_B = 1 - s_A$.[1]

The profit function for firm $j$ is $\pi_j = (p_j - c_j - a_j k)s_j$. The best response functions imply that $p_j^*(a_A, a_B) - c_j - a_j k = s_j^*$. As a result, the maximum profit is $\pi_j^* = (s_j^*(a_A, a_B))^2$, subject to the range between 0 and 1. Solving the best response functions simultaneously for both firms, we derive the equilibrium market shares, $s_A^*(a_A, a_B) = \frac{1}{3}(c_B - c_A + 2 - e + (\lambda - 1)(a_A - a_B)k)$, and $s_B^*(a_A, a_B) = 1 - s_A^*(a_A, a_B)$.

Given the second-stage profits, we then solve the first-stage marketing strategies case by case. Consider firm $A$'s strategy. Since $s_A^*(1, a_B) = s_A^*(0, a_B) + \frac{1}{3}(\lambda - 1)k$, $a_A = 1$ is a weakly dominant strategy if $\lambda > 1$. Similarly, the results hold for firm $B$. We summarize this result in proposition 1:

[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 $p_A < v$. Patients prefer product $B$ over the outside option if $p_B - \varepsilon_i < v$. As we will show next, the equilibrium prices are functions of the production costs and the kickbacks, not of $v$. 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.

**Proposition 1** Under no centralized procurement policy, $a_j = 1$ is a (weakly) dominant strategy for firm $j$ if physicians prioritize their financial interests over patient utility, i.e., $\lambda > 1$.

If $\lambda > 1$, firms set $a_A = a_B = 1$ in the first stage. The equilibrium market shares will be the same as $a_A = a_B = 0$ because $s_j^*(0,0) = s_j^*(1,1)$. The equilibrium prices under the case where both firms pay the kickbacks will be higher by $k$ than under the case where neither firm pays the kickbacks, as $p_j^* = c_j + a_j k + s_j^*$. In this model, 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 product price when there is no centralized procurement known to both firms before the auction.[2] We also assume firms have complete information about the cost distribution. Let $b$ denote the winning bid, $m$ denote the losing firm, and $-m$ denote the winning firm.

We solve the model backward. In the last stage, the losing firm $m$ takes the winning bid, $b$, guaranteed market share, $t$, and the marketing strategies, $a_m$ and $a_{-m}$, as given, and sets its price accordingly. The profit of the losing firm is:

$$(p_m - c_m - a_m k) \times \min\{1 - t, s_m\},$$

where $s_m = b - p_m + \lambda(a_m - a_{-m})k + 1 - e$, if $m = A$, and $s_m = b - p_m + \lambda(a_m - a_{-m})k + e$, if $m = B$, both subject to between 0 and 1. When $s_m < 1 - t$, the optimal pricing requires that the profit margin equals the market share: $p_m^* - c_m - a_m k = s_m^*$, so profits are increasing with regard to the equilibrium market share. Solving the model gives $s_m^* = \frac{1}{2}(b - c_m - \lambda a_{-m} k + 1 - e + (\lambda - 1)a_m k)$, if $m = A$, and $s_m^* = \frac{1}{2}(b - c_m - \lambda a_{-m} k + e + (\lambda - 1)a_m k)$, if $m = B$. Hence, the optimal marketing strategy for the losing firm is $a_m = 1$ if $\lambda > 1$, and 0 otherwise.

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

When $s_m \geq 1-t$, i.e., the guaranteed quantity binds, the losing firm sets the price so that its market share is exactly $1-t$. Lowering the price further would not result in a larger market share and would, therefore, reduce profits. The losing firm's optimal profit is $(b-\lambda a_{-m}k+t-e-c_m+(\lambda-1)a_m k)(1-t)$ if $m=A$, and $(b-\lambda a_{-m}k+t+e-1-c_m+(\lambda-1)a_m k)(1-t)$ if $m=B$. Hence, the optimal marketing strategy for the losing firm is $a_m=1$ if $\lambda>1$, and 0 otherwise.

**Proposition 2** Under the centralized procurement policy, $a_m=1$ is a (weakly) dominant strategy for the losing firm $m$ if $\lambda>1$.

For the remaining derivation, we consider the case where $e=0.5$ to simplify notations; thus, the two firms have the same expected value to patients. We also assume $\lambda>1$. As derived above, $a_m=1$ is a dominant strategy for the losing firm, so we set $a_m=1$ for all derivations afterward.

The losing firm $m$'s profit under the best-response price given $b$ and $t$ is:

$$\pi_m^l(b;t,a_{-m})=\begin{cases}0, & \text{if } s_m^*\leq 0,\\ {s_m^*}^2, & \text{if } 0<s_m^*<1-t,\\ (b-c_m-k+t-\frac{1}{2})(1-t), & \text{otherwise,}\end{cases}$$

where $s_m^*$ is the losing firm's optimal market share. When the winning firm sets $a_{-m}=1$, $s_m^*=s_m'=\frac{1}{2}(b-c_m-k+\frac{1}{2})$. When the winning firm sets $a_{-m}=0$, $s_m^*=s_m''=\frac{1}{2}(b-c_m-k+\frac{1}{2}+\lambda k)$. Note that when $s_m^*\geq 1-t$, $t$ is binding, and the winning firm is indifferent between $a_{-m}=1$ and $0$ because it will not supply the remaining market and pay the kickback in equilibrium. We assume that the winning firm always sets $a_{-m}=1$ when $t$ is binding (though not paid in equilibrium).[3]

In the second last stage, the winning firm observes the losing firm's price and also correctly

[3]This assumption ensures that with a sufficiently large $t$ (thus, it is binding), the losing firm would not charge an excessively high price to the remaining patients due to the lack of payments to physicians from the winning firm.

infers that $a_m = 1$. Given the losing firm's strategy, the winning firm $-m$ decides whether it pays kickback for the market beyond the guaranteed share, taking the winning bid $b$ and guaranteed market share $t$ as given. The winning firm's profit function is:

$$\pi^w_{-m}(b;t,a_{-m}) = \begin{cases} b - c_{-m}, & \text{if } s^*_m \leq 0, \\ (b-c_{-m})t + (b - c_{-m} - a_{-m}k)(1 - s^*_m - t), & \text{if } 0 < s^*_m < 1 - t, \\ (b-c_{-m})t, & \text{otherwise.} \end{cases}$$

Note that the winning product is guaranteed a market share of $t$, so no payments to physicians are made for sales up to $t$.

The winning firm then picks the marketing strategy to maximize its profit, and its decision also determines the losing firm's profit given $b$ and $t$:

$$\pi^w_{-m}(b;t) = \max\{\pi^w_{-m}(b;t,a_{-m}=0), \pi^w_{-m}(b;t,a_{-m}=1)\},$$

$$\pi^l_m(b;t) = \begin{cases} \pi^l_m(b;t,a_{-m}=0), & \text{if } \pi^w_{-m}(b;t,a_{-m}=0) > \pi^w_{-m}(b;t,a_{-m}=1), \\ \pi^l_m(b;t,a_{-m}=1), & \text{otherwise.} \end{cases}$$

Finally, in the first stage, the firms compete in the auction taking $r$ and $t$ as given. Firms' bidding strategy depends on $\pi^w_{-m}(b;t)$, $\pi^l_m(b;t)$, and also the guaranteed share $t$. We illustrate the nature of the equilibrium using the following numeric example. We set $c_A = 0$, $c_B = 0.2$, $k = 0.1$, $\lambda = 8$, $e = 0.5$, and $v = 1$. In this numeric example, firm $A$ has a lower price $p^N_A$ than firm $B$'s price $p^N_B$ when there is no centralized procurement program, so $r = p^N_A$. Let $\pi^N_j$ denote the equilibrium profit when there is no procurement policy.

1. When $t \in [0, \frac{11}{120})$, $\pi^w_B(b;t) < \pi^l_B(b;t), \forall b \leq r$. This implies that firm $B$ has no incentive to participate in the auction. Hence, firm $A$'s best response is to set $b = r = p^N_A$ and pay the kickback to physicians in the remaining market. Given firm $A$'s strategy, firm $B$'s best response is to set $p = p^N_B$ and $a_B = 1$, and hence the market shares are the same as without the procurement. If $t = 0$, both firms earn the same profits as in the case with no procurement (as shown in Appendix Figure A1, Panel A.) If $t > 0$, firm $A$ earns higher

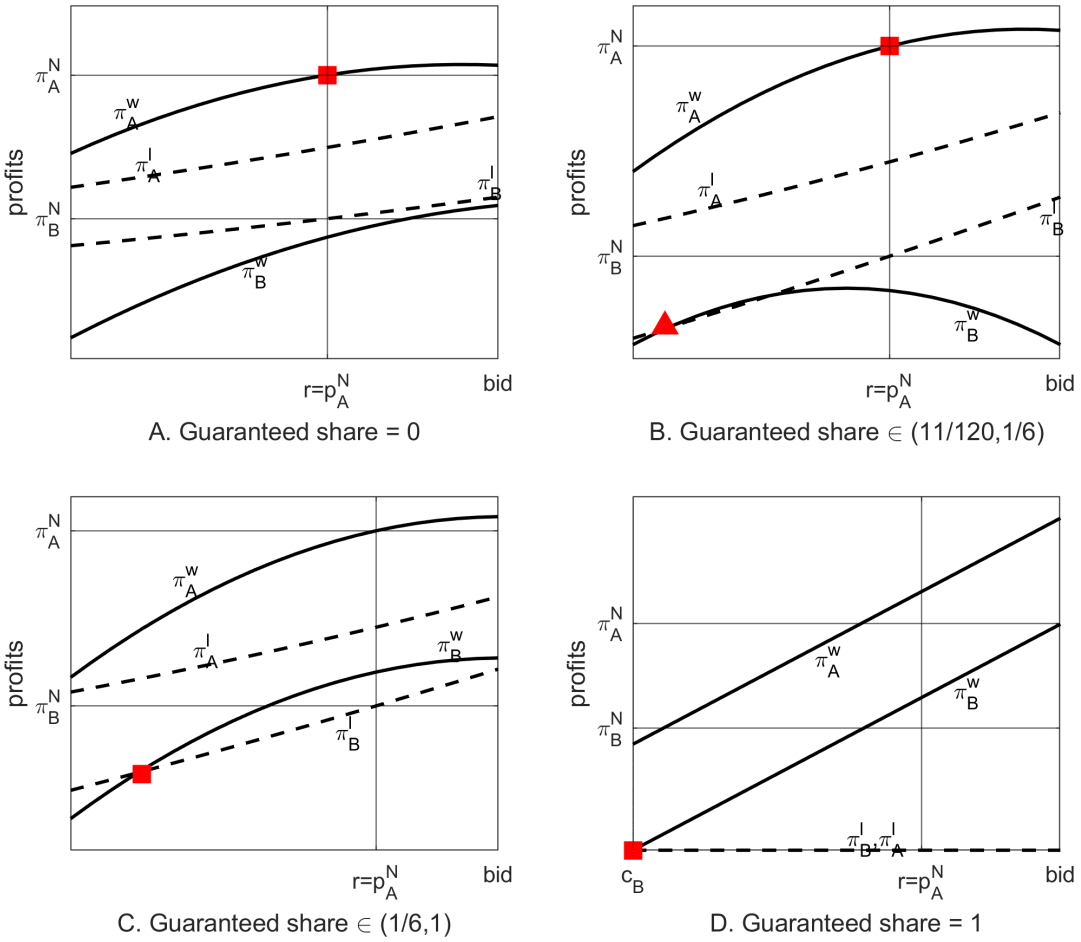


Figure A1: Bidding Strategy Illustration

*Notes*: We set $c_A = 0$, $c_B = 0.2$, $k = 0.1$, $\lambda = 8$, $e = 0.5$, and $v = 1$. We keep the relative positions of points and curves but adjust the scales so that the figures are easy to read. Hence, the sizes may not match the actual values. The red square and triangle points denote the equilibria.

profits than $\pi_A^N$ because it saves the marketing expenditure for share $t$.

2. When $t \in (\frac{11}{120}, \frac{1}{6})$, $\pi_B^w(r;t) < \pi_B^l(r;t)$. However, there exists $b' < r$ such that $\pi_B^l(b';t) = \pi_B^w(b';t)$. Firm $A$ bidding at $r$ and firm $B$ not participating is still a Nash equilibrium (the red square point in Panel B). Moreover, firm $A$ setting a bid slightly lower than $b'$ to undercut firm $B$'s bid $b'$ is another Nash equilibrium (the red triangle point in Panel B).

3. When $t \in (\frac{1}{6}, 1]$, the profit functions are shown in Panels C and D. Firm $B$ has the incentive to undercut the bid until the level $b'$ where $\pi_B^l(b';t) = \pi_j^w(b';t)$. The equilibrium bid is $b'$, and firm $A$ wins the auction. Note that $b' \geq c_B$ because otherwise, firm $B$ earns a negative profit. When $t$ is small, firm $A$ sets $a_A = 1$ . When $t > 0.76$, the guaranteed quantity binds, and firm $B$ sets the price capturing the whole remaining market. The resulting $p_B$ increases with $t$ because patients in the remaining market value $B$ more. When $t = 1$, $\pi_j^l = 0$. As a result, the winning bid equals $c_B$ (as in Panel D.)

Appendix Figure A2 summarizes how the equilibrium price changes when the guaranteed share increases. The price drop happens only when the guaranteed share is large enough.[4] We also illustrate how producer surplus, consumer surplus, and physician payment change when $t$ increases in Appendix Figure A3. We consider two types of consumer surplus: "consumer surplus 1" is the one with $\varepsilon$ being not relevant for welfare, and "consumer surplus 2" is the opposite. In general, centralized procurement reduces the marketing expenditure and producer surplus while increasing consumer surplus through lowered prices.

## 1.3 Model Caveat

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

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 at

[4] In the graph, we pick $A$ biding at $r$ and $B$ not bidding as the equilibrium when $t \in (\frac{11}{120}, \frac{1}{6})$.

the same time, so firms were not able to observe the bidding outcomes of other auctions when submitting bids, 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 less than 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, and 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 via enhanced reputation by 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 conduct interviews with several pharmaceutical firms engaging in centralized procurement, and none of them report any significant changes in production costs in the short run. 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 costs 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.

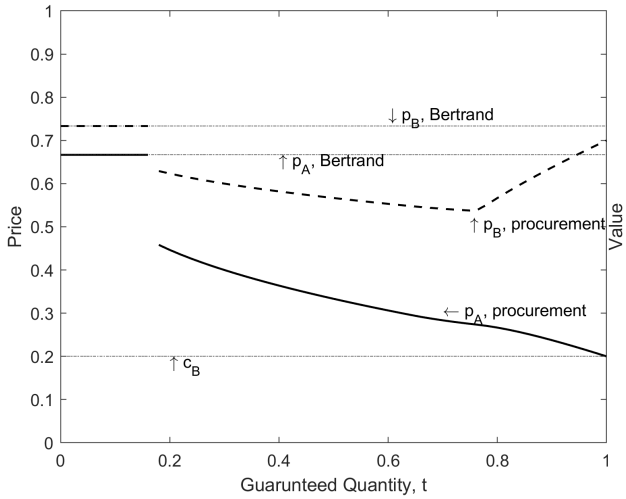


Figure A2: Equilibrium Prices

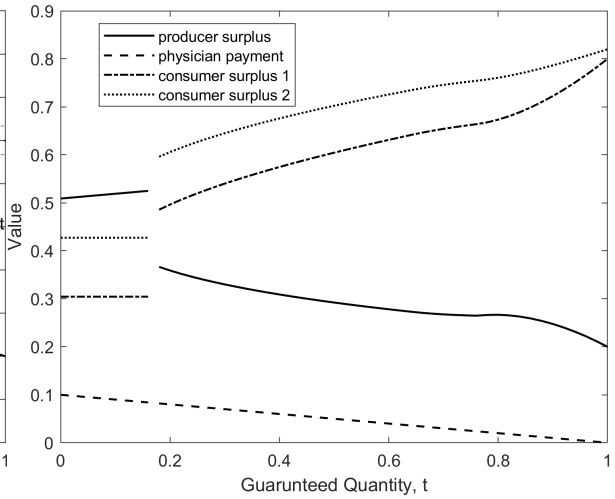


Figure A3: Equilibrium Surplus

*Notes*: These figures display the model predictions with $c_A = 0$, $c_B = 0.2$, $k = 0.1$, $\lambda = 8$, $e = 0.5$, and $v = 1$. "Consumer surplus 1" is the consumer surplus assuming $\varepsilon_i$ is not relevant for welfare, while "consumer surplus 2" is the consumer surplus assuming $\varepsilon_i$ is relevant for welfare. "Producer surplus" is the total profits for both firms and "physician payment" is the market-wide physician kickback.

# 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 de-trend 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

| Variables | Log Sales Revenue (1) | Log Sales Quantity (2) | Log Price (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. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and de-trend 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 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. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and de-trend 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 C4: Summary Statistics for Products

| | Winning Products | | Other Products | |
|---|---|---|---|---|
| | mean | std dev | mean | std dev |
| Variables | (1) | (2) | (3) | (4) |
| Panel A. Quality of Products before the Pilot Procurement | | | | |
| Branded Products | 0.10 | 0.31 | 0.10 | 0.30 |
| Passing Bioequivalence Tests | 0.90 | 0.31 | 0.12 | 0.33 |
| 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: Robustness Results for Product-Level Results in Non-Pilot Cities

| | Log Sales Revenue | Log Sales Quantity | Log Price |
|---|---|---|---|
| Variables | (1) | (2) | (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. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and de-trend 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 C6: 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. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and de-trend the coefficients accordingly. 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 C7: 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 | 0.89 | 0.69 |
| 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 | 19.05 | 51.61 |
| 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 | 17.68 | 49.93 |
| 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 | 2.57 | 4.74 |
| 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 |
| Panel C. Job Posts | | | | |
| Average Quarterly No. of Job Posts in 2017-2018 | 56.10 | 45.43 | 7.03 | 13.82 |
| Average Quarterly No. of Job Posts in 2019 | 56.72 | 52.97 | 4.06 | 11.65 |
| Average Quarterly No. of Marketing-Related Job Posts in 2017-2018 | 5.93 | 5.47 | 1.52 | 4.87 |
| Average Quarterly No. of Marketing-Related Job Posts in 2019 | 5.74 | 6.42 | 4.06 | 11.65 |
| Average Quarterly No. of Job Vacancies Posted in 2017-2018 | 1,669.56 | 3,808.69 | 29.85 | 163.77 |
| Average Quarterly No. of Job Vacancies Posted in 2019 | 76.07 | 80.06 | 6.77 | 31.04 |
| Average Quarterly No. of Marketing-Related Job Vacancies Posted in 2017-2018 | 149.08 | 350.71 | 8.87 | 51.30 |
| Average Quarterly No. of Marketing-Related Job Vacancies Posted in 2019 | 7.05 | 8.74 | 1.56 | 7.60 |

*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 the average annual total revenues, total costs, sales costs, advertising-related costs, and conferences, entertainment, and travel-related (ETC) costs before or after the pilot procurement. Panel C shows the results for the average quarterly numbers of job posts, marketing-related job posts, job vacancies posted, and marketing-related job vacancies posted before or after the pilot procurement.

Table C8: 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 × Winning_Firm | -0.6293*** | -0.5730*** | -2.6795*** | -2.4563*** |
| | (0.0721) | (0.1170) | (1.0094) | (0.5723) |
| Revenue_Share × Post | 0.0226 | 0.0146 | -2.0999** | -0.7032 |
| | (0.0234) | (0.0294) | (0.8444) | (0.4931) |
| N | 1,751 | 1,751 | 52,317 | 52,317 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | 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. We follow Dobkin et al. (2018) to parameterize the linear trend of the estimated coefficients in the pre-pilot period and de-trend the coefficients accordingly. 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 de-trending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

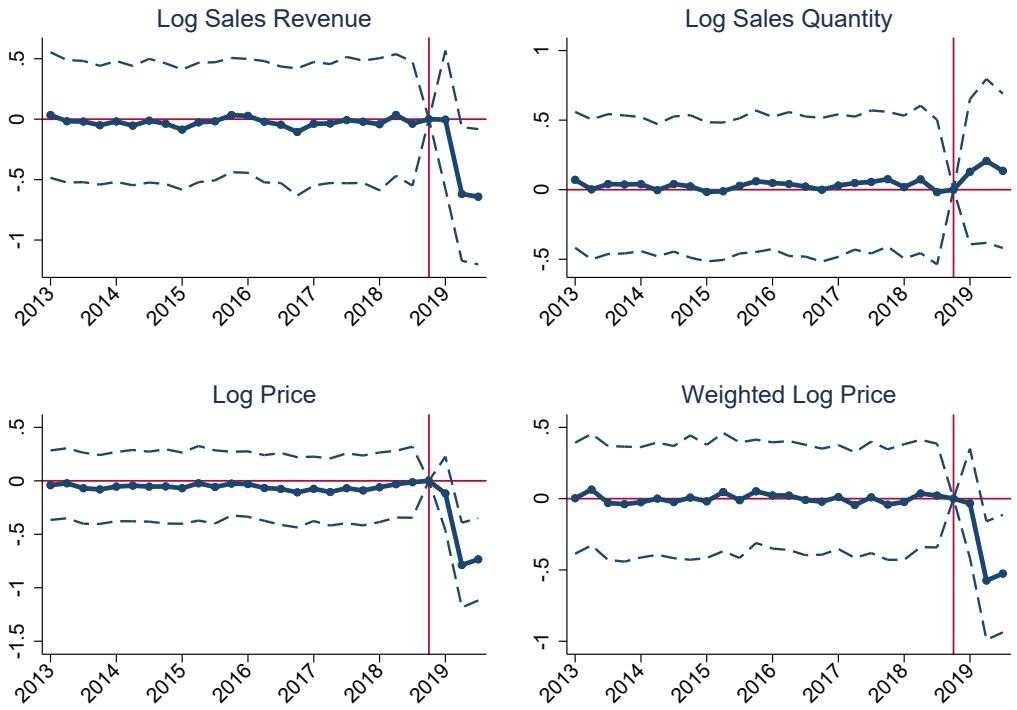


Figure C2: Impacts of Pilot on Sales Revenue, Sales Quantity, and Price, for Triple Difference Analysis

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 de-trending all the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

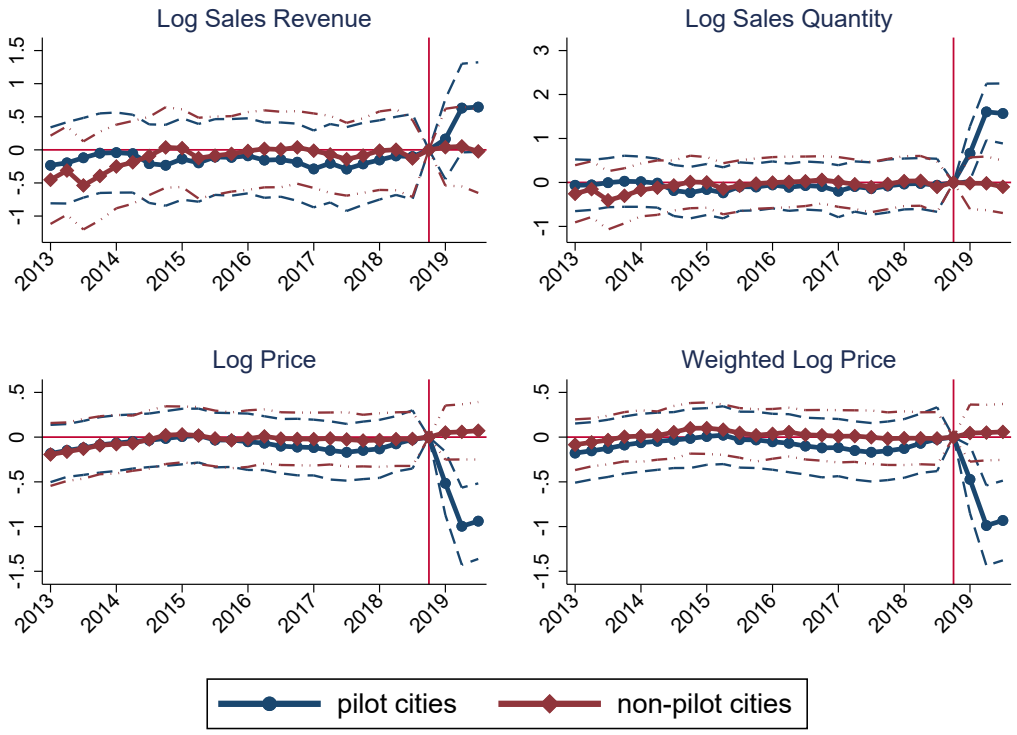


Figure C3: Impacts of Pilot on Winning Products, by Pilot and Non-Pilot Cities

Notes: This figure compares the sales revenues, sales quantities, prices, and weighted prices of treatment and control products. 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. 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 product dummy in pilot cities (non-pilot cities) after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and de-trending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

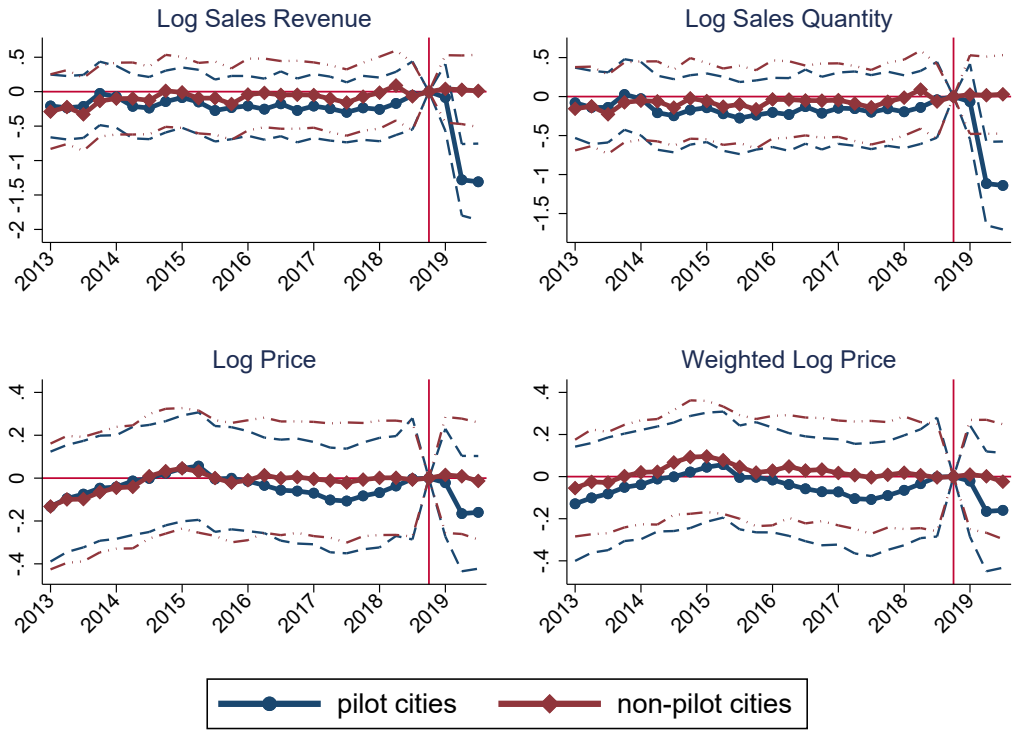


Figure C4: Impacts of Pilot on Non-winning Products, by Pilot and Non-Pilot Cities

Notes: This figure compares the sales revenues, sales quantities, prices, and weighted prices of treatment and control products. Treatment products are defined as the ones of pilot molecules produced by firms not winning the auction in the pilot bidding. Control products are defined as the ones of the molecules for the second national round and in different ATC 4 levels with 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. 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 product dummy in pilot cities (non-pilot cities) after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and de-trending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

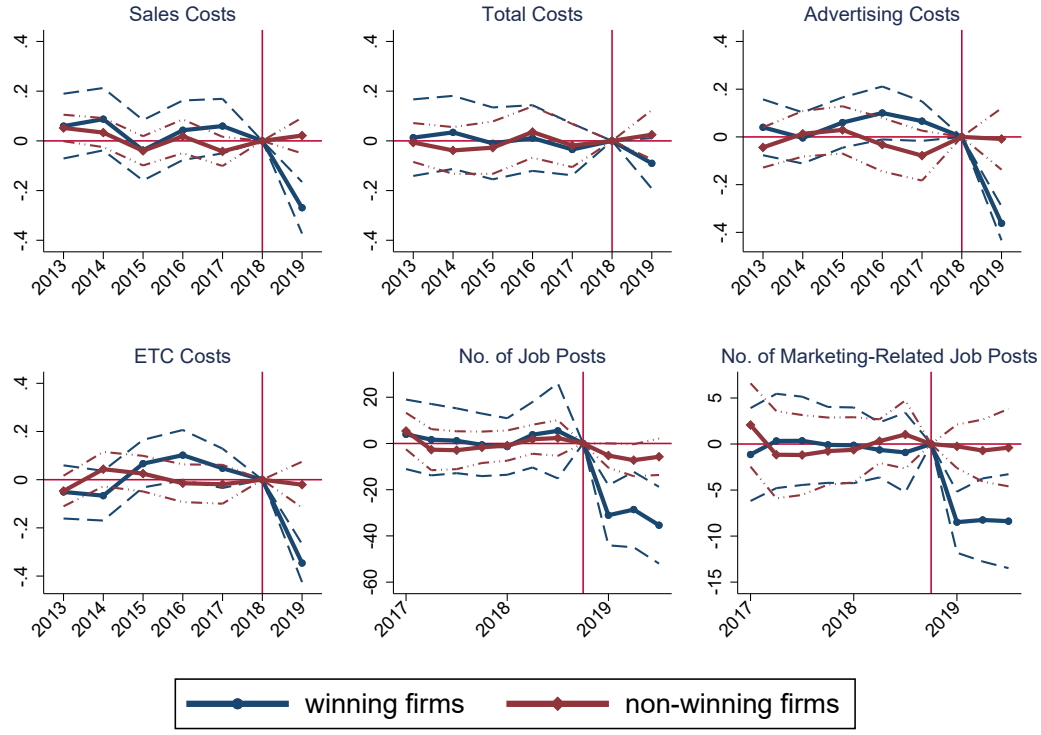


Figure C5: Impacts of Pilot on Costs and Labor Demand of Firms

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 between firms with 2013-2018 sales revenue share from the pilot molecules above and below the mean value in winning firms sample and other firms sample. 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 the dummy indicating the 2013-2018 sales revenue share from the pilot molecules being larger than the mean value for winning firms (other firms), after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and de-trending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.

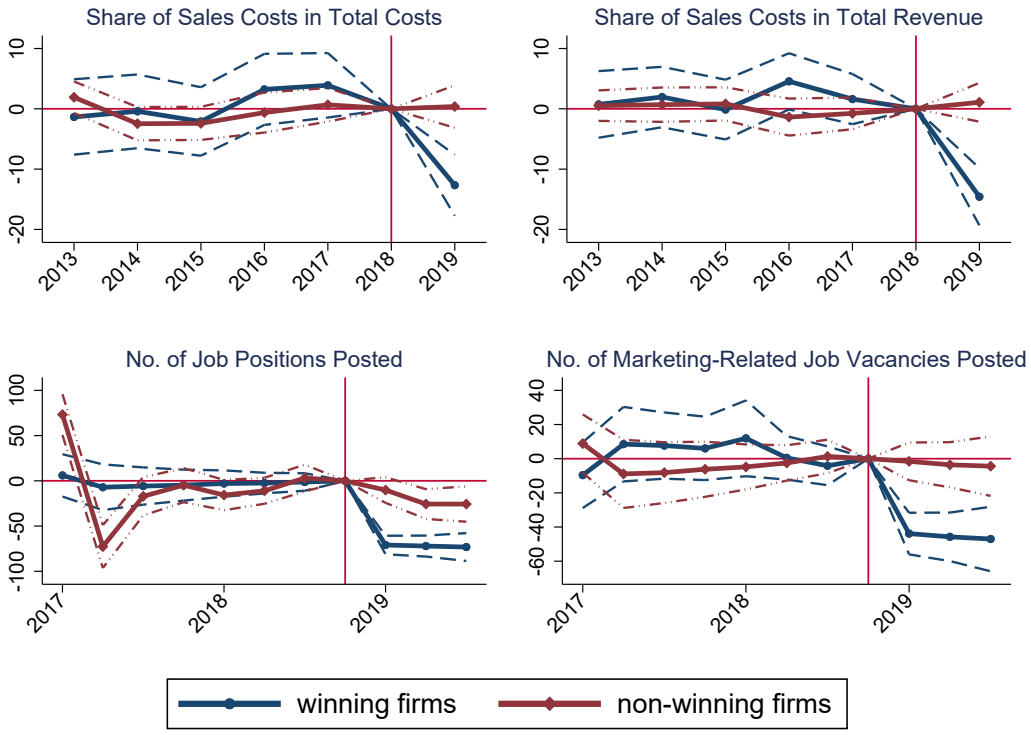


Figure C6: Impacts of Pilot on Costs and Labor Demand of Firms, Robustness Checks

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-relate job vacancies posted between firms with 2013-2018 sales revenue share from the pilot molecules above and below the mean value in winning firms sample and other firms sample. 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 the dummy indicating the 2013-2018 sales revenue share from the pilot molecules being larger than the mean value for winning firms (other firms), after parameterizing the linear time trend of the estimated coefficients in the pre-pilot period and de-trending the coefficients accordingly following Dobkin et al. (2018). Standard errors are estimated by using 200 bootstrapped samples.