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Beyond Price Reduction: Heterogeneous Needs, Quality Control, and Supplier Stability in Centralized Drug Procurement *

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Abstract

Centralized procurement is a viable way of reducing drug prices. However, the effective price reduction might be discounted if there are backfires from the demand and the supply sides. In this study, we analyze the impacts of the world's largest centralized procurement –China's Centralized Volume-Based Drug Procurement (CVBP)–using comprehensive drug transaction data from all healthcare institutions in China. Using a staggered difference-in-differences model, we show that CVBP lowers drug price by 54% and reduces drug expenditure by 50%. Despite of the radical price reduction, which especially benefits low-income people, patients who primarily used branded drugs before the CVBP resist switching drugs but use higher doses when they do switch from branded to generics. Moreover, when a winning firm changes its manufacturing process for a winning drug, the utilization of such drugs increases. Finally, manufacturing and transportation capacity can ensure supply sufficiency.

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1 Introduction

Escalating healthcare costs are a pressing policy challenge worldwide. Drug expenditures, which account for a substantial share of total health spending (10%–20% in most OECD countries), are growing at a faster rate than other healthcare costs (Wager et al., 2023).[1] Policymakers have explored various cost-containment measures (Emanuel et al., 2012), yet yield mixed results. Among these measures, centralized/pooled procurement has been widely discussed (WHO, 2020), but its implementation remains limited in scale, and its effectiveness varies across different procurement mechanisms and enforcement.[2] Moreover, while price reductions and cost savings are direct evaluation measures, the broader economic and behavioral impacts on patients, physicians, and drug producers are critical to assess inefficiencies and the net effect of a centralized procurement, which can inform future procurement designs.

As the world's second-largest pharmaceutical market, China's Centralized Volume-Based Procurement (CVBP) program presents a unique opportunity to evaluate centralized drug procurement. Initiated in 2018 with a pilot "4+7" city program and expanded nationwide in 2019, CVBP leverages competitive bidding with volume guarantees as an incentive for firms to drive down drug prices. Although the large-scale implementation of CVBP benefits from China's single-payer system and centralized policy enforcement, the core mechanisms of CVBP—demand aggregation, volume commitment, and competitive bidding—offer valuable insights for other healthcare systems, including those with more decentralized structures. Despite its significance, existing studies remain fragmented, relying on limited timeframes, regional subsets, or select hospital samples. A thorough, nationwide analysis is missing: Accurately quantifying its effectiveness provides a benchmark for future centralized procurement designs. Furthermore, despite the substantial reduction in drug prices, to understand the actual effectiveness of the policy and the welfare implications, we need to assess the responses from both the demand and the supply sides, which may undermine or boost the apparent effectiveness of centralized procurement. However, these more in-depth responses have not been well studied.

To fill these gaps, this paper provides the most comprehensive evaluation of CVBP, addressing

[1] China's drug spending is 35% of total health spending in 2018, the year before the CVBP (Li and Zhang, 2024).

[2] By aggregating demand for certain goods or services, pooled procurement could leverage monopsony power and the aggregating volume for better prices. In this paper, we use pooled procurement and centralized procurement interchangeably.

not only its price effects but also its broader economic and behavioral impacts. With complete population-level drug transaction data, we aim to achieve the following objectives: (1) Quantify the full economic impact of CVBP on drug prices, utilization, expenditures, and market structure at a national scale; (2) Examine heterogeneous effects on different patient subgroups, with a focus on low-income populations and patients who experience a drug disruption from a branded to a generic drug; (3) Analyze strategic responses and stability of drug suppliers.

Our study leverages complete procurement order records from all healthcare institutions in China from January 2019 to June 2023, encompassing every prescription drug transaction and capturing key details such as price, quantity, manufacturer, molecule, dosage, and distributor. Given the enormous size of this dataset, we focus our empirical analysis on four major drug classes (ACE inhibitors, statins, PPIs, and SSRIs) that treat prevalent chronic and acute diseases in China. To causally estimate CVBP's effects, we use a staggered difference-in-differences (DID) approach, exploiting variation in treatment timing across different drug molecules and using non-procured molecules within the same drug class as a control group. This rigorous empirical design allows us to isolate the true impact of CVBP from confounding factors and market trends.

Our results demonstrate that CVBP achieves significant cost savings while reshaping China's pharmaceutical market: Drug prices drop by 54%, drug utilization rises by 8%, and total drug expenditure falls by 50%. Due to the guaranteed volume for winning drugs, the market share of winning drugs (most are generics) expands by 50%, while the branded drug market share declines by 13%. Finally, drug price reductions are mainly driven by winning drugs, whereas the spillover effects on non-winning drugs are only between 5–10%.

Beyond these average effects, our study uncovers important behavioral responses and welfare implications. First, we show that low-income patients benefit the most, increasing drug utilization to meet previously unmet medical needs. Second, switching from branded to generics leads to mixed patient responses: For drugs used primarily to treat chronic diseases, utilization decreases moderately, suggesting resistance from patients and potential challenges to drug adherence (Go et al., 2011; Bronnenberg et al., 2015; Straka et al., 2017). However, for drugs treating both acute and chronic conditions, utilization increases, possibly due to lower efficacy of generics requiring higher doses (Straka et al., 2017). Third, winning firms alter their manufacturing processes post-CVBP, and these changes correlate with higher drug utilization, raising concerns about a decrease in drug

quality (lower efficacy). Finally, supply chain stability depends on firm characteristics: Firms with higher production capacity and shorter hospital supply distances see higher purchase volumes.

The above evidence suggests that the effective price reduction of drugs may not be as big as we initially estimated if we take into account of the (potential) lower efficacy of drugs. Therefore, more stringent quality control is needed to ensure that drug safety and efficacy are maintained at the same level as before CVBP.

Our study makes several key contributions to the literature on centralized procurement, healthcare access, and supplier behavior in pharmaceutical markets. First, we extend research on centralized procurement and competitive bidding in healthcare by providing the most comprehensive nationwide evaluation of China's CVBP program. Using population-level data and examining dynamic effects over time, our study offers a more complete assessment from wide-scope perspectives to illuminate how large-scale procurement alters pharmaceutical markets. In this study, we not only echo previous studies by showing that centralized procurement could greatly reduce prices, but also find that CVBP leads to moderate increases in drug utilization– a result that contrasts with findings from the U.S. Medicare procurement of durable medical devices (Ding et al., 2025; Ji, 2023). This finding sheds light on the broader notion in the healthcare sector that cost reduction can play a critical role in improving access to care.

Furthermore, China's centralized enforcement, mandatory participation of public hospitals, and limited local government discretion (Bucciol et al., 2020; Bosio et al., 2022; Carril et al., 2022; Best et al., 2023) enable CVBP to achieve greater savings and more effective execution than existing pooled procurement programs in other countries (Toulemon, 2018; Dubois et al., 2021; Wang and Zahur, 2024). Although several recent studies have analyzed CVBP (Cao et al., 2024; Liu et al., 2023; He and Yang, 2025; Julie and Li, 2025; He et al., 2025), they are often limited in scope, focusing on early stage implementation or regional data. Our study expands this literature by examining the full national roll-out of CVBP, capturing persistent effects over time, and providing a more comprehensive understanding of the impact of the policy on China's pharmaceutical market (Wang and Yang, 2021).

Beyond average treatment effects, we further contribute to the literature on healthcare access by highlighting heterogeneous effects across patient subgroups. Our findings show that lower drug prices benefit low-income patients, helping to meet previously unmet medical needs (Baicker et al.,

2017; Chandra et al., 2024; He and Yang, 2025). However, switching from branded to generics leads to mixed patient responses: chronic condition patients show lower utilization and potential adherence challenges (Go et al., 2011; Bronnenberg et al., 2015; Straka et al., 2017). In comparison, patients with acute conditions show higher utilization, likely due to the lower perceived efficacy of generics that require higher doses (Straka et al., 2017). These findings reveal trade-offs between patient adherence and health outcomes under centralized procurement policies.

A major innovation of our study is its detailed examination of supplier behavior, an area largely neglected in prior research. We provide novel empirical evidence that winning firms modify their manufacturing processes post-CVBP, and these changes correlate with increased drug utilization. This raises critical questions about potential shifts in drug efficacy and supplier-driven moral hazard, an issue previously undocumented in the literature. Additionally, we contribute to research on supplier performance (Decarolis, 2014; Clark et al., 2021) by demonstrating that: Larger firms, firms with API production capacity, and those closer to hospitals see higher procurement volumes, highlighting the role of supply chain efficiency in centralized procurement success.

By integrating nationwide data, dynamic effects, heterogeneous patient responses, and supplier strategies, our study goes beyond prior research, offering the most comprehensive evaluation of CVBP to date. Our findings provide crucial insights for policymakers in both centralized and decentralized healthcare systems, informing the design of effective procurement policies worldwide. This paper is structured as follows: Section 2 provides an overview of the pharmaceutical market and CVBP in China. Section 3 details the data and sample used in the study. Section 4 outlines the empirical strategy employed for the analysis, Section 5 presents the main effects. Section 6 explores the heterogeneous effects of both the demand and the supply sides. Section 7 concludes.

2 Background

2.1 Health Care Provision and Health Insurance in China

In China, hospitals, especially public hospitals, are the main health care providers, for both outpatient and inpatient care, accounting for 83.5% of total health care services in 2023 (National Health Commission of the PRC, 2024). In addition, China's healthcare system has traditionally featured a

integration of prescribing and dispensing within medical institutions, with 85% of prescription drugs dispensing by hospitals (IQVIA, 2023). Physicians (in public hospitals) are salaried employees, with compensation schemes directly tied to hospitals' financial performance, an inappropriate incentive system introduced in China during the mid-1980s, when the country reformed its socialistic economic system into a market system. This leads to the government reduced subsidies to public hospitals and clinics from more than 50% to about 10%, and the rest is earned by hospitals themselves (Yip et al., 2010). In addition to these legitimate income sources, it is well recognized that many physicians receive kickbacks from pharmaceutical companies and red pockets from patients, especially physicians in top-tier hospitals (Marco et al., 2006; Currie et al., 2013; Khazzaka, 2019).

95% of the Chinese population is covered by public insurance, either the Urban Employee Basic Medical Insurance or Urban-rural Integrated Resident Basic Medical Insurance. Insurance provides generous coverage for inpatient care, with an reimbursement rate up to 90%. Outpatient care and prescription drugs are also covered by insurance but with deductibles and copayments. For example, Class A drugs are fully covered by insurance, Class B drugs have a coinsurance rates between 10%–20%, and Class C drugs are not covered by insurance at all. Most CVBP-procured drugs are Class B drugs.

2.2 Pharmaceutical Market in China

China has over 3,000 pharmaceutical firms, but most domestic firms only produce generics. In the past, many of the generics are considered as low quality. However, with the adoption of good manufacturing practice (GMP) and stricter monitoring programs, quality of drugs has improved over the last two decades. In addition, China started to implement the bio-equivalence checks for generics since 2016, which paves the foundation for the CVBP (State Council of the PRC, 2016).

Drug spending has long been the major health care spending in China, accounting for around 40% of the overall health care expenditures in 2010s. In addition, prescription drugs have long been a major profit generator for hospitals, as hospitals were allowed to add 15% markup on drug prices (ended in 2017) (National Development and Reform Commission of the PRC, 2017). Moreover, rebates from pharmaceutical firms are well-known gray income of many physicians.

To deal with high drug costs in China, the government has implemented different policies, such as Drug Price Zero-Markup policy, setting caps on the share of drug expenditures for hospitals, and Two Invoices Systems. The CVBP is one of the most recent policies towards high drug prices in China, which targets generics and expired patented drugs with a high market demand.

2.3 The CVBP in China

The CVBP was first implemented in 4+7 cities (4 mega-cities + 7 other cities) in China as a pilot program. The pilot bidding started in December 2018 and the implementation started from March 2019 for one year. In this pilot stage, 25 molecules were successfully procured, and only one winner was selected for each molecule. Due to the success of the pilot program (the average price reduction among these 25 molecules is over 50%), the National Healthcare Security Administration (NHSA) decided to expand the program to the whole country. Therefore, by December 2019, all of the rest part of China also implemented the CVBP of the same 25 molecules that were initially procured in the pilot stage, with minor changes in winners and bidding prices (three molecules have changes). Since then, the NHSA has implemented another seven rounds of CVBP at the national level between 2020 and 2023, and the procured molecules range from 16 to 61 in each round. Table 1 shows the timeline of each round of the CVBP and the corresponding number of successfully procured molecules.

The process of the CVBP is as follows: First, the NHSA determines the molecules (generic names) to procure for each round, and it collects quantity demanded from each province. Second, the NHSA announces the list of molecules to be procured to pharmaceutical firms and provides a list of quantity demanded by each province (with total, 50%, 60%, 70%, and 80% of the total quantity) for each molecule. Only producers of *branded-name* drugs or *bioequivalent* generics can sign up for the competitive bidding. Third, producers with the lowest prices in the competitive bidding win. If there is only one winner, this winner will supply the whole country with 50% of the reported quantity. If there are multiple winners, these winners will take turns to choose their supplying provinces, and for each chosen province, they are given 60%–80% of the reported quantity depending on the number of winners. The general rule of the *volume* and the contract length is stipulated by the official document of 4+7 pilot expansion (National Healthcare Security

Administration of the PRC, 2019a), which is that, one winner will be guaranteed with 50% of the market size (based on the reported quantity collected by the NHSA) with one year of procurement period; two winners will split 60% of the market with one year of procurement period (except for round 2 for two years of contract); three winners will split 70% of the market with three years of procurement period; and four and above winners will split 80% of the market with three years of procurement period.

In addition to these general rules at the national level, the central government also proposes guidelines to supplement the CVBP (National Healthcare Security Administration of the PRC, 2019b). However, whether to follow these guidelines or not are decided by each province. The guidelines from the central government include the following: (1) prepayment to suppliers to make sure that drug producers receive payment timely; (2) setting out-of-pocket payment higher for non-winning drugs, such as reference pricing or increasing coinsurance rates; (3) allowing hospitals to retain insurance savings from drug purchase and allowing hospitals to utilize part of these savings for staff compensation; and (4) monitoring, evaluating, and penalizing hospitals when needed.

3 Data and Sample

3.1 Data

Our main data source is the administrative drug procurement data, which contains detailed drug transaction records from all public healthcare institutions and private medical facilities participating in the public health insurance payment network in China.[3] Our data starts from January 2019 to June 2023, covers the CVBP from the 4+7 pilot stage up to the seventh round.[4] The dataset includes health care facilities' name, province, drug purchase date, active ingredient/molecule (generic name), formulation, strength, package size, price, quantity, producer, and distributor information. To compare quantity across different molecules directly, we convert the quantity into the number of Defined Daily Doses (DDDs). Similarly, to compare price across different molecules, we calculate the unit price, defined as price per DDD.

[3]The majority of the sample is hospitals, as they are the main health care providers in China. Clinics only account for a tiny share.

[4]The sixth round of CVBP focuses on insulin and follows different rules, which is therefore outside the scope of drugs studied in our research.

We supplement our main data with various hospital information to obtain hospital-level characteristics, such as hospital location and hospital tier, i.e., tertiary/secondary/community hospitals.[5] We also supplement our main data with firm-level data (China's Industrial and Commercial Registered Enterprises Database and https://www.yaozh.com/) to acquire characteristics of drug producers, such as firm location, capacity of producing APIs, and firm size. In addition, we collect bioequivalence approval information from the China's National Medical Products Administration to identify bioequivalent and non-bioequivalent generics. We also obtain city-level income and education attainment data as approximate measures for affordability, where the 2019 average annual salary of employees in each city is from the 2020 China Urban Statistical Yearbook, and the city-level average years of education come from the 2020 China Population Census.[6]

3.2 Sample

Due to the enormous size of the main dataset, we focus on four drug classes (ATC 4-th level) only: C09AA Angiotensin-converting-enzyme (ACE) inhibitors (antihypertensives), C10AA Hydroxymethylglutaryl -CoA (HMG-CoA) reductase inhibitors (Statins), A02BC Proton pump inhibitors (PPIs, anti-stomach acid), and N06AB Selective serotonin reuptake inhibitors (SSRIs, antidepressants). Within each drug class, we have 7–9 molecules. Due to lack of pre-periods, we exclude the pilot round (December 2018) from our analysis. To guarantee enough time period after the procurement, we limit our analysis to Rounds 1–5 only. According to the procured timing, we keep data from relative quarter -4 to 5 for procured molecules to focus on a relatively balanced panel. In the meantime, we keep all data for non-procured molecules in these drug classes as the control group.

A *winning firm* for a given molecule is defined as one of the drug producers win the competitive bidding with a (nearly) lowest price. However, as *winning firms* take turns to choose supplying provinces when there are multiple winners, we define *winning drugs* at the molecule-producer-province level. For example, if firm A is one of the winners for drug B, this drug B in supplying

[5]We mainly use hospital data from the following sources: https://yyk.99.com.cn/. For unavailable hospitals in this database, we did web scraping via Baidu.

[6]To avoid the effect of COVID-19 on individual income, we use the city-level income before the outbreak of COVID-19.

provinces is regarded as a *winning drug*, but it is a non-winning drug in non-supplying provinces.[7]

Our data includes all public healthcare institutions and private medical facilities participating in the medical insurance payment network in China, but only hospitals that have purchased drugs from one of the four drug classes (ACE, HMG, PPI, SSRI) are included in the sample. As shown in panel (a) of Figure A1, 2,992 tertiary hospitals and 9,046 secondary hospitals in China have purchased drugs from one of the four drug classes from January 2019 to June 2023. Moreover, there are also 72,660 community hospitals in our sample, mainly including community and township hospitals/health services centers. However, despite that tertiary hospitals account for a small share in total number of hospitals, panel (b) indicates that the market share of tertiary hospitals is 48.3%, and the remaining 50.7% of the drug market is occupied by other lower-level health care facilities.

3.3 Summary Statistics

Table A1 presents the summary statistics for the sample used in this study. After aggregating data at the hospital-molecule-quarter level, the dataset includes 2,206,641 observations. We present the the summary statistics of total sample, as well as the sample divided into pre- and post-CVBP periods, and we also calculate the difference between the pre-CVBP and post-CVBP sample.[8] Panel (a) provides details on the quarterly average unit prices, total DDDs, expenditures, share of winning and share of branded drug for purchases made by hospitals. The average unit prices decrease significantly from 5.12 RMB to 1.87 RMB, with a slight increase in the quarterly total DDDs from 8,808 to 10,755. As a result, expenditure decreases from 42,891 RMB to 17,051 RMB. Due to promised market share by the CVBP, the market share of winning drugs increases rapidly from 6% to 71%, while the market share of branded drugs decrease from 19% to 10%. We also provide characteristics at the hospital level. The share of tier 1, tier 2, and tier 3 hospitals remain similar across time. The number of drug producers remain at a similar level before and after the CVBP at the hospital level with a slight substitution from branded to generic drug producers.

Panel (b) of Table A1 reports the city-level market structure. Although there is a slight increase in the number of producers at the hospital level, the number of producers decreases by 0.6 at the

[7]Winning firm A do not need to stick to the CVBP-winning price in non-supplying provinces, and we will show in Section 5.2 that there is a gap between the winning price and the average price in non-supplying provinces.

[8]Non-procured molecules are assigned to pre-CVBP.

city level after the CVBP, driven by the decrease of both branded (-0.05) and generic (-0.55) drug producers. Finally, panel (c) presents the city-level characteristics. The average annual wage is 76,928 RMB in 2019, and the average years of education at the city level is 9.27 in 2020, which is slightly longer than nine years of compulsory education.

4 Empirical Strategy

4.1 Average Effects of the CVBP

We first document the average impact of the CVBP on various outcomes at the hospital-molecule-relative quarter level following equation (1) and equation (2):

$$y_{idk(t)} = \beta_0 + \beta_1 procured_d * post_t + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \tag{1}$$

$$y_{idk(t)} = \beta_0 + \sum_{k=-4, k\neq -2}^{k=5} \beta_k procured_d * 1(t - t_d^* = k) + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \tag{2}$$

where i represents hospital, d represents a molecule/generic name, $k(t)$ represents relative quarter with respect to the procurement date of molecule d. $y_{idk(t)}$ represents the following outcomes: average unit price, quantity (DDDs), and expenditure of molecule d by hospital i in relative quarter $k(t)$.[9] In addition, we examine the share of winning drugs (by quantity) and share of branded drugs of molecule d by hospital i in relative quarter $k(t)$.[10] $procured_d$ takes value 1 if a molecule d is procured by the CVBP up to Wave 5 (October, 2021); $procured_d$ equals to 0 if a molecule d is not procured until the end of our observed time period, i.e., June 2023. $post_t$ is a dummy variable, indicating whether a transaction is before or after the centralized procurement of molecule d. To deal with the potential anticipatory effect due to competitive bidding in relative quarter -1, we use relative quarter -2 as the reference period. To control for time-invariant characteristics of

[9] We aggregate our transaction data into quarterly level for each hospital.

[10] A winning drug of molecule d is defined as a drug produced by a competitive-bidding winning firm in its selected supplying province and of its winning strengths during the CVBP contract period. Therefore, it is the molecule-firm-strength-province pair. However, given that in general a firm either only produces one strength or all strengths of a molecule by a firm are selected by CVBP, the molecule-firm-strength-province pair can be reduced as molecule-firm-province pair.

hospitals and molecules, we include hospital-molecule fixed effects α_{id}. In addition, μ_t captures the calendar quarter fixed effects. To keep a relatively clean comparison window (balanced sample), we restrict our analyses to four relative quarters before and six relative quarters after the centralized procurement of molecule d.[11] Standard errors are clustered at the hospital level to adjust for potential serial correlation within hospitals.

For market structure, we consider market concentration (as measured by Herfindahl-Hirschman Index [HHI]) and variety of drugs at different levels: hospital, city, and province level. We follow the same specification as equation (1). However, i represents hospital, city, and province, respectively when assessing the market structure at different levels. We consider the following $y_{idk(t)}$: HHI, number of producers, number of high-price drugs, number of low-price drugs, number of branded drugs, and number of generics, where high-price and low-price is defined as above and below the median price of all drugs of molecule d in the pre-CVBP period.

In addition to the two-way fixed effects (TWFE) model, due to the staggered treatment timing, we also show results using the advanced estimation method from Callaway and Sant'Anna (2021); Sun and Abraham (2021); Borusyak et al. (2024) as robustness checks.

4.2 Spillover effects on non-winning drugs

The above section examines the changes in average price of procured molecules. However, the changes in average price can be driven by either price reduction of each drug (molecule-firm pair) or the composition change of drugs purchased by each hospital or both. The second channel is largely mechanical, as CVBP encourages utilization of winning drugs.

Therefore, we mainly consider the price change of winning drugs and the spillover effects on non-winning drugs. Specifically, we divide non-winning drugs into three sub-categories: non-winning branded drugs, non-winning bioequivalent drugs, and non-winning non-bioequivalent drugs. Due to competitive bidding, prices of winning drugs will certainly decrease. However, it remains an empirical question to examine the price changes of non-winning drugs. Moreover, if there are multiple winners, given that winners in non-supplying provinces do not need to follow

[11] There are always two winners since Round 2, and thus the contracts since Round 2 are always at least two years. Since our data ends by June 2023, molecules procured in Round 5 can only be observed with six full quarters after procurement.

the bid-winning price, it is also worthy examining how winners price in non-supplying provinces for their winning drugs. We expect to see a larger price decrease for more substitutable drugs, i.e. generics, and a smaller effect on branded drugs, but we are more unsure how winning firms would charge in non-supplying provinces. In addition to the post-CVBP average effects, we also show the event study results to explore how fast competing drugs decrease their price following the price reduction of winning drugs.[12]

4.3 Trade-offs in the demand and supply sides

While we have documented the average effects of the CVBP in reducing drug prices, drug expenditures, and shuffling the market structure, we still need to understand the trade-offs behind the program, which can lead to important welfare implications and will inform the design of future policies. Specifically, we look at the heterogeneous effects on different patient groups to understand the direct impacts on the demand side. In addition, we examine suppliers' responses and suppliers' characteristics to understand how firms can affect patient welfare under the CVBP.

4.3.1 Who benefits?

First, we expect the CVBP to increase drug utilization due to lower prices of drugs, and such effect should be more pronounced among molecules with a higher price before the CVBP and among patients with lower affordability, as they are more likely to have unmet medical needs due to higher drug prices before the CVBP.

To test these hypotheses, we estimate the equation (3):

$$ln(Q_{idk(t)}) = \beta_0 + \beta_1 procured_d * post_t + \beta_2 procured_d * post_t * \textit{affordability}_i + \beta_3 procured_d * post_t * \textit{Pgeneric}_{dt-} + \beta_4 procured_d * post_t * \textit{Pgeneric}_{dt-} * \textit{affordability}_i + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \quad (3)$$

where $Q_{idk(t)}$ represents total quantity of molecule d at hospital i in relative quarter $k(t)$. $\textit{affordability}_i$

[12] In the context of the CVBP, Cao et al. (2022) also study the spillover effects, focusing on how the CVBP has affected pharmaceutical firms' pricing and advertising strategies. They find that non-winning firms raised prices in non-procurement retail markets (especially for public-insured/essential medicines) and shifted advertising focus toward brand-building (notably for low-awareness brands) over product features, revealing unintended spillover effects of market centralization. Similar with previous literature, they also only focus on the first "4+7" round of the CVBP. However, we extend our analysis to the national level and include dynamic effects over time.

takes different affordability measures: (1) city-level average income, and (2) city-level average education level. $Pgeneric_{dt-}$ indicates the average price of generics of molecule d in the pre-VBP period $t-$. We also consider the interaction between these two factors: $Pgeneric_{dt-} * affordability_i$.

We expect β_2 to be negative when $affordability_i$ increases, as richer people are likely to have less unmet medical need before CVBP. We expect β_3 to be positive, as molecules with a higher (generic) price before CVBP should see a greater increase in demand after the price reduction under CVBP.[13] Finally, we expect β_4 to be negative, as for more expensive drugs, the increase in demand should be lower among richer people than poorer people after price reduction under CVBP.

4.3.2 Who is potentially hurt?

Second, many patients would face a switch of drugs under CVBP given that winning drugs are guaranteed with a *volume*. As winning drugs are mostly bioequivalent generics, patients who switch from a branded drug to a winning generic are expected to experience a greater disruption in drug utilization. Such a switch in drug may lead to ambiguous effects in drug utilization. On the one hand, (perceived) decrease in drug quality may lead to an increase in drug utilization due to less effectiveness and more dosages needed for a winning drug; on the other hand, patients may refuse to switch drugs, but under CVBP, they might have a hard time accessing branded drug within a hospital (and even in outside pharmacies), which might lead to a decrease or even a cease in drug utilization.

To test hypothesis 2, ideally, we would use individual-level claim data and estimate the following equation:

$$ln(Q_{jdk(t)}) = \beta_0 + \beta_1 procured_d * post_t + \beta_2 procured_d * post_t * switchBG_{jd} + \alpha_{jd} + \mu_t + \epsilon_{jdk(t)}, \quad (4)$$

where $Q_{jdk(t)}$ represents drug utilization of molecule d by individual j in relative quarter $k(t)$. $switchBG_{jd}$ indicates whether individual j switches from a branded drug to a winning generic under CVBP.[14] α_{jd} represents individual-molecule fixed effects, which captures a patient's branded drug preference, affordability, and other time-invariant characteristics.

[13] Here, we implicitly assume that demand elasticities for drugs in our sample are similar.

[14] Assuming that a patient who used branded drug before CVBP would prefer branded drug after CVBP, such a switch is more likely to be a forced switch.

However, given the lack of individual-level claim data, we can only approximate such variation with hospital-level data and estimate the following econometric specification:

$$ln(Q_{idk(t)}) = \beta_0 + \beta_1 procured_d * post_t + \beta_2 procured_d * post_t * switchBG_{id} + \beta_3 procured_d * post_t * priceDif_{id} + \beta_4 procured_d * post_t * X_i + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \quad (5)$$

where $switchBG_{id}$ takes 1 if the dominant drug of molecule d in a hospital i before CVBP is a branded drug and the post-VBP winning drug of molecule d for hospital i is a generic drug. Compared to hospitals which mainly experience a smoother transition (from a dominant generic to the winning generic), hospitals which switch from a dominant branded drug to a winning generic experience a larger shock under CVBP. However, such a more profound switch may capture not only the change in (perceived) drug quality but also other confounding factors. First, hospitals with $switchBG_{id} = 1$ experience a greater reduction in drug prices ($priceDif_{id}$); second, hospitals with different drug utilization patterns before CVBP can be different in various aspects (X_i), such as hospital tier, location (rural/urban, rich/poor, etc.), and relationship with winning and non-winning firms. As we cannot perfectly control for all potential confounding factors, we should take β_2 for caution, as it not only reflects the quality effect but also other potential confounding effects.[15]

In addition to the average change in drug utilization, we also divide drug classes into two subgroups: (1) drugs for chronic conditions (ACE inhibitors and Statin) and (2) drugs not only for chronic conditions (PPI and SSRI). We expect β_2 to be slightly negative for the first group due to potential resistance from patients who have developed brand loyalty due to prolonged use a given drug, whereas for the second group, we are less agonistic, but if $\beta_2 > 0$, it suggests that generics might be less effective than branded drugs and thus patients need higher doses.

4.3.3 Suppliers' moral hazard?

Related to the potential quality downgrade from branded to generic drugs, we next examine a potential quality downgrade driven by suppliers, where we focus on winning firms, who are the main drug provider after the CVBP. Although bio-equivalence checks are done by the state-level

[15]To deal with selection on unobservables, we gradually add more controls to show if the estimates of β_2 are robust across specifications (Altonji et al., 2005; Oster, 2019).

CFDA, manufacturing process changes (MPCs) are done at the province level. Anecdotal evidence suggests that such MPCs are mostly due to cost savings and may undermine the drug quality but undergo less strict scrutiny by local FDAs. To test for this hypothesis, we collect information on MPCs for each firm and estimate the following equation:

$$ln(Q_{idk(t)}) = \beta_0 + \beta_1 procured_d * post_t + \beta_2 procured_d * post_t * \textbf{\textit{winMPC}}_{idt} + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \quad (6)$$

where $\textbf{\textit{winMPC}}_{idt}$ indicates that a winning generic drug of molecule d for hospital i has done a MPC at time t, which could potentially lower the drug quality. The other variables remain the same as in equation (5). We expect β_2 to be positive, as quality downgrade is likely to lower drug efficacy and thus more dosages are needed.

Moreover, if a winning firm's MPC is related to a downgrade in drug quality among winning generics, then such a quality difference would be more salient for hospitals which predominantly used a branded drugs before the CVBP. As such, we estimate equation (7) to test our hypothesis:

$$\begin{aligned} ln(Q_{idk(t)}) = \beta_0 + \beta_1 procured_d * post_t + \beta_2 procured_d * post_t * \textbf{\textit{winMPC}}_{idt} + \beta_3 procured_d * post_t * switchBG_{id} \\ + \beta_4 procured_d * post_t * switchBG_{id} * \textbf{\textit{winMPC}}_{idt} + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \quad (7) \end{aligned}$$

Following the same logic as in equation (6), we expect both β_2 and β_4 to be positive, as if there were quality downgrade (less efficacy) for a winning drug due to MPC, hospitals switching from a branded drug to such a winning drug would experience a greater disruption than the rest hospitals.

4.3.4 Suppliers' reliability?

As winning firms are guaranteed with a large *volume* under CVBP, it casts doubt on whether winning firms can sufficiently meet the increased demand in the market, especially for a big country like China. Zhou et al. (2023) shows that supply shortage reports are more often among procured molecules after the CVBP, especially among winning drugs. It is possible that small winning firms are more likely to have the shortage problem due to limited capacity in production and/or lack of sufficient supply of APIs, which accounts for 40–60% of the total production cost. In addition, hospitals that are located far away from a winning firm might also suffer more from drug shortage

due to higher transportation costs.

To test this hypothesis, we estimate the following equations:

$$ln(Q_{idk(t)}) = \beta_0 + \beta_1 procured_d * post_t + \beta_2 procured_d * post_t * Z_{id} + \alpha_{id} + \mu_t + \epsilon_{idk(t)}, \quad (8)$$

where Z_{id} represents different characteristics of winning firms: (1) whether a winning firm for hospital i of molecule d is a top-100 pharmaceutical firm in China, (2) whether a winning firm for hospital i of molecule d is able to produce APIs for this winning drug, (3) number of API producers of molecule d, (4) whether the winning firm of drug d and hospital i is located in the same province, and (5) distance between the city where hospital i is located and the city where the headquarters of the winning firm of molecule d are located. The first two measure the manufacturing capacity of winning firms, the third one measures molecule-level capacity of producing APIs, and the last two measure the transportation efficiency from a winning firm to a supplying hospital. We expect β_2 to be positive for the first fours measures, as big firms, firms with the capacity of producing APIs, molecules with more API producers, and firms that are closer to a supplying hospital are more likely to have stable supply and are more likely to be trusted by buyers. Similarly, we expect β_2 to be negative when Z_{id} takes the distance between a hospital and a winning firm, as longer distance is more likely to lead to supply shortages.

5 Average and Dynamic Effects of the CVBP

5.1 Average effects at the hospital level

Table 2 presents results from regression (1). We examine the average price effect in column (1). It indicates that the average price significantly decreases by 54%. Column (2) explores the effect of CVBP on quantity, which shows a significant increase in total DDDs. After the CVBP, the quantity of procured molecules increases by 8% relative to non-procured molecules. The increase in quantity and the decrease in price simultaneously affect the total expenditure. The result in column (3) shows that the decrease in price dominates, as the total expenditure of hospitals for procured molecules decreases by 50% compared to non-procured molecules. In columns (4) and (5), we estimate the changes in share of winning drugs of each molecule at the hospital level. Recall that government

commit specific market share for winning firms according to the total number of winning firms for one molecule. To account for the inconsistency of different molecules, we standardize this outcome variable by the commitment share. The coefficient of the interaction term between the $procured_d$ and the $post_t$ dummy is positive and significant, indicating that after the implementation of the CVBP, completion rate increases by 0.749 relative to that of non-procured molecules (always zero). Along this line, the market share of winning drugs increases 50% after the implementation of the CVBP. Finally, most of winning firms' drugs are generic drugs. Therefore, the share of branded drugs decreases by 12.9% after the implementation of CVBP, where the average share of branded drug is only 19%.

In addition to the DID average effects, we show the event study results with the TWFE model together with three advanced estimation methods in Figure 1. All methods yield similar estimates. The parallel trends assumption holds across estimators, as coefficients for quarters preceding CVBP implementation at a hospital-molecule level are close to zero, though they may be significant due to the potential anticipatory effect of CVBP. As shown in Table 1, the bidding period typically begins one quarter or more before implementation, which allows for this anticipatory effect. However, the divergence between procured and non-procured molecules before CVBP is considerably smaller than after CVBP. Figure 1 also highlights the dynamics of treatment effects, showing that all recently developed robust estimators indicate treatment effects that increase and stabilize in the post-periods.

Having documented the average effects across the first five national rounds of the CVBP, Figure A2 shows the estimates by each round. The effects are generally comparable across each round, except for drug utilization, which only increased in the first two round but not in the following three rounds.

A back-of-envelope calculation suggests that the CVBP can potentially save drug expenditures by 603.6 billion RMB (50.3%*1200 billion RMB, the generics sales in 2023), equivalent to 0.48% of China's GDP (126 trillion RMB) in 2023.

5.2 Spillover effects on price of non-winning drugs

The competitive bidding of the CVBP may not only lower prices of winning drugs, but may also force non-winning drugs to lower their prices due to competitive pressure. We examine

such spillover effects in Table 3. Although Panel A shows that unit prices of all drug subgroups decrease after the CVBP, Panel B reveals that reductions are much smaller among other groups than winning drugs in the supplying provinces. Despite that winning drugs' prices decrease by 43% in the supplying provinces, their prices in non-supplying provinces only decrease by 10%. Among competing drug groups, branded drugs' prices decrease by 11%, other bioequivalent generic drugs' prices decrease by 5%, and nonbioequivalent drugs' prices even increase by 5%.

Figure 2 shows the dynamic changes in drug prices. Despite that reductions of winning drugs remain stable over time, the price reductions of competing drugs are most salient in the second quarter after the CVBP, and they gradually recover to the pre-CVBP level since then. By the six quarter after the CVBP, the reductions in prices of competing drugs (branded and bioequivalent drugs) are almost negligible.

5.3 Robustness Checks

We run a series of robustness checks for our average effects of the CVBP. First, one concern regarding using the non-procured molecules within the same drug class as the control group is that there might be substitution between treatment and control molecules within the same drug class. To alleviate such a concern, we randomly assign a treatment timing for the non-procured molecules (out of the respective implementation times of the CVBP across rounds 1–5 within a drug class) and then present the raw trends in relative quarters for procured and non-procured molecules. Figure A3 suggests that substitution may not be a big issue, as there is no structural break in the control group. In addition, we conduct an event study without the control group as a robustness check, shown in Figure A4. The results are robust and similar to our main estimates in Figure 1.

Second, one may be concerned that our baseline regression are driven by a particular molecule. To check this possibility, we drop one treated molecule from our baseline sample each time and re-run the analysis with the rest molecules to examine whether the estimated effects vary considerably. As shown in Figure A5, for all five outcome variables, the estimated effects of the CVBP remain similar to the baseline estimates.

Third, our identification relies on the parallel trend assumption, which has been shown in Figure 1 across multiple methods. While we find substantial differences in our event-study coefficients

before and after the CVBP, one concern is that the small confidence intervals cause some coefficients to be significant in the pre-period. Therefore, we explore how well-powered these pretrends tests are in our context. We turn to the approach proposed by Rambachan and Roth (2023) and present sensitivity analysis to alternative assumptions about possible violations of parallel trends in the pre-treatment period. The analysis can support checking the estimator developed by Callaway and Sant'Anna (2021) in the setting of staggered treatment timing. Therefore, we present the results in Figure A6 for each outcome variable. Findings indicate a "breakdown value" of 2, meaning that in order for the statistically significant coefficient to be fully explained by confounding factors, a violation in parallel trends in the post-period would need to be at least two times of the size of the maximum deviation in the pre-period.[16]

6 Beyond Price Reductions: Trade-offs and Lessons

6.1 Satisfying patients' unmet medical need

Table 4 reports estimated results from equation (3). In column (1), we calculate the average price of generic drugs in each province and analyze whether an increase in the quantity of molecules with a higher average price is due to unmet needs. The positive and significant coefficient indicates that a one RMB increase in the average price of generic drugs corresponds to an increase of 0.4% DDDs for procured molecules compared to non-procured molecules after the CVBP.

Columns (2) through (5) reveal more nuanced effects. In columns (2) and (3), we use city-level income data to investigate whether price reductions enable lower-income groups to purchase drugs they previously avoided. The coefficient in column (3) is negative and significant, suggesting that after the CVBP, lower-income groups are more likely to purchase drugs from procured molecules compared to non-procured ones. This effect is more pronounced for molecules with a higher average price of generic drugs, as shown in column (4). Similarly, we examine the effects using education

[16]Recently, there are some studies adopting this method to assess the sensitivity of their results. For example, Jones and Pineda-Torres (2024) report that the confidence interval contains 0 when $\bar{M}$ equals 1.25. Barrot et al. (2024) also find that many of their confidence intervals for the dependent variables contain 0 when $\bar{M}$ equals 1. The results in Fu et al. (2024) show that the confidence interval contains 0 when $\bar{M}$ equals 2. Our results indicate that confidence intervals in panels (b) and (e) contain 0 when $\bar{M}$ equals 2, confidence intervals in other panels do not contain 0 even when $\bar{M} > 2$. Therefore, in order for the statistically significant coefficients to be fully explained by confounding factors, a violation in parallel trends in the post period would need to be at least 200% of the size of the maximum deviation in the pre-period. Compared with the above literature, our baseline results are robust enough.

data as a proxy for affordability. The statistically significant results in columns (4) and (5) confirm the same unmet needs effect observed previously.

6.2 Patient's drug disruption: Switching from branded to generics

We estimate the equations (5) to examine the effects on patients' drug utilization due to (perceived) changes in drug quality after switching from a branded to a (generic) winning drug after the CVBP. Column (1) of table 5 shows the changes at the extensive margin, where the outcome variable is a dummy variable indicating whether the hospital buy winning drugs of molecule d after the CVBP. The coefficient is negative and significant, demonstrating that hospitals which predominantly used branded drugs before the CVBP are less likely to buy winning drugs afterwards, indicating a resistance from the demand side.

Columns (2)–(5) explore the intensive margin for procured molecules, i.e., the utilization of drugs after a hospital switch from branded drug-dominated before the CVBP to winning generic-dominated after the CVBP. We gradually add more control variables across columns. After controlling for different price reductions across hospitals, hospital characteristics, and city-level characteristics, we find that for hospitals who predominantly relied on branded drugs before, switching drugs under the CVBP is associated with a 16% increase in drug utilization.[17] Since we have teased out most compelling confounding factors that can drive an increase in drug utilization, we interpret such a positive correlation as lower efficacy incurring an increase in higher doses.

To better understand what drives such an increase in utilization after switching from branded to generic drugs, we divide our four drug classes into two groups: drug classes for chronic conditions (CCs) and drug classes with more flexible use.[18] Our reasoning is that patients with CCs may have more decision power and stickiness to their preferred drugs, while the later group is more likely to be directed by physicians due to lack of knowledge of drugs and/or acute situations of their diseases. Figure 3 demonstrates the different responses by different drug classes. For CC drug classes, we find a slight decrease in drug utilization after the CVBP, whereas for drug classes with more flexible

[17] If we take into account of the higher doses needed to maintain the same efficacy of a drug, the post-CVBP effective price becomes (1-54%)*116%=0.53 of the pre-VBP original price, and thus the actual price reduction is only 47% rather than 54%.

[18] Drug classes primarily for CCs include ACE inhibitors, SSRIs and Statins. Drug classes with more flexible use include PPIs.

use, we find a sharply 70% increase in drug utilization after the CVBP. This reveals that patients with CCs show a resistance to winning generics, while other patients need to use more doses after the switch from branded to winning generic drugs.

6.3 Suppliers' manufacturing process change

Related to the (perceived) quality change due to switch from branded to generic drugs directly from the CVBP, there are also potential quality changes among winning drugs. We detect a few suspicious manufacturing process changes of winning producers after the implementation of CVBP, with examples shown in Table A2. Table 6 shows that drug utilization increases by 13% after a winning firm changes its MPC, and such effects are more pronounced (with an additional 47% increase in drug utilization) among hospitals that predominantly used branded drugs before the CVBP.[19] This evidence suggests that winning producers' suspicious manufacturing process change leads to lower efficacy and thus higher doses needed.

6.4 Suppliers' capacity and reliability

Table 7 shows the coefficients by estimating equation (8). Columns (1) and (2) indicate that hospitals are around 20% more likely to buy winning drugs from a big firm and firms that can produce APIs by themselves. Furthermore, despite that prices of winning drugs are fixed under the CVBP, prices of raw materials can fluctuate, especially when raw materials (especially APIs) are monopolized. Therefore, when there is a shortage or high price of raw materials, there is a high possibility of a shortage in the supply of winning drugs. Column (3) confirms that supply would be more sufficient when there are more API producers.

As transportation cost is also a key factor affecting the supply side, especially for the promised big market under the CVBP, columns (4) and (5) consider how transportation costs affect the delivery of drugs after the CVBP. Column (4) shows that total quantity increases additionally by 13% for hospitals that is located in the same province as the winning firm. Similarly, column (5)

[19] Due to the significant price decreases of winning drugs and the increased market to serve, producers may reduce costs by changing manufacturing processes, which includes changing their raw material providers and/or modifying their manufacturing processes across different procedures. However, anecdotal evidence suggests that such changes may lead to a decrease in drug quality of winning drugs. In fact, any part of the manufacturing process can be manipulated to make data look good for drug evaluations by FDAs (Eban, 2019).

shows that when hospitals and winning firms are more distant, the supply would be lower.

7 Discussion and Conclusion

This paper documents the effectiveness and lessons from the CVBP. Firstly, we examine the average effects, and we document a substantial reduction in drug prices, a modest increase in drug utilization, and a great saving of drug expenditure. In addition, the market shuffles for generic and branded drugs. Except for drug utilization, which only increases in the first two rounds, the other outcomes remain comparable across rounds. Secondly, we examine the trade-offs of both the demand and the supply sides. We show that lower drug prices especially benefit low-income people by improving their access to cheaper drugs. However, for patients who predominantly used branded drugs before the CVBP, they show resistance for drugs treating chronic conditions and their utilization increases for drugs not only for chronic conditions, suggesting that they are potentially hurt due to switching drugs. Furthermore, we show that winning firms may react to the low bid-winning price and a huge market need by changing their raw material providers and/or modifying their manufacturing processes. Such changes also lead to an increase in drug utilization, suggesting lower efficacy of drugs. Finally, we show that big firms, firms that can produce their own APIs, and firms that are close to a hospital can better ensure delivery sufficiency.

Our findings show that centralized procurement can be an effective policy in saving drug expenditures, and low-income people would especially be benefited. However, there is a trade-off between allocated market share for winning (generic) drugs and the rest, especially given that many hospital buyers tend to take the one-size-fits-all approach by only buying winning drugs to easily meet the requirement from local and central government. In addition, both the central and local governments should be more cautious with modifications made by drug producers after winning a CVBP bid to ensure the quality of drugs do not change due to budget and capacity constraints faced by winning firms. Finally, the government could offer favorable conditions to incentivize winning firms to select close-by provinces in the supplying-province selection step.

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Figures and Tables

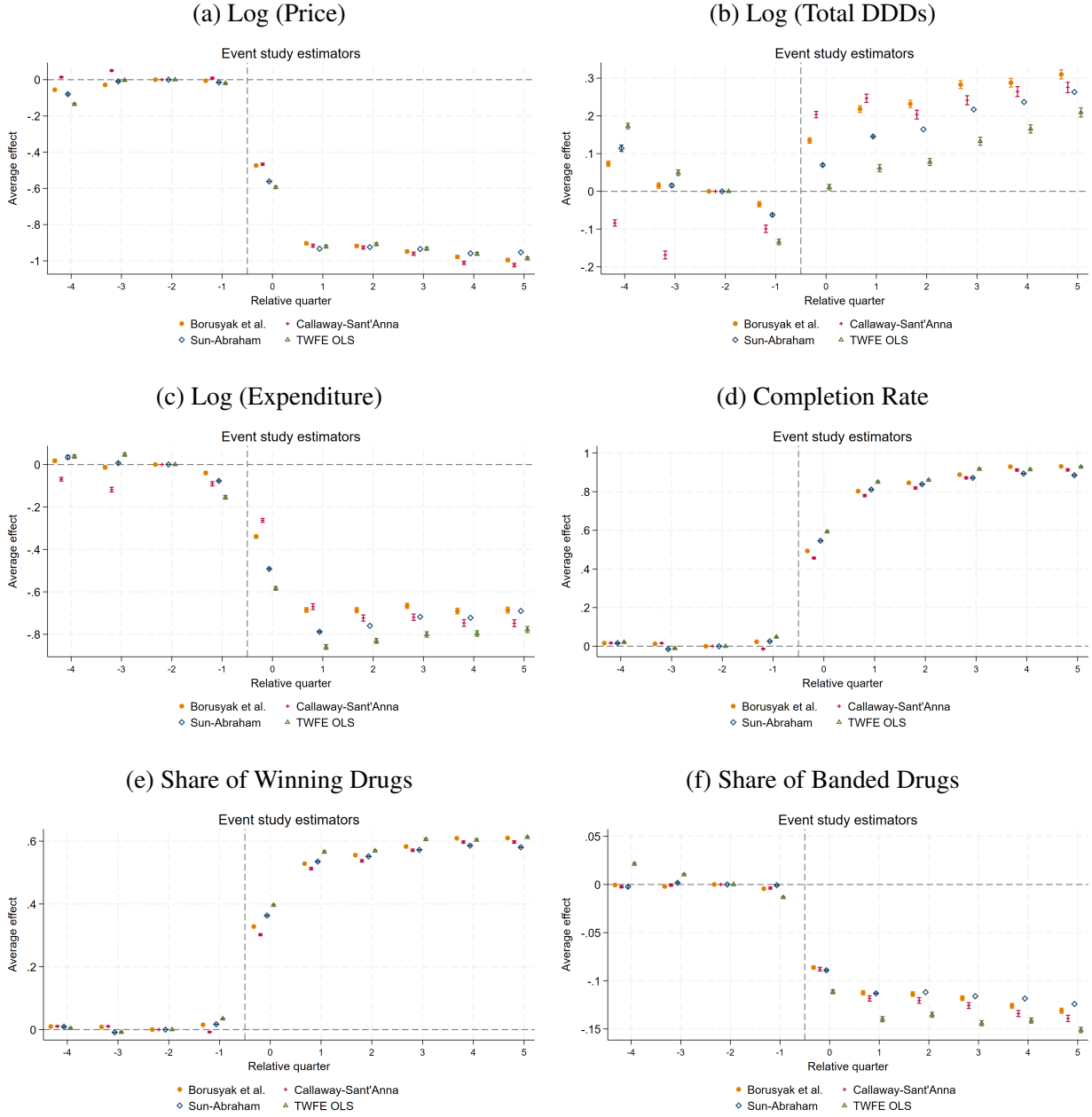
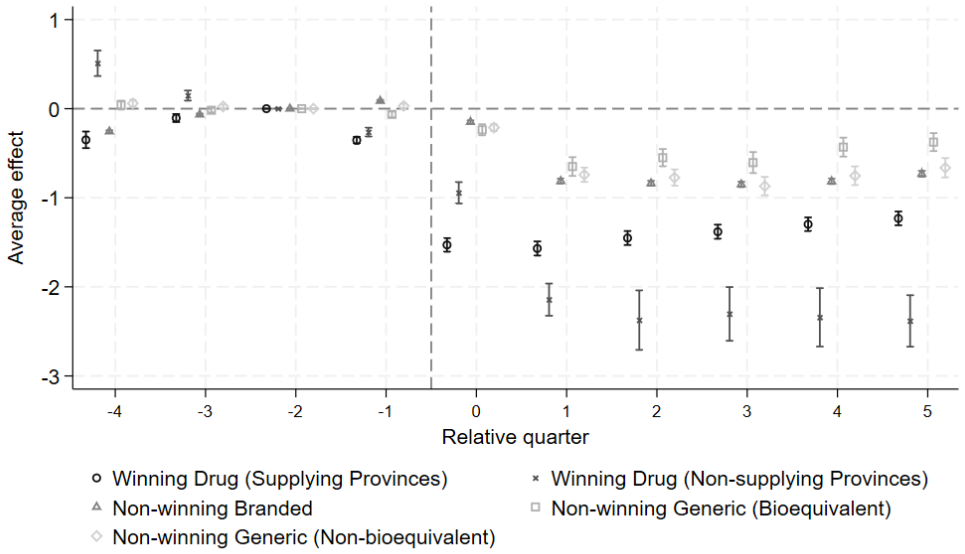


Figure 1: Event Study with Different Estimators

Notes: These figures use the total sample including four drug classes. These figures overlay the event-study plots constructed using four different estimators: Borusyak et al. (2024) (in orange with circle markers); Callaway and Sant'Anna (2021) (in red with cross markers); Sun and Abraham (2021) (in blue with diamond markers); and a dynamic version of the TWFE model estimated using OLS (in green with triangle markers). Reference quarter of estimators is set as -2. All estimations control quarter and hospital-molecule fixed effects if the estimation requires fixed effects. The quarters in these figures are natural quarters, but the CVBP may not have been implemented at the beginning of relative quarter 0. Therefore, the effects in relative quarter 0 are smaller than subsequent quarters as they may contain some transactions that took place before the policy was implemented. Moreover, the confidence intervals that doesn't seem to exist in most of these figures does not stem from methodological oversight but reflects their negligible width relative to the magnitude of the coefficient estimates.

(a) Price



(b) Log (Price)

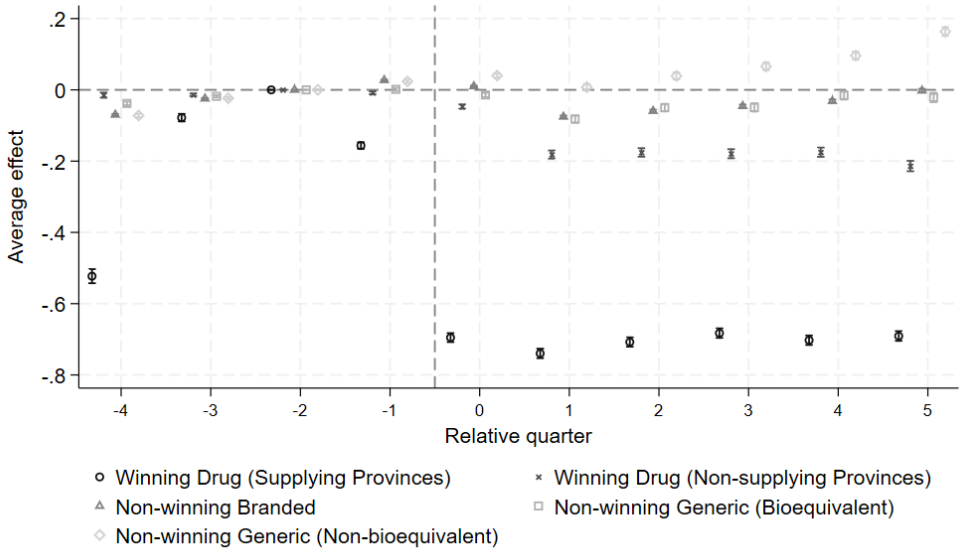


Figure 2: Dynamic Effects of Winning and Non-winning Drugs

Notes: This figure presents the dynamic effects of CVBP on price of different types of drugs. In fact, the confidence intervals that doesn't seem to exist in most of these figures does not stem from methodological oversight but reflects their negligible width relative to the magnitude of the coefficient estimates.

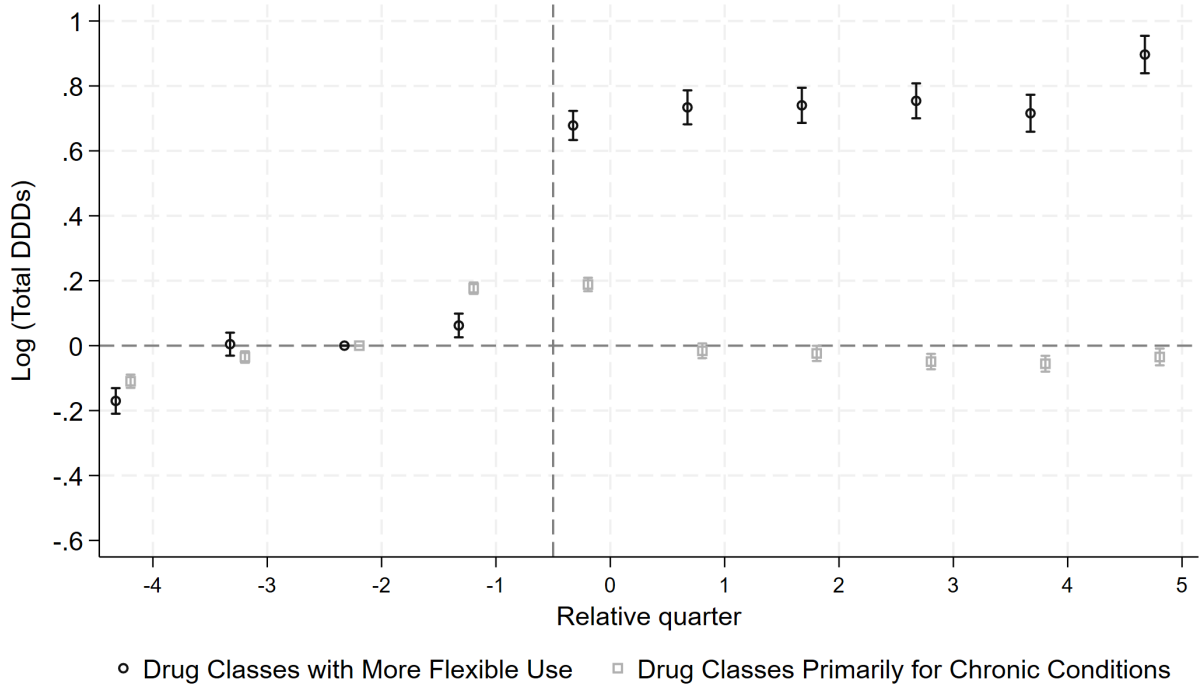


Figure 3: Dynamic Effects of Heterogeneous Effects by Whether a Hospital Switching from Branded to Generic Drugs

Notes: This figure presents the dynamic effects of the CVBP on drug utilization among hospitals switching from branded drug-dominated to winning generic drug-dominated. We divide drug classes into two subgroups: (1) drug classes with more flexible use and (2) drug classes primarily for chronic conditions. The former includes PPIs, and the later includes ACE inhibitors, SSRIs, and Statins.

Table 1: Timeline of CVBP

Round	No. of molecules	Competitive bidding time	Implementation time
0 (4+7 pilot)	25	2018.12	2019.3
1 (The rest of China)	25	2019.9	2019.12
2	32	2020.1	2020.4
3	55	2020.8	2020.11
4	45	2021.2	2021.5
5	61	2021.6	2021.10
6 (Insulin only)	16	2021.11	2022.5
7	61	2022.7	2022.11
8	39	2023.3	2023.7

Table 2: Average Effects of the CVBP

	(1) Log (Price)	(2) Log (Total DDDs)	(3) Log (Expenditure)	(4) Completion Rate	(5) Share of Winning	(6) Share of Branded Drugs
Procured × Post	-0.775***	0.077***	-0.698***	0.749***	0.498***	-0.129***
	(0.004)	(0.003)	(0.005)	(0.002)	(0.002)	(0.001)
Constant	0.727***	7.649***	8.377***	0.220***	0.136***	0.207***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Hospital × Molecule FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Mean of Y (Before VBP)	0.98	7.46	8.44	0.10	0.06	0.19
Mean of Y (After VBP)	-0.31	7.75	7.44	1.09	0.71	0.10
Percentage Change	-53.91	8.01	-50.22			
# of observations	2099156	2099156	2099156	2099156	2099156	2099156
R^2	0.88	0.82	0.85	0.80	0.79	0.81

Notes: This table presents DID estimators from equation 1 by using all sample including ACE, HMG, PPI, and SSRI. The observation period contains relative quarters -4 to 5. The outcome variables are unit price in column (1), quantity (total DDDs) in column (2), expenditure in column (3), completion rate in column (4), share of winning drugs (by quantity) in column (5), and share of branded drugs (by quantity) in column (6) respectively. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3: Effects of the CVBP on Average Unit Price by Drug Types

(a) Price

	(1) Winning Price (Supplying Provinces)	(2) Winning Price (Non-supplying Provinces)	(3) Non-winning Price	(4) Non-winning Branded Price	(5) Non-winning Bioequivalent Generics Price	(6) Non-winning Non-bioequivalent Generic Price
Procured × Post	-1.578***	-2.371***	-0.889***	-0.719***	-0.448***	-0.698***
	(0.055)	(0.151)	(0.035)	(0.011)	(0.043)	(0.034)
Constant	2.443***	8.055***	5.444***	7.190***	4.797***	4.396***
	(0.051)	(0.069)	(0.011)	(0.005)	(0.011)	(0.006)
Hospital × Molecule FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Mean of Y (Before VBP)	2.75	8.55	5.28	7.29	5.12	4.15
Mean of Y (After VBP)	0.84	4.78	4.80	6.40	3.20	4.43
Market Share (Before VBP)	0.14	0.21	0.65	0.26	0.22	0.17
Market Share (After VBP)	0.77	0.05	0.17	0.08	0.06	0.04
Market Share Per Firm (Before VBP)	0.06	0.09	0.04	0.26	0.04	0.01
Market Share Per Firm (After VBP)	0.23	0.02	0.01	0.08	0.01	0.00
# of observations	859589.00	185372.00	1374459.00	368656.00	423977.00	505526.00
R^2	0.77	0.96	0.91	0.99	0.94	0.98

(b) Log (Price)

	(1) Winning Price (Supplying Provinces)	(2) Winning Price (Non-supplying Provinces)	(3) Non-winning Price	(4) Non-winning Branded Price	(5) Non-winning Bioequivalent Generics Price	(6) Non-winning Non-bioequivalent Generic Price
Procured × Post	-0.433***	-0.099***	-0.023***	-0.111***	-0.054***	0.048***
	(0.008)	(0.006)	(0.002)	(0.001)	(0.004)	(0.003)
Constant	-0.327***	0.868***	0.996***	1.732***	0.923***	0.706***
	(0.007)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)
Hospital × Molecule FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Mean of Y (Before VBP)	0.24	0.90	1.02	1.71	1.02	0.78
Mean of Y (After VBP)	-0.82	0.69	0.82	1.66	0.42	0.22
# of observations	859589	185372	1374459	368656	423977	505526
R^2	0.95	0.98	0.94	0.99	0.96	0.95

Notes: This table presents the effects of CVBP on average price of different drug types. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4: Heterogeneous Effects of the CVBP on Drug Utilization by Affordability

	(1)	(2)	(3)	(4)	(5)
Procured × Post	0.051***	2.916***	2.291***	0.683***	0.565***
	(0.004)	(0.119)	(0.130)	(0.027)	(0.033)
PreVBP Generic Price	0.005***		0.136***		0.023***
	(0.000)		(0.016)		(0.004)
Procured × Post × Log (Wage)		-0.249***	-0.196***		
		(0.010)	(0.011)		
Procured × Post × PreVBP Generic Price × Log (Wage)			-0.012***		
			(0.001)		
Procured × Post × Years of Education				-0.062***	-0.052***
				(0.003)	(0.003)
Procured × Post × PreVBP Generic Price × Education					-0.002***
					(0.000)
Constant	7.653***	7.663***	7.666***	7.662***	7.666***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hospital × Molecule FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Mean of Y (Before VBP)	7.46				
Mean of Y (After VBP)	7.75				
# of observations	2062320	1972394	1939926	1997243	1963761
R^2	0.82	0.82	0.82	0.82	0.82

Notes: This table shows heterogeneous results of CVBP on log (total DDDs) by affordability. The sample is a little less than baseline sample due to the data limitation of wage and education data in some small cities in China. $PreVBPGPrice$ represents pre-CVBP average price of generic drug for molecule d in every province. More expensive in molecule's average price, more people can not afford this molecule. $Log(Wage)$ and $YearsofEducation$ are the Log of average wage and average years of education in each city, respectively. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5: Heterogeneous Effects of the CVBP on Drug Utilization by Whether Switch from Branded to Generic Drugs

	Whether Buy Win	Log (Total DDDs)			
	(1)	(2)	(3)	(4)	(5)
Branded-dominated	-0.060***				
	(0.003)				
Procured × Post × Branded-dominated		0.052***	0.050***	0.112***	0.158***
		(0.007)	(0.007)	(0.007)	(0.008)
Procured × Post × Price Diff			0.005***	0.005***	0.006***
			(0.000)	(0.000)	(0.000)
Procured × Post × Tertiary Hospitals				-0.131***	-0.186***
				(0.012)	(0.012)
Procured × Post × Secondary Hospitals				-0.034***	-0.084***
				(0.009)	(0.009)
Procured × Post × Rural Hospital				0.127***	0.056***
				(0.008)	(0.008)
Procured × Post × Log (Wage)					-0.305***
					(0.019)
Procured × Post × Years of Education					-0.018***
					(0.005)
Procured × Post		0.155***	0.130***	0.072***	3.750***
		(0.004)	(0.004)	(0.007)	(0.184)
Constant	0.708***	7.810***	7.812***	7.811***	7.823***
	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
Hospital × Molecule FE		✓	✓	✓	✓
Quarter FE		✓	✓	✓	✓
Hospital FE	✓				
Molecule FE	✓				
Mean of Y	0.69				
Mean of Y (Before VBP)		7.46			
Mean of Y (After VBP)		7.75			
# of observations	383175	1514907	1514907	1514907	1443210
R^2	0.48	0.81	0.81	0.81	0.81

Notes: This table shows heterogeneous results of CVBP on log (total DDDs) by whether branded changing to winning drugs. We show the event study results for two groups in Figure 3. $Branded - dominated$ equals to one if the molecule d of hospital i is dominated by branded drug in pre-CVBP. In column (1), the dependent variable is a dummy variable indicating whether this hospital has purchased a winning drug after CVBP. We regress at hospital-molecule level rather than hospital-quarter-molecule level and control hospital FE and molecule FE. In columns (2) to (5), the dependent variable is log (total DDDs). The sample in these columns includes hospitals that purchase winning drugs in procured molecules after the CVBP. $PriceDiff$ is the price differences between pre-CVBP dominated and post-CVBP winning drug. Columns (4) and (5) control for characteristics of hospitals and cities, respectively. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Heterogeneous Effects of the CVBP on Drug Utilization by Whether Supplier Changing Manufacturing Process

	(1)	(2)
Procured × Post	0.075***	0.067***
	(0.003)	(0.004)
Procured × Post × winMPC	0.138***	0.133***
	(0.035)	(0.035)
Procured × Post × Branded-dominated × winMPC		0.473**
		(0.150)
Procured × Post × Branded-dominated		0.033***
		(0.007)
Constant	7.650***	7.651***
	(0.002)	(0.002)
Hospital × Molecule FE	✓	✓
Quarter FE	✓	✓
Mean of Y (Before VBP)	7.46	
Mean of Y (After VBP)	7.75	
# of observations	2099156	2099156
R^2	0.82	0.82

Notes: This table shows heterogeneous results of CVBP on log (total DDDs) by whether the producers changes their methods after the CVBP. $winMPC$ represents whether the winning firms have changed their producing method after the CVBP, which equals to one for quarters after the changing. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 7: Heterogeneous Effects of the CVBP on Drug Utilization by Suppliers' Capacity

	(1)	(2)	(3)	(4)	(5)
Procured × Post	-0.031***	0.032***	-0.082***	0.071***	0.515***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.020)
Procured × Post × Top Winning Producers	0.218***				
	(0.005)				
Procured × Post × Whether can produce API		0.196***			
		(0.006)			
Procured × Post × Number of API Producers			0.005***		
			(0.000)		
Procured × Post × Same Province				0.131***	
				(0.011)	
Procured × Post × Log (Distance)					-0.065***
					(0.003)
Constant	7.640***	7.646***	7.650***	7.649***	7.644***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hospital × Molecule FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Mean of Y (Before VBP)	7.46				
Mean of Y (After VBP)	7.75				
# of observations	2099156	2099156	2099156	2099156	2046406
R^2	0.82	0.82	0.82	0.82	0.82

Notes: This table shows heterogeneous results of CVBP on log (total DDDs) by potential shortage. $TopWinningProducers$ represents whether the winning firm is a top firm in China. $WhethercanproduceAPI$ equals to one if the winning firm can produce the raw material of the molecule d. $NumberofAPIProducer$ measures the number of raw procuers in each molecule d in China. $SameProvince$ is a dummy variable indicating whther the winning firm is in the same provnce with the hospital. And $Log(Distance)$ represents the distance between the winning firm and hospital's city. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Appendix

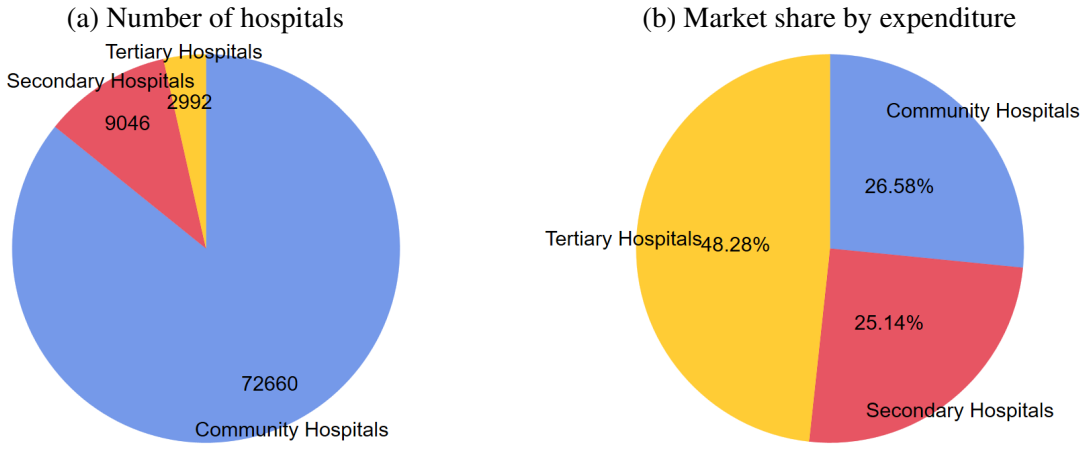


Figure A1: Summary of hospitals in our sample

Notes: These figures show the distribution of hospitals in our dataset according to their hospital level. Panel (a) reports the number of hospitals and panel (b) presents their market share by expenditure.

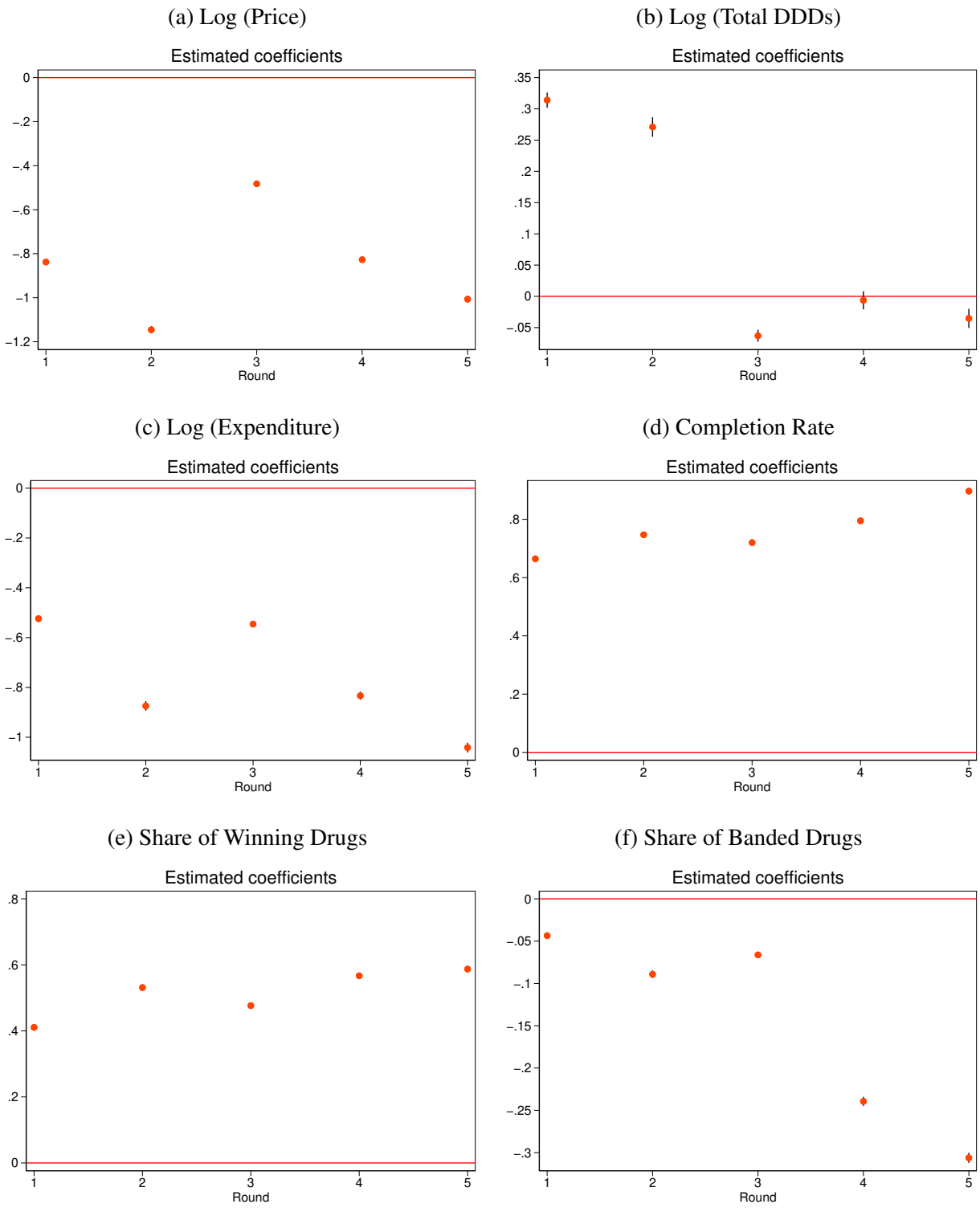
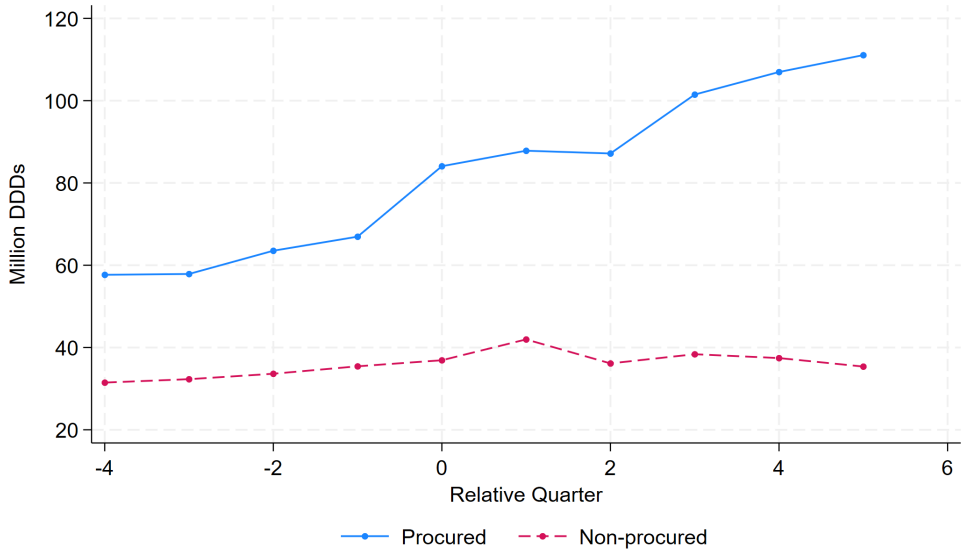


Figure A2: Average Effects of the CVBP by Round

Notes: This figure shows average results of CVBP by rounds. In fact, the confidence intervals that doesn't seem to exist in most of these figures does not stem from methodological oversight but reflects their negligible width relative to the magnitude of the coefficient estimates.

(a) Total DDDs



(b) Total Expenditure

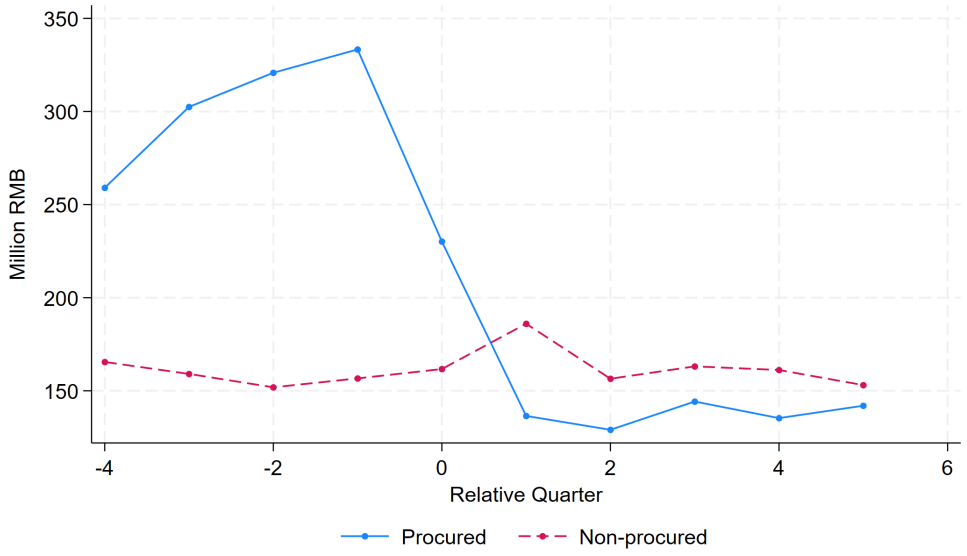


Figure A3: Drug Utilization and Expenditure Trends of Procured and Non-procured Molecules

Notes: These figures present the trends for the procured and non-procured molecules. We first calculate the total DDDs and expenditure for each molecule in each relative quarter, and then take the average by procured and non-procured molecules.

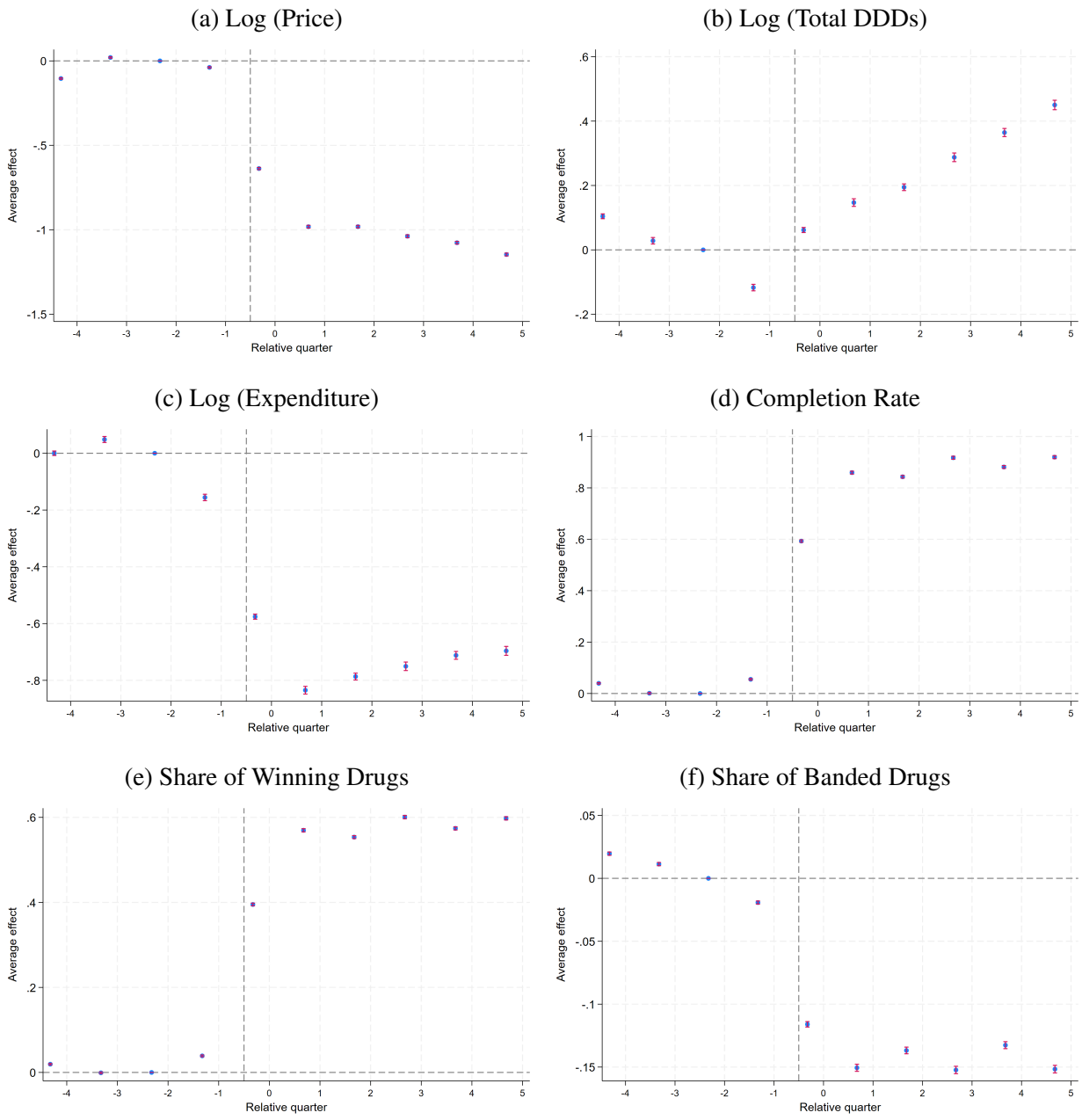


Figure A4: Robustness: Event Study without the Control Group

Notes: These figures present the event study only using treatment group molecules. In fact, the confidence intervals that doesn't seem to exist in most of these figures does not stem from methodological oversight but reflects their negligible width relative to the magnitude of the coefficient estimates.

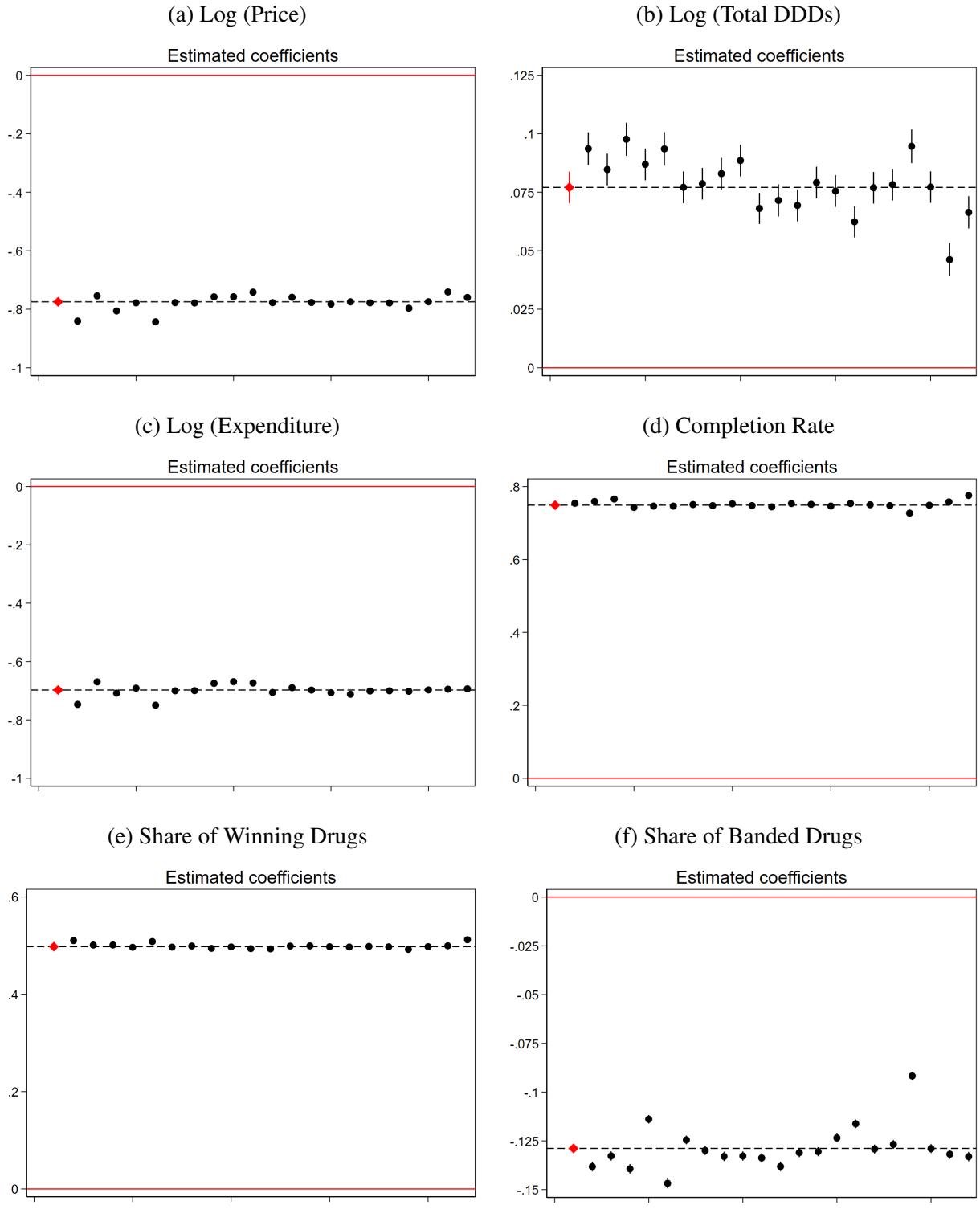


Figure A5: Robustness: Leave-one-out Analysis

Notes: These figure present the results for the robustness of the effects of CVBP. Red rhombus points show the estimated coefficients with all sample. Each black cycle point reports the result from a subsample regression in which one particular molecule is dropped. All specifications use the same form as the baseline regression. In fact, the confidence intervals that doesn't seem to exist in most of these figures does not stem from methodological oversight but reflects their negligible width relative to the magnitude of the coefficient estimates.

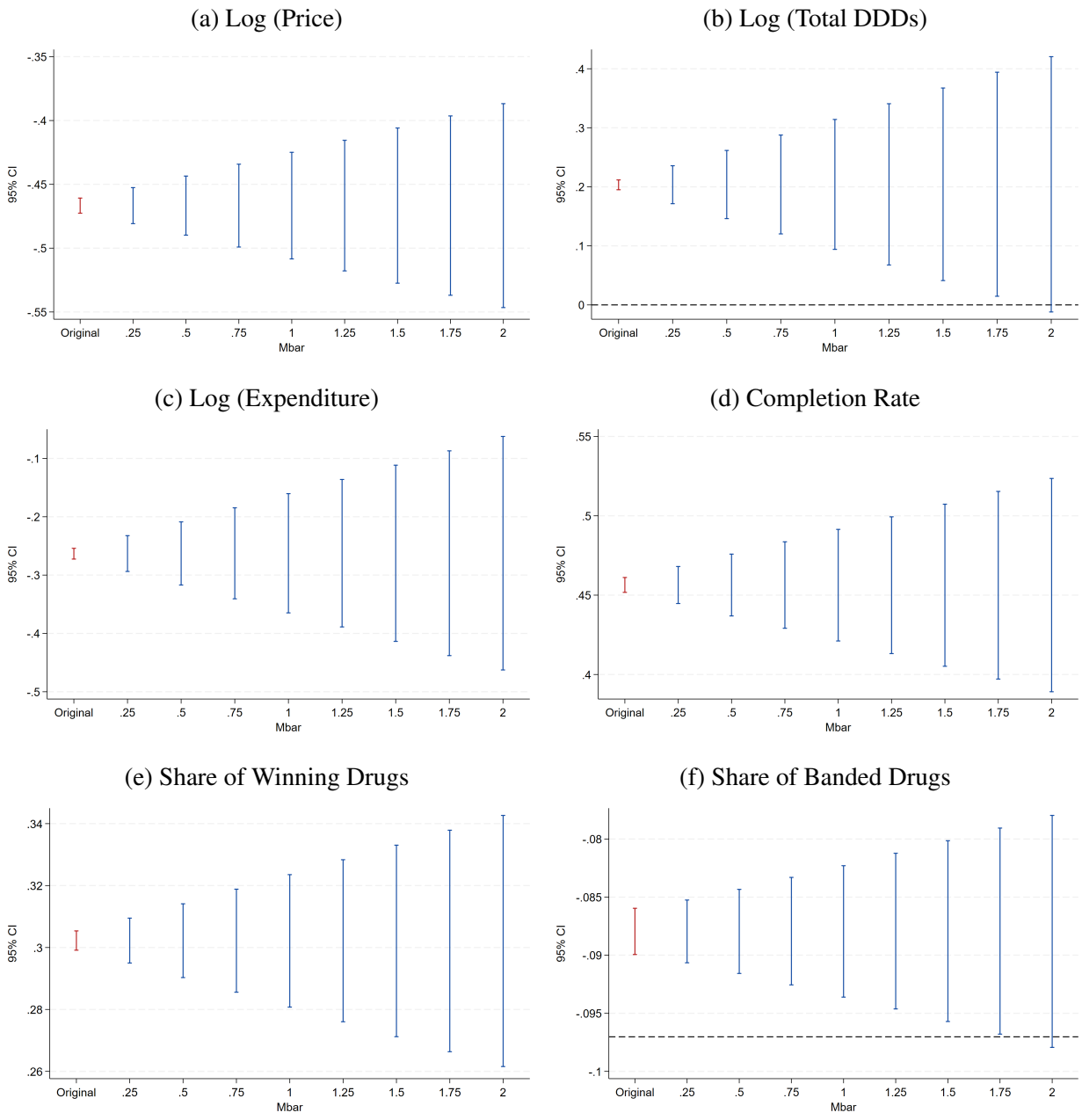


Figure A6: Robustness: Sensitivity Analysis

Notes: These figure present the results for the sensitivity analysis of parallel trend tests proposed by Rambachan and Roth (2023). Under the setting of staggered DID, we use the DID estimator developed by Callaway and Sant'Anna (2021).

Table A1: Summary Statistics

	ALL		Pre-CVBP		Post-CVBP		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Mean	SD	Mean	SD	Mean	SD	Diff	P-Value
	Panel (a): Hospital-quarter-molecule Level							
Average Price	3.45	8.90	5.12	11.70	1.87	4.37	-3.25	0.00
Total DDDs	9805.74	33187.33	8808.90	27986.10	10755.97	37454.61	1947.07	0.00
Expenditure	29661.86	140660.30	42891.26	175522.80	17051.11	94615.30	-25840.15	0.00
Share of winning	0.39	0.47	0.06	0.23	0.71	0.43	0.65	0.00
Share of branded	0.14	0.33	0.19	0.38	0.10	0.28	-0.09	0.00
Tertiary hospitals	0.12	0.33	0.13	0.34	0.12	0.32	-0.02	0.00
Secondary hospitals	0.20	0.40	0.20	0.40	0.20	0.40	0.00	0.00
Community hospitals	0.68	0.47	0.66	0.47	0.69	0.46	0.02	0.00
Hospital HHI	0.94	0.14	0.95	0.14	0.94	0.14	-0.01	0.00
# of producers	1.20	0.47	1.18	0.45	1.22	0.49	0.04	0.00
# of new producers	0.42	0.56	0.00	0.00	0.82	0.53	0.82	0.00
# of high-price producers	0.40	0.53	0.44	0.54	0.35	0.51	-0.09	0.00
# of low-price producers	0.64	0.59	0.73	0.59	0.55	0.58	-0.18	0.00
# of branded producers	0.18	0.39	0.22	0.41	0.15	0.36	-0.07	0.00
# of generic producers	1.01	0.54	0.96	0.57	1.06	0.50	0.11	0.00
Observations	2,206,641		1,076,905		1,129,736			
	Panel (b): City-quarter-molecule level							
City HHI	0.74	0.25	0.71	0.27	0.76	0.24	0.05	0.00
# of producers	2.71	2.20	3.08	2.64	2.48	1.83	-0.60	0.00
# of high-price producers	1.03	1.03	1.30	1.18	0.87	0.88	-0.43	0.00
# of low-price producers	1.37	1.62	1.79	1.94	1.10	1.31	-0.68	0.00
# of branded producers	0.41	0.51	0.45	0.52	0.39	0.51	-0.05	0.00
# of generic producers	2.30	2.18	2.64	2.67	2.09	1.78	-0.55	0.00
Observations	65,826		25,379		40,447			
	Panel (c): City level							
Wage	76,928.73	15,984.14						
Log (wage)	11.23	0.19						
Education	9.27	0.86						
Observations	322 (337)							

Notes: This table reports the summary statistics of the sample used in this paper. We report the summary statistics of total sample, pre-CVBP sample, and post-CVBP sample. The sample of non-procured molecules is divided into pre-CVBP. Then we compare the differences between pre- and post-CVBP sample with the p-value reported. We also show the number of observations in the bottom of each panel. The number of observations is 322 for wage and 337 for education data in panel (c) due to the different data sources.

Table A2: Details for Manufacturing Process Changes

Producer	Molecule	Consistency Evaluation Time	CVBP Implementation Time	Process Change Time	Process Change Content	Approving Province
Shandong Yuxin Pharmaceutical Co., LTD	Esomeprazole (Injection)	2021/2/2	2021/10/1	2021/10/28	Change production process parameters. Increase API suppliers, and revise the internal control standards for API of new suppliers.	Shandong
Yangzijiang Pharmaceutical Group Co., LTD	Esomeprazole (Injection)	2021/5/25	2021/10/1	2022/10/29	Change the method of analysis in the internal control standard of the raw material. Delete the detection items of the residual solvents "acetonitrile" and "methyl isobutyl ketone" due to supplier process change.	Jiangsu
Yangzijiang Pharmaceutical Group Co., LTD	Pantoprazole (Injection)	2020/10/27	2021/5/1	2021/5/18	Change production time limit process parameters.	Jiangsu