Contracting on Price, Compensating on Quality: Evidence from Centralized Drug Procurement*

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Abstract

Centralized procurement sharply lowers drug prices, but competitive pressure may incentivize quality deterioration—a moral hazard problem with large welfare consequences. Using China's national drug procurement rollout and universal hospital transaction data, we provide evidence of this quality-price tradeoff. Winning firms are more likely to change manufacturing processes post-award, some consistent with quality reduction. Hospitals assigned to winners that altered packaging materials exhibit greater utilization increases, suggesting compensatory dosing. Prior branded-drug users resist switching to winning generics but use higher doses when switching. Accounting for compensation, the effective price reduction is 3–18 percentage points smaller than the headline 64%.

Keywords: centralized procurement, drug quality, moral hazard, generic drugs, compensatory dosing

JEL code: I11, I18, L15, L51, D82, L65

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1 Introduction

Governments increasingly rely on centralized procurement to contain public spending. But when contracts are written mainly on price and quantity, lower bid prices need not translate one-for-one into lower effective costs. By intensifying price competition, centralized procurement compresses suppliers' margins and can weaken incentives to maintain product quality on dimensions that are difficult to verify after award. This trade-off is central to procurement under incomplete contracts (Laffont and Tirole, 1993), yet direct empirical evidence on post-award quality distortions remains scarce. Existing studies document renegotiation, delivery delays, and cost overruns (Bajari and Tadelis, 2001; Decarolis, 2014; Lewis and Bajari, 2014), but these outcomes reflect contractual frictions rather than deterioration in the delivered product itself. Moreover, even when quality deteriorates, its welfare consequences depend on how buyers respond, a margin that prior work has largely overlooked. If consumers compensate for lower quality by purchasing more, procurement savings measured at face value may overstate the policy's true welfare gains.

Pharmaceutical procurement is a particularly consequential setting in which to study this problem, because drug quality directly affects treatment effectiveness and patient health. For most consumer goods, higher quality raises demand. For prescription drugs, higher efficacy can reduce utilization, because fewer doses or shorter treatment courses are needed to achieve the same therapeutic goal. This implies that if a supplier cuts quality after winning a fixed-price contract, physicians and patients may respond through compensatory dosing: higher doses, more frequent administration, or longer treatment duration. In that case, the contractual price cut overstates the reduction in the effective cost of treatment, because part of the apparent saving is offset by greater use of a less effective product. Despite its policy importance, this compensatory margin has received little empirical attention.

We study this mechanism in China's national Centralized Volume-Based Procurement (CVBP), which provides an ideal setting for three reasons. First, the program is economically important: it covers roughly 85% of prescription drug sales in China through the public hospital system, and it has reduced drug prices by an average of 64%. Second, like many procurement systems, CVBP screens quality mainly at entry through bioequivalence certification while post-award quality monitoring remains limited, creating clear scope for post-award moral hazard. Third, our data allow us

to observe both the supply and demand sides of the response, tracing the chain from procurement-induced price pressure, to firms' post-award production choices, to downstream drug utilization.

Our analysis combines two novel data sources. First, we collect all approved applications for post-approval manufacturing process changes (MPCs) filed with China's drug regulatory authorities. Through systematic text analysis, we classify each MPC by the type of manufacturing change and its relevance to affect drug quality, isolating modifications to packaging materials, active pharmaceutical ingredient (API) suppliers, and production capacity from routine administrative updates. Second, we link these supply-side records to administrative transaction data covering the universe of hospitals in China's public health insurance network from January 2019 through June 2023, providing near-complete coverage of the national pharmaceutical market.[1]

Our empirical strategy exploits two sources of variation. To study suppliers' responses, we use staggered procurement timing across drug molecules in a difference-in-differences (DiD) design. To study downstream utilization, we exploit the fact that a procured molecule may have multiple winning firms and that each province is assigned with one of the winners. This province-level assignment allows us to compare hospitals exposed to winning suppliers that do and do not alter their manufacturing processes after award. Among the changes we observe, modifications to packaging materials are especially useful for isolating the quality effect. Unlike changes to active ingredients or production capacity, modifications to packaging materials are unlikely to expand supply (U.S. Food and Drug Administration, 2019), so any associated increase in utilization is difficult to attribute to improved availability and more plausibly reflects compensatory dosing due to lower drug quality (U.S. Food and Drug Administration, 1999).

We find evidence of moral hazard on the supply side. Winning firms are 8.5 times more likely to undertake manufacturing process changes after securing a contract than in their pre-procurement baseline, whereas non-winning firms show no comparable shift. These responses are more concentrated among firms facing tighter margins, greater projected revenue losses, and smaller scale, and are not systematically related to demand conditions in the provinces they supply, consistent with cost-cutting incentives under aggressive price competition rather than routine operational adjust-

[1]Direct measures of drug quality in China are largely unavailable, motivating our indirect approach: product recall records are not publicly disclosed, case-level adverse drug reaction data from the national monitoring system are not accessible to researchers, and administrative health claims data are limited to individual cities and restricted time periods.

ment.

On the demand side, hospitals assigned to winners that modify packaging materials exhibit 24.7% greater utilization increases than hospitals assigned to winners without such changes. This pattern is difficult to reconcile with a pure supply-expansion story, because changes in packaging materials do not raise supply capacity. Under CVBP, hospitals are required to fulfill procurement volume targets for winning drugs, which limits substitution toward alternatives and makes higher utilization a natural response when therapeutic efficacy falls.[2] If these post-award changes instead improved quality, utilization should decline rather than rise, because fewer doses would be needed to achieve the same therapeutic effect. Consistent with the compensatory-dosing interpretation, the utilization response is larger for injection drugs and for drug classes with mixed acute-chronic use, whose efficacy is more sensitive to packaging material changes (U.S. Pharmacopeial Convention, 2016).

Finally, we find complementary evidence from branded-to-generic substitution: hospitals that relied more heavily on branded drugs before CVBP experience larger utilization increases after switching to winning generics, especially for drugs with mixed acute-chronic use, where compensatory adjustments face less resistance from patients. For chronic-only drugs, utilization changes are muted, consistent with patients either resisting the switch by seeking branded alternatives through other channels or facing adherence problems when forced to switch.[3]

These responses erode the policy's headline savings. While a companion paper shows that CVBP reduced nominal procurement prices by 64% (Jiang et al., 2025), the effective reduction in treatment cost is smaller once compensatory quantity responses are taken into account. Depending on the type of post-award manufacturing change and the drug class's scope for compensatory dosing, we estimate effective price reductions of only 46–61%. The wedge is largest for drug classes with mixed acute-chronic use and for products whose manufacturers undertook packaging material changes after award. The policy implication is straightforward: when quality is incompletely contractible, procurement savings cannot be assessed from unit prices alone, because part of the

[2]Volume requirements mandate that a hospital allocate a predetermined share of its total purchases of each procured molecule to the winning firm, with the required share ranging from 50% to 80% depending on the number of winners.

[3]In a parallel and independent work, Xia and Zhao (2026) use pharmacy data to show that retention rates for procured winning drugs decrease and that patients are more likely to switch to branded alternatives following the CVBP, consistent with perceived quality deterioration.

apparent savings is offset by higher utilization, a shift from an explicit unit price to an implicit, quality-adjusted treatment cost.

This paper makes three main contributions. First, we provide direct evidence of supplier moral hazard under fixed-price centralized procurement, showing how quality distortions arise through post-award production decisions. A large theoretical literature emphasizes moral hazard under incomplete contracts (Laffont and Tirole, 1993), and empirical work documents post-award distortions such as renegotiation, delivery delays, and cost overruns (Bajari and Tadelis, 2001; Lewis and Bajari, 2011; Decarolis, 2014; Lewis and Bajari, 2014). Recent work further shows that price-only mechanisms can reduce buyer welfare when quality is endogenous (Camboni et al., 2025) and that omitting quality preferences in procurement significantly reduces the equilibrium share of high-quality products (Ishitani, 2025). We contribute new evidence by documenting quality distortions that operate through firms' production decisions rather than contractual adjustments, drawing on a large-scale national procurement program.

Second, our findings contribute to the literature on competition and quality in healthcare. While hospital competition can improve quality (Cooper et al., 2011; Gaynor et al., 2013), the evidence is mixed across settings (Colla et al., 2016). Competitive pressure in pharmaceutical markets can also induce unethical behavior (Currie et al., 2023; Janssen and Zhang, 2023). We document a distinct channel: whereas Diwan et al. (2026) show that competitive bidding in U.S. Medicare DME adversely selected fraudulent firms, we show that centralized procurement creates moral hazard among winners, who reduce costs along less observable margins such as packaging materials.

Third, we identify compensatory dosing as a demand-side consequence of quality shortfalls induced by the policy.[4] When drug quality declines and contractual volume obligations restrict switching to alternatives, physicians prescribe higher doses or longer treatment courses to maintain clinical outcomes (WHO, 2017; Ozawa et al., 2018), partially offsetting procurement savings through higher utilization. We provide two pieces of evidence for this channel: hospitals assigned to winners that altered packaging materials exhibit significantly greater utilization increases, and hospitals switching from branded to generic drugs use higher quantities, especially for drug classes

[4] Xia and Zhao (2026) use retail pharmacy data to estimate that quality decline offsets 15.8% of statin cost savings under CVBP, inferring quality reduction from lower patient retention. Our paper differs in directly linking specific post-award manufacturing process changes to differential utilization responses in the hospital market, isolating the supply-side mechanism driving quality distortions.

where efficacy is more salient. The resulting estimates allow us to recover the effective (quality-adjusted) price reduction, which is 3–18 percentage points smaller than the headline 64%. More broadly, these findings illustrate a general challenge for price-only procurement: the buyer pays less per unit, but not necessarily less per effective treatment.

The paper is organized as follows. Section 2 provides an overview of China's pharmaceutical market and the CVBP. Section 3 introduces our conceptual framework. Section 4 describes the data and sample used in the study, and Section 5 outlines the empirical strategy. Section 6 presents baseline effects on drug utilization, identifies compensatory quantity effect, and quantifies effective price reductions. Finally, Section 7 concludes.

2 Institutional Background

2.1 Healthcare Delivery and the Pharmaceutical Market in China

In China, public hospitals are the primary providers of both outpatient and inpatient care, accounting for 83.5% of total health services (National Health Commission of China, 2024). Unlike many Western systems where routine care is delivered through independent clinics, China channels most outpatient visits through hospital departments. Hospitals also dominate pharmaceutical distribution: approximately 85% of prescription drugs are dispensed directly by hospital pharmacies rather than retail pharmacies (IQVIA, 2023), making hospital procurement data exceptionally comprehensive for studying pharmaceutical markets. Public health insurance coverage is nearly universal, with roughly 95% of the population covered (National Health Commission of China, 2020). Most CVBP-targeted drugs require patient cost-sharing, with effective out-of-pocket rates varying by care setting—generally lower for inpatient than outpatient prescriptions. Patients therefore bear a meaningful share of drug costs, making CVBP price reductions directly salient for out-of-pocket spending.

China's pharmaceutical sector comprises over 3,000 firms, the majority manufacturing only generics. Historically, concerns regarding the quality and therapeutic equivalence of domestic generics were widespread (Nie et al., 2020; Qu et al., 2021; He et al., 2022). A watershed reform in 2016 introduced bioequivalence requirements for generics (State Council of China, 2016), estab-

lishing the regulatory foundation for large-scale pooled procurement. To address drug expenditures accounting for approximately 40% of total healthcare spending during the 2010s, the government implemented several interventions, including the Zero Markup Drug Policy (Fang et al., 2021) and the Two-Invoice System (Li et al., 2025). While these reforms weakened links between pharmaceutical sales and provider income, they did not fundamentally alter fragmented purchasing. The CVBP represents the most ambitious departure, using coordinated national purchasing to achieve substantial price reductions for off-patent, high-volume generics (see Jiang et al. (2025) for a detailed institutional overview).

2.2 The CVBP in China

The CVBP was first piloted in the 4+7 major cities, with bidding in December 2018 and implementation in March 2019 for 25 molecules, each with a single winner. The pilot produced price reductions averaging over 50%, prompting nationwide expansion by December 2019. Since then, ten additional rounds have been conducted through February 2026, procuring 16 to 62 molecules per round (Table B.1).

The program operates as follows. The NHSA determines the molecules to be procured and collects expected quantity demand from each province. Only manufacturers of branded drugs or bioequivalent generics are eligible. Firms submit bids, and the lowest-bid producers win.[5] Under a single-winner design, the winner supplies 50% of reported quantity nationwide. Under multi-winner designs, firms select provinces in ascending bid-price order, with each allocated 60–80% of reported quantity depending on the number of winners.[6] Contract duration and guaranteed market share increase with the number of winners.

To encourage uptake, the central government issued supplementary guidelines with implementation varying across provinces (National Healthcare Security Administration of China, 2019), including coinsurance policies, reference pricing, and incentive policies allowing hospitals to retain procurement savings. Figure B.1 summarizes the timing of provincial adoption.

[5]While both branded and generic drugs may participate, generics overwhelmingly win the competitive bidding due to their lower prices.

[6]From round 2 onward, the program designates multiple winning manufacturers per molecule to mitigate supply risks and ensure continuity of access (National Healthcare Security Administration of China, 2020).

2.3 Post-Approval Changes in China

Center for Drug Evaluation, National Medical Products Administration (2021) regulates post-approval manufacturing changes for marketed drugs, classifying them into major, moderate, and minor categories. Moderate and major changes, such as altering packaging materials, APIs or production scales, can significantly affect drug quality and stability (see also Center for Drug Evaluation, National Medical Products Administration, 2024, for specific API rules). In contrast, minor changes like updating pack size, package inserts or expiration dates have little impact on quality.

In practice, major changes are rare. Because they carry a high risk of degrading drug quality, they require strict approval from the central National Medical Products Administration (NMPA). The vast majority of changes are moderate or minor and are subject only to a provincial-level record-filing system for supplementary drug registration. However, moderate changes can still compromise quality. Due to local economic concerns, provincial regulators have limited incentives to block changes that benefit local firms (Fisman and Wang, 2015; Eberhardt et al., 2016). Given this regulatory context, we define these potentially quality-impacting modifications, primarily moderate changes, as MPCs.

Public concern over drug safety led policymakers to initially propose banning all post-award MPCs in the 11th CVBP round (Pharnexcloud, 2025). However, lacking empirical evidence that MPCs actually harm quality, regulators replaced the ban with a simple disclosure rule. Winning bidders now only need to report MPCs on the CVBP portal (National Healthcare Security Administration of China, 2025). This policy shift highlights a pressing need for empirical research on the causal link between MPCs and drug quality, ensuring that the CVBP program reduces costs without sacrificing clinical efficacy.

3 Conceptual Framework

The CVBP creates a procurement environment in which the government commits to purchasing from winning suppliers at a fixed price determined through competitive bidding, while drug quality, though subject to minimum standards, remains imperfectly observable and non-contractible ex post. This section develops a simple framework to organize our empirical predictions.

3.1 Model Setting

Consider a market for a specific drug molecule. A regulator awards a contract at a fixed unit price p determined via a first-price auction among n symmetric bidders with independent private costs. Under standard regularity conditions, the equilibrium bid function is strictly increasing in cost type and the winning price declines with n (Appendix A.1).

Firm Behavior. Post-award, the winning firm chooses non-contractible quality $q \in [\underline{q}, \bar{q}]$, to maximize post-award profit:

$$\max_q \Pi(p, q) = (p - c)X(p, q, \gamma) - \psi(q) \tag{1}$$

where $X(\cdot)$ is total demand, γ represents the *efficacy salience* of the drug (defined below), c is the marginal production cost, $\psi(q)$ is the cost of maintaining quality, with $\psi'(q) > 0$ and $\psi''(q) > 0$, $\underline{q}$ is the minimum regulatory standard and $\bar{q}$ denotes the contracted or reference level. The key insight is that aggressive price competition compresses margins $(p - c)$, weakening firms' incentives to maintain costly quality standards.

Patient and Physician Demand. Patients, acting jointly with physicians, makes two choices. First, a patient initiates treatment if the net benefit $B_0(\gamma, q) - \alpha p$ exceeds an idiosyncratic friction K (e.g., hassle costs, switching costs); the resulting participation rate $M(p; \gamma)$ is decreasing in p. Second, conditional on participation, the patient chooses dosage x^* to maximize $U = B(\gamma, x, e(q)) - \alpha p x$, where $e(q)$ is effective efficacy per unit (with $e'(q) > 0$), α is the out-of-pocket rate, and $B(\cdot)$ captures health benefits with diminishing returns. The first-order condition $B_x(\gamma, x, q) = \alpha p$ yields optimal dosage $x^*(p, q, \gamma) = \frac{1}{\gamma e(q)}(B')^{-1}\left(\frac{\alpha p}{\gamma e(q)}\right)$ and aggregate demand is $X(p, q, \gamma) = M(p; \gamma) \cdot x^*(p, q, \gamma)$.

The parameter γ captures the efficacy salience of the drug—how directly and rapidly a patient experiences treatment response. We assume $\gamma_a > \gamma_c$ (acute conditions are more salient than chronic maintenance). Quality q can fall below the reference level $\bar{q}$ through two channels: post-award cost-cutting by the winner, or policy-induced substitution from a branded product to a lower-quality generic. Both generate the same downstream predictions.

3.2 Key Predictions

Quality Shading under Price Pressure As the procurement price p falls, the firm's return to costly quality maintenance declines. Under standard conditions, $\frac{\partial q^*}{\partial p} > 0$: lower procurement prices induce quality shading (Appendix A.3). This predicts that winning firms with lower bids and tighter margins should be more likely to undertake manufacturing process changes after award.

Compensatory Dosing. Our central hypothesis is that if drug quality declines, patients may increase the quantity consumed to achieve the same therapeutic effect.

Proposition 1 *If the marginal utility of dosage increases as quality decreases ($B_{xq} < 0$), then a reduction in quality q leads to an increase in the optimal dosage x^*: $\frac{dx^*}{dq} = -\frac{B_{xq}}{B_{xx}} < 0$. The condition $B_{xq} < 0$ holds under standard CRRA preference with $\sigma > 1$ (Appendix A.2).*

When each unit of the drug delivers less therapeutic benefit, more units are required to reach the same clinical outcome. Under CVBP's volume mandates, substitution toward alternatives is limited, making higher utilization a natural response when efficacy falls.

Heterogeneity by Efficacy Salience. The compensatory dosing response varies with how directly patients experience treatment effects. Under the same CRRA conditions, the cross-partial $\partial^2 x^*/(\partial\gamma\partial q) < 0$: for acute conditions (high γ), quality reductions trigger larger utilization increases than for chronic maintenance drugs (low γ), where patients are less able to detect efficacy changes and more likely to resist switching (proof in Appendix A.4).

The Effective Price Wedge. Finally, we derive the welfare implication of compensatory dosing.

Proposition 2 *Define the "Effective Price" as $p_{eff} = \frac{p}{e(q)}$, where $e(q)$ is the therapeutic efficacy per unit. The change in the effective price is:*

$$\Delta \ln p_{eff} \approx \underbrace{\Delta \ln p}_{\textit{Price Effect}} \underbrace{- \frac{e'(q)q}{e(q)} \Delta \ln q}_{\textit{Quality Effect}} \tag{2}$$

If procurement induces both $dp < 0$ and $dq < 0$, then $|d \ln p_{eff}| < |d \ln p|$: the contractual price cut overstates the reduction in effective price (Appendix A.5).

To operationalize this result, note that if compensatory quantity ΔQ fully reflects the quality-driven efficacy loss, the discrete effective price reduction is $\Delta p_{eff} = 1 - (1 - 0.64)(1 + \Delta Q)$, where 0.64 is the headline price cut documented in Jiang et al. (2025) and ΔQ is the utilization increase driven by quality changes (Section 6.3).

Discussion. Our framework abstracts from several institutional features: physicians and patients may have heterogeneous information about quality; some quality dimensions (bioequivalence) are verifiable while others (manufacturing processes) are not; and we do not model the government's optimal mechanism design. These simplifications are appropriate: the reduced-form demand specification accommodates joint physician-patient optimization without modeling their interaction explicitly; the verifiable/non-verifiable distinction maps directly onto our empirical categorization of MPCs. And our goal is to measure the quality-price tradeoff under the existing mechanism rather than to characterize the optimal one.

4 Data and Sample

4.1 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. These hospitals roughly dispense 85% of prescription drugs in China's pharmaceutical market (IQVIA, 2023). Our data span from January 2019 to June 2023, covering the CVBP from the 4+7 pilot stage up to the seventh round.[7] The dataset includes hospital's name, province, drug purchase date, active ingredient/molecule, 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), following the WHO guidelines (WHO, 2025). Similarly, to compare price across different molecules, we calculate the unit price, defined as price per DDD.

We supplement our main data with various hospital-level information to obtain hospital-level

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

characteristics, such as hospital location and hospital tier, i.e., tertiary/secondary/community hospitals.[8] We also supplement our main data with firm-level data (China's Industrial and Commercial Registered Enterprises Database and the YAOZH database) to obtain characteristics of drug producers, such as firm location, capacity of producing APIs, and firm size. In addition, we collect bioequivalence approval information from China's NMPA (aka FDA) to identify bioequivalent and non-bioequivalent generics. We collect MPC information of all firms from the YAOZH database, containing the product, the timing of approval, and the content of each changes. We also obtain city-level income and education attainment data as socioeconomic controls. Average annual salary comes from the 2020 China Urban Statistical Yearbook (China Urban Statistical Yearbook 2020), and the city-level average years of education come from the 2020 China Population Census (China Seventh National Census 2020).

4.2 Sample

Due to the enormous size of the main dataset, we focus on five common drug classes (ATC 4th level) only: C09AA ACE inhibitors (antihypertensives), C10AA Statins (cholesterol control), A02BC PPIs (anti-stomach acid), N06AB SSRIs (antidepressants), and R03AC SABAs (quick relief for asthma and COPD). Within each drug class, we have 7–9 molecules. We include procured molecules between round 1 and 5 as the treatment group. Due to a lack of data in pre-periods, we exclude the pilot round (March 2019) from our analysis. Similarly, due to a lack of post-period observations, we exclude two molecules in round 7 (November 2022) from our analysis. We keep data from relative quarter -4 to 5 for procured molecules to focus on a relatively balanced panel. In our main analysis, we keep all data of the non-procured molecules in these drug classes as the control group.[9] In total, we have 22 procured molecules and 12 non-procured molecules. Table B.2 lists the procurement rounds for molecules within each therapeutic class.

The dataset for these five drug classes comprises 11,999,758 transactions. We exclude a small number of hospitals (0.6% of the sample) whose locations cannot be identified at the city level. In addition, we drop hospitals located in county-level cities directly administered by provincial

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

[9] We exclude these non-procured molecules in our robustness checks.

governments due to missing data on wages and education (3.09%). We also exclude hospital-molecule pairs with transactions only in the pre- (1.84%) or post-CVBP (8.32%) period, as they do not contribute to the DiD estimation.[10] The final analytical sample consists of 10,324,901 transactions. We further collapse the transaction data into 2,099,782 hospital-molecule-quarter observations to obtain quarterly quantities.

A *winning firm* for a given molecule is defined as one of the drug producers winning the competitive bidding with the (nearly) lowest price. However, as *winning firms* take turns to choose supplied provinces when there are multiple winners, we define *winning drugs* at the molecule-producer-province level. For example, if a firm is one of the winners for drug D, this drug D in supplied provinces chosen by the firm is regarded as a *winning drug*, but it is a non-winning drug in non-supplied provinces.[11]

As shown in panel (a) of Figure B.2, 2,769 tertiary hospitals and 7,356 secondary hospitals in China have purchased drugs from one of the five drug classes from January 2019 to June 2023. Moreover, there are also 54,790 community hospitals in our sample, mainly including community hospitals in urban areas and township hospitals/health services centers in rural areas. However, despite that tertiary hospitals account for a small share in total number of hospitals, Figure B.2 panel (b) indicates that tertiary hospitals account for 49.9% of prescription drug sales, and the remaining 50.1% of the drug market is occupied by other lower-level health care facilities.

4.3 Summary Statistics

Table B.3 presents the summary statistics for the sample used in this study. Panel (a) reports summary statistics for the treated group, split by pre- and post-CVBP periods, along with the control group. Average unit prices fall from 7.23 RMB to 2.79 RMB after CVBP, while quarterly DDDs rise modestly from 9,037 to 12,833, resulting in a net decrease in expenditure from 48,668 RMB to 23,293 RMB. The market share of winning drugs increases from 10% to 67%, and the

[10] Some small hospitals were newly required by the government to report their procurement orders. Consequently, some observations in the dataset pertain exclusively to the post-CVBP period. Among these post-CVBP-only samples in the transaction data, community hospitals account for 71%, compared with 52% among other samples in the same period. The average city-level wage for this group is 86,976, significantly lower than the 94,778 observed for other sample after the CVBP. Likewise, the mean number of DDDs per order is 2,249, compared with 2,597 for the other group. The results remain robust when the previously excluded observations are retained.

[11] By the CVBP rules, a winning firm does not need to stick to the CVBP-winning price in non-supplied provinces.

share of branded drugs falls from 24% to 10%. The composition of hospitals by tier remains stable across periods. Panel (b) reports city-level characteristics: the average annual wage is 77,993 RMB and average years of education is 9.27, slightly above the nine-year compulsory threshold.

5 Empirical Strategy

5.1 Baseline Effects of the CVBP on Drug Utilization Patterns

We begin by estimating the average effect of CVBP on drug utilization at the hospital-molecule-quarter level:

$$y_{idt} = \beta_0 + \sum_{k=-4, k\neq -2}^{k=5} \beta_k D_{dt}^k + \alpha_{id} + \mu_t + \epsilon_{idt}, \tag{3}$$

where i indexes hospitals, d molecule, and t calendar quarters. y_{idt} represents quantity (DDDs) purchased, share of winning drugs (by quantity), and share of branded drugs (by quantity). $D_{dt}^k = 1(t - t_d^* = k)$, where k is the relative quarter with respect to the procurement date of molecule d.[12] To account for the potential anticipatory effect due to competitive bidding in relative quarter -1, we use relative quarter -2 as the reference period. We also estimate an average-effect version that replaces the relative-quarter indicators with a single post-treatment indicator $procured_{dt}$.[13] We include hospital-molecule fixed effects α_{id} and calendar quarter fixed effects μ_t, and restrict analyses to four relative quarters before and six after procurement. Standard errors are clustered at the hospital level.

5.2 Trade-offs between Price and Quality

Lower prices generate unambiguous welfare gains only if quality remains stable. We now examine whether this assumption holds.

[12] Molecules with different routes of administration are defined as different molecules, for example, omeprazole and injected omeprazole are treated as different molecules and are procured in different rounds.

[13] Relative quarter 0 is excluded from the estimation of average effects but retained in the estimation of dynamic effects, since it serves as a transition period that spans both pre- and post-CVBP phases. This approach is consistently applied across all remaining DiD specifications, except for firms' responses in MPC.

5.2.1 Suppliers' Moral Hazard?

MPC after Bid Winning. As discussed in Section 2.3, post-award quality monitoring is limited, creating scope for moral hazard through MPCs. To test whether winning firms undertake more MPCs after winning a bid, we estimate the following specification and its dynamic version:

$$MPC_{fdt} = \beta_0 + \beta_1 procured_{dt} + \beta_2 procured_{dt} * Win_{fd} + \alpha_{fd} + \mu_t + \varepsilon_{fdt} \tag{4}$$

where f represents firm. MPC_{fdt} is the number of MPCs conducted by producer f's molecule d in quarter t. We decompose MPCs into three categories: (i) changes or additions of API producers, (ii) adjustments in production line capacity, and (iii) modifications to packaging materials. The remaining other changes involve less critical adjustments. Win_{fd} is a dummy variable indicating whether producer f wins the bidding of molecule d. We control for producer-molecule fixed effects and quarter fixed effects.

Motives for MPC. To understand incentives behind winning firms' MPC, we explore the following variation at the winning firm-molecule-supplying province level:

$$winMPC_{fdp} = \beta_1 g(bid_{fd}) + \beta_2 X_f + \beta_3 h(demand_{fdp}) + \alpha_d + \varepsilon_{fdp}, \tag{5}$$

where $winMPC_{fd}$ is a dummy variable indicating whether winning producer f conducts an MPC after winning molecule d. The vector bid_{fd} captures the bidding characteristics of winning firm f, including its bidding price, expected sales changes, and projected profit changes resulting from the CVBP; X_f represents characteristics of winning firm f. $demand_{fdp}$ includes supplying province p's demand faced by a winning firm f, where we use province-level supplementary policies as a proxy: more favorable policies are more likely to lead to a greater increase in demand. We also include pre-CVBP total drug utilization, share of rural hospitals, average wages, and average education of supplying province p as demand proxies.

Impact of MPC on Drug Utilization. Then to test whether MPCs affect drug utilization, we estimate the following specification at hospital-molecule-quarter level:[14]

$$ln(Q_{idt}) = \beta_0 + \beta_1 procured_{dt} + \beta_2 procured_{dt} \cdot \textit{winMPC}_{idt} + \beta_3 procured_{dt} \cdot \textit{winMPC}_{id} + \alpha_{id} + \mu_t + \epsilon_{idt}, \tag{6}$$

where Q_{idt} represents total DDDs of molecule d in hospital i in quarter t. For procured molecule d in quarter t, $procured_{dt} = 1$ when $t \geq t_d^*$ and $\textit{winMPC}_{idt} = 1$ when $t \geq t'_{id}$, where t_d^* is the procurement quarter and t'_{id} $(\geq t_d^*)$ is the first quarter when we detect a winning producer of molecule d for hospital i conducted an MPC due to CVBP. $\textit{winMPC}_{id}$ is the time-invariant version of $\textit{winMPC}_{idt}$, indicating whether hospital i's winning supplying firm has any MPC after CVBP.[15] We expect β_2 to be positive, as quality downgrade is likely to lower drug efficacy and thus more dosages are needed to achieve the same therapeutic effect as before the MPC. We also examine heterogeneous effects by condition type (chronic vs. acute), urban-rural status, and drug formulation (injection vs. non-injection).

Event Study. In addition, as the main source of variation arises from whether a hospital's designated winning firm conducts an MPC for a given procured molecule, we keep procured molecules only and conduct the following event study model:

$$ln(Q_{idt}) = \beta_0 + \sum_{n=-6, n\neq -1}^{n=4} \beta_n MPC_{idt}^n + \alpha_{id} + \mu_t + \epsilon_{idt}, \tag{7}$$

where MPC_{idt} indicates whether a hospital i's designated winning firm of molecule d conducted an MPC in calendar quarter t after winning a bid. n represents relative quarters with respect to a winning firm's MPC time. The underlying assumption is that conditional on hospital-molecule and quarter fixed effects, drug utilization would have trended similarly across hospitals supplied

[14]The ideal measure for drug quality would be adverse drug effect report, drug recalls, or individual health outcomes. However, China's drug quality reporting system is still under development, and thus direct drug quality measures are lacking (Song et al., 2023). For individual health outcomes, given the restrictive access to fragmented insurance claim data, it is also beyond the scope of this paper.

[15]As a robustness check, we also include controls for different changes in prices between firms doing and not doing an MPC and hospitals' location-specific characteristics to capture demand-side shifters.

by MPC and non-MPC winning firms in the absence of the MPC.[16]

We estimate equations (6) and (7) separately for each MPC category. Among the three types, production capacity changes are directly related to supply expansion; thus, any associated utilization increase could reflect either expanded production or diminished efficacy, and we cannot disentangle these two channels. API changes present a similar ambiguity, as firms may switch to cheaper suppliers to cut costs or to secure additional supply. By contrast, packaging material changes are unlikely to expand supply quantities. If packaging MPCs are associated with greater drug utilization, this points to a compensatory quantity effect consistent with decreased drug efficacy.

5.2.2 Branded-to-Generic Switching and Patients' Drug Utilization

Under CVBP, hospitals must prioritize winning drugs to meet guaranteed volume targets, effectively forcing many patients to switch from branded drugs to winning generics, which account for 96% of winners. The utilization effects of this switch are ambiguous, but may partly reflect the same mechanism as MPC-driven changes: if patients or physicians perceive generics as less effective, a long-standing concern in China (He et al., 2022), they may compensate by increasing dosage (Go et al., 2011). Alternatively, patients may resist switching entirely (Hermosilla and Ching, 2024), but with limited access to branded alternatives within hospitals, such resistance could reduce in-hospital utilization as patients seek branded alternatives through retail pharmacies or cause patients to exit treatment.

To test this, we explore hospital-level variation in pre-CVBP prescribing patterns—specifically, whether a hospital predominantly used branded or generic drugs—and estimate the following specification:

$$ln(Q_{idt}) = \beta_0 + \beta_1 procured_{dt} + \beta_2 procured_{dt} * switchBG_{id} + \beta_3 procured_{dt} * priceDif_{id} + \beta_4 procured_{dt} * X_i + \alpha_{id} + \mu_t + \epsilon_{idt}, \quad (8)$$

[16] As a robustness check, we exclude MPCs occurring in the same quarter as CVBP implementation. For these cases, there is no post-CVBP, pre-MPC window to assess parallel trends, making it impossible to distinguish whether elevated utilization reflects the MPC itself or systematic differences between MPC and non-MPC firms that independently affect demand. For MPCs beginning at least one quarter after CVBP, the intervening period provides pre-treatment observations to verify parallel trends, enabling our DiD design to identify the causal effect of MPCs on utilization.

where $switchBG_{id}$ equals 1 if hospital i's predominant drug of molecule d before CVBP was a branded drug and the post-CVBP winning drug is a generic.[17] Relative to hospitals experiencing a smoother generic-to-generic transition, hospitals switching from branded to generic drugs face a larger disruption. However, β_2 may capture factors beyond (perceived) drug quality changes. Hospitals with $switchBG_{id} = 1$ also experience larger price reductions due to the higher baseline price of branded drugs, and they differ systematically in observable characteristics X_i that may independently affect CVBP implementation (Table B.5). We therefore control for the percentage change in prices ($priceDif_{id}$) and interact hospital-level characteristics with CVBP implementation. Nevertheless, we still interpret β_2 with caution given potential unobserved confounding factors.

We also examine heterogeneous responses by dividing drug classes into chronic-only (ACE inhibitors, statins, SSRIs) and mixed acute-chronic use (PPIs, SABAs). We expect a larger $\hat{\beta}_2$ for mixed acute-chronic use drugs, because chronic patients have stronger attachment to their previous branded drug and may resist switching, whereas acute patients are more likely to follow physician recommendations, making their utilization changes more reflective of compensatory dosing.

6 Results

6.1 Changes in Drug Utilization at the Hospital Level

Table 1 presents the average effects from regression (3). Column (1) shows that total DDDs of procured molecules increases by 23.8% relative to non-procured molecules after CVBP. The market share of winning drugs increases 60.1% after the implementation of the CVBP, as shown in column (2). Finally, column (3) demonstrates that the share of branded drugs falls by 15.7 percentage points from a base of 24%, reflecting that nearly all winners are generic producers.

In addition to the DiD average effects, we show the event study results with the TWFE model together with four advanced estimation methods in Figure 1. All methods yield similar estimates.

[17] Table B.5 presents summary statistics by branded-to-generic switching status. Hospitals with a higher reliance on branded drugs tend to be larger, purchase more drugs overall, and exhibit a higher share of branded drugs, resulting in higher average prices. These hospitals are disproportionately tertiary or secondary institutions and situated in cities with higher average wages and education levels. As a robustness check, we implement propensity score matching on these characteristics to improve balance between switching and non-switching hospitals (Section 6.2.2).

The parallel trends assumption generally holds across estimators, as coefficients for quarters preceding CVBP implementation at a hospital-molecule level are close to zero, except for a slight downward pre-trend for drug utilization. In general, the effects on drug utilization and market share of different types of drugs occur immediately after the implementation, with slight increases in magnitude over time.

As further detailed in Appendix C, we conduct several robustness checks, including event-study designs that exploit quasi-random variation in rollout timing, leave-one-molecule-out analyses, and honest DiD sensitivity tests (Rambachan and Roth, 2023). Our baseline results remain perfectly consistent across all these alternative specifications.

6.2 When More Is Less: Quality-Driven Utilization Increases

6.2.1 Suppliers' Manufacturing Process Change

In this section, we examine firms' MPCs before and after winning a CVBP bid, investigate the motives behind winning firms' MPCs, and document their impact on drug utilization.

Table 2 examines the changes in MPCs for winning firms relative to non-winning firms after CVBP implementation based on equation (4). Column (1) demonstrates that winning a bid is associated with an increase in MPCs of 0.085 times after CVBP. This magnitude is 8.5 times larger than the pre-CVBP level, given that the pre-CVBP mean is only 0.010, indicating that MPCs are otherwise rare. In contrast, non-winning firms exhibit no significant increase. Similar patterns are observed when we decompose MPCs into three categories: (i) modifications to packaging materials, (ii) changing or adding API producers, and (iii) adjustments to production line capacity. Column (2) shows that winning firms exhibit a significant increase of 0.015 in the number of package MPCs, a magnitude 3 times the size of the pre-CVBP mean. In contrast, columns (3) and (4) indicate much larger effects for API and capacity adjustments: the estimated increase of 0.042 and 0.038, corresponds to 8 times and 19 times their respective pre-CVBP means. As a placebo test, column (5) shows no significant increase in changes unrelated to the manufacturing process, such as pack size adjustments that could independently affect purchasing quantities.[18]

[18] Other changes include changes in the number of tablets per blister pack, changes in shelf life, modifications made in accordance with the *Chinese Pharmacopoeia*, and revisions to package inserts. Results by subtype are presented in Table B.4.

Figure 2 presents the event study estimates. Winning producers conduct more MPCs following procurement compared with non-winning producers, particularly around the procurement quarter.[19] Panel (b) decomposes these dynamic effects by the three types of MPCs, which largely mirror the aggregate trends.

Motives behind Winning Firms' MPCs

Given that MPCs are predominantly undertaken by winning firms, we investigate the drivers of this behavior at the winning firm-molecule-province level. Table 3 analyzes these motivations from both supply and demand perspectives based on equation (5). For the supply side, column (1) shows that winning firms with lower bid prices are significantly more likely to engage in MPCs, likely reflecting the intensified pressure on profit margins. To quantify this, we calculate the projected revenue by multiplying the winning bid price by the cumulative expected demand across all supplying provinces. By scaling this against pre-CVBP sales and revenue, we derive measures for the expected percentage changes in revenue and the expected increase in supply volume. Winning firms facing lower expected revenue and higher supply pressure are significantly more likely to engage in MPCs. In contrast, top winning firms face lower pressure and are thus less likely to engage in MPCs. Columns (2)–(4) decompose these effects by MPC type. We find that MPCs on packaging materials are significantly associated with lower bid prices, suggesting that firms use packaging changes primarily as a cost-saving mechanism in response to price compression. Conversely, API and capacity MPCs are significantly correlated with higher expected supply increases, indicating that these changes are driven by the need to ensure supply stability.

Turning to demand-side factors, we largely observe no significant relationship between MPCs and the characteristics of supplying provinces. Winning firms that engage in MPCs after CVBP do not preferentially select larger provinces (proxied by pre-CVBP drug utilization) nor do they favor poorer regions with higher unmet needs, as indicated by the concentration of rural hospitals, average wages, or education levels. Furthermore, while the staggered rollout of supplementary CVBP policies at the provincial level could potentially shift patient demand, we do not observe any significant correlation between these policy variations and the MPC behavior of winning firms.

[19] Our relative quarter 0 refers to the quarter when CVBP was implemented. As shown in Table B.1, bidding quarters are 1–2 quarters before the procurement quarter, and therefore, the slight increase in MPCs in relative quarter -1 is also likely to be driven by winning a bid under CVBP.

Compensatory Drug Utilization due to MPCs

Finally, we examine whether these MPCs can affect drug utilization in Table 4 based on equation (6). Since we are interested in the effects driven by winning drugs, we restrict our sample to hospitals that have bought any winning drugs in the post-period. Column (1) shows that for this sample, the average increase in drug utilization is higher than our baseline estimate in Table 1. Column (2) reveals that if a winning firm conducts an MPC, drug utilization for the affected hospitals is 17.1% higher than that of the non-affected hospitals. In contrast, column (3) shows that for winning firms implementing changes unrelated to the manufacturing process, drug utilization in their supplied hospitals is similar to that in non-supplied hospitals.

To better understand the underlying mechanisms, we examine three MPC categories separately.[20] Column (4) reveals that changes in all these MPCs are associated with a greater drug utilization. However, MPCs on packaging materials lead to the greatest increase in drug utilization at 24.7%, followed by MPCs on production capacity (13.3%), and the increase due to MPCs on API suppliers is smallest (8.5%).

Among these three types of MPCs, an increase in drug utilization due to MPCs on production capacity expansion could reflect a positive improvement in supply if such MPCs are not subject to quality decrease. An increase in drug utilization due to adding/changing APIs is more complicated, because on the one hand, such MPCs might be in response to an expanded market due to CVBP to guarantee sufficient supply; but on the other hand, changing APIs, especially cheaper APIs, may lead to lower drug efficacy if cheaper APIs have lower quality. By contrast, MPCs on packaging materials should not lead to an increase in drug utilization if there were no quality decrease, given the selling price is fixed under CVBP.

Although the results in Table 3 indicate that the MPC behavior of winning firms is uncorrelated with demand factors, we further control for the interaction between the DiD estimator (*Procured*) and hospital or city characteristics in columns (5) and (6). These controls include hospitals' price difference between pre-CVBP dominant drugs and post-CVBP winning drugs, hospital tier, urban/rural status, and the city-level average wage and education. The resulting coefficients remain

[20] Eban (2019)'s Bottle of Lies: The Inside Story of the Generic Drug Boom reveals that any part of the manufacturing process can be manipulated to make data look good for drug evaluations, which is especially problematic when generics are produced in developing countries.

consistent with the baseline estimates in columns (2) and (4).[21]

Figure 3 plots the event study estimates derived from equation (7). As shown in panel (a), drug utilization increases significantly starting two quarters after the MPC implementation. When decomposing these effects by MPC type, the increase is most pronounced for packaging material MPCs, while the utilization growth associated with API and capacity MPCs is relatively modest. Notably, the negative pre-trend observed for capacity MPCs suggests that hospitals supplied by these winning firms likely experienced supply shortages prior to the capacity expansion. Finally, panel (b) demonstrates that our findings remain robust when excluding MPCs implemented in the exact quarter of the CVBP implementation. Overall, we regard MPCs on packaging materials as the most direct evidence of quality decrease and the associated utilization increases as compensatory quantity effects.

Heterogeneity in Compensatory Drug Utilization due to MPCs

Patients' compensatory drug utilization due to MPCs is heterogeneous. First, comparing columns (1) and (2) of Table 5, we observe a stronger treatment effect for mixed acute-chronic use drugs relative to chronic conditions, consistent with our model prediction, as the dosage compensation response is stronger when efficacy is more salient. Second, columns (3) and (4) reveal that the MPC-driven volume expansion is statistically indistinguishable between urban and rural regions. This result is particularly important for ruling out the demand-side mechanism: if the volume growth due to MPCs were driven by the fulfillment of previously unmet needs, we would expect a larger effect in underserved rural areas. Instead, the uniform increase between rural and urban areas points to MPCs as a broad supply-side shock common to all markets.

Moreover, if MPCs on packaging materials indeed worsen drug quality, it should be most salient for injection drugs, as their efficacy is more sensitive to the quality of glass bottles, rubbers, and other materials (U.S. Food and Drug Administration, 1999; U.S. Pharmacopeial Convention,

[21] We use the sensitivity test proposed by Oster (2019) to evaluate potential biases in our baseline results arising from omitted variables. In this framework, the parameter δ quantifies how much more influential unobserved variables must be relative to observed ones to completely explain away the baseline effect. While a threshold of $\delta = 1$ is typically used to indicate robustness, our analysis shows that the estimated coefficient would only be driven to zero if the influence of unobservables were 23.7 times greater than that of the observed controls (including the hospital and city characteristics shown in columns (5) and (6)). We calculate the bounding set by setting $\delta = 1$ and $\delta = -1$, capturing scenarios where the bias from unobservables either aligns with or directly opposes the direction of selection on observed variables. Under these assumptions, the estimated coefficient interval is tightly bounded at $[0.162, 0.171]$.

2016). Columns (5) and (6) confirm this pattern. For MPCs on packaging materials, the positive effect on drug utilization is only among injection drugs, consistent with evidence that the efficacy of injection drugs is more difficult to maintain, subject to stricter internal and external quality controls. For capacity-related MPCs, the effect is also much stronger for injection drugs, consistent with evidence that injection drugs are more prone to drug shortages (U.S. Food and Drug Administration, 2019; Shukar et al., 2021).[22] Given this evidence, we believe that an increase in drug utilization due to MPCs on packaging materials is more likely to reflect lower efficacy of drugs.[23]

6.2.2 Branded-to-Generic Switching and Drug Utilization

We next 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. First, column (1) of Table 6 shows the changes at the extensive margin, where the outcome variable is $switch_{id}$, a dummy variable indicating whether a hospital buys winning drugs of a molecule after the CVBP. The coefficient is negative and significant, demonstrating that hospitals which predominantly used branded drugs before the CVBP are 1.9 percentage points less likely to buy winning drugs afterwards, indicating demand-side resistance to switching.

Columns (2)–(5) explore the intensive margin for procured molecules, exploring the variation by whether a hospital predominantly bought branded drugs for a molecule before the CVBP. Based on equation (8), we progressively introduce partial controls in columns (2) and (3), finding that switching from a branded to a generic drug increases utilization by 3.8% to 5.6%. Our preferred specification in column (4), which incorporates the full set of hospital and city-level controls, reveals a substantially larger effect: a 10.3% increase in drug utilization. Finally, column (5) corroborates these findings using a PSM-DiD approach, yielding a 16.2% increase among matched

[22]The negative CVBP average effect for injection molecules may reflect two factors: they are more prone to supply disruptions than oral drugs, and simultaneous price cuts for oral alternatives may increase access to oral drugs and thus reduce the need for injections.

[23]In response to public concerns regarding quality, the second draft of the 11th Round of CVBP initially proposed banning all post-award MPCs to safeguard the quality of winning drugs (Pharnexcloud, 2025). However, citing a lack of scientific evidence on quality downgrading after MPCs, the final rule mandated only that winning firms disclose MPCs on the CVBP website for public oversight (National Healthcare Security Administration of China, 2025). Our findings provide causal evidence suggesting that MPCs involving packaging materials are likely to lead to quality deterioration. In contrast, MPCs related to production capacity and APIs present a trade-off: while they may compromise quality, they also contribute to supply stability. Finally, changes unrelated to the manufacturing process do not affect quality.

hospital pairs.[24] The progressive increase in coefficients across specifications points to a potential downward bias from omitted variables, suggesting the true effect may be even larger if this pattern holds for unobservables (Oster, 2019).

Heterogeneity by Whether Drugs Treating Chronic Conditions

To further examine whether the increase in drug utilization after switching drugs can be explained by lower drug efficacy and how patients may respond to the drug switch driven by the CVBP, we divide our five drug classes into two groups: drug classes mainly for chronic conditions (CCs) and drug classes with mixed acute-chronic use.[25] Our reasoning is that patients with CCs may have a stronger preference for their previously-used branded drug and may resist switching drugs. By contrast, patients with acute conditions, due to lack of previous knowledge on any relevant drugs, are more likely to be passive users simply following physician's prescriptions. Figure 4 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 mixed acute-chronic use, we find a sharp 50% increase in drug utilization after the CVBP. This reveals that patients with CCs show a resistance to winning generics, while patients with acute conditions (or who do not resist switching) are likely to use higher doses after the switch from a branded to a winning generic drug.

6.3 Welfare Implications: Effective Price Reduction

The results in Sections 6.2.1 and 6.2.2 demonstrate that the increases in drug utilization after CVBP are driven by both a price effect (lower prices) and a quality effect (lower efficacy).[26] If we take into account the higher doses needed to maintain the same efficacy of a drug, the effective price reduction becomes $\Delta P = 1 - (1 - 64\%) * (1 + \Delta Q)$, where 64% represents the nominal price reduction by directly estimating the CVBP's impact on drug prices (Jiang et al., 2025). Taking the

[24] Using hospital-level and city-level controls for the variable $switchBG_{id}$ of the procured molecules, as shown in Figure B.3, the standardized bias across covariates is substantially reduced after matching, confirming the balance between the two groups. The distribution of propensity scores is more comparable between the two groups, as shown in Figure B.4.

[25] Drug classes primarily for CCs include ACE inhibitors, SSRIs and Statins. Drug classes with mixed acute-chronic use include PPIs and SABAs.

[26] In fact, if we consider the outflow of prescriptions to pharmacies which is not captured by our data, what we estimate is the lower bound of the actual increase in drug utilization, especially for drugs treating chronic conditions.

estimate from Table 4 column (4) for MPCs on packaging materials and changing API suppliers, we show that the effective price reduction after incorporating such MPCs becomes 55% and 61%, respectively. Figure 5 summarizes these calculations. If we assume that generic-to-generic drug switch does not involve any change in drug quality and use the estimated drug utilization increase from Table 6 column (4), the effective price reductions become 60%. Similarly, if we believe that the estimate from drug classes with mixed acute-chronic use reflects the quality effect more accurately, applying the 50% increase in drug utilization in Figure 4, the effective price reduction becomes 46%.

7 Conclusion

This paper provides large-scale causal evidence that centralized procurement, by contracting on price while leaving quality unmonitored, creates scope for supplier moral hazard. Winning firms are significantly more likely to undertake MPCs after award, particularly those with lower bids. These MPCs, especially changes to packaging materials, drive additional utilization increases consistent with compensatory dosing rather than improved quality. Branded-to-generic switching yields similar patterns. Accounting for these quality-driven utilization responses, effective price reductions are 3–18 percentage points smaller than the headline 64%.

These findings carry important implications for the design of centralized procurement systems. First, procurement mechanisms that select winners primarily on price risk systematically favoring lower-quality drugs over higher-quality alternatives that cannot compete on cost alone, suggesting that quality dimensions should be incorporated into selection criteria beyond minimum regulatory thresholds. Second, ongoing quality monitoring after contract award is essential, as our evidence on post-award MPCs highlights the scope for undetected quality erosion even among firms that cleared pre-award screening. Third, while these concerns are especially acute in developing countries where weaker regulatory capacity leaves greater room for quality degradation, the underlying mechanism—moral hazard under incomplete contracting—applies to any procurement system in which quality is imperfectly contractible, including generic drug and medical device procurement programs in developed economies.

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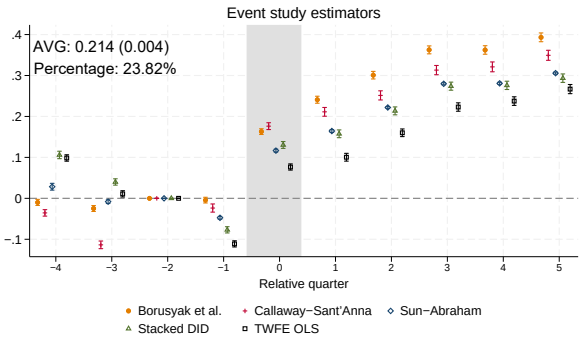
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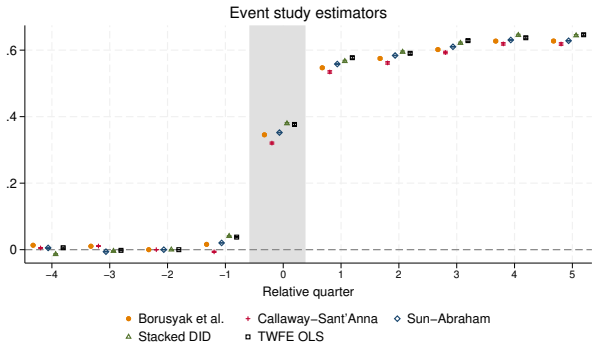
Xia, Tianli and Liyu Zhao, "The Cost of Cost Savings: Procurement Auctions and Moral Hazard in Drug Market," 2026.

Figures and Tables

(a) Log (DDDs)



(b) Share of Winning Drugs



(c) Share of Branded Drugs

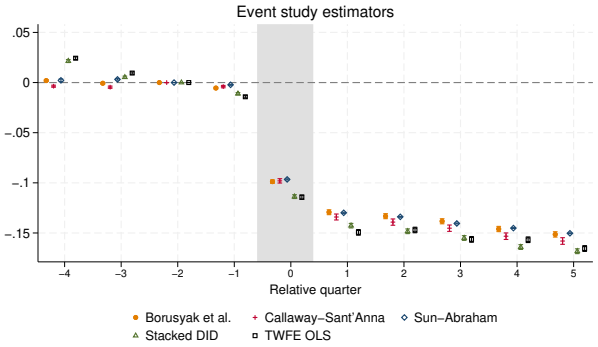
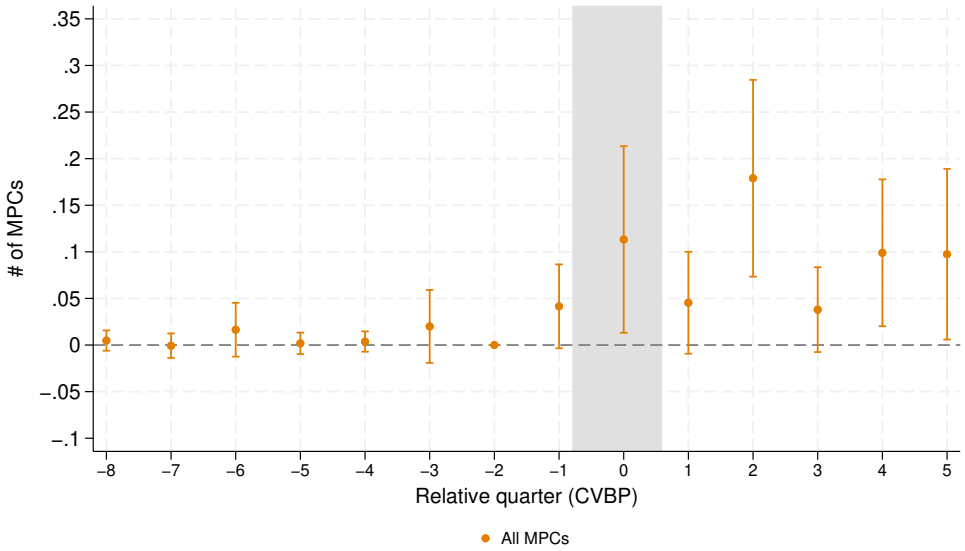


Figure 1: Event Study: Baseline Effects of CVBP on Drug Utilization

Notes: This figure presents event-study estimates from five different estimators: Borusyak et al. (2024) (orange circles); Callaway and Sant'Anna (2021) (red crosses); Sun and Abraham (2021) (blue diamonds); Cengiz et al. (2019) for stacked DiD (green triangles) and the TWFE model (black squares). The reference period is the relative quarter -2. All specifications include calendar-quarter and hospital-molecule fixed effects. Relative quarter 0 is a transition period that spans both pre- and post-CVBP phases, so estimates at quarter 0 may be attenuated. 95% confidence intervals are displayed but are visually negligible due to the large sample size. Full regression results are reported in Table 1.

(a) All MPCs



(b) MPCs by Type

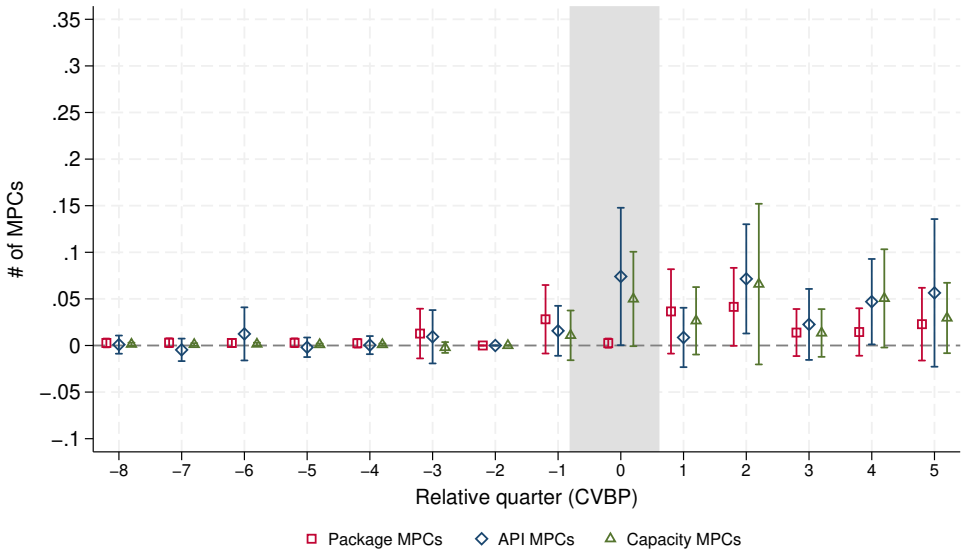
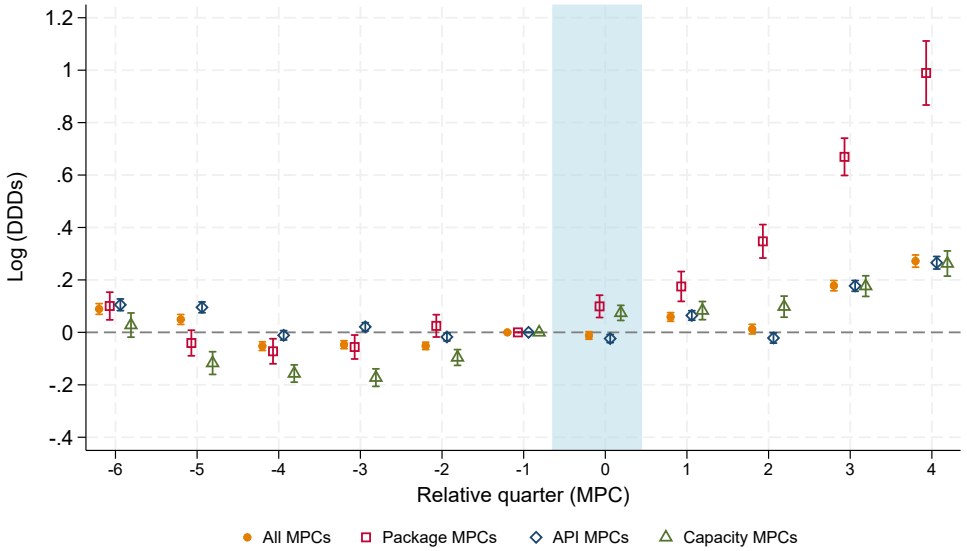


Figure 2: Event Study: Effects of CVBP on Winning Firms' MPCs

Notes: This figure plots the dynamic effects of the CVBP on winning firms' MPCs (β_2 in Equation (4)). Symbols denote MPC types: all MPCs (orange circles), packaging materials (red squares), API changes (blue diamonds), and production capacity (green triangles). Panel (a) shows the aggregate effects, while Panel (b) decomposes by MPC type. Corresponding regression estimates are reported in Table 2.

(a) Full Sample



(b) Excluding MPCs Concurrent with CVBP Implementation

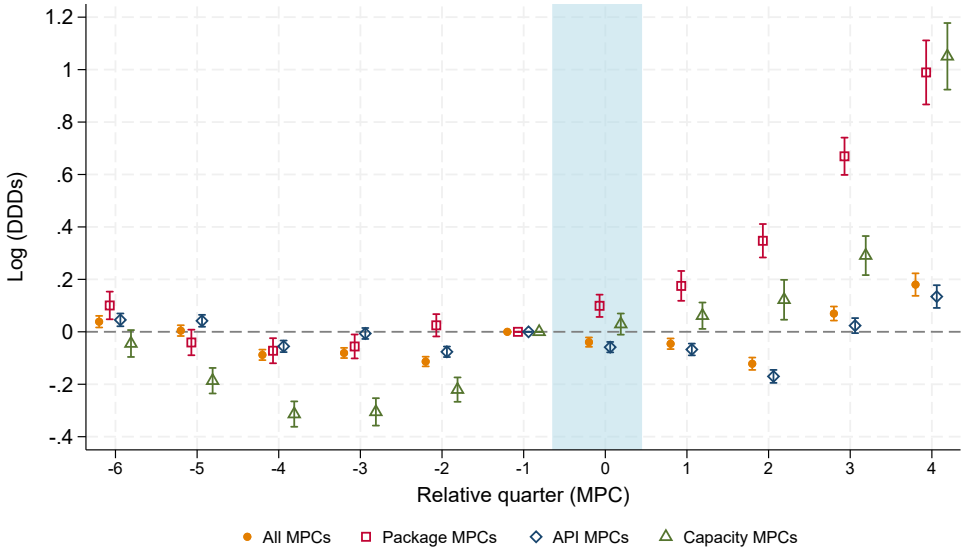


Figure 3: Event Study: Effects of MPCs on Drug Utilization

Notes: This figure illustrates the dynamic impacts of winning firms' MPCs on hospital-level drug utilization, based on estimates from equation (7). The event time (relative quarters) is centered around the timing of a winning firm's MPC, rather than the CVBP implementation date. Symbols denote MPC types: all MPCs (orange circles), packaging materials (red squares), API changes (blue diamonds), and production capacity (green triangles). Panel (a) uses the full sample, whereas Panel (b) excludes MPCs occurring in same quarter as CVBP implementation.

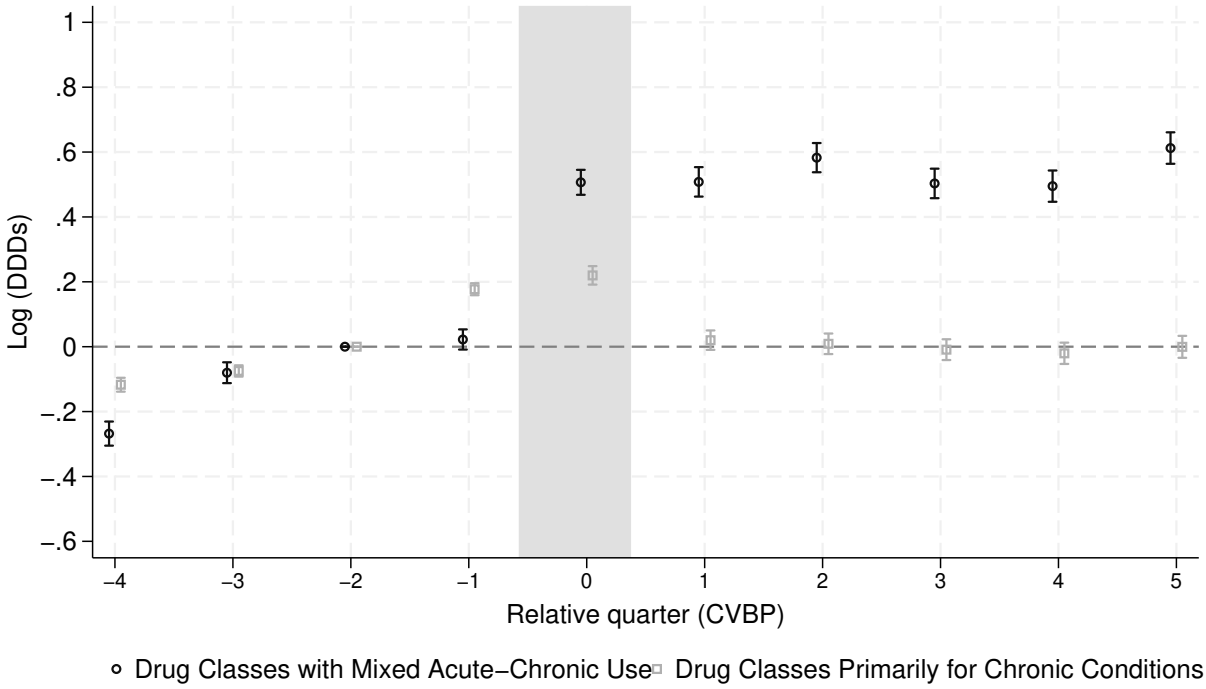


Figure 4: Event Study: Heterogeneous Effects by Branded-to-Generic Switch

Notes: This figure plots event study estimates of the effect of branded-to-generic switching on drug utilization, separately by drug class type: (1) mixed acute-chronic use (PPIs and SABAs) and (2) chronic only (ACE inhibitors, SSRIs, and statins). Both specifications include the full set of controls as in column (4) of Table 6.

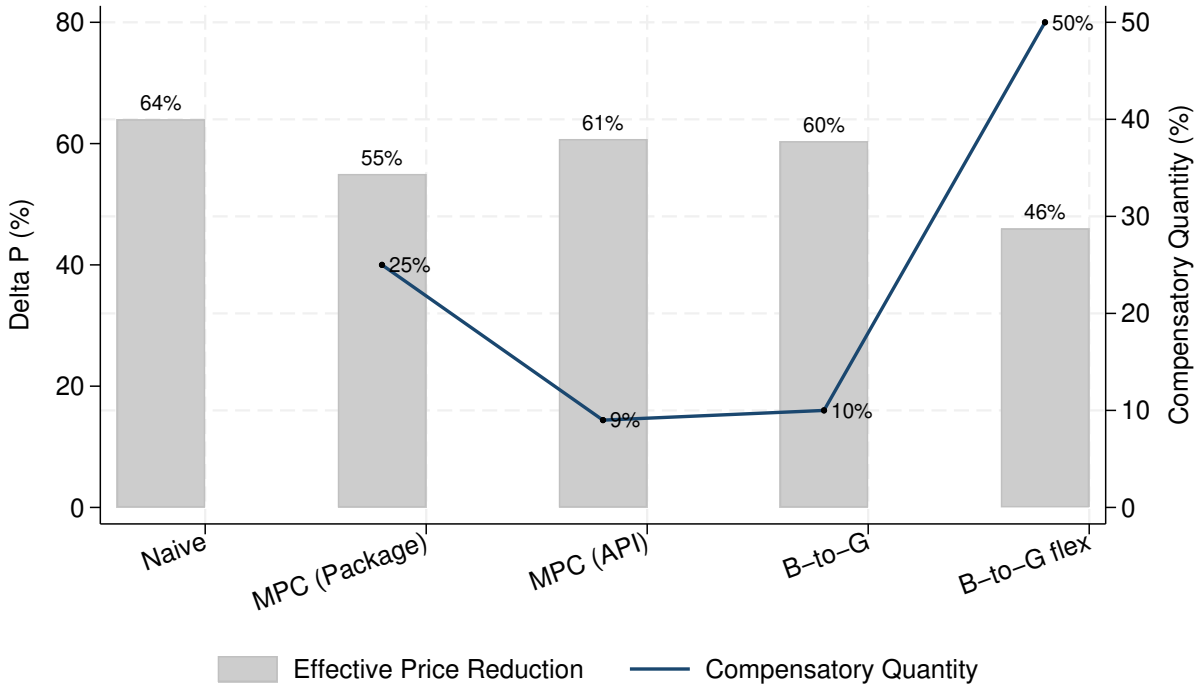


Figure 5: Effective Price Reduction Accounting for Compensatory Dosing

Notes: This figure presents effective price reduction after accounting for compensatory dosing. Compensatory quantity estimates (ΔQ) are from: column (4) of Table 4 for *MPC (Package)* and *MPC(API)*, column (4) of Table 6 for *B-to-G*, and Figure 4 for *B-to-G flex*. Effective price reductions are calculated as: $\Delta P = 1 - (1 - 64\%) \times (1 + \Delta Q)$.

Table 1: Average Effects of CVBP on Drug Utilization

	(1) Log (DDDs)	(2) Share of Winning	(3) Share of Branded Drugs
Procured	0.214***	0.601***	-0.157***
	(0.004)	(0.002)	(0.001)
Hospital × Molecule FE	✓	✓	✓
Quarter FE	✓	✓	✓
Mean of Y (Before CVBP)	9037.47	0.10	0.24
Percentage Change	23.82		
# of observations	1923491	1923491	1923491
R^2	0.81	0.80	0.86

Notes: This table presents DiD estimates using the full sample. The observation window spans relative quarters -4 to 5. Outcome variables are: quantity (DDDs) in column (1), share of winning drugs in column (2), and share of branded drugs in column (3), respectively. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2: Average Effects of CVBP on MPCs

	MPCs				Other Changes
	(1) All	(2) Package	(3) API	(4) Capacity	(5)
Procured	-0.003	-0.000	0.001	-0.004**	0.019
	(0.005)	(0.002)	(0.004)	(0.002)	(0.012)
Procured × Winning	0.085***	0.015**	0.042***	0.038**	-0.035
	(0.024)	(0.008)	(0.015)	(0.015)	(0.027)
Producer × Molecule FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
Mean of Y (Before CVBP)	0.010	0.005	0.005	0.002	0.145
# of observations	8510	8510	8510	8510	8510
R^2	0.13	0.08	0.12	0.11	0.20

Notes: This table presents the effects of CVBP on MPCs. Dependent variables are: the number of all MPCs in column (1), package material MPCs in column (2), API MPCs in column (3), capacity MPCs in column (4), and non-manufacturing process in column (5). The panel is balanced by imputing zeros for quarters without observed changes. Relative quarter 0 is retained in the estimation sample. Pre-CVBP means are calculated for winning firms only. Standard errors clustered at the producer level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3: Winning Firms' MPCs: Supply- and Demand-Side Factors

	(1) All MPCs	(2) Package	(3) API	(4) Capacity
(a) Supply-Side Factors				
Bid Price	-0.168***	-0.087*	0.003	-0.013
	(0.044)	(0.050)	(0.048)	(0.051)
Changes in Revenue	-0.360***	-0.058***	-0.288***	-0.036*
	(0.022)	(0.020)	(0.018)	(0.022)
Changes in Supply	0.031***	0.002	0.021***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Top Producers	-0.108***	-0.102***	-0.074**	-0.068*
	(0.036)	(0.032)	(0.029)	(0.035)
(b) Demand-Side Factors				
Log (Pre-CVBP DDDs)	-0.012	-0.005	-0.018*	0.004
	(0.010)	(0.007)	(0.010)	(0.009)
Share of Rural Hospitals	0.087	-0.101	0.177	0.101
	(0.145)	(0.095)	(0.145)	(0.117)
Log (Average Wage)	0.034	0.035	0.092	-0.059
	(0.093)	(0.060)	(0.089)	(0.070)
Log (Education)	0.258	-0.218	0.231	0.203
	(0.186)	(0.138)	(0.186)	(0.142)
Payment Policies (Before MPCs)	-0.009	-0.032	-0.021	0.028
	(0.041)	(0.031)	(0.039)	(0.032)
Balance Policies (Before MPCs)	-0.054	0.013	-0.010	-0.025
	(0.043)	(0.034)	(0.040)	(0.033)
Payment Policies (After MPCs)	-0.077	-0.040	-0.047	0.012
	(0.049)	(0.027)	(0.046)	(0.035)
Balance Policies (After MPCs)	-0.065	0.032	-0.042	-0.056*
	(0.043)	(0.026)	(0.041)	(0.030)
Molecule FE	✓	✓	✓	✓
Mean	0.30	0.08	0.21	0.09
# of observations	499	499	499	499
R^2	0.63	0.56	0.53	0.48

Notes: This table examines correlations between winning firms' MPCs and firm and province characteristics, based on Equation (5). The unit of observation is winning firm-molecule-province. Panel (a) reports supply-side factors and panel (b) reports demand-side factors. Dependent variables are indicators for: any MPC in column (1), packaging material MPCs in column (2), API MPCs in column (3), and capacity MPCs in column (4) Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: The Effects of MPCs on Drug Utilization

	Log (DDDs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Procured	0.276***	0.277***	0.288***	0.273***	5.421***	5.514***
	(0.004)	(0.005)	(0.006)	(0.005)	(0.200)	(0.201)
Procured × winMPC		0.171***			0.168***	
		(0.008)			(0.008)	
Procured × otherChanges			0.007			
			(0.004)			
Procured × winMPC (Package)				0.247***		0.278***
				(0.021)		(0.021)
Procured × winMPC (API)				0.085***		0.071***
				(0.009)		(0.009)
Procured × winMPC (Capacity)				0.133***		0.172***
				(0.019)		(0.019)
Hospital × Molecule FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Procured × Hospital's Controls					✓	✓
Procured × City's Controls					✓	✓
Mean of Y (Before CVBP)	10203.28					
# of observations	1763809	1763809	1763809	1763809	1763809	1763809
R^2	0.81	0.81	0.81	0.81	0.81	0.81

Notes: This table reports the effects of winning firms' MPCs on drug utilization, exploring heterogeneity based on whether a hospital's designated winning firm undertakes an MPC. The dependent variable is log(DDDs). Column (1) re-estimates the baseline specification of column (1) in Table 1, restricting the sample to hospitals purchasing winning drugs after CVBP. In Column (2), *winMPC* equals to one for quarters following a winning firm's MPC. Column (3) is a placebo test using changes unrelated to the manufacturing process. Column (4) disaggregates MPCs into three categories: package materials, APIs, and production capacity. Columns (5) and (6) augment the specifications in columns (2) and (4) with interactions between *Procured* and price differences, hospital-, and city-level characteristics. Price difference is defined as $priceDif_{id} = (prePrice_{id} - postPrice_{id})/preprice_{id}$, where pre-price is the average price of drugs from the dominant firm and post-price is the price of the winning drug for hospital i's province. Hospital-level controls include tier and urban/rural status; city-level controls include average wage and education. 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 MPCs on Drug Utilization by Drug Use, Location, and Formulation

	By Drug Use		By Affordability		By Injection	
	(1) Mixed Acute-Chronic Use	(2) Chronic Conditions	(3) Urban	(4) Rural	(5) Injection	(6) Non-Injection
Procured	0.201***	0.149***	0.224***	0.313***	-0.262***	0.299***
	(0.008)	(0.006)	(0.007)	(0.006)	(0.024)	(0.005)
Procured × winMPC	0.175***	0.121***	0.162***	0.182***		
	(0.015)	(0.009)	(0.010)	(0.014)		
Procured × winMPC (Package)					0.422***	-0.069*
					(0.023)	(0.036)
Procured × winMPC (API)					-0.050	0.150***
					(0.112)	(0.009)
Procured × winMPC (Capacity)					0.312***	0.069***
					(0.037)	(0.021)
Hospital × Molecule FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Mean of Y (Before CVBP)	9297.87	10717.99	14613.68	6464.55	6735.52	10451.46
# of observations	1020777	743032	849959	913850	936375	1709447
R^2	0.81	0.81	0.84	0.78	0.83	0.81

Notes: This table reports the heterogeneous effects of MPCs on drug utilization across different drug attributes and market environments. The dependent variable is the logarithm of DDDs. Columns (1) and (2) divide the sample by drug use, mixed acute-chronic use versus chronic only. Columns (3) and (4) split the sample by urban and rural areas, respectively. Columns (5) and (6) split by formulation: injection versus non-injection. In columns (5) and (6), the MPC interaction is further disaggregated into packaging materials, API, and production capacity. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Effects of Branded-to-Generic Switch on Drug Utilization

	Extensive	Intensive			
	(1)	(2)	(3)	(4)	(5)
SwitchBG	-0.019***				
	(0.003)				
Procured_post		0.157***	5.398***	5.455***	6.355***
		(0.011)	(0.200)	(0.200)	(0.390)
Procured × SwitchBG		0.038***	0.056***	0.103***	0.162***
		(0.008)	(0.008)	(0.008)	(0.020)
Procured × PriceDif		0.095***	0.095***	0.105***	0.631***
		(0.011)	(0.011)	(0.012)	(0.134)
Hospital FE	✓				
Molecule FE	✓				
Hospital × Molecule FE		✓	✓	✓	✓
Quarter FE		✓	✓	✓	✓
Procured × Post × Hospital's Controls		✓		✓	✓
Procured × Post × City's Controls			✓	✓	✓
Mean of Y	0.79				
Mean of Y (Before CVBP)		10203.28			
# of observations	170990	1763809	1763809	1763809	1106112
R^2	0.46	0.81	0.81	0.81	0.83

Notes: This table estimates effects of branded-to-generic switching on drug utilization. Column (1) examines the extensive margin: whether a hospital purchases the winning drug after CVBP. The independent variable switchBG equals one if branded drugs dominated the hospital's pre-CVBP purchases for that molecule. Columns (2) through (5) examine the intensive margin, with log DDDs as the dependent variable. *PriceDif* is the relative price reduction between the pre-CVBP dominant drug and the post-CVBP winning drug. Columns (2) and (3) add interactions with hospital controls (tier, urban/rural) and city controls (average wage, education), respectively. Column (4) includes both. Column (5) uses propensity score matching based on *switchBG*, *PriceDif*, and hospital and city characteristics. Results are robust to controlling for post-2020 COVID-19 lockdowns and excluding three molecules without branded alternatives.Standard errors clustered at the hospital level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. Proofs and Derivations

A.1 First-Price Auction and Price Determination

The central government runs a first-price procurement auction. Each firm i submits a bid b_i, and let $b : [\underline{c}, \bar{c}] \to \mathbb{R}_+$ be a strictly increasing, differentiable symmetric Bayesian-Nash equilibrium (SBNE) bid function. Firms' types capture baseline unit costs only; post-award hidden actions (quality shading) are not priced in.[1]

A firm with cost type c bidding $p = b(c)$ wins if and only if its bid is the lowest, which under symmetry occurs with probability $(1 - F(c))^{n-1}$. Expected profit for type c is $\pi(c) = \big(b(c) - c\big)\, Q_0\, (1 - F(c))^{n-1} - \psi_0$, where $Q_0 > 0$ is the expected quantity the winner anticipates at award and ψ_0 denotes the cost to maintain a status-quo quality level.

Under standard regularity conditions (independence, risk neutrality, IPV), the SBNE satisfies the envelope condition

$$\pi'(c) = -Q_0\, (1 - F(c))^{n-1}. \tag{A.1}$$

Differentiating $\pi(c)$ and using (A.1) yields the ODE

$$b'(c) = \frac{(n-1) f(c)}{1 - F(c)} \big(b(c) - c\big), \qquad b(\overline{c}) = \overline{c}, \tag{A.2}$$

with solution

$$b(c) = c + \int_c^{\overline{c}} \frac{(1 - F(t))^{n-1}}{(1 - F(c))^{n-1}}\, dt, \qquad b'(c) > 0. \tag{A.3}$$

The realized award price is $p = b(c_{(1)})$, where $c_{(1)}$ is the lowest order statistic among n draws. The award price declines with n. Post-award, the winner privately chooses non-contractible quality $q \in [\bar{q}_{\min}, \bar{q}]$ at cost $\psi(q)$ and serves demand $Q(p, q)$ at price p.

We do not allow bidding to anticipate post-award quality shading for two reasons: (i) the promised quantity is determined before the auction through government-hospital negotiations; (ii) empirical evidence suggests firms behave as boundedly rational agents who optimize sequentially rather than solving the full dynamic problem at once.

[1] This deliberately treats hidden actions as a pure moral hazard problem, consistent with observed practice and analytically convenient.

Because quality is unverifiable, the principal cannot contract on q. After the tender, the winner chooses q^* to maximize expected payoffs given realized demand. As established by Laffont and Tirole (1993), whenever quality is non-contractible, the first-best allocation is unattainable. We solve by backward induction, beginning with patients' choices.

A.2 Patients' Decision

Patients are a unit mass. They observe quality through experience and make two decisions: participation $m \in \{0, 1\}$ and, conditional on $m = 1$, dosage intensity $x \geq 0$.[2]

Participation (Extensive Margin). Let the gross benefit of initiating treatment be $B_0(\gamma)$, depending on efficacy salience γ. Patients face out-of-pocket price αp (coinsurance rate $\alpha > 0$) and idiosyncratic participation friction $K \sim G(\cdot)$. A patient participates iff

$$m = 1 \quad \Longleftrightarrow \quad B_0(\gamma) - \alpha p - K \geq 0. \tag{A.4}$$

The participation rate is

$$M(p; \gamma) \equiv G\big(B_0(\gamma) - \alpha p\big), \qquad M_p < 0, \quad M_\gamma > 0. \tag{A.5}$$

Intensity (Intensive Margin). Conditional on $m = 1$, patients solve

$$\max_{x \geq 0} \; U(x; p, q, \gamma) \equiv B\big(\gamma\, x\, e(q)\big) - \alpha p\, x, \qquad B' > 0,\; B'' < 0. \tag{A.6}$$

Letting $z \equiv \gamma x e(q)$, the FOC is $\gamma e(q) B'(z) = \alpha p \quad \Longleftrightarrow \quad B'(z) = \frac{\alpha p}{\gamma e(q)}$. The optimal intensity is

$$x^*(p, q, \gamma) = \frac{1}{\gamma\, e(q)} \, (B')^{-1}\left(\frac{\alpha p}{\gamma\, e(q)}\right). \tag{A.7}$$

Comparative Statics. Differentiating with respect to p: $\frac{\partial x^*}{\partial p} = \frac{\alpha}{\gamma^2 e(q)^2 B''(z)} < 0$.

[2] We assume patients and physicians decide jointly.

For quality, differentiating the FOC with respect to q yields

$$\frac{\partial x^*}{\partial q} = -\frac{e'(q)\big[B'(z) + zB''(z)\big]}{\gamma e(q)^2 B''(z)}. \tag{A.8}$$

Similarly, differentiating with respect to γ:

$$\frac{\partial x^*}{\partial \gamma} = -\frac{B'(z) + zB''(z)}{\gamma^2 e(q) B''(z)}. \tag{A.9}$$

Since $\gamma, e(q), e'(q) > 0$ and $B''(z) < 0$, the signs of $\partial x^*/\partial q$ and $\partial x^*/\partial \gamma$ depend on $B'(z) + zB''(z)$. If $B'(z) + zB''(z) < 0$, then both derivatives are negative.

CRRA Example. For $B(z) = z^{1-\sigma}/(1-\sigma)$ with $\sigma \neq 1$: $B'(z) + zB''(z) = (1-\sigma)z^{-\sigma} < 0$ iff $\sigma > 1$. This establishes **Proposition 1**.

A.3 Post-Award Hidden Action: Quality Choice

The winning firm chooses q to maximize $\Pi(p, q) = (p-c)X(p, q, \gamma) - \psi(q)$, where market demand is $X(p, q, \gamma) = M(p; \gamma) \cdot x^*(p, q, \gamma)$.

An interior optimum $q^*(p, \gamma)$ satisfies

$$(p - c)X_q(p, q^*, \gamma) = \psi'(q^*), \tag{A.10}$$

with SOC

$$(p - c)X_{qq}(p, q^*, \gamma) - \psi''(q^*) < 0. \tag{A.11}$$

Applying the implicit function theorem to (A.10):

$$\frac{\partial q^*}{\partial p} = -\frac{X_q + (p - c)X_{qp}}{(p - c)X_{qq} - \psi''(q^*)}. \tag{A.12}$$

Sign of X_{qp}. Since M depends only on (p, γ): $X_p = M_p x^* + M x_p^*$, $X_{qp} = M_p x_q^* + M x_{qp}^*$.

From the patient's problem: $x_p^* < 0$, $x_q^* < 0$, and under the curvature condition $B' + zB'' < 0$: $x_{qp}^* = \frac{\partial}{\partial p}\left(-\frac{e'(q)[B'+zB'']}{\gamma e(q)^2 B''}\right) > 0$.

Since $M_p < 0$, $M > 0$, $x_q^* < 0$, and $x_{qp}^* > 0$: $X_{qp} = \underbrace{M_p x_q^*}_{>0} + \underbrace{M x_{qp}^*}_{>0} > 0$.

Conclusion. The denominator of (A.12) is negative by (A.11). The numerator captures two offsetting effects: $X_q < 0$ (higher quality reduces physical volume through lower required doses) but $X_{qp} > 0$ (higher quality stabilizes demand and reduces price sensitivity). When the stabilization effect is sufficiently strong, i.e., when $(p - c)X_{qp} + X_q > 0$, we obtain $\partial q^*/\partial p > 0$: lower procurement prices induce quality shading.

A.4 Heterogeneity

We examine how efficacy salience γ affects dosage responses to quality. Define $A(q) \equiv \frac{e'(q)}{e(q)^2}$, $H(z) \equiv \frac{B'(z)+zB''(z)}{B''(z)}$. Then (A.8) becomes $\frac{\partial x^*}{\partial q} = -\frac{A(q)H(z)}{\gamma}$.

Differentiating with respect to γ:

$$\frac{\partial^2 x^*}{\partial \gamma \, \partial q} = \frac{A(q)}{\gamma^2}\left[H(z) - \gamma H'(z)\frac{\partial z}{\partial \gamma}\right]. \tag{A.13}$$

Since $z = \gamma e(q) x^*$ and using (A.9): $\frac{\partial z}{\partial \gamma} = e(q)x^* + \gamma e(q)\frac{\partial x^*}{\partial \gamma} = e(q)x^* - \frac{H(z)}{\gamma}$.

The derivative of H is

$$H'(z) = 2 - \frac{B'(z)B'''(z)}{[B''(z)]^2}. \tag{A.14}$$

CRRA Case. Under CRRA preferences $B(z) = z^{1-\sigma}/(1-\sigma)$: $H(z) = \frac{(1-\sigma)z^{-\sigma}}{-\sigma z^{-\sigma-1}} = \frac{\sigma-1}{\sigma}z$, $H'(z) = \frac{\sigma-1}{\sigma}$.

Substituting into (A.13) and simplifying yields $\frac{\partial^2 x^*}{\partial \gamma \, \partial q} < 0$ for $\sigma > 1$.

A.5 Effective Price Wedge

Define the effective price as $p_{\text{eff}}(p, q, \gamma) = p/e(q;\gamma)$. Taking logs and differentiating: $d\ln p_{\text{eff}} = d\ln p - \frac{e_q(q;\gamma)}{e(q;\gamma)}dq$. If $dp < 0$ and $dq < 0$, the second term is positive, so the effective price falls less than the contractual price and can rise if quality deteriorates sufficiently. This establishes **Proposition 2**.

Appendix B. Additional Figures and Tables

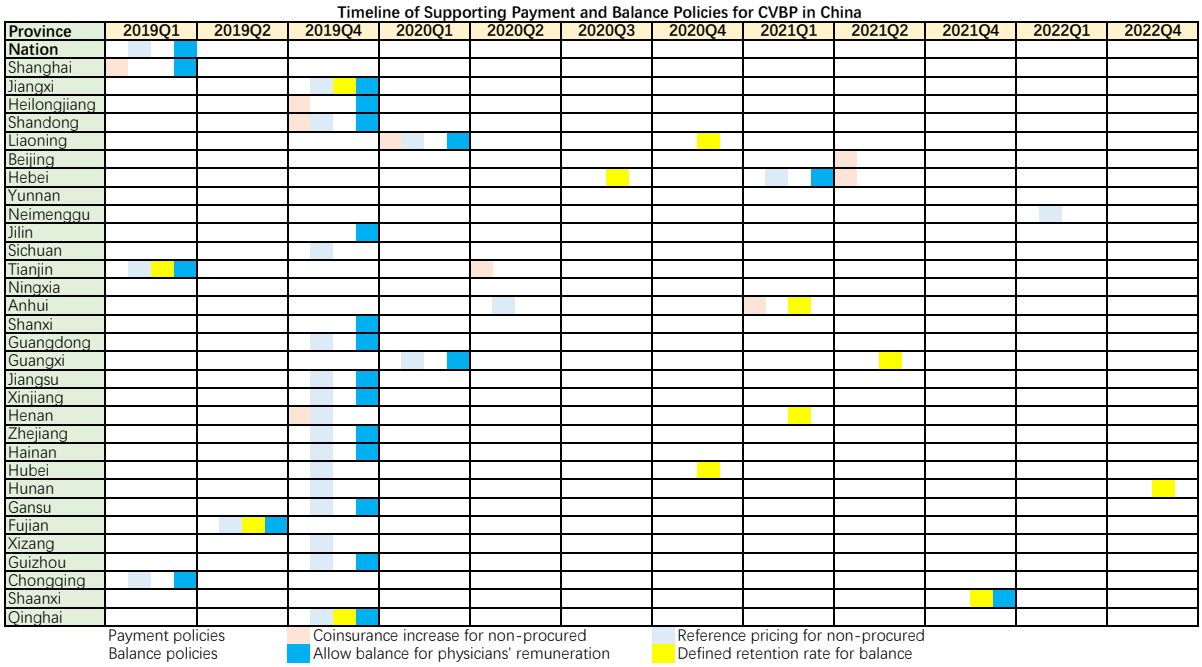


Figure B.1: Timeline of Supplementary Payment and Balance Policies for CVBP in China

Notes: This figure plots the timeline of supporting policies for CVBP across provinces in China. Payment policies steer patient demand through Co-Insurance (applying higher cost-sharing rates to non-winning drugs based on manufacturer price reductions) and Reference Pricing (setting the reimbursement benchmark at the winning bid price, increasing out-of-pocket costs for non-winning alternatives). Balance policies incentivize provider compliance through Retention (allowing institutions meeting procurement targets to retain a portion of savings) and Salary (permitting institutions to exceed wage ceilings and reward staff using medical service revenues).

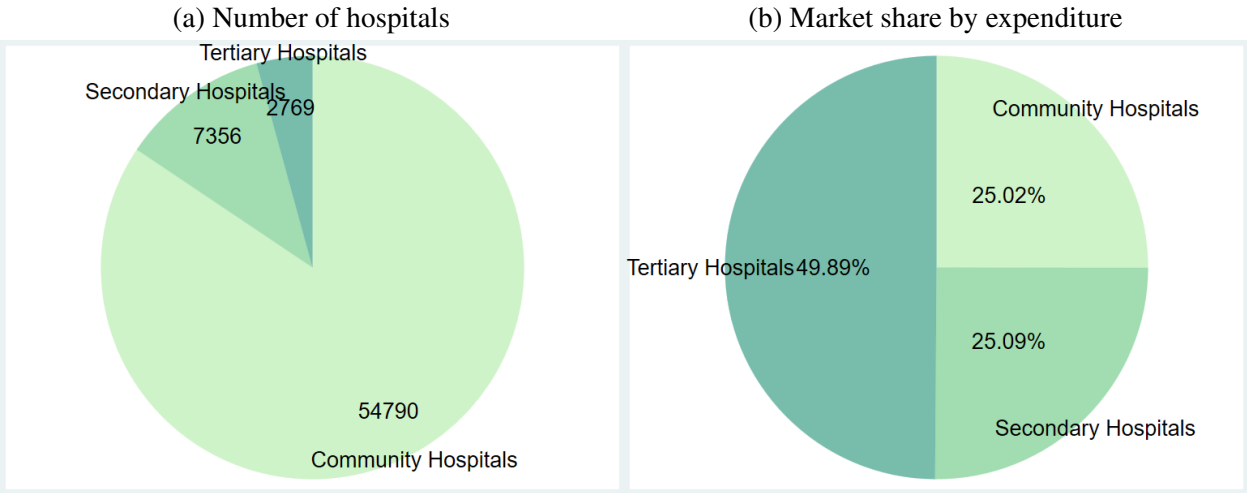


Figure B.2: Summary of Hospitals in Our Sample

Notes: This figure shows 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.

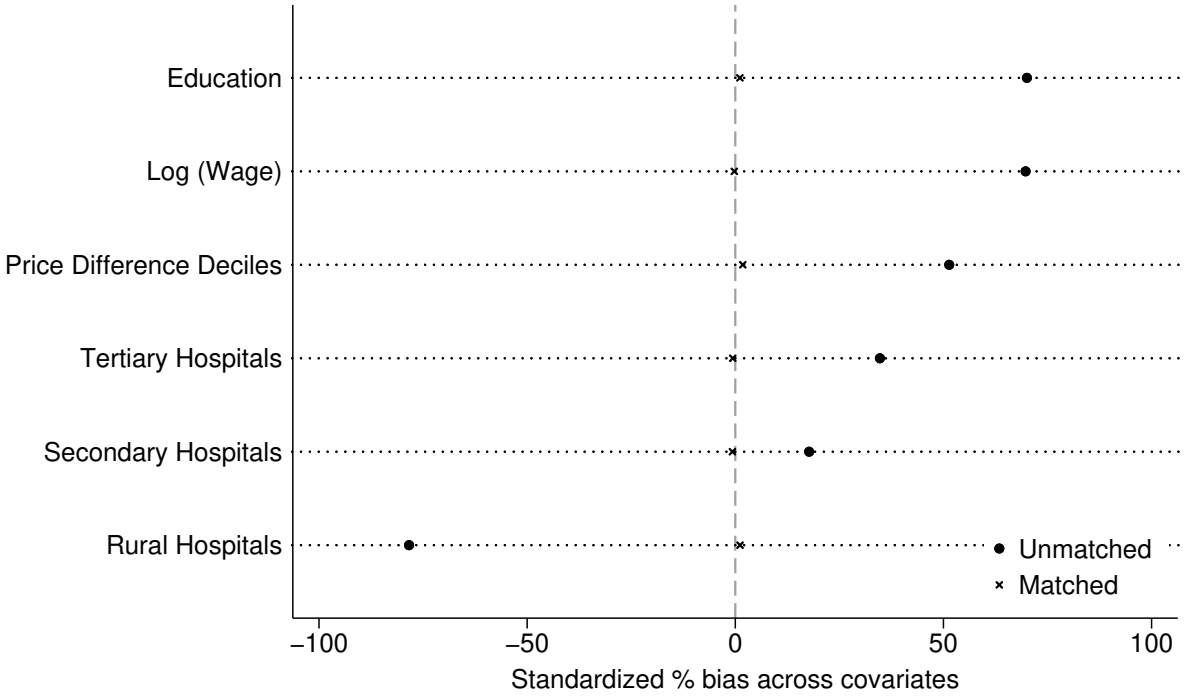


Figure B.3: Balance Check before and after Propensity Score Matching

Notes: This figure illustrates the standardized percentage bias across covariates before and after propensity score matching for *SwitchBG*. Each dot represents the mean difference between *switchBG* and *non-switchBG* hospitals prior to matching (unmatched), and each cross represents the bias after matching (matched).

(a) Before Propensity Score Matching

(b) After Propensity Score Matching

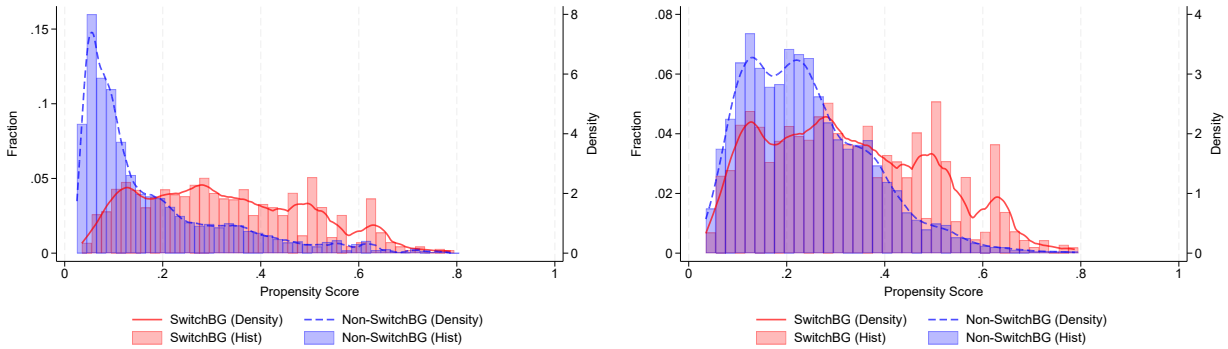


Figure B.4: Propensity Score Distribution before and after Matching

Notes: This figure plots the distribution of estimated propensity scores for *SwitchBG*. The bars represent the fraction of observations, and the solid (dashed) lines represent the kernel density for the *SwitchBG* (*Non-SwitchBG*) group.

Table B.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
9	41	2023.11	2024.3
10	62	2024.12	2025.4
11	55	-	-

Table B.2: List of Molecules across Five Drug Classes

Drug Class	Round	Molecules
ACE	Rounds 0 & 1	Enalapril, Fosinopril, Lisinopril
	Round 3	Captopril
	Round 4	Perindopril
	Round 5	Benazepril
	Non-Procured	Imidapril, Ramipril
HMG	Rounds 0 & 1	Rosuvastatin, Atorvastatin
	Round 2	Simvastatin
	Round 3	Pitavastatin
	Non-Procured	Pravastatin, Fluvastatin, Lovastatin
PPI	Round 3	Omeprazole
	Round 4	Pantoprazole for Injection, Pantoprazole, Esomeprazole
	Round 5	Lansoprazole for Injection, Esomeprazole for Injection
	Non-Procured	Lansoprazole, Rabeprazole
SSRI	Rounds 0 & 1	Paroxetine, Escitalopram
	Round 3	Fluoxetine, Sertraline, Citalopram
	Non-Procured	Fluvoxamine
SABA	Rounds 0 & 1	Salbutamol (Solution)
	Non-Procured	Salmeterol, Formoterol, Indacaterol, Salbutamol (Aerosol)

Table B.3: Summary Statistics

	Procured ALL	Pre-CVBP	Post-CVBP	Difference		Non-Procured
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean (SD)	Mean (SD)	Mean (SD)	Diff	P-Value	Mean (SD)
Average Price	4.55 (12.16)	7.23 (16.72)	2.79 (7.31)	-4.44	0.00	3.79 (4.48)
Total DDDs	11326.78 (38502.85)	9037.4 (30435.57)	12833.2 (42926.89)	3795.76	0.00	10083.47 (33165.82)
Expenditure	33364.49 (180789.80)	48668.3 (247584.20)	23293.9 (116623.80)	-25374.36	0.00	32356.91 (123733.40)
Share of winning	0.44 (0.48)	0.10 (0.28)	0.67 (0.44)	0.57	0.00	0.00 (0.00)
Share of branded	0.16 (0.34)	0.24 (0.41)	0.10 (0.28)	-0.14	0.00	0.33 (0.46)
Tertiary Hospitals	0.14 (0.34)	0.14 (0.34)	0.14 (0.35)			0.14 (0.35)
Secondary Hospitals	0.21 (0.41)	0.20 (0.40)	0.21 (0.41)			0.21 (0.41)
Community Hospitals	0.65 (0.48)	0.66 (0.47)	0.65 (0.48)			0.65 (0.48)
Rural Hospitals	0.55 (0.50)	0.55 (0.50)	0.56 (0.50)			0.49 (0.50)
Observations	1,190,023	472,293	717,730			909,759

Notes: This table reports the summary statistics of the sample used in this paper. We report the summary statistics of treated group by total sample, pre-CVBP sample, and post-CVBP sample. 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.

Table B.4: The Effects of the CVBP on Other Firms' Changes

	(1) Pack Size	(2) Shelf Life	(3) Pharmacopoeia	(4) Package Inserts
Procured	-0.000	-0.003	0.006	0.023***
	(0.005)	(0.005)	(0.004)	(0.007)
Procured × Winning	-0.012	0.002	0.016	-0.008
	(0.015)	(0.014)	(0.011)	(0.015)
Producer × Molecule FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
Mean of Y (Before CVBP)	0.046	0.024	0.015	0.012
# of observations	8510	8510	8510	8510
R^2	0.11	0.12	0.10	0.23

Notes: This table presents the effects of the CVBP on firms' additional changes unrelated to the manufacturing process. The dependent variables are the number of changes regarding pack size in column (1), shelf life in column (2), modifications made in accordance with the Chinese Pharmacopoeia in column (3), and package insert revisions in column (4). For column (4), we exclude revisions that add bioequivalence information. Because winning firms are already required to be bioequivalent, including these updates would introduce a mechanical bias, as winning firms inherently make such revisions less frequently than non-winning firms after the CVBP. We construct a balanced panel, imputing a value of zero for the dependent variable in newly added quarters. Relative quarter 0 is retained in the estimation sample. The reported mean of the dependent variable is calculated exclusively for winning firms. Standard errors clustered at the producer level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table B.5: Summary Statistics by Branded-to-Generic Switch

	SwitchBG=1	SwitchBG=0	Difference	
	(1)	(2)	(3)	(4)
Variables	Mean (SD)	Mean (SD)	Diff	P-Value
Pre 1Y Total DDDs	31073.70 (109568.70)	21367.57 (81743.95)	9706.13	0.00
Post 1Y- Pre 1Y Total DDDs	10138.22 (96711.95)	8791.84 (83426.42)	1346.38	0.01
Pre 1Y Average Price	6.93 (8.22)	6.72 (17.31)	0.21	0.02
Pre 1Y Share of Branded	0.96 (0.11)	0.01 (0.07)	0.95	0.00
Tertiary Hospitals	0.20 (0.40)	0.09 (0.29)	0.11	0.00
Secondary Hospitals	0.25 (0.43)	0.18 (0.39)	0.07	0.00
Community Hospitals	0.55 (0.50)	0.72 (0.45)	-0.18	0.00
Rural Hospitals	0.29 (0.45)	0.66 (0.47)	-0.37	0.00
Wage	104368.60 (37494.82)	82633.32 (24223.10)	21735.29	0.00
Education	10.28 (1.22)	9.45 (0.96)	0.82	0.00
Observations	38,606	143,615		

Notes: This table reports the summary statistics of the sample by branded-to-generic switch.

Appendix C. Robustness Checks

We conduct three additional robustness exercises to assess whether the findings are sensitive to the choice of comparison group, sample composition, or identifying assumptions. First, Figure C.1 re-estimates dynamics using procured molecules only by exploiting quasi-random variation in treatment timing, and the dynamic responses remain stable.[1] Second, Figure C.2 implements leave-one-molecule-out analyses, indicating that our findings are not driven by any single procured molecule. Third, Figure C.3 presents the honest DiD analysis proposed by Rambachan and Roth (2023). We compute conservative ("honest") confidence intervals for our estimates. Our analysis yields breakdown values at which the confidence intervals first include zero: $\bar{M} = 2.5$ for $\log$(DDDs), and even larger values for prices and expenditures. This implies that, to attribute the observed significance to a violation of parallel trends (rather than to causal effects), one would require post-treatment departures from parallel trends that are at least 2.5 times the largest pre-treatment deviation. Thus, relative to recent applications of this method, our baseline results appear particularly robust.[2]

[1] The pre-trend is flatter without control molecules, and the effect sizes are bigger for increases in drug utilization and thus smaller for decreases in drug expenditures using the Callaway and Sant'Anna (2021) and Borusyak et al. (2024) methods. Nevertheless, the overall conclusions remain unchanged.

[2] For comparison, Jones and Pineda-Torres (2024) report that their confidence intervals contain 0 when $\bar{M} = 1.25$; Barrot et al. (2024) find many estimates become insignificant when $\bar{M} = 1$; and Fu et al. (2024) show confidence intervals contain 0 when $\bar{M} = 2$.

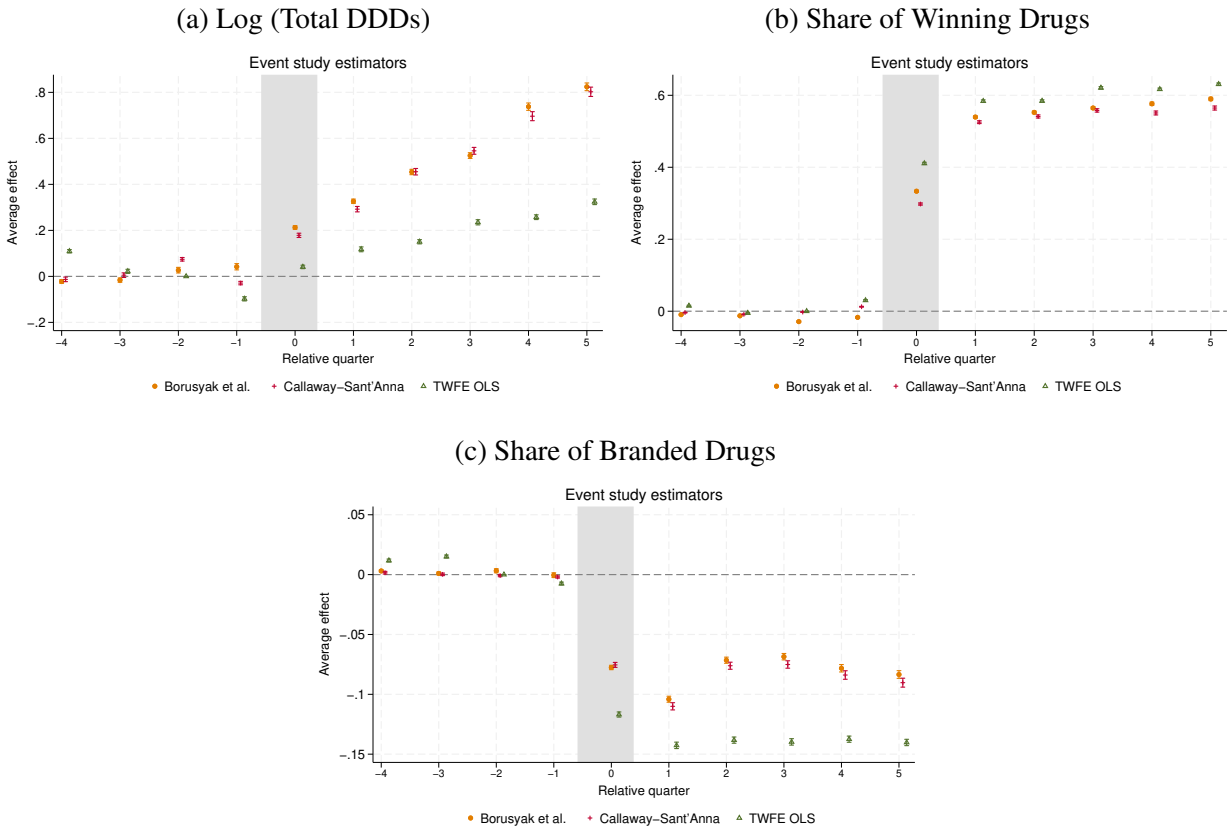
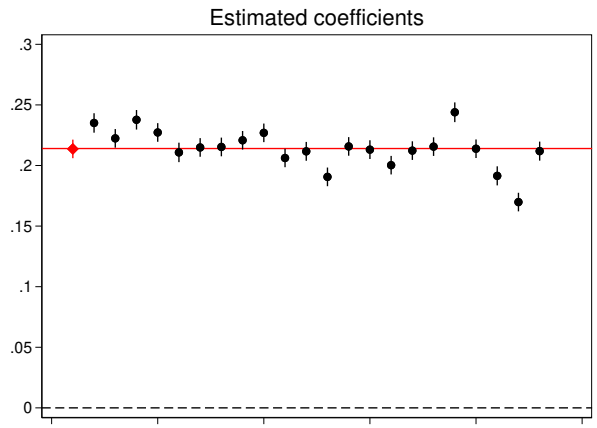


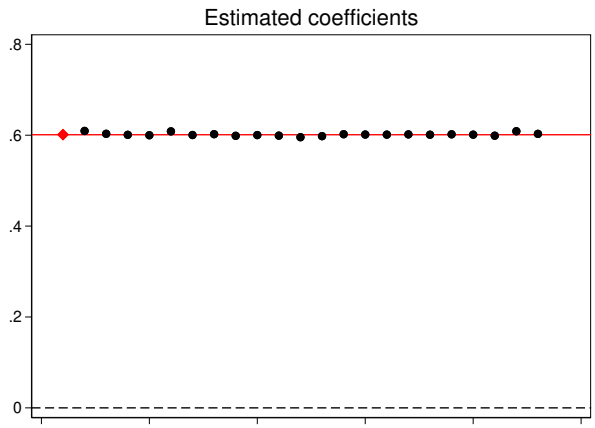
Figure C.1: Robustness: Event Study without the Control Group

Notes: This figure presents event-study estimates using only treated molecules. Without a control group, a balanced window yields incomplete comparisons; we therefore retain all quarters for treated molecules to estimate the dynamic effects, but report coefficients only for the balanced quarters (-4 to 5). These figures overlay results from three different estimators: Borusyak et al. (2024) (orange, circles); Callaway and Sant'Anna (2021) (red, crosses); and a dynamic TWFE model (green, triangles). Because CVBP implementation does not necessarily occur at the beginning of the relative quarter 0, estimates at 0 may be attenuated. 95% confidence intervals are displayed but are visually negligible relative to the coefficient estimates due to the large sample size.

(a) Log (DDDs)



(b) Share of Winning Drugs



(c) Share of Branded Drugs

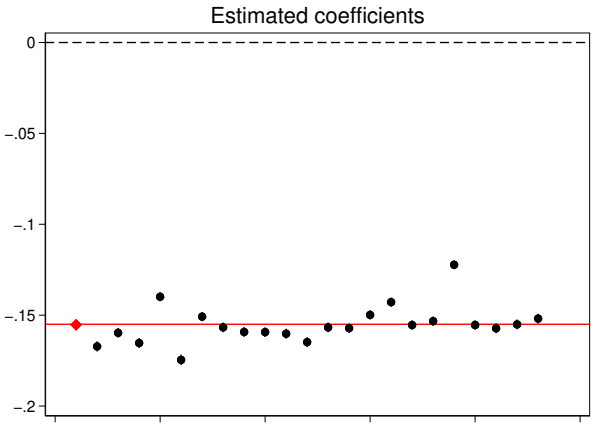
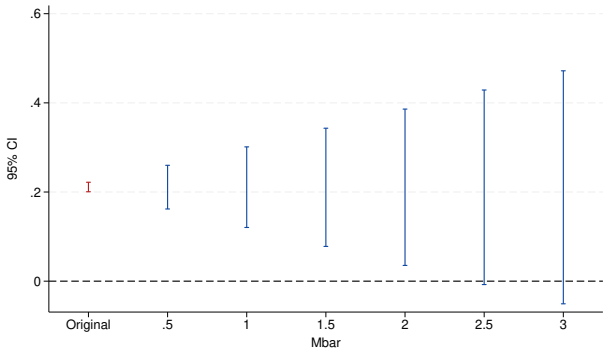


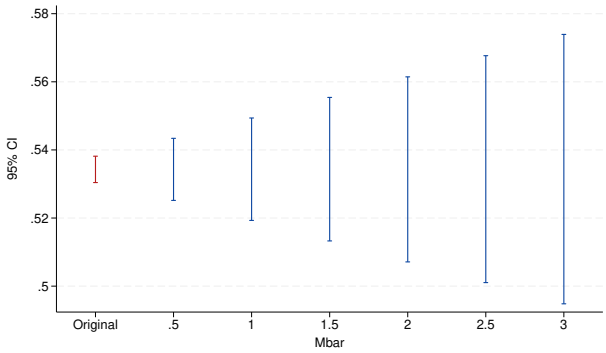
Figure C.2: Robustness: Leave-one-out Analysis

Notes: This figure presents leave-one-out robustness checks for the effects of CVBP. The red diamond shows the baseline coefficients estimated on the full sample. Each black circle reports the result from re-estimating the same specification after dropping one treated molecule at a time. 95% confidence intervals are displayed but are visually negligible relative to the coefficient estimates due to our large sample size.

(a) Log (DDDs)



(b) Share of Winning Drugs



(c) Share of Branded Drugs

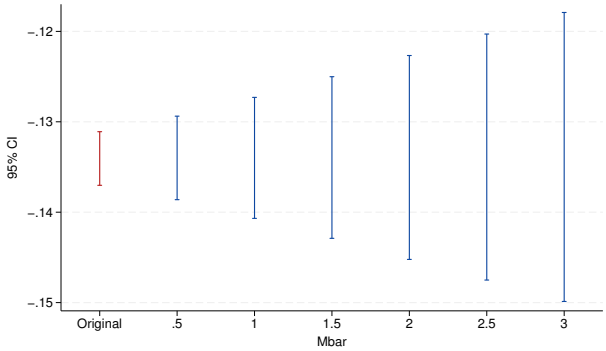


Figure C.3: Robustness: Sensitivity Analysis

Notes: This figure implements the Rambachan and Roth (2023) honest sensitivity analysis for departures from parallel trends. Under the staggered adoption setting, effects are estimated with the Callaway and Sant'Anna (2021) DiD estimator. Relative quarter 0 is the implementation quarter and spans both pre- and post-CVBP periods. Accordingly, the sensitivity analysis is conducted at relative quarter 1, the first full post-treatment period.