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 consequential moral hazard problem. Using China's national drug procurement rollout and universal hospital transaction data, we document this quality-price trade-off. After contract award, winning firms are more likely to make post-approval changes to manufacturing, including changes consistent with quality reduction. Hospitals assigned to winners that modify drug packaging show larger utilization increases, suggesting compensatory dosing. Reinforcing this, patients switching from branded to winning generics use higher doses than before. Accounting for higher utilization, the effective price reduction is 3–18 percentage points smaller than the nominal price cut.

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

"Anesthetics that fail to sedate, antihypertensives that fail to lower blood pressure, and laxatives that offer no relief."

— A widespread public critique for the first few batches of procured generics in China

Governments increasingly rely on centralized procurement to contain public spending. But when contracts are written mainly on price and quantity, a lower purchase price does not guarantee proportionally lower costs to the buyer if quality falls. In sectors such as pharmaceuticals, quality deterioration can reduce therapeutic efficacy and, in extreme cases, pose risks to patient safety. By intensifying price competition, centralized procurement compresses suppliers' margins. This 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; Hart et al., 1997), yet direct empirical evidence on post-award quality distortions remains scarce. Existing studies document renegotiation, delivery delays, and cost overruns (Bajari and Tadelis, 2001; Bajari et al., 2014; 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.

Pharmaceutical procurement is a particularly consequential setting 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, the relationship can reverse: higher efficacy per dose reduces the quantity needed for 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 this case, the contractual price cut overstates the reduction in the effective cost of treatment, because part of the apparent savings is offset by greater use of a less effective product. Despite its importance, this compensatory margin has received little empirical attention.

This paper provides direct empirical evidence on both sides of this problem: post-award quality deterioration by suppliers and the compensatory demand response by buyers, using China's national Centralized Volume-Based Procurement (CVBP) program. CVBP is well-suited for two

reasons.[1] First, it screens quality only at entry through bioequivalence certification, while post-award quality monitoring is limited, creating scope for post-award moral hazard. Second, hospitals must fulfill mandatory volume and market share targets for winning drugs under CVBP, restricting substitution toward alternatives even when drug quality declines. This demand rigidity is central to our identification of compensatory dosing. The program is also economically important: it covers roughly 85% of prescription drug sales in China, which are dispensed through hospitals in the public health insurance network, and it has reduced drug prices by an average of 64% (Jiang et al., 2025).

Our analysis combines two novel data sources. First, we collect all manufacturing post-approval changes (MPACs) filed with China's drug regulatory authorities. We classify each MPAC by its relevance to drug quality, focusing on the three categories with the clearest quality implications, including modifications to packaging materials, active pharmaceutical ingredient (API) supplier changes, and production process changes. 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.[2]

Our empirical strategy exploits two sources of variation. To study whether winning suppliers cut quality along non-contractible margins after securing contracts, 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 one of the winners. This province-level assignment allows us to compare hospitals exposed to winning suppliers that do and do not alter their MPACs after award.

We distinguish between MPACs that can plausibly expand production capacity (e.g., scaling manufacturing or adding/switching API suppliers) and those that cannot. Changes to packaging

[1] China's National Drug Price Negotiation policy is another Chinese program designed to lower drug prices through one-on-one negotiations with each innovation drug, while simultaneously expanding insurance coverage for these drugs to increase the effective market size (Barwick et al., 2025; Liu et al., 2025). In contrast, CVBP targets the off-patent market—where multiple generic and originator products compete—and achieves price reductions through competitive bidding among manufacturers. However, CVBP raises quality concerns for generic drugs. Such concerns are not unique to China or other developing countries; generic drug quality problems are equally prevalent and well-documented in the U.S. (Ishitani, 2025; Cuddy and Schnell, 2026).

[2] Direct measures of drug quality in China are largely unavailable, motivating our indirect approach: regulatory violation records are rare (we provide descriptive evidence only); case-level adverse drug reaction data from the national monitoring system are not accessible to researchers; and administrative health claims data are available only for individual cities and restricted time periods.

materials have no direct link to production scale but may compromise drug stability and efficacy (U.S. Food and Drug Administration, 2019). If the utilization increase were driven solely by supply expansion, it should not appear for packaging material changes. A utilization increase tied to packaging material changes cannot reflect supply expansion and instead points to compensatory dosing (U.S. Food and Drug Administration, 1999).

We first document moral hazard on the supply side. Winning firms are 8.5 times more likely to undertake MPACs 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 operating 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 adjustment.

On the demand side, hospitals assigned to winners that modify packaging materials exhibit 24.7% greater utilization increases than those assigned to winners without such changes. This pattern is difficult to reconcile with a supply-expansion story, because changes in packaging materials do not raise supply capacity. We further rule out alternative mechanisms, including more aggressive marketing, larger pack sizes, and coincidental shifts in unmet medical demand. Because hospitals must fulfill mandatory volume targets for winning drugs, the observed increase in utilization is most consistent with compensatory dosing in response to reduced drug efficacy. Consistent with this interpretation, the utilization response is greater for injection drugs and for drug classes whose efficacy is more sensitive to packaging material changes (U.S. Pharmacopeial Convention, 2016).

In addition, we find complementary evidence from branded-to-generic substitution: hospitals that relied more heavily on branded drugs before CVBP experience larger increases in utilization 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 nominal savings. While Jiang et al. (2025) show that CVBP reduced nominal procurement prices by 64%, the effective reduction in treatment cost is smaller

[3]In 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 CVBP, where procurement is voluntary.

once compensatory quantity responses are taken into account. Depending on the type of MPACs and the drug class, 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.

This paper makes three main contributions. First, we trace a complete causal chain from centralized procurement to post-award product quality deterioration to demand-side behavioral response. On the supply side, winning firms alter production processes after award in ways consistent with cost-cutting along less observable quality margins, a pattern predicted by multitask agency theory (Holmström and Milgrom, 1991) when contracts emphasize a measurable dimension (price) at the expense of non-contractible ones (quality). Prior empirical work documents post-award distortions such as renegotiation, delays, and cost overruns (Bajari and Tadelis, 2001; Bajari et al., 2014; Decarolis, 2014; Lewis and Bajari, 2014), and recent studies show that price-only mechanisms can reduce buyer welfare when quality is endogenous (Camboni et al., 2025; Ishitani, 2025). We extend this evidence by documenting quality distortions through production decisions rather than contractual adjustments.

On the demand side, we identify compensatory dosing as the behavioral response: hospitals whose suppliers altered packaging materials exhibit significantly greater utilization increases, and branded-to-generic switchers use higher quantities, especially where efficacy is more salient.[4] Accounting for these responses, the effective price reduction is 3–18 percentage points smaller than the nominal 64%. Buyers pay less per unit, but not necessarily less per effective treatment.

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 durable medical equipment (DME) adversely selected fraudulent firms, we show that centralized procurement creates moral hazard among winners, who reduce costs along less observable margins

[4] Xia and Zhao (2026) use retail pharmacy data to document customer avoidance of procured drugs and estimate that quality decline offsets 15.8% of statin cost savings under CVBP. Our analysis covers five CVBP drug classes in the hospital market—which accounts for the bulk of CVBP volume—and directly links specific post-award MPACs to differential utilization responses, isolating the supply-side mechanisms behind quality distortions.

such as packaging materials.[5]

Third, our findings carry implications for pharmaceutical regulation on generic drug quality. We show that certain MPACs, particularly those involving packaging materials, predict subsequent quality deterioration, suggesting that not all post-approval changes are neutral and that some warrant closer regulatory scrutiny. Moreover, the quality indicators we identify are detectable in routine data: compensatory dosing leaves a footprint in transaction and claims records, offering a low-cost tool for post-market surveillance. Procurement design can act on these same indicators by incorporating historical post-award MPAC records into scoring auctions (Che, 1993; Lewis and Bajari, 2011) to improve supplier selection.

The paper is organized as follows. Section 2 provides an overview of China's pharmaceutical market and 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 the 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

[5] Similarly, Carril et al. (2026) document adverse selection when competition intensifies in U.S. defense procurement, suggesting this mechanism operates across sectors beyond healthcare.

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). A watershed reform in 2016 introduced bioequivalence requirements for generics (State Council of China, 2016), establishing the regulatory foundation for large-scale pooled procurement. To curb drug spending, which accounted for roughly 40% of total healthcare expenditures 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 Program 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 A.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 producers with the lowest bids win.[6] 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.[7] Contract duration and guaranteed market share increase with the number of winners. During hospital performance assessments,

[6]While both branded and generic drugs may participate, generics overwhelmingly win the competitive bidding because of their lower prices.

[7]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).

institutions must meet two targets: an absolute target requiring fulfillment of the agreed procurement volume, and a relative target capping the share of non-winning drugs in total purchases (National Healthcare Security Administration of China, 2024).

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 A.1 summarizes the timing of provincial adoption.

Finally, in contrast to the adverse selection of fraudulent firms observed in U.S. procurement settings (Carril et al., 2026; Diwan et al., 2026), the results in Appendix B suggest that CVBP does not disproportionately award low-quality or opportunistic firms. Instead, the program itself tends to select large, cost-efficient, and highly capable manufacturers.

2.3 Post-Approval Changes in China

Center for Drug Evaluation, NMPA (2021) classifies PACs for marketed drugs into major, moderate, and minor categories. Moderate and major changes, such as altering packaging materials, APIs, or production processes, can significantly affect drug quality and stability (U.S. Food and Drug Administration, 2022; Center for Drug Evaluation, NMPA, 2024). 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 and require strict assessment from the central National Medical Products Administration (NMPA, China's equivalent of the U.S. FDA). The vast majority of changes are classified as moderate or minor, requiring only a provincial-level record-filing procedure for supplementary drug registration. Firms are only required to file with the province-level NMPA, bypassing the need for a technical review. Moderate changes can still compromise quality; because of local economic interests, however, provincial regulators have limited incentives to block changes that benefit local firms even when they pose potential risks (Fisman and Wang, 2015; Eberhardt et al., 2016). Given this regulatory context, we define these potentially quality-impacting modifications, primarily moderate changes related to manufacturing, as MPACs. The minor changes are defined as other PACs.

Public concern over drug safety led policymakers to initially propose banning all PACs in the 11th CVBP round (Pharnexcloud, 2025). However, lacking empirical evidence that PACs actually

harm quality, regulators replaced the ban with a simple disclosure rule. Winning bidders are now required only to report PACs 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 PACs 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 C.1).

Firm Behavior. Post-award, the winning firm chooses non-contractible quality $q \in [\underline{q}, \bar{q}]$,[8] 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

[8]Throughout this paper, q captures the therapeutic potency of each dose, i.e. the efficacy delivered per unit consumed, $e(q)$. This is distinct from safety dimensions of quality (e.g., contamination risk), which would reduce rather than increase utilization when quality falls. Our empirical design identifies potency-related quality changes through their compensatory dosing signature.

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, make 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 C.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 rises when quality falls ($B_{xq} < 0$), 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 C.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 C.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 $\Delta p < 0$ and $\Delta q < 0$, then $|\Delta \ln p_{eff}| < |\Delta \ln p|$: the contractual price cut overstates the reduction in effective price (Appendix C.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 nominal 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 at entry while others (post-award manufacturing processes) are not continuously monitored; 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 MPACs. Our goal is to measure the quality-price trade-off under the existing mechanism rather than to characterize the optimal one.

4 Data and Sample

4.1 Data

Hospital Drug Transaction 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 dispense roughly 85% of prescription drugs in China's pharmaceutical market (IQVIA, 2023). Our data span from January 2019 to June 2023, covering CVBP from the 4+7 pilot stage up to the seventh round.[9] The dataset includes hospital 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.

Post-Approval Changes. We compile a dataset of PACs across all firms from China's NMPA, capturing the product, filing date, and specific details of each change.[10] Among all PACs, we focus on MPACs, which are primarily moderate changes and are most directly linked to drug quality.[11] MPACs comprise three categories: (i) packaging material changes, including replacing or adding packaging suppliers and physical modifications to packaging materials; (ii) API changes, including replacing or adding API suppliers and revisions to API standards; and (iii) production process changes, including changes in production scale, machines, or methods. We examine both the aggregate effect of these three categories and their individual impacts. The remaining PACs,

[9]The sixth round of CVBP focuses on insulin and follows different rules, and is therefore outside the scope of this study.

[10]The NMPA website (https://www.nmpa.gov.cn/datasearch/home-index.html#category=yp) provides filing information for all drugs sold in China. In the standard filing process, minor and moderate changes are automatically approved upon submission, while major changes require further review and are processed through a separate channel. Occasionally, moderate changes are reclassified as major by the NMPA and rejected pending additional review. No such case has occurred within our five drug classes.

[11]Minor and moderate changes represent 85% and 15% of all PACs, respectively. MPACs account for almost all moderate changes; the remainder consists of excipient-related changes, which hold a negligible 0.05% share and are thus grouped under other PACs.

such as changes in the number of tablets per blister pack, shelf-life adjustments, modifications made in accordance with the *Chinese Pharmacopoeia*, and revisions to package inserts, consist almost entirely of minor changes defined by the NMPA, which are purely administrative or labeling changes. Details are provided in Tables A.2 and A.3.

Supplementary Data. We augment our main data with several auxiliary sources. First, we obtain hospital-level characteristics, including hospital location and tier (tertiary, secondary, or primary), from the 99 Health hospital dataset (https://yyk.99.com.cn/); for hospitals not covered in this database, we supplement with information collected via Baidu web scraping. Second, we draw firm-level information from China's Industrial and Commercial Registered Enterprises Database, *Aiqicha*,[12] and the YAOZH database, capturing firm location, API production capacity, and firm size. We obtain stock market and financial data from CSMAR and WIND, respectively, for winning firms of the five drug classes that are China A-shares listed. Third, we collect bioequivalence approval records from China's NMPA to identify bioequivalent and non-bioequivalent generics. Finally, we obtain city-level socioeconomic controls: average annual salary from the 2020 China Urban Statistical Yearbook (China Urban Statistical Yearbook 2020), and average years of education 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 5–8 molecules. We include procured molecules between rounds 1 and 5 as the treatment group. Due to a lack of data in pre-periods, we exclude the pilot round (implemented in 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 quarters -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

[12] *Aiqicha* is a comprehensive business data search platform operated by *Baidu*, providing detailed public records on firm registration, ownership structures, and operational status in China.

control group.[13] In total, we have 22 procured molecules and 12 non-procured molecules. Table A.4 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 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 have sufficient pre-post variation in a DiD framework.[14] 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 at or near the lowest price. However, as *winning firms* take turns choosing the provinces they will supply 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, drug D is regarded as a *winning drug* in the provinces the firm chooses to supply, and as a non-winning drug in the remaining provinces.[15]

As shown in panel (a) of Figure A.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. In addition, there are 54,790 primary care institutions in our sample, mainly including community hospitals in urban areas and township hospitals/health services centers in rural areas. Although tertiary hospitals account for a small share of the total number of hospitals, Figure A.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.

[13] We exclude these non-procured molecules as a robustness check by exploiting variation in treatment timing only.

[14] Among the sample with post-period only, 71% are primary care institutions (the lowest tier of health care institutions in China). These hospitals also tend to locate in a city with lower average wage. The results remain similar when we include these pre- or post-period only subsamples.

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

4.3 Summary Statistics

Table A.5 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 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 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.[16] 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 $procured_{dt}$.[17] 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.

[16] 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.

[17] 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' MPAC responses.

5.2 Trade-off between Price and Quality

The welfare benefits of lower prices depend critically on whether quality is preserved. We now test this assumption by examining behavioral response from both the supply and the demand side.

5.2.1 Suppliers' Moral Hazard?

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

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

where f represents firm. $MPAC_{fdt}$ is the number of MPACs conducted by producer f's molecule d in quarter t. Additionally, we re-estimate this specification using alternative dependent variables for several MPAC subtypes, including packaging materials, APIs, and production processes. 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 MPACs. To understand incentives behind winning firms' MPACs, we explore the following variation at the winning firm-molecule-supplying province level:

$$winMPAC_{fdp} = \beta_0 + \beta_1 g(bid_{fd}) + \beta_2 X_f + \beta_3 h(demand_{fdp}) + \alpha_d + \varepsilon_{fdp}, \tag{5}$$

where $winMPAC_{fdp}$ is a dummy variable indicating whether winning producer f in supplying province p conducts an MPAC 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 CVBP; X_f represents characteristics of winning firm f. $demand_{fdp}$ includes supplying province p's demand faced by winning firm f of molecule d, 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.

5.2.2 Impact of MPAC on Drug Utilization

To test whether MPACs affect drug utilization, we estimate the following specification at hospital-molecule-quarter level:[18]

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

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 $\textit{winMPAC}_{idt} = 1$ 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 conducting an MPAC due to CVBP. $\textit{winMPAC}_{id}$ is the time-invariant version of $\textit{winMPAC}_{idt}$, indicating whether hospital i's winning supplying firm had any MPAC after CVBP.[19] We expect β_2 to be positive, as potency downgrade is likely to lower drug efficacy and thus higher doses are needed to achieve the same therapeutic effect as before the MPAC. This prediction is specific to the potency dimension of quality; safety deterioration would instead reduce utilization as patients discontinue use. We also examine heterogeneous effects by condition type (chronic vs. acute) 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 MPAC for a given procured molecule, we keep procured molecules only and conduct the following event study model:

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

where $MPAC_{idt}$ indicates whether a hospital i's designated winning firm of molecule d conducted an MPAC in calendar quarter t after winning a bid. n represents relative quarters with respect to a

[18] 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.

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

winning firm's MPAC time. The underlying assumption is that conditional on hospital-molecule and quarter fixed effects, drug utilization would have trended similarly across hospitals supplied by MPAC and non-MPAC winning firms in the absence of the MPAC.[20]

We estimate equations (6) and (7) separately for each MPAC category. Among the three types, MPACs on production processes are often directly related to supply expansion.[21] Therefore, 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 MPACs are associated with greater drug utilization, this points to a compensatory quantity effect consistent with decreased drug efficacy.

5.2.3 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 MPAC-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

[20] As a robustness check, we exclude MPACs occurring in the same quarter as CVBP implementation. For these cases, there is no post-CVBP, pre-MPAC window to assess parallel pre-trends, making it impossible to distinguish whether elevated utilization reflects the MPAC itself or systematic differences between MPAC and non-MPAC firms in response to CVBP. For MPACs beginning at least one quarter after CVBP, the intervening period provides pre-MPAC observations to verify parallel pre-trends, providing more credible causal effect of MPACs on drug utilization.

[21] 80% of the MPACs on production process changes are changes related to capacity expansion.

specification:

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

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.[22] 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 A.6). 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 Baseline Changes in Drug Utilization

Table 1 presents the average effects from regression (3). Column (1) shows that total DDDs of procured molecules increase by 23.8% relative to non-procured molecules after CVBP. The market share of winning drugs increases by 60.1 percentage points after the implementation of CVBP, as

[22] Table A.6 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 6.3.2).

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. 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.[23]

6.2 Supplier Moral Hazard: MPACs

In this section, we examine firms' MPACs before and after winning a CVBP bid and investigate the motives behind winning firms' MPACs.

6.2.1 Changes in MPACs

Table 2 examines the changes in MPACs 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 of 0.085 MPACs per quarter 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 MPACs are otherwise rare. In contrast, non-winning firms exhibit no significant increase. Similar patterns are observed when we decompose MPACs into three categories. Column (2) shows that winning firms exhibit a significant increase of 0.015 in the number of package MPACs, a magnitude 3 times the size of the pre-CVBP mean. In contrast, columns (3) and (4) indicate much larger effects for API and process adjustments: the estimated increase of 0.042 and 0.038 correspond to 8 times and 19 times their respective pre-CVBP means. As a placebo test, column (5) shows no significant increase in other PACs unrelated to manufacturing, such as pack size adjustments that could independently affect purchasing quantities. Results by subtype for other PACs are presented in Table A.7.

[23] As further detailed in Appendix D, 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 consistent across all these alternative specifications.

Figure 2 presents the event study estimates. Winning producers conduct more MPACs following procurement compared with non-winning producers, particularly around the procurement quarter.[24] Panel (b) decomposes these dynamic effects by the three types of MPACs, which largely mirror the aggregate trends.

6.2.2 Motives Behind Winners' MPACs

Given that MPACs 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 MPACs, 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 MPACs. In contrast, top winning firms face lower pressure and are thus less likely to engage in MPACs. Columns (2)–(4) decompose these effects by MPAC type. We find that MPACs 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 process MPACs 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 MPACs and the characteristics of supplying provinces. Winning firms that engage in MPACs 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 MPAC behavior of winning firms.

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

Beyond these correlational patterns, we find suggestive evidence linking MPACs to quality degradation in extreme cases. Across the first ten CVBP rounds, nine winning firms were placed on the governmental regulatory violation list (blacklist) due to quality issues with a specific molecule. To benchmark against these cases, we compile MPAC records for all winning firm-molecule pairs not subject to blacklisting. As shown in Figure A.3, 78% of blacklisted firms conducted an MPAC after winning a bid, compared with only 54% of non-blacklisted firms. A similar gap appears for MPACs on packaging materials and production processes, though the difference for API changes is smaller. These patterns suggest that MPACs may be detrimental to drug quality: severe degradation results in blacklisting, while milder degradation manifests as reduced efficacy. However, blacklisted firms account for only 0.5% of all winning firm-molecule pairs, so these findings should be interpreted as suggestive only.[25]

6.3 Compensatory Dosing

6.3.1 Drug Utilization Responses to MPACs

We examine whether these MPACs 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 had 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 MPAC, 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 MPAC categories separately.[26] Column (4) reveals that changes in all these MPACs are associated with greater drug utilization. However, MPACs on packaging materials lead to the greatest increase in drug utilization

[25] In early 2025, a widespread public critique of the first few batches of procured generics in China crystallized into a telling phrase: *"Anesthetics that fail to sedate, antihypertensives that fail to lower blood pressure, and laxatives that offer no relief."* Prompted by such quality concerns, the government has increasingly tightened its regulation of winning drugs, leading to a rising number of winning firms being blacklisted due to quality issues in recent CVBP rounds.

[26] 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.

at 24.7%, followed by MPACs on production process (13.3%), and the increase due to MPACs on API suppliers is the smallest (8.5%). Although the increases in drug utilization due to MPACs on production processes and APIs may be driven by an increase in supply, the increases in utilization due to MPACs on packaging materials are consistent with compensatory dosing due to decreased drug efficacy.

We further control for the interaction between the DiD estimator (*Procured*) and hospital or city-level characteristics in columns (5) and (6) to mitigate potential confounding effects at these levels. 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 consistent with the baseline estimates.

Figure 3 plots the event study estimates derived from equation (7). As shown in panel (a), drug utilization increases significantly starting from two quarters after a winning firm's MPAC implementation. When decomposing these effects by MPAC type, the increase is most pronounced for packaging material MPACs, while the utilization growth associated with API and process MPACs is relatively modest. Notably, the negative pre-trend observed for process MPACs 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 MPACs implemented in the exact quarter of the implementation of CVBP, where CVBP and MPACs occurred simultaneously and therefore no "pre-period" exists for a post-CVBP award MPAC event. Overall, we view MPACs 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 MPACs

Patients' compensatory drug utilization due to MPACs 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-only conditions, consistent with our model prediction, as the dosage compensation response is stronger when efficacy is more salient. Moreover, if MPACs 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, 2016). Columns (3)–(6) confirm this pattern.

We first observe a much stronger effect of MPACs for injection drugs. Furthermore, for MPACs on packaging materials, the positive effect on drug utilization appears only for 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 process-related MPACs, 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).[27] Given this evidence, we believe that an increase in drug utilization due to MPACs on packaging materials is more likely to reflect lower efficacy of drugs.[28]

Ruling Out Alternative Mechanisms

We conduct several analyses to rule out alternative mechanisms that could also explain the increases in drug utilization due to firm MPACs.

First, if firms conducting an MPAC also engage in more aggressive marketing to promote their drugs, we may also find higher utilization among these firms. To test this, we collect 2016–2023 financial statements of publicly listed winning firms and conduct a firm-year level analysis, comparing those that implement an MPAC to those that do not. We examine changes in selling expenses, advertising and promotion expenses, and sales-related employee compensation around each firm's first post-award MPAC, following the same logic as equation (7). Table A.8 shows that MPAC adoption is unrelated to changes in marketing efforts, which largely supports that simultaneous marketing effort accompanying MPACs is not a likely channel.

Second, pack size adjustments could affect purchasing quantities (Wansink, 1996; Lam et al., 2023). If firms simultaneously alter pack sizes alongside an MPAC, we might also observe higher measured utilization. However, Table A.7 shows no significant post-CVBP increases in non-MPACs,

[27]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.

[28]In response to public concerns regarding quality, the second draft of the 11th Round of CVBP initially proposed banning all post-award MPACs to safeguard the quality of winning drugs (Pharnexcloud, 2025). However, citing a lack of scientific evidence on quality downgrading after MPACs, the final rule mandated only that winning firms disclose MPACs on the CVBP website for public oversight (National Healthcare Security Administration of China, 2025). Our findings provide causal evidence suggesting that MPACs involving packaging materials are likely to lead to quality deterioration. In contrast, MPACs related to production processes 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.

such as adjustments to pack size, shelf life, or package inserts. We further estimate equation (6) using the average quarterly pack size for winning drugs as the dependent variable. Table A.9 columns (3) and (4) show a coefficient of only 4%, compared to the baseline increase of 17.7% of winning drugs due to MPACs as shown in columns (1) and (2). Together, these results indicate that while larger pack sizes may contribute to part of the increase in drug utilization, the vast majority of the observed utilization increase is driven by compensatory dosing.

Third, we examine whether the utilization increases coincidentally reflect unmet medical need rather than compensatory dosing. If MPAC-driven utilization increases happen to be among patients who previously had poor access to drugs, we would expect the effect to be concentrated in rural regions, where unmet need is typically higher. Table A.10, however, shows that MPAC-driven utilization increase is statistically indistinguishable between urban and rural regions, making it unlikely that unmet need accounts for the observed increases in drug utilization.

Finally, we examine whether patients' awareness of higher drug quality due to MPACs drives the demand increase. We can rule out this channel out on basic economic grounds: CVBP contracts fix the selling price and drastically compress suppliers' markups (Yan et al., 2025), so incurring higher production costs to improve non-contractible quality dimensions would further squeeze firms' profit margin. Firms therefore lack the economic incentive to implement quality-enhancing manufacturing changes, making it unlikely that quality-driven demand accounts for the observed utilization increases. Furthermore, even if patients wrongly perceive drug quality improvement after an MPAC, this would lead to a reduction rather than an increase in utilization, as higher drug efficacy allows patients to achieve the same therapeutic effect with fewer doses.

6.3.2 Branded-to-Generic Switching

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 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 CVBP. The coefficient is negative and significant, demonstrating that hospitals that predominantly used branded drugs before CVBP are 1.9 percentage points less likely to buy winning drugs afterward, indicating demand-side resistance to switching.

Columns (2)–(5) examine the intensive margin for procured molecules, exploiting the variation by whether a hospital predominantly bought branded drugs for a molecule before 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 hospital pairs.[29] 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).

Furthermore, Figure 4 demonstrates the heterogeneous responses across drug classes. For chronic-only drug classes, we find a slight decrease in drug utilization after CVBP, whereas for drug classes with mixed acute-chronic use, we find a sharp 50% increase in drug utilization after CVBP. This reveals that patients with chronic conditions show a resistance to winning generics, while patients with acute conditions (or who do not resist switching) are likely to use higher doses to maintain the same efficacy.

6.4 Welfare Implications

The results in Sections 6.3.1 and 6.3.2 demonstrate that the increases in drug utilization after CVBP are driven by both a price effect (lower prices) and a quality effect (reduced efficacy).[30] 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 CVBP's impact on drug prices (Jiang et al., 2025). Taking the estimate from Table 4 column (4) for MPACs on packaging materials and changing API suppliers, we show that the effective price reduction after incorporating such MPACs becomes 55% and 61%, respectively. Figure 5 summarizes these calculations. If we assume that generic-to-generic drug

[29] Using hospital-level and city-level controls for the variable $switchBG_{id}$ of the procured molecules, as shown in Figure A.4, 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 A.5.

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

switch does not involve any change in drug quality and use the estimated drug utilization increase from Table 6 column (4), the effective price reduction becomes 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 MPACs after award, particularly those with lower bids. These MPACs, 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 nominal 64%.

Our findings carry important implications for procurement design. First, compensatory dosing has a practical implication for quality monitoring: the utilization response to quality degradation leaves a detectable footprint in routine transaction or claims data, offering governments a low-cost quality signal without requiring laboratory testing. Second, given that MPACs on packaging materials are a strong predictor of efficacy decline, governments can incorporate a firm's packaging-related MPACs from previous CVBP rounds into a scoring auction (Che, 1993; Lewis and Bajari, 2011) to select bidders with more reliable historical records. Finally, our findings speak directly to a recent policy change: the 11th round of CVBP initially proposed banning all MPACs, but then relaxed to public disclosure only due to lack of evidence. Our analysis provides an evidence-based path: scrutinizing packaging material changes linked to quality deterioration while allowing for capacity-expanding adjustments that support supply stability.

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Figures and Tables

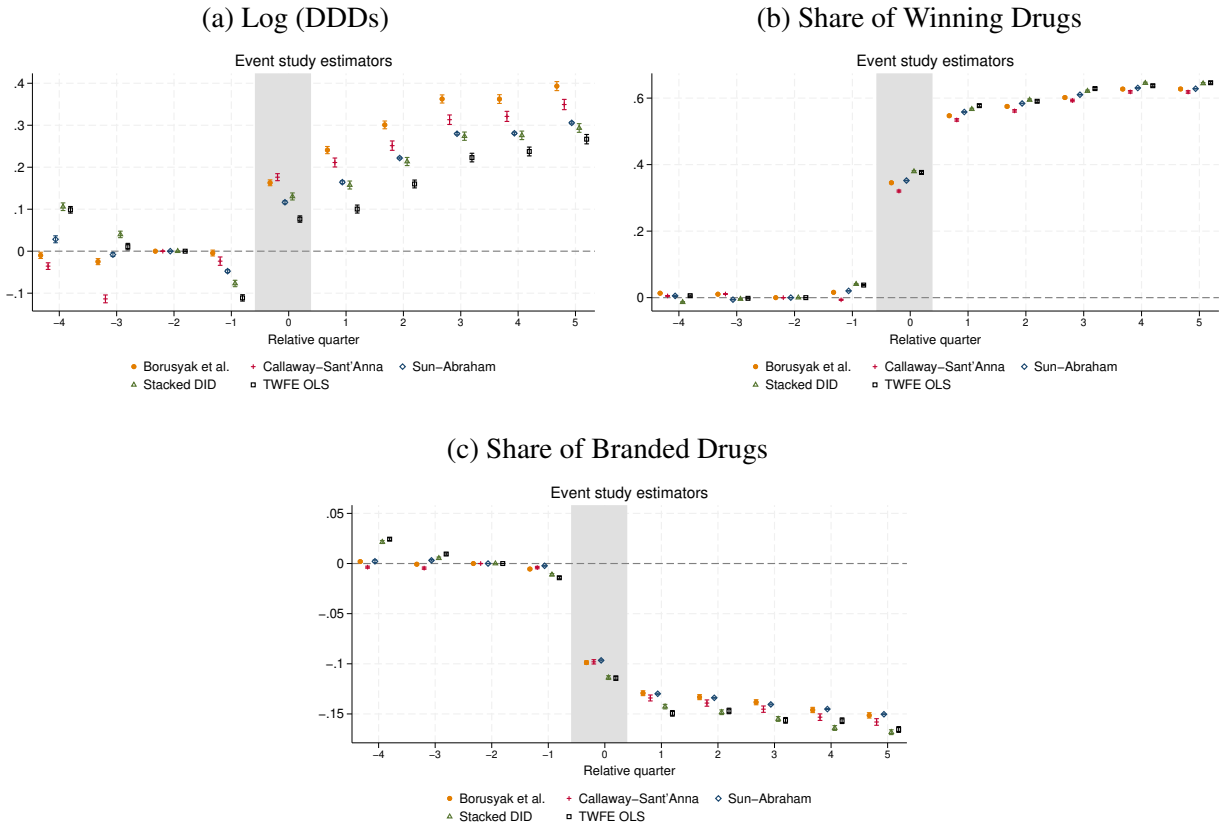
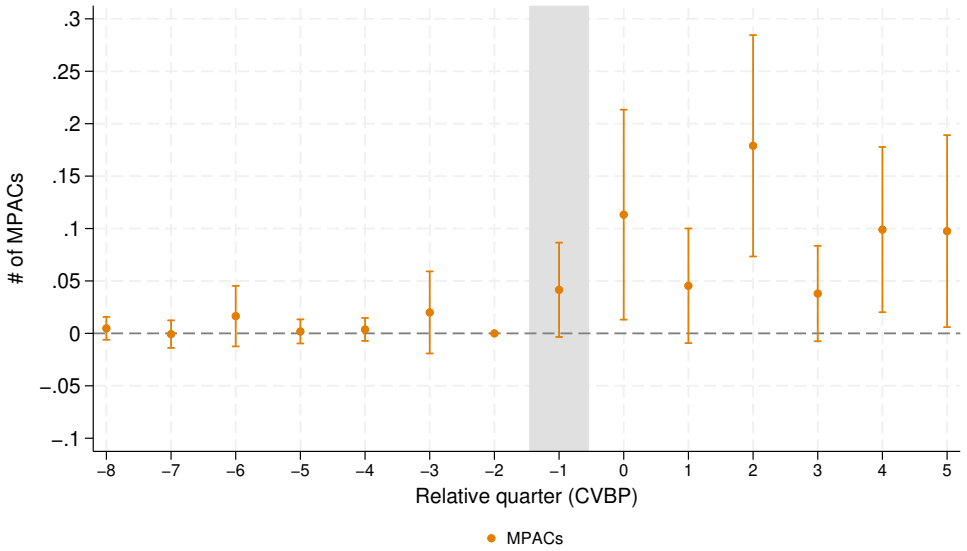


Figure 1: Event Study: Baseline Effects of CVBP on Drug Utilization

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 MPACs



(b) MPACs by Type

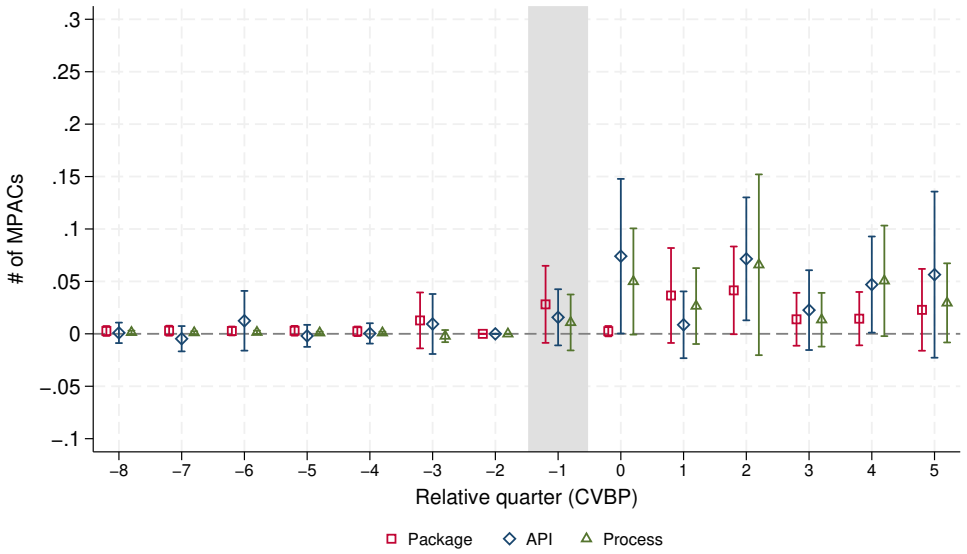
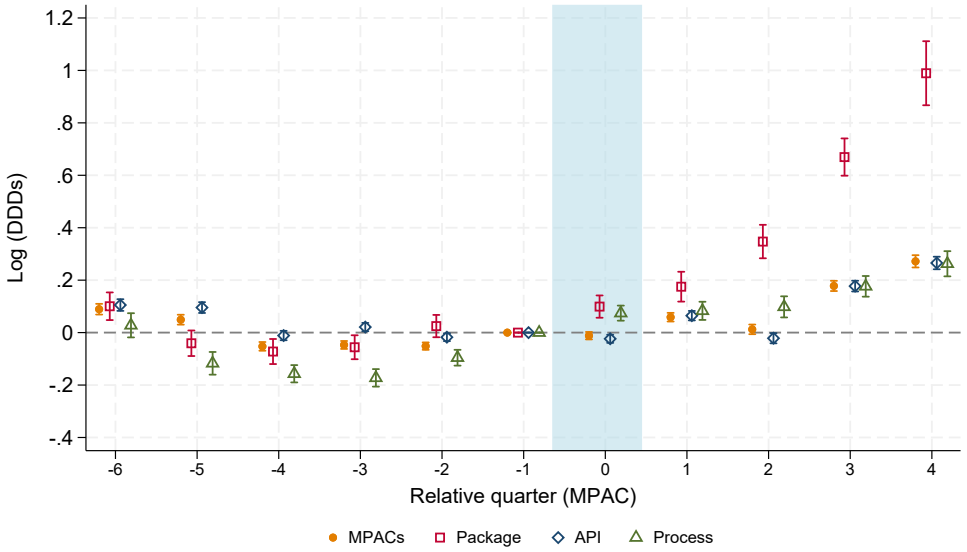


Figure 2: Event Study: Effects of CVBP on Winning Firms' MPACs

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

(a) Full Sample



(b) Excluding MPACs Concurrent with CVBP Implementation

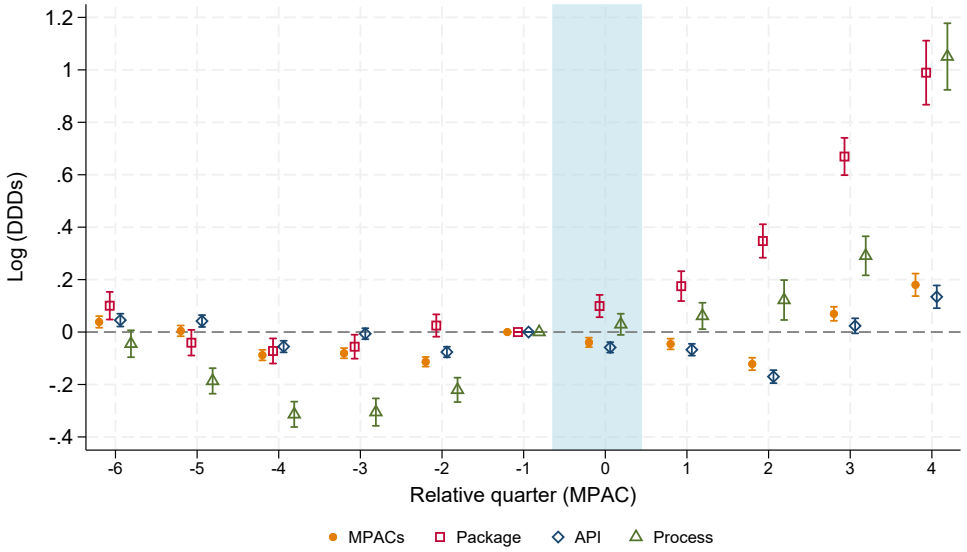


Figure 3: Event Study: Effects of MPACs on Drug Utilization

Notes: This figure illustrates the dynamic impacts of winning firms' MPACs on hospital-level drug utilization, based on estimates from equation (7). Hospitals whose designated winning supplier did not undertake an MPAC serve as the control group. The event time (relative quarters) is centered around the timing of a winning firm's MPAC, rather than the implementation date of CVBP. Symbols denote MPAC types: all MPACs (orange circles), packaging materials (red squares), API changes (blue diamonds), and production process (green triangles). Panel (a) uses the full sample, whereas panel (b) excludes the subsample with MPACs occurring in the same quarter as CVBP implementation, because the absence of a post-CVBP, pre-MPAC window precludes parallel trend verification for this subsample. The negative pre-trend for process-related MPACs suggests supply shortages at hospitals served by these firms prior to their corresponding MPACs.

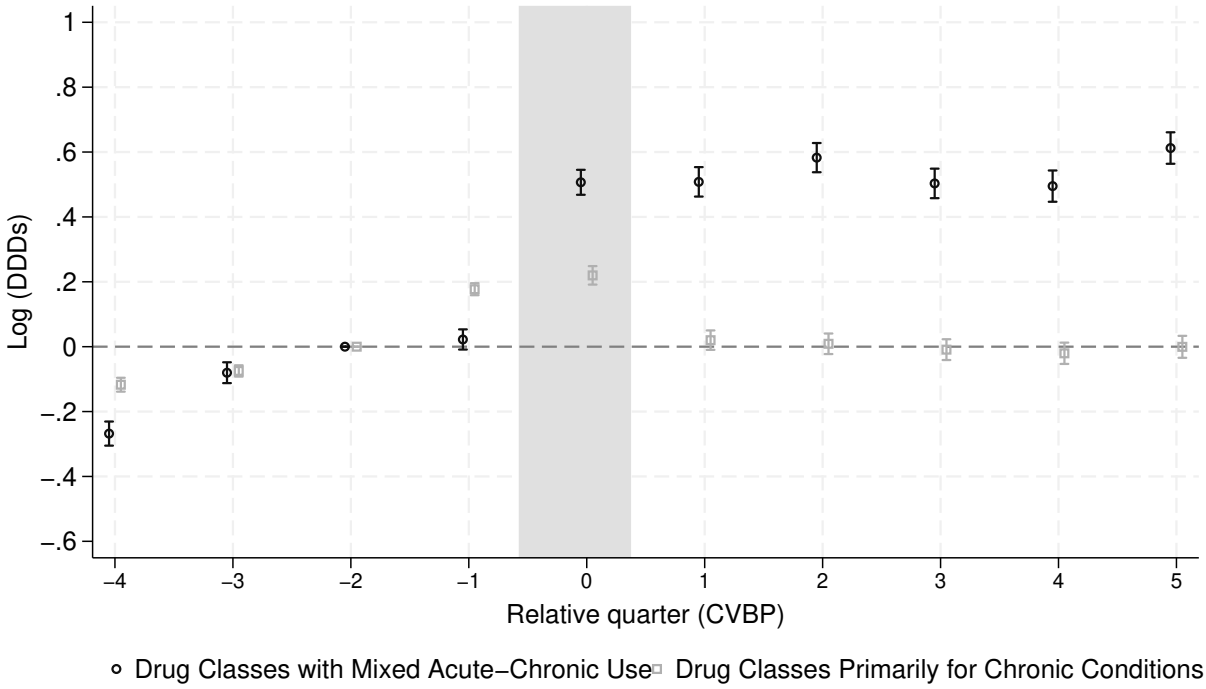


Figure 4: Event Study: Heterogeneous Effects on Drug Utilization by Branded-to-Generic Switch

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 are the same as in column (4) of Table 6.

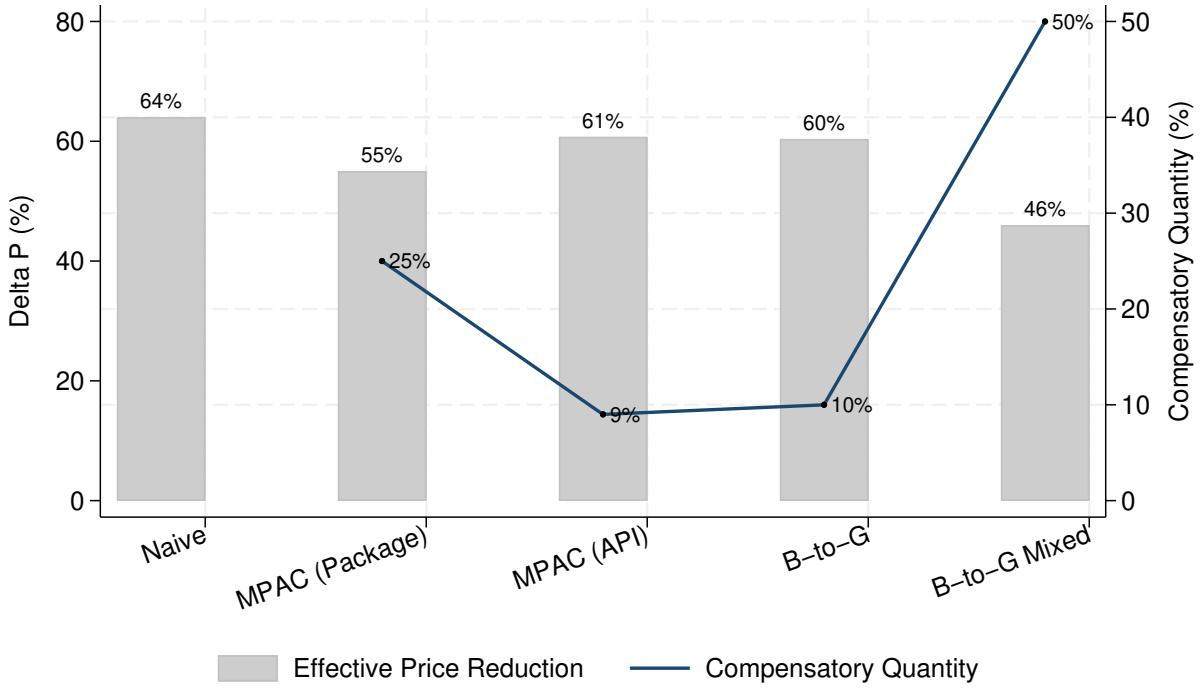


Figure 5: Effective Price Reduction Accounting for Compensatory Dosing

Notes: This figure presents effective price reduction after accounting for compensatory dosing. Bars (left axis) show effective price reduction, while the line (right axis) shows the corresponding compensatory quantity increase. Compensatory quantity estimates (ΔQ) are derived from: coefficients of *Procured* $\times$ *winMPAC (Package)* and *Procured* $\times$ *winMPAC (API)* in column (4) of Table 4 for *MPAC (Package)* and *MPAC (API)*, coefficient of *Procured* $\times$ *SwitchBG* in column (4) of Table 6 for *B-to-G*, and event study for drug classes with mixed acute-chronic use in Figure 4 for *B-to-G mixed*. Effective price reduction is 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 MPACs

	MPACs				Other PACs
	(1) All	(2) Package	(3) API	(4) Process	(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 MPACs. Dependent variables are: the number of all MPACs in column (1), packaging material MPACs in column (2), API MPACs in column (3), process MPACs in column (4), and other PACs unrelated to manufacturing 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' MPACs: Supply- and Demand-Side Factors

	(1) MPACs	(2) Package	(3) API	(4) Process
(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 MPACs)	-0.009	-0.032	-0.021	0.028
	(0.041)	(0.031)	(0.039)	(0.032)
Balance Policies (Before MPACs)	-0.054	0.013	-0.010	-0.025
	(0.043)	(0.034)	(0.040)	(0.033)
Payment Policies (After MPACs)	-0.077	-0.040	-0.047	0.012
	(0.049)	(0.027)	(0.046)	(0.035)
Balance Policies (After MPACs)	-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' MPACs 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 MPAC in column (1), packaging material MPACs in column (2), API MPACs in column (3), and process MPACs 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 MPACs 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 × winMPACs		0.171***			0.168***	
		(0.008)			(0.008)	
Procured × otherPACs			0.007			
			(0.004)			
Procured × winMPACs (Package)				0.247***		0.278***
				(0.021)		(0.021)
Procured × winMPACs (API)				0.085***		0.071***
				(0.009)		(0.009)
Procured × winMPACs (Process)				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' MPACs on drug utilization, exploring heterogeneity based on whether a hospital's designated winning firm undertakes an MPAC (β_2 in equation (6)). 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), *winMPACs* equals to one for quarters following a winning firm's MPAC. Column (3) is a placebo test using changes unrelated to the manufacturing process. Column (4) disaggregates MPACs into three categories: packaging materials, APIs, and production process. 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. $Procured_{dt} \cdot winMPAC_{id}$ is controlled in the regressions and the estimates of $\hat{\beta}_3$s are negative, in line with evidence from Table 3 that small firms are more likely to conduct post-award MPACs. 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 MPACs on Drug Utilization

	By Drug Use		By Injection			
	(1) Mixed Use	(2) Chronic	(3) Injection	(4) Non-Injection	(5) Injection	(6) Non-Injection
Procured	0.201***	0.149***	-0.318***	0.298***	-0.262***	0.299***
	(0.008)	(0.006)	(0.025)	(0.005)	(0.024)	(0.005)
Procured × winMPACs	0.175***	0.121***	0.392***	0.147***		
	(0.015)	(0.009)	(0.025)	(0.009)		
Procured × winMPACs (Package)					0.422***	-0.069*
					(0.023)	(0.036)
Procured × winMPACs (API)					-0.050	0.150***
					(0.112)	(0.009)
Procured × winMPACs (Process)					0.312***	0.069***
					(0.037)	(0.021)
Hospital × Molecule FE	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
Mean of Y (Before CVBP)	9297.87	10717.99	6735.52	10451.46	6735.52	10451.46
# of observations	1020777	743032	936375	1709447	936375	1709447
R^2	0.81	0.81	0.83	0.81	0.83	0.81

Notes: This table reports the heterogeneous effects of MPACs 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)–(6) split by formulation: injection versus non-injection. In columns (5) and (6), the MPAC interaction is further disaggregated into packaging materials, API, and production process. 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) Hospital	(3) City	(4) Both	(5) PSM
SwitchBG	-0.019***				
	(0.003)				
Procured		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 presents estimates of the 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. Additional Figures and Tables

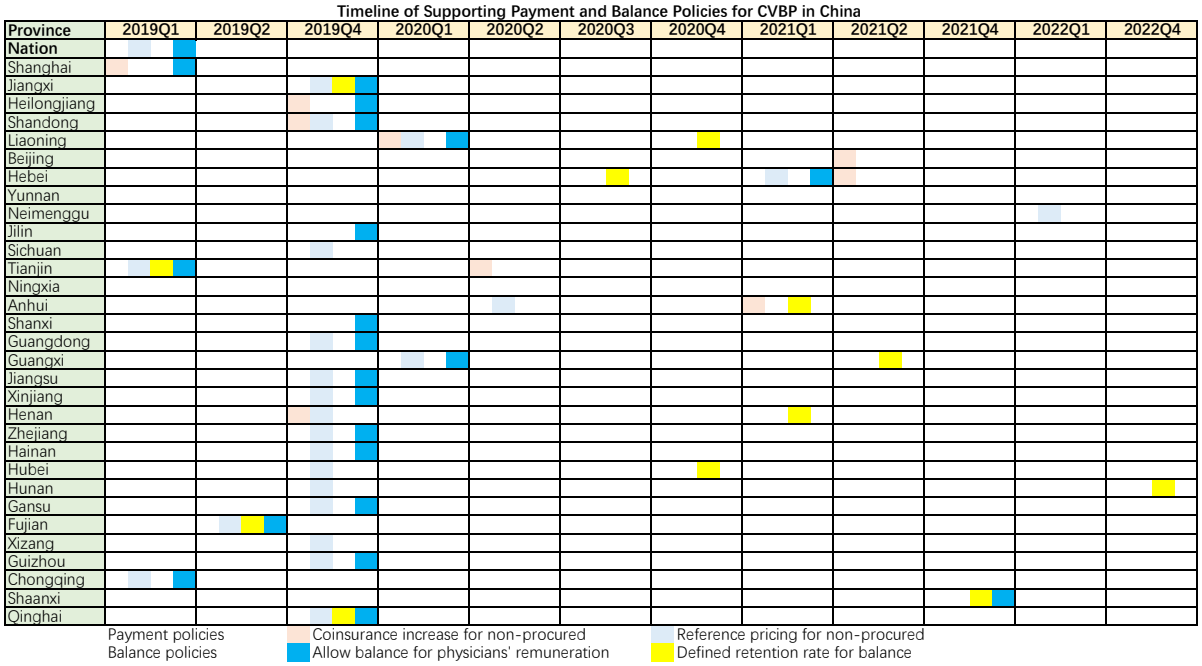


Figure A.1: Timeline of Supplementary Payment and Balance Policies for CVBP in China

Notes: This figure plots the timeline of supplementary 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).

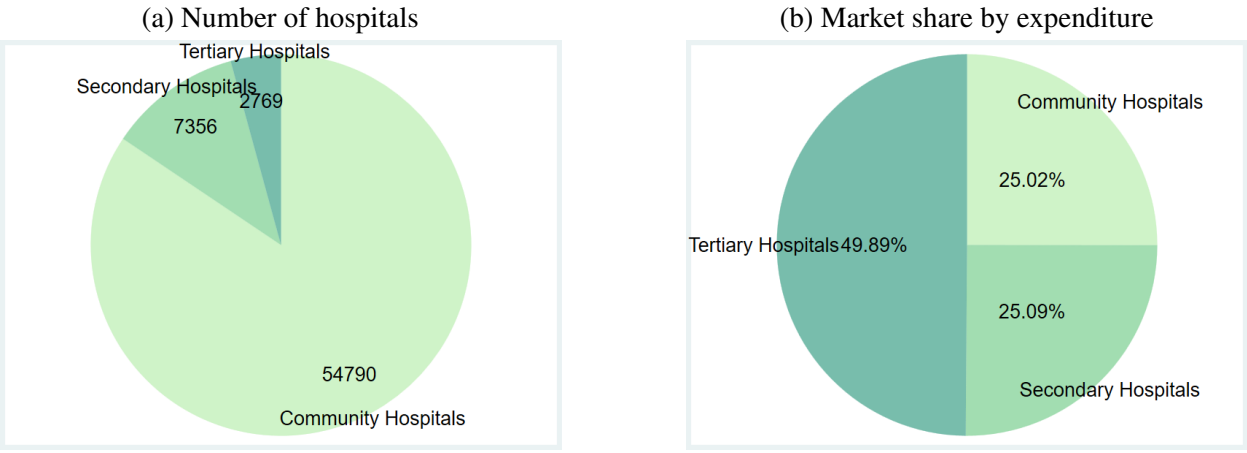


Figure A.2: Summary of Hospitals in Our Sample

Notes: This figure illustrates the distribution of hospitals in our sample by hospital tier. Panel (a) reports the number of hospitals within each tier, while panel (b) presents the corresponding market share, measured by total drug expenditure.

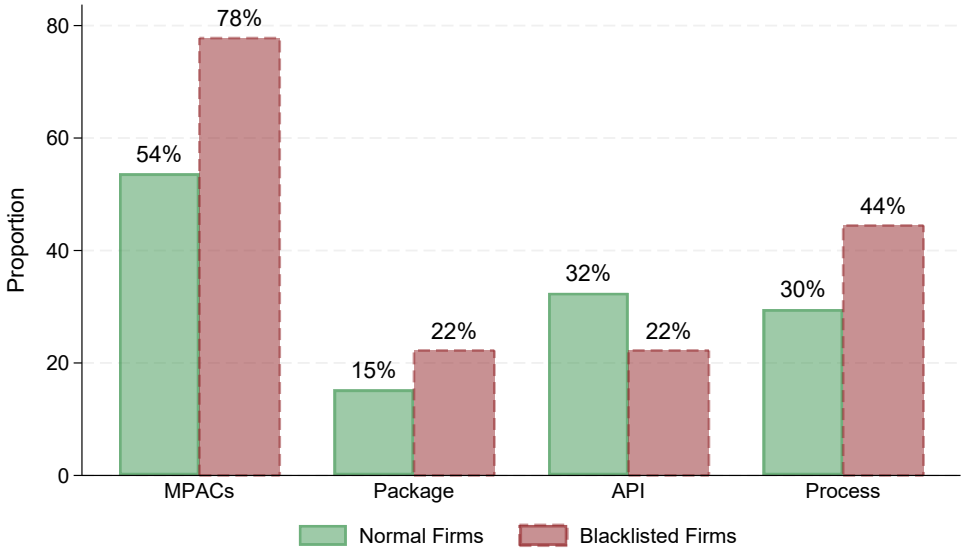


Figure A.3: The Comparison of MPACs between Normal Firms and Blacklisted Firms

Notes: This figure illustrates the comparison of MPACs between normal firms and blacklisted firms. Blacklisted firms refer to nine winning firms that were placed on the governmental regulatory violation list (blacklist) due to quality issues for a specific molecule. The normal firms include all other winning firms through the first 10 CVBP rounds. The solid green bars on the left represent the proportion of normal firms, while the dashed red bars on the right represent the proportion of blacklisted firms.

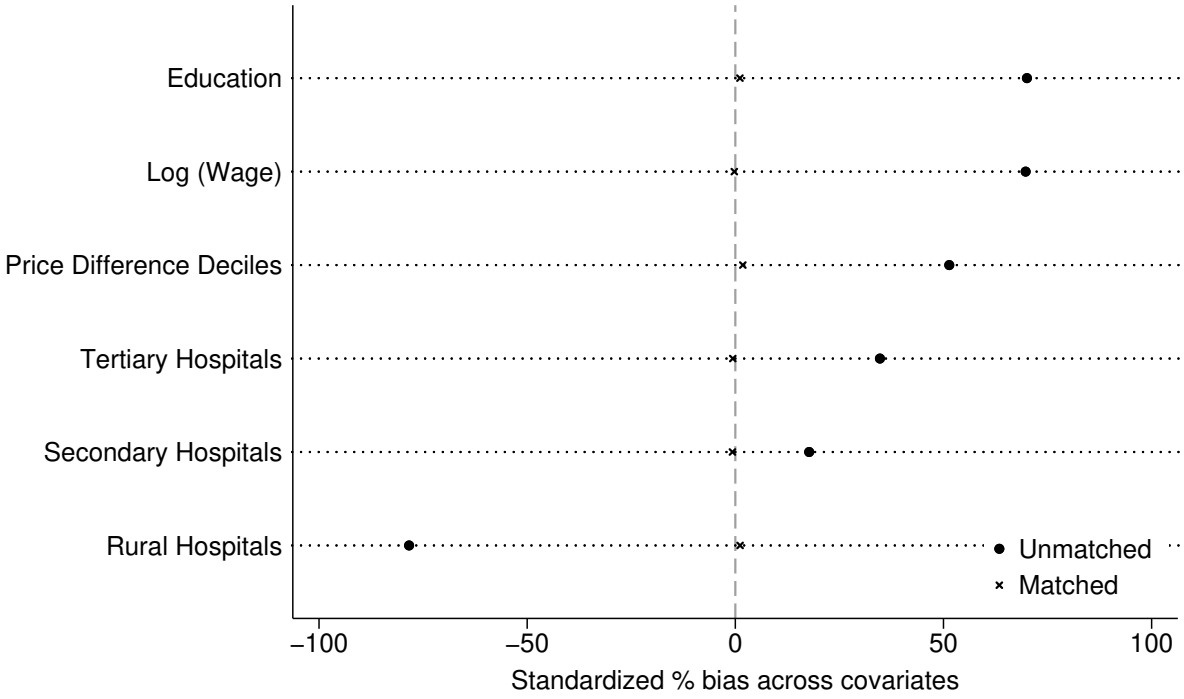


Figure A.4: Covariate Balance Before and After PSM

Notes: This figure illustrates the standardized percentage bias across covariates before and after PSM for the *switchBG* indicator. Each dot represents the standardized bias between *switchBG* and non-*switchBG* hospitals prior to matching (unmatched sample), while each cross represents the corresponding bias after matching (matched sample).

(a) Before PSM

(b) After PSM

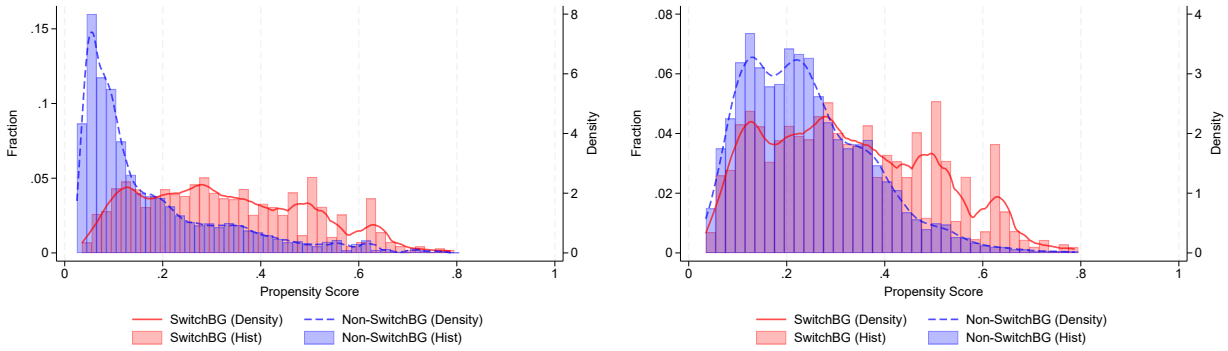


Figure A.5: Propensity Score Distributions Before and After PSM

Notes: This figure plots the distributions of the estimated propensity scores before and after PSM. The bars represent the fraction of observations, while the solid and dashed lines plot the kernel densities for the *switchBG* and non-*switchBG* groups, respectively.

Table A.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	2025.10	2026.2

Table A.2: Details of manufacturing-related PACs by Type

(i) ***Changes about packaging materials***

Replacing or adding packaging materials suppliers

Added "Chongqing Zhengchuan Yongcheng Pharmaceutical Material Co., Ltd." as the supplier of "neutral borosilicate glass tubular injection vials coated with polydimethylsiloxane film" for this product.

Changes in packaging materials

Added aluminum-plastic (pharmaceutical aluminum foil and PVC/PVDC solid pharmaceutical composite rigid sheet) packaging in addition to the existing double aluminum film (polyester/aluminum/PE pharmaceutical composite film) packaging.

(ii) ***Changes about APIs***

Replacing or adding API suppliers

Added "Jiangxi Dadi Pharmaceutical Co., Ltd." as the manufacturing site for the active pharmaceutical ingredient (API) "Simvastatin" for Simvastatin Tablets.

Changes in standards about API

Applied to modify the identification analysis method in the internal control standards of the API (Esomeprazole Sodium) used in this product.

(iii) ***Production Process changes***

Production scale changes

Increased the production batch size by 400,000 tablets, based on the originally approved batch size of 200,000 tablets.

Changes in production machines

English: The drying equipment for the refining, drying, and packaging process was changed from a hot air circulation oven to a vacuum drying oven.

Changes in production method

Applied to change the formulation production process, specifically altering the setting method of the filling volume for this product.

Table A.3: Details of other PACs by Type

(i) ***Pack Size***
Added packaging specifications of "7 tablets/blister, 2 blisters/box" and "14 tablets/blister, 1 blister/box; 2 blisters/box; 4 blisters/box".
(ii) ***Shelf Life***
The shelf life of this product was 12 months and is now extended to 18 months.
(iii) ***China Pharmacopoeia***
The execution standard of this product was changed from "WS1-XG-018-2017" to the "Chinese Pharmacopoeia 2015 Edition, First Supplement".
(iv) ***Package Inserts***
Corresponding revisions were made to sections such as [Adverse Reactions], [Precautions], and [Drug Interactions] in the package insert of this product.

Table A.4: 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 A.5: 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)
Primary Care Institutions	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 presents summary statistics for the main analysis sample. For the treated group, means, with standard deviations in parentheses, are reported for the full sample, as well as separately for the pre- and post-CVBP periods. Differences in means between the pre- and post-CVBP periods are reported, along with their corresponding p-values. The total number of observations is reported at the bottom of the table.

Table A.6: 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
Primary Care Institutions	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 presents summary statistics for the sample by branded-to-generic switch indicator *switchBG*. Columns (1) and (2) report means, with standard deviations in parentheses, for the two groups, respectively. Column (3) reports the differences in means between the two groups, and column (4) reports the corresponding p-values. The total number of observations is reported at the bottom of the table.

Table A.7: Average Effects of CVBP on Other PACs

	(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 CVBP on firms' additional changes unrelated to the manufacturing process. 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). 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 A.8: The Effects of MPACs on Selling and Marketing Expenses

	Log(SellingExp)		SellingExp/TA		SellingExp_Adv/TA		SellingExp_wage/TA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
winMPACs	0.175		0.002		-0.001		0.010	
	(0.160)		(0.019)		(0.019)		(0.006)	
winMPACs (Package)		0.087		-0.041		0.016		0.008
		(0.243)		(0.040)		(0.037)		(0.009)
winMPACs (API)		-0.012		0.031		0.001		0.013*
		(0.158)		(0.019)		(0.019)		(0.007)
winMPACs (Process)		0.193*		0.020		0.003		0.001
		(0.104)		(0.019)		(0.017)		(0.006)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Mean of Y (Before MPAC)	21.62		0.23		0.05		0.04	
# of observations	191	191	191	191	191	191	191	191
R^2	0.87	0.87	0.79	0.79	0.75	0.75	0.84	0.85

Notes: This table examines the effect of MPACs on firms' selling expenses, using the following model: $Y_{i,t} = \alpha_i + \beta MPAC_{i,t-1} + X_{i,t-1} + \delta_i + \gamma_t + \epsilon_{i,t}$. The treatment group consists of A-share listed firms that secured at least one CVBP bid and conduct an MPAC. The control group comprises listed firms that also secured a bid but do not conduct any MPAC. The sample period spans from 2016 to 2023. The dependent variables across the columns are: (1) the natural logarithm of selling expenses; (2) selling expenses scaled by total assets *(SellingExp/TA)*; (3) advertising and promotion expenses scaled by total assets *(SellingExp Adv/TA)*; and (4) employee compensation under selling expenses, normalized by total assets *(SellingExp Wage/TA)*. The key independent variable is an indicator variable that equals 1 for all years after firm i conducting an MPAC, and 0 otherwise. Control variables include one-period lagged firm characteristics: the natural logarithm of total assets, ROA, Tobin's Q, total debt to assets, cash holdings to assets, capital expenditures to assets, and property, plant, and equipment to assets. All regressions incorporate firm and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table A.9: The Effects of MPACs on Pack Size

	Winning DDDs		Log (Pack Size)	
	(1)	(2)	(3)	(4)
Procured	1.842***	1.852***	0.225***	0.233***
	(0.031)	(0.031)	(0.003)	(0.003)
Procured × winMPACs	0.177***		0.040***	
	(0.020)		(0.002)	
Procured × winMPACs (Package)		0.293***		0.039***
		(0.041)		(0.007)
Procured × winMPACs (API)		0.171***		0.048***
		(0.022)		(0.002)
Procured × winMPACs (Process)		-0.045		-0.006***
		(0.040)		(0.002)
Hospital × Molecule FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
Mean of Y (Before CVBP)	1068.62		13.42	
# of observations	866666	866666	1356508	1356508
(Pseudo) R^2	0.86	0.86	0.94	0.94

Notes: This table reports the effects of winning firms' MPACs on pack size. In columns (1) and (2), the dependent variable is winning DDDs; we employ a Poisson regression to account for zero values in winning DDDs. In columns (3) and (4), the dependent variable is log(pack size), which represents the weighted average days' supply per box of winning drugs procured by a hospital in a given quarter, which is missing for hospitals that do not purchase any winning drugs. The empirical specification is identical to that in Table 4. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table A.10: Heterogeneous Effects of MPACs on Drug Utilization by Location

	(1) Urban	(2) Rural
Procured	0.224***	0.313***
	(0.007)	(0.006)
Procured × winMPACs	0.162***	0.182***
	(0.010)	(0.014)
Hospital × Molecule FE	✓	✓
Quarter FE	✓	✓
Mean of Y (Before CVBP)	14613.68	6464.55
# of observations	849959	913850
R^2	0.84	0.78

Notes: This table reports the heterogeneous effects of MPACs on drug utilization by splitting the sample into urban and rural areas. The dependent variable is the logarithm of DDDs. Standard errors clustered at the hospital level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Appendix B. Adverse Selection

Diwan et al. (2026) show that competitive bidding in the U.S. Medicare durable medical equipment (DME) market led to the adverse selection of fraudulent firms. Similarly, Carril et al. (2026) document adverse selection driven by intensified competition in U.S. defense procurement, suggesting this mechanism operates across various sectors. Building on these findings, an important empirical question arises: does similar adverse selection occur within China's CVBP program? Table B.1 presents the determinants of bidding success in CVBP. Contrary to the adverse selection observed in U.S. procurement markets, our results suggest that CVBP does not disproportionately reward low-quality or opportunistic firms. Instead, the policy selects large, low-price, and highly capable manufacturers.

Specifically, columns (1) and (2) show that top-tier and API producers are significantly more likely to secure contracts, leveraging their cost advantages and production capacities to meet the massive demands of CVBP. Conversely, branded producers are disadvantaged by their substantial price premiums. Using firm attributes collected from *Aiqicha*, column (3) indicates that larger firms (measured by registered assets) have a significant bidding advantage. In contrast, older firms are penalized. Furthermore, we find no evidence that SOEs receive preferential treatment through political connections. Column (4) incorporates pre-CVBP market dynamics, revealing that higher historical market shares and lower baseline prices positively predict bidding success. Finally, the full specification in column (5) confirms that the effects of top producers, firm assets, branded identity, and historical price remain robust and statistically significant.

While MPACs are correlated with drug quality deterioration after CVBP, a natural question arises: do firms exhibit a continuous pattern of opportunistic behavior, engaging in pre-CVBP changes to secure a contract and subsequently making further modifications post-CVBP? Columns (6) and (7) examine such correlation, and the results indicate that pre-CVBP changes do not significantly affect the probability of bidding success.

Table B.1: The Determinants of Bidding Success

	Firm Attributes					Pre-MPACs	
	(1) Firm Status	(2) Supply Chain	(3) Fundamentals	(4) Market Power	(5) Full	(6) Total	(7) By Type
Top 100 Producers	0.534***				0.527***		
	(0.073)				(0.082)		
Branded Producers	-0.223***				-0.467***		
	(0.052)				(0.165)		
API Producers		0.112**			-0.017		
		(0.055)			(0.052)		
Log(Assets)			0.057***		0.019*		
			(0.011)		(0.010)		
Firm Age			-0.004**		-0.002		
			(0.002)		(0.002)		
SOE			-0.031		0.015		
			(0.058)		(0.056)		
Pre-CVBP Market Share				0.450	0.311		
				(0.278)	(0.294)		
Log(Pre-CVBP Price)				-0.042**	-0.041*		
				(0.020)	(0.022)		
Pre-CVBP MPACs						0.011	
						(0.076)	
Pre-CVBP Package MPACs							0.223
							(0.251)
Pre-CVBP API MPACs							0.003
							(0.081)
Pre-CVBP Process MPACs							-0.037
							(0.209)
Constant	0.105***	0.128***	-0.836***	0.144***	-0.195	0.144***	0.143***
	(0.014)	(0.015)	(0.203)	(0.023)	(0.177)	(0.015)	(0.015)
Molecule FE	✓	✓	✓	✓	✓	✓	✓
# of observations	511	511	476	429	398	511	511
R^2	0.35	0.15	0.20	0.19	0.45	0.14	0.14

Notes: This table presents the determinants of bidding success. The dependent variable is an indicator equal to one if firm i wins the bid for molecule d. The sample consists of all producer-molecule pairs with documented public hospital purchasing records between January 2019 and June 2023. Columns (1) through (5) examine the role of firm attributes, while columns (6) and (7) investigate the impact of pre-CVBP MPACs on the probability of winning. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix C. Proofs and Derivations

C.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

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

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

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

with solution

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

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.

C.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

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

The participation rate is

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

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

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

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

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

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

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

Similarly, differentiating with respect to γ:

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

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**.

C.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

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

with SOC

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

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

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

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 (C.12) is negative by (C.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.

C.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 (C.8) becomes $\frac{\partial x^*}{\partial q} = -\frac{A(q)H(z)}{\gamma}$.

Differentiating with respect to γ:

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

Since $z = \gamma e(q) x^*$ and using (C.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

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

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

C.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 D. 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 D.1 re-estimates dynamics using procured molecules only by exploiting quasi-random variation in treatment timing, and the dynamic responses remain stable.[3] Second, Figure D.2 implements leave-one-molecule-out analyses, indicating that our findings are not driven by any single procured molecule. Third, Figure D.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). 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.[4]

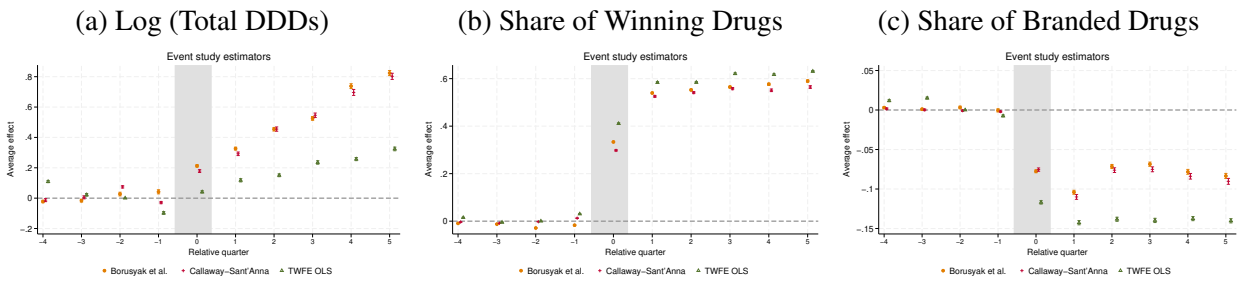


Figure D.1: Robustness: Event Study without the Control Group

Notes: This figure presents event-study estimates derived exclusively from the sample of treated molecules. Because restricting the sample to a balanced window without a control group would yield incomplete comparisons, we retain all available quarters for the treated molecules to estimate the dynamic effects, but report coefficients only for the balanced event window spanning relative quarters -4 to 5. The figure overlays results from three distinct estimators: Borusyak et al. (2024) (orange circles), Callaway and Sant'Anna (2021) (red crosses), and a dynamic TWFE model (green triangles). Because the implementation of CVBP does not necessarily align with the beginning of relative quarter 0, the estimates for this transition period may be attenuated. 95% confidence intervals are displayed but are visually negligible due to the large sample size.

[3]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.

[4]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 $\bar{M} = 2$.

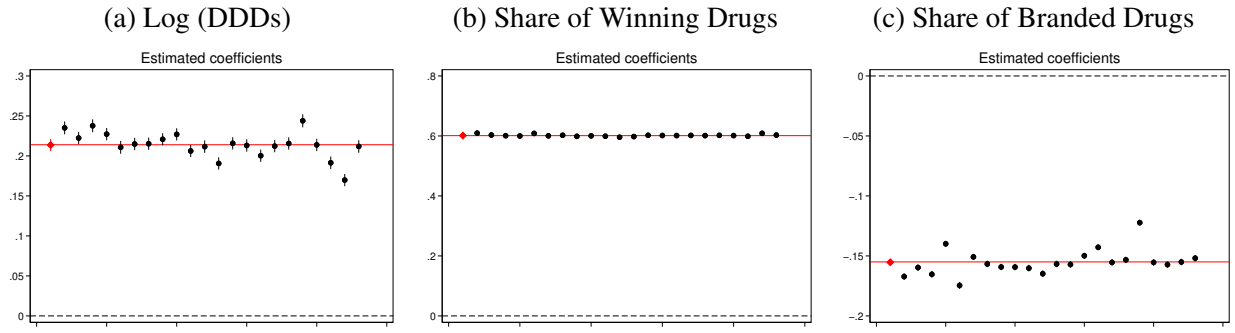


Figure D.2: Robustness: Leave-one-out Analysis

Notes: This figure presents a leave-one-out robustness check for the effects of CVBP. The red diamond represents the baseline coefficient estimated using the full sample. Each black circle plots the point estimate obtained by re-estimating the baseline specification, excluding one treated molecule at a time. 95% confidence intervals are displayed but are visually negligible due to the large sample size.

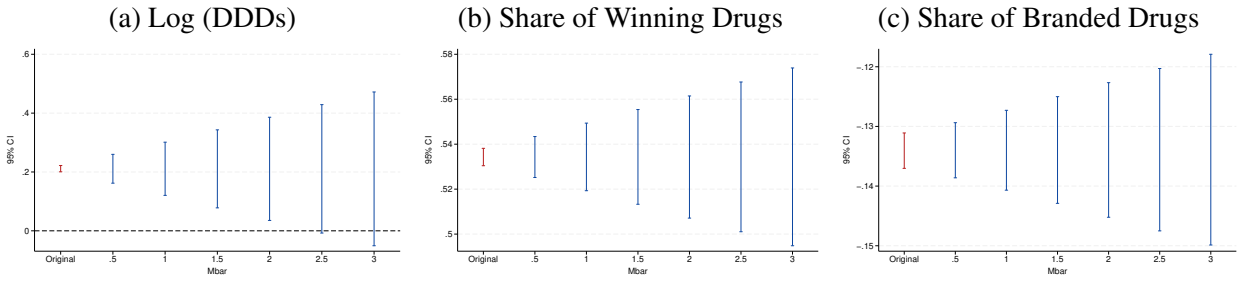


Figure D.3: Robustness: Sensitivity Analysis

Notes: This figure presents an honest DiD sensitivity analysis for potential departures from parallel trends, following Rambachan and Roth (2023). Given the staggered adoption setting, the dynamic effects are estimated using the Callaway and Sant'Anna (2021) DiD estimator. Because relative quarter 0 serves as a transition period spanning both pre- and post-CVBP phases, the sensitivity analysis is evaluated at relative quarter 1, the first full post-treatment period.