Unlocking the Hidden Pharmaceutical Financing: Resilient R&D Investment and Malleable Selling Expenses

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Abstract

Conventional wisdom holds that when firms face adverse shocks to revenues and market valuations, their R&D investment should contract. This paper shows otherwise: innovation can remain remarkably resilient when firms adjust their internal cost structures. Exploiting China's centralized drug procurement (CVBP) reform as an exogenous shock, we find that the policy sharply reduces pharmaceutical firms' revenues and market capitalization. Yet, contrary to concerns that price regulation suppresses long-term innovation, we detect no decline in firms' R&D expenditures or innovation output. The stability in R&D arises from substantial operational restructuring—specifically, a 19.5% reduction in selling expenses—that offsets revenue losses without reliance on external financing such as bond issuance or bank borrowing. Our findings reveal a cost reallocation channel through which firms can buffer R&D from financial stress, challenging the canonical view that innovation is primarily constrained by access to capital.

Keywords: Innovation, Cost Structure, Pharmaceutical Companies, Regulatory Shock, Financing

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1 Introduction

Innovation is among the most fragile investments firms make–long-horizon, uncertain, and acutely dependent on financial slack. For this reason, regulation that compresses profits or depresses market valuations is thought to chill innovative effort. A central prediction in corporate finance holds that innovative investment is sensitive to fluctuations in firms' internal and external financing capacity (Brown et al., 2009). Therefore, when cash flow or external financing contracts, R&D — being costly, risky, and non-pledgeable — should fall disproportionately (Fang et al., 2014). Yet this logic rests on an implicit rigidity: that firms' expenditure structures are fixed. In practice, regulation may alter not only revenues but also how resources are deployed within the firm, opening the possibility that some adjust internally to preserve innovation even under financial strain. We explore this possibility through a rare, large-scale policy experiment — China's Centralized Volume-Based Procurement (CVBP) — which simultaneously compressed pharmaceutical firms' revenues and valuations while transforming their operating costs.

We exploit China's Centralized Volume-Based Procurement (CVBP) reform as a natural experiment to examine how firms sustain innovation when regulation simultaneously disrupts product and financial markets. Launched in late 2018, the CVBP unified public drug procurement under a single national buyer—the National Healthcare Security Administration (NHSA)—which used its monopsony power to exchange large, guaranteed purchase volumes for deep price concessions. In the initial "4+7 Pilot", prices of targeted drugs fell on average by 75% (Cao et al., 2024), and subsequent rounds expanded coverage nationwide to 435 molecules across ten bidding waves. By mid 2023, the program had greatly shrunk the drug expenditure on the targeted molecules by 56% (Zhang et al., 2025). This reform thus generated a sharp and plausibly exogenous contraction in revenues, market valuations, and operating strategies—an ideal setting to study how innovation endures under policy-induced financial stress.

The institutional design of CVBP introduced two opposing forces. Steep price reductions tightened liquidity and depressed investor expectations, conditions that typically curtail R&D. Yet by guaranteeing hospital-level demand and eliminating the need for costly marketing and physician promotion, the policy also removed one of the largest discretionary expenses in the pharmaceutical sector. Whether

this offset allowed firms to preserve innovation becomes an empirical question. Our analysis quantifies these competing channels, tracing how firms reallocate resources when external financing is constrained but internal inefficiencies are simultaneously eliminated.

We first document how capital markets and firm fundamentals responded to the CVBP shock. Using daily stock returns for A-share-listed pharmaceutical firms around bid-winning announcements across nine procurement rounds, we find that the average three-day cumulative abnormal return (CAR) declined by 1.1%, implying a market-value loss of roughly 135 million RMB per firm. Bid-winning firms lost about 0.9%, while rivals—those producing the same active ingredients but not selected—lost an additional 2.2%. These reactions reveal that investors viewed the policy as a major contraction in expected cash flows. At the product-market level, a staggered difference-in-differences (DiD) analysis shows that revenues of winning firms fell by 18% following participation, while net income remained statistically unchanged. Stable profitability amid falling revenues points to substantial internal cost adjustment.

The next question is whether such financial pressure undermined innovation. Surprisingly, it did not. We find no significant change in firms' R&D expenditures or innovation outputs—measured by patents, citations, or applications—after procurement entry. The absence of any decline indicates that firms absorbed the shock elsewhere. Selling expenses, encompassing marketing, promotion, and sales-force costs, fell sharply by 19.5% relative to total assets. This contraction was not a discretionary optimization but a mechanical result of the procurement rules: once hospitals were required to purchase directly from winning suppliers at fixed prices and quantities, promotional spending toward physicians became redundant. The policy thus compelled firms to cut non-productive expenditures, freeing internal resources that sustained R&D despite revenue losses. Consistent with this interpretation, we find no evidence that firms raised external funds through equity, debt, or bank borrowing after the reform. Innovation resilience therefore reflects policy-induced cost reallocation rather than new capital inflows.

We corroborate this mechanism by examining rival firms, which endured even deeper financial distress. Their revenues declined by roughly 26%, and their abnormal stock returns were more negative than those of winners. Yet their R&D investments also remained steady, supported by an even larger 31% reduction in selling

expenses. For both winners and rivals, CVBP eradicated the economic rationale for costly marketing—previously the primary link between revenue and promotion. The uniformity of these adjustments indicates a systemic, policy-driven shift in internal capital allocation rather than firm-specific discretion. In effect, the reform restructured firms' internal capital markets, enforcing efficiency gains that insulated R&D from external financial shocks.

To ensure robustness, we complement the baseline two-way fixed-effects model with modern staggered-DiD estimators that account for treatment-effect heterogeneity (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Event-study analyses confirm parallel pre-trends and show persistent post-treatment reductions in selling intensity with no decline in R&D. Results remain consistent when restricting to a balanced 2015–2022 panel, after propensity-score matching on firm fundamentals, when controlling for repeated participation across procurement rounds, and when employing a continuous measure of policy shock intensity. Across all specifications, the evidence converges: CVBP depressed revenues but left innovation intact, sustained through internally reallocated resources rather than external financing.

Our findings yield three contributions to the finance literature. First, we extend the broad discussion about the financing of innovation (Brown et al., 2009, 2012; He and Tian, 2013; Chemmanur et al., 2014; Cornaggia et al., 2015; Howell, 2017; Moshirian et al., 2021). While prior work emphasizes that capital-market frictions constrain R&D through liquidity and valuation channels, we reveal a complementary mechanism: when regulation compresses both revenues and financing access, firms can maintain innovation by redeploying resources from policy-displaced costs. This internal substitution channel highlights the role of cost structure flexibility in mediating the impact of financial shocks—an element largely absent from canonical models of financing constraints.

Second, we contribute to the literature on the R&D effects of product-market regulation and competition (Giroud and Mueller, 2015; Gu, 2016; Lyandres and Palazzo, 2016; Li et al., 2021; Krieger et al., 2022; Thakor and Lo, 2022; Bonaimé and Wang, 2024). Most studies find that price controls depress innovation by eroding expected returns (Golec et al., 2010). Our results qualify this view: when price regulation is coupled with guaranteed volume, it can reduce rents while improving allocative efficiency. The CVBP's design eliminated wasteful marketing expendi-

tures that once distorted prescribing behavior (Carey et al., 2021; Agha and Zeltzer, 2022), redirecting funds toward productive R&D. Thus, the trade-off between innovation and cost containment depends crucially on which expenditure margins policy compresses.

Third, we add to the growing literature on how firms in emerging markets adapt when weak institutions and imperfect financial systems heighten the impact of policy and financing frictions. While prior work on emerging-economy finance emphasizes that weak legal enforcement and underdeveloped financial systems amplify firms' exposure to policy and financing frictions (Allen et al., 2005; Beck et al., 2005; Cull and Xu, 2005; Ayyagari et al., 2010), direct micro-level evidence on how firms reorganize internally in response is scarce. Our findings show that firms in China's pharmaceutical sector actively reshaped their internal capital allocation when a national procurement reform altered competitive structure, demonstrating that corporate adaptability in emerging markets extends beyond conventional concerns about capital scarcity.

The remainder of the paper proceeds as follows. Section 2 outlines the institutional background of the CVBP reform. Section 3 describes the data, sample construction, and empirical design. Section 4 presents evidence on market reactions and firm fundamentals. Section 5 analyzes the effects of CVBP on innovation and the mechanisms of internal cost reallocation. Section 7 concludes with implications for regulation, financing constraints, and welfare.

2 Institutional Background: The Introduction of CVBP

China's CVBP program marked a structural transformation of the country's pharmaceutical market. The initial "4+7 Pilot" targeted 25 drug molecules across four municipalities and seven major cities. Following the pilot, the program rapidly expanded nationwide through nine subsequent rounds, ultimately encompassing 374 drug molecules (Table 1). The National Healthcare Security Administration (NHSA), established in 2018 as the single national payer, now aggregates over half of China's prescription drug demand, leveraging its monopsony power to negotiate

deeply discounted prices with manufacturers.[1] To ensure compliance, the NHSA incentivizes hospitals to allocate 50-80% of their previous drug volumes to winning suppliers, guaranteeing a fixed quantity of sales in exchange for steep price reductions.

Procurement process. The CVBP proceeds in three sequential stages: (1) quantity reporting, (2) competitive bidding, and (3) hospital procurement. First, all public and designated private hospitals are required to report their anticipated purchase quantities for the coming year, typically amounting to 60-80% of their annual prescriptions.

Second, the NHSA consolidates these reports to form a national procurement pool and invites qualified producers, including branded originator and bioequivalent generics, to bid. Pharmaceutical firms with the lowest bids win the procurement. If there is only one winner, this winner supplies 50% of the national demand. If there are multiple winners, each takes turn to choose its supplying provinces, typically receiving 60%–80% of the reported volume per province depending on the number of winners.

Third, during the subsequent contract period, hospitals place direct orders with winning firms at the bid price. To ensure the effective implementation of the centralized procurement policy, local Healthcare Security Administrations (HSAs) monitor hospitals' fulfillment of procurement quotas and implement complementary mechanisms, including insurance payment standards, surplus retention schemes, and advance-payment policies, to align incentives among pharmaceutical companies, hospitals, and patients.

Market implications. The CVBP's large-scale, top-down design has fundamentally reshaped China's pharmaceutical industry. Most winning firms are domestic generic manufacturers, as the selected molecules are typically off-patent with multiple generic substitutes and widely used. In addition, the NHSA prioritizes high-expenditure molecules that account for a substantial share of public spending. Unlike global Big Pharmas, which typically balance R&D and marketing, China's generics manufacturers have historically prioritized sales promotion over R&D. By removing the need for intensive marketing, the CVBP compresses firms' selling

[1]The NHSA oversees both the Urban Employee Basic Medical Insurance (UEBMI) and the Urban and Rural Resident Basic Medical Insurance (URRBMI), covering approximately 1.33 billion individuals. See: https://www.nhsa.gov.cn/art/2024/7/25/art_7_13340.html (Accessed Oct. 28, 2024).

expenses while preserving guaranteed demand, forcing a structural reallocation of resources. Empirically, Zhang et al. (2025) document that the average price of procured drugs fell by roughly 70%, resulting in a 67% decrease in overall expenditure for these molecules.[2] Given that over 50% of hospital drug purchases now occur under the procurement[3], the reform effectively internalizes much of the pharmaceutical distribution, which sharply reduces the necessity for traditional promotional activities. Firms must adapt to redesign their cost structures and innovation strategies. These profound industry shifts motivate our central research question: how do firms reoptimize R&D and financing behavior under the dual pressures of revenue compression and guaranteed market access?

3 Data, Sample, and Empirical Strategy

3.1 Data Sources

We construct a novel firm-level panel by linking public procurement outcomes to financial, patent, and stock market data for Chinese A-share healthcare firms. This unified dataset enables us to capture both immediate valuation effects and longer-term adjustments in innovation and financing behavior following the implementation of the CVBP program.

Procurement Data. We collect detailed information on the eight rounds of centralized volume-based procurement (CVBP) from the Shanghai Sunshine Medical Procurement All-in-One platform.[4] The dataset includes the procured drug molecules, winning firms, winning prices, procured volumes, and both preliminary and formal disclosure dates. We focus on the preliminary announcement date, which marks the first public release of award results and therefore represents the relevant

[2]Similar effects were reported in studies on the 4+7 Pilot program (Cao et al., 2024; Liu et al., 2024).

[3]According to IQVIA (IQVIA, 2023), over 85% of prescription drugs in China are dispensed through hospitals rather than retail pharmacies. Of this hospital-dispensed volume, 50-80% is procured through the CVBP, meaning that approximately 51%(=60%*85%) of total prescription drug utilization is now secured by the program.

[4]See https://www.smpaa.cn/gjsdcg/index.shtml (Accessed March 18, 2024).

information event for investors.[5] Because our event-study design relies on a short observation window, precise timing of this disclosure is essential to avoid contamination of the estimation by other market events. We link each awarded molecule to its corresponding producers using DXY Insight, a commercial pharmaceutical intelligence platform, to identify non-winning producers of the same molecules (hereafter referred to as "rivals").[6] These data form the basis for both our event-study analysis of stock-market reactions and our staggered difference-in-differences (DiD) estimation of firms' post-procurement outcomes.

Financial and Market Data. We obtain stock market data for A-share listed healthcare firms from the China Securities Market & Accounting Research (CSMAR) database, and financial fundamentals from the WIND database. CSMAR provides daily stock trading data, market index data, firm announcements, and firm profiles including IPO dates and industry classifications. Among several classification systems available, we adopt the Shenyin & Wanguo industry classification, which provides a more granular sub-industry breakdown within healthcare and allows us to define the control group in the DiD analysis. We rely on WIND for firms' financial statements because it directly reports R&D expenditures (Wind Code: s_stmnote_rdexp), based on its manual extraction from the "***Notes*** to Financial Statements—Administrative Expenses" section before 2018.[7]

Innovation Data. We retrieve patent application and grant information from the State Intellectual Property Office (SIPO) of China and patent citation data from Google Patent to measure firms' innovation outputs and the quality of their inventions.

[5] We posit that investor reactions primarily occur around the preliminary disclosure date. Given the anticipation and digestion of information following this date, we expect minimal market reaction around the formal disclosure date, a hypothesis further supported by the comparison of Table 2-3 with Table A.1-A.2.

[6] *DXY Insight* is a global pharmaceutical data intelligence platform that provides information on new drugs, clinical trial outcomes, and pharmaceutical transactions worldwide, and is widely used by academic researchers and practitioners in the healthcare field. See https://db.dxy.cn/v5/home#home-footer (Accessed Oct 21, 2024).

[7] Following the implementation of China's new accounting standards in June 2018, a dedicated "R&D" item was introduced in the income statement of annual reports.

3.2 Sample

Our analyses draw on two complementary samples: (i) publicly listed healthcare firms used in the event study of stock-market reactions, and (ii) a firm-year panel comprising bid-winning firms and their rivals, with unaffected firms serving as the control group, used in the staggered difference-in-differences (DiD) analysis of post-CVBP performance.

Event-Study Sample. We begin with all A-share listed healthcare firms traded on the Shanghai and Shenzhen stock exchanges that have been listed for at least one year as of the end of 2023. Firms are categorized according to the Shenyin & Wanguo industry classification, which provides detailed sub-industry groupings within healthcare. We exclude firms under Special Treatment (ST) or Particular Transfer (PT) designations due to abnormal trading patterns.[8] We also remove firms with insufficient estimation windows around the CVBP announcement dates. After applying these filters, the final event-study sample comprises 484 firms, of which 109 are CVBP bid winners. [9]

Panel Sample for DiD Analysis. The DiD sample covers 2015–2023 and comprises bid-winning firms, their rivals, and firms from unaffected healthcare sub-industries that serve as controls. Because the dependent variables are lagged by one year, the treatment period runs from the first pilot round (2019) through Round 7 (2022). We exclude firms with missing R&D data and drop those without pre-shock accounting information. Finally, the panel DiD sample comparing Winners and Controls contains 1,070 firm-year observations, and the sample comparing Rivals and Controls contains 575 firm-year observations, drawn from a total of 208 unique firms.

[8] ST firms typically face financial distress or have failed to meet regulatory requirements. PT firms are subject to restructuring or delisting and face stricter trading rules.

[9] Matching the government-released list of winning suppliers with listed firms presents substantial challenges. Many winning entities are subsidiaries rather than the listed parent, and numerous firm names appear only in abbreviated or non-standard forms, complicating precise identification. The detailed matching procedure is provided in Appendix A.1

3.3 Empirical Strategy for Market Reactions

To measure investors' perceptions of the CVBP's impact on firm value, we conduct an event study around the procurement award announcements. We calculate the three-day cumulative abnormal return (CAR) centered on the preliminary disclosure date t, which represents the first public revelation of winning firms.

Formally, we estimate the market model:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \epsilon_{i,t} \tag{1}$$

where $R_{i,t}$ represents the return of stock i on day t, and $R_{M,t}$ denotes the market return on the same day. We estimate Equation (1) over the pre-event window $[-80, -20]$ to obtain firm-specific parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$. The abnormal return for firm i on event day d is then computed as

$$AR_{i,d} = R_{i,d} - (\hat{\alpha}_i + \hat{\beta}_i R_{M,d}), \tag{2}$$

and the cumulative abnormal return over the three-day event window $d \in [-1, 1]$ is given by $CAR_i = \sum_{d=-1}^{1} AR_{i,d}$.

We implement two benchmark specifications for $R_{M,t}$: the value-weighted market return from CSMAR and the return on the healthcare index 000991.SH, which tracks 117 A-share healthcare firms.[10] The 80-day pre-event window is intentionally short to minimize contamination from overlapping events across procurement rounds, which were often closely spaced in time.[11] We then aggregate firm-level CAR_i across all affected firms to compute the cumulative average abnormal return (CAAR), which captures the average market valuation effect of procurement announcements.

[10] As robustness checks, we also use alternative sector indices such as 000933.SH (Medicine 800) and 000857.SH (Medicine 500).

[11] For example, the interval between CVBP Round 4 and the first Medical Device Procurement Round is only 90 days (See Table 1). A longer estimation window would overlap with prior events, potentially biasing abnormal return estimates. Furthermore, Round 6, which focused on insulin products, was announced only 73 days after the preceding Medical Device CVBP round. Because that earlier round targeted coronary stents, the overlap minimally affected insulin-related firms.

3.4 Empirical Strategy for Firm Performance

To assess how the CVBP reshapes firm performance and innovation, we exploit its staggered rollout across drug molecules and firms using a difference-in-differences (DiD) design. This framework treats each procurement round as an exogenous shock to the product portfolios of affected firms, allowing us to compare post-treatment outcomes between treated and unaffected firms.

We estimate the following model:

$$Outcome_{i,t+1} = \alpha_i + \beta_1 Procured_i \times Post_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

where i denotes firms, t denotes years. The interaction term $Procured_i \times Post_{i,t}$ equals one for firm i in the year of its first procurement win and subsequent years, and zero otherwise.

The dependent variables $Outcome_{i,t+1}$ are lagged by one year to mitigate simultaneity concerns and capture post-shock adjustments. We consider three categories of outcomes: (i) product-market performance, including sales and profitability; (ii) innovation activities, measured by innovation inputs (R&D expenses) and outputs (Patent applications, grants and citations); and (iii) financial structure, covering internal and external R&D funding channels. Firm fixed effects δ_i control for time-invariant firm heterogeneity, and year fixed effects γ_t capture common macroeconomic trends. We further add firm-level controls, $X_{i,t}$, widely used in the literature to account for other confounding factors, including Ln(Assets) (TA), ROA, Tobin's Q, leverage (Total Debt/TA), cash holdings (Cash/TA), capital expenditures (CapEx/TA), and fixed assets (PPE/TA). Standard errors are clustered at the firm level. The coefficient of interest, β_1, reflects the average effect of CVBP on subsequent firm outcomes.

Treatment and Control Design. Our analysis considers two distinct treatment groups examined separately: procurement-winning firms, which experience direct cash-flow shocks from regulated price cuts and guaranteed purchase volumes, and rival firms producing the same molecules but not winning the bid, which are exposed to indirect competitive pressures. The control group includes firms operating in four healthcare sub-industries: *non-vaccine biological products*, *blood products*, *medical equipment*, and *APIs*. Two considerations guide their selection: the firms

should be operationally and financially comparable to the treated firms yet minimally exposed to the CVBP program, and they must not participate in COVID-related product chains such as vaccines, diagnostic kits, or antiviral treatments.

The first criterion ensures comparability in production technology, innovation cycles, and financial structure between treated and control firms. To further prevent contamination, we also exclude firms engaged in other procurement initiatives (e.g., provincial medical-device tenders) and those primarily involved in traditional Chinese medicine, where cross-product spillovers with chemical drugs are common. The second criterion eliminates confounding shocks from pandemic-driven demand surges by excluding firms directly involved in COVID-related activities. [12]. After these exclusions, the final panel comprises 1,270 firm-year observations (98 winners, 27 rivals and 83 controls), as summarized in Table 4.

The summary statistics for the DiD anaylsis are presented in Table 4. Although the regressions later apply logarithmic transformations or truncation adjustments to certain variables, Table 4 reports the raw value to provide a more transparent overview. It shows that firms in our sample generally exhibit substantial selling expenses, yielding average selling expenses to total assets of 15.1%. In contrast, the R&D to total assets is merely 1/5 of this figure, highlighting the financial imbalance characteristic of the healthcare sector. This pattern differs from that of U.S. listed firms: over the same sample period, R&D/TA (COMPUSTAT XRD/AT) averages 18.24%, compared with only 3.4% for marketing intensity (COMPUSTAT XAD/AT).

Together, these data and empirical designs provide a comprehensive framework to evaluate both investors' immediate valuation responses and firms' subsequent adjustments in innovation and financing behavior following the CVBP.

[12]For example, Shijiazhuang Yiling Pharmaceutical Co., Ltd. (002603.SZ) reported a 50.6% revenue increase and more than a tenfold profit surge in 2020 from its COVID treatment *Lianhua Qingwen Granules*

4 Negative Market Reaction and Revenue Loss Due to CVBP

4.1 Overall Market Reaction to CVBP Announcements

We begin by examining investors' reactions to the CVBP and its impact on the market value of healthcare firms. Since investor responses may differ across procurement rounds and industry subsectors, we further decompose results by both dimensions.

Panel A of Table 2 reports the CAARs for all listed healthcare firms across nine procurement rounds, starting from the 4+7 Pilot (Round 0). The sample includes 3,230 firm-round observations. On average, $CAR1$ declined by –1.13%, implying an average wealth loss of roughly 134.8 million RMB per firm during the three-day window, based on the average pre-event market capitalization of 11.97 billion RMB as of September 2018.

Panel B decomposes the results by round. Except for Rounds 2 and 6, all other rounds show significantly negative CAARs. Round 6, which targeted insulin and involved fewer firms, generated a positive $CAAR1$, but the effect becomes insignificant once benchmarked against the industry index ($CAAR2$). Round 2 coincided with the initial COVID-19 outbreak in China[13], when rumors that antibiotics could prevent infection triggered a temporary surge in several antibiotic producers' stock prices, for example, *Lukang Pharmaceutical Co., Ltd.* gained 5.4%. This helps us understand why $CAAR1$ is positive in Round 2; while the $CAAR2$ that benchmarked against the health industry index becomes insignificant. Excluding Round 2 strengthens the overall negative effect, as shown in Panel C.

Investor reactions appear to attenuate over time as the CVBP becomes institutionalized. Although the decline is not strictly monotonic, the magnitudes of $CAAR1$ and $CAAR2$ in Rounds 7-8 are roughly one-quarter to one-half of those observed in the initial rounds, suggesting that later announcements were increasingly anticipated by the market.

Given that the CVBP primarily targets chemical drugs, we next examine how this shock propagated across other healthcare subsectors. Using the Shenyin &

[13]On the same announcement date, Wuhan reported the risk of human-to-human transmission and confirmed 17 new cases.

Wanguo Industry classification, we divide firms into seven groups: Chemical Drugs (N=109), Chinese Medicine (N=74), APIs (N=40), Biological Products (N=52), Distribution (N=25), Medical Device and Equipment (N=79), and Medical Services (N=94). Panel C shows that firms in the Chemical Drugs category experienced the largest value decline, consistent with their direct exposure to CVBP. Distribution firms suffered the steepest drop (–3.26%), reflecting reduced intermediation as hospitals began contracting directly with manufacturers under centralized procurement.

4.2 Differential Reactions Across Winners, Rivals, and Untreated Firms

The previous subsection examined overall market responses to CVBP announcements across rounds and subsectors. We now focus on cross-firm heterogeneity, analyzing how investors differentiated between bid-winning firms, rivals, and untreated firms during the three-day event window.

We categorize firms into three groups: bid winners, rivals, and prospective participants. *Bid winners* are firms awarded contracts in any CVBP round (See Appendix A for the firm list). *Rivals* are chemical-drug firms manufacturing the same molecules as winning firms but not selected for procurement. [14] *Prospective participants* are chemical-drug producers neither winning nor competing on the same molecules, often smaller firms producing niche or low-volume drugs that do not meet "large volume, low price" bidding criteria.

Table A.3 presents summary statistics for these three categories, based on the most recent fiscal reports preceding each annoucement. As expected, bid winners are substantially larger, with average total assets of 15.99 billion RMB versus 4.79 billion RMB for prospective participants. Both winners and rivals exhibit higher profitability whereas prospective participants display notably low ROE (0.94), highlighting the structural disadvantages faced by smaller firms under centralized procurement.

Table 3 compares the three-day CAR across groups. Panel A pools all nine rounds, beginning with the CVBP 4+7 Pilot (Round 0). Both $CAR1$ and $CAR2$ are negative for winners, though statistically insignificant, consistent with investors' concerns over the expected revenue declines induced by steep price cuts although

[14] Our data are structured by firm and round, so we exclude firms from the rival category if they won bids for other molecules within the same round.

winning bids. Rivals, by contrast, experienced markedly larger losses: their average CAR declines by 2.45% over the three-day window. Winners' returns are, on average, 2.03% higher than rivals', a gap consistent with the asymmetric exposure implied by the CVBP rules-winning firms retain/expand market share despite price reductions, whereas rivals lose volume, in some cases entirely. Under the procurement design, hospitals are required to prioritize winning drugs and can only purchase non-winning alternatives once quota targets are met, sharply limiting rivals' post-award sales opportunities.

To mitigate contamination from concurrent events durign Round 2, which coincided with the onset of COVID-19, we re-estimate the results excluding this round. Panel B shows that both $CAR1$ and $CAR2$ become statistically significant once Round 2 is removed, reinforcing the evidence of investors' negative assessment toward winning firms' valuations.

Table A.4 further tests these differences using OLS regressions with firm-level controls and round fixed effects. Columns (1) and (2) compare winners to rivals, while Columns (3) and (4) compare winners to prospective participants. Across all specifications, the coefficients on $Bid\ Winner_i$ are significantly positive: bid winners experience 1.17% higher abnormal returns compared to rivals (Column (1)) and 1.19% higher returns relative to prospective participants (Column (3)). Together, these findings indicate that: while the CVBP reform triggers significant investor concern, pessimism is more pronounced among firms that lose bids or remain outside the procurement program.

4.3 Impact of CVBP on Firms' Sales and Profitability

The stock-market evidence indicates that investors anticipated substantial revenue compression following the CVBP. We now examine whether such expectations are reflected in firms' fundamentals—specifically, in sales and profitability.

Theoretically, the CVBP introduces a trade-off between price concessions and volume expansion. Whether total revenues decline depends on which effect dominates. Column (1) of Table 5 demonstrates that, on average, firms wining CVBP contracts experienced an 18% decline in sales, implying that the negative price effects outweighed the potential increase in market share. We omit firm size (log of total assets) from the regression since the dependent variable, sales already capture

firm scale.

Despite the sharp decline in revenues, Columns (2)-(3) reveal no significant decline in firms' net income, suggesting that they adjusted internally rather than experienced a collapse in operating efficiency. This stability reflects two forces: the persistently high profitability of Chinese pharmaceutical firms and a reallocation of internal resources to offset price-induced revenue losses. In the next section, we examine this adjustment mechanism—specifically, whether firms reduced selling expenses to buffer R&D investment and sustain innovation activity under price regulation.

5 The Resilience of Firm R&D: Evidence and Mechanisms

The above findings demonstrated that following the CVBP reform, investors downgraded their valuation of bid-winning firms, which subsequently experienced notable revenue declines. A natural next question is how firms adjust to simultaneous shocks in both capital and product markets. Do they curtail their innovation investment, or instead reallocate resources to protect R&D activity? We address these questions using the staggered DiD framework described in Section 3.4.

5.1 Impact of CVBP on Firms' Innovation Input and Output

We begin by investigating the impact of winning procurement bid on firms' innovation input and output. Columns (1)–(2) of Table 6 present estimates from Equation (3), where the dependent variable is the natural log of R&D expenditure, and R&D scaled by total assets. We avoid using the common R&D-to-sales ratio because the denominator, sales, declines sharply following CVBP participation (see Table 5), which could mechanically bias estimates. Columns (3)–(6) then examine innovation output using ln(1+granted patents), ln(1+forward citations), ln(1+filed patent applications), and the raw number of filed applications. We focus exclusively on invention patents (IPs), which are considered the most original and challenging

type to obtain(Tian and Xu, 2022).[15] To address the issues of truncation, following Hall et al. (2001), we normalize patent counts/citations by the average number of patents applied/citations within the same technology class and year to mitigate truncation bias.[16] [17]

Table 6 shows that all coefficients are statistically insignificant. Despite experiencing negative shocks in both valuation and product-market revenues as shown in Section 4, procurement winners maintain stable R&D spending and innovation output. In other words, firms neither scale back innovation inputs nor experience deterioration in the quality of inventive activity.

Compared with the results of innovation input, the null response in innovation output is plausible. Patent grants and citations are long-horizon outcomes that may not fully materialize within the five-year post-treatment window spanning the initial 4+7 pilot through 2023. Such temporal lags are particularly pronounced in chemical and pharmaceutical industries (Brav et al., 2018). Nevertheless, the absence of any short-run contraction in R&D expenditure is striking, contradictory to the conventional view that negative financial shocks depress innovation, as shown in the US context (e.g., Ji and Rogers, 2024). We uncovers the mechanisms enabling firms to sustain innovation despite price and revenue pressures in the next section.

5.2 Mechanisms

5.2.1 Buffering R&D Through Reduction in Selling Expenses

We first explore whether firms adjust internal funding sources following CVBP. To explore this, we replace the dependent variable in Equation (3) with the log of selling expenses, and selling expenses scaled by total assets. Column (1) of

[15]China recognizes three patent types: invention patents (IPs), utility model patents (UMPs), and design patents (DPs). IPs cover novel technical solutions for products or processes; UMPs protect new practical solutions related to product shape or structure; and DPs protect new industrial designs. IPs undergo substantive examination, ensuring stricter standards and higher inventiveness. Notably, filings of IPs and UMPs often overlap, as UMPs are withdrawn once the corresponding IP is granted.

[16]Because we observe both patent applications and grants in the Chinese dataset, truncation bias affects only the latter. Our adjustments remove this concern for the grant-based measures.

[17]Recent literature cautions that estimating linear models using $\log(1+x)$ transformations of count outcomes can yield biased or inconsistent estimates when the underlying process is non-linear (e.g., Poisson). However, since our normalized patent and citation measures are continuous rather than discrete, concerns about functional-form bias are minimal.

Table 7 reveals that procurement winners reduce selling expenses by roughly 19.5% relative to total assets compared to the control group. This result aligns with the institutional design of CVBP: by guaranteeing substantial procurement volumes in exchange for price concessions, the policy reduces sales uncertainty and diminishes the need for aggressive marketing. Consequently, firms can scale back promotion-related expenditures, as confirmed by the negative coefficient in Column (3) when using advertising and promotion expenses scaled by total assets as the dependent variable. By contrast, employee wages associated with sales functions remain largely unaffected.

These results suggest that cost saving from reduced selling expenses create financial flexibility. Rather than representing distress-driven cost cutting, this internal reallocation acts as a buffer, allowing firms to preserve R&D investment despite weakened external conditions. We next examine whether other potential funding channels, such as external financing, played any comparable role.

5.2.2 Testing Alternative Channels: External Funding

The results in Section 5.2.1 indicate that CVBP leads to a decline in selling expenses without affecting R&D levels, suggesting that firms might use the savings from selling expenses as a buffer to sustain innovation efforts. This internal cost reallocation mechanism enables firms to cut back inefficient selling expenditures and redirect resources toward strategic priorities like innovation. To verify whether there are alternative comparable channels, we examine changes in firms' external funding sources for R&D after procurement.

We test three alternative channels, seasoned equity offerings, bond issuance, and borrowing, each normalized by total assets. Results reported in Columns (5) - (7) of Table 7 shows that all coefficients are statistically insignificant, suggesting that firms did not expand external financing to sustain R&D post CVBP, consistent with the notion that constrained capital-market access and weak investor sentiment limited their ability to raise funds (Baker and Wurgler, 2000; McLean and Zhao, 2014; López-Salido et al., 2017).

Combined with earlier evidence of firms' decreased revenue and stable R&D, these findings support a clear interpretation: firms maintained innovation primarily through cost savings induced by the CVBP's procurement design rather than

through new external capital. By guaranteeing purchase volumes and fixing prices, the policy effectively displaced the need for costly marketing and promotion, leading to a decline in selling expenses. This policy-driven cost compression created internal financial slack that firms could reallocate toward sustaining R&D investment. Accordingly, the observed stability in innovation reflects not a discretionary managerial decision, but an adaptive response to a regulatory environment that rendered traditional marketing expenditures redundant.

6 Robustness Checks and Additional Analyses

In this subsection, we conduct a series of robustness checks to further validate our findings: 1) We first examine the dynamic effects of the CVBP on firms' R&D and selling expenses, and employ robust staggered DiD estimators to account for treatment effect heterogeneity; 2) We then address potential concerns related to sample composition and selection bias through a balanced panel analysis and Propensity Score Matching (PSM); and (3) We consider the implications of repeated procurement participation and analyze the impact on rival firms producing the same molecules as procured products but not selected in any CVBP round.

6.1 Dynamic Effects of CVBP and Alternative Estimators

We conduct an event study to test the pre-trends and to evaluate the dynamic effects of the CVBP on firm's innovation and selling expenses:

$$Outcomes_{i,t+1} = \alpha_i + \beta_k \sum_{k=-7}^{4} Procured \times Post_{i,k} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \qquad (4)$$

where $Procured \times Post_{i,k}$ equals one if year t for firm i is k years from its first procurement record. We set k = -1 as the reference year. The dependent variables include R&D and selling expenses, both normalized by total assets, with firm-specific controls ($X_{i,t}$), firm (δ_i) and year (γ_t) fixed effects included.

Because two-way fixed effects (TWFE) estimators may yield biased estimates when treatment effects vary across cohorts or over time (Goodman-Bacon, 2021). We complement the baseline with robust staggered DiD estimators developed by Callaway and Sant'Anna (2021),Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2020).

Figure 2 presents the dynamic estimates across several estimators. The coefficients in pre-treatment periods (prior to the introduction of CVBP) are statistically equal to zero, suggesting the holding of the parallel trends assumption. At $k = 3$, the confidence interval widens significantly due to limited sample size, as only firms from the earliest procurement rounds remain in the set. Across all estimators, selling expenses decline sharply following CVBP, while R&D remains unaffected. These findings underscore the sustained cost-cutting effect of CVBP on selling expenses with preserved R&D investment.

Table 8 reports the static estimators corresponding to the robust staggered DiD estimators [18]. The results are consistent across all methods: CVBP has no significant impact on firm innovation, while significantly reducing selling expenses. These findings confirm that our main conclusions are not driven by estimator choice or treatment-effect heterogeneity.

6.2 Matched and Balanced Sample Analyses

To rule out potential biases arising from changes in sample composition, we restrict the analysis to a balanced panel covering 2015-2022. Sample imbalance may arise if newly listed firms differ systematically from older firms in their likelihood of bid winning or shorter pre-treatment periods (e.g., firms IPO-ing in 2020) distort the ATT estimation. Restricting to a balanced panel ensures comparable pre- and post-treatment histories across firms. [19]

This restriction yields 792 firm-year observations. Columns (1)-(2) of Table 8 show that the results remain robust: CVBP has no impact on firm innovation but leads to a pronounced reduction in selling expense. These findings confirm that our main conclusions are not driven by biases introduced by unbalanced panel data.

[18] Sun and Abraham (2021) is excluded because it only applies to the dynamic setting.

[19] For example, a firm that IPO in 2020 and participated in CVBP in 2022 has only one pre-treatment observation (2021, noting that we exclude the IPO year to isolate its effect). In contrast, a firm listed before 2015 and participated in CVBP in 2022 contributes seven pre-periods (2015–2021).

Leveraging the aforementioned balanced $STKCD \times Year$ data, we further implement a propensity score matching (PSM) to further mitigate selection bias. Treatment and control firms are matched based on log(total assets), ROA, Tobin's Q, leverage, cash holdings, capital expenditures, and fixed-asset intensity, applying radius matching (caliper=0.5). After dropping the observations without common support, the matched sample includes 608 firm-year observations. Columns (3)-(4) of Table 8 demonstrate that our results remain consistent using this more comparable subsample through PSM.

6.3 Firms with Multiple CVBP Wins and Continuous Measurement

Next, we account for the effects of repeated treatment in our analysis. Some firms win bids in multiple procurement rounds for different molecules, generating repeated treatment exposure. Because standard staggered DiD models assume constant treatment effects after initial exposure, they may misstate cumulative effects. We extend Equation (3) by introducing measures of repeated treatment intensity:

$$Outcomes_{i,t+1} = \alpha_i + \beta_1 Procured \times Post_{i,t} + \beta_2 RepeatedTreated_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{5}$$

where $RepeatedTreated_{i,t}$ takes two metrics: (1) a binary indicator (*Dummy of Repeated Treatment*), equal to 1 if a firm wins additional bids in subsequent years; and (2) a continuous variable (*Number of Repeated Treatments*), counting the total number of rounds won after the firm's initial procurement [20]. Table A.5 shows that the coefficients before Procured × post are similar with those in our earlier analysis, indicating that including these variables leaves our conclusions unaffected.

What's more, we estimate a modified version of Equation (3) that incorporates firm-level treatment intensity. Specifically, we replace the binary interaction term, Procured Exposure × Post, with a continuous measure, the natural logarithm of the total value of a firm's CVBP-winning contracts up to year t. The procured

[20]For instance, if a firm first won a bid in 2018 and later won bids in 2020 and 2021, then *Dummy of Repeated Treatment* = 1 in 2020 and 2021, and 0 otherwise *Number of Repeated Treatment* = 2 for 2020 *Number of Repeated Treatment* = 3 for 2021 and thereafter.

value in each year is calculated as the product of the bid-winning unit price and the first-year government-promised procurement volume.

Table A.6 reports the results. In Column (1), although the coefficient is statistically significant at the 10% level, its magnitude is economically negligible. By contrast, Column (2) shows that a 1% increase in cumulative procured exposure is associated with a 0.3% reduction in selling expenses relative to total assets. Taken together, these findings underscore meaningful heterogeneity in firms' exposure to CVBPs: firms with higher cumulative procurement volumes experience more pronounced shifts in selling expenses.

6.4 Responses of Rival Firms

Finally, we analyze how rival firms-those producing the same molecules but not selected in any CVBP round-respond to the reform. We re-estimate Equation (3) by replacing the interaction term $Procured_i \times Post_{i,t}$ with $Rival_i \times Post_{i,t}$. The results are presented in Table 9. As shown in Column (1) of Table 9, rival firms experience a sharper contraction in revenues (26.2%) than bid winners (18.5%), consistent with market-share allocation under price-cap competition. Yet, similar to winners, rivals' profitability, in terms of ROE and ROA (Columns (2)–(3) of Table 9), remains stable, implying substantial internal cost adjustments.

Notably, rivals exhibit a sharper reduction in selling expenses by 31.1 percentage points (Table 9, Column (6)), exceeding the 19.5 percentage point reduction observed among winners, reflecting forced cost compression as they lose access to the hospital procurement channels. Interestingly, the composition of cost adjustments differs: winners reduce advertising and promotion, while rivals cut selling-related wages, consistent with layoffs following market exit. Columns (10)–(12) of Table 9 show no significant change in rivals' external financing, and Columns (4)–(5) indicate stable R&D. Overall, although rivals face more severe revenue and valuation losses (as shown in Table 3), they also decreased more in the selling expenses, maintaining innovation levels despite diminished market presence.

7 Discussion and Conclusion

This study investigates how firms adjust their innovation in response to negative financial shocks, using China's CVBP as a quasi-natural experiment. Despite significant revenue declines and gloomy equity market performances following CVBP, pharmaceutical firms maintained their R&D investment. This seemingly counterintuitive finding is explained by a resource-reallocation mechanism: firms substantially reduced selling expenses by an average of 19.5%, which provided the internal financial flexibility to sustain innovation. These findings challenge the conventional view that external shocks, which may disrupt stock markets and weaken product-market revenues, necessarily suppress R&D investment and alleviate concerns that price reduction yields short-term fiscal relief at the cost of long-term innovation.

Our findings show that, when centralized procurement combines price reductions with guaranteed market access, it can curb wasteful marketing expenditures without undermining firms' innovative capacity. Such a mechanism provides a novel perspective on how regulatory design can enhance allocative efficiency in the healthcare sector. For countries facing persistently high drug prices, the CVBP offers an instructive model: it achieves price containment through guaranteed bulk procurement while easing fiscal pressures on national healthcare systems (Cao et al., 2024; Zhang et al., 2025), and simultaneously streamlines firms' sales processes, lowering inefficient promotional costs. In aggregate, the policy generates a welfare-improving outcome across key stakeholders. Governments benefit from reduced procurement expenditures; firms, though facing lower revenues, maintain profitability through internal cost restructuring; and patients enjoy lower drug prices without sacrificing long-term access to innovation.[21]

Overall, this study contributes to the literature at the intersection of regulation, corporate finance, and innovation. While prior research has emphasized the adverse effects of price regulation on R&D investment, our findings highlight a countervailing channel through which cost restructuring mitigates financial shocks. The evidence underscores the adaptive capacity of pharmaceutical firms in reoptimizing internal resource allocation under policy-imposed constraints. Nonetheless, whether such

[21] Concerns may arise regarding potential declines in drug efficacy, as patients might need higher dosages to achieve equivalent therapeutic outcomes. However, even accounting for this compensatory effect, the quantity increase does not offset the magnitude of price reductions (Zhang et al., 2025), implying that patients continue to experience net price benefits.

adaptation remains sustainable in the long run—and how it influences the development of truly novel drugs—are critical questions that warrant future investigation.

References

Leila Agha and Dan Zeltzer. Drug diffusion through peer networks: The influence of industry payments. *American Economic Journal: Economic Policy*, 14, 2022.

Franklin Allen, Jun Qian, and Meijun Qian. Law, finance, and economic growth in China. *Journal of Financial Economics*, 77(1):57–116, 2005.

Meghana Ayyagari, Asli Demirgüç-Kunt, and Vojislav Maksimovic. Formal versus informal finance: Evidence from China. *The Review of Financial Studies*, 23(8): 3048–3097, 2010.

Malcolm Baker and Jeffrey Wurgler. The equity share in new issues and aggregate stock returns. *the Journal of Finance*, 55(5):2219–2257, 2000.

Thorsten Beck, Asli Demirgüç-Kunt, and Vojislav Maksimovic. Financial and legal constraints to firm growth: Does firm size matter? *The Journal of Finance*, 60 (1):137–177, 2005.

Alice Bonaimé and Ye Emma Wang. Mergers, product prices, and innovation: Evidence from the pharmaceutical industry. *The Journal of Finance*, 79(3):2195–2236, 2024.

Alon Brav, Wei Jiang, Song Ma, and Xuan Tian. How does hedge fund activism reshape corporate innovation? *Journal of Financial Economics*, 130(2):237–264, 2018.

James R Brown, Steven M Fazzari, and Bruce C Petersen. Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance*, 64(1):151–185, 2009.

James R Brown, Gustav Martinsson, and Bruce C Petersen. Do financing constraints matter for R&D? *European Economic Review*, 56(8):1512–1529, 2012.

Brantly Callaway and Pedro HC Sant'Anna. Difference-in-Differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, 2021.

Shengmao Cao, Lisa Xuejie Yi, and Chuan Yu. Competitive bidding in drug procurement: Evidence from China. *American Economic Journal: Economic Policy*, 16(3):481–513, August 2024. doi: 10.1257/pol.20220505. URL https://www.aeaweb.org/articles?id=10.1257/pol.20220505.

Colleen Carey, Ethan M. J. Lieber, and Sarah Miller. Drug firms' payments and physicians' prescribing behavior in Medicare Part D. *Journal of Public Economics*, 197(8):104402, 2021.

Thomas J. Chemmanur, Elena Loutskina, and Xuan Tian. Corporate venture capital, value creation, and innovation. *The Review of Financial Studies*, 27 (8):2434–2473, 05 2014. ISSN 0893-9454. doi: 10.1093/rfs/hhu033. URL https://doi.org/10.1093/rfs/hhu033.

Jess Cornaggia, Yifei Mao, Xuan Tian, and Brian Wolfe. Does banking competition affect innovation? *Journal of Financial Economics*, 115(1):189–209, 2015.

Robert Cull and Lixin Colin Xu. Institutions, ownership, and finance: the determinants of profit reinvestment among Chinese firms. *The Journal of Finance*, 60 (3):1253–1272, 2005.

Clément De Chaisemartin and Xavier d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110 (9):2964–2996, 2020.

Vivian W Fang, Xuan Tian, and Sheri Tice. Does stock liquidity enhance or impede firm innovation? *Journal of Finance*, 69(5):2085–2125, 2014.

Xavier Giroud and Holger M. Mueller. Firm leverage and product market competition: Evidence from the natural gas industry. *Review of Financial Studies*, 28 (2):473–508, 2015.

Joseph Golec, Shantaram Hegde, and John A Vernon. Pharmaceutical R&D spending and threats of price regulation. *Journal of Financial and Quantitative Analysis*, 45(1):239–264, 2010.

Andrew Goodman-Bacon. Difference-in-Differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021.

Lifeng Gu. Product market competition, R&D investment, and stock returns. *Journal of Financial Economics*, 119(2):441–455, 2016.

Bronwyn H Hall, Adam B Jaffe, and Manuel Trajtenberg. The nber patent citation data file: Lessons, insights and methodological tools, 2001.

Jie Jack He and Xuan Tian. The dark side of analyst coverage: The case of innovation. *Journal of financial economics*, 109(3):856–878, 2013.

Sabrina T Howell. Financing innovation: Evidence from R&D grants. *American Economic Review*, 107(4):1136–1164, 2017.

IQVIA. A panoramic interpretation of the Chinese pharmaceutical market in 2022. 2023. URL https://finance.sina.com.cn/stock/med/2023-08-15/doc-imzhhkpz5189608.shtml.

Yunan Ji and Parker Rogers. The long-run impacts of regulated price cuts: Evidence from Medicare. Technical report, National Bureau of Economic Research, 2024.

Joshua L Krieger, Xuelin Li, and Richard T Thakor. Find and replace: R&D investment following the erosion of existing products. *Management Science*, 68 (9):6552–6571, 2022.

Xuelin Li, Andrew W Lo, and Richard T Thakor. Paying off the competition: Market power and innovation incentives. Technical report, National Bureau of Economic Research, 2021.

Chenyuan Liu, Yi Lu, and Wanyu Wang. Excessive Pharmaceutical Marketing Expenditure: Social Costs and Policy Remedies from China. Technical report, 2024.

David López-Salido, Jeremy C Stein, and Egon Zakrajšek. Credit-market sentiment and the business cycle. *The Quarterly Journal of Economics*, 132(3):1373–1426, 2017.

Evgeny Lyandres and Berardino Palazzo. Cash holdings, competition, and innovation. *Journal of Financial and Quantitative Analysis*, 51(6):1823–1861, 2016.

R David McLean and Mengxin Zhao. The business cycle, investor sentiment, and costly external finance. *The Journal of Finance*, 69(3):1377–1409, 2014.

Fariborz Moshirian, Xuan Tian, Bohui Zhang, and Wenrui Zhang. Stock market liberalization and innovation. *Journal of Financial Economics*, 139(3): 985–1014, 2021. ISSN 0304-405X. doi: https://doi.org/10.1016/j.jfineco.2020.08.018. URL https://www.sciencedirect.com/science/article/pii/S0304405X20302464.

Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2): 175–199, 2021.

Richard T Thakor and Andrew W Lo. Competition and R&D financing: Evidence from the biopharmaceutical industry. *Journal of Financial and Quantitative Analysis*, 57(5):1885–1928, 2022.

Xuan Tian and Jiajie Xu. Do place-based policies promote local innovation and entrepreneurship? *Review of Finance*, 26(3):595–635, 2022.

Xuan Zhang, Nina Yin, Jiayu Zhang, Qingyuan Xue, and Bin Jiang. Centralized drug procurement for affordable and sustainable healthcare: Evidence from China. *Available at SSRN 5632870*, 2025.

Figure 1: Market Reaction to CVBP Initial Launch

Note: This figure presents the equal-weighted average abnormal returns of all A-share listed pharmaceutical firms (blue solid line), chemical drug firms (red dashed line) and firms in the later DiD control group (includes listed firms engaged in non-vaccine biological products, blood products, medical equipment, and APIs, green dashed line) around the initial implementation of China's Centralized Volume-Based Procurement (CVBP) policy—specifically the "4+7 Pilot" round, which was announced on December 7, 2018. Abnormal returns are estimated using the market model. These visuals provide evidence of a sharp negative market reaction at both the industry and firm levels immediately following the policy event.

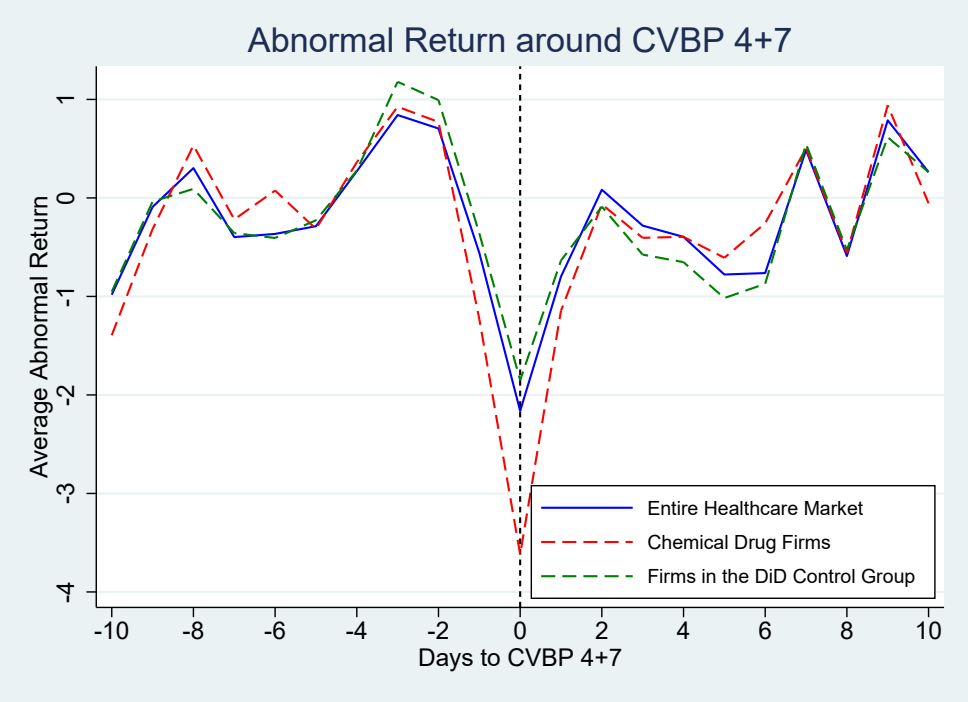
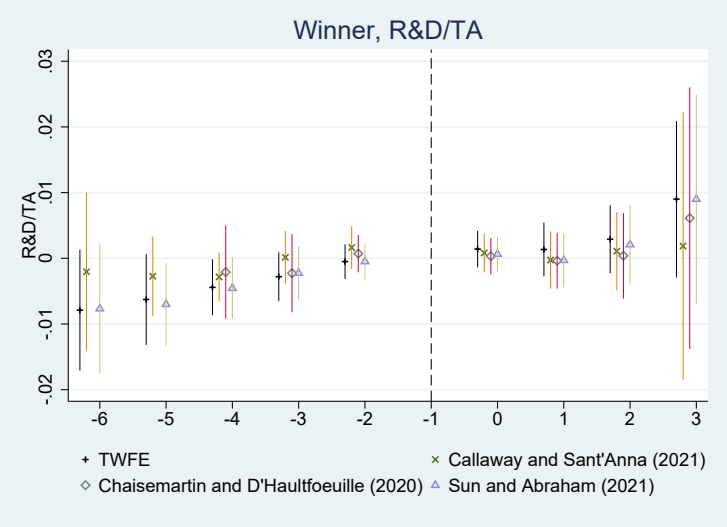


Figure 2: Dynamic Effect: Winning Procurement, R&D Input and the Selling Expense

Note: This figure presents dynamic event-study plots based on four alternative estimators: (1) Two-way fixed effects (TWFE), (2) Callaway and Sant'Anna (2021), (3) Chaisemartin and D'Haultfoeuille (2020), and (4) Sun and Abraham (2021). Panel (a) displays the estimated dynamic treatment effects on R&D/TA for CVBP-winning firms. Panel (b) shows corresponding estimates for Selling Expenses/TA. The vertical dashed line indicates the first year of treatment (i.e., the year in which a firm first won a CVBP bid). Event time is measured in years relative to that initial treatment year. Estimates are reported from six years before to three years after treatment. The window is truncated at year +3 due to limited post-treatment sample coverage. These plots provide visual evidence of pre-trend stability and post-treatment divergence, and allow for comparison across identification strategies that accommodate heterogeneous treatment timing and effects.

Panel (a)



Panel (b)

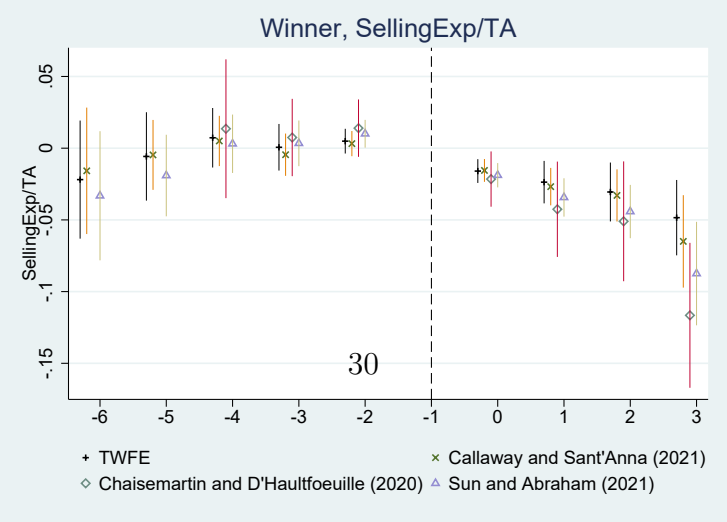


Table 1: **Timeline of CVBP in China**

Note: This table reports the dates of preliminary and formal disclosures for each round of China's Centralized Volume-Based Procurement (CVBP), along with the number of days between them (Interval Days). To avoid analytical overlap, we distinguish Drug CVBP from Medical Device CVBP ("Med. Dev.") and Chinese Medicine CVBP ("Chi. Med."). **Preliminary Disclosure Dates** refer to when provisional bid winners are announced on the Shanghai Sunshine Medical Procurement All-in-one Website for public comment. **Formal Disclosure Dates** indicate when final winning firms are officially confirmed and published. **Gap Days** denote the time span between the preliminary and formal disclosures.

CVBP Round	Preliminary Disclosure Date	Interval (Days)	Formal Disclosure Date	Gap Days
4+7 Pilot	2018/12/7		2018/12/17	10
4+7 Expansion	2019/9/25	292	2019/9/30	5
Round 2	2020/1/17	114	2020/1/21	4
Round 3	2020/8/20	216	2020/8/24	4
Med. Dev. Round 1	2020/11/5		2020/11/9	4
Round 4	2021/2/3	90	2021/2/8	5
Round 5	2021/6/23	140	2021/6/28	5
Med. Dev. Round 2	2021/9/14		2021/9/18	4
Round 6 (Insulin)	2021/11/26	73	2021/11/30	4
Round 7	2022/7/13	229	2022/7/18	5
Med. Dev. Round 3	2022/9/27		2022/9/30	3
Round 8	2023/3/29	183	2023/4/12	14
Chi. Med. Round 1	2023/6/21		2023/7/5	14

Table 2: **Overview of the CVBP' Impact on the Whole Healthcare Market**

Note: This table reports the Cumulative Average Abnormal Returns (CAARs) for firms in the healthcare sector in response to the **preliminary disclosure dates** of CVBP bid results, using a three-day event window. **Panel A** presents average market reactions across all CVBP rounds. **Panel B** disaggregates CAARs by individual rounds. **Panel C** excludes Round 2 (due to potential confounding effects) and further dissects CAARs by healthcare subcategories. Two measures are used: **CAR1** is computed using the CSMAR value-weighted market return as $R_{M,t}$; **CAR2** uses the healthcare industry index 000991.SH as $R_{M,t}$. Both use an estimation window of $[-80,-20]$ relative to the event date. In Panel C, the healthcare sector is divided into seven distinct subgroups based on firm specialization, as defined in the CSMAR database: Chemical Drugs (109 firms) Chinese Medicine (74), APIs (40), Biological Products (52), Distribution and Circulation (25), Medical Device and Equipment (79), and Medical Services (94). In total, the analysis covers 473 A-share listed firms. **t-values** indicate statistical significance.

Panel A. Market Reaction (Whole Market)				
	CAAR1	t	CAAR2	t
Whole Healthcare Market	-1.126***	-9.48	-0.884***	-7.69
Panel B. Separate Results for Each Round				
	CAAR1	t	CAAR2	t
Round0	-3.518***	-12.98	0.926***	3.46
Round1	-2.111***	-6.35	-2.177***	-6.59
Round2	1.923***	5.41	0.089	0.26
Round3	-1.796***	-4.35	-0.916**	-2.24
Round4	-2.220***	-5.24	-2.744***	-6.56
Round5	-2.615***	-7.07	-1.910***	-5.18
Round6	2.157***	5.24	0.562	1.39
Round7	-1.339***	-5.37	-0.563**	-2.27
Round8	-1.088***	-4.50	-1.108***	-4.63
Panel C. Results Exclude Round2 & Different Sub-categories				
	CAAR1	t	CAAR2	t
Chemical Drugs	-2.404***	-8.48	-1.890***	-6.97
Chinese Medicine	-0.909***	-5.02	-0.506***	-2.84
API	-0.689**	-2.37	-0.256	-0.91
Biological Products	-1.125***	-3.93	-0.700***	-2.66
Circulation	-3.260***	-3.83	-2.837***	-3.32
Medical Devices and Equipment	-1.230***	-3.38	-0.818**	-2.29
Medical Service	-0.803***	-2.89	-0.278	-1.01

Table 3: **Univariate Tests: How Market Reacts to the Bid Winning News**

Note: This table presents the cumulative abnormal returns (CARs) over a three-day window centered around the preliminary disclosure dates of CVBP bid results. Panel A includes events from all CVBP rounds (Round 0 to Round 8). Panel B excludes Round 2 due to its temporal overlap with the initial COVID-19 outbreak in China. CARs are estimated using an event window of [-80,-20]. CAR1 is computed using the CSMAR value-weighted market return as the benchmark. CAR2 is computed using an industry-specific value-weighted index. Firm groups are defined as follows: **Winners:** Firms awarded procurement contracts in any round from the 4+7 Pilot through Round 8. **Rivals:** Chemical drug firms producing the same active ingredients as procured products but not selected in any round. **Prospective Participants:** Other chemical drug firms not selected and not considered direct rivals, but potentially eligible for future procurement. Asterisks on Mean values indicate significance based on a t-test for a mean different from zero. Asterisks on Diff values reflect significance from two-sample t-test comparing group means.

Panel A, Round 0 - Round 8					
	Winners		Rivals		
	N	Mean	N	Mean	Diff
CAR1	291	-0.428	249	-2.452***	2.025***
CAR2	291	-0.210	249	-1.790***	1.580***
	Winners		Prospective Participants		
CAR1	291	-0.428	462	-2.400***	1.972***
CAR2	291	-0.210	462	-2.255***	2.045***
Panel B, Exclude Round 2					
	Winners		Rivals		
	N	Mean	N	Mean	Diff
CAR1	262	-0.910***	221	-3.112***	2.203***
CAR2	262	-0.493*	221	-2.156***	1.662***
	Winners		Prospective Participants		
CAR1	262	-0.910***	410	-2.666***	1.756***
CAR2	262	-0.493*	410	-2.291***	1.798***

Table 4: **Summary Statistics for the Main Variables**

Note: This table provides summary statistics for the key variables used in the staggered difference-in-differences (DiD) regressions, focusing on bid-winning firms and their control group. Firm-level financial data are obtained from the Wind Database. The sample consists of A-share listed firms in mainland China's healthcare sector, with at least one year of listing history. The observation window spans from 2015—three years prior to the launch of CVBP Round 0—through 2023.

	Treatment Group					Control Group				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
R&D (in million RMB)	695	366.422	581.721	10.371	3896.336	375	212.779	490.049	10.371	3896.336
R&D/TA	695	0.035	0.029	0.001	0.187	375	0.037	0.035	0.003	0.187
Patents	631	9.008	12.027	0	54	349	5.507	10.091	0	54
Citations	448	27.788	45.424	0	253	193	16.549	27.790	0	209
Filed	695	20.351	26.042	0	124	375	15.011	24.886	0	124
SellingExp (in million RMB)	695	1546.196	1919.084	9.716	9171.176	375	358.945	782.876	9.716	7304.458
SellingExp/TA	695	0.151	0.103	0.003	0.472	375	0.067	0.065	0.003	0.398
Sales (in million RMB)	695	9413.367	18733.050	244.219	120764.700	375	2553.696	4064.698	244.219	34931.900
Procured * Post	695	0.364	0.482	0	1	375	0	0	0	0
Cumulative Procured Exposure (in million RMB)	695	94.359	319.374	0	2250.176	375	0	0	0	0
Total Assets (TA)	695	11472.790	15352.320	631.633	83686.010	375	5138.366	7188.030	631.633	55184.710
ROA	695	0.051	0.065	-0.215	0.219	375	0.061	0.071	-0.215	0.219
Tobin's Q	695	2.582	1.837	0.865	13.204	375	3.830	2.657	1.080	13.204
Book Leverage	695	0.378	0.183	0.045	0.826	375	0.273	0.162	0.045	0.826
Cash/TA	695	0.161	0.111	0.019	0.550	375	0.204	0.123	0.019	0.550
CapExp/TA	695	0.049	0.041	0.003	0.227	375	0.064	0.050	0.003	0.227
PPE/TA	695	0.219	0.119	0.019	0.523	375	0.181	0.115	0.019	0.523

Table 5: **Impact of CVBPs on Firm Performance**

Note: This table explores firms' sales and profitability changes post the procurement for the bid winners. We use the following TWFE model:

$$Performance_{i,t+1} = \alpha_i + \beta_1(Procured \times Post)_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

The treatment group consists of listed firms that successfully won bids under the CVBP program. The control group includes listed firms operating in related but unaffected sectors—specifically, non-vaccine biological products, blood products, medical equipment, and active pharmaceutical ingredients (APIs). The sample period spans from 2015 (three years prior to CVBP Round 0) through 2023. The dependent variables across columns include: (1) Log of Sales; (2) Net Income on Equity (ROE); (3) Net Income on Assets (ROA). The key independent variable, *Procured* × *Post*, is a binary indicator equal to 1 for a firm-year observation if the firm had already won a CVBP bid by that time, and 0 otherwise. Control variables include lagged values of: Log of total assets, Total debt-to-assets, Total cash holdings-to-assets, Capital expenditures-to-assets, Property, plant, and equipment-to-assets (PPE/TA). All regressions include firm fixed effects and year fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	Sales	Profitability	
	(1) ln(Sales)	(2) ROE	(3) ROA
Procured × Post	-0.185***	-0.000	-0.005
	(0.060)	(0.015)	(0.007)
Ln(Assets)		-0.056***	-0.027***
		(0.016)	(0.009)
Leverage	0.209	0.024	-0.014
	(0.263)	(0.053)	(0.027)
Cash/TA	-0.266	0.067*	0.050**
	(0.250)	(0.037)	(0.023)
CapExp/TA	0.544	-0.060	-0.020
	(0.430)	(0.119)	(0.067)
PPE/TA	-0.262	-0.122	-0.037
	(0.440)	(0.094)	(0.040)
Firm FE	✓	✓	✓
Year FE	✓	✓	✓
No. of Firms	181	181	181
Mean of Y (Before)	21.520	0.073	0.052
Observations	1070	1070	1070
R^2	0.240	0.067	0.086

Table 6: **Baseline: Impact of CVBPs on Firm Innovation Input and Output**

Note: This table reports the effect of winning a centralized volume-based procurement (CVBP) bid on firms' innovation input and output, using a staggered difference-in-differences (DiD) specification with two-way fixed effects:

$$Innovation_{i,t+1} = \alpha_i + \beta_1 Procured \times Post_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

The treatment group comprises listed pharmaceutical firms that successfully won at least one CVBP bid. The control group includes listed firms engaged in non-vaccine biological products, blood products, medical equipment, and APIs. The sample period spans from 2015 (three years before CVBP Round 0) through 2023. **Column (1)**: Natural logarithm of firm R&D expenses. **Column (2)**: firm R&D expenses, normalized by TA (total assets). **Column (3)**: Natural logarithm of one plus the number of granted patents filed by the firm (adjusted for truncation bias). **Column (4)**: Natural logarithm of one plus the number of forward citations to those granted patents (truncation-adjusted). **Columns (5)–(6)**: Number of patent applications filed. Column (6) is estimated using a Poisson regression; all other columns use OLS. The key independent variable, *Procured* × *Post*, is the interaction of: $Procured_i$: An indicator equal to 1 if firm i ever wins a CVBP bid. $Post_t$: An indicator equal to 1 for all years after a firm's first win, and 0 otherwise. Control variables include lagged values of: log total assets, ROA, Tobin's Q, total debt-to-assets, total cash holdings-to-assets, capital expenditures-to-assets, and property, plant, and equipment-to-assets. All regressions include firm and year fixed effects. Standard errors, clustered at the firm level, are reported in parentheses.Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	Innovation Input		Innovation Output			
	(1) Ln(R&D)	(2) R&D/TA	(3) Ln(1+Patents)	(4) Ln(1+Citations)	(5) Ln(1+Filed)	(6) Filed
Procured × Post	-0.011	0.002	-0.013	-0.084	-0.140	-0.080
	(0.043)	(0.002)	(0.059)	(0.102)	(0.114)	(0.091)
Ln(Assets)	0.621***	0.003	0.166***	-0.068	0.328***	0.302**
	(0.076)	(0.003)	(0.059)	(0.116)	(0.102)	(0.143)
ROA	0.735***	-0.016	0.026	0.360	0.691	0.209
	(0.255)	(0.010)	(0.282)	(0.578)	(0.518)	(0.534)
Tobin's Q	0.028**	0.001*	0.011	-0.013	0.001	-0.019
	(0.012)	(0.000)	(0.009)	(0.025)	(0.025)	(0.022)
Leverage	-0.276	-0.017**	0.295*	0.078	0.307	0.151
	(0.181)	(0.008)	(0.178)	(0.284)	(0.351)	(0.455)
Cash/TA	-0.113	-0.000	0.674***	-0.005	0.271	0.388
	(0.190)	(0.008)	(0.197)	(0.452)	(0.379)	(0.469)
CapExp/TA	1.773***	0.045**	0.829*	-0.732	2.616**	2.955**
	(0.471)	(0.018)	(0.424)	(0.921)	(1.034)	(1.243)
PPE/TA	0.615**	0.028***	0.015	-0.507	0.180	-0.379
	(0.281)	(0.011)	(0.238)	(0.529)	(0.535)	(0.828)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
No. of Firms	181	181	181	181	161	161
Mean of Y (Before)	18.552	0.034	0.572	1.087	2.280	19.150
Observations	1070	1070	1070	1070	871	871
R^2	0.623	0.192	0.086	0.389	0.773	
Log pseudolikelihood						-3355.486

Table 7: **Internal V.S. External Funding**

Note: This table examines the effect of centralized volume-based procurement (CVBP) on firms' selling expenses and external financing behavior, using the following two-way fixed effects (TWFE) model:

$$SellingExp/TA_{i,t+1} = \alpha_i + \beta_1 Procured \times Post_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

The treatment group consists of A-share listed firms that successfully secured at least one CVBP bid. The control group includes listed firms operating similarly but unaffected healthcare sectors: non-vaccine biological products, blood products, medical equipment, and active pharmaceutical ingredients (APIs). The analysis covers the period from 2015 (three years prior to Round 0) through 2023. The dependent variables across columns are: (1) Natural logarithm of selling expenses; (2) Selling expenses, normalized by total assets (SellingExp/TA); (3) Advertising and promotion expenses to total assets (SellingExp_Adv/TA); (4) Employee compensation under selling expenses, normalized by total assets (SellingExp_Wage/TA); (5) Seasoned equity offerings to total assets (SEO/TA); (6) Cash inflows from bond issuance to total assets (CashBond/TA); (7) Cash inflows from borrowings to total assets (CashBorrow/TA). The key independent variable, $Procured \times Post$, is the interaction of: $Procured_i$: An indicator equal to 1 if firm i ever wins a CVBP bid. $Post_t$: An indicator equal to 1 for all years after a firm's first win, and 0 otherwise. Control variables include lagged firm characteristics: log 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 include firm fixed effects and year fixed effects. Standard errors, clustered at the firm level, are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	Selling and Marketing Expenses				External Financing		
	(1) Ln(SellingExp)	(2) SellingExp/TA	(3) SellingExp_Adv/TA	(4) SellingExp_wage/TA	(5) SEO/TA	(6) CashBond/TA	(7) CashBorrow/TA
Procured × Post	-0.195***	-0.023***	-0.012**	-0.000	-0.016*	-0.002	0.003
	(0.065)	(0.006)	(0.006)	(0.002)	(0.008)	(0.002)	(0.009)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓
No. of Firms	181	181	168	168	181	181	181
Mean of Y (Before)	19.600	0.118	0.053	0.053	0.025	0.004	0.120
Observations	1070	1070	1003	1003	1070	1070	1070
R^2	0.381	0.214	0.102	0.089	0.125	0.065	0.164

Table 8: **Robustness: Alternative Estimators and Matching**

Note: This table compares the baseline two-way fixed effects (TWFE) estimates with alternative estimators that account for potential treatment effect heterogeneity across cohorts or over time, further, this table assesses the robustness by using a balanced panel analysis and propensity score matching (PSM). The model specifications are consistent with those presented in prior tables. Panel A employs R&D expenses scaled by total assets as the dependent variable. Panel B uses selling expenses scaled by total assets as the dependent variable. All specifications include firm and year fixed effects. Standard errors are clustered at the firm level. Confidence intervals (95%) are also presented for each estimate. The alternative estimators are implemented using the following Stata packages: csDiD (Callaway and Sant'Anna, 2021); DiD_imputation (Chaisemartin and D'Haultfoeuille, 2020). To construct the balanced panel, we restrict the sample to firms with continuous data from 2015 to 2022, dropping observations with missing years. For the PSM exercise, we use firms' 2015 (pre-treatment) characteristics to estimate propensity scores and match treated and control firms using radius matching meathod (caliper=0.5). Matching covariates include: log 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. Matched firms off common support are excluded. Significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

Estimator	Coefficient	Std Err.	Significance	Lower 95% CI	Upper 95% CI
Panel A, R&D/TA					
TWFE	0.002	0.002		-0.001	0.006
Callaway and SantaAnna (2021)	0.001	0.002		-0.003	0.004
Chaisemartin and D'Haultfoeuille (2020)	0.000	0.001		-0.002	0.003
Balanced Sample	0.002	0.002		-0.001	0.005
Propensity Score Matching	0.002	0.002		-0.001	0.006
Panel B, Selling Expenses/TA					
TWFE	-0.023	0.006	***	-0.033	-0.012
Callaway and SantaAnna (2021)	-0.025	0.006	***	-0.038	-0.013
Chaisemartin and D'Haultfoeuille (2020)	-0.022	0.008	***	-0.038	-0.005
Balanced Sample	-0.022	0.006	***	-0.034	-0.010
Propensity Score Matching	-0.027	0.007	***	-0.040	-0.014

Table 9: **The Impact of Procurement for the Rivals**

Note: This table explores changes in firm fundamentals among **rival firms** following the implementation of CVBPs, using the following two-way fixed effects (TWFE) specification:

$$Outcomes_{i,t+1} = \alpha_i + \beta_1 Rival \times Post_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

The sample consists of firms that produce the same active pharmaceutical ingredients (APIs) as the procured products but were not selected in any CVBP round (defined as rivals), as well as firms in unaffected segments of the healthcare sector—namely, non-vaccine biological products, blood products, medical equipment, and APIs (control group). The analysis period spans from 2015 (three years before CVBP Round 0) through 2023. The dependent variables include: (1) Log of Sales; (2) Net Income on Equity (ROE); (3) Net Income on Assets (ROA); (4): Natural logarithm of firm R&D expenses; (5): firm R&D expenses, normalized by TA (total assets); (6) Natural logarithm of selling expenses; (7) Selling expenses, normalized by total assets (SellingExp/TA); (8) Advertising and promotion expenses to total assets (SellingExp_Adv/TA); (9) Employee compensation under selling expenses, normalized by total assets (SellingExp_Wage/TA); (10) Seasoned equity offerings to total assets (SEO/TA); (11) Cash inflows from bond issuance to total assets (CashBond/TA); (12) Cash inflows from borrowings to total assets (CashBorrow/TA). The key independent variable, $Rival \times Post_{i,t}$, is a binary indicator equal to 1 if a firm produces molecules included in any CVBP round but did not win a bid, and the observation year is after that molecule's inclusion. Control variables include lagged values of: log 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 include firm and year fixed effects. Standard errors, clustered at the firm level, are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Sales)	ROE	ROA	Ln(R&D)	R&D/TA	Ln(SellingExp)	SellingExp/TA	SellingExp_Adv/TA	SellingExp_wage/TA	SEO/TA	CashBond/TA	CahBorrow/TA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rival × Post	-0.262***	-0.005	-0.010	-0.004	0.002	-0.311***	-0.023**	-0.000	-0.005**	-0.023	0.002	-0.017
	(0.075)	(0.016)	(0.014)	(0.084)	(0.002)	(0.089)	(0.009)	(0.008)	(0.002)	(0.015)	(0.002)	(0.019)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Firms	110	110	110	110	110	110	110	102	102	110	110	110
Observations	575	575	575	575	575	575	575	545	545	575	575	575
R^2	0.394	0.102	0.109	0.603	0.154	0.424	0.138	0.034	0.106	0.134	0.061	0.111

A Appendix

A.1 Matching Stock Code Based on Molecular Producer Identification

In this section, we will explain how we match the CVBP winning producers announced at the Sunshine All-in-one Website with the listed stock code(STKCD) and firms from CSMAR. The disclosed information on aforementioned *Sunshine All-in-one Website* provides us with the molecular names and their associated producer names. However, these producers 1) may be listed or non-listed in China's A-share market; 2)and may be subsidiaries or second-tier subsidiary companies of listed firms. Therefore, merging the procured-based producer names with related STKCD poses a huge challenge. To achieve this, we use the following four processes:

First, we download the linkage table of listed firms and their subsidiary companies from CSMAR. This table provides information centered on the listed companies as the main entities, detailing their subsidiaries and ownership structures.

Next, we merge the product-based producer names with the firm subsidiary table as mentioned earlier, which helps us obtain *Product-Producer-Round-STKCD* information. While this method is functional, it appears to be less effective, as it inevitably overlooks certain observations due to the complexities associated with Chinese names and contextual information. For instance, one dataset may include province prefixes in firm names while another omits them; despite representing the same firms, they cannot be merged.

Further, considering that tendering and bidding are significant operational information that CSRC necessarily requires, we downloaded all the firm announcements within listed firms in the pharmaceutical and healthcare industry since the initiation of CVBP reform (2018). Then, we compile a specialized dictionary, featuring key terms that identify the bidding activities related to CVBP. The dictionary includes terms such as "CVBP", "Bidding", "Volume", "Procured", "Drug League", and "Centralized". After this, we manually check whether the found items are what we need and drop the observations that have nothing to do with CVBP, such as "Centralized Strike", "Province Procured"[22], and "Procured continue". In this

[22]In this paper, we only consider the national CVBP actions, and omit the province level CVBP due to the less procurement amount within particular regions.

process, we directly narrow the search period to within two weeks before and after the CVBP' bidding dates in each round to simplify the hand-collecting work. Consequently, We categorize the information of bid rounds and procured drug names based on the announcement dates.

Finally, we combine the datasets from Step 2 and Step 3 and remove duplicate *Product-Producer-Round-STKCD* observations.

Hereafter, we have successfully filtered out all the listed bid-winning firms with their specific STKCD. A similar process can be applied to the rivals. From Round 0 (The 4+7 Pilot of CVBP) to Round 8, we identify overall 114 A-share listed procured firms, accounting for one-fourth of all bid-winning manufacturers. This indicates that using listed firms to investigate the impact of CVBP on firms offers a strong level of representativeness.

Table A.1: **Overview of the CVBP Impact on the Whole Healthcare Market (Using Formal Disclosure Date)**

Panel A Market Reaction (Whole Pharmaceutical Market, using Formal Disclosure Date)				
	CAAR	t	N (Events)	Sig
CAR1	0.334	2.84	3233	***
CAR2	0.179	1.55	3233	
Panel B Separate Results for Each Round (Using Formal Disclosure Date)				
	CAAR1	N (Events)	CAAR2	N (Events)
Round0	-1.091***	295	-0.012	295
Round1	0.784**	302	0.384	302
Round2	3.700***	305	1.653***	305
Round3	-0.820**	321	-0.844**	321
Round4	0.235	352	-1.480***	352
Round5	0.680*	371	-0.360	371
Round6	-0.496	395	0.131	395
Round7	-0.919***	428	1.727***	428
Round8	1.191***	464	0.210	464
Panel C Results Exclude Round2 & Different Sub-categories (CAR1, Using Formal Disclosure Date)				
	CAAR1	t	N (Events)	Sig
Whole Healthcare Market	-0.016	-0.13	2928	
Sub Categories				
Chemical Drugs	-0.511	-1.89	712	*
Chinese Medicine	0.835	5.09	548	***
API	0.282	1.09	251	
Biological Products	-0.069	-0.24	278	
Circulation	-1.521	-1.81	176	*
Medical Equipment	0.107	0.31	436	
Medical Service	0.048	0.17	527	

Table A.2: **Bivariate Tests: How Market Reacts to the Bid Winning News (Using Formal Disclosure Date)**

Panel A, Round 0 - Round 8 (Using Formal Disclosure Date)					
	Winners		Rivals		
	N	Mean	N	Mean	Diff
CAR1	291	0.678**	249	0.836**	-0.158
CAR2	291	0.548**	249	0.789**	-0.241
	Winners		Prospective Participants		
CAR1	291	0.678**	462	-0.875**	1.553***
CAR2	291	0.548**	462	-0.973**	1.521***
Panel B, Exclude Round 2 (Using Formal Disclosure Date)					
	Winners		Rivals		
	N	Mean	N	Mean	Diff
CAR1	262	0.205	221	0.194	0.011
CAR2	262	0.259	221	0.384	-0.125
	Winners		Prospective Participants		
CAR1	262	0.205	410	-1.088**	1.293**
CAR2	262	0.259	410	-0.956**	1.215**

Table A.3: **Summary Statistics for Winners, Rivals and Prospective Participants**

Note: This table reports summary statistics for three distinct groups of firms analyzed in the study. **Winners** are firms that secured bids across all rounds of the CVBP program from the 4+7 Pilot to the 8th Round. **Rivals** are chemical drug firms whose products were not procured but directly compete with procured drugs—i.e., they produce the same active pharmaceutical ingredient (API). **Prospective Participants** are other chemical drug firms that are neither winners nor rivals. Although their products have not yet been included in CVBP rounds, these firms may be considered for future participation. The variables reported include firm age, size (total assets), return on equity (ROE), net profit, leverage ratio (LEV), and equity value. All financial figures are reported in millions of RMB.

Panel A. Winners					
Variable	Obs	Mean	Std. Dev.	Min	Max
Age	290	14.710	7.883	1.000	30.000
Size	290	15993.560	22665.340	694.030	163435.500
ROE	290	9.353	11.266	-79.280	35.940
Net Profit	290	856.051	1243.294	-1990.729	6308.893
LEV	290	39.411	17.725	4.201	82.557
Equity	290	8206.152	9903.778	171.747	59066.210
Panel B. Rivals					
Variable	Obs	Mean	Std. Dev.	Min	Max
Age	246	13.874	8.396	1.000	30.000
Size	246	10805.320	19740.580	631.633	163435.500
ROE	246	7.342	17.506	-128.480	42.580
Net Profit	246	514.559	1024.323	-2654.938	6274.569
LEV	246	37.464	17.320	3.485	80.935
Equity	246	5490.383	7848.657	410.253	59066.210
Panel C. Prospective Participants					
Variable	Obs	Mean	Std. Dev.	Min	Max
Age	454	12.051	8.994	1.000	31.000
Size	454	4789.794	5598.775	58.176	34729.590
ROE	453	0.949	31.408	-402.110	55.730
Net Profit	454	158.888	690.007	-3249.544	6308.893
LEV	454	33.712	18.894	2.084	97.419
Equity	454	2946.283	3280.803	1.502	30787.000

Table A.4: **Regression Results of Abnormal Returns on Procurement Bid Winning**

Note: This table reports the impact of winning a CVBP bid on firms' cumulative abnormal returns (CARs) over the three-day window surrounding the preliminary disclosure date of the procurement results. We estimate the following OLS regression model:

$$CAR_i = \alpha_i + \beta_1 BidWinner_i + \beta_2 X_i + \delta_k + \varepsilon_i$$

Columns (1)–(2) compare **winners** and their **rivals**, i.e., firms producing the same molecule but not selected. **Columns (3)–(4)** compare **winners** with **prospective participants**, defined as other chemical drug firms not currently included in CVBPs. The dependent variable is each firm's CAR measured over the [-1,+1] window relative to the event date. The estimation window is [-80,-20]. CAR1 is computed using the CSMAR value-weighted market index. CAR2 is computed using an industry-specific value-weighted index. Firm-level controls include 1-year lagged values of log total assets, debt-to-asset ratio, asset growth rate, and return on equity (ROE). CVBP round fixed effects are included to control for cross-round variation. Standard errors, clustered at the firm level, are reported in parentheses. Significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.1.

	Winner V.S. Rivals		Winners V.S. Prospective Participants	
	(1) CAR1	(2) CAR2	(3) CAR1	(4) CAR2
Bid Winner	1.172**	1.046**	1.187*	1.080*
	(0.542)	(0.524)	(0.675)	(0.650)
Constant	-31.147	-11.931	-49.686***	-32.218**
	(32.612)	(33.242)	(17.699)	(15.194)
Firm-level Controls	✓	✓	✓	✓
CVBPs Round FE	✓	✓	✓	✓
Observations	479	479	663	663
R^2	0.251	0.153	0.118	0.065

Table A.5: **Robustness Check: Does the Repeated Treatment Affect the Impact of Initial Year Wins?**

Note: This table examines whether repeated participation in CVBP bidding—i.e., winning bids in multiple years—alters the baseline results on R&D and selling expenses. We extend the baseline staggered DiD specification by including two additional control variables:

$$R\&D/TA_{i,t+1} = \alpha_i + \beta_1 Procured \times Post_{i,t} + \beta_2 Repeated_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

The sample includes A-share listed firms that won at least one CVBP bid (treatment group) and firms in unaffected segments of the healthcare sector—specifically, non-vaccine biological products, blood products, medical equipment, and APIs (control group). The analysis period runs from 2015 (three years before CVBP Round 0) to 2023. The dependent variables are R&D-to-TA (Columns 1–2) and selling expenses-to-TA (Columns 3–4). The key variable, *Procured* × *Post*, equals 1 for firm-year observations in and after the year a firm wins its first bid. *Dummy of Repeated Treatment*$_{i,t}$ equals 1 if firm wins an additional CVBP bid in year following its initial win. *Number of Repeated Treatment*$_{i,t}$ is a continuous variable counting the number of additional bids won by firm *inyear* after its first win. All regressions include firm and year fixed effects, and control for lagged values of: log 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. Standard errors clustered at the firm level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	R&D/TA		SellingExpenses/TA	
	(1)	(2)	(3)	(4)
Procured × Post	0.002	0.002	-0.020***	-0.021***
	(0.002)	(0.002)	(0.005)	(0.005)
Dummy of Repeated Treatment	0.001		-0.011	
	(0.003)		(0.007)	
Number of Repeated Treatment		0.001		-0.006
		(0.002)		(0.004)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
No. of Firms	181	181	181	181
Observations	1070	1070	1070	1070
R^2	0.193	0.192	0.216	0.215

Table A.6: **Heterogeneity: Procurement Exposure**

Note: This table examines heterogeneity in firms' responses to CVBP policy shocks based on the magnitude of their exposure. We estimate the following two-way fixed effects (TWFE) model:

$$Outcome_{i,t+1} = \alpha_i + \beta_1 Procured\ Exposure_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

The sample includes A-share listed CVBP-winning firms (treatment group) and control firms operating in unaffected healthcare sectors—non-vaccine biological products, blood products, medical equipment, and APIs. The analysis period spans from 2015 (three years before CVBP Round 0) through 2023. The dependent variables are R&D expenses to total assets in Column (1) and Selling expenses to total assets in Column (2). The key independent variable, Ln(*Cumulative Procured Exposure*$_{i,t}$), is defined as the natural logarithm of the total value of a firm's CVBP-winning contracts up to year t. The procured value in each year is calculated as the product of the bid-winning unit price and the first-year government-promised procurement volume. Control variables include lagged firm characteristics: log 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 include firm and year fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	(1) R&D/TA	(2) SellingExp/TA
Ln(Cumulative Procured Exposure)	0.000*	-0.003***
	(0.000)	(0.001)
Firm Controls	✓	✓
Firm FE	✓	✓
Year FE	✓	✓
No. of Firms	181	181
Observations	1070	1070
R^2	0.197	0.216