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

Tianyuan Jiang* Xuan Tian† Nina Yin‡ Xuan Zhang§

June 29, 2025

Abstract

It has long been well recognized that when firms experience a negative shock, their R&D investment would decrease. However, this paper reveals that R&D investment is more resilient than one would expect when facing revenue losses and market value declines, because firms can optimize their cost structures. Using China's centralized drug procurement as an exogenous shock, we find that it undermines pharmaceutical firms' revenue and stock market performance. However, despite the well-believed concern that such price-control policies can hinder long-term benefits by restraining firms' R&D investment, we find an increase in firms' R&D intensity. We uncover that this is due to the adjustments in firms' operational cost structures, particularly a 14% reduction in selling expenses. We exclude other alternative channels, such as bond issuance and bank borrowing. Our findings suggest that, through cost reallocation, firms can buffer R&D spending from capital market shocks, challenging conventional views on the primacy of financial constraints in innovation funding.

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

JEL Codes: O31, G30, G32, L65

*Guanghua School of Management, Peking University. Email:jiangtianyuan2000@gmail.com.

†PBC School of Finance, Tsinghua University. Email:tianx@pbcsf.tsinghua.edu.cn.

‡Center for Human Capital and Labor Market Research, Central University of Finance and Economics. Email: ninayin@cufe.edu.cn.

§School of Economics, Singapore Management University. Email: xuanzhang@smu.edu.sg.

We thank seminar participants at the Central University of Finance and Economics, SDU International Industrial Organization Workshop. All remaining errors are our own.

1 Introduction

Do regulatory interventions that disrupt financial markets inevitably lead to a reduction in corporate R&D investment? Conventional wisdom suggests that capital markets play a critical role in funding innovation, particularly for firms dependent on equity financing. Unlike debt financing, which typically requires collateral and repayment obligations, capital markets provide a relatively low-cost, low-pressure source of funding for R&D. However, when capital markets experience shocks—whether from market downturns or regulatory reforms—can R&D spending remain resilient, or must firms cut back on innovation to conserve resources? This question lies at the heart of our study, which explores the complex dynamics between capital market shocks and corporate R&D decisions in the context of the Chinese pharmaceutical sector.

The pharmaceutical industry, known for its high R&D intensity, serves as a particularly compelling setting for investigating this issue. Innovation is central to the survival and competitiveness of pharmaceutical firms, making R&D expenditure a crucial element of their long-term strategy. If an external shock, such as a policy-induced disruption, significantly impacts firms' fundamentals and stock market performances, one might expect firms to scale back R&D investments. Yet, surprisingly, our findings challenge this assumption. We observe that R&D spending is not merely a function of financial constraints but is also shaped by a firm's broader operational cost structure. When both financing conditions and cost structures are affected by external shocks, the impact on R&D investment is not straightforward and depends on the relative magnitude of these influences.

We provide empirical evidence on R&D investment by exploiting an exogenous shock: the implementation of China's centralized volume-based procurement (CVBP), which aims to lower drug prices in the Chinese pharmaceutical market. Under this policy, the government requires pharmaceutical firms to offer a significant reduction in unit drug prices, by more than 50% on average. However, they guarantee pharmaceutical firms substantial procurement volumes and attractive market shares, with the post-CVBP market structure expected to consist of only 3 to 5 key players per active ingredient. This market consolidation reduces the need for extensive marketing and selling expenses for winning firms. Given the sharp drop in product unit prices, it is unlikely that the gains in market share will fully offset the revenue losses, as evidenced by our subsequent analysis. Consequently, we hypothesize that the capital market will hold a pessimistic outlook in response to this policy (Li and Zhan, 2019). This pessimistic outlook is evidenced by sharp declines in healthcare stock prices and the returns of five listed bid-winning firms during the CVBP (4+7 Pilot) initiation, as shown in Figure 1. If such trends persist in later rounds, firms may encounter obstacles in raising external equity funding, thereby providing a compelling setting to investigate how innovation investments are affected by these dynamics.

Using daily stock returns from pharmaceutical firms listed in China's A-share

markets before and after the past 9 rounds of CVBPs bid-winning announcements, we find that the average three-day cumulative abnormal returns decreased by 1.126%, corresponding to an estimated wealth loss of 134.78 million yuan for an average healthcare firm. When examining the effects across individual rounds and subcategories, the negative impact remains statistically significant, while we observe a diminishing effect in later rounds, and for non-chemical drugs, which were not the primary target of the CVBP policies. More importantly, our results reveal that bid-winning firms experience a cumulative abnormal return decline of 0.91% over the three-day event window. In contrast, rival firms, defined as chemical drug companies whose products were not included in the procurement, but who compete directly with the procured drugs, experience a 1.17% lower CAR compared to bid winners, after controlling for firm characteristics and bid round effects. Therefore, our findings suggest that the capital markets hold a pessimistic outlook on the market value of pharmaceutical companies in the aftermath of the CVBP shock, leading to reduced external equity funding, which is a key source of capital for R&D activities in pharmaceutical firms.

We then employ a staggered Difference-in-Differences (DID) approach to analyze firms' responses to the phased rollout of the CVBPs, with a particular emphasis on their innovation inputs. Using a nine-year window around CVBP events, we focus on a treatment group consisting of bid-winning firms, and a control group including firms operating in non-vaccine biological products, blood products, medical equipment, and active pharmaceutical ingredients.[1] Our results show that bid-winning firms experience significant reductions in operating revenues, decreasing by 14%. Given these negative fundamental changes, however, we observe a significant increase in firms' R&D intensity measured by R&D/Sales. In other words, despite poor performance in the capital markets, firms appear to sustain their R&D investments relative to their declining revenues.

What then explains this unexpected outcome? We argue that, akin to a buffering mechanism, firms can sustain R&D spending despite capital market shocks by making adjustments to their cost structures. Specifically, we observe a 2.8 percentage point reduction in selling expenses to sales among bid-winning firms following CVBP implementation. This reduction aligns with the expected effects of CVBPs, as these firms gain substantial market share, which reduces the need for heavy marketing and selling expenditures. To further support this hypothesis, we examine alternative funding sources and find that they didn't increase their bond issuance, bank borrowing, and seasoned equity offering post-CVBPs. This provides strong evidence that regulatory constraints on selling expenses may effectively subsidize R&D investments.

Our interpretation is further reinforced by the strategies of rival firms, which also experience a reduction in selling expenses. We interpret this as a voluntary ad-

[1]The criteria for selecting the control group are twofold: on the one hand, the firms should have negligible exposure to the CVBPs; on the other hand, they should not have been directly or positively affected by COVID-related disruptions to product chains.

justment to their cost structures–these firms did not actively expand to compensate for the loss of market share but instead reallocated savings to sustain their R&D investments. Notably, the operational changes in rival firms post-CVBP closely mirror those of winning firms, further validating our hypothesis of a sector-wide reallocation of resources toward R&D.

To test the robustness of our results, we perform several additional analyses. First, we address recent concerns in the econometrics literature regarding staggered difference-in-difference designs, demonstrating that our results are robust to a variety of alternative estimators. We also show that there are no discernible pre-treatment trends in our data. Second, we complement the DID approach with an alternative specification that exploits variation in firms' cumulative bid-winning amounts, which does not rely on the parallel trends assumption for identification. This alternative specification accounts for the varying intensity of CVBPs between different firms. Third, we use a balanced sample to mitigate potential biases that might arise from changes in sample composition over time. We also implement a propensity score matching (PSM) process to control for observable differences between the treatment and control groups. Finally, we show that our results remain robust to the issue of repeated treatments by including additional controls that allow flexible treatment strength trends based on bid-winning characteristics.

Our study contributes to the broad scope of literature examines the role of various funding sources, including equity markets (Brown et al., 2009, 2012, 2013; Moshirian et al., 2021), bank loans (Cornaggia et al., 2015), corporate cash flows (Brown et al., 2012), and public funds (Howell, 2017), in enabling firms to finance their R&D investments. Equity market is quite important for R&D investment (Brown et al., 2012), especially for small and young firms (Brown et al., 2009, 2013). It can explain the large fluctuations in R&D (Brown et al., 2009). And stronger shareholder protections and better access to stock market financing also lead to substantially higher long-run rates of R&D investment (Brown et al., 2013). In terms of innovation outcome, compared to firms that rely on relationship-based financing(e.g., bank loans), firms relying on arm's length financing (e.g., public equity or debt) tend to produce higher-quality innovations (Atanassov, 2016).

On the other hand, financing constraints do influence R&D investment (Brown et al., 2012). Especially for firms that are struggling to seek funding from the equity market, public R&D grants serve as an important mechanism in smoothing R&D investment (Howell, 2017). Brown et al. (2012) suggests that corporate cash flow management matters in identifying the existence of financing constraints and the role of external equity finance in R&D investment. Our study adds to this body of literature by showing that while equity financing and public R&D grants are crucial for sustaining innovation investments, cost reallocations within firms—such as shifting resources from marketing expenses to R&D—can also provide firms with the necessary financial flexibility to maintain innovation during periods of capital market distress.

Our study also contributes to the literature related to determinants to R&D in-

vestment other than the financing channels, including product market competition (Gu, 2016; Lyandres and Palazzo, 2016; Thakor and Lo, 2022), corporate governance quality (Giroud and Mueller, 2011), and market consolidation (Bonaimé and Wang, 2024), etc. These studies are investigated across varied industries. By complementing the literature, our empirical analysis highlights the role of operational cost adjustments in sustaining R&D spending.

Among these, the most relevant studies to ours are those exploring the impact of the regulatory interventions on the R&D investment in the pharmaceutical industry (Golec et al., 2010; Li et al., 2021). Adopting a court ruling as an unexpected regulatory change, Li et al. (2021) documented how the changes in the regulatory environment that restricts the firms' activities to impede competition could promote firms' innovation activities. Golec et al. (2010) investigate how the threat of price regulation under the Clinton administration's Health Security Act led to a significant reduction in R&D spending within the pharmaceutical sector. The study shows that uncertainty about future regulatory policies can diminish the incentives for firms to invest in long-term innovation, as market conditions become unpredictable. Our study complements this by investigating how government regulations—specifically, China's centralized volume-based procurement (CVBP) policy—can affect R&D investment. While price regulation generally leads to decreased innovation investment due to reduced profitability, we find that pharmaceutical firms were able to maintain their total R&D investment by reallocating resources from other areas, particularly sales and marketing, despite the price cuts induced by the CVBP reform. This highlights that internal cost management strategies can mitigate the negative impact of regulatory shocks on R&D investment.

Our study is relevant to the literature on pharmaceutical innovation activities and incentives. Krieger et al. (2022a) finds that firms' risk aversion may impede them from conducting more innovative drug development projects, while positive cash flow shocks may relax their financial constraints and therefore reduce their effective risk aversion. Krieger et al. (2022c) explores how firms react to negative shocks to existing products by adjusting their R&D spending towards acquiring external innovations rather than developing novel products internally.

Our study also contributes to the literature on the impact of public procurement. Goldman (2020) finds that during times of economic crises, government spending can stabilize industries by serving as a "customer of last resort", maintaining production capacity and innovation. Among all the existing studies that specifically explore the impact of CVBPs on drug prices and consumer welfare (Cao et al., 2024), selling expenses (Liu et al., 2024), drug utilization (He and Yang, 2024) and the overall effectiveness in prices, utilization and expenditure (Jiang et al., 2024), our study is the first to explore the financial impact of CVBPs and its subsequent impact on R&D spending.

When we shift the perspective to focus on the policy itself, this paper also tries to provide valuable insights for policymakers globally, and we conclude that CVBPs generate a net welfare gain. On one hand, governments worldwide, not just in

China, are grappling with the growing financial burden of healthcare expenditures. According to the World Health Organization[2], the average share of GDP allocated to current health expenditure globally is 10.36%, with the U.S. spending 16.16%. In response, governments are seeking policies that can reduce drug prices, yet they must be cautious not to undermine the long-term incentives for pharmaceutical companies to innovate. Lower drug prices can erode firms' revenues, which in turn might discourage investment in new drug development. On the other hand, high marketing expenses are a global issue for the pharmaceutical industry. At the firm level, U.S. pharmaceutical companies spend approximately 33% of sales on selling expenses, which is even 10% higher than the corresponding figure for Chinese firms in our sample. A significant portion of these marketing expenditures——over 76%——is directed at influencing physician prescriptions (Krieger et al., 2022b), and existing literature highlights how such payments boost drug sales (Carey et al., 2021; Agha and Zeltzer, 2022).

In this context, China's volume-based procurement policy presents an intriguing and potentially instructive case: it reduces drug prices through bulk procurement, easing the fiscal burden of national healthcare systems (Cao et al., 2024; Jiang et al., 2024), while simultaneously lowering firms' "Resigned" selling expenses by consolidating market competition to just 3 or 4 dominant players. Therefore, when considering the three main players —— government, firms, and patients——the policy generates a net welfare gain. The government benefits from reduced healthcare expenditures, while firms, despite a reduction in revenue, maintain profitability, as evidenced by the non-decreased EBITDA/TA and other profitability proxies. For patients, the immediate benefit is the reduction in drug prices, while the long-term gain may come from increased access to future new drugs, as firms significantly ramp up their R&D investments.

Our paper is organized in the following structure. Section 2 documents the institutional background and hypothesis development for our analysis; Section 3 introduces the data and sample; Section 4 presents the event study analysis that focuses on the short-run market reactions towards CVBPs; Section 5 displays the comprehensive analysis about the impact of CVBPs on the R&D investment with staggered difference-in-difference model; Section 6 discusses the welfare implications of CVBP; Section 7 concludes.

2 Institutional Background: The Introduction of CVBPs

China's Centralized Volume-based Drug Procurement (CVBP) program, launched in late 2018, initially targeted 25 drug molecules across four major metropolitan areas and seven additional large cities—a phase known as the "4+7 Pilot Program." As detailed in Table 1, following this pilot, the CVBP was expanded nationwide in

[2]See: https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS

nine rounds, ultimately encompassing 374 drug molecules. The National Healthcare Security Administration (NHSA), as the single payer for China's national health insurance, now aggregates over half of the country's demand for prescription drugs, leveraging its monopsony power to secure the lowest possible prices from pharmaceutical producers.[3][4]

The implementation of CVBP involves three main stages: quantity reporting, competitive bidding, and hospital purchase. First, as a single payer, NHSA requires each medical insurance designated institution (including all public institutions and some private ones) to report the quantity of procured drugs they are going to purchase for the next year. The reported quantity is required to be at least around 60-80% of their annual prescription.

Second, with the aggregating the reported demand from the medical institutions, the single payer, NHSA, leverage its monopsony power to the producers for a cheaper price. Only the branded drugs and the bio-equivalent generics can participate in the competitive bidding. Providers with the lowest bids win the procurement. If there is only one winner, this winner will supply the whole country with 50% of the reported quantity. If there are multiple winners, these winners will take turns to choose their supplying provinces, and for each chosen province, they are in principle given 60%–80% of the reported quantity depending on the number of winners.

Third, During the subsequent contract period, hospitals will directly place orders with the winning firms for the selected drugs at the bid price. To ensure the effective implementation of the centralized procurement policy, local HSA continuously monitor the completion of procurement targets by hospitals in their respective regions, checking whether the agreed procurement volume, as reported by the hospitals, is met. Additionally, each provincial HSA have implemented a series of complementary policies to align the incentives of pharmaceutical companies, hospitals, and patients with the successful execution of the procurement process. These measures include the establishment of payment standards by the insurance system, surplus retention policies, advance payment schemes, and other supportive policies.

The CVBP's large-scale, top-down structure has reshaped China's pharmaceutical industry. Most winning firms are domestic generic manufacturers, as the selected drugs are typically off-patent with multiple generic substitutes. And the NHSA prioritizing high-expenditure, widely used molecules. Unlike global Big Pharma companies, which typically balance R&D and marketing, China's generics manufacturers have traditionally prioritized selling expenses over R&D investment. This results in a strategic shift within the industry. According to Jiang et al. (2024), the procurement process has driven price reductions averaging 70% for selected ac-

[3]Established in 2018, the NHSA oversees the Urban Employee Basic Medical Insurance (UEBMI) and the Urban and Rural Resident Basic Medical Insurance (URRBMI), which together provide coverage for 1.33 billion people in China. See: https://www.nhsa.gov.cn/art/2024/7/25/art_7_13340.html (Accessed Oct. 28, 2024).

[4]The NHSA enforces procurement compliance by incentivizing prescribers (physicians) to allocate 60-80% of past demand for procured drugs to winning firms, thereby guaranteeing sales volumes and encouraging firms to reduce prices substantially in exchange for secure demand.

tive ingredients over the first five rounds, resulting in a 67% decrease in overall expenditure for these drugs.[5] With over 50% of market demand now met through procurement, the CVBP limits opportunities for traditional promotional activities, prompting firms to reallocate resources and adjust strategies.[6] These industry shifts motivate several hypotheses in our study regarding how firms adapt financially to this new competitive landscape.

3 Data and Sample

3.1 Data Source

Our dataset is composed of two primary components, sourced from multiple origins. The first component includes detailed procurement information for drugs and their producers under the CVBP, obtained from official announcement websites, as well as data on non-procured producers sourced from the commercial vendor DXY Insight. The second component consists of stock market data for publicly listed healthcare firms, along with their financial fundamentals, sourced from CSMAR and WIND databases, respectively.

We obtained data related to the eight rounds of CVBP bidding information from the Shanghai Sunshine Medical Procurement All-in-one website (later as "Sunshine All-in-one Website")[7]. This dataset includes details on the target drug molecules procured, the names of the firms that won the bids, and the dates of both the preliminary and formal bid-winning announcements. The preliminary disclosure dates refer to the initial announcement of the winners on the website, after which a public notification period is required to ensure the transparency and fairness of the bidding process. Following this period, the final winners are confirmed and published on the formal disclosure dates. Table 1 provides these two dates for each round, along with the duration of the gap between them, which can extend up to 10 days. This timing is crucial, as our event study estimation relies on a very short observation window, making accurate event dating essential to avoid biased results. In this study, 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 that is further supported by our robustness checks.

To investigate the post-CVBPs performance of firms that have not been procured but produce the same molecules as the winning firms, treated as direct competitors of the winning firms, hereafter referred to as "rivals", we download the $(Molecule \times Firm)$ list from the commercial data vendor *DXY Insight*, which is a

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

[6] 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, 60-80% is procured through the CVBP, meaning that approximately 51%(=60%*85%) of total prescription drug utilization is now secured by the program.

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

global pharmaceutical data intelligence platform that provides information on new drugs, clinical trial outcomes, and pharmaceutical transactions worldwide, widely used by the academic researchers and practitioners in the healthcare area[8].

Additionally, we obtain daily stock trading data, market index data, firm announcements, and firm basic profiles including IPO dates and industry categories from China Securities Market & Accounting Research (CSMAR) database. CSMAR offers several industry classification options, such as the China Securities Regulatory Commission Industry Code, China Securities Industry Code, and Shenyin&Wanguo Industry Code. We adopt Shenyin&Wanguo Industry classification in the main analysis, providing a detailed sub-industry breakdown within the healthcare industry compared to other classification systems.

Moreover, We acquire firms' fundamental data from the WIND database. Although CSMAR also includes a module for firms' financial reports, we chose WIND as it directly provides firms' R&D information (Wind Code: s_ stmnote_rdexp), that necessarily required a manual extraction from the ***notes*** in the financial statements before 2018. In China, R&D-related entries were recorded in the "***Notes*** to Financial Statements—Administrative Expenses" section prior to 2018 and can not be directly captured in the income statement. Following the implementation of China's new accounting standards in June 2018, a dedicated "R&D" section was introduced in the income statements within annual reports.

3.2 Sample Selection

Our initial sample includes all publicly listed healthcare firms that have been traded on the A-share market in mainland China for at least one year as of the end of 2023. We categorize these firms into detailed sub-industries within the healthcare sector according to Shenyin&Wanguo Industry classification. This classification is essential for conducting our event study by sub-category and for defining treatment and control groups in the Staggered DiD analysis. We identify daily anomalies from daily trading data and exclude firms designated as ST (Special Treatment) and PT (Particular Transfer) due to their abnormal trading patterns.[9] Additionally, firms with insufficient sample periods or missing key variables, such as R&D input or selling expenses, which are critical for estimation are excluded from the sample. After applying these criteria, our final sample comprises 484 firms, of which 109 are bid-winning firms. A list of these 109 firms, along with their stock codes is presented in Appendix A, organized at Round-Firm level.

The analytic sample for Staggered DiD estimation comprises bid winning firms, rival firms, and firms from other non-chemical drug category that have never been procured. Both bid-winning firms and rival firms are subjected to the CVBP imple-

[8]See https://db.dxy.cn/v5/home#home-footer (Accessed Oct 21, 2024).

[9]ST firms typically face financial difficulties or have failed to meet regulatory requirements. They are subject to special trading rules and increased scrutiny by the Chinese exchanges to warn potential investors of higher risks. PT firms are undergoing specific processes, such as restructuring or delisting, subject to closely monitoring and strict trading rules to protect investors.

mentation, and therefore, they constitute two distinct treatment groups and will be investigated separately. The last group of firms, after carefully selection, serves as the control group and includes four-subcategory firms whose major business involves non-vaccine biological products, blood products, medical equipment, and APIs, respectively. The criteria used to select the control group is detailed explained in the following section 5.1. Our sample spans from three years before the initiation of CVBP as of 2015 till 2023. Given that the dependent variable is lagged by one year, our study is restricted to focus on CVBP Round 0 to Round 7 and our independent variables span from 2015 to 2022. We exclude all observations of firms in the treatment group that lack data prior to their first treatment record. Finally, this approach yields an unbalanced panel, with 1094 firm-year observations and 184 unique firms included in our staggered DiD regressions.

4 The Market Reaction

4.1 Abnormal Returns from CVBPs

We assess the market's reaction to the CVBP bid-winning announcements, by calculating the three-day cumulative abnormal return(CAR) with market model, centered on the preliminary disclosure date t, which marks the bid-winning announcement. First, we use the following regression to estimate β_i:

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

where $R_{i,t}$ represents the return on stock i on day t, and $R_{M,t}$ denotes the market return on day t. Given that our sample is confined to the healthcare industry, we employ two versions of $R_{M,t}$: first, the CSMAR value-weighted market return, and second, a return from the SH000991 healthcare index, which tracks 117 components in China's A-share market.[10] The components are selected by China Securities Index Company based on their liquidity and market representativeness. Compared to the traditional use of a value-weighted market return, this index choice provides a more comprehensive reflection of the performance of companies within the pharmaceutical and healthcare sectors.

To estimate the model, we use a minimum of 60 days of data prior to the event to obtain the estimated coefficients $\hat{\alpha}$ and $\hat{\beta}$, which results in an estimation window of $[-80, -20]$. This 80-day pre-event window is chosen to minimize contamination from

[10]To ensure robustness, we also use the returns of 000933.SH Medicine 800 and 000857.SH Medicine 500 as alternative proxies for $R_{M,t}$, and subsequently reevaluate our results.

earlier events.[11] The realized market returns ($R_{M,d}$) and individual firm returns ($R_{i,d}$) over the event window (where $d = -1,\ 0,\ 1$, with 0 being the CVBP bid-winning announcement date) are used to compute the abnormal return $AR_{i,d}$ as follows:

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

Next, by summing the daily abnormal returns ($AR_{i,d}$) across the three-day event window, we obtain the cumulative abnormal return(CAR). We use $CAR1$ to represent the cumulative abnormal return calculated using the CSMAR value-weighted market return as $R_{M,t}$, and $CAR2$ to denote the cumulative abnormal return using industry-specific return as $R_{M,t}$. To capture the average changes in market value across firms in our sample, we also compute the cumulative average abnormal return (CAAR) by averaging the CARs across firms.

4.2 The Effects of CVBPs on the Entire Pharmaceutical Market

In this subsection, we examine investor reactions to CVBPs, with a particular focus on how these programs impact the market value of firms within the broader healthcare sector. Given that investors may respond differently across various CVBP rounds and industry segments, we further break down the results by rounds and subcategories to explore these heterogeneous effects.

4.2.1 Overview of the Impact of CVBPs on the Entire Healthcare Sector

Panel A of Table 2 presents the cumulative abnormal returns (CAR) for all listed firms in the healthcare sector across the past nine rounds of CVBPs, beginning with Round 0 (the CVBP 4+7 Pilot). The sample includes a total of 3,230 $Stock \times Round$ events. The results in Panel A indicate that both $CAR1$ and $CAR2$ are negative and statistically significant at the 1% level. Specifically, cumulative abnormal returns decreased by approximately -1.126% (t-stat = -9.48) based on $CAR1$. This effect is not only statistically significant but also economically meaningful. The average market value in our sample was 11.97 billion RMB prior to the launch of the 4+7 Pilot (at the end of September 2018). Thus, this implies an additional wealth loss of approximately 134.78 million RMB for healthcare firms during the three-day event window.

[11] Specifically, as shown in Table 1, the gap between the national CVBP Round 4 and Medical Equipment Round 1 is only 90 days, implying that a longer estimation window could overlap with the prior event window. Furthermore, in Round 6, which focused specifically on insulin products, the bid-winning announcement occurred just 73 days after the previous Medical Equipment CVBP round, leading to overlap between the estimation window and event window. Fortunately, since the earlier Medical Equipment CVBP round targeted coronary stents rather than insulin-related products, this had minimal impact on the firms involveed in Round 6.

4.2.2 Impact Across Different Rounds

Investor reactions may vary across different CVBP rounds, so we further decompose the results by round. Some rounds target a narrow range of drug types, such as Round 6, which focused specifically on insulin and involved fewer companies. As a result, the estimation results using data from the entire healthcare sector may differ for this round. Panel B of Table 2 supports our hypothesis. With the exception of Round 2 and Round 6, all other rounds show significantly negative CARs. As mentioned earlier, Round 6, which focused on insulin products, produced a positive $CAR1$ due to its narrower focus. However, the results for Round 6 are less robust, with CAR_2 turning insignificant.

As for Round 2, the announcement date—January 17, 2020—coincided closely with the initial outbreak of COVID-19 in China. On this date, Wuhan reported the risk of "human-to-human" transmission and confirmed 17 new cases, all of which were tested using reagent kits. Meanwhile, rumors circulated suggesting that antibiotics could prevent COVID-19. These factors contributed to a significant 5.4% increase in the stock price of *Lukang Pharmaceutical Co., Ltd.*, a prominent producer of antibiotics. As a result, we observe a significantly positive $CAR1$ and an insignificant $CAR2$ for Round 2.

However, the interference from these unclean events does not undermine our conclusion. By excluding Round 2 (which occurred during the initial outbreak of COVID-19), we observe a significantly negative $CAR1$ with a larger magnitude, as shown in Panel C of Table 2.

Furthermore, compared with the initial launch of CVBP, we expect that the impact may diminish in later rounds, as investors become less surprised once CVBPs become a regular program. This hypothesis is supported by the results in Panel B of Table 2. Although the magnitude of cumulative average abnormal returns doesn't decrease monotonically with each round, it is evident that investors react less strongly in the later rounds. For instance, $CAR1$ and $CAR2$ in Round 7 and Round 8 are only one-quarter to one-half of those observed in Round 1.

4.2.3 Impact Across Multiple Sub-Industries

In addition to analyzing the impact across rounds, we are also interested in examining how market value changes across different subcategories within the healthcare sector. Although CVBPs have expanded their scope to include non-chemical products in certain bidding programs (see Table 1), the events analyzed in this paper—national CVBPs—only involved chemical drugs. This has led to heterogeneous shocks across different subcategories. To explore this further, we use the Shenyin & Wanguo Industry classification, which divides firms into seven groups: Chemical Drugs (109 firms), Chinese Medicine (74), Active Pharmaceutical Ingredients (APIs) (40), Biological Products (52), Distribution and Circulation (25), Medical Equipment (79), and Medical Services (94). Panel C of Table 2 presents these results.

Unsurprisingly, firms in the Chemical Drugs category experienced the largest decline in market value during the three-day event window, as they are the primary target of the national CVBP. Notably, firms in the Circulation category experienced the greatest drop, with a decrease of 3.26%. This can be attributed to the fact that under the CVBP, hospitals contract directly with manufacturers, bypassing intermediaries and reducing the role of circulation firms. As a result, the market has a more pessimistic outlook on these firms. Our results remain robust even when we adjust for multi-product firms, such as those in the Chinese Medicine group, that produce both Chinese medicine products and chemical drugs. We apply a 30% criterion to determine the primary business activity: firms with more than 30% of sales from traditional Chinese medicine remain in the Chinese Medicine classification, while those with a higher proportion of chemical drugs are reclassified as Chemical Drugs producers. Instances of reclassification are rare, and this adjustment does not significantly affect our results.

4.3 Market Attitudes Toward Winners, Rivals, and Prospective Participants

In the previous subsection, we provided an overview of the effects of CVBPs on the market value of the entire healthcare sector, breaking down these effects by round and subcategory. We now focus specifically on the impact of bid-winning announcements. In particular, we investigate how investors differentiate their valuations of bid winners from other firms within the three-day CVBP event window.

4.3.1 Firm Categorization Based on Bid-Winning Status

In the following analysis, we categorize firms into three groups: bid winners, rivals, and prospective participants. Bid winners are defined as firms that were awarded contracts in any of the CVBP rounds (for further clarification, see Section 3.2). Rivals are chemical drug firms whose products were not procured but are direct competitors of the winning drugs. For instance, rivals may produce the same molecules as the winning firms but did not enter the procurement supplier pool, either by their self-choice or because they were unsuccessful. Importantly, our data is structured by firm and round, so we exclude firms from the rival category if they won the bid in the same round. Prospective participants are chemical drug firms in each round that are neither winners nor rivals. These firms often produce drugs targeting less common diseases and may be smaller than the other two categories, making it challenging for them to compete in a "large orders, low price" strategy.

Before delving into the market reaction, we first present summary statistics (Table 3) for the three firm categories, based on the latest available fiscal report period around the event. In China's A-share market, listed firms must disclose their annual financial reports within four months after the fiscal year ends on December 31. To ensure that investors have access to necessary financial data for portfolio

decision-making, stock returns from May t to April $t+1$ are matched with financial data from the fiscal year ending in the prior calendar year (t-1). We report seven key measures: age (years since IPO), size (log of total assets), profitability (return on equity; net profit), financial leverage (total debt to total assets), and shareholders' equity. As expected, the average size of winners is significantly larger than that of rivals or prospective participants, with an average total asset value of 15.99 billion RMB, compared to just 4.79 billion RMB for prospective participants. This aligns with our earlier hypothesis that larger firms are generally better positioned to make the necessary price sacrifices to secure large procurement contracts. Similarly, both winners and rivals exhibit higher profitability compared to prospective participants, with the latter displaying a particularly low ROE of just 0.94, reinforcing the idea that smaller firms may struggle to compete in such procurement schemes.

4.3.2 Do Winners Gain Market Applause? Univariate and Multivariate Tests

Table 4 reports the cumulative abnormal returns ($CAR1$ and $CAR2$) over the three-day window centered around the CVBP bid-winning announcements. The results compare CAR for winners versus rivals and winners versus prospective participants. Panel A presents the results from all nine rounds, beginning with Round 0 (the CVBP 4+7 Pilot). Both $CAR1$ and $CAR2$ are negative, though statistically insignificant, suggesting that investors were likely concerned about the sharp revenue declines expected for the bid-winning firms due to significantly discounted prices. While patients and healthcare systems might view these price cuts positively, investors appear pessimistic, reflecting their concerns about impaired revenue-generating potential, as shown in the diminished stock valuations.

Rivals, however, suffered more severe consequences. Panel A shows significantly negative CARs for rivals across both metrics, with a cumulative abnormal return dropping by 2.45% over the three-day event window. Differences between winners and rivals reveal that bid winners experienced, on average, a 2.025% higher return than their rivals, statistically significant at the 1% level. This finding is intuitive: although winners face revenue reductions due to lower prices, they maintain or expand their market shares. In contrast, rivals experience sharper declines in revenue as their market share diminishes, sometimes to zero. Under CVBP regulations, hospitals are required to prioritize the use of bid-winning drugs and only procure non-bid drugs after meeting the procurement quotas, significantly constraining rivals' market opportunities. This hypothesis is further validated in Section 5.

To address potential contamination in the event window for Round 2, we re-estimate the results excluding this round, as shown in Panel B of Table 4. Without Round 2, both $CAR1$ and $CAR2$ become statistically significant, reinforcing evidence of investors' pessimism toward bid winners. Even though these firms secure procurement contracts, the anticipated revenue losses weigh heavily on market sentiment.

Figure 2 provides a visual representation of these trends, plotting the 6-day $CAAR1$ for winners, rivals, and prospective participants. On Day t=-1, the $CAAR1$ hovers near zero before declining significantly on the announcement date. The negative trend persists through Day 5, with rivals and prospective participants experiencing larger losses compared to bid winners.

To further examine whether bid-winning firms experience higher CARs compared to rivals and prospective participants, we employ an OLS regression specification controlling for firm-specific characteristics and CVBP round fixed effects. The model is specified as:

$$CAR_{ik} = \alpha_i + \beta_1 WinningFirms_{ik} + \beta_2 X_i + \delta_k + \varepsilon_{ik} \tag{3}$$

where i denotes firm i; k indexes round k; The dependent variable is the three-day cumulative abnormal returns $CAR1$ and $CAR2$ uses CSMAR value-weighted market return and industry-specific return as $R_{M,t}$ respectively; The key independent variable, $WinningFirms_i$, equals 1 if a firm won the bid in Round k, and 0 otherwise. Control variables X_i include size (the natural logarithm of assets), financial leverage (Debt/Assets ratio), return on equity (ROE), and asset growth rate. To account for variations across bidding rounds, we include the round fixed effect δ_k. Our interest lies in the coefficient β_1.

Table 5 demonstrates these results. Columns (1) and (2) compare winners to rivals, while Columns (3) and (4) compare winners to prospective participants. Round 2 is excluded to avoid bias from the polluted event window, and missing control variable data for nine firms slightly reduces the sample size compared to Table 3. Consistent with our earlier findings, all columns show significantly positive coefficients for $WinningFirms_i$. Controlling for firm characteristics and bidding rounds, bid winners realize a 1.17% higher stock return compared to rivals (Column (1)) and a 1.19% higher return compared to prospective participants (Column (3)). These results reinforce our conclusion: while the CVBP reform generates significant investor concern, pessimism is more pronounced for rivals and prospective participants.

5 Strategic Responses of Firms to CVBPs

In the previous section, we demonstrated that post-CVBPs, investors exhibit a pessimistic sentiment toward the healthcare sector, as evidenced by significantly negative cumulative abnormal returns (CARs) surrounding the announcement events (Table 2). Even for firms that successfully secured procurement deals, investor caution persists, with CARs remaining negative (Table 4), signaling concerns over future revenue streams. Existing literature links stock market declines with reduced innovation investments, emphasizing the critical role of capital markets in alleviating financial constraints on R&D (Golec et al., 2010; Brown et al., 2013). Therefore, we can't help asking, would CVBPs also lead to a decreased R&D investment? If

not, how the firms accommodate the shocks from capital markets and product markets. Have they buffering the shock through other external funding channels? To explore these questions, in this section, we employ staggered difference-in-difference (DiD) method and explore the performance, the innovation input and output, the internal v.s. external funding channels of the firms after the CVBPs. We discover that, as selling expenditures typically account for approximately one-third of total revenue in the Chinese pharmaceutical market, as indicated by firms' annual reports——providing substantial room for cost reallocation. Although on one hand, poor stock performance could directly lead to lower R&D spending, as the external funding sources are reduced. On the other hand, firms can sustain R&D spending despite capital market shocks by making adjustments to their cost structures. This subsection leverages the exogenous shock of CVBPs to explore these dynamics, and we examine strategic shifts in firm fundamentals, focusing on both procurement winners and their competitors.

5.1 Empirical Specification

To account for the phased rollout of CVBPs across different drugs and firms, we employ a staggered difference-in-differences model to examine changes in corporate performance. The model is specified as follows:

$$Outcome_{i,t+1} = \alpha_i + \beta_1 Procured \times Post_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{4}$$

where i denotes firm i, t indexed year t. The key independent variable $Procured \times Post$ is an indicator variable, equal to 1 for firm i wins its first procurement bid and afterwards. For firms that have never been procured, $Procured \times Post$ will always be 0. The dependent variables include three main sets, as we discussed above. The first set describes the product market performance of the firms after CVBPs, including the sales and the profitability; the second set of dependent variables documents firms' innovation activities, including innovation inputs (R&D expenses) and outputs (Patents and Citations); the third set captures all the potential internal and external funding channels for firms' R&D financing. δ_i and γ_t represent firm and year fixed effects, respectively. We further add controls wildly used in the literature to account for other confounding factors, including Ln(Asset), ROA, Tobin's Q, Total Debt/TA, Total Cash Holdings/TA, Capital Expenditures/TA, Property, Plant, and Equipment/TA. Standard errors are clustered at the firm level. The coefficient of interest, β_1, reflects the impact of CVBPs on firms' financial performance.

Our sample consists of two categories of firms: the treatment group (procurement winners) and the control group (firms that have never participated in CVBPs). Specifically, the control group includes firms operating in *non-vaccine biological products*, *blood products*, *medical equipment*, and *active pharmaceutical ingredients* (APIs). The selection is based on two critical considerations: (1) operational and financial similarity to the winners, and minimal or no exposure to the CVBP pro-

gram; (2) no direct involvement in COVID-related product chains.

The first criterion ensures that the control group represents a counterfactual –how the winners would have evolved without CVBP procurement. Given the distinctive traits of pharmaceutical firms, such as high innovation intensity and lengthy R&D cycles, selecting controls from firms within the healthcare sector is more appropriate than from other industries. However, challenges arise because, besides the nationwide CVBP program for drugs, other provincial or special rounds of procurement (e.g., for medical devices like heart stents) may influence our results. Furthermore, the procurement of chemical drugs may trigger spillover effects to Chinese medicine, as Chinese medicine and chemical drugs can both be substitutes and complements in Chinese medical practices. Given these considerations, firms in these sectors (medical devices and Chinese medicine) are excluded from the control group.

The second concern involves the overlap of our sample period with the COVID-19 pandemic. While the negative economic shock from the pandemic affects both the treatment and control groups, which can be addressed through our DID specification, firms directly engaged in COVID-related activities–such as vaccine production, diagnostics, and treatments– experienced extraordinary shifts in both R&D and sales, which could significantly distort our results. For example, *Shijiazhuang Yiling Pharmaceutical Co., Ltd.* (002603.SZ), saw a dramatic surge in demand in 2020 due to its flagship COVID-related product, "*Lianhua Qingwen Granules*," leading to an unusual 50.6% revenue boost and a tenfold increase in net profits. This extraordinary performance makes such firms unsuitable as controls, as their experiences diverge sharply from those of firms outside the COVID-related product space.

After excluding firms with missing variables, our final sample consists of 1,070 $Firm \times Year$ observations, including 99 unique winners and 85 unique controls (23 from *non-vaccine biological products*, 29 from *medical equipment*, 28 from APIs, and 5 from *blood products*). The summary statistics are presented in Table 6. It shows that firms in our sample generally exhibit substantial selling expenses, yielding average selling expenses to sales ratio of 23.6%. In contrast, the R&D to sales ratio is merely one-third of this figure, highlighting a highly imbalanced financial structure in the healthcare sector. Among the winners, the impact of CVBPs varies significantly; the first successful and pledged bid constitutes 2.4 % of their sales on average (Mean of $ProcuredExposure_i = 0.024$). However, the max value can reach as high as 10.8%, indicating the profound influence of CVBPs on a firm's product market.

5.2 Impact of CVBPs on Firm Performance

In this subsection, we first examine how winning in CVBPs impacts firms' fundamentals, including operating revenue, and profitability——key determinants of a firm's ability to finance innovation. We begin by analyzing the impact of CVBPs

on firm revenues. The net revenue effects of CVBPs remain an empirical question, as the program creates a trade-off between price concessions and market size expansion. Column (1) of Table 7 demonstrates that, on average, firms that won CVBP procurement contracts experienced an 14% decline in sales. This finding suggests that the downward pressure on prices outweighs any benefits from increased market share. In terms of their sales to total asset ratio, those winning firms also suffers from a 4.3% drop. Fortunately, their profitability remains stable (Columns (3)-(5)), which suggests two key points. On one hand, the high profitability of pharmaceutical firms is evident; despite significant price reductions due to CVBPs, they are still able to maintain unchanged profits. This implies that the CVBPs and other drug price controls are, in fact, well-calibrated—the topic frequently discussed in health economics and industrial organization literature. On the other hand, given the revenue reduction, it is clear that certain expenditures must have decreased substantially to sustain the same level of profit. We will focus on this aspect in greater detail later.

5.3 Impact of CVBPs on Firms' Innovation Input and Output

In this subsection, we investigate the impact of winning a centralized volume-based procurement (CVBP) bid on firms' innovation input and output. Columns (1)–(2) of Table 8 present estimates from Equation (4), where the dependent variable is R&D intensity, measured as R&D expenditures scaled by operating revenue. Columns (3)–(6) report the effects on innovation output, including the number of granted patents, forward citations, and filed patent applications.

Between Columns (1) and (2), we progressively include standard firm-level controls. The coefficient on the interaction term remains both statistically significant and stable in magnitude, suggesting a robust increase in R&D intensity following CVBP participation. Specifically, firms that win CVBP bids experience an increase in R&D intensity of approximately 1.3 percentage points.

Notably, this result suggests that despite facing potentially adverse market signals due to price reductions and volume commitments associated with CVBPs, firms do not cut back on innovation input. This observation prompts a critical question: how do firms sustain their R&D investment in the face of such financial pressures?

In contrast, Columns (3)–(6) reveal no statistically significant effects on innovation output. While R&D intensity increases, there is no corresponding improvement in patent-related outcomes. One plausible explanation is that innovation outputs such as granted patents and citations are inherently long-term in nature and may not manifest within the relatively short post-treatment window—only five years from the initial 4+7 pilot to the end of our observation period, and this temporal lag effect is further enlarged in the CHMD industries (chemical, healthcare, medical equipment, and drug, Brav et al. (2018)). Alternatively, the observed stability in R&D investment levels (as shown in Table A.3) may simply reflect in propor-

tionately stable output levels, which is consistent with innovation production lag structures.

5.4 Channels

5.4.1 Buffering R&D Through Selling Expenses

So far, we find that firms' market cap and operating revenue declined following the CVBP, potentially constraining firms' cash flows available for innovation. Surprisingly, however, firms did not reduce their innovation inputs, and even increased their R&D intensity. What explains this seemingly counterintuitive outcome? In this subsection, we examine how the internal and external funding sources change after CVBP.

To explore this, we first replace the dependent variable in Equation (4) with selling expenses to total sales. Column (1) of Table 9 reveals that procurement winners experience a significant 2.2% reduction in the ratio of selling expenses to total sales compared to the control group, following their staggered participation in CVBPs. This result aligns with expectations, as CVBPs compensate winners by guaranteeing substantial procurement volumes in exchange for price concessions, thereby reducing uncertainty about sales. Consequently, firms can scale back their reliance on sales representatives and other promotional activities, leading to a notable decline in selling expenses. This is further supported by the significantly negative coefficient in Column (2), where advertising and promotion expenses to sales is used as the dependent variable. More importantly, these reduced selling expenses act as a "buffer", offering firms financial flexibility to reallocate resources toward other priorities, such as innovation. In the context of poor stock market performance, these savings potentially serve as a critical funding source to sustain R&D. We will further validate this hypothesis in the subsequent analysis by eliminating alternative potential funding channels.

5.4.2 Alternative Channels

The results shown in 5.4.1 indicate that CVBPs lead to a decline in selling expenses without changing R&D levels, suggesting that firms might use selling expenses as a buffer to sustain innovation efforts. This reallocation mechanism appears to mitigate resource misallocation by enabling firms to cut back inefficient selling expenditures and redirect resources toward strategic priorities like innovation. To further support this channel, we empirically design other tests to rule out alternative explanations, with a particular focus on external funding sources for R&D.

We assess three main external funding channels, seasoned equity offerings, bond issuance, and borrowing, each normalized by Sales. The results are reported in Columns (3) - (5) of Table 9. Across all three specifications, the main coefficients are insignificant, suggesting that firms did not rely on external funding sources to finance R&D post CVBP. Combined with earlier evidence of firms' decreased

operating revenue post CVBP (Section 5.2), these results strengthen the hypothesis that savings from selling expenses, driven by regulatory constraints under CVBPs, were likely reallocated to support R&D activities.

In summary, these results confirm that CVBPs impose downward pressure on both internal and external funding sources for firms. However, regulatory constraints on selling expenses appear to create financial flexibility, allowing firms to reallocate resources to sustain R&D. This reallocation mechanism highlights the critical role of cost restructuring in maintaining innovation under resource-constrained conditions.

5.5 Dynamic Effects and Robustness Checks

In this subsection, we first show the dynamic effects of CVBPs, and present a series of robustness checks to further validate our findings. This includes: 1) employing robust staggered DiD estimators to account for treatment effect heterogeneity; 2) restricting our sample to a balanced panel to address biases from changes in sample composition over time; 3) conducting a Propensity Score Matching analysis to further mitigate selection bias; and (4) incorporating additional variables to account for repeated treatment effects.

5.5.1 Dynamic Effects of CVBPs

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

$$R\&D/Sales_{i,t+1} = \alpha_i + \beta_k \sum_{k=-7}^{4} Procured \times Post_{i,k} + \delta_i + \gamma_t + \varepsilon_{i,t} \tag{5}$$

where $Procured \times Post_{i,k}$ takes the value of 1 if year t for firm i is k years from the first procurement record. We set $k = 0$ as the year of the first procurement win and use k = -1 as the reference year. The analysis spans from $k = 7$ to $k = 4$, corresponding to the firms that joined the CVBPs in Round 7 (2022), and the first 5 firms that entered the CVBPs in Round 0 (2018), respectively. However, due to small sample sizes, the data points for $k = 7$ and $k = 4$ are omitted from the figures. The dependent variables include R&D and selling expenses, both normalized by total sales, with firm (δ_i) and year(γ_t) fixed effects included.

Following Sun and Abraham (2021), we acknowledge that the traditional TWFE (two-way fixed effects) model yields consistent estimates only under strong assumptions regarding treatment effect homogeneity. To accommodate potential heterogeneity in treatment effects across firms and over time, we supplement the TWFE results with event study figures derived from robust estimators, including those proposed by (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Gardner, 2022).

Figure 3 presents the event-study results. Across all estimators, the coefficients

on pre-treatment periods (prior to the introduction of CVBPs) are consistently close to zero, confirming the validity of the parallel trends assumption. However, one point needs our further clarification at $k = 3$, where the confidence interval widens significantly. This is likely due to the small sample size, as only firms from the first two procurement rounds are included at this stage. Moreover, Figure 3 also reveals the dynamics of treatment effects: across all estimators, CVBPs lead to a progressively larger reduction in selling expense intensity over time, while a progressively larger increment in R&D intensity over time throughout the post-treatment period. These findings underscore the sustained cost-cutting effect of CVBPs on selling expenses without decreasing the R&D investment.

5.5.2 Alternative Staggered DiD Estimators

To address concerns about the reliability of TWFE estimator, we replicate our analysis using the robust estimators proposed by Callaway and Sant'Anna (2021), Gardner (2022), and Sun and Abraham (2021). While TWFE models are commonly used in staggered adoption research, they assume treatment effect homogeneity and provide consistent estimates only under stringent conditions. As highlighted by Goodman-Bacon (2021), TWFE estimators represent a weighted average of all possible 2×2 difference-in-differences comparisons, which can be biased when treatment effects vary across groups or over time. These robust estimators exclude comparisons between newly treated and already treated units, ensuring consistency under treatment effect heterogeneity.

Table 10 confirms that our results remain robust across these alternative estimators. Specifically, CVBPs significantly increase R&D intensity, while selling expenses intensity decreases significantly. These consistent findings reinforce the validity of our conclusions under more flexible assumptions.

5.5.3 Balanced Sample and Results after Mactching

To address potential biases arising from changes in sample composition, we restrict the sample to a balanced panel of firm-year observations from 2015 to 2022. Changes in sample composition can selection bias if younger or newly listed firms differ systematically from older firms in their likelihood of winning CVBP bids. Furthermore, firms with shorter pre-treatment periods (e.g., firms IPO-ing in 2020) contribute fewer pre-treatment observations, potentially skewing the estimation of ATT. By focusing on a balanced panel, we ensure that all firms contribute equally to the analysis. [12]

This restriction reduces the sample size to 792 firm-year observations. Columns (1) and (2) of Table 11 show that the results remain robust: CVBPs significantly

[12]For example, firms that IPO in 2020 and participated in CVBPs in 2022 would only have one pre-treatment observation (2021, noting that we exclude the IPO year to isolate its effect). In contrast, firms that IPO before 2015 and participated in CVBPs in 2022 would have pre-1 to pre-7 observations from 2015 to 2021.

increase R&D intensity, while selling expense intensity decreases by 2.5%. These findings confirm that our main conclusions are not driven by biases introduced by unbalanced panel data.

Leveraging the aforementioned balanced $STKCD \times Year$ data, we further implement a PSM approach by matching treatment (bid winners) and control (non-affected) firms based on observable characteristics. Specifically, we match firms using ln(Market Cap), ROA, Tobin's Q, Total Debt/TA, Total Cash Holdings/TA, Capital Expenditures/TA, Property, Plant, and Equipment/TA, applying the 1-Nearest Neighbor matching method. We drop the observations without common support, resulting in a final size of 608 firm-year observations. Columns (3) and (4) of Table 11 demonstrate that our results remain consistent after controlling for selection bias through PSM. This robustness further strengthens the evidence for our findings.

5.5.4 Firms with Multiple CVBP Wins

Last, we account for the effects of repeated treatment in our analysis. Since firms can participate in multiple CVBP rounds (e.g., at the molecule or product level), some firms experience repeated treatments. This creates challenges for traditional staggered DiD models, which assume treatment effects remain constant after first exposure. To address this, we extend Equation (4) by introducing additional variables that capture the intensity of repeated treatments:

$$R\&D/Sales_{i,t} = \alpha_i + \beta_1 Procured \times Post_{i,t} + \beta_2 RepeatedTreated_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (6)$$

where $RepeatedTreated_{i,t}$ is proxied by 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*), representing the total number of rounds won after the firm's initial procurement year[13]. Table 12 shows that including these variables does not meaningfully affect our results.

5.6 Heterogeneity: Varing Exposure Among Winners

In our earlier Staggered DiD framework, we assumed that the impact of CVBPs was homogeneous across the treatment group (bid-winning firms). However, this assumption merits closer examination. Firms' exposure to CVBPs varies substantially, some won smaller procurement volumes (still significant in absolute terms), while others secured larger volumes through a single substantial bid or multiple aggregated bids. While potential econometric concerns were addressed in Section

[13]For instance, if a firm first won a bid in 2018 and subsequently won bids in 2020 and 2021, thus, *Dummy of Repeated Treatment* would be coded as 1 in 2020 and 2021, and 0 in all other years. Similarly, considering multiple CVBP rounds within a single year, we define *Number of Repeated Treatment* as the total number of rounds a firm i wins in year t, where t occurs after the firm's initial bid-winning year, taking integers between 0 and 3.

5.5.2–through alternative estimators and additional controls to ensure the robustness of our findings, this subsection delves deeper into the heterogeneity of treatment effects by exploiting variation in cumulative procurement exposures (volumes) across firms. Specifically, we examine whether firms with higher bid-winning amounts experience more pronounced changes in R&D investment and selling expenses.

We estimate a modified version of Equation 4 incorporating firm-level treatment intensity. In this specification, we replace the interaction term *Procured Exposure* $\times$ *Post* with a continuous variable, *Cumulative Procured Exposure*, defined as the natural log of the cumulative procured amount. This amount is calculated for firm i in year t as the product of the unit price and the first-year procured quantity promised by the government.

The results are summarized in Table 13, a 100% increase in cumulative procured exposure is associated with an approximately 0.002 increase in R&D relative to sales, while a larger 0.004 decrease in selling expenses relative to sales. In other words, firms with the greater cumulative procurement volumes experience more pronounced impacts on these metrics.

These findings complement the difference-in-differences strategy by leveraging variation in cumulative procurement exposures across firms, offering additional insights that do not rely on the parallel trends assumption for identification. This approach enriches our understanding of how firms' responses to CVBPs are shaped by their level of exposure, particularly in terms of promotional activities.

5.7 Actions Taken by Rivals

In the preceding analyses, we used firms from sub-industries that are largely unaffected by CVBPs –such as non-vaccine biological products, medical equipment, and APIs–as the control group. A natural question arises: why not directly compare bid winners to "non-winning" firms? The key reason is that the non-winning category includes two distinct types of firms: (1) those in unaffected sectors (our control group), and (2) those we define as rival firms—firms producing the same active pharmaceutical ingredients (APIs) as the procured products but not selected in any CVBP round. We regard rivals as another treated group because they are likely affected by the policy through indirect market channels. However, due to data limitations, we cannot further separate firms that actively bid but lost from those that did not participate in the bidding process.

To capture the effects on these rival firms, we re-estimate Equation 4 by replacing the interaction term *Procured* $\times$ *Post* with *Rival* $\times$ *Post* . The results are presented in Table 14 and 15. Overall, most of the estimated effects on rival firms are qualitatively similar to those on bid-winning firms. As shown in Column (1) of Table 14, rival firms experienced a statistically significant decline in sales of approximately 13.2% following the implementation of CVBPs– only slightly smaller than the 14.0% observed for winners. Similarly, the profitability metrics such as ROE, ROA, and EBITDA-to-assets (Columns (2)–(4)) remains unchanged, mirroring the

findings for bid winners. Notably, rivals exhibit a sharper reduction in selling expenses, with selling expenses-to-sales decreasing by 4.9 percentage points (Table 15, Column (1)), compared to a 2.8 percentage point reduction among winners. This suggests that rival firms also actively reduce non-essential expenditures in response to CVBP-induced market pressures.

Columns (3)–(5) of Table 15 examine changes in external financing. The results indicate that rivals' financing capacity remains largely stable. While seasoned equity offerings (SEOs) to sales decline by 9 percentage points, this is offset by a 1 percentage point increase in bond issuance (both significant at the 10% level). There is no evidence of significant shifts in borrowings. These patterns suggest that rivals do not face severe financing constraints in the aftermath of CVBP implementation.

Finally, as shown in Column (5) of Table 14, rivals do not exhibit any significant change in R&D intensity. This finding suggests two important implications: first, rival firms are not suffering budget constraints that would force them to reduce innovation investment; second, they also do not appear to increase R&D as a strategic response to potential market share erosion—an outcome that may seem counterintuitive in light of the competitive pressure induced by CVBPs.

6 Welfare and Regulatory Implications

In the previous sections, by exploiting China's volume-based procurement as an exogenous shock, we tell a finance story that government regulations, while disruptive to financial markets, do not necessarily undermine corporate innovation. In this subsection, we shift the perspective to focus on the policy itself, and discuss the welfare aggregation of CVBPs, aiming to provide valuable insights for policymakers globally.

On one hand, governments worldwide, not just in China, are grappling with the growing financial burden of healthcare expenditures. According to the World Health Organization[14], the average share of GDP allocated to current health expenditure globally is 10.36%, with the U.S. spending 16.16%. In response, governments are seeking policies that can reduce drug prices, yet they must be cautious not to undermine the long-term incentives for pharmaceutical companies to innovate. Lower drug prices can erode firms' revenues, which in turn might discourage investment in new drug development. On the other hand, high marketing expenses are a global issue for the pharmaceutical industry. At the firm level, U.S. pharmaceutical companies spend approximately 33% of sales on selling expenses, which is even 10% higher than the corresponding figure for Chinese firms in our sample. A significant portion of these marketing expenditures——over 76%——is directed at influencing physician prescriptions (Krieger et al., 2022b), and existing literature highlights how such payments boost drug sales (Carey et al., 2021; Agha and Zeltzer, 2022).

In this context, China's volume-based procurement policy presents an intriguing

[14]See: https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS

and potentially instructive case: it reduces drug prices through bulk procurement, easing the fiscal burden of national healthcare systems (Cao et al., 2024; Jiang et al., 2024), while simultaneously lowering firms' "Resigned" selling expenses by consolidating market competition to just 3 or 4 dominant players. Therefore, when considering the three main players —— government, firms, and patients——the policy generates a net welfare gain. The government benefits from reduced healthcare expenditures, while firms, despite a reduction in revenue, they maintain profitability, as evidenced by the non-decreased EBITDA/TA and other profitability proxies, as shown in Table 9. For patients, the immediate benefit is the reduction in drug prices, while the long-term gain may come from increased access to future new drugs, as firms significantly ramp up their R&D investments.

However, one might raise concerns regarding the impact of CVBPs on "drug efficacy." While we acknowledge that such effects may exist, we argue that they do not significantly alter our aggregation welfare analysis. For instance, some news and media report that the average dosages have increased following the implementation of CVBPs, which could be linked to concerns about drug efficacy (although this specific insight has not yet been conclusively proven in the literature). However, existing studies indicate a reduction in out-of-pocket expenses for patients, suggesting that despite potential increases in dosage, patients financially and finally benefit from lower unit drug prices.

What is more important, however, is the impact on patients' access to drug diversity, particularly the reduction in the availability of different drug options and the decreased access to branded drugs. To fully understand these effects, more precise data on physicians' and patients' demand for alternative drugs within the same molecular class is required, which remains difficult to capture in the current stage. We recognize this limitation in our welfare analysis and consider it an important issue for future research.

7 Conclusion

This study investigates how firms adapt their R&D investment strategies in response to financial market shocks, using China's centralized volume-based procurement (CVBP) policy as a natural experiment. Despite significant revenue declines and negative investor sentiment following CVBP implementation, pharmaceutical firms maintained their total R&D expenditures. This counterintuitive outcome is explained by a strategic reallocation of resources: firms substantially reduced selling expenses to sales ratio—by 1.8 percentage points on average—which provided the financial flexibility to sustain innovation efforts. These findings challenge the conventional assumption that external funding constraints necessarily result in reduced R&D investment.

The results reveal a nuanced picture of adaptation. Bid-winning firms faced steep price reductions and corresponding revenue losses, yet their market share

gains reduced the need for costly promotional activities, allowing them to redirect resources toward R&D. Rival firms, despite suffering sharper declines in market share and revenue, exhibited similar cost-cutting behaviors, reflecting a sector-wide shift in financial priorities. While R&D intensity increased due to falling sales, total R&D spending remained stable, highlighting the importance of operational adjustments in mitigating the effects of external shocks.

These findings contribute to the literature on the intersection of regulation, corporate strategy, and innovation. While prior research emphasizes the negative impact of price regulation on R&D, this study highlights the role of cost restructuring in offsetting financial constraints. It also underscores the adaptability of pharmaceutical firms, particularly in a policy environment that incentivizes cost efficiency. However, the long-term sustainability of these strategies and their impact on innovation outcomes, such as new drug development, remain open questions.

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

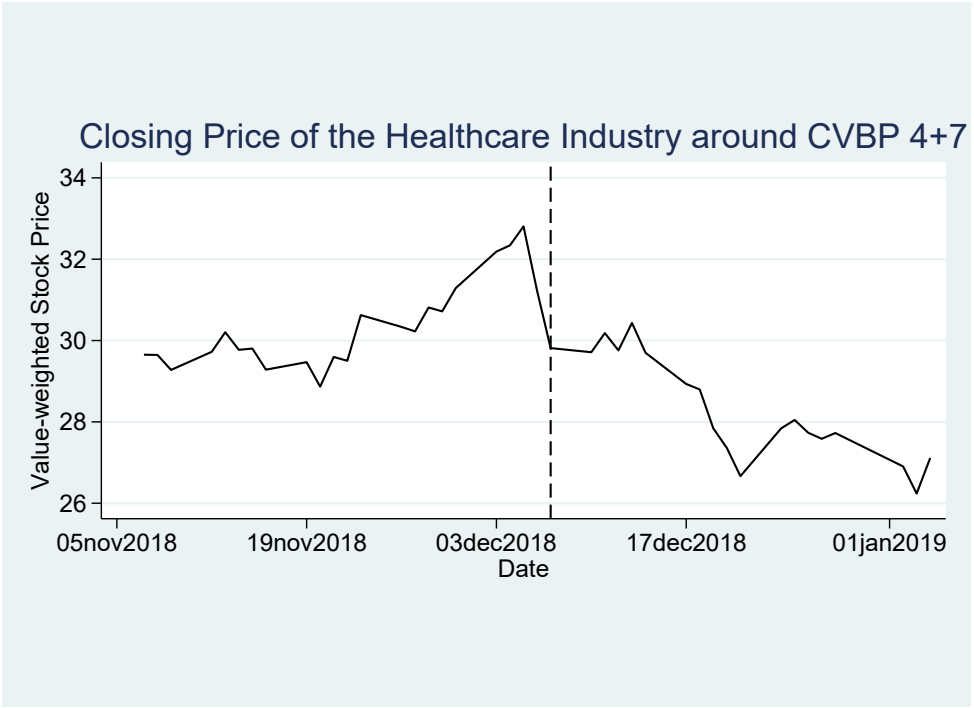
Note: This table reports the dates of preliminary and formal disclosures for each round of China's Centralized Volume-Based Procurement (CVBP), along with the number of days between them (Interval Days). To avoid analytical overlap, we distinguish Drug CVBPs from Medical Equipment CVBPs ("Med. Equ.") and Chinese Medicine CVBPs ("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. Equ. 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. Equ. 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. Equ. 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

Figure 1: Market Reaction to CVBP Initial Launch

Note: This figure illustrates stock price movements and raw returns 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 (indicated by the black dashed line). Panel (a) displays the value-weighted closing stock price of the overall healthcare industry in the period surrounding the CVBP 4+7 announcement. Panel (b) plots the raw daily returns of five publicly listed pharmaceutical firms that were among the first winners of the CVBP 4+7 round: 002020.SZ (JingXin), 002294.SZ (Salubris), 002422.SZ (KeLun), 600521.SH (HuaHai), 000813.SZ (DeZhan). These visuals provide evidence of a sharp negative market reaction at both the industry and firm levels immediately following the policy event.

Panel (a)



Panel (b)

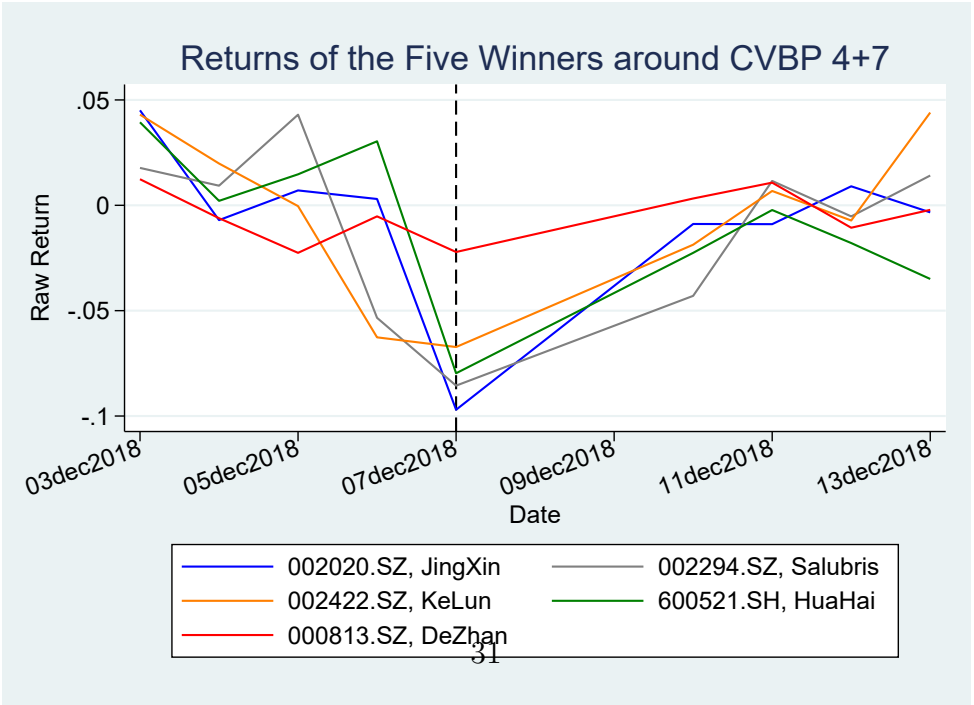


Figure 2: Cumulative Average Abnormal Return for Winners, Rivals and Prospective Participants

Note: This figure plots the **six-day cumulative average abnormal returns (CAAR)** for three groups of firms—**bid winners, rivals** (firms producing the same molecules as winners but not selected), and **prospective participants** (other chemical drug firms excluding winners and rivals). The analysis covers eight CVBP bid-winning events (Rounds), excluding **Round 2** due to confounding effects from the initial COVID-19 outbreak. The **event window** includes the event day (Day 0), one day prior (Day 1), and five days following the event (Days +1 to +5). Abnormal returns are estimated using the market model with a value-weighted market return from CSMAR as the benchmark ($R_{M,t}$). The **estimation window** is defined as the 60-day period from Day 80 to Day 20 before each event. The plot illustrates differential stock market reactions across firm types in response to the CVBP policy shocks.

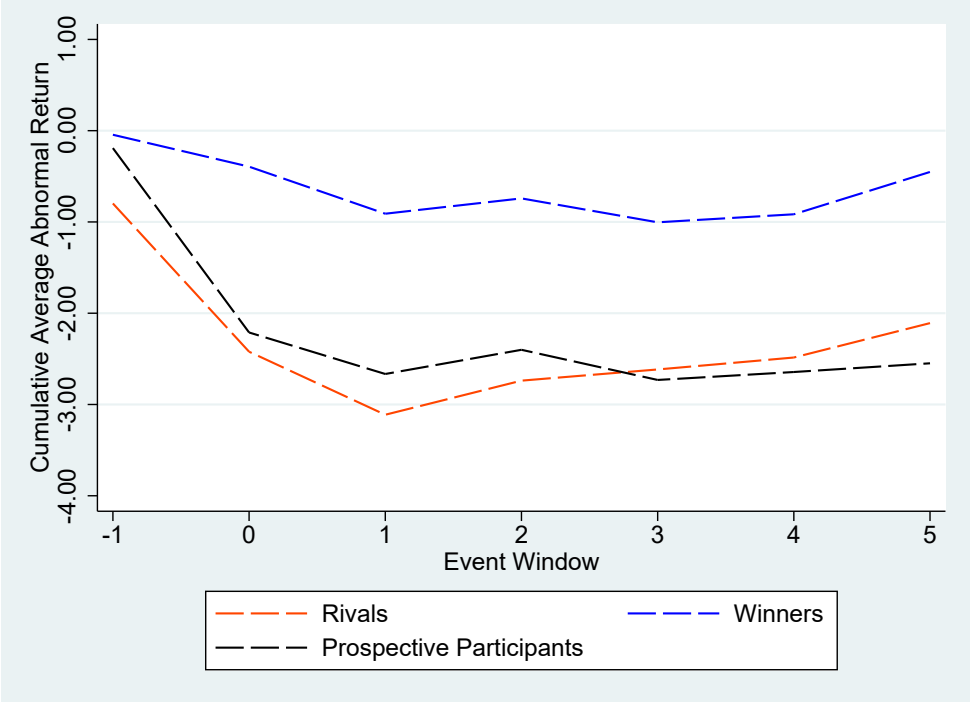
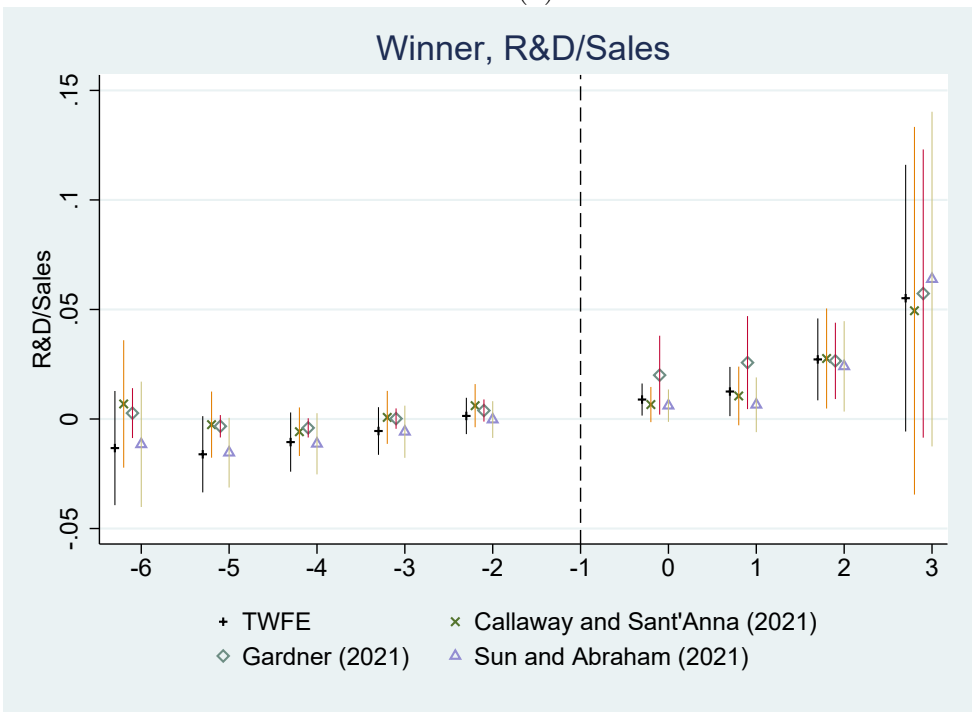


Figure 3: Dynamic Effect: Winning Procurement, R&D Input and the Selling Expense

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) Gardner (2021), and (4) Sun and Abraham (2021). Panel (a) displays the estimated dynamic treatment effects on R&D-to-sales ratio for CVBP-winning firms. Panel (b) shows corresponding estimates for selling expenses-to-sales ratio. 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)

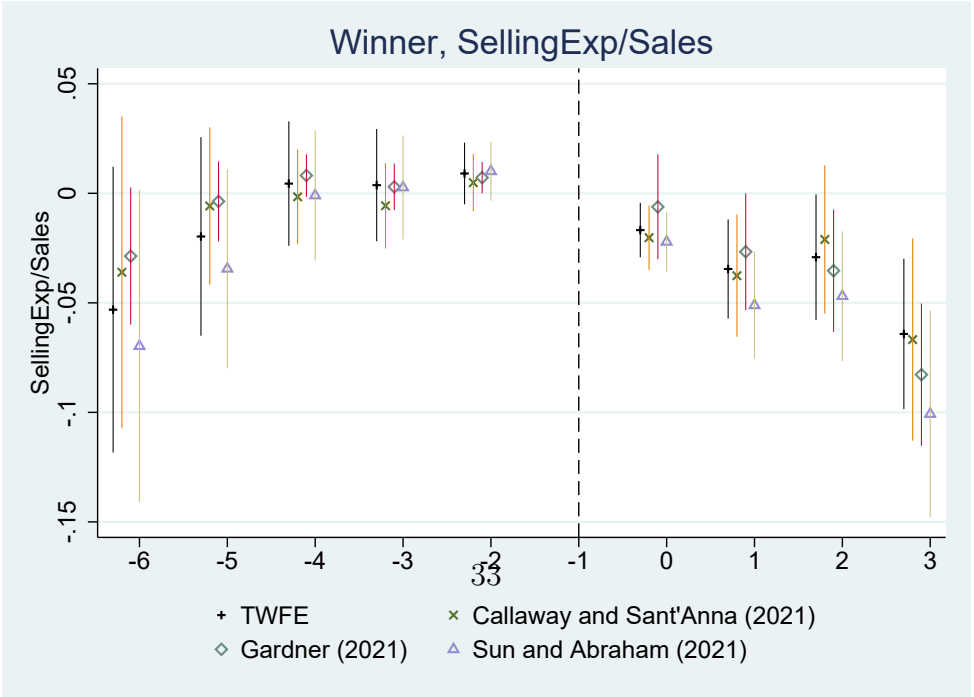


Table 2: **Overview of the CVBPs' Impact on the Whole Healthcare Market**

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 based on the CSMAR value-weighted market return **CAR2** uses an industry-specific value-weighted return index. 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), Active Pharmaceutical Ingredients (API) (40), Biological Products (52), Distribution and Circulation (25), Medical Devices and Equipment (79), and Medical Services (94). In total, the analysis covers 473 A-share listed firms. **t-values** indicate statistical significance, and asterisks in the "Significance" column denote the corresponding confidence levels based on these t-tests.

Panel A. Market Reaction (Whole Pharmaceutical Market)				
	CAAR	t	N (Events)	Significance
CAR1	-1.126	-9.48	3230	***
CAR2	-0.884	-7.69	3230	***
Panel B. Separate Results for Each Round				
	CAAR1	N (Events)	CAAR2	N (Events)
Round0	-3.518***	295	0.926***	295
Round1	-2.111***	302	-2.177***	302
Round2	1.923***	305	0.089	305
Round3	-1.796***	321	-0.916**	321
Round4	-2.220***	352	-2.744***	352
Round5	-2.615***	370	-1.910***	370
Round6	2.157***	395	0.562	395
Round7	-1.339***	429	-0.563**	429
Round8	-1.088***	461	-1.108***	461
Panel C. Results Exclude Round2 & Different Sub-categories (CAR1)				
	CAAR	t	N (Events)	Significance
Whole Healthcare Market	-1.444	-11.61	2925	***
Sub Categories				
Chemical Drugs	-2.404	-8.48	712	***
Chinese Medicine	-0.909	-5.02	548	***
API	-0.689	-2.37	250	**
Biological Products	-1.125	-3.93	278	***
Circulation	-3.260	-3.83	176	***
Medical Devices and Equipment	-1.230	-3.38	433	***
Medical Service	-0.803	-2.89	528	***

Table 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 4: **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 5: **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 **bid-winning firms** 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 6: **Summary Statistics for the Main Variables (add definition later)**

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. Variable definitions are provided in detail in Appendix I.

Variables	N	Mean	S.D.	Min	P25	P75	Max
Dependent Variables							
R&D/TA	1070	0.036	0.031	0.001	0.017	0.046	0.187
R&D/Sales	1070	0.084	0.100	0.001	0.036	0.095	0.735
Patent	975	17.122	36.012	0.000	1.017	16.267	252.525
Citation	1038	13.393	20.339	0.000	1.807	14.673	115.503
SellingExp/TA	1070	0.122	0.100	0.003	0.043	0.175	0.472
SellingExp/Sales	1070	0.236	0.168	0.005	0.087	0.345	0.671
Independent Variables							
Procured × Post	1070	0.236	0.425	0	0	0	1
Dummy of Repeated Treatment	1070	0.084	0.278	0	0	0	1
Number of Repeated Treatment	1070	0.108	0.381	0	0	0	2
Ln(Cumulative Procured Exposure)	1070	2.016	3.693	0	0	0	11.190
Controls							
Ln(TA)	1070	22.391	1.103	20.358	21.553	23.152	25.254
Ln(MV)	1070	22.965	0.981	21.197	22.217	23.630	25.992
Ln(Sales)	1070	21.664	1.315	19.314	20.645	22.553	25.517
Sales/TA	1070	0.548	0.296	0.108	0.365	0.648	1.799
ROE	1070	0.089	0.125	-0.392	0.037	0.149	0.499
ROA	1070	0.049	0.071	-0.232	0.021	0.087	0.219
EBITDA/TA	1070	0.086	0.063	-0.135	0.054	0.120	0.254
Book Leverage	1070	0.108	0.104	0	0.014	0.178	0.428
Market Leverage	1070	0.101	0.149	0	0.005	0.132	0.779
SEO/TA	1070	0.021	0.078	0	0	0	0.486
CashBond/TA	1070	0.004	0.020	0	0	0	0.133
CashBorrow/TA	1070	0.124	0.118	0	0.018	0.201	0.472
SEO/Sales	1070	0.052	0.208	0	0	0	1.389
CashBond/Sales	1070	0.009	0.050	0	0	0	0.393
CashBorrow/Sales	1070	0.288	0.331	0	0.029	0.430	1.619

Table 7: **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:

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

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) Sales-to-Total Assets; (3) Return on Equity (ROE); (4) Return on Assets (ROA); (5) EBITDA-to-Total Assets. 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, Return on assets (ROA), Tobin's Q, 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) Sales/TA	(3) ROE	(4) ROA	(5) EBITDA/TA
Procured × Post	-0.140***	-0.043*	-0.001	-0.006	-0.006
	(0.050)	(0.023)	(0.015)	(0.007)	(0.006)
Ln(Asset)	0.585***	-0.059**	-0.050***	-0.024***	-0.008
	(0.065)	(0.028)	(0.016)	(0.009)	(0.008)
ROA	1.573***	0.258*			
	(0.307)	(0.143)			
Tobin's Q	0.027**	0.005	0.006**	0.004**	0.005***
	(0.012)	(0.005)	(0.002)	(0.002)	(0.002)
Leverage	0.210	0.202***	0.026	-0.012	0.003
	(0.179)	(0.075)	(0.053)	(0.027)	(0.025)
Cash/TA	-0.206	0.019	0.062*	0.047**	0.030
	(0.163)	(0.065)	(0.036)	(0.023)	(0.021)
CapExp/TA	0.334	-0.164	-0.071	-0.027	-0.041
	(0.356)	(0.144)	(0.119)	(0.066)	(0.065)
PPE/TA	0.500*	0.204**	-0.112	-0.031	0.033
	(0.267)	(0.089)	(0.093)	(0.040)	(0.034)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
No. of Firms	181	181	181	181	181
Mean of Y (Before)	21.520	0.544	0.073	0.052	0.089
Observations	1070	1070	1070	1070	1070
R^2	0.454	0.151	0.071	0.093	0.103

Table 8: **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:

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

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. **Columns (1)–(2)**: R&D intensity, measured as the ratio of R&D to Sales. **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 (also 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) R&D/Sales	(2) R&D/Sales	(3) Ln(1+Patents)	(4) Ln(1+Citations)	(5) Ln(1+Filed)	(6) Filed
Procured × Post	0.011**	0.013***	-0.013	-0.084	-0.140	-0.080
	(0.004)	(0.004)	(0.059)	(0.102)	(0.114)	(0.091)
Ln(Asset)		0.016**	0.166***	-0.068	0.328***	0.302**
		(0.008)	(0.059)	(0.116)	(0.102)	(0.143)
ROA		-0.153***	0.026	0.360	0.691	0.209
		(0.051)	(0.282)	(0.578)	(0.518)	(0.534)
Tobin's Q		-0.001	0.011	-0.013	0.001	-0.019
		(0.001)	(0.009)	(0.025)	(0.025)	(0.022)
Leverage		-0.059**	0.295*	0.078	0.307	0.151
		(0.027)	(0.178)	(0.284)	(0.351)	(0.455)
Cash/TA		0.001	0.674***	-0.005	0.271	0.388
		(0.023)	(0.197)	(0.452)	(0.379)	(0.469)
CapExp/TA		0.153***	0.829*	-0.732	2.616**	2.955**
		(0.052)	(0.424)	(0.921)	(1.034)	(1.243)
PPE/TA		0.038	0.015	-0.507	0.180	-0.379
		(0.035)	(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)	0.079	0.079	0.572	1.087	2.280	19.150
Observations	1070	1070	1070	1070	871	871
R^2	0.127	0.182	0.086	0.389	0.773	

Table 9: **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:

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

The treatment group consists of A-share listed firms that successfully secured at least one CVBP bid. The control group includes listed firms operating in adjacent 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) Selling expenses to total sales (SellingExp/Sales); (2) Advertising and promotion expenses to sales (SellingExp_Adv/Sales); (3) Seasoned equity offerings to total sales (SEO/Sales); (4) Cash inflows from bond issuance to total sales (CashBond/Sales); (5) Cash inflows from borrowings to total sales (CashBorrow/Sales). The key explanatory variable, *Procured* × *Post*, is an interaction term equal to 1 if firm i has won a CVBP bid and the observation year is post-treatment, 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 Expenses		External Financing		
	(1) SellingExp/Sales	(2) SellingExp_Adv/Sales	(3) SEO/Sales	(4) CashBond/Sales	(5) CashBorrow/Sales
Procured × Post	-0.028***	-0.018**	-0.035	-0.004	0.024
	(0.009)	(0.008)	(0.022)	(0.006)	(0.022)
Ln(Asset)	-0.014	-0.023	-0.119***	0.007	0.167***
	(0.021)	(0.016)	(0.045)	(0.005)	(0.046)
ROA	-0.117	-0.096	0.693***	0.026	-0.214
	(0.078)	(0.086)	(0.182)	(0.029)	(0.211)
Tobin's Q	-0.002	-0.005	-0.007	-0.000	-0.009
	(0.003)	(0.003)	(0.009)	(0.001)	(0.007)
Leverage	0.007	0.069	0.455***	-0.011	0.275**
	(0.040)	(0.043)	(0.129)	(0.020)	(0.125)
Cash/Sales	0.021	0.041	-0.305**	-0.009	-0.375***
	(0.038)	(0.044)	(0.134)	(0.022)	(0.115)
CapExp/Sales	0.011	-0.025	-0.345	-0.008	0.427
	(0.124)	(0.106)	(0.304)	(0.039)	(0.443)
PPE/Sales	0.037	0.028	-0.112	0.019	-0.092
	(0.079)	(0.066)	(0.194)	(0.036)	(0.210)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
No. of Firms	181	165	181	181	181
Observations	1070	984	1070	1070	1070
R^2	0.171	0.118	0.106	0.052	0.124

Table 10: **Robustness: Alternative Estimators**

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. The model specifications are consistent with those presented in prior tables. Panel A employs R&D intensity (R&D/Sales) as the dependent variable. Panel B uses selling expenses to sales (SellingExp/Sales) as the dependent variable. All specifications include firm and year fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. 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 (Borusyak, Jaravel, and Spiess, 2021); did2s (Gardner, 2021). 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/Sales					
TWFE	0.014	0.004	***	0.005	0.022
Callaway and SantaAnna (2021)	0.017	0.007	**	0.004	0.030
Borusyak, Jaravel, and Spiess (2021)	0.018	0.005	***	0.009	0.028
Gardner (2021)	0.026	0.008	***	0.011	0.042
Panel B, Selling Expenses/Sales					
TWFE	-0.027	0.009	***	-0.045	-0.009
Callaway and SantaAnna (2021)	-0.025	0.013	**	-0.050	-0.001
Borusyak, Jaravel, and Spiess (2021)	-0.033	0.009	***	-0.051	-0.015
Gardner (2021)	-0.025	0.011	**	-0.047	-0.003

Table 11: **Robustness: Balanced Panel and Results After Matching**

Note: This table assesses the robustness of the baseline results using two complementary strategies: a balanced panel analysis and propensity score matching (PSM). The following staggered difference-in-differences (DiD) model with two-way fixed effects is estimated:

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

To construct the balanced panel, we restrict the sample to firms with continuous data from 2015 to 2022, dropping observations with missing years. Columns (1)–(2) report results using this balanced panel. For the PSM exercise in Columns (3)–(4), we use firms' 2015 (pre-treatment) characteristics to estimate propensity scores and match treated and control firms using 1-nearest-neighbor matching without replacement. 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. The dependent variables are: R&D/Sales (Columns 1 & 3) and Selling Expenses/Sales (Columns 2 & 4). The key independent variable, *Procured* × *Post*, equals 1 for firm-year observations following a firm's first CVBP win, and 0 otherwise. All specifications 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. Standard errors shown in parentheses are clustered at the firm level.

	Balanced Panel		After Matching	
	(1) R&D/Sales	(2) SellingExp/Sales	(3) R&D/Sales	(4) SellingExp/Sales
Procured × *Post*	0.010**	-0.026***	0.019***	-0.021*
	(0.004)	(0.009)	(0.005)	(0.011)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
No. of Firms	99	99	68	68
Observations	792	792	544	544
R^2	0.228	0.238	0.256	0.253

Table 12: **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:

$$Outcome_{i,t+1} = \alpha_i + \beta_1 Procured \times Post_{i,t} + \beta_2 Repeated_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}$$

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-sales (Columns 1–2) and selling expenses-to-sales (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 i wins an additional CVBP bid in year t following its initial win. *Number of Repeated Treatment*$_{i,t}$ is a continuous variable counting the number of additional bids won by firm i in year t 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/Sales		SellingExpenses/Sales	
	(1)	(2)	(3)	(4)
Procured × Post	0.011***	0.012***	-0.024***	-0.025***
	(0.004)	(0.004)	(0.009)	(0.009)
Dummy of Repeated Treatment	0.008		-0.014	
	(0.008)		(0.010)	
Number of Repeated Treatment		0.004		-0.010
		(0.005)		(0.006)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
No. of Firms	181	181	181	181
Observations	1070	1070	1070	1070
R^2	0.184	0.183	0.173	0.173

Table 13: **Heterogeneity: Procurement Exposure**

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

$$Outcome_{i,t+1} = \alpha_i + \beta_1 ln(Cumulative\ Procured\ Exposure_{i,t}) + \delta_i + \gamma_t + \varepsilon_{i,t}$$

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: Column (1): R&D expenses to sales, Column (2): Selling expenses to sales. 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.

	Input	
	(1) R&D/Sales	(2) SellingExp/Sales
Ln(Cumulative Procured Exposure)	0.002***	-0.004***
	(0.001)	(0.001)
Firm Controls	✓	✓
Firm FE	✓	✓
Year FE	✓	✓
No. of Firms	181	181
Observations	1070	1070
R^2	0.185	0.175

Table 14: **The Impact of Procurement for the Rivals (Continued)**

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:

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

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 (i.e., 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: Column (1): ln(Sales); Column (2): Return on Equity (ROE); Column (3): Return on Assets (ROA); Column (4): EBITDA/Total Assets; Column (5): R&D/Sales. 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	EBITDA/TA	R&D/Sales
	(1)	(2)	(3)	(4)	(5)
Rival × Post	-0.132**	-0.003	-0.009	-0.011	0.007
	(0.066)	(0.017)	(0.015)	(0.013)	(0.005)
Ln(Asset)	0.527***	-0.038**	-0.022	-0.016	-0.002
	(0.076)	(0.019)	(0.013)	(0.014)	(0.006)
ROA	1.460***				-0.008
	(0.449)				(0.052)
Tobin's Q	0.043***	0.007**	0.005**	0.005**	-0.001
	(0.015)	(0.003)	(0.002)	(0.002)	(0.002)
Leverage	0.571**	0.165**	0.054	0.059*	-0.034*
	(0.235)	(0.068)	(0.043)	(0.035)	(0.017)
Cash/TA	0.367**	0.157***	0.100***	0.103***	-0.027
	(0.185)	(0.043)	(0.030)	(0.027)	(0.026)
CapExp/TA	1.283**	-0.010	0.047	0.108	0.002
	(0.562)	(0.099)	(0.102)	(0.108)	(0.060)
PPE/TA	0.329	-0.028	-0.064	0.013	0.008
	(0.344)	(0.089)	(0.053)	(0.051)	(0.040)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
No. of Firms	110	110	110	110	110
Observations	575	575	575	575	575
R^2	0.542	0.116	0.125	0.141	0.074

Table 15: **The Impact of Procurement for the Rivals**

Note: This table explores changes in selling expenses and financing behavior among **rival firms** following the implementation of CVBP, using a two-way fixed effects (TWFE) specification:

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

The sample includes firms that manufacture the same active pharmaceutical ingredients (APIs) as those included in CVBP rounds but were not selected (i.e., rival firms), along with firms in unaffected segments of the healthcare sector—namely, non-vaccine biological products, blood products, medical equipment, and APIs (control group). The sample period spans from 2015 (three years prior to CVBP Round 0) to 2023. The dependent variables across columns are: (1) Selling expenses to sales, (2) Advertising and promotion expenses to sales, (3) Seasoned equity offering to sales, (4) Cash received from issuing bonds to sales, (5) Cash received from borrowings to sales. The key explanatory variable, $Rival \times Post_{i,t}$, equals 1 if a firm produces molecules included in CVBP but has not participated in the bidding, and the year is after the molecule was subject to procurement. Control variables include lagged values of: log market capitalization, 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. Standard errors shown in parentheses are clustered at the firm level.

	SellingExp/Sales	SellingExp_Adv/Sales	SEO/Sales	CashBond/Sales	CashBorrow/Sales
	(1)	(2)	(3)	(4)	(5)
Rival × Post	-0.049***	-0.040**	-0.090*	0.010*	-0.048
	(0.018)	(0.017)	(0.050)	(0.005)	(0.048)
Ln(Asset)	-0.021	-0.014	-0.291***	0.012*	0.028
	(0.018)	(0.017)	(0.074)	(0.006)	(0.067)
ROA	-0.149	-0.113	0.847***	0.075*	0.037
	(0.106)	(0.107)	(0.306)	(0.043)	(0.235)
Tobin's Q	-0.003	-0.002	0.008	0.000	-0.007
	(0.002)	(0.002)	(0.015)	(0.001)	(0.008)
Leverage	0.057	0.041	0.532**	-0.042	0.375**
	(0.043)	(0.043)	(0.210)	(0.027)	(0.164)
Cash/TA	-0.049*	-0.044	-0.190	-0.021	-0.296**
	(0.027)	(0.028)	(0.189)	(0.024)	(0.125)
CapExp/TA	-0.077	-0.067	-0.032	-0.008	0.316
	(0.127)	(0.124)	(0.564)	(0.036)	(0.489)
PPE/TA	-0.108	-0.059	-0.818**	0.044**	-0.141
	(0.074)	(0.070)	(0.332)	(0.022)	(0.256)
Firm FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
No. of Firms	110	110	110	110	110
Observations	575	545	575	575	575
R^2	0.144	0.112	0.112	0.057	0.082

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 CVBPs reform (2018). Then, we compile a specialized dictionary, featuring key terms that identify the bidding activities related to CVBPs. 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 CVBPs, such as "Centralized Strike", "Province Procured"[15], and "Procured continue". In this process, we directly narrow the search period to within two weeks before and after the CVBPs' 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

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

procured firms, accounting for one-fourth of all bid-winning manufacturers. This indicates that using listed firms to investigate the impact of CVBPs on firms offers a strong level of representativeness.

A.2 Tables

Table A.1: **Overview of the CVBPs' 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: **Appendix: Impact of CVBPs on Firm Innovation**

Note: This table evaluates the impact of successful procurement under the CVBP reform on firms' innovation input, using the following staggered difference-in-differences (DiD) specification with two-way fixed effects:

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

The treatment group includes A-share listed firms that successfully won at least one CVBP bid. The control group comprises firms in unaffected healthcare sectors, including non-vaccine biological products, blood products, medical equipment, and APIs. The estimation period spans from 2015 (three years before CVBP Round 0) through 2023. The dependent variables are: Columns (1)–(2): Natural logarithm of R&D expenditure; Columns (3)–(4): R&D expenditure as a share of total assets (R&D/TA). The key independent variable, $Procured \times Post_{i,t}$, is an interaction term; $Procured_i = 1$ if firm i ever won a CVBP bid; $textitPost_t = 1$ for all years after a firm's first win, 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 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.

	Raw R&D		R&D/TA	
	(1) Ln(R&D)	(2) Ln(R&D)	(3) R&D/TA	(4) R&D/TA
Procured × Post	-0.061	-0.011	0.002	0.002
	(0.053)	(0.043)	(0.002)	(0.002)
Ln(Asset)		0.621***		0.003
		(0.076)		(0.003)
ROA		0.735***		-0.016
		(0.255)		(0.010)
Tobin's Q		0.028**		0.001*
		(0.012)		(0.000)
Leverage		-0.276		-0.017**
		(0.181)		(0.008)
Cash/TA		-0.113		-0.000
		(0.190)		(0.008)
CapExp/TA		1.773***		0.045**
		(0.471)		(0.018)
PPE/TA		0.615**		0.028***
		(0.281)		(0.011)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
No. of Firms	181	181	181	181
Mean of Y (Before)	18.552	18.552	0.034	0.034
Observations	1070	1070	1070	1070
R^2	0.485	0.623	0.158	0.192