Financial Shocks, Intangible Reallocation, and Innovation

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Abstract

Innovation is often viewed as vulnerable to financial shocks. We show that this view is incomplete: when a shock also lowers the value of non-R&D intangible spending, innovation need not be the margin firms cut. We study China's centralized volume-based drug procurement reform, which reduced pharmaceutical firms' revenues and market valuations while weakening the return to hospital-directed promotion. Exposed firms experience negative abnormal returns and substantial sales declines, yet average R&D investment and short-run patent outcomes do not fall. Instead, firms sharply reduce selling and promotion expenses, while administrative expenses do not decline and external financing does not increase. R&D resilience is stronger among firms with greater pre-shock scope to compress selling expenses and stronger innovation capacity; similar patterns appear among rival firms that lose procurement-prioritized market access. The evidence is consistent with an internal reallocation channel: firms absorb financial stress by changing the composition of intangible spending rather than by raising outside capital or cutting innovation.

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

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1 Introduction

Innovation is widely viewed as particularly vulnerable to financial shocks. Because R&D is risky, intangible, and difficult to collateralize, firms facing weaker cash flows or tighter external financing are thought to scale back innovative investment before other forms of spending. A substantial corporate-finance literature builds on this view, documenting that R&D is sensitive to internal cash flow (Himmelberg and Petersen, 1994; Brown et al., 2009; Brown and Petersen, 2011), hinges on access to external equity and debt markets (Hall and Lerner, 2010; Fang et al., 2014; Kerr and Nanda, 2015; Mann, 2018), and contracts following adverse financial shocks(Aghion et al., 2012; Granja and Moreira, 2023). Yet this perspective abstracts from an important margin of adjustment. Firms allocate substantial resources to intangible activities beyond R&D, including marketing, promotion, distribution relationships, and customer acquisition. These expenditures, like R&D, generate long-lived but illiquid assets. When a shock simultaneously reduces available resources and depresses the return to some of these non-R&D intangibles, innovation need not be the margin firms cut first.

This paper investigates this overlooked margin. We ask whether financial shocks shape innovation not only by changing the level of internal funds, but also by changing the composition of intangible investment inside the firm. A standard negative cash-flow shock that leaves relative returns unchanged predicts a contraction in R&D. By contrast, a shock that simultaneously reduces cash flows and erodes the return to a competing intangible margin creates a different trade-off. Firms may preserve R&D by compressing the now less valuable non-R&D margin, especially when they have both redeployable spending and innovation opportunities worth protecting. Our central argument is therefore not that innovation is generally immune to financial shocks, but that the effect of such shocks depends on the structure and redeployability of firms' other expenditures.

We test this mechanism in the context of China's centralized volume-based drug procurement (CVBP) reform. The reform replaces decentralized, hospital-level purchasing with a centralized tendering system that allocates guaranteed procurement volumes to suppliers selected through competitive bidding. This setting is useful in that CVBP delivers two concurrent shocks to pharmaceutical firms. First, it sharply compresses procurement prices, eroding revenues and depressing market valuations. Second, by substituting

centralized purchase commitments for hospital-level sales competition, it diminishes the marginal return to promotional expenditure, distribution relationships, and sales efforts directed at hospitals. This dual structure renders the setting uniquely suited to our question: the very policy that tightens financial constraints simultaneously lowers the shadow value of selling expenses, opening an internal margin through which firms can shield R&D investment.

We construct a panel of publicly listed Chinese pharmaceutical firms by linking procurement outcomes to stock-market data, financial statements, and innovation measures. We first use event studies around procurement announcements to assess whether investors viewed CVBP as a negative shock to firm value. We then exploit the staggered rollout of procurement across molecules and firms to examine how procurement exposure affects revenue, profitability, R&D, selling expenses, administrative expenses, external financing, and innovation outputs. This empirical design connects market-based valuation effects and product market performance to subsequent real adjustments inside the firm.

We find that procurement exposure generates a substantial negative financial shock. Around procurement announcements, affected firms experience negative abnormal returns, indicating that investors revise downward their expectations of future profitability. The shock also appears in accounting data: procurement winners experience large declines in sales, showing that the price reductions dominate any offsetting increase in guaranteed volume. These results establish the central empirical tension of the paper. CVBP reduces firm value and revenues, yet firms do not respond by cutting R&D.

We next examine innovation investment. Despite the negative valuation and revenue effects, average R&D investment does not decline after procurement exposure. R&D scaled by assets is also statistically unchanged, and patent-based measures also show no short-run deterioration. We interpret these results cautiously: the absence of an average decline does not imply that innovation is unaffected for all firms, nor does it prove that long-run innovation quality is unchanged. Instead, the average result motivates the central question of the paper: how do firms preserve R&D when a shock reduces both market value and revenues?

The evidence points to a targeted internal adjustment rather than broad cost cutting or external financing. Procurement winners sharply reduce selling expenses, especially advertising and promotion expenses, the category most directly linked to hospital-level

sales competition. By contrast, administrative expenses do not decline significantly. This contrast is important: it suggests that firms are not simply cutting operating expenses across the board. The adjustment is concentrated in the spending margin, whose value is most directly reduced by centralized procurement. At the same time, firms do not increase seasoned equity offerings, bond issuance, or borrowing after the shock. Thus, the stability of R&D is not accompanied by replacement financing from external capital markets.

Cross-sectional evidence further disciplines this interpretation. If selling expenses provide a potential internal buffer, the pattern should be stronger among firms with more scope to compress such expenses before the shock. Consistent with this prediction, firms with higher pre-shock selling expenses reduce selling-expense intensity more after procurement exposure and exhibit a stronger increase in R&D intensity. The R&D response is also concentrated among firms with stronger innovation capacity, measured by pre-shock innovation orientation and R&D intensity. These patterns suggest that R&D resilience requires two conditions: a spending margin whose value has declined and can be compressed, and innovation opportunities valuable enough to protect.

We also examine rival firms that produce the same molecules as procurement winners but are not selected in the corresponding CVBP round. Rivals face a sharper loss of market access and larger revenue declines, but they also maintain R&D, reduce selling-related expenses, and do not increase external financing. The rival-firm evidence shows that R&D resilience is not confined to winners receiving guaranteed procurement volumes. Rather, the same qualitative pattern appears among firms exposed to procurement-induced displacement without the benefit of guaranteed demand.

We interpret these findings as evidence consistent with an internal reallocation channel, while recognizing the limits of what the data can identify. We do not directly observe firms' internal budgeting process, nor do we claim that each dollar saved from selling expenses is mechanically transferred into R&D. An alternative interpretation is that firms independently adjust along two margins: reducing selling expenses because promotion becomes less valuable, while maintaining R&D because R&D budgets are sticky or because firms have pre-existing innovation pipelines. Our evidence cannot fully rule out this view. However, the institutional design of the shock, the targeted decline in selling and promotion expenses, the absence of broad administrative cost cuts, the lack of external

financing, the heterogeneity by pre-shock selling-expense scope and innovation capacity, and the parallel evidence from rivals together make the reallocation interpretation economically plausible. The contribution is therefore to show that the innovation consequences of financial shocks depend on the composition and redeployability of intangible spending inside firms, not only on the level of financing available to them.

The paper contributes first to the literature on finance and innovation. Prior work shows that cash-flow shocks, financing frictions, and capital-market access shape R&D and innovation outcomes. Internal cash flow and external equity are especially important for young and high-tech firms (Brown et al., 2009), while public capital-market access and financial conditions affect both the level and nature of innovative activity (Acharya and Xu, 2017; Bernstein, 2015). We add a different margin: the redeployability of internal spending. Our findings suggest that innovation is not always the first casualty of financial stress. Whether R&D falls depends not only on the severity of the shock, but also on whether other spending margins become less valuable and can be compressed.

Second, the paper contributes to research on intangible investment. Much of the finance literature treats R&D, advertising, selling expenses, and organizational capital as related components of intangible capital. Our results show that these components need not move together. When hospital-directed promotion becomes less valuable, firms cut selling and promotion expenses while preserving R&D, especially when they have stronger innovation capacity. The results therefore highlight a hierarchy within intangible spending: some intangible investments are more redeployable than others, and their relative value changes with the economic environment.

Third, the paper contributes to the literature on corporate responses to regulation. Regulation is often studied as a shock that constrains firms, reduces profits, or changes investment incentives.Our setting shows that regulation can also change the relative productivity of different expenditures. CVBP compresses revenues, but it also weakens the return to promotion. This dual effect helps explain why a large negative shock to revenues and market valuations does not translate into an average decline in R&D. More broadly, the real effects of regulation depend not only on how much cash flow regulation removes, but also on which activities regulation makes less valuable.

Finally, the paper speaks to ongoing debates over pharmaceutical price regulation. A central concern in these debates is that lower drug prices may reduce firms' incentives

or ability to innovate. Our evidence does not imply that price regulation is generally harmless for innovation. Instead, it identifies a condition under which adverse innovation effects may be muted: when price regulation also reduces the return to promotional expenditures that are less central to long-run innovation. This distinction matters for policy design. Price regulation may have different innovation consequences depending on whether it primarily compresses productive investment or also curbs spending margins that firms can redeploy.

The rest of the paper proceeds as follows. Section 2 describes China's centralized procurement reform and develops the empirical predictions. Section 3 presents the data, sample construction, and empirical design. Section 4 documents the stock-market and revenue effects of procurement exposure. Section 5 examines R&D resilience, targeted internal adjustment, heterogeneity, and rival-firm responses. Section 6 presents robustness tests. Section 7 concludes.

2 Institutional Background: The Introduction of CVBP

China's CVBP program marked a structural transformation of the country's pharmaceutical market. The initial "4+7 Pilot" targeted 25 drug molecules across four municipalities and seven major cities. Following the pilot, the program rapidly expanded nationwide through nine subsequent rounds, ultimately encompassing 374 drug molecules (Table A.1). The National Healthcare Security Administration (NHSA), established in 2018 as the single national payer, now aggregates over half of China's prescription drug demand, leveraging its monopsony power to negotiate deeply discounted prices with manufacturers.[1] To ensure compliance, the NHSA incentivizes hospitals to allocate 50-80% of their previous drug volumes to winning suppliers, guaranteeing a fixed quantity of sales in exchange for steep price reductions.

Procurement process. The CVBP proceeds in three sequential stages: (1) quantity reporting, (2) competitive bidding, and (3) hospital procurement. First, all public and

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

designated private hospitals are required to report their anticipated purchase quantities for the coming year, typically amounting to 60-80% of their annual prescriptions.

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

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

Market implications. The CVBP's large-scale, top-down design has fundamentally reshaped China's pharmaceutical industry. Most winning firms are domestic generic manufacturers, as the selected molecules are typically off-patent with multiple generic substitutes and widely used. In addition, the NHSA prioritizes high-expenditure molecules that account for a substantial share of public spending. Unlike global Big Pharmas, which typically balance R&D and marketing, China's generics manufacturers have historically prioritized sales promotion over R&D. By removing the need for intensive marketing, the CVBP compresses firms' selling expenses while preserving guaranteed demand, forcing a structural reallocation of resources. Empirically, Jiang et al. (2026) document that the average price of procured drugs fell by roughly 64%, resulting in a 56% decrease in overall expenditure for these molecules.[2] Given that over 50% of hospital drug purchases now occur under the procurement[3], the reform effectively internalizes much of the pharmaceutical distribution, which sharply reduces the necessity for traditional promotional activities. Firms must adapt to redesign their cost structures and innovation strategies.

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

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

These profound industry shifts motivate our central research question: how do firms re-optimize R&D and financing behavior under the dual pressures of revenue compression and guaranteed market access?

3 Data, Sample, and Empirical Strategy

3.1 Data Sources

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

Procurement Data. We collect detailed information on the eight rounds of centralized volume-based procurement (CVBP) from the Shanghai Sunshine Medical Procurement All-in-One platform.[4] The dataset includes the procured drug molecules, winning firms, winning prices, procured volumes, and both preliminary and formal disclosure dates. We focus on the preliminary announcement date, which marks the first public release of award results and therefore represents the relevant information event for investors.[5] Because our event-study design relies on a short observation window, precise timing of this disclosure is essential to avoid contamination of the estimation by other market events. We link each awarded molecule to its corresponding producers using DXY Insight, a commercial pharmaceutical intelligence platform, to identify non-winning producers of the same molecules (hereafter referred to as "rivals").[6] These data form the basis for

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

[5] We focus on the preliminary disclosure date because it is the first public release of procurement award results and therefore represents the relevant information event for investors. The subsequent formal disclosure typically follows shortly after the preliminary release and contains limited incremental information.

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

both our event-study analysis of stock-market reactions and our staggered difference-in-differences (DiD) estimation of firms' post-procurement outcomes.

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

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

3.2 Sample

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

Event-Study Sample. We begin with all A-share listed healthcare firms traded on the Shanghai and Shenzhen stock exchanges that have been listed for at least one year as of the end of 2023. Firms are categorized according to the Shenyin & Wanguo industry classification, which provides detailed sub-industry groupings within healthcare. We exclude firms under Special Treatment (ST) or Particular Transfer (PT) designations due to

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

abnormal trading patterns.[8] We also remove firms with insufficient estimation windows around the CVBP announcement dates. After applying these filters, the final event-study sample comprises 484 firms, of which 109 are CVBP bid winners. [9]

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

3.3 Empirical Strategy for Market Reactions

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

Formally, we estimate the market model:

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

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

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

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

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

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

We estimate CARs and CAARs using two alternative benchmarks for $R_{M,t}$: the value-weighted market return from CSMAR and the return on the healthcare index 000991.SH, which tracks 117 A-share healthcare firms.[10] We denote the corresponding measures as CAR1/CAAR1 and CAR2/CAAR2, respectively. The 80-day pre-event window is intentionally short to minimize contamination from overlapping events across procurement rounds, which were often closely spaced in time.[11] We then aggregate firm-level CAR_i across all affected firms to compute the cumulative average abnormal return (CAAR), which captures the average market valuation effect of procurement announcements.

3.4 Empirical Strategy for Firm Performance

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

We estimate the following model:

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

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

The dependent variables $Outcome_{i,t+1}$ are lagged by one year to mitigate simultaneity concerns and capture post-shock adjustments. We consider three categories of outcomes:

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

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

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

Treatment and Control Design. Our analysis considers two distinct treatment groups examined separately: procurement-winning firms, which experience direct cash-flow shocks from regulated price cuts and guaranteed purchase volumes, and rival firms producing the same molecules but not winning the bid, which are exposed to indirect competitive pressures. The control group includes firms operating in four healthcare sub-industries: *non-vaccine biological products*, *blood products*, *medical equipment*, and *APIs*. Two considerations guide their selection: the firms should be operationally and financially comparable to the treated firms yet minimally exposed to the CVBP program, and they must not participate in COVID-related product chains such as vaccines, diagnostic kits, or antiviral treatments.

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

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

marized in Table 2.

The summary statistics for the DiD analysis are presented in Table 2. Although the regressions later apply logarithmic transformations or truncation adjustments to certain variables, Table 2 reports the raw value to provide a more transparent overview. It shows that firms in our sample generally exhibit substantial selling expenses, yielding average selling expenses to total assets of 15.1%. In contrast, the R&D to total assets is merely 1/5 of this figure, highlighting the financial imbalance characteristic of the healthcare sector. This pattern differs from that of U.S.-listed firms: over the same sample period, R&D/TA (COMPUSTAT XRD/AT) averages 18.24%, compared with only 3.4% for marketing intensity (COMPUSTAT XAD/AT).

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

4 Negative Market Reaction and Revenue Loss Due to CVBP

4.1 Overall Market Reaction to CVBP Announcements

We begin by examining whether CVBP announcements were viewed by investors as negative valuation shocks to healthcare firms. Since investor responses may differ across procurement rounds and industry subsectors, we further decompose the announcement effects by both dimensions. Panel A of Table 1 reports the CAARs for all listed healthcare firms across nine procurement rounds, starting from the 4+7 Pilot (Round 0), covering 3,230 firm-round observations. On average, $CAAR1$ is –1.13%, implying an average wealth loss of roughly 134.8 million RMB per firm during the three-day window.[13] Using the healthcare industry index as the benchmark, which nets out broad healthcare-sector movements and therefore provides a more conservative comparison, $CAAR2$ remains negative at -0.884%.

[13]It is calculated based on the average pre-event market capitalization of 11.97 billion RMB as of September 2018.

Panel B decomposes the results by round. Under the broad market benchmark, all rounds except Rounds 2 and 6 generate significantly negative abnormal returns. Under the healthcare-industry benchmark, the negative pattern remains for most rounds, except the pilot round, Round 2, and Round 6. Round 6, which targeted insulin and was narrower in product scope, generated a positive $CAAR1$, but the effect becomes insignificant once benchmarked against the industry index ($CAAR2$). Round 2 coincided with the initial COVID-19 outbreak in China[14], when COVID-related news generated unusually positive returns for several antibiotic producers.[15]. This contemporaneous shock is consistent with the positive *CAAR1* in Round 2 and with the disappearance of the effect under the healthcare-industry benchmark. Investor reactions appear to attenuate over time as the CVBP becomes institutionalized. Although the decline is not strictly monotonic, the magnitudes of $CAAR1$ and $CAAR2$ in Rounds 7-8 are substantially smaller than the large negative reactions observed in the earlier rounds, suggesting that later announcements were increasingly anticipated by the market.

We next examine whether the valuation shock is concentrated in subsectors most exposed to the procurement reform. Panel C reports CAARs by Shenyin & Wanguo healthcare subcategory,[16] excluding Round 2 to reduce contamination from the early COVID-19 shock. The largest losses occur in Distribution/Circulation and Chemical Drugs. Under *CAAR1*, Distribution/Circulation falls by -3.26%, while Chemical Drugs falls by -2.40%; the corresponding *CAAR2* estimates are -2.84% and -1.89%.

The results are consistent with the economics of the reform. Chemical-drug producers are directly exposed to procurement-driven price compression, while distributors face a decline in intermediation rents as centralized procurement replaces decentralized hospital-level purchasing and weakens the value of traditional distribution relationships. Taken together, these results establish the first empirical fact of the paper: CVBP announcements were perceived by equity investors as negative valuation shocks, especially for firms

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

[15]For example, *Lukang Pharmaceutical Co., Ltd.* gained 5.4% around the COVID-related event window.

[16]Using the Shenyin & Wanguo Industry classification, we divide firms into seven groups: Chemical Drugs (N=109), Chinese Medicine (N=74), APIs (N=40), Biological Products (N=52), Distribution (N=25), Medical Device and Equipment (N=79), and Medical Services (N=94).

and subsectors most closely tied to drug procurement and distribution.

4.2 Cross-Firm Heterogeneity in Market Reactions

The previous subsection shows that CVBP announcements generated a negative valuation shock for the healthcare sector as a whole. We now examine whether investors differentiated across firms with different positions in the procurement process. We classify firms into three groups: *winners*, defined as firms awarded contracts in any CVBP round; *Rivals*, defined as chemical-drug firms producing the same molecules as winning firms but not selected for procurement;[17] and *Prospective participants*, defined as chemical-drug producers that neither win bids nor produce the same molecules as winning firms, but may be exposed to future procurement as the program expands. Table A.2 shows that winners are substantially larger and more profitable than prospective participants, so we complement raw CAR comparisons with regressions controlling for firm characteristics and procurement-round fixed effects.

Table A.3 compares three-day CAR across groups. Panel A pools all nine rounds. Winners experience negative but statistically insignificant abnormal returns, whereas rivals and prospective participants experience much larger and statistically significant losses. Under the broad market benchmark, rivals lose 2.45% and prospective participants lose 2.40%, compared with 0.43% for winners. The same ranking holds under the healthcare-index benchmark. This pattern is consistent with the asymmetric exposure embedded in the CVBP design: winners accept steep price cuts but receive guaranteed procurement volume, whereas rivals lose access to prioritized hospital demand and therefore face sharper market-share losses.

To mitigate contamination from Round 2, which coincided with the onset of COVID-19, Panel B excludes this round. The pattern remains: winners' abnormal returns become negative and statistically significant, but their losses remain substantially smaller than those of rivals and prospective participants. Table A.4 confirms this ranking in OLS regressions with firm-level controls and round fixed effects. winners experience 1.17 percentage points higher abnormal returns than rivals and 1.19 percentage points higher

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

abnormal returns than prospective participants under the broad market benchmark, with similar estimates under the healthcare-index benchmark. Overall, investors did not price CVBP as a uniform negative shock. Instead, they distinguished between firms receiving guaranteed procurement volume and firms facing current or anticipated exclusion from the procurement channel. This heterogeneity clarifies the nature of the shock we study: winners face price-induced revenue compression, while rivals face a sharper loss of expected market access.

4.3 Impact of CVBP on Firms' Sales and Profitability

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

Theoretically, the CVBP introduces a trade-off between price concessions and volume expansion. Whether total revenues decline depends on which effect dominates. Column (1) of Table 3 demonstrates that, on average, firms winning CVBP contracts experienced an 18% decline in sales, implying that the negative price effects outweighed the potential increase in market share. We omit firm size (log of total assets) from the regression since the dependent variable, sales, already captures firm scale.

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

5 The Resilience of R&D under Procurement-Induced Financial Stress

The evidence in Section 4 establishes that CVBP exposure generated a negative shock to both firm valuation and product-market revenues. A natural next question is how firms

adjust to simultaneous shocks in both capital and product markets. Do they curtail their innovation investment, or instead reprioritize internal spending in a way that preserves R&D? We study this question in two steps. We first examine whether R&D investment and innovation output decline after procurement exposure. We then ask whether the stability of R&D is accompanied by targeted adjustments in other financing and spending margins, especially selling expenses, administrative expenses, and external financing. We address these questions using the staggered DiD framework described in Section 3.4.

5.1 R&D Does Not Decline after the Procurement Shock

We begin by estimating the effect of winning a procurement bid on firms' innovation inputs and outputs. Columns (1)–(2) of Table 4 present estimates from Equation (3), where the dependent variables are the natural logarithm of R&D expenditure and R&D scaled by total assets. We avoid using the common R&D-to-sales ratio because sales decline sharply following CVBP participation, as shown in Table 3, and using sales as the denominator would mechanically inflate R&D intensity after the shock.

Columns (3)–(6) examine innovation output using $\ln(1 +$ granted patents$)$, $\ln(1 +$ forward citations$)$, $\ln(1 +$ filed patent applications$)$, and the raw number of filed patent applications. We focus on invention patents (IPs), which are generally considered the most original and technologically demanding patent type in China (Tian and Xu, 2022).[18] To mitigate truncation concerns in patent-based outcomes, following Hall et al. (2001), we normalize patent counts and citations by the average number of patents applied for or citations received within the same technology class and year.[19] [20]

Table 4 shows that the coefficients on procurement exposure are statistically insignif-

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

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

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

icant across all six outcomes. Thus, despite the negative valuation and revenue effects documented in Section 4, procurement winners do not reduce R&D spending on average. Nor do we find evidence of a short-run deterioration in patent-based innovation outcomes.

The null response of patent outcomes should be interpreted with caution. Patents, grants, and citations are long-horizon measures, and their response may not fully materialize within the post-treatment window available in our sample. Such lags are particularly relevant in chemical and pharmaceutical innovation, where development cycles are long and patenting outcomes may reflect projects initiated before the procurement shock (Brav et al., 2018). For this reason, we place greater weight on the R&D input results when interpreting firms' short-run real responses. Nevertheless, the absence of any contraction in R&D expenditure is economically striking. It contrasts with the conventional view that negative financial shocks depress innovative investment, especially when innovation is risky, intangible, and difficult to finance externally (e.g., Ji and Rogers, 2024). This result creates the central puzzle for the remainder of the section: how do firms preserve R&D when procurement exposure reduces both firm value and revenues?

5.2 Targeted Internal Adjustment: Selling Expenses, Administrative Expenses, and External Financing

We next examine whether the stability of R&D is accompanied by adjustments in other spending and financing margins. The reallocation interpretation predicts that the adjustment should be concentrated in the category whose marginal return was most directly reduced by CVBP: hospital-directed selling and promotion. By contrast, if firms were simply engaging in broad-based cost-cutting, we would expect reductions across other operating expense categories as well. To test this prediction, we re-estimate Equation (3) using selling expenses, promotion-related expenses, administrative expenses, and external financing measures as dependent variables.

Column (1) of Table 5 shows that procurement winners reduce selling expenses by roughly 19.5% after CVBP exposure. Column (2) confirms this pattern when selling expenses are scaled by total assets. This decline is consistent with the institutional design of CVBP: by guaranteeing purchase volumes in exchange for lower prices, the CVBP reform reduces the value of decentralized hospital-level sales competition. Consequently,

firms have less need to maintain costly promotion and distribution relationships aimed at influencing hospital purchasing decisions.

The composition of the expense response further supports this interpretation. Column (3) shows a significant decline in advertising and promotion expenses, the component most directly linked to hospital-directed marketing. By contrast, employee wages associated with sales functions remain statistically unchanged. Importantly, administrative expenses also do not decline significantly. This null result is informative because administrative expenses are not the spending category most directly affected by the procurement reform. The contrast between the sharp decline in selling and promotion expenses and the insignificant response of administrative expenses suggests that firms did not cut operating expenses indiscriminately. Instead, the adjustment is concentrated in the margin whose economic value was most directly weakened by centralized procurement. When administrative expenses are measured net of R&D, this comparison also alleviates the concern that the stability of administrative expenses mechanically reflects the stability of R&D.

These results support the reallocation interpretation in two ways. First, they show that firms respond to the shock by compressing a large non-R&D intangible spending category. Second, because the decline is concentrated in selling and promotion rather than administrative expenses, the evidence is more consistent with targeted reprioritization than with generalized austerity. We then examine whether external capital markets provide an alternative explanation for R&D resilience. If firms preserved R&D by replacing lost internal funds with outside capital, we should observe increases in equity issuance, bond financing, or borrowing after procurement exposure. We test three external financing channels: seasoned equity offerings, bond issuance, and borrowing, each normalized by total assets. Results reported in Columns (5)–(7) of Table 5 show that the coefficients are statistically insignificant across all three outcomes. Thus, we find no evidence that procurement winners increased external financing after the shock. This pattern is consistent with the negative announcement returns documented earlier and with the broader view that weak investor sentiment and costly external finance limit firms' ability to raise capital following adverse shocks (Baker and Wurgler, 2000; McLean and Zhao, 2014; López-Salido et al., 2017).

Taken together, Table 5 shows that the stability of R&D is accompanied by a targeted decline in selling and promotion expenses, no comparable decline in administrative ex-

penses, and no increase in external financing. These patterns do not by themselves prove that each dollar saved from selling expenses was mechanically redirected to R&D. Rather, they indicate that procurement exposure changed the composition of internal spending in a way that is consistent with selling-expense compression serving as an internal buffer for R&D. The next subsection examines whether this interpretation is stronger among firms with greater pre-shock scope to compress selling expenses and stronger innovation opportunities to protect.

5.3 Scope for Reallocation and Innovation Capacity

The insignificant average effect on R&D in Table 4 does not necessarily imply that all firms respond similarly to the procurement shock. Instead, the average effect may mask substantial heterogeneity in firms' capacity to absorb the shock and in the value of preserving innovation. In particular, if some firms are better positioned to reprioritize internal resources to maintain R&D, while others are not, the average effect may appear close to zero even when meaningful adjustments occur within important subgroups.

We therefore examine heterogeneity along two dimensions that speak directly to the internal resource reallocation channel. The first dimension is the firms' pre-shock scope to compress selling expenses. If procurement reduces the return to promotional spending, firms with higher pre-shock selling expenses should have more room to cut such expenditures after the reform. This does not mechanically imply that the savings are redirected dollar-for-dollar into R&D, but it implies that these firms have a larger internal margin through which they can buffer innovation spending. The second dimension is the firms' innovation capacity. Even if resources are freed internally, not all firms are equally likely to redeploy them into R&D. Firms with stronger innovative capability may have more valuable pipelines to protect and a greater ability to translate internal funds into innovation activity.

Panel A of Table 6 shows a heterogeneous effect by pre-shock selling expenses. We define an indicator, $\mathbb{1}\{PreSelling_i \geq Q_{1/2}(PreSelling)\}$, equal to one if firm i's average pre-shock selling expenses exceed the sample median. The interaction term, $Procured \times Post \times \mathbb{1}\{PreSelling_i \geq Q_{1/2}(PreSelling)\}$ is positive and statistically significant when the dependent variable is R&D scaled by total assets. Economically, the estimate implies

that, following the procurement shock, firms with high pre-shock selling expenses increase R&D intensity by about 0.6 percentage points more than firms with low pre-shock selling expenses. Relative to a pre-shock mean R&D-to-assets ratio of roughly 3%, this effect is economically meaningful.

At the same time, the same subgroup exhibits a significantly larger decline in selling-expense intensity after treatment. Taken together, these results are consistent with the first condition of the reallocation channel: firms with greater pre-existing selling expenses have a larger margin to compress once procurement reduces the value of hospital-directed promotion, and these firms are also the ones for which R&D intensity rises more after the shock. This pattern is difficult to reconcile with a purely broad-based cost-cutting interpretation, especially in light of the evidence in Table 5 that administrative expenses do not decline significantly.

Panel B then turns to heterogeneity in innovation capacity. We use two proxies. The first is an indicator for whether a firm is a Type-I pharmaceutical producer, which is commonly associated with stronger innovative capability. The second is an indicator for whether the firm's average pre-shock R&D expenditure exceeds the sample median, $\mathbb{1}\{PreR\&D_i \geq Q_{1/2}(PreR\&D)\}$. Across both measures, the data suggest that the post-procurement response of R&D is stronger among firms with greater innovative capacity. In contrast, firms with weaker innovation orientation, such as more generic-focused producers, show little evidence of increasing R&D following the shock.

These heterogeneous patterns help reinterpret the baseline null result in Table 4. Rather than implying that procurement has no implications for innovation, the average null masks differences in how firms absorb the shock. Firms with stronger innovation capacity appear more likely to preserve or expand R&D, whereas firms with weaker innovation orientation show little evidence of such adjustment. This conditional response is consistent with the view that the innovation consequences of price regulation depend not only on the size of the revenue shock, but also on firms' internal margins of adjustment and their underlying innovation capability.

Overall, the heterogeneity results point to two necessary conditions for R&D resilience under financial stress. Firms need a spending margin whose value has declined and can therefore be compressed, and they need innovation opportunities valuable enough to protect. The evidence is strongest where these conditions are most likely to hold: among firms

with high pre-shock selling expenses and among firms with stronger innovation capacity. We view these patterns as disciplined evidence consistent with internal reallocation, rather than as definitive causal mediation from selling-expense cuts to R&D.

We also explore heterogeneity by ownership type. The estimates suggest that non-SOEs exhibit a stronger positive response of R&D intensity following procurement, whereas the corresponding effect for SOEs is substantially weaker. By contrast, both SOEs and non-SOEs reduce selling-expense intensity after the reform, with no strong evidence of a statistically meaningful difference in the size of that decline. One interpretation is that the procurement reform reduces the return to promotional expenditures for all firms, but non-SOEs may have greater budgeting flexibility or stronger incentives to use the resulting internal slack to support innovation. This pattern is consistent with differences in governance, innovation incentives, or internal budgeting flexibility across ownership types. At the same time, given the limited precision of these interaction estimates, we view the ownership results as suggestive rather than definitive.

5.4 Internal Adjustment Beyond Bid Winners: Evidence from Rival Firms

The preceding results focus on procurement winners, which face price compression but also receive guaranteed procurement volumes. This institutional feature raises a natural question: is R&D resilience unique to winners, or does a similar adjustment occur among firms exposed to the same molecule-level procurement shock without receiving guaranteed demand? To address this question, we examine rival firms, defined as firms producing the same molecules as winning firms but not selected in the corresponding CVBP round. Rivals provide a useful comparison because they are exposed to the same procurement-induced decline in the value of hospital-level sales competition, but they face a sharper loss of prioritized market access.

We re-estimate Equation (3) by replacing the interaction term $Procured_i \times Post_{i,t}$ with $Rival_i \times Post_{i,t}$. The results are presented in Table 7. As shown in Column (1) of Table 7, rival firms experience a sharper contraction in revenues (26.2%) than bid winners (18.5%), consistent with market-share allocation under price-cap competition. Yet, similar to winners, rivals' profitability, in terms of ROE and ROA (Columns (2)–(3)

of Table 7), remains stable. This stability suggests that rivals also adjust along other margins rather than experiencing a proportional deterioration in accounting profitability.

Columns (4)–(5) show that rivals do not significantly reduce R&D spending or R&D intensity after procurement exposure. This finding is informative because rivals face a more severe product-market displacement than winners and do not benefit from guaranteed procurement volume. If the stability of R&D among winners were driven solely by the mechanical demand guarantee embedded in winning contracts, we would expect a weaker R&D response among rivals. Instead, R&D remains stable for this group as well.

Notably, rivals exhibit a sharper reduction in selling expenses than winners, with the estimated decline exceeding that observed for bid winners (Table 7, Column (6)). This larger decline is consistent with the loss of hospital procurement access and the reduced value of maintaining sales efforts for molecules displaced by centralized procurement. Interestingly, the composition of the adjustment differs between winners and rivals. Winners primarily reduce advertising and promotion expenses, whereas rivals reduce selling-related wages, consistent with a contraction of sales operations following reduced market access. Columns (10)–(12) show no significant change in rivals' external financing. Thus, as with winners, the preservation of R&D among rivals is not accompanied by increased equity issuance, bond financing, or borrowing.

Overall, the rival-firm results complement the evidence from bid winners. Rivals experience larger revenue losses and more negative market reactions, as shown in Table A.3, yet they also maintain R&D while compressing selling-related expenses and without increasing external financing. This pattern suggests that R&D resilience is not confined to firms that receive guaranteed procurement volumes. Rather, it appears among procurement-exposed firms more broadly, alongside adjustments in the selling-expense margin most directly affected by the reform.

We interpret the rival evidence as complementary rather than definitive. It does not prove that reductions in selling expenses causally finance R&D. Instead, it strengthens the reallocation interpretation by showing that the same qualitative pattern—stable R&D, lower selling-related expenses, and no increase in external financing—also holds for firms facing procurement-induced displacement without the benefit of guaranteed demand.

5.5 Interpreting the Reallocation Channel

The evidence in this section points to an internal reallocation channel, but it is useful to clarify what this interpretation does and does not require. Our empirical design identifies the effect of procurement exposure on firms' spending composition: CVBP reduces firm value and revenues, leaves average R&D investment statistically unchanged, sharply compresses selling and promotion expenses, does not reduce administrative expenses, and is not accompanied by an increase in external financing. These facts establish that firms adjust the composition of internal spending after the shock. They do not, by themselves, allow us to observe the internal budgeting process or to prove that each dollar saved from selling expenses is mechanically transferred into R&D. We therefore interpret reallocation as an economically disciplined reading of the joint response of spending margins, rather than as a fully identified causal mediation from selling-expense cuts to R&D.

This distinction is important because an alternative interpretation is possible: firms may independently adjust along two margins, reducing selling expenses because promotion becomes less valuable while maintaining R&D because R&D budgets are sticky or because firms have pre-existing innovation pipelines. Our evidence cannot completely rule out this interpretation. However, several features of the results make the reallocation interpretation more plausible than a simple independent-adjustment story. First, the institutional design of CVBP directly changes the relative return to different intangible expenditures. The reform does not merely reduce cash flows. By centralizing procurement decisions and assigning guaranteed purchase volumes, it weakens the role of decentralized hospital-level promotion, distribution relationships, and sales efforts. Selling expenses therefore, become the spending category whose marginal value is most directly reduced by the policy, whereas R&D is not mechanically targeted by the procurement rule.

Second, the observed cost adjustment is targeted rather than broad-based. If firms were simply responding to financial stress by cutting operating expenses indiscriminately, we would expect reductions across multiple expense categories. Instead, Table 5 shows that the decline is concentrated in selling and promotion expenses, while administrative expenses do not decline significantly. This pattern is difficult to reconcile with generalized austerity. It is more consistent with firms reducing a particular intangible margin whose value falls after centralized procurement. The absence of increased equity issuance, bond

financing, or borrowing further suggests that the stability of R&D is not financed by replacing lost revenues with outside capital.

Third, the cross-sectional evidence is consistent with the two conditions under which internal reallocation should matter most. If selling expenses provide a potential buffer, the response should be stronger among firms with greater pre-shock scope to compress that margin. This is what we find: firms with higher pre-shock selling expenses reduce selling-expense intensity more and exhibit a stronger increase in R&D intensity after procurement exposure. At the same time, reallocation toward R&D should be valuable only when firms have innovation opportunities worth protecting. Consistent with this prediction, the R&D response is stronger among firms with greater pre-shock innovation capacity. These patterns do not prove causal mediation, but they discipline the mechanism by showing that R&D resilience is concentrated where both the available margin of adjustment and the incentive to preserve innovation are likely to be strongest.

Fourth, the evidence from rival firms suggests that the pattern is not unique to bid winners receiving guaranteed procurement volumes. Rivals face a sharper loss of market access and larger revenue declines, yet they also maintain R&D, reduce selling-related expenses, and do not increase external financing. This result helps address the concern that R&D stability among winners is driven only by the demand guarantee embedded in winning contracts. Instead, the same qualitative adjustment appears among firms exposed to procurement-induced displacement without the benefit of guaranteed demand.

Taken together, these results support a specific interpretation of how firms absorb the shock. CVBP is not a standard negative cash-flow shock that leaves all investment returns unchanged. It simultaneously reduces revenues and lowers the value of a competing non-R&D intangible margin. Firms respond by reducing the spending category most directly devalued by the reform, while preserving R&D when innovation opportunities are sufficiently valuable. Thus, our contribution is not to claim that selling-expense cuts are the only causal reason R&D does not fall. Rather, we show that the innovation consequences of financial shocks depend on the composition and redeployability of internal spending. When a shock reduces the return to non-R&D intangible investment, firms may absorb financial stress by reprioritizing across intangible categories instead of cutting innovation first.

6 Robustness Checks

We conduct several robustness checks to assess the stability of our main findings. First, we examine dynamic treatment effects and implement alternative staggered DiD estimators that address treatment-effect heterogeneity. Second, we test whether the results are sensitive to sample composition by using a balanced panel and a propensity-score-matched sample. Third, we account for repeated procurement wins and replace the binary treatment indicator with a continuous measure of procurement exposure. Across these exercises, the core pattern remains unchanged: CVBP significantly reduces selling expenses, while R&D investment remains statistically unaffected.

6.1 Dynamic Effects of CVBP and Alternative Estimators

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

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

where $Procured_i \times Post_{i,k}$ equals one if year t for firm i is k years from its first procurement win. We set k = -1 as the reference year.

The dependent variables are R&D and selling expenses, both scaled by total assets. The specification includes the same firm-level controls ($X_{i,t}$), firm (δ_i) and year (γ_t) fixed effects as in the baseline model.

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

Figure 2 presents the dynamic estimates across these estimators. The coefficients in pre-treatment periods are statistically indistinguishable from zero, supporting the parallel trends assumption. At $k = 3$, the confidence interval widens because only firms treated in the earliest rounds contribute to this event-time bin. Across all estimators, selling

expenses decline sharply following CVBP, while R&D remains unaffected. The dynamic evidence therefore mirrors the baseline result: the reform changes the composition of internal spending rather than reducing R&D.

Table 8 reports the corresponding static estimators from alternative staggered DiD methods. [21]. The results are consistent across all methods: CVBP has no significant impact on R&D investment, while significantly reducing selling expenses. These findings confirm that our main conclusions are not driven by estimator choice or treatment-effect heterogeneity.

6.2 Matched and Balanced Sample Analyses

We next address potential concerns about sample composition. We restrict the analysis to a balanced panel covering 2015-2022. Sample imbalance may arise if newly listed firms differ systematically from older firms in their likelihood of winning procurement bids or if short pre-treatment histories distort treatment-effect estimates. Restricting to a balanced panel ensures comparable pre- and post-treatment histories across firms. [22]

This restriction yields 792 firm-year observations. Columns (1)-(2) of Table 8 show that the results remain robust: CVBP has no impact on R&D investment but leads to a pronounced reduction in selling expenses. Thus, the baseline findings are not driven by changes in sample composition over time.

We also implement propensity score matching (PSM) on the balanced panel to improve comparability between treated and control firms. Treatment and control firms are matched based on log(total assets), ROA, Tobin's Q, leverage, cash holdings, capital expenditures, and fixed-asset intensity, applying radius matching (caliper=0.5). After dropping the observations without common support, the matched sample includes 608 firm-year observations. Columns (3)-(4) of Table 8 demonstrate that our results remain consistent in this matched sample. The PSM estimates therefore alleviate concerns that the baseline effects are driven by observable differences between procurement winners and control firms.

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

[22] For example, a firm that went public in 2020 and participated in CVBP in 2022 has only one pre-treatment observation if the IPO year is excluded. In contrast, a firm listed before 2015 and participated in CVBP in 2022 contributes seven pre-periods (2015–2021).

6.3 Firms with Multiple CVBP Wins and Continuous Measurement

Next, we account for heterogeneity in treatment intensity. Some firms win bids in multiple procurement rounds for different molecules, generating repeated treatment exposure. Because standard staggered DiD models typically define treatment by the first exposure, they may fail to capture the additional exposure created by subsequent wins. We extend Equation (3) by introducing measures of repeated treatment intensity:

$$Outcomes_{i,t+1} = \alpha_i + \beta_1 Procured_i \times Post_{i,t} + \beta_2 RepeatedTreated_{i,t} + X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (5)$$

where $RepeatedTreated_{i,t}$ takes two metrics: (1) a binary indicator (*Dummy of Repeated Treatment*), equal to one if a firm wins additional bids after its initial procurement win; and (2) a continuous variable

Number of Repeated Treatments

, counting the cumulative number of procurement rounds won by firm i up to year t. [23]. Table A.5 shows that the coefficients on Procured×post are similar to those in the baseline analysis, indicating that repeated procurement wins do not drive our main conclusions.

We further replace the binary treatment indicator in Equation (3) with a continuous measure of procurement exposure: the natural logarithm of the cumulative value of firm i'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.

Table A.6 reports the results. In Column (1), although the coefficient on R&D is statistically significant at the 10% level, its economic magnitude is small. By contrast, Column (2) shows that greater cumulative procurement exposure is associated with a larger decline in selling expenses scaled by total assets. Taken together, these findings

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

underscore meaningful heterogeneity in firms' exposure to CVBP: firms with higher cumulative procurement volumes experience more pronounced shifts in selling expenses, while the conclusion of no economically meaningful decline in R&D remains intact.

7 Discussion and Conclusion

This study examines how firms adjust innovation when a negative financial shock also changes the relative value of other intangible expenditures. Using China's centralized volume-based procurement (CVBP) reform as a quasi-natural experiment, we show that procurement exposure reduces firm value and revenues, but does not lead to an average decline in R&D investment. This finding is striking because R&D is typically viewed as especially vulnerable to financial stress. The evidence is consistent with an internal reallocation channel: firms sharply reduce selling and promotion expenses, while administrative expenses do not decline and external financing does not increase. The adjustment is therefore not a broad contraction in operating expenditures, nor does it appear to be financed by new outside capital. Rather, it is concentrated in the spending category whose marginal value is most directly reduced by centralized procurement.

The cross-sectional and rival-firm evidence further clarifies this interpretation. R&D resilience is stronger among firms with greater pre-shock scope to compress selling expenses and among firms with stronger innovation capacity, suggesting that the ability to preserve innovation depends on both a redeployable spending margin and innovation opportunities worth protecting. Rival firms, which face a sharper loss of market access without receiving guaranteed procurement volume, display a similar qualitative pattern: stable R&D, lower selling-related expenses, and no increase in external financing. Taken together, these findings suggest that firms' responses to financial shocks depend not only on the severity of the shock, but also on how the shock reshapes the relative productivity of different spending margins inside the firm.

We interpret the reallocation channel with appropriate caution. Our data do not allow us to observe internal budgeting decisions directly, nor do they prove that every dollar saved from selling expenses is mechanically transferred into R&D. An alternative interpretation is that firms independently reduce selling expenses because promotion becomes less valuable while maintaining R&D because innovation budgets are sticky or because

firms have pre-existing pipelines. However, the targeted decline in selling and promotion expenses, the absence of comparable administrative cost cuts, the lack of external financing, the heterogeneity by pre-shock selling-expense scope and innovation capacity, and the evidence from rivals together make the internal reallocation interpretation economically plausible. The broader lesson is that financial shocks affect innovation through the composition of internal spending, not only through the level of available funds.

These findings contribute to the literature at the intersection of corporate finance, regulation, and innovation. Prior work emphasizes that adverse cash-flow shocks and costly external finance can depress R&D. Our results highlight a countervailing margin: when a shock also lowers the value of non-R&D intangible spending, firms may preserve innovation by reprioritizing internal expenditures. This perspective suggests that intangible investment should not be treated as a homogeneous category. R&D, promotion, distribution relationships, and organizational spending may respond differently to the same shock depending on how the shock changes their relative returns.

The results also have implications for pharmaceutical price regulation. A central concern is that lower drug prices may undermine firms' ability or incentives to innovate. Our evidence does not imply that price regulation is generally harmless for innovation, nor does it establish the long-run effects of procurement on the development of truly novel drugs. Instead, it identifies a condition under which adverse innovation effects may be muted: price regulation may have less negative short-run effects on R&D when it also reduces promotional expenditures that are less central to long-run innovative capacity. For countries facing high drug prices and large promotional spending, centralized procurement may therefore improve allocative efficiency when it combines price reductions with a reduction in low-value selling efforts. Whether this adjustment remains sustainable over longer horizons, and whether it affects the quality and direction of pharmaceutical innovation, remain important questions for future research.

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Figure 1: Market Reaction to CVBP Pilot Launch

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

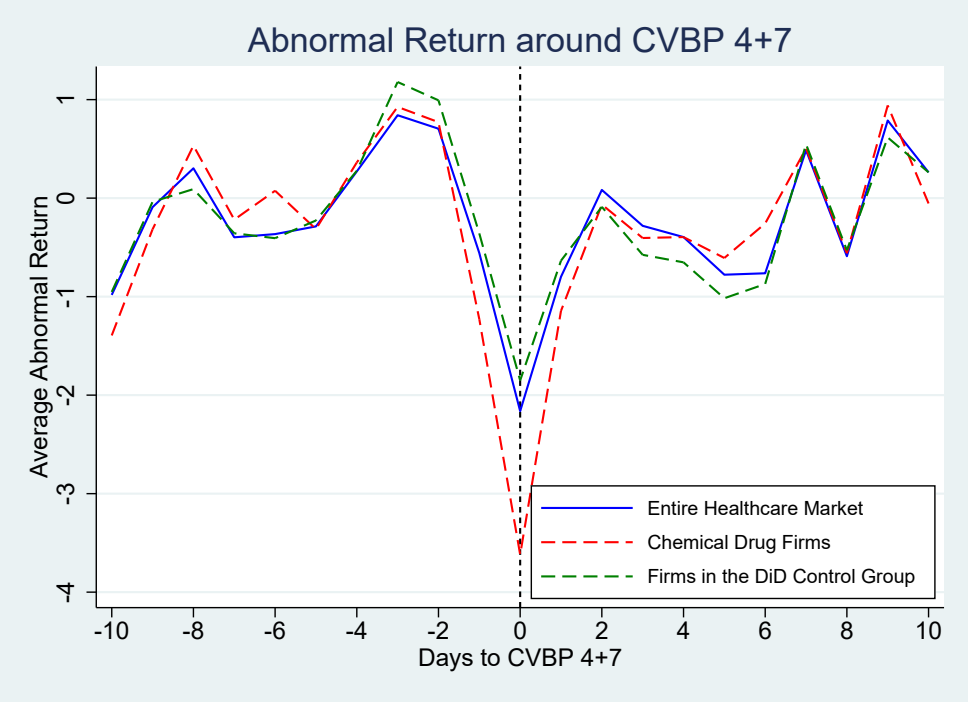
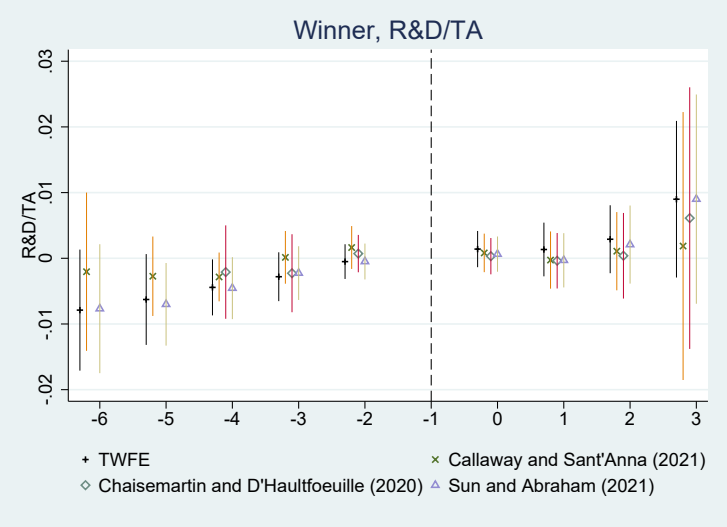


Figure 2: Dynamic Effect: Winning Procurement, R&D Input and the Selling Expense

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

Panel (a)



Panel (b)

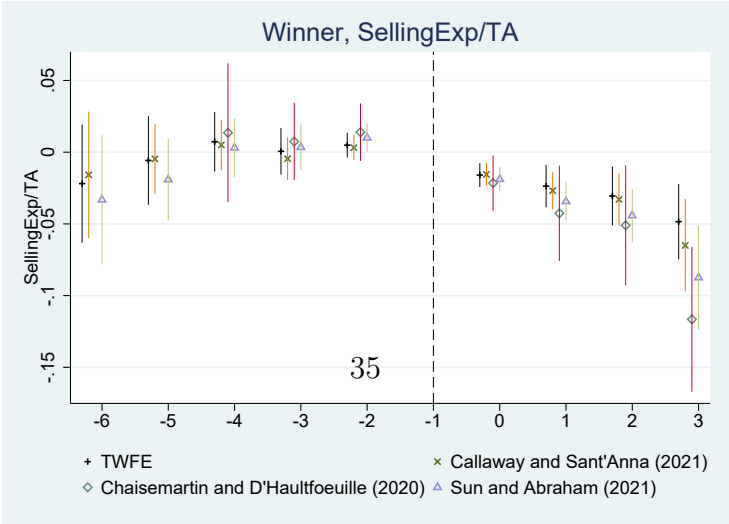


Table 1: **Overview of the CVBP's Impact on the Whole Healthcare Market**

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

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

Table 2: **Summary Statistics**

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. We winsorized all continuous variables at the 1st and 99th percentiles.

	Winners					Controls					Rivals				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
R&D (in million RMB)	695	366.422	581.721	10.371	3896.336	375	212.779	490.049	10.371	3896.336	200	137.820	139.086	12.696	776.835
R&D/TA	695	0.035	0.029	0.001	0.187	375	0.037	0.035	0.003	0.187	200	0.025	0.021	0.003	0.109
Patents	631	9.008	12.027	0	54	349	5.507	10.091	0	54	188	4.489	7.264	0	55
Citations	448	27.788	45.424	0	253	193	16.549	27.790	0	209	121	10.405	13.538	0	74
Filed	695	20.351	26.042	0	124	375	15.011	24.886	0	124	200	10.510	14.201	0	116
SellingExp (in million RMB)	695	1546.196	1919.084	9.716	9171.176	375	358.945	782.876	9.716	7304.458	200	891.083	1006.574	24.867	4165.564
SellingExp/TA	695	0.151	0.103	0.003	0.472	375	0.067	0.065	0.003	0.398	200	0.140	0.096	0.003	0.398
Sales (in million RMB)	695	9413.367	18733.050	244.219	120764.700	375	2553.696	4064.698	244.219	34931.900	200	4210.525	5692.186	358.231	30365.640
Procured (Rival) * Post	695	0.364	0.482	0	1	375	0	0	0	0	200	0.360	0.481	0	1
TA	695	11472.790	15352.320	631.633	83686.010	375	5138.366	7188.030	631.633	55184.710	200	6415.383	7261.635	580.647	46745.240
ROA	695	0.051	0.065	-0.215	0.219	375	0.061	0.071	-0.215	0.219	200	0.054	0.062	-0.220	0.216
Tobin's Q	695	2.582	1.837	0.865	13.204	375	3.830	2.657	1.080	13.204	200	2.481	1.435	1.096	9.978
Book Leverage	695	0.378	0.183	0.045	0.826	375	0.273	0.162	0.045	0.826	200	0.311	0.160	0.043	0.683
Cash/TA	695	0.161	0.111	0.019	0.550	375	0.204	0.123	0.019	0.550	200	0.154	0.104	0.013	0.559
CapExp/TA	695	0.049	0.041	0.003	0.227	375	0.064	0.050	0.003	0.227	200	0.038	0.031	0.003	0.177
PPE/TA	695	0.219	0.119	0.019	0.523	375	0.181	0.115	0.019	0.523	200	0.195	0.108	0.021	0.523

Table 3: **Baseline: Impact of CVBP on Firm Performance**

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

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

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

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

Table 4: **Baseline: Impact of CVBP on Firm Innovation Input and Output**

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

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

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

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

Table 5: **Targeted Internal Cost Adjustment and External Financing after CVBP**

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

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

The treatment group consists of A-share listed firms that successfully secured at least one CVBP bid. The control group includes listed firms operating similarly but in unaffected healthcare sectors: non-vaccine biological products, blood products, medical equipment, and active pharmaceutical ingredients (APIs). The analysis covers the period from 2015 (three years prior to Round 0) through 2023. The dependent variables across columns are: (1) Natural logarithm of selling expenses; (2) Selling expenses, normalized by total assets (SellingExp/TA); (3) Advertising and promotion expenses to total assets (SellingExp_Adv/TA); (4) Employee compensation under selling expenses, normalized by total assets (SellingExp_Wage/TA); (5) Administration expenses to total assets (Admin/TA); (6) Seasoned equity offerings to total assets (SEO/TA); (7) Cash inflows from bond issuance to total assets (CashBond/TA); (8) Cash inflows from borrowings to total assets (CashBorrow/TA). 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 firm characteristics: log of total assets, ROA, Tobin's Q, total debt-to-assets, cash holdings-to-assets, capital expenditures-to-assets, and property, plant, and equipment-to-assets. All regressions include firm fixed effects and year fixed effects. Standard errors, clustered at the firm level, are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	Selling and Marketing Expenses					External Financing		
	(1) Ln(SellingExp)	(2) SellingExp/TA	(3) SellingExp_Adv/TA	(4) SellingExp_wage/TA	(5) Admin/TA	(6) SEO/TA	(7) CashBond/TA	(8) CashBorrow/TA
Procured × Post	-0.195***	-0.023***	-0.012**	-0.000	0.000	-0.016*	-0.002	0.003
	(0.065)	(0.006)	(0.006)	(0.002)	(0.001)	(0.008)	(0.002)	(0.009)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
No. of Firms	181	181	168	168	181	181	181	181
Mean of Y (Before)	19.600	0.118	0.053	0.020	0.026	0.025	0.004	0.120
Observations	1070	1070	1003	1003	1070	1070	1070	1070
R^2	0.381	0.214	0.102	0.089	0.206	0.125	0.065	0.164

Table 6: **Heterogeneous Effects of Procurement**

Note: This table presents heterogeneous treatment effects of procurement exposure on R&D intensity and selling-expense intensity. The dependent variables are R&D expenditure and selling expenses, each scaled by total assets. Panel A interacts the treatment indicator with an indicator for firms whose pre-treatment selling-expense intensity is above the sample median, $\mathbb{1}\{PreSelling_i \geq Q_{1/2}(PreSelling)\}(HighPreSelling_i)$. Panel B interacts the treatment indicator with proxies for innovation capacity, including Type-I producer status and above-median pre-treatment R&D. Panel C interacts the treatment indicator with the SOE dummy, indicating whether the firm is a state-owned enterprise. 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.

Panel A. Heterogeneity by Pre-Period Selling Expenses

	(1) R&D/TA	(2) SellingExp/TA
Procured × Post	-0.002	-0.007
	(0.002)	(0.012)
Procured × Post × $HighPreSelling_i$	0.006**	-0.021*
	(0.003)	(0.012)
R^2	0.198	0.218

Panel B. Heterogeneity by Innovation Capacity

	(1) R&D/TA	(2) SellingExp/TA	(3) R&D/TA	(4) SellingExp/TA
Procured × Post	0.002	-0.023***	-0.002	-0.024**
	(0.002)	(0.006)	(0.002)	(0.010)
Procured × Post × $TypeI_i$	0.011**	0.010		
	(0.005)	(0.022)		
Procured × Post × $HighPreRD_i$			0.007***	0.002
			(0.002)	(0.011)
R^2	0.201	0.214	0.203	0.213

Panel C. Heterogeneity by SOE status

	(1) R&D/TA	(2) SellingExp/TA
Procured × Post	0.004*	-0.021***
	(0.002)	(0.006)
Procured × Post × SOE_i	-0.005*	-0.005
	(0.002)	(0.010)
Firm FE	✓	✓
Year FE	✓	✓
Firm Controls	✓	✓
No. of Firms	181	181
Mean of Y (Before)	0.034	0.118
Observations	1,070	1,070
R^2	0.197	0.214

Table 7: **The Impact of CVBP on Rivals' Performance and Responses**

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

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

The sample consists of firms that produce the same active pharmaceutical ingredients (APIs) as the procured products but were not selected in any CVBP round (defined as rivals), as well as firms in unaffected segments of the healthcare sector—namely, non-vaccine biological products, blood products, medical equipment, and APIs (control group). The analysis period spans from 2015 (three years before CVBP Round 0) through 2023. The dependent variables include: (1) Log of Sales; (2) Net Income on Equity (ROE); (3) Net Income on Assets (ROA); (4): Natural logarithm of firm R&D expenses; (5): firm R&D expenses, normalized by TA (total assets); (6) Natural logarithm of selling expenses; (7) Selling expenses, normalized by total assets (SellingExp/TA); (8) Advertising and promotion expenses to total assets (SellingExp_Adv/TA); (9) Employee compensation under selling expenses, normalized by total assets (SellingExp_Wage/TA); (10) Administration expenses to total assets (Admin/TA); (11) Seasoned equity offerings to total assets (SEO/TA); (12) Cash inflows from bond issuance to total assets (CashBond/TA); (13) Cash inflows from borrowings to total assets (CashBorrow/TA). The key independent variable, $Rival \times Post_{i,t}$, is a binary indicator equal to 1 if a firm produces molecules included in any CVBP round but did not win a bid, and the observation year is after that molecule's inclusion. Control variables include lagged values of: log total assets, ROA, Tobin's Q, total debt-to-assets, cash holdings-to-assets, capital expenditures-to-assets, and property, plant, and equipment-to-assets. All regressions include firm and year fixed effects. Standard errors, clustered at the firm level, are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Sales)	ROE	ROA	Ln(R&D)	R&D/TA	Ln(SellingExp)	SellingExp/TA	SellingExp_Adv/TA	SellingExp_wage/TA	Admin/TA	SEO/TA	CashBond/TA	CahBorrow/TA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Rival × Post	-0.262***	-0.005	-0.010	-0.004	0.002	-0.311***	-0.023**	-0.000	-0.005**	0.001	-0.023	0.002	-0.017
	(0.075)	(0.016)	(0.014)	(0.084)	(0.002)	(0.089)	(0.009)	(0.008)	(0.002)	(0.002)	(0.015)	(0.002)	(0.019)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
No. of Firms	110	110	110	110	110	110	110	102	102	110	110	110	110
Observations	575	575	575	575	575	575	575	545	545	575	575	575	575
R^2	0.394	0.102	0.109	0.603	0.154	0.424	0.138	0.034	0.106	0.159	0.134	0.061	0.111

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

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

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

A Appendix

A.1 Matching Stock Code Based on Molecular Producer Identification

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

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

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

Further, considering that tendering and bidding are significant operational information that CSRC necessarily requires, we downloaded all the firm announcements within listed firms in the pharmaceutical and healthcare industry since the initiation of CVBP reform (2018). Then, we compile a specialized dictionary, featuring key terms that identify the bidding activities related to CVBP. The dictionary includes terms such as "CVBP", "Bidding", "Volume", "Procured", "Drug League", and "Centralized". After this, we manually check whether the found items are what we need and drop the observations that have nothing to do with CVBP, such as "Centralized Strike", "Province Procured"[24],

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

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

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

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

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

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

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

Table A.2: **Summary Statistics for Winners, Rivals and Prospective Participants**

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

Panel A. Winners

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	290	14.710	7.883	1.000	30.000
Size	290	15993.560	22665.340	694.030	163435.500
ROE	290	9.353	11.266	-79.280	35.940
Net Profit	290	856.051	1243.294	-1990.729	6308.893
LEV	290	39.411	17.725	4.201	82.557
Equity	290	8206.152	9903.778	171.747	59066.210

Panel B. Rivals

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	246	13.874	8.396	1.000	30.000
Size	246	10805.320	19740.580	631.633	163435.500
ROE	246	7.342	17.506	-128.480	42.580
Net Profit	246	514.559	1024.323	-2654.938	6274.569
LEV	246	37.464	17.320	3.485	80.935
Equity	246	5490.383	7848.657	410.253	59066.210

Panel C. Prospective Participants

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	454	12.051	8.994	1.000	31.000
Size	454	4789.794	5598.775	58.176	34729.590
ROE	453	0.949	31.408	-402.110	55.730
Net Profit	454	158.888	690.007	-3249.544	6308.893
LEV	454	33.712	18.894	2.084	97.419
Equity	454	2946.283	3280.803	1.502	30787.000

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

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

Panel A, Round 0 - Round 8

	Winners		Rivals		
	N	Mean	N	Mean	Diff
CAR1	291	-0.428	249	-2.452***	2.025***
CAR2	291	-0.210	249	-1.790***	1.580***
	Winners		Prospective Participants		
CAR1	291	-0.428	462	-2.400***	1.972***
CAR2	291	-0.210	462	-2.255***	2.045***

Panel B, Exclude Round 2

	Winners		Rivals		
	N	Mean	N	Mean	Diff
CAR1	262	-0.910***	221	-3.112***	2.203***
CAR2	262	-0.493*	221	-2.156***	1.662***
	Winners		Prospective Participants		
CAR1	262	-0.910***	410	-2.666***	1.756***
CAR2	262	-0.493*	410	-2.291***	1.798***

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

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

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

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

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

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

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

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

The sample includes A-share listed firms that won at least one CVBP bid (treatment group) and firms in unaffected segments of the healthcare sector—specifically, non-vaccine biological products, blood products, medical equipment, and APIs (control group). The analysis period runs from 2015 (three years before CVBP Round 0) to 2023. The dependent variables are R&D-to-TA (Columns 1–2) and selling expenses-to-TA (Columns 3–4). The key variable, *Procured* × *Post*, equals 1 for firm-year observations in and after the year a firm wins its first bid. *Dummy of Repeated Treatment*$_{i,t}$ equals 1 if firm wins an additional CVBP bid in year following its initial win. *Number of Repeated Treatment*$_{i,t}$ is a continuous variable counting the number of additional bids won by firm *inyear* after its first win. All regressions include firm and year fixed effects, and control for lagged values of: log of total assets, ROA, Tobin's Q, total debt-to-assets, cash holdings-to-assets, capital expenditures-to-assets, and property, plant, and equipment-to-assets. Standard errors clustered at the firm level are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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

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

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

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

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

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