# Welfare Effects of Resale Price Maintenance: Evidence from the Chinese Pharmaceutical Industry*

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**Abstract**

This paper studies how resale price maintenance (RPM), a vertical practice that allows upstream manufacturers to directly control downstream retail prices, affects welfare. This effect is theoretically ambiguous because RPM can increase consumer welfare by eliminating double markups, but decrease it by facilitating price coordination across competing retailers. I provide empirical evidence of these effects by examining a high-profile antitrust case involving a pharmaceutical firm that was found to practice RPM and ruled to stop. Difference-in-differences estimates using a novel retail pharmacy-level dataset suggest the net effect of RPM decreases retail prices and is pro-competitive in this setting. The results also suggest that RPM reduces retailer markups and suppresses price dispersion across retailers. These findings are consistent with manufacturers' incentives of using RPM to both eliminate the double markup and coordinate the retail price. I build and estimate a structural model to disentangle these incentives. The model confirms that RPM is overall welfare-improving in this setting. However, the consumer surplus gain from RPM would have been 77% higher absent price coordination incentives. In addition, I show that under different market conditions RPM can lead to anti-competitive outcomes.

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# 1 Introduction

Producers usually reach consumers through intermediaries (retailers) and may seek to increase profits via vertical control. Whether various forms of vertical control should be allowed is an open regulatory question.[1] One important example is Resale Price Maintenance (RPM), a practice wherein upstream manufacturers control downstream retail prices. RPM is prevalent in many industries, including gas, automobiles, pharmaceuticals, and digital platforms, but regulation of RPM is controversial.[2] On the one hand, RPM can achieve vertical efficiency gains by eliminating double marginalization along the supply chain (Spengler, 1950). On the other hand, RPM can facilitate price coordination across competing retailers and soften downstream competition when a brand is sold by many retailers (Clark et al., 2023). Furthermore, RPM may be used to foreclose rival brands and limit upstream competition (Asker and Bar-Isaac, 2014). Thus, the welfare effect of RPM is theoretically ambiguous.

Despite the prevalence and controversy of RPM, an FTC commissioner once complained: "The truth is, there is very little empirical evidence to support any of these conflicting economic theories of benefit or harm (of RPM)."[3] The lack of evidence is partly due to the difficulty in observing business contracts, especially so for RPM, which is not always legal (MacKay and Smith, 2017). In addition, the data requirement for empirical analysis is high. The researcher ideally needs to observe wholesale prices, retail prices, and quantity extensively at different retailers to study RPM because it is essentially a vertical practice between a manufacturer and many retailers.

This study empirically examines the welfare implications of RPM with two goals. The first objective is to test the pro-competitive and anti-competitive theories of RPM. The second objective is to evaluate how the welfare impact would change under counterfactual market conditions and contract structures. To answer these research questions, my paper exploits a high-profile anti-trust case concerning RPM. Yangtze River Pharma Group (YRPG), a top

[1] The 2020 version of vertical merger guidelines issued by the Federal Trade Commission (FTC) and Department of Justice (DOJ) were withdrawn due to the "flawed discussion of the purported procompetitive benefits." The 2023 version of the guideline downplays the efficiency arguments. On the other hand, the courts have favored firms in all recent vertical merger cases— e.g., *AT&T/Time Warner (2018)*, *UnitedHealth/Change(2022)*, and *Illumina/GRAIL(2022)* on the basis of insufficient real-world evidence of competitive harm.

[2] In the U.S., RPM agreements were per se illegal under Section 1 of the Sherman Act for decades. *State Oil Co. v. Khan, 522 U.S. 3 (1997).* and *Leegin Creative Leather Products Inc. v. PSKS, Inc., 551 U.S. 877 (2007)* made maximum and minimum RPM no longer illegal per se, respectively, under federal law. China, the E.U., and many U.S. states still take a more stringent approach to RPM.

[3] Pamela Jones Harbour's Opening Remarks of FTC's Resale Price Maintenance Workshop on February 17, 2009.

pharmaceutical manufacturer in China, was found to use RPM to fix retail prices of five top-selling herb-based health supplements and OTC drugs in retail pharmacies. The regulatory agency eventually banned and terminated this instance of RPM because of its illegal per se status in China. To achieve my first research objective, I use design-based methods to estimate the treatment effects of terminating the RPM practice on retail prices, wholesale prices, quantities, and assortments of RPM products and competing products. To achieve the second objective, I estimate a flexible structural model of the supply chain, including demand for drugs and pharmacies, and Nash-in-Nash bargaining among drug manufacturers and retail pharmacies with or without RPM.

I exploit this quasi-natural experiment on RPM using a monthly panel of drugs sold in more than 80,000 retail pharmacies. The dataset's broad coverage of drugs and pharmacies provides insights into both brand and retailer competition. Also, critically for my analysis, the dataset includes retailer-specific wholesale prices of each drug, along with retail prices and quantities sold, enabling a detailed analysis of mechanisms of RPM, and a rich structural model of vertical relationships and bargaining power. To my knowledge, this dataset constitutes the most comprehensive coverage of the Chinese pharmaceutical market available to researchers.

To begin with, I map the institutions into a research design to estimate a causal effect of RPM on prices and quantities. I identify five products manufactured by YRPG under RPM before the investigation, henceforth referred to as "RPM products." The investigation led to a ban on RPM for these products. I define two additional groups of products: rival products, which are products within the same categories of RPM products produced by other firms, and control products, which include drug products in categories that do not include any products produced by YRPG. I use a difference-in-differences design comparing the outcomes of products under RPM and those in the control group before and after the investigation to estimate the treatment effects of banning RPM, and test whether the results support each theoretical hypothesis.

The design-based findings are as follows. First, I find that the retail prices of RPM products increased by approximately 5%, and the wholesale prices dropped by around 3% after RPM was banned. As a result, retail margins for these products nearly doubled, and the quantity sold dropped 12%. This is consistent with the efficiency argument that RPM eliminates the double markup and expands the market. Second, I find evidence consistent with the theory that RPM facilitates price coordination among competing retailers: after RPM was banned, retail prices of RPM products increased more in regions with low retailer competition,

and within-city-across-retailer price dispersion for RPM products also rose. Third, I do not find evidence that RPM leads to exclusion because the product assortments remained stable after RPM was banned.

Motivated by the findings from the design-based analyses, I develop a structural model to examine the trade-off between eliminating double markups and facilitating retailer coordination. In this model, I assume that the manufacturer and retailers negotiate wholesale prices, with this flexible assumption encompassing the take-it-or-leave-it offer scenarios. In the absence of RPM, retailers set retail prices. Under RPM, the manufacturer directly controls retail prices, with retailers selling at the prices determined by RPM. The manufacturer sets retail prices with two primary incentives: first, to eliminate double markups and therefore expanding quantities, and second, to achieve price coordination by selecting retail prices that maximize joint brand profits across retailers. The first incentive of RPM tends to drive prices down, while the second tends to drive them up.

The relative size of the two incentives is shifted by three critical model primitives: brand differentiation, retailer differentiation, and bargaining power. When brands are relatively more differentiated (horizontally) , consumers are more likely to view the same brand sold in different retailers as close substitutes. When retailers are relatively more differentiated (horizontally), consumers view different brands sold in the same retailer as close substitutes. Upstream bargaining power characterizes vertical relations by capturing the ability of the upstream firm to receive a larger share of the channel's profits. The intuition is as follows. Holding product differentiation fixed, higher manufacturer bargaining power yields higher wholesale prices, aggravating the double markup issue. Similarly, the double markup problem is more salient if retailers are differentiated from each other and have strong market power. RPM can help mitigate double markup, and so is likely to be pro-competitive when upstream holds more bargaining power or when retailers are differentiated. On the other hand, when the RPM brand is differentiated from rival brands, it can raise retail prices uniformly across retailers without substantial profit loss to rival brands. In this case, RPM is more likely to facilitate price coordination and reduce retail competition, making it potentially anti-competitive under conditions of large brand differentiation.

I estimate a random coefficient nested logit model to capture consumer demand for herb-based sleep disorder drugs. This drug category is affected by the antitrust investigation, and Bailemian, one of the top three products in this category, is an "RPM product" produced by YRPG. I recover flexible brand and retailer differentiation via a consumer panel that docu-

ments the substitution patterns of consumers. The results show that both brands and retailers are differentiated in this market, with the former being 3.6 times stronger measured by the diversion ratio. On the supply side, I use the post-investigation period data to estimate a Nash-in-Nash bargaining model between drug manufacturers and retail pharmacies. Rich variations in wholesale prices across retailers allow me to recover pairwise bargaining parameters. I find that upstream firms possess larger bargaining power, capturing about 70% of the profit they would obtain under full bargaining power with a take-it-or-leave-it offer. I also find that larger pharmacy chains hold more bargaining power. I validate my model estimates by simulating the market outcomes of the pre-investigation period when YRPG adopted RPM. The model's predictions closely replicate the estimated effects from the difference-in-differences analysis. In addition, the model shows that RPM achieves a ¥20 million (80%) gain in profit for YRPG and a ¥10 million gain in consumer surplus, at the ¥16 million (5%) loss of category profit for downstream retailers.

Next, I use counterfactual simulations to evaluate the possible welfare gains under RPM if it were feasible to eliminate double markups while preventing price coordination. I do so by simulating the counterfactual retail prices that only eliminate double markups but do not seek to coordinate prices across retailers. In the model, retail prices are still marked up over marginal costs but maximize each retailer's profit instead of brand profit across retailers. As a result, the consumer surplus gain could have been 77% higher in the absence of price coordination incentives. This highlights that ignoring retailer competition when evaluating RPM leads to upward biases in welfare effects.

In the second counterfactual, I shift model primitives and find that RPM is more likely to be anti-competitive with a strong upstream bargaining power, low retailer differentiation, and large brand differentiation. For example, if the diversion ratio of the RPM brand to the same brand in a different retailer is 40% higher, the model would predict that the RPM used by YRPG is anti-competitive. This finding delivers a key policy message: the same vertical contract can have different welfare implications in different market environments. Whether it is pro-competitive or anti-competitive depends on the relative market power of upstream and downstream, as well as the severity of the double markup issue along the vertical chain.

Lastly, I use my framework to compare various types of vertical contracts: fixed-price RPM, maximum-price RPM (specifying the maximum retail price), minimum-price RPM (specifying the minimum retail price), and a benchmark two-part tariff contract, where the wholesale price is at the marginal cost and the manufacturer uses licensing fees to extract the

retail profit. I show that YRPG's fixed-price RPM contract effectively establishes price ceilings for most retailers and is closer to a *de facto* maximum-price RPM. However, shifting to the two-part tariff discussed above would increase consumer surplus gains by 31% (16%) compared to fixed-price (maximum-price) RPM. The gap is explained by the price coordination achieved by RPM, which drives retail prices higher than under a two-part tariff. Hence, even when RPM serves as an effective price ceiling, regulators may still want to encourage other non-linear contracts that only mitigate double markups but do not lessen competition via price coordination.

**Related Literature** This research is related to four strands of literature. The paper primarily contributes to the literature on RPM by offering the first direct design-based evidence on its welfare effects. RPM has long generated interest from regulatory agencies (OECD, 2008) and economists— but theorists find ambiguous results under different modeling assumptions (for instance, Shaffer, 1991; Dobson and Waterson, 2007; Foros et al., 2011; Rey and Vergé, 2010; Heywood et al., 2018). Empirical exercises that study RPM are limited due to the scarcity of visible RPM contracts and granular data. The most relevant empirical exercise is Bonnet and Dubois (2010), wherein the authors estimate a demand model for a bottled water brand and use conduct testing to conclude the data cannot reject the hypothesis that firm behavior is consistent with RPM. My paper benefits from observing the RPM from an anti-trust investigation so I can directly study the effects of RPM.

The second set of literature focuses on vertical arrangements. It is well-established that vertical arrangements shape competition and market performance since Sudhir (2001) and Villas-Boas (2007). However, it is still largely an open question of how vertical arrangements should be restricted. Many papers focus on vertical integration (Crawford et al., 2018; Luco and Marshall, 2020; Chen et al., 2023). RPM is different from vertical integration (VI) because RPM only controls downstream retail price, and is usually implemented between one upstream and many downstream firms, while VI is usually full integration between two firms. Others study various types of vertical contracts: parallel trade (Dubois and Sæthre, 2020), bundling (Crawford and Yurukoglu, 2012), rebates (Conlon and Mortimer, 2021), slot payments (Hristakeva, 2022), relational contracts (Luo, 2024), and non-linear wholesale pricing (Bonnet et al., 2013). This paper's findings contribute to the literature on vertical contracts by highlighting how market forces mediate welfare impacts and providing practical guidance to regulators. I show that RPM can be pro-competitive when retailers are differentiated and

hold weak bargaining power. RPM can be anti-competitive when brands are differentiated and hold weak bargaining power.

Third, this paper contributes to the methodology of the vertical literature by accommodating RPM in a Nash-in-Nash bargaining framework. Nash-in-Nash bargaining has been a powerful model in characterizing vertical relations in healthcare (Grennan, 2013; Gowrisankaran et al., 2015; Ho and Lee, 2017, 2019), broadcasting (Crawford et al., 2018), retail industry (De los Santos et al., 2021; Draganska et al., 2010; Noton and Elberg, 2018), and many others. This paper extends this framework by explicitly modeling RPM as a contractual arrangement that alters the strategic incentives of upstream and downstream firms.

Finally, while research on firm conduct is largely model-based, using government investigations as an exogenous shock has gained attention in the literature, such as Miller and Weinberg (2017); Cuddy (2021); Clark et al. (2023); Chaves and Duarte (2023); Starc and Wollmann (2022); Igami and Sugaya (2022). My paper is another example of exploiting an anti-trust investigation to evaluate RPM. I utilize the shock as a quasi-natural experiment to test different hypotheses of RPM and validate the model.

**Outline** The remainder of the paper is organized as follows. Section 2 offers the details of the investigation on YPRG, a glance at regulatory debates about RPM, and information about the dataset. Section 3 uses design-based tools to examine how RPM affects market outcomes. Section 4 describes the structural model of the supply chain, along with identification and estimation. Section 5 shows counterfactual results. Section 6 concludes.

# 2 Institutional Background

**Investigation on YRPG** In October 2019, the Chinese State Administration for Market Regulation (SAMR) initiated an investigation into the potential fixed-price resale price maintenance (RPM) behavior of Yangtze River Pharma Group (YRPG).[4] YRPG is a top 10 pharmaceutical company in China and produces more than 100 different products, with total revenue in 2021 reaching ¥78.6 billion (or around $11 billion). At the time of the investigation, RPM was considered illegal per se under antitrust law, meaning that the regulatory agency only needed legal evidence of RPM practices, rather than proof of anti-competitive harm, to

[4]There were no investigations against any pharmacy stores, indicating RPM is largely initiated and enforced by the upstream manufacturer.

impose a ban on RPM.[5]

In April 2021, the final decision made by the State Administration for Market Regulation (2021 No. 29) found YRPG guilty of abusing its power to control downstream prices. YRPG was ordered to stop their RPM behaviors and fined ¥764 million (US$116.84 million, Quote 1 in Appendix A.1), which was the largest fine on RPM in the anti-trust history in China. YRPG accepted the decision and did not further appeal to the court.

There are several notable features of this RPM case. First, YRPG signed contracts with retail pharmacies specifying the *fixed* retail prices (see Quote 3 in Appendix A.1).[6] In addition, 92% of the interviewed pharmacies admitted to the implementation of RPM (Quote 5 in Appendix A.1). Hence, RPM was widespread and affected almost all retailers. Furthermore, YRPG split the national market into nine regions and formed "regional bureaus" to set retail prices in nine regions (Quote 2 in Appendix A.1). This centralized pricing strategy raised anti-trust concerns on price coordination. To ensure that retailers follow the prices set by YRPG, YRPG also hired a third-party agent to monitor retailers' prices (Quote 4 in Appendix A.1). If YRPG found that retailers were not complying with prices specified in RPM, it sent out notifications to pharmacies via telephone, APP message, and direct door-to-door communication. In some cases, YRPG even threatened to stop drug supplies to the downstream retailers (Quote 5 in Appendix A.1). Since YRPG is one of the leading drug producers in China, the threat of withdrawing its supply presented a substantial threat to retail pharmacies. It is notable that certain downstream pharmacies expressed dissatisfaction with the RPM and had incentives to deviate. Consequently, enforcing and monitoring the RPM was costly for YRPG. Moreover, YRPG exposed itself to the legal risk in implementing the RPM contract, implying that such a contract must have benefited YRPG economically.

Finally, the report lists five popular products produced by YRPG (Quote 6 Appendix A.1), where SAMR finds strong evidence of RPM practices. This paper focuses on these five "RPM products." They are popular drugs for sleep disorders, anti-coughing, sore-throat, diabetes-relieving, and restorative indications. The appearance of the drug package can be found in Appendix Figure E.1. The market performance of these products can be found in

[5]Technically speaking, though the Chinese approach is closer to "prohibition plus exemptions", many law researchers tend to compare the antitrust agencys approach to per se illegal in the U.S., as the exemptions were seldom applied in practice. I list other notable cases in Appendix A.2. RPM practice was banned and fined in all these cases, but the fines were smaller than the YRPG case. For a thorough discussion on the legal approach towards RPM in China, see Jiang and Sokol (2015).

[6]Since YRPG adopted fixed-price RPM contracts, I use RPM to refer to fixed-price RPM and primarily focus on fixed-price RPM in this paper. In the counterfactual, I compare the welfare effects of maximum or minimum-price RPM contracts.

Table 1. All five RPM products are in the top 20 products produced by YRPG in terms of monetary sales. Their combined revenues account for 15% of the total revenues of YRPG.

**Resale Price Maintenance** There are conflicting theories of RPM. In this section, I link how various effects are related to the YRPG case. The discussion focuses on fixed-price RPM, which YRPG adopted.

Economists have recognized that RPM can sometimes offer efficiency gains and be pro-competitive (Gilligan, 1986). Two primary pro-competitive arguments are that RPM promotes retail services and reduces double marginalization.[7] Note that the classical retail service argument is unlikely to apply to the YRPG case. First, there are no valuable presale retail services related to OTC drugs that can benefit consumers. Second, even if such a service exists, consumers are unlikely to get the service from a store and buy the drug in another. The elimination of double markups, on the other hand, is a more plausible channel in this environment. Double markups are severe in environments where upstream manufacturers and downstream retailers both have pricing power. The downstream pricing power is supported by substantial profit margins, as evidenced by the data and the financial statements of retail pharmacies.[8] RPM grants upstream the power to recalibrate the final prices to internalize the double marginalization. In the empirical analysis, I abstract away from retail service and focus on the welfare gain from the double marginalization channel.[9]

Critics of RPM mainly focus on the possibility that it facilitates price "coordination" among manufacturers or among retailers.[10] Retailer coordination is a prominent concern since RPM directly specifies the retail price, which prevents retailers from undercutting. RPM may facilitate manufacturer coordination by making retailer prices transparent and thus easy to monitor, so producers can credibly penalize the deviating retailers (Jullien and Rey, 2007; Holler and Rickert, 2022). In the YRPG case, the alleged RPM agreement is unlikely to

[7]Valuable retail services, such as presales advice and on-site trials, may be provided by high-quality retailers. However, without RPM, consumers may "free ride" by getting premium services in high-quality stores but purchasing from discount stores that do not provide those services. Eventually, this leads to a bad equilibrium where stores have a disincentive to provide valuable services.

[8]For example, according to financial reports of six pharmacy chains in China, the markups range from 30% to 40%. The gross margins of pharmacies in the U.S. are around 20% to 30%. Pharmacies' ability to mark up prices may be due to the relatively weak pharmacy competition within a local geographic area.

[9]Notably, Pitofsky (1982) and Ippolito (1991) reports that RPM appears in many industries that have nothing to do with retail service. Similarly, incentives for vertical control exist even without service argument. Therefore, though this study abstracts from the service story, it still applies to many broader settings.

[10]Note that I slightly abuse the term "retailer coordination" in this setting since an upstream manufacturer achieves de facto downstream coordination prices via RPM. Downstream retailers do not actively coordinate because they are not in charge of setting retail prices.

support brand coordination for two reasons. There were no government investigations in companies other than YRPG, nor did I observe any data patterns suggesting rival brands participating in RPM in Section 3. Instead, retail coordination is more concerning since four out of five "RPM products" are highly differentiated and popular herb-based health supplements, which are less substitutable than chemical medications. Hence, the scope of brand coordination is more limited than retailer coordination.[11]

Another concern of RPM — which perhaps applies to all vertical contracts — is its potential to motivate downstream retailers to exclude rival brands. The argument is that downstream retailers may have incentives to block new upstream brand entries to preserve the "monopoly rent" sustained by the incumbent brand's RPM (Asker and Bar-Isaac, 2014). A priori, exclusions may not be the first-order concern in this instance. First, multisourcing is a common feature in the retail pharmacy market.[12] Second, all the RPM products and their rivals have been on this market over the entire sample period. So, retailers are unlikely to gain "monopoly rent" by supporting upstream brand foreclosures in this saturated market.

To sum up, RPM can positively or negatively impact the competition when market power is present both upstream and downstream. The theoretical ambiguity of RPM motivates the empirical exercises of this paper in which I study the case of YRPG.

**Data** I combined several proprietary datasets from Sinohealth, a publicly listed health consulting firm, for the empirical analysis.[13] I discuss the construction of the variables in this section.

The primary dataset of the paper includes monthly level sales for around 80,000 sampled retail pharmacies in 150 cities in China from 2018 to 2021. In the main results, I aggregate the data at the quarterly level.[14] The sample period covers one year before the public announcement of the investigation and roughly one year following the final decision. The store-level dataset covers around 30% of all pharmacy stores in China and covers stores affiliated with

[11] I revisit the effect of an industry-wide RPM in the counterfactual analysis. The results confirm that downstream collusion raises a bigger concern in the YRPG case. However, industry-wide RPM may be costly under other market conditions.

[12] Multisourcing means that retailer pharmacies usually work with multiple competing suppliers under each category.

[13] Sinohealth's data is widely utilized by major international and domestic pharmaceutical companies, including Pfizer, Roche, Bayer, AstraZeneca, GlaxoSmithKline, Merck, and Eli Lilly, among others. It has the unique advantage of covering retailer-level drug sales, which suits the goal of this paper.

[14] Demand over a longer time horizon is more robust to dynamic behaviors such as stocking. In the data, a median consumer purchases an 18 days' usage amount in each shopping. The 95th percentile consumer purchases 48 days' usage amount for each shopping trip. Hence, stocking behavior is unlikely to affect quarterly demand.

chains better than independent stores. I additionally construct a sample of cities with better coverage (>50% of total stores) for robustness checks in the design-based evidence and the structural model. The variables in the dataset include the total quantity sold, the number of orders, total sales, and total inventory costs (pharmacies' payments to manufacturers), which allows me to infer retail prices, wholesale prices, and pharmacy markups of each SKU (stock-keeping unit) as follows.

I construct the average retail price of a product by dividing its total monetary value of sales (TS) by the total quantity of units sold (TQ) across all different packages.[15] That is, $p_j = \frac{TS_j}{TQ_j}$ for product $j$. Total monetary values of sales include retailer discounts and promotions. The observed total inventory costs are what retailers pay to the manufacturers for drugs. These costs are credible because they are collected for VAT (value-added tax) purposes. I define the wholesale price as the average per-unit cost. Therefore, I construct the wholesale price of a product by dividing its total monetary value of inventory costs (TC) by the total quantity of units sold (TQ) across all different packages. That is, $w_j = \frac{TC_j}{TQ_j}$ for product $j$.[16]

In addition, I obtained a consumer panel dataset that tracks a sample of consumers' purchasing records in pharmacies in ten cities. The raw data is at the receipt level, where I observe all brands and retailers consumers made drug purchases from 2018 to 2021. Details of the dataset can be found in Appendix C.2. The summary statistics in Table C.10 suggest that consumers switch more often across retailers than brands.

# 3 Design-Based Evidence

I begin the empirical analysis by exploring the data patterns of the YRPG case. I organize the findings to test the theory that RPM eliminates double markup, facilitates coordination, and forecloses competitors, respectively.

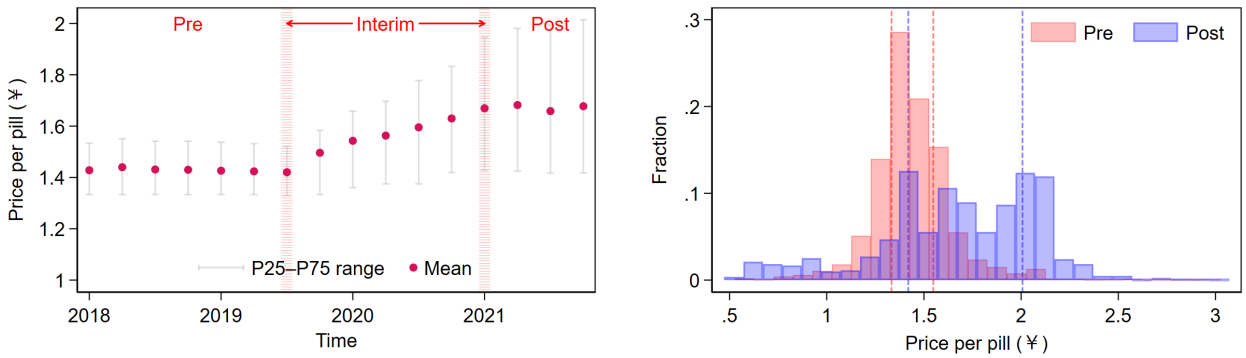
[15] I aggregate the same pill sold under different package sizes as a single product by converting the quantity into the number of pills. Most products are sold only in one SKU in a market.

[16] A common issue in vertical literature is that there may be non-linear contracts between manufacturers and retailers that are unobservable to researchers. If so, the average wholesale prices may not capture those side payments. While the possibility of unobservable non-linear contracts between manufacturers and retailers exists, this may not be a primary concern in this context. As mentioned in Section 2, non-linear contracts are prohibited in the pharmaceutical industry. According to industry experts, domestic firms like YRPG mostly adopt linear contracts. Consequently, this paper assumes linear contracts.

## 3.1 Descriptive Evidence

I begin with a visualization of the pricing pattern of an "RPM" product (Bailemian), which I later focus on in the structural model, in the raw data. In Figure 1(a), I plot the within-city quarterly average and interquartile range of retail price per pill of Bailemian in retail pharmacies, averaged across all the cities in the sample. The first vertical line denotes the one quarter prior to the SAMR investigation, and the second vertical line denotes when the final decision was made. There are two key takeaways. First, the average retail price increases in the post period compared to the RPM price in the pre period. In addition, many retailers started deviating from RPM prices in the interim period. Second, the price dispersion across retailers before the investigation was small but surged after.

Figure 1(b) shows the distributional plot of retail prices nationwide before and after the investigation. Similarly, there was a clear increase in both the level and dispersion of retail prices after the investigation. The pricing patterns (both level and dispersion) of this product represent the other four investigated products.




(a) Time series (b) Pre-post Distribution

Figure 1: Raw Data Patterns of RPM

*Note*: Panel (a) plots the mean and interquartile prices of Bailemian in each city-quarter, averaged across cities. Panel (b) plots the distribution of mean-adjusted retail prices in the RPM period and after the final report. The dashed vertical line denotes the interquartile range of the retail prices in both periods.

## 3.2 Empirical Strategy

**RPM, rival, and control products** To interpret the changes in pricing pattern as the causal effect of RPM, a primary threat to identification is the simultaneity of cost or demand shocks that differ across retailers. In addition, some retailers may enter, exit, or merge with others over time, resulting in changing market concentrations in some cities and affecting

outcome variables.

To address these concerns, I adopt a difference-in-differences approach. I do not use rival products that compete with RPM products as the control group since rival products may be affected by the spillover effects of RPM or the investigation. Instead, I picked six popular OTC health supplements that are also sold over the entire sample period as the control group. They are chosen such that they do not directly compete with any YRPG products (including the ones outside the investigation) to rule out potential spillover effects from RPM. The selection rules can be found in Appendix C.1. [17] In addition, these control products are produced by other top drug manufacturers in China and share many ingredients similar to those of the treated products. Therefore, control groups capture some of the co-movement in cost and demand shocks of RPM products. The summary statistics of all treated and control products used in the design-based analysis can be found in Table 1.

**Specification** To quantify the impact of RPM on price dispersion, I stack the five treated "RPM" products and six chosen control products together and estimate a pooled model with variables of interest $y_{jmt}$ for product $j$ in city $m$ at time $t$:

$$y_{jmt} = \rho_1 \cdot \text{Interim}_t \cdot \mathbb{1}(j \in \text{RPM}) + \rho_2 \cdot \text{Post}_t \cdot \mathbb{1}(j \in \text{RPM}) + \mu_{jm} + \xi_{mt} + \epsilon_{jmt}, \quad (1)$$

where $y_{jmt}$ could represent price, quantity, and distribution. The independent variables include $\text{Interim}_t$, an indicator for the investigation period (from October 2019 to February 2021), and $\text{Post}_t$, an indicator for the period after March 2021. $\mathbb{1}(j \in \text{RPM})$ indicates whether a product is one of the five RPM products. $\mu_{jm}$ is the market-product fixed effect, and $\xi_{mt}$ is the market-time fixed effect. The parameters of interest, $\rho_2$, capture the relative change of the dependent variable after RPM was banned and is our primary variable of interest. $\rho_1$ captures the effects in the interim period, when the investigation has begun. A priori, $|\rho_1| \in [0, |\rho_2|]$ as some retailers in certain regions may deviate from the RPM in the interim period, but other places until the final decision was made. Therefore, $\rho_1$ is likely to capture the partial effect of banning RPM. I calculate robust standard errors clustered at the product-province level. The model assumes a uniform effect on dependent variables for all five "RPM" products in the entire interim or post-period, which may be restrictive. I further relax this assumption to allow time-varying $\rho_\tau$ in the following event study design:

[17] Their indications are abdominal pain, indigestion, common cold, rhinitis, heat-clearing, and osteoporosis, respectively.

Table 1: Summary Statistics of Products

| Product Group | Producer | Indication | Sales (million ¥) | Retail P (¥/DDD) | Wholesale P (¥/DDD) | Distribution Rate |
|---|---|---|---|---|---|---|
| **RPM products** | | | | | | |
| Bailemian | YRPG | sleep disorder | 3.5 | 4.23 | 3.52 | 0.35 |
| Suhuang | YRPG | anti-coughing | 8.0 | 33.70 | 24.69 | 0.40 |
| Lanqin | YRPG | sore-throat | 24.6 | 10.73 | 7.39 | 0.78 |
| Huangqi | YRPG | restorative | 18.2 | 7.75 | 3.72 | 0.48 |
| Tanglin | YRPG | ARI | 6.3 | 10.78 | 8.61 | 0.23 |
| **Rival products** | | | | | | |
| Wuling | Zuoli | sleep disorder | 3.2 | 3.40 | 3.01 | 0.28 |
| Aodong | Aodong | sleep disorder | 8.6 | 3.92 | 3.31 | 0.72 |
| Sweet Sleep | Rongchang | sleep disorder | 1.2 | 4.45 | 4.20 | 0.20 |
| Pipagao | NinJiom | anti-coughing | 21.9 | 3.73 | 2.99 | 0.91 |
| Zhikebao | Yeyi | anti-coughing | 10.3 | 6.38 | 3.69 | 0.64 |
| Bailing | Huadong | anti-coughing | 15.8 | 20.77 | 19.91 | 0.49 |
| Feilike (liquid) | Jianxing | anti-coughing | 9.5 | 10.74 | 9.27 | 0.74 |
| Feilike (capsule) | Jianxing | anti-coughing | 3.0 | 7.32 | 6.25 | 0.37 |
| Pudilan | Jichuan | sore-throat | 27.2 | 12.51 | 11.27 | 0.84 |
| Jinzhen | Kangyuan | sore-throat | 9.9 | 17.56 | 11.55 | 0.36 |
| Huangqi | Jurong | restorative | 9.3 | 9.13 | 4.05 | 0.17 |
| Huangqi | Nanfeng | restorative | 7.9 | 7.67 | 2.70 | 0.15 |
| Huangqi | Kangyuan | restorative | 1.1 | 3.16 | 2.35 | 0.21 |
| Yiheng | Dayin | ARI | 7.1 | 9.60 | 7.39 | 0.18 |
| **Control products** | | | | | | |
| Weitai | Sanjiu | abdominal pain | 12.4 | 4.39 | 3.86 | 0.67 |
| Xianlinggubao | Guoyao | osteoporosis | 12.1 | 4.87 | 3.90 | 0.36 |
| Huanglian | Hayao | internal heat | 17.8 | 6.04 | 4.69 | 0.53 |
| Ganmaoling | Sanjiu | common cold | 70.2 | 3.64 | 3.55 | 0.74 |
| Qizhiweitong | Guangyao | indigestion | 5.9 | 6.15 | 5.44 | 0.39 |
| Biyankang | Guoyao | rhinitis | 8.7 | 0.89 | 0.80 | 0.59 |

*Note*: This table summarizes the products used in the design-based analysis. All the variables are calculated using sampled pharmacies. The sample includes around 80,000 stores and 1,369 chains. The sales reflect the national monthly average sales. Retail and wholesale prices are reported at the defined daily dose (DDD) level. RPM products are the products that were investigated. "Rival products" are the major rivals to the "RPM products" in the same category. The consumer panel also confirms that the rival products are the closest brand substitutes that a consumer would switch to. "Control products" are sold by other competing drug manufacturers but do not directly compete with "RPM" products.

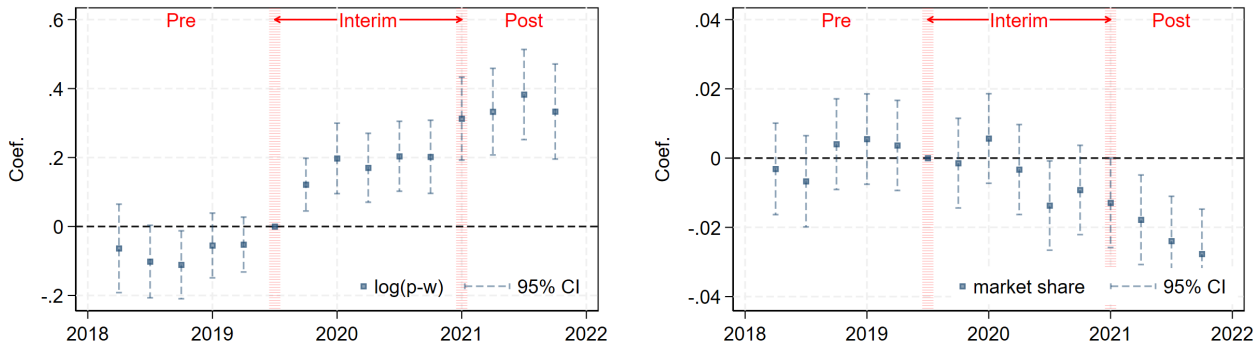
$$y_{jmt} = \sum_{\tau \neq -1} \rho_\tau \cdot \mathbb{1}(\chi_t = \tau) \cdot \mathbb{1}(j \in \text{YRPG}) + \mu_{jm} + \xi_{mt} + \epsilon_{jmt}, \tag{2}$$

where $\chi_t$ is the period $t$ relative to the start of the investigation, and the omitted group $\tau = -1$ is one period before the investigation. Finally, I allow product-specific coefficients ($\rho_{j\tau}$) as a robustness check.

## 3.3 The Effect of RPM on Eliminating Double Markups

I first document changes in average prices and quantities of RPM products. Table 2 summarizes the results of estimation Equation (1). The event study results of Equation (2) are shown in Figure 2. The pre-period exhibits a parallel trend between the two groups and Appendix Figure E.2 formally confirms the results are robust even under some violations of parallel

trend assumptions (Rambachan and Roth, 2023). I show the product-specific estimates for five RPM brands in Appendix Section E.5.




(a) downstream margin

(b) market share

Figure 2: Event study: Market Performance of RPM Brands

*Note*: This figure plots the time-varying coefficient in Equation (2) for downstream margins in logarithms and market shares. The first vertical dashed red line denotes the start of the investigation, and the second one denotes when the final decision was released. The blue dashed lines denote 95 percent confidence intervals of estimated coefficients based on standard errors clustered at the city level.

**Prices** I observe a significant increase in the average final retail price (5.4% increase after the final report as in Column (1) of Table 2), which indicates that the RPM imposed by YRPG was effective in *containing* drug prices and thus likely increases consumer surplus. This price increase is consistent with the efficiency gains from the elimination of double markups dominating the downstream price coordination as the main incentive for RPM. The wholesale price dropped slightly after the investigation (-4%, as shown in Column (3) of Table 2), also indicating the mitigation of double markups as the main incentive. To see this, note that in the case of RPM, the wholesale price is not passed through to retail prices because manufacturers choose both. However, without RPM, the wholesale price is passed through to the retail price. Hence, upstream producers are incentivized to drop wholesale prices to mitigate double markups.[18] The increasing retail prices and decreasing wholesale prices broadened the downstream margins (exp(0.563)-1= 76% increase in Column (2) of Table 2). The net effect on prices supports the theory that RPM alleviates double markups in this market.

[18]The interim effect on retail price is similar to the post effect, while the interim effect on wholesale price is close to zero. This may reflect that many retailers have deviated from the RPM prices quickly in response to the investigation, while the wholesale contract takes much longer to adjust (until the final ban on RPM).

Table 2: Market Performance after the Investigation

| | log(p) retail price (1) | log(p-w) downstream margin (2) | log(w) wholesale price (3) | log(q) quantity (4) | dist. rate (5) |
|---|---|---|---|---|---|
| **Panel A: RPM products** | | | | | |
| Interim | 0.048*** | 0.356*** | -0.005 | 0.008 | 0.003 |
| | (0.011) | (0.083) | (0.008) | (0.036) | (0.005) |
| Post | 0.054*** | 0.563*** | -0.040** | -0.120*** | -0.002 |
| | (0.012) | (0.144) | (0.015) | (0.043) | (0.005) |
| **Panel B: Rival products** | | | | | |
| Interim | -0.003 | 0.068** | -0.010** | 0.023 | 0.017*** |
| | (0.004) | (0.031) | (0.005) | (0.022) | (0.003) |
| Post | -0.001 | 0.007 | -0.011 | 0.044** | 0.026*** |
| | (0.006) | (0.038) | (0.008) | (0.018) | (0.003) |
| City-time FE | Yes | Yes | Yes | Yes | Yes |
| City-brand FE | Yes | Yes | Yes | Yes | Yes |

*Note*: The regression is based on difference-in-differences design (Equation (1)) at the city-product-quarter level (observation=24k for RPM products, 130k for rival products, and 51k for control products), and the standard errors are clustered at the city level. The dependent variables are the logarithm of sales-weighted average values. Column (4) additionally controls for pre-investigation trends. Panel (A) shows the performance of five RPM products. Panel (B) reports the performance of rival products that compete with RPM products. *** p<0.01, ** p<0.05, * p<0.1.

**Quantity** Another critical dimension is quantity responses. Figure 2(b) shows a 2.5 percentage point decrease in market share of RPM products post-investigation. To measure quantity change in the difference-in-differences framework, I add a secular trend variable, which is constructed by using pre-investigation data following Dobkin et al. (2018), and extrapolated trends are subtracted from observed quantities in later years.[19] The results show a 12% decrease in the total quantity of "RPM" products (Column (4) of Table 2), which supports that double markup limits the quantities sold.[20]

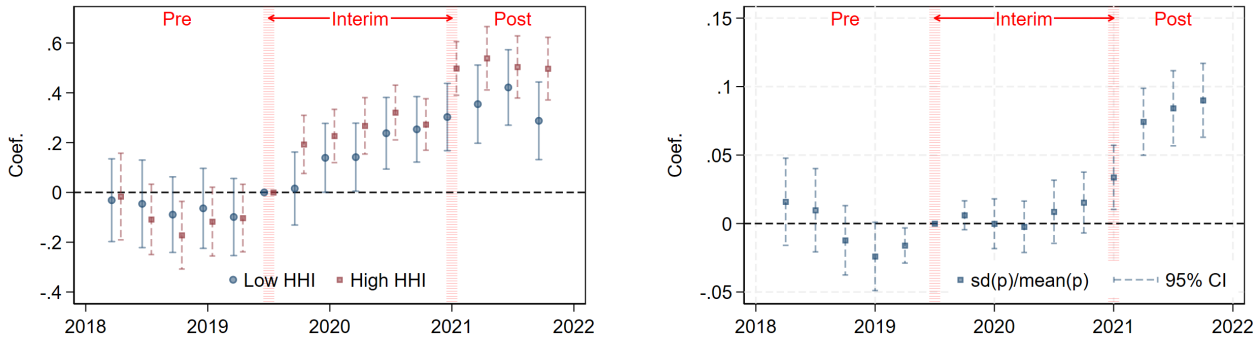
[19] I do so because the observed demand change may be due to market expansions of all health supplements. The underlying assumption of using pre-trend to estimate the trajectory is that the increasing trend of "RPM" products in 2018 would persist in the following years.

[20] The retail price increased by 5.4%, this indicates an aggregate demand elasticity=$\frac{-12\%}{5.4\%} = -2.2$. The elastic is small because the quantity response is calculated at the market level, therefore smaller than the estimated price elasticity (-3.4) at the retailer level in structural estimation in Section 4.

## 3.4 The Effect of RPM on Retailer Price Coordination

As discussed in Section 2, YRPG implemented RPM in a centralized manner, which raises a red flag for potential price coordination across retailers. To test this hypothesis, I check the heterogeneous effects of RPM in regions with different retailer concentrations and the price dispersion of RPM products across different retailers.

Figure 3: The Effect of RPM on Price Coordination




(a) log(downstream margin)

(b) sd(retail price)

*Note*: Figure (a) plots the time-varying coefficient $\rho_\tau$ in Equation (2) for downstream markup, separated by the high retailer HHI (low competition) and low HHI (high competition) regions. Figure (b) plots the time-varying coefficient $\rho_\tau$ in Equation (2) for retail price dispersion. In both figures, the first vertical dashed red line denotes the start of the investigation, and the second one denotes when the final decision was released. In Figure (b), the blue dashed lines denote 95 percent confidence intervals of estimated coefficients based on city-clustered standard errors. The increasing coefficients during the interim period and right after the collapse of "RPM" show that the "RPM" was effective in restricting downstream price dispersion.

**Evidence from regional heterogeneity** If YRPG uses RPM to achieve price coordination, this incentive ought to be stronger in regions with stronger retailer competition. To test this hypothesis, I group regions into two time-invariant types: high (retailer) HHI and low (retailer) HHI regions, which are calculated based on the total drug sales of pharmacy chains in the pre-period.[21] I plot the event study on downstream markups separately, and the results are in Figure 3(a). There are two patterns. First, note that the markups are economically similar for the two regions in the pre-period, consistent with the hypothesis that RPM would suppress retailer competition so the downstream market structure would not matter. Second, the markups are lower in the post-period for the high-competition regions (t-test on the joint

[21] To calculate HHI based on total drug sales instead of sales of RPM products alleviates the simultaneity issue of using HHI. The median regional retailer HHI is 1933.

post-period coefficients indicates the $\rho_{post}^{low} - \rho_{post}^{high} = -0.23$ with $p$ value$= 0.01$). Overall, the heterogeneity results are consistent with the incentives of using RPM to achieve retailer coordination, though even in the regions with the stronger incentives to coordinate prices, the price coordination incentives are still dominated by the double markup incentives.

**Evidence from price dispersion** If YRPG uses RPM to coordinate prices across retailers, I should see retailers charge similar prices and tend not to undercut, which depresses price dispersion across retailers.[22] I define three different sets of measures of price dispersion across retailers at the product-city-time level: standard deviations, inter-quartile, and inter-decile range of product prices. I further normalize these metrics by the average price level.[23]

Figure 3(b) shows the estimation results of Equation (2) with normalized standard deviations as the dependent variable. The pre-investigation is small, indicating that RPM supressed price dispersions. I find a five percentage point increase in standard deviations of within-city retail prices post-investigation. The results are consistent when I use different sets of measures for price dispersion, weighted by sales or not, as shown in Appendix Table E.2. In addition, Appendix Figure 3 and Table E.2 shows the base level of dispersion in the pre-investigation period for RPM and non-RPM products. I find that the surging dispersion mainly comes from the low price dispersion of "RPM" products converging to the normal level of control products.

**Robustness** First, I calculate the changes in within-city price dispersion for each of the five RPM products separately in Appendix Figure E.4 in which all products exhibit an increasing dispersion range from 3 to 18 percentage points. Second, as a placebo test, I find an economically small and insignificant increase (<1 percentage point) in the level of retail price dispersion for rival products after the investigation in Appendix Table E.3. Third, as another supporting evidence, I find that downstream retailers revised prices for RPM products less frequently during the RPM period, as shown in Appendix Table E.4.[24]

[22] Technically speaking, it can be shown that in a market with *vertically differentiated products*, the price level will be higher, and the price dispersion will be lower when the prices are coordinated.

[23] Normalizing enables cross-product comparisons— I can interpret a one-unit increase in the dependent variable as a 100 basis point increase in dispersion around the mean.

[24] The intuition is that, under RPM, downstream retailers are forced to charge the upstream-specified price; without RPM, downstream retailers may revise prices more actively when there are chain-level promotions or other local sales events.

## 3.5 The Effect of RPM on Rival Brands

This subsection discusses how RPM affects rival demand, and I find no evidence of using RPM to exclude rival brands in this setting.

**Rival price and quantity** Panel B of Table 2 shows the responses of rival products. First, in Column (4), I find a 4% increase in rival quantities, which supports the cross-substitution between RPM and rival products. Second, in Column (1), I find rival brands' retail prices remain roughly the same because of the simultaneous increase in downstream margins and decrease in wholesale prices. In Column (2), the downstream margin for rival products increased by 0.7%-6.8%, but the increase was much smaller than that of "RPM products." This simultaneous increase is consistent with downstream competition because retail markups are strategic complements. I also find a small (1%) decrease in wholesale prices in Column (3).The increasing bargaining leverage of downstream retailers explains this change. After the investigation, downstream retailers can gain higher profits from selling YRPG products in the event of a failed negotiation because retailers regain pricing autonomy. Thus, carrying rival brands is not as profitable as when YRPG adopts RPM. This allows downstream to bargain lower wholesale prices for rival products.

**Exclusion** One critical point made by Asker and Bar-Isaac (2014) is that RPM can facilitate foreclosure.[25] I test whether there is any evidence of such foreclosure by using the distribution rate (the proportion of stores carrying a brand) as an outcome variable in the difference-in-differences specifications. Column (5) of Table 2 shows that the distribution rate does not change for RPM products but slightly increases for rival products (2.6 percentage points), which is also small compared to the average distribution rates (54%). The effects are small, partly because of the multi-sourcing feature of the market, where retailers carry multiple brands and a brand is usually sold across many retailers.

## 3.6 Summary of the Design-Based Evidence

To sum up, this section offers empirical evidence to examine each theory regarding RPM using a novel retailer-level dataset. Increasing average prices combined with surging down-

[25]This argument is that a monopolistic upstream firm may offer downstream firms extra rents via RPM that would disappear once the retailer begins carrying rivals' products. As a result, retailers are motivated to refuse to carry rival brands to preserve the collusive rents.

stream markups after the investigation aligns with the theory that RPM can eliminate double markups, supporting the efficiency justification for RPM. At the same time, the low dispersion under RPM, and the stronger net effects in low-competition regions suggest the presence of price coordination. I find limited evidence of product exclusion, which is likely not a first-order concern in this case.

# 4 Structural Model

In this section, I model and estimate the upstream and downstream incentives in a structural model. The first goal of the model is to disentangle the two competing incentives of RPM: eliminating double markups and facilitating retailer coordination. Also, the model enables evaluating how welfare effects would change under counterfactual market primitives and regulatory policies. I focus on the category of herb-based sleep disorder drugs and describe a static model of price competition of all products in that category. There are four upstream manufacturers, each producing one brand in the market. Bailemian is produced by YRPG and was under RPM before the investigation, while there was no evidence of RPM for other brands.[26] I first discuss some features of this market and then introduce the model.

## 4.1 The Retail Pharmacy market in China

All four products in the sleep disorder drug category are OTC drugs and do not require a prescription. A distinctive feature is that OTC drugs are mainly sold in retail pharmacies (92% on average) in China, while hospitals, groceries, and online virtual pharmacies (trending only since 2022) account for a small market share. Hence, this paper abstracts away from the hospital competition and focuses on retail pharmacies as the downstream market.

In the pharmaceutical industry, upstream drug manufacturers display a significant market concentration. The categories studied in this paper have four to six competing brands. In contrast, the downstream pharmacy market is more fragmented. In 2020, the retail market was characterized by a few prominent national or regional pharmacy chains in tandem with a considerable fraction (44% in terms of number of stores) of small, independent pharmacies. Essentially, downstream retailer pharmacies function as market intermediaries. They choose

[26] Bailemian is representative of YRPG's investigated product lines. Herb-based drugs account for 61% of YRPG's total revenue, and Bailemian is a typical and popular herb-based drug, accounting for 3% of the total revenue of YRPG.

what brands to carry and negotiate wholesale prices with upstream drug suppliers while also setting retail prices charged to consumers. I show five key features of this market, which justifies some of my model assumptions. The data evidence can be found in Appendix Table E.1.

First, assortments, retail, and wholesale prices across different stores within a chain are close to uniform. Sixty percent of the variation in store-level carriage decisions is at the chain-brand level. In addition, stores affiliated with a chain have similar retail (wholesale) prices in the data. Chain-brand fixed effects explain 72% (82%) of retail (wholesale) price variations, suggesting that chains make uniform decisions for all stores. Therefore, I aggregate the stores in a market at the chain level and use a retailer to refer to a retailer chain in my model, effectively treating each chain as a single agent and abstracting away from competition within a chain, reducing the computational burden. Second, linear contracts are the most popular form of contract in the industry, according to both regulatory reasons and anecdotal evidence.[27] Third, the observed wholesale prices of the same brand are dispersed across retailer chains, consistent with a bilateral negotiation between brands and chains. Fourth, consumers generally cannot use insurance to purchase OTC drugs from private pharmacies; they pay entirely out-of-pocket. Lastly, multisourcing is a common feature in this market. I also find no evidence of complete exclusion due to RPM in Section 3.5. Therefore, I assume product assortments in each retailer are fixed with or without RPM.

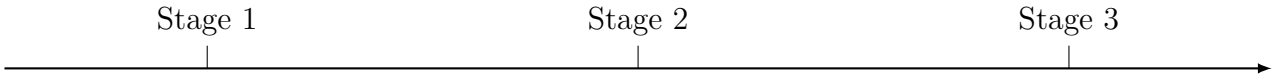
## 4.2 Timeline

The model is a three-stage game, as shown in Figure 4. In the first stage, upstream drug manufacturers set wholesale prices via multilateral negotiation with downstream retailers simultaneously for all products. In the second stage, downstream retailers take these wholesale prices as given and set retail prices for non-RPM products to maximize retailer profits. RPM manufacturers directly control downstream retail prices for RPM products to maximize the brand's joint channel profit.[28] Finally, consumers make purchasing decisions conditional on the observed retail prices of all products. I solve the model backward. I first present consumer demand and then move on to the profit-maximization problem of manufacturers and retailers.

[27] According to Article 88 of the Chinese Drug Management Law, "Drug marketing groups, drug manufacturers, and medical institutions are prohibited from giving or receiving kickbacks or other illegitimate benefits in the purchase and sale of drugs."

[28] The joint channel profit of a brand is the sum of upstream and downstream profit from selling the brand.

Figure 4: Timeline of the game




- Wholesale prices ($\boldsymbol{w}$) are chosen via pairwise Nash-in-Nash bargaining between manufacturers and retailers.
- Retail prices ($\boldsymbol{p}$) are chosen by retailers for non-RPM products.
- Retail prices ($\boldsymbol{p}$) are chosen by manufacturers for RPM products.
- Idiosyncratic demand shocks are realized.
- Consumers purchase products.

## 4.3 Demand

A product $j \in \{1, 2, ..., J\}$ is defined as a brand-retailer pair. That is, a product is a specific drug brand ($\mathcal{K}(j) \in K$) sold by a specific retailer ($\mathcal{R}(j) \in R$). $K$ is the set of upstream brands, and $R$ is the set of retailers. The choice set $G$ includes all product $j$ sold in the market plus the outside option. I assume that the utility of consuming drug $j$ in market $t$ (a market is defined as a city-time pair) for individual $i$ follows a random coefficient nested logit structure:

$$u_{ijt} = -\alpha_i p_{jt} + \lambda_j + \eta_t + \xi_{jt} + \sum_{k \in K} \sigma_{ik} \mathbb{1}(\mathcal{K}(j) = k) + \epsilon_{irt} + (1 - \rho)\varepsilon_{ijt},$$

where $p_{jt}$ denotes out-of-pocket costs, which are the same as the retail prices since OTC drugs are not insured. $\lambda_j$ is the product fixed effects and $\eta_t$ is the market-time fixed effects. $\xi_{jt}$ is an unobserved quality valuation of the product $j$ in market $t$.

I allow flexible substitution patterns via both random coefficients and nesting structure in the main specification. The brand-specific random coefficient $\boldsymbol{\sigma}_i \sim MVN(\mathbf{0}, \Sigma)$, governs the consumers' horizontal preference for brand $k$. A larger $\sigma_{ik}$ indicates weaker brand competition, as consumers are more likely to stick with the same brand when substituting. Following nested logit assumptions, I assume that $\varepsilon_{ijt}$ and $\epsilon_{irt} + (1-\rho)\varepsilon_{ijt}$ follow T1EV. I define a nest as the set of products sold at a given retailer, with the number of nests equal to the number of retailers in each market. The nesting parameter $\rho$ governs consumers' horizontal preferences for retailers, where higher $\rho$ indicates a stronger correlation in unobserved preferences for products sold by the same retailer, leading to weaker retailer competition. All together, random coefficients $\sigma_{ik}$ and nesting parameter $\rho$ break the IIA property, so substitution patterns are not solely based on market shares. Lastly, I define market size as proportional to the population and include

an outside option that aggregates chemical drugs, other unobserved retailers, or no purchase, assuming outside option prices are non-strategic.

For the purpose of estimation, the observed portion of a patient's utility function is further divided into two parts: the utility specific to individual $i$, $\mu_{ijt} = \sum_k \sigma_{ik} \mathbb{1}(\mathcal{K}(j) = k)$, and the product intrinsic utility, $\delta_{jt} = -\alpha p_j + \lambda_j + \eta_t + \xi_{jt}$, where $\sigma_{ik}$ denotes a individual $i$ specific taste for brand $k$. I can then express the market share of good $j$ in market $t$ by integrating over the distribution of consumers $F(i)$:

$$s_{jt} = \int \frac{exp((\delta_{jt} + \mu_{ijt})/(1-\rho))}{exp(I_{ir(j)t}/(1-\rho))} \frac{exp(I_{ir(j)t})}{exp(I_{it})} dF(i), \tag{3}$$

where the mean indirect utility of the outside good is equal to zero due to normalization. The inclusive value of the products at a retailer $r$ is given by $I_{ir(j)t} = (1-\rho) log \sum_{j \in r} exp(\delta_{jt} + \mu_{ijt}/(1-\rho))$ and the inclusive value of all goods is given by $I_{it} = log(1 + \sum_r I_{ir(j)t})$. Note that this random coefficient nested logit model reduces to a nested logit when $\Sigma = 0$.

**Estimation** The estimation combines GMM and MLE objective functions. The GMM part follows Berry et al. (1995): for a given set of non-linear parameters $\theta = \{\Sigma, \rho, \alpha\}$, I calculate the mean utility levels $\delta_{jt}(\theta)$ that match the predicted market share $\hat{s}_{jt}$ to the observed market share $s_{jt}$. Specifically, I solve for $\delta^*_{jt}$ such that $s(x, p, \delta^*_{jt}; \theta) = s_{jt}$. The structural error $\omega(\theta)$ is then estimated following Somaini and Wolak (2016), where I first transform $\delta$ to remove brand-retailer and market-time fixed effects $\lambda_j = \lambda_{k(j)r(j)}$ and $\eta_t$, resulting in $\delta^+_{jt} = \delta_{jt} - \lambda_j - \eta_t$. Similarly, $X^+$ and $Z^+$ are the transformed product attribute and instrument matrices, respectively.

The GMM estimator exploits the orthogonality condition $E\left[Z^{+\prime} \omega\left(\theta^\star\right)\right] = 0$, which implies, at the true value of the parameters $(\theta^\star)$, the instruments $Z^+$ are orthogonal to the structural errors $\omega\left(\theta^\star\right)$, that is, The GMM objective function is:

$$\mathcal{L}_{GMM}(\theta) = \omega\left(\theta\right)' Z^+ W^+ Z^{+\prime} \omega\left(\theta\right),$$

for some positive definite weighting matrix $W^+$. To efficiently incorporate information from the consumer panel, instead of constructing micro-moments from consumer-level data, I combine a likelihood function based on consumer-level data with the defined GMM objective as suggested in Grieco et al. (2022) to achieve efficiency. In the consumer-level dataset, I observe a group of consumers denoted by $n = 1, ...N$. I also observe multiple choices made

by a consumer $n$ repeated $D_n$ times. Each time is denoted as $d_n = 1, ..., D_n$, which helps me construct the following (log) likelihood function:

$$log\mathcal{L}_{MLE}(\theta) = -\sum_{n=1}^{N} \log\Big\{ \frac{1}{H} \sum_{h=1}^{H} \underbrace{\prod_{d_n=1}^{D_n} \sum_{j \in C(n)} \mathbb{1}(j \text{ chosen in } d_n) P_{njth}(\theta, \delta(\theta))}_{\text{Log likelihood of individual n with random draw h}} \Big\}, \text{ where}$$

$$P_{njth}(\theta, \delta) = \frac{exp((\delta_{jt} + \mu_{njth})/(1-\rho))}{exp(I_{nr(j)th}/(1-\rho))} \frac{exp(I_{nr(j)th})}{exp(I_{nth})},$$

where $\mu_{njth} = \sum_k \sigma_{nkh} \mathbb{1}(\mathcal{K}(j) = k)$, where $h$ in $\sigma_{nkh}$ refers to the halton draw $h = 1, ...H$. I take $H = 200$ draws for the estimation. Finally, a grid search is performed over the non-linear parameter $\theta$ to minimize this combined objective function:

$$\hat{\theta}_A = \arg\min_{\theta_A} \left\{ \mathcal{L}_{GMM}(\theta) + log\mathcal{L}_{MLE}(\theta) \right\}, s.t.\ s_{jt} = s(x, p, \delta^*_{jt}; \theta).$$

**Identification of price coefficients** Prices likely correlate with the structural error term $\xi_{jt}$, i.e., unobserved local demand shocks. I use the following sets of instruments for estimation. First, I use the investigation shock, which the design-based evidence shows affects retail prices. The investigation is led by SAMR, a central government agency, so its timing is likely orthogonal to any downstream market shocks. I construct an instrument by interacting with the post-investigation dummy with each upstream brand. While this is an ideal instrument, it largely shifts the prices of YRPG products but less so for rivals. Therefore, I include two additional sets of instruments. The second instrument is the average wholesale prices of the brand sold in the same retail chain in different regions. These instruments shift retail prices as long as the passthrough is positive (DellaVigna and Gentzkow, 2019). Ideally, this variation reflects differences in retailer bargaining power and is uncorrelated with local demand shocks. The third one is the number of direct competitors to proxy for local competition intensity (number of chains that carry the same products).

**Identification of substitution coefficients** The consumer panel identifies substitution patterns governed by $\{\Sigma, \rho\}$.[29] Consumers' choices and substitution patterns are governed by both horizontal and vertical preferences but with different implications. Strong vertical

[29]Since sleep disorder drugs are maintenance drugs, the consumers usually make repeated purchases over time in the consumer panel. On average, each consumer in the panel makes six purchases of sleep disorder drugs.

preferences suggest consumers are more likely to purchase popular products with high market shares, while strong horizontal preferences imply some consumers will stick to their preferred brand. Big brand random coefficients $\Sigma$ indicate that consumers are unlikely to switch brands, while a large nesting parameter $\rho$ suggests they are unlikely to switch retailers. The MLE objective function estimates the non-linear parameters to fit the observed substitution patterns in the panel.

Table 3 presents the demand estimates of my preferred specification of the RCNL model using the estimation procedure outlined above. The parameters are precisely estimated. The logit model in Column (1) delivers a relatively inelastic demand (mean elasticity -1.37) while price elasticity (-3.46) is more reasonable under the IV approach in Column (2). The first stage Kleinberg-Paap F-statistic is 76, indicating strong instruments. Columns (3)-(5) deliver similar price elasticities. I focus on Column (5) in the discussion as the preferred specification because it allows the most flexible substitution patterns. As a robustness test, I only use the (preferred) investigation instrument to estimate the specification (5), and this leads to a similar price coefficient ($\hat{\alpha} = -0.913$, with standard error 0.09). In terms of the substitution, on average, I find a large and significant $\Sigma$ for all four brands, indicating that consumers tend to prefer keeping the same brand when substituting. Cross-brand substitution is limited, especially for Zuoli, where $\sigma$ is highest. I also estimate a significant retailer nesting parameter $\rho = 0.463$, showing that products within the same retailer are closer substitutes than those from different retailers. In summary, consumers are more likely to stick with the same brand and retailer when substituting.

**Demand parameter estimates** To quantify substitution magnitudes, Panel (A) of Table 4 shows diversion ratios for each product, grouped into four categories: (1) same brand, different retailers, (2) different brands, same retailer, (3) different brands, different retailers, and (4) outside options. These ratios closely match observed substitutions from the consumer panel in Panel (B). The high same-brand, different-retailer substitution suggests strong brand differentiation, while smaller same-retailer, different-brand substitution indicates weaker retailer differentiation. Substitution to a product of different brands and different retailers is unlikely. Overall, the demand estimates yield reasonable substitution patterns that align with the data.

Turning to the own-price responsiveness of demand, the estimates in Table 4 imply an

Table 3: Demand Estimates: Non-linear Parameters

| Data frequency: | Chain-Quarterly | | | | |
|---|---|---|---|---|---|
| Coefficients | Logit (1) | Logit IV (2) | NL (3) | RCNL (4) | RCNL (5) |
| **Random Coefficient** | | | | | |
| $\sigma_1$ (Zuoli) | | | | 6.165 | 7.244 |
| | | | | (0.020) | (1.721) |
| $\sigma_2$ (YRPG) | | | | 4.482 | 5.313 |
| | | | | (0.030) | (1.271) |
| $\sigma_3$ (Rongchang) | | | | 4.004 | 5.010 |
| | | | | (0.011) | (1.142) |
| $\sigma_4$ (Aodong) | | | | 6.784 | 5.562 |
| | | | | (0.117) | (1.499) |
| $\sigma_{j,j'}$ (Covariance) | | | | Zero | Any |
| **Nesting Coefficient** | | | | | |
| $\rho$ (retailer nest) | | | 0.715 | 0.517 | 0.463 |
| | | | (0.072) | (0.005) | (0.089) |
| **Price Coefficient** | | | | | |
| $\alpha$ | -0.345 | -0.871 | -0.299 | -0.986 | -0.992 |
| | (0.024) | (0.093) | (0.079) | (0.045) | (0.046) |
| Mean own elasticity | -1.37 | -3.46 | -3.07 | -3.46 | -3.14 |
| Median own elasticity | -1.34 | -3.38 | -3.08 | -3.45 | -3.07 |
| Own elasticity<-1 | 79.0% | 100% | 100% | 100% | 100% |
| Manufacturer-Retailer FE | Yes | Yes | Yes | Yes | Yes |
| Market-Time FE | Yes | Yes | Yes | Yes | Yes |

*Note*: The number of markets is 2,286, and the micro-sample includes 17,336 consumers in 10 representative cities. Columns (2)-(5) include the three sets of instruments defined in 4.3. The brand-specific distribution is specified as a joint normal distribution, where covariance is set to zero in Column (4) and estimated in Column (5). Standard errors are displayed below parameter estimates.

average elasticity for a given product of -3.5.[30] The elasticity estimates are also robust in various price instrument choices. The model-implied average markup (40%, with 95% confidence interval [34%- 46%]) is broadly consistent with the average observed markup (32%) in the data. The wedge can be potentially explained by the retailer's marginal cost.[31] I also project linear parameters from the fixed effects and they mostly align with expectations. Discussions can be found in Appendix Table E.5.

[30]These elasticities are similar but slightly bigger than those reported in Cao and Chatterjee (2022) estimated demand for chemical drugs using aggregated brand-level sales data.

[31]Note that my model sometimes predicts negative retailer marginal costs. This can be explained by the category's potential to attract retailer traffic. To fully model this incentive is beyond the scope of this paper. Still, it can be captured by the negative retailer marginal cost or the shadow value of lowering prices to obtain revenues from the other products in the store, as discussed in Ellickson et al. (2022).

Table 4: Summary of Estimated Substitution Patterns

| **Panel A: Estimated Diversion ratio $D_{ij}$** | | | | |
|---|---|---|---|---|
| Product $j$: | Same Brand Different Retailer | Different Brand Same Retailer | Different Brand Different Retailer | Outside goods |
| Product $i$: | | | | |
| Firm 1 (Zuoli) | -0.648 | -0.021 | -0.003 | -0.328 |
| Firm 2 (YRPG) | -0.348 | -0.101 | -0.076 | -0.475 |
| Firm 3 (Rongchang) | -0.432 | -0.014 | -0.005 | -0.549 |
| Firm 4 (Aodong) | -0.245 | -0.165 | -0.179 | -0.411 |
| Average | -0.449 | -0.051 | -0.045 | -0.455 |

| **Panel B: Empirical Diversion Probability** | | | | |
|---|---|---|---|---|
| | Same Brand Different Retailer | Different Brand Same Retailer | Different Brand Different Retailer | Outside goods (= Panel A) |
| Primary choice: | | | | |
| Firm 1 (Zuoli) | -0.548 | -0.091 | -0.032 | -0.328 |
| Firm 2 (YRPG) | -0.344 | -0.134 | -0.047 | -0.475 |
| Firm 3 (Rongchang) | -0.351 | -0.079 | -0.021 | -0.549 |
| Firm 4 (Aodong) | -0.401 | -0.152 | -0.036 | -0.411 |
| Average | -0.411 | -0.114 | -0.034 | -0.455 |

*Note*: This table shows the model-predicted diversion ratio and observed second choices in the consumer panel. In Panel (A), the diversion ratio $D_{ij}$ from the primary choice $i$ to product group $j$ is defined as $D_{ij} = \sum_j \frac{ds_j/dp_i}{ds_i/dp_i}$. It describes the proportion of consumers who switch to product group $j$ when they switch from product $i$. Higher absolute values of the diversion ratio of $i$ and $j$ denote higher substitutability of $i$ and $j$. In Panel (B), I group consumers based on their most frequently purchased products. Each entry shows the fractions of their other purchases $j$ conditional on having $i$ as the primary choice. For example, "Same brand, different retailers" denotes purchases of the same brand in a different retailer. I do not observe outside options (or no purchase) in the consumer panel, so I set them equal to the diversion ratio to outside options in Panel (A), and I normalize choice probabilities so rows sum up to one.

## 4.4 Supply

**Wholesale price** The wholesale prices are determined in the first stage via Nash-in-Nash bargaining between retailers and manufacturers. As shown in Figure 4.[32] The profit function

[32]In the vertical literature, while some papers adopt simultaneous timing assumptions on both wholesale and retail prices (Draganska et al., 2010; Ho and Lee, 2017; Crawford et al., 2018), papers on the retail sectors tend to assume that wholesale and retail prices are sequentially determined (Crawford and Yurukoglu, 2012; Miravete et al., 2018; De los Santos et al., 2021). In addition, as I will illustrate, the model has the advantage of nesting a canonical linear pricing game (when upstream make the take-it-or-leave-it offer).

for upstream manufacturer $k$ ($\Pi_k$) and downstream retailer $r$ ($\pi_r$) is defined as follows:

$$\Pi_k(G) = \sum_{j \in J_k} s_j\left(G; \mathbf{p}\right)\left(w_j - mc_j^k\right), \forall k, \tag{4}$$

$$\pi_r(G) = \sum_{j \in J_r} s_j\left(G; \mathbf{p}\right)\left(p_j - w_j - mc_j^r\right), \forall r, \tag{5}$$

where the quantity depends on $G$, the choice set, which includes all products $j$ in the market, and $\mathbf{p}$, the vector of retail prices of all products in the choice set $G$. $w_j$ denotes the wholesale price of product $j$, $mc_j^r$ ($mc_j^k$) denotes the retailer $r$ (manufacturer $k$) marginal cost of selling product $j$. The profit $\Pi_k$ for manufacturer $k$ is defined over the combined profit of all products produced by $k$ ($J_k$). Similarly, the profit $\pi_r$ for retailer $r$ is defined over the combined profit of all products sold in retailer $r$ ($J_r$).[33]

In the first stage, to characterize the optimal wholesale price of a product $j$ via Nash-in-Nash bargaining, I define threat points, which are the profits of manufacturers and retailers if they cannot make a deal on product $j$ so $j$ is excluded from the choice set $G$: $\Pi_k\left(G \backslash \{j\}\right)$ and $\pi_r\left(G \backslash \{j\}\right)$, where $G \backslash \{j\}$ denotes the new choice set when product $j$ is excluded. Gains-from-trade to the upstream manufacturers $k$, which produces $j$, and downstream retailer $r$ that carries $j$ are derived from the value addition of forming a contract over their respective threat points:

$$\begin{aligned} \Delta_j \Pi_k\left(G\right) &= \Pi_k\left(G\right) - \Pi_k\left(G \backslash \{j\}\right) \\ \Delta_j \pi_r\left(G\right) &= \pi_r\left(G\right) - \pi_r\left(G \backslash \{j\}\right). \end{aligned}$$

Note that demand primitives influence bargaining outcomes (wholesale prices) through bargaining leverage. If consumers tend to switch brands within the same retailer, the retailers gains from carrying each brand are relatively low, giving them more leverage to negotiate lower wholesale prices. Conversely, if consumers switch to the same brand sold by other retailers, the retailer has less leverage. Thus, accurately capturing the consumer substitution pattern is crucial for understanding the bargaining mechanics. Nash-in-Nash wholesale prices are determined by the following $J$ first-order conditions:

$$w_j = \arg\max_{w_j} \left[\Delta_j \Pi_k\left(G\right)\right]^{\tau_j} \left[\Delta_j \pi_r\left(G\right)\right]^{1-\tau_j}, \forall j, \text{ where } k = \mathcal{K}(j) \text{ and } r = \mathcal{R}(j), \tag{6}$$

[33] Throughout the paper, I use capital $\Pi$ to denote upstream profits and lowercase $\pi$ to denote downstream profits.

which is a solution to the bilateral Nash-in-Nash bargaining problem of manufacturer $k$ and retailer $r$ with Nash bargaining parameter $\tau_j \in [0,1]$. Bilateral Nash implies optimality conditioning on the outcomes of other contracts. Following Crawford and Yurukoglu (2012), I assume that agreements are binding in all contingencies. In other words, if a pair disagrees, all other firms do not renegotiate wholesale prices. Note that the question becomes a standard successive markup game when $\tau_j = 1$ (when the upstream has full negotiation power and makes a take-it-or-leave-it offer). The double markup is eliminated when $\tau_j = 0$ (when the downstream has full negotiation power and makes a take-it-or-leave-it offer).

**Retail price** The second stage is a standard Bertrand-Nash game, taking the first stage to negotiate wholesale prices as given. To clarify the notation, I further divide manufacturers into a set of RPM adopters $K_{RPM}$ and non-adopters $K_N$, where $k \in K = K_{RPM} \cup K_N$. Manufacturers choose retail prices of RPM products, while retailers choose retail prices of non-RPM products. I define a modified profit function that manufacturers and retailers optimize in the second stage as follows:

$$\widetilde{\Pi_k} = \sum_{j \in J_k} s_j\left(G; \mathbf{p}\right)\left(p_j - mc_j^k - mc_j^r\right), \forall k \in K_{RPM} \tag{7}$$

$$\widetilde{\pi_r} = \sum_{j \in J_r} s_j\left(G; \mathbf{p}\right)\left(p_j - w_j^k - mc_j^r\right), \forall r \tag{8}$$

Note that the objective function of the RPM manufacturers $\widetilde{\Pi_k}$ differs from retailers' objective $\pi_r$. First, the RPM manufacturer considers *marginal costs of production* instead of wholesale prices when choosing retail prices $p_j$. In other words, manufacturers care about the joint channel profit (manufacturer plus retailer profit). This reflects the elimination of double markups, which is the vertical efficiency gain from RPM. Second, the manufacturer maximizes *joint profits of selling its brand across all retailers* ($j \in J_k$) when picking $p_j$. The incentives to maximize joint profits across retailers means that the manufacturer internalizes business stealing across retailers, hence softening the downstream competition, which may drive up retail prices. The problem is more complex because there are multiple upstream brands, and RPM firms need to take the brand competition into account when setting retail prices.

I can write the $J$ first-order conditions for RPM and non-RPM products separately as

follows:

$$\frac{\partial \widetilde{\Pi_k}}{\partial p_j} = s_j + \sum_{j \in J_k} \frac{\partial s_j}{\partial p_j}(p_j - mc_j^k - mc_j^r) = 0, \forall j : \mathcal{K}(j) \in K_{RPM} \tag{9}$$

$$\frac{\partial \widetilde{\pi_r}}{\partial p_j} = s_j + \sum_{j \in J_r} \frac{\partial s_j}{\partial p_j}(p_j - w_j^k - mc_j^r) = 0, \forall j : \mathcal{R}(j) = r, \mathcal{K}(j) \in K_N \tag{10}$$

I characterize the solution of the game in the next subsection.

**Solution concept** From Equation (9) and (10), the first-order conditions of the retail prices, I can rearrange the joint system of $J$ first-order conditions in matrix form:

$$\mathbf{s} + \widehat{T^D} \cdot \Delta \times (\mathbf{p} - \mathbf{mc^r}) - \widehat{T^D} \cdot (1 - \psi) \cdot \Delta \times \mathbf{w} - \widehat{T^D} \cdot \psi \cdot \Delta \times \mathbf{mc^k} = 0, \tag{11}$$

where $s$ is the market share of each product, $\widehat{T^D}$ is the modified downstream ownership matrix, with $\widehat{T^D} = (1-\psi) \cdot T^D + \psi \cdot T^U$, where $T^U$ and $T^D$ are the upstream and downstream ownership matrix, and $\psi$ is a $J \times 1$ vector with $\psi(j) = 1$ if $\mathcal{K}(j) \in K_{RPM}$.[34] Intuitively, $\psi$ specifies whether the manufacturer sets the retail price of a product via RPM contract.[35] $\Delta(j_1, j_2) = \frac{ds_{j_1}}{dp_{j_2}}$ denotes the elasticity matrix of demand of product $j$ with respect to retail prices. $\mathbf{p}$ and $\mathbf{w}$ indicate the retail and wholesale price vector, respectively, and $\mathbf{mc^k}$ ($\mathbf{mc^r}$) denotes the marginal cost of the manufacturer (retailer).

To get more intuition from the retail pricing first-order conditions, it is be useful to rearrange Equation (11) into a familiar markup equation:

$$(\mathbf{p} - \mathbf{w} - \mathbf{mc^r}) = -\underbrace{\left(\widehat{T^D} \cdot \Delta\right)^{-1}}_{\text{coordination}} \times \left( \mathbf{s} + \underbrace{\widehat{T^D} \cdot \psi \cdot \Delta \times \left(\mathbf{w} - \mathbf{mc^k}\right)}_{\text{mitigation of double markup}} \right). \tag{12}$$

Compare this equation with the regular markup equation under the non-RPM setting:

$$(\mathbf{p} - \mathbf{w} - \mathbf{mc^r}) = -\left(T^D \cdot \Delta\right)^{-1} \times (\mathbf{s}).$$

There are two differences. The price coordination incentives are captured by replacing

[34] I use dot product ($\cdot$) to denote element-wise product multiplication and cross product ($\times$) to denote matrix multiplication throughout the paper.

[35] $\widehat{T^D}(j_1, j_2) = 1$ if $\mathcal{R}(j_1) = \mathcal{R}(j_2)$ and $\mathcal{K}(j_1) \in K_N$, or $\mathcal{K}(j_1) = \mathcal{K}(j_2)$ and $\mathcal{K}(j_1) \in K_{RPM}$. In other words, $\widehat{T^D} = T^D$ for non-RPM products, while $\widehat{T^D} = T^U$ for RPM products.

the standard ownership matrix $T^D$ with $\widehat{T^D}$, reflecting that the upstream firm is coordinating retail prices of its brand across retailers. This tends to increase the retail margin of RPM products when retailer competition is stronger than brand competition. On the other hand, the mitigation of the double markup effect is captured by the term $\widehat{T^D}\cdot\psi\cdot\Delta\times\left(\mathbf{w}-\mathbf{mc^k}\right)$ added to the market share. It takes the value of zero for non-RPM products and negative values for the RPM products, decreasing downstream markups of RPM products on the left-hand side.

I can rewrite Equation (6), i.e., the first order condition for wholesale prices $\frac{\partial NE_j}{\partial w_j}=0$ in matrix forms (derivations can be found in Appendix Section D.1):

$$\begin{aligned}&\tau\cdot\underbrace{\left(T^D\cdot S^U\times\left(\mathbf{p}-\mathbf{w}-\mathbf{mc^r}\right)\right)}_{\Lambda}\cdot\left(\mathbf{w}+\left(T^U\cdot Z^w\right)\times\left(\mathbf{w}-\mathbf{mc}^k\right)\right)+\\&\left(T^U\cdot S^U\times\left(\mathbf{w}-\mathbf{mc}^k\right)\right)\cdot(1-\tau)\cdot\underbrace{\left(-\mathbf{s}+\left(T^D\cdot p_w^T\right)\times\mathbf{s}+\left(T^D\cdot Z^w\right)\times\left(\mathbf{p}-\mathbf{w}-\mathbf{mc^r}\right)\right)}_{\Xi}=0,\end{aligned}\tag{13}$$

which can be written into the following upstream margin equation:

$$\left(\mathbf{w}-\mathbf{mc}^k\right)=-\left[\underbrace{\left(T^UZ^w\right)}_{\text{linear pass-through}}+\underbrace{\frac{(1-\tau)\Xi}{\tau\Lambda}T^US^U}_{\text{bargaining}}\right]^{-1}\times\mathbf{s},\tag{14}$$

where $Z^w(j_1,j_2)=\frac{\partial S_{j_1}}{\partial w_{j_2}}=(\Delta\times p_w)^T$. The exclusion matrix $S^U(j_1,j_2)=s_{j1}-s_{j1,-j2}$ reflects the changes in demands of product $j_1$ when $j_2$ is excluded.[36] $p_w(j_1,j_2)=\frac{\partial p_{j_1}}{\partial w_{j_2}}$ is the commonly called pass-through matrix in the vertical literature.[37]

The wholesale pricing equation (14) consists of two parts. The first part $\left(T^UZ^w\right)$ is the standard pass-through effect in a two-stage game, reflecting the double markup effect. The pass-through matrix $p_w$ for RPM products takes the value of zero for RPM products because $\mathbf{p}$ will not depend on $\mathbf{w}$. Thus, only the second term matters for RPM products.[38] The

[36] $s_{j_1,-j_2}=s_{j_1}(G)-s_{j_2}(G\backslash\{j_2\})$ denotes the share of $j_1$ when $j_2$ is excluded.

[37] It shows how the second-stage retail price responds to the wholesale price, which is solved by applying the implicit function theorem in the second-stage first-order conditions: $p_w=-\left(\wp_w\right)^{-1}\left(\wp_p\right)$ where $\wp\equiv\mathbf{s}+\widehat{T^D}\cdot\Delta\times\left(\mathbf{p}-\mathbf{mc^r}\right)-\widehat{T^D}\cdot(1-\psi)\cdot\Delta\times\mathbf{w}-\widehat{T^D}\cdot\psi\cdot\Delta\times\mathbf{mc^k}$. Appendix Section D.1 provide useful implementation details on how to calculate values of $p_w$ under a random coefficient nested logit framework with RPM.

[38] This argument simplifies the equilibrium effects because rising wholesale prices $w$ of RPM products can still affect $p$ of RPM products by affecting $p$ of rival non-RPM brands. In practice, $p_w$ is small but non-zero for RPM products.

second term $\frac{(1-\tau)\Xi}{\tau\Lambda}T^U S^U$ reflects the bargaining effect. The numerator equals 0 when $\tau = 1$. So, the bargaining degenerates to an upstream take-it-or-leave-it offer. The denominator $= 0$ when $\tau = 0$, therefore driving $(\mathbf{w} - \mathbf{mc^k}) = 0$. This corresponds to the downstream take-it-or-leave-it offer. When $\tau \in (0, 1)$, bargaining effects move wholesale prices between those two extremes. The equilibrium retail and wholesale price vector $(\mathbf{p}, \mathbf{w})$ solves the equation system (11) and (13). Discussions of the model property with simulated data can be found in Appendix Section B.1.

**Identification & Estimation** There are two challenges in the supply-side estimation. First, it is difficult to disentangle the retailer's marginal costs ($\mathbf{mc^r}$) and the manufacturer's marginal costs ($\mathbf{mc^k}$). Second, it is difficult to separate marginal costs from bargaining parameters $\tau$ in Equation (14). I can address the first challenge because I observe both retail and wholesale prices from the data. All demand side parameters are recovered via demand estimation, so the retailer markup ($\mathbf{mk^r}$) is known from Equation (12). Therefore, I can infer the retailer's marginal cost at the product level nonparametrically as the residual from the following equation without imposing any structures on the costs:

$$\mathbf{mc^r} = \mathbf{p} - \mathbf{w} + \underbrace{\left(T^D \cdot \Delta\right)^{-1} s}_{=-\mathbf{mk^r}} \Rightarrow mc^r_{jt} = p_{jt} - w_{jt} - mk^r_{jt}.$$

To address the second challenge, note that given demand and bargaining parameter $\tau$, upstream markup $\mathbf{mk^k} = \mathbf{w} - \mathbf{mc^k}$ is known via Equation (13). If the negotiation parameter $\tau$ is known, under the non-RPM regime, the marginal cost of production ($\mathbf{mc^k}$) can be expressed as a function of bargaining parameter $\tau$ and observables:

$$\mathbf{mc^k} = \mathbf{w} + \underbrace{\left[\left(T^U Z^w\right) + \frac{(1-\tau)\Xi}{\tau\Lambda} T^U s^U\right]^{-1} s}_{=-\mathbf{mk^k}} \Rightarrow mc^k(\tau_{jt}) = w_{jt} - mk^k_{jt}(\tau_{jt}). \tag{15}$$

I specify the marginal cost of production as $mc^k_{jt} = \eta_{\mathcal{K}(j)t} + u_{jt}$, where it depends on brand-market-time fixed effects ($\eta_{\mathcal{K}(j)t}$) and product-time specific cost shocks $u_{jt}$. The implicit assumption is that marginal costs of production do not depend on retailers ($\mathcal{R}(j)$), implying that the same brand sold by different retailers in the same market has the same expected marginal cost of production. Hence, holding demand fixed, observed differences in wholesale prices of a brand across retailers are driven solely by bargaining parameters. In the estimation,

I further assume that $\tau$ is chain type-brand specific, and I define three chain types according to their sizes: national chain, local chain, and independent retailer, so I estimate $3 \times 4 = 12$ bargaining parameters. If I plug the specified $mc^k$ back to equation (15), I can express the error $u_{jt}$ as follows:

$$u_{jt} = w_{jt} - mk^k_{jt}(\tau_{jt}) - \eta_{\mathcal{K}(j)t},$$

which is a function of the non-linear parameter $\tau$. I use non-linear GMM to estimate $\tau$ with the orthogonality condition $E(u_{jt}(\tau)|Z_{jt}) = 0$. To identify parameters $\tau$, I construct the following instruments. The first set of instruments ($Z^1_{jt}$) includes the dummy variable that denotes chain type interacted with brand dummies. Importantly, $Z^1_{jt}$ is excluded from the marginal cost equation, and residuals $u_{jt}$ are assumed to be orthogonal to $Z^1_{jt}$. Intuitively, if demand conditions are the same, differences in observed wholesale prices of the same brand in two retailers can be explained only by differences in bargaining power but not differences in the marginal cost of production. This exclusion condition helps pin down bargaining powers across retailers.

The second set of instruments is the gains from trade (GFT). As discussed in Ho and Lee (2017), the correlation between gains from trade (GFT) and wholesale prices helps identify bargaining parameters. Consider retailer (A) carries multiple substitutable brands, each brand offers little GFT for the retailer; retailer (B) carries only one brand so it offers high GFT for the retailer. If we see the wholesale prices tend to be higher in retailer (B), this implies that brands have some bargaining power, i.e., $\tau > 0$; if the wholesale price remains similar in (A) and (B), this implies that brands have little bargaining power and forced to charge marginal production cost, i.e., $\tau = 0$. This implies the usage of relative GFT measure $Z^2_{jt} = \frac{\Xi}{\Lambda} T^U s^U$ in Equation (13) as an instrument.

However, there is a potential simultaneity issue: GFT can change in response to supply shifts as well as demand shifts: higher brand bargaining power can lead to a higher wholesale price and lower GFT for retailers, biasing $\tau$ downward. I expect the endogeneity to be small for two reasons. First, the variations in GFT come mainly from the rich variations in the assortments across retailers but not the prices, so the negotiated prices shift GFT only marginally. Second, in practice, I follow Grennan (2014), take advantage of the panel structure of the data, and evaluate $Z^2_{jt}$ at the lagged brand-market average whole price $\bar{w}_{b(j)t-1}$. This assumes that predictions of the GFT formed based on previous $\bar{w}_{b(j)t-1}$ are not correlated with simultaneous product-specific cost shocks $u_{jt}$.

Table 5: Upstream Bargaining Parameter Estimates

| **Panel A: Upstream bargaining power $\tau$** | | | | |
|---|---|---|---|---|
| | Zuoli | YRPG | Aodong | Rongchang |
| National Chain | 0.19 | 0.82 | 0.47 | 0.67 |
| | (0.06) | (0.11) | (0.03) | (0.07) |
| Local Chain | 0.29 | 0.67 | 0.42 | 0.72 |
| | (0.03) | (0.03) | (0.04) | (0.06) |
| Independent | 0.33 | 0.84 | 0.76 | 0.83 |
| | (0.03) | (0.04) | (0.10) | (0.21) |
| **Panel B: marginal cost of production (¥/DDD)** | | | | |
| | Zuoli | YRPG | Aodong | Rongchang |
| Northeast | 1.67 | 3.08 | 2.06 | 2.88 |
| North | 1.66 | 2.57 | 2.19 | 2.90 |
| East | 1.53 | 2.34 | 2.14 | 2.91 |
| South | 1.51 | 2.34 | 2.28 | 3.19 |
| Central | 1.51 | 2.69 | 2.08 | 3.13 |
| Northwest | 1.68 | 3.12 | 2.11 | 2.86 |
| Southwest | 1.49 | 2.85 | 2.22 | 2.48 |

*Note*: This table shows the results from supply-side estimation. Panel (A) shows estimated upstream bargaining parameters for each retailer category-brand pair. Panel (B) shows the brand-region average marginal cost aggregated from the fixed cost estimates $\eta_{\mathcal{K}(j)t}$. Standard errors are in parenthesis.

**Supply parameter estimates** In the supply side estimation, I limit my analysis to cities where the dataset has better coverage, defined as the observed number of downstream pharmacy stores $>$ 50% of the total pharmacy stores in that city. This decreases the number of regional markets to 110.[39] The results of estimated bargaining parameters of my main specification can be found in Table 5. On average, upstream firms capture 70% of the profit compared to an upstream take-it-or-leave-it offer. Upstream bargaining parameters in Panel (A) are intuitive— YRPG, the biggest company in this market, is estimated to have the strongest bargaining power. National and local chains tend to have higher bargaining weights than independents, except when negotiating with YRPG, where I find statistically insignificant differences across chain categories. Marginal costs of production for brands are relatively similar across regions. Nonetheless, recovered marginal costs tend to be greater in more distant areas (such as the Northeast and Northwest), which could result from varying transportation

[39]The biases of observing only a partial set of retailers are likely minor because the dataset contains most big-player chain retailers. Besides, the validation exercise in Section 5 indicates that the model replicates well the observed effects of RPM in the data.

costs associated with delivering products to these regions.[40]

# 5 Counterfactual Analysis

The counterfactual analysis relates to the ongoing policy debate on RPM regulations. Recent discussions focus on when RPM's efficiency gains outweigh its potential anti-competitive effects. The roadmap of the counterfactual analysis is as follows. I begin with a validation exercise, demonstrating that the model accurately predicts the estimated design-based effects of YRPG-led RPM.[41] I then report how RPM affects consumer surplus, firm profits, and market efficiency, where I also decompose the pro-competitive effect of eliminating double markups and the anti-competitive effect of facilitating price coordination. I further change model primitives and illustrate how RPM interacts with market fundamentals and subsequently affects welfare outcomes. Lastly, I compare the effects of RPM with several other vertical contracts to offer regulatory insights.

## 5.1 Validation

By estimating the supply model only using the post-investigation data (None of the products adopted RPM), I can validate the model by simulating the outcome if YRPG adopts RPM and compare the model-predicted effects of YRPG-led RPM to the design-based treatment effects of YRPG.[42] Table 6 reports the results. Panel A shows a 13.1% decrease in retail prices, a 5.7% increase in wholesale prices, and a 41% (=exp(0.537)-1) increase in quantities under the YRPG-RPM regime. These numbers align well with the design-based estimates of the RPM effect reported in Panel B. The model also predicts the reduced price dispersion due to RPM well.

[40] I verify the supply estimates using the financial reports of two brands (Zuoli and Aodong) produced by public-listed firms. The reported production costs of the products of interest in their financial report from 2018-2021 match their products' estimated national average quantity-weighted predicted marginal cost with the reported average costs.

[41] In the counterfactual, I fix the bargaining power as model primitives in all counterfactual analyses and assume that they remain the same as estimated using the RPM period data. The validation exercise indicates the assumptions may be reasonable.

[42] It's important to note that this is an out-of-sample validation exercise, as no information about RPM was used, and I can obtain the model estimates and compute model-predicted effects even without the RPM case.

Table 6: Validation: Model Predicted Effects of RPM and Design-based Estimates

| | Level terms (in logs) | | | Dispersions | |
|---|---|---|---|---|---|
| | Retail price | Wholesale price | Quantity | Retail price | Markup |
| **Panel A: Model** | | | | | |
| $\mathbb{1}$(RPM)×YRPG | -0.131*** | 0.057*** | 0.537*** | -0.033*** | -0.024*** |
| | (0.012) | (0.010) | (0.018) | (0.004) | (0.006) |
| **Panel B: Data** | | | | | |
| $\mathbb{1}$(RPM)×YRPG | -0.131*** | 0.090*** | 0.446*** | -0.075*** | -0.018*** |
| | (0.020) | (0.024) | (0.079) | (0.014) | (0.006) |
| Post-period level | ¥4.36/DDD | ¥3.24/DDD | 26 mil. DDD | 0.16 | 0.07 |

*Note*: In Panel A, the model predicted effects are obtained via the regression of outcomes (prices, quantities, dispersion) over RPM dummy and market fixed effects. The estimated effects from data in Panel B are based on Equation (1) with the sample restricted to Bailemian and control products in 2018-2021.

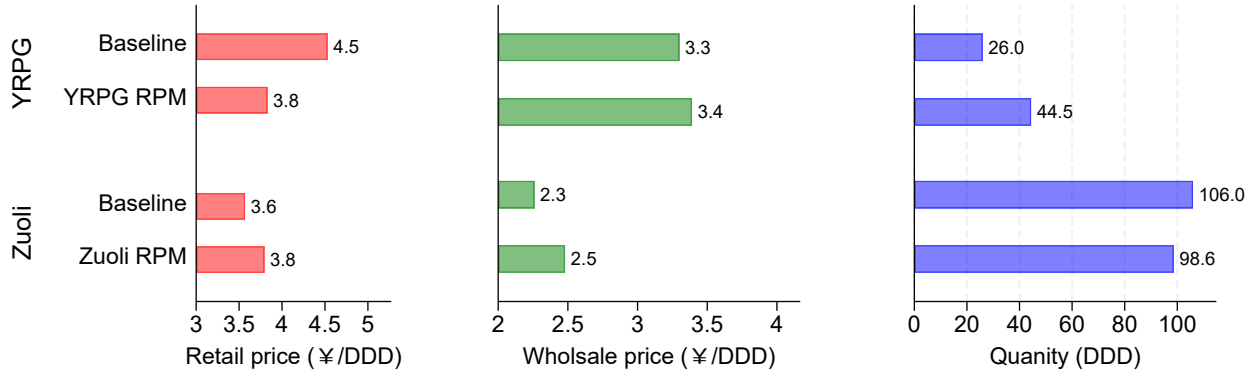
## 5.2 Welfare Effects of RPM

Note that the upstream manufacturer adopts RPM with two distinct incentives as summarized in Equation (12):

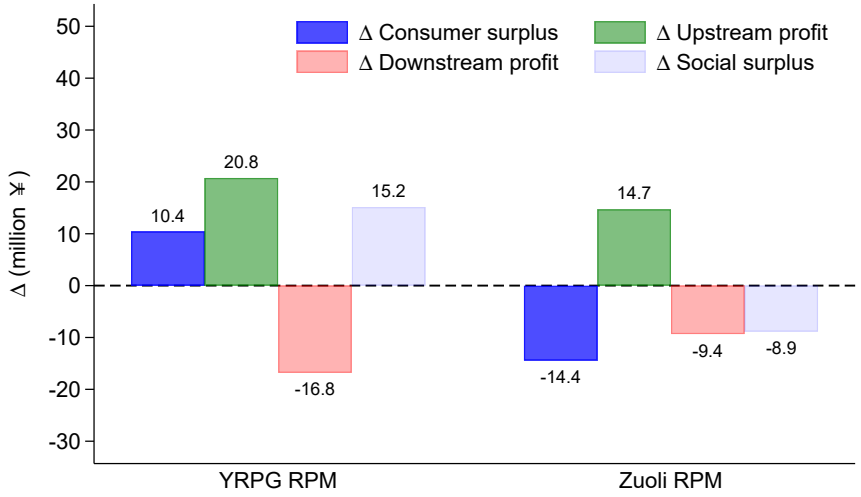
$$(\mathbf{p}-\mathbf{w}-\mathbf{mc^r}) = -\underbrace{\left(\widehat{T^D}\cdot\Delta\right)^{-1}}_{\text{coordination}} \times \left(\mathbf{s}+\underbrace{\widehat{T^D}\cdot\psi\cdot\Delta\times\left(\mathbf{w}-\mathbf{mc^k}\right)}_{\text{mitigation of double markup}}\right).$$

Coordination incentives and mitigation of double markup incentives have the opposite effects on welfare by increasing or decreasing retail prices. The goal of this section is to quantify the size of the welfare effects of the two incentives and, in Section 5.3, how they vary according to market conditions.

All scenarios are compared to a baseline scenario in the second half of 2022 when RPM did not exist for the rest of my counterfactual analysis. In this subsection, I break down the welfare effects of RPM and show that RPM adopted by different brands may lead to heterogeneous welfare implications by solving the new equilibrium under two different scenarios: (1) only YRPG imposes RPM, (2) only Zuoli (another brand) imposes RPM. Scenario (1) resembles the pre-investigation market, while scenario (2) is hypothetical. The results are summarized in Figure 5, and detailed numbers can be found in Appendix Table E.6. Details of implementation are discussed in Appendix D.2. There are four takeaways.




(a) Price and Quantity




(b) Welfare Breakdown

Figure 5: Overview of the Counterfactual Results

*Note*: This figure illustrate counterfactual changes in market outcomes under YRPG RPM and Zuoli RPM. Subplot (a) summarizes counterfactual retail prices, wholesale prices, and quantity with or without RPM. Panel (b) depicts changes in consumer surplus (CS), upstream profit, downstream profit, and total social surplus relative to the baseline. More details can be found in Appendix Table E.6.

**Effects of RPM by YRPG** First, the results clearly indicate that the RPM contract established by YRPG enhances market efficiency. YRPG gains from the RPM contracts by expanding their quantities (+71%) via the elimination of double markups. YRPG also negotiates higher wholesale prices (+3%) due to RPM. These two effects jointly contribute to an additional ¥20 million profit (80%) increase in YRPG profit, where quantity expansion explains 88% of the profit increase, and the bargaining leverage explains the remaining 12%. The YRPG gain comes at the cost of the downstream retailers, who jointly experience a loss of ¥16.8 million or a 52% drop in the profits of selling YRPG products. Consumers benefit

from RPM, gaining ¥10.4 million due to a significant reduction in retail prices. The social surplus amounts to ¥15.2 million. The joint upstream and downstream surplus also rises by ¥4 million.[43] Counterfactual results also show that RPM has a small spillover effect on rival brands. The impact on rivals seems negligible because the market stealing across brands is relatively low.[44]

**Effects of RPM by another brand** The pro-competitive effects of RPM vary by brand. In the counterfactual where only Zuoli adopts RPM, the model predicts a 6% increase in average retail prices and anti-competitive outcomes. The differences in market fundamentals explain these effects. Zuoli faces weaker brand competition than YRPG, with a higher same-brand-different-retailer diversion ratio (0.548 vs. 0.344, Table 4). In addition, Zuoli faces stronger retailer competition than YRPG— the sales of Zuoli products are much more diverse across retailers, while YRPG's sales are concentrated chiefly on big chains, and downstream HHI for Zuoli is 410 lower than YRPG. Zuoli also has a relatively minor double markup issue— retailers have big bargaining power and have a significant influence on the wholesale prices of Zuoli products (Table 5.) Therefore, in Zuoli's case, downstream retailer competition undermines the pricing power that Zuoli could have exerted. Hence, Zuoli has stronger incentives to use RPM to soften retailer competition than to eliminate double markups. From an anti-trust standpoint, Zuoli's RPM would reduce welfare for consumers (-¥14.33 million) and downstream retailers (-¥9.4 million), and they outweigh the manufacturer gain, leading to a -¥8.9 million net loss in social surplus. This highlights that RPM's welfare effects can differ greatly across brands, even within the same market.

**Disentangle the price coordination incentives** I decompose overall welfare changes into incentives for price coordination and eliminating double markups. This is done by replacing

[43]This indicates that RPM can be incentive compatible with a transfer from upstream to downstream in a static setting. Note the RPM practice is self-enforcing in a repeated game even when retailers lose from RPM, because upstream firms can use supply cuts as a threat (Buehler and Gärtner, 2013). If there were any transfers not observed by the author, they would not affect the results on consumer/social surplus; only the distributional effects between upstream and downstream would be different.

[44]Theoretically speaking, the RPM's effects on rivals are ambiguous. On the one hand, since retail markups are strategic complements in a Bertrand-Nash game, rivals should adjust their prices in the same direction as YRPG, which is referred to as the competition effect. However, since downstream retailers' profits from selling YRPG products are low under RPM, gains from trade of including rival brand are higher for retailers, resulting in increased wholesale prices. In the YRPG RPM scenario, the wholesale prices of all products increase by ¥0.01-0.09, while the competitor's retail price decreases slightly. Hence, the competition effect prevails over the bargaining leverage effect. This partially explains why we observe relatively small responses of rival prices in the design-based evidence.

the "conduct matrix" under RPM, $\widehat{T^D} = \psi \cdot T^U + (1-\psi) \cdot T^D$, with the standard downstream ownership matrix $T^D$.[45] The welfare gain from this practice is ¥18.2 million, 77% higher than RPM. The net gain from RPM is ¥10.4 million. Thus, the coordination incentive leads to a ¥7.8 million (=¥18.2-10.4) loss in consumer surplus. A similar analysis of Zuoli's RPM contract shows a ¥51 million gain from reducing double markups, offset by a ¥65.4 million loss from coordinating prices, explaining its anti-competitive effect. These results underscore the risk that RPM can soften retail competition, even when primarily aimed at eliminating double markups.

**Effects of RPM by all brands** Lastly, if RPM is adopted independently by all four brands, the welfare effects remain pro-competitive in this context, as shown in Column (4) of Table E.6. Prices decrease for three out of four brands (except Zuoli), resulting in the highest consumer welfare gains of my counterfactuals (¥18 million).[46]

**Policy Implications** To sum up, the counterfactual analyses in this section show the subtlety required to investigate RPM. RPM can lead to different welfare outcomes for two brands in the same market and share a similar supply chain. Therefore, the "rule of reason" analysis on RPM practice should be conducted on a brand rather than an industry basis. In addition, I show that under some market conditions, granting drug manufacturers more control along the supply chain can shift profits from retailers to manufacturers without harming consumers, which may be deemed desirable if the government wants to encourage innovation from pharmaceutical manufacturers, as discussed in Dubois and Sæthre (2020).

## 5.3 Importance of market primitives

In this exercise, I shift different primitives of the model to simulate how the effects of RPM change. The results are summarized in Table 7.

Column (4) of Table 7 confirms that the effect of RPM on the retail price of a brand can be explained mainly by the three model primitives ($R^2 = 0.9$). If the RPM brand is different from its rivals, this means a bigger scope for price coordination since the brand can use RPM

[45] Intuitively, this implies that YRPG has individual sales representatives in each retailer to set retail prices, and sales representatives in each retailer maximize solely on YRPG's profit for that particular retailer.

[46] Additional counterfactual results indicate that the welfare improvement persists even when upstream firms collude under industry-wide RPM in Column (5) of Table E.6. Supporting the findings in the government report, brand collusion seems not to be the primary concern in this market compared to retailer collusion.

| | Δ log(retail price) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\sigma$ (YRPG differentiation) | 0.043 | | | 0.044 |
| | (0.002) | | | (0.001) |
| $\rho$ (retailer differentiation) | | -0.075 | | -0.087 |
| | | (0.022) | | (0.007) |
| $\tau$ (upstream bargaining power) | | | -0.505 | -0.510 |
| | | | (0.016) | (0.007) |
| Constant | -0.240 | 0.040 | 0.251 | 0.058 |
| | (0.011) | (0.014) | (0.009) | (0.007) |
| $R^2$ | 0.369 | 0.011 | 0.508 | 0.900 |

Table 7: The Effect of RPM depends on Model Primitives

*Note*: This table shows how the effects of RPM on retail prices depend on different model primitives. I simulated the model 1000 times, and each time with varied model primitives: $\sigma \in \{0, 1, ..., 9\}$ (YRPG brand random coefficient), $\rho \in \{0, 0.1, ..., 0.9\}$ (retailer nesting parameter), and $\tau \in \{0.05, 0.1, ..., 0.95\}$ (upstream bargaining power). I compute changes in the quantity-weighted average equilibrium retail prices from no RPM to (YRPG) RPM and regress the changes on parameter values: $\Delta p_j = \beta_1 \sigma_j + \beta_2 \rho_j + \beta_3 \tau_j + \epsilon_j$. The results confirm that RPM tends to benefit consumers by decreasing retail prices when $\rho$ and $\tau$ are high and $\sigma$ is low.

to raise retail prices of all retailers without losing sales to rival brands (or outside options), making RPM more likely anti-competitive. On the other hand, large retailer differentiation or large upstream bargaining power aggravates the double markup issue, making RPM more likely pro-competitive.

From a regulatory standpoint, the exercises emphasize the importance of understanding market primitives when evaluating RPM. For instance, assuming that retailers are monopolists and ignoring retailer competition (effectively having $\rho \to 1$) can result in substantial biases in welfare assessments. A vertical model helps decompose the forces behind observed markups: brand market power, retailer market power, and double markups. If inefficiency stems from high brand market power, RPM complements price coordination, making it anti-competitive. However, if inefficiency comes from high retailer market power or double markups, RPM can reduce double markups and be pro-competitive.

## 5.4 Comparisons with Other Vertical Contracts

RPM's legal status has changed in the U.S. in the past years. While *State Oil (1997)* applies the rule of reason to maximum-price RPMs, and *Leegin (2007)* to minimum-price RPMs at the federal level, many states, such as California, still regulate minimum-price RPM as illegal

per se. I offer insights into this ongoing policy debate by evaluating the effects of different types of RPM.

As a recap of fixed-price RPM in the model, I can write down the objective function of a RPM manufacturer $k$ for setting retail prices follows:

$$\max_{p_j} \Pi_k^{RPM} = \sum_{j \in J_k} s_j\left(G; \mathbf{p}\right)\left(p_j - mc_j^k - mc_j^r\right), \forall \mathcal{K}(j) \in K_{RPM}.$$

Under maximum-price RPM, the upstream manufacturer does not set the retail prices. Rather, I assume that the manufacturer picks a price *ceiling* $\overline{p}_j$ for each product $j$. Consequently, the retailers face a constrained optimization problem in which they cannot pick a price higher than $\overline{p}_j$:

$$\max_{p_j} \pi_r = \sum_{j \in J_r} s_j\left(G; \mathbf{p}\right)\left(p_j - w_j - mc_j^r\right), \text{ s.t. } p_j \leq \overline{p_j}, \forall \mathcal{K}(j) \in K_{Max-RPM}.$$

A similar argument holds for minimum-price RPM, but retailers now face a price floor, $\underline{p_j}$:

$$\max_{p_j} \pi_r = \sum_{j \in J_r} s_j\left(G; \mathbf{p}\right)\left(p_j - w_j - mc_j^r\right), \text{ s.t. } p_j \geq \underline{p_j}, \forall \mathcal{K}(j) \in K_{Min-RPM}.$$

In principle, $\overline{p_j}$ and $\underline{p_j}$ should be chosen by upstream retailers optimally. For computational reasons, I simplify the problem by assuming that the upstream manufacturer sets $\underline{p_j} = \overline{p_j} = p_j^{RPM}$. In other words, the manufacturer uses the optimal price they would have chosen under fixed-price RPM as the price ceiling (floor) for maximum (minimum) price RPM contracts, which may not be optimal but serves the purpose of this exercise. Furthermore, note if all the constraints are binding for a one-sided RPM, then the one-sided RPM is equivalent to the fixed-price RPM. Some constraints may be non-binding— for example, a retailer with low costs facing a price ceiling may be willing to sell below the ceiling. It is thus an empirical question to measure the wedge between the fixed and one-sided RPM.

Finally, I consider a two-part tariff as a benchmark, where upstream manufacturers can charge a linear wholesale price and a lump-sum payment (sometimes called a franchise fee) from downstream retailers. I consider a classical scenario, where the wholesale price is set at the marginal cost of production ($\mathbf{w} = \mathbf{mc^k}$) to eliminate double markups and upstream demands a lump-sum payment that extracts all the downstream profits.[47] Therefore, in the

[47]Note that when retailers compete with each other, this two-part tariff scheme may not be optimal for the

second stage, retailers solve the following problem:

$$\max_{p_j} \pi_r = \sum_{j \in J_r} s_j\left(G; \mathbf{p}\right)\left(p_j - w_j - mc_j^r\right), \text{ s.t. } w_j = mc_j^k, \forall \mathcal{K}(j) \in K_{TT}.$$

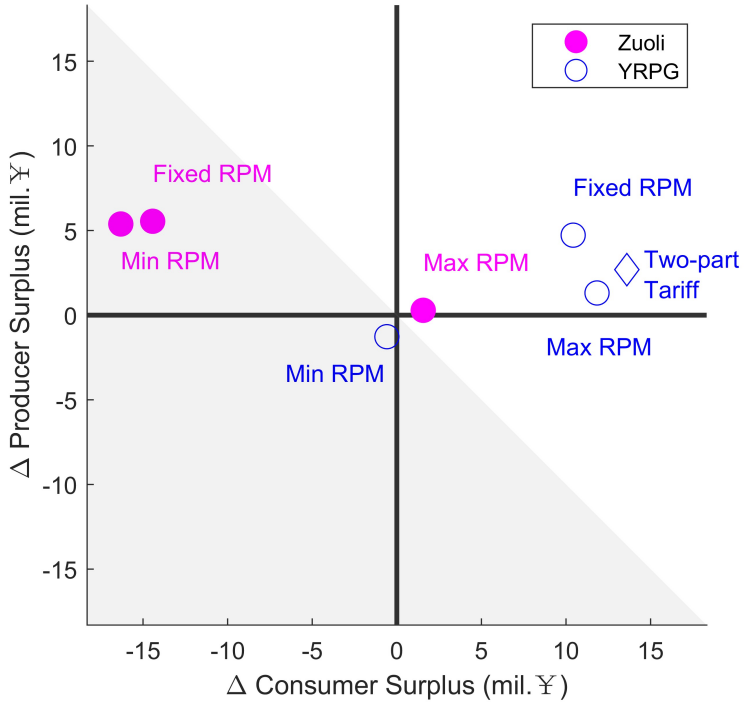



Figure 6: Welfare Effects of Maximum-, Minimum-, Fixed-price RPMs, and Two-Part Tariffs

*Note*: The counterfactual results are based on estimates from Column (6) of Table 3. The horizontal axis denotes the changes in consumer surplus under different vertical contracts compared to the baseline (linear contracts). The vertical axis denotes the changes in producer surplus (joint upstream profit plus downstream profits). The grey region denotes a net loss in social surplus. Pink solid circles denote the effects of Zuoli-only contracts, and blue hollow circle denotes the effects of YRPG-only contracts. The effect of Zuoli's two-part tariff is not shown because it is outside the plotting region (at ($\Delta CS$=50, $\Delta PS$=-31)).

**Simulation outcomes** The results are presented in Figure 6, where I show the changes in consumer surplus and producer (sum of upstream and downstream) surplus under YRPG's or Zuoli's different types of contracts. There are three main findings. First, a minimum-price RPM always hurts consumers, and a maximum-price RPM always benefits consumers. The fixed-price RPM led by YRPG is close to a de facto maximum-price RPM, while Zuoli's is close to a minimum-price RPM. This is not surprising because the results indicate that

upstream manufacturer. Upstream would prefer to set a wholesale price that elicits the optimal retail price. However, it serves as a benchmark for comparison.

YRPG mainly uses RPM to contain prices to mitigate double markups, while Zuoli's primary incentive is to raise prices to achieve price coordination.

Second, I find that compared to the fixed-price RPM, YRPG's maximum-price RPM achieves a significantly 13% higher gain in consumer surplus. Zuoli's minimum-price RPM further decreases consumer surplus by 13%. The differences between fixed-price RPM and one-sided RPM are due to non-binding constraints for some retailers. Also, fixed-price RPM achieves higher joint producer surpluses than one-sided contracts, which explains why upstream firms prefer specifying downstream prices over imposing a one-sided constraint.

Lastly, the two-part tariff achieves the highest consumer and social surplus gains. The intuition is that the specified two-part tariff eliminates double markups without raising concerns about price coordination, which can be substantial given strong brand differentiation and (relatively) smaller retailer differentiation in this industry. In YRPG's case, the two-part tariff would have increased consumer (social) surplus by 31% (8%) compared to a fixed-price RPM. However, the joint producer gain is 50% lower. This explains why firms would prefer RPM over non-linear contracts such as a two-part tariff.

To sum up, contrary to the common wisdom, even in markets where firms adopt maximum RPMs as effective retail price ceilings, there can be a substantial gap in consumer surplus of maximum RPMs compared to a contract that solely eliminates double markups. This is because RPM can further distort prices due to upstream price coordination incentives. Therefore, despite the empirical evidence in this paper that shows RPM achieves net efficiency gains, regulatory agencies may still want to promote the usage of non-linear contracts that do not facilitate potential price coordination.

# 6 Conclusion

In this article, I empirically investigate an RPM case in the pharmaceutical industry. This papers first contribution is to combine an anti-trust investigation with a novel dataset to provide direct empirical evidence of how RPM affects market outcomes. I illustrate that when retailers have market power and manufacturers have strong bargaining power along the vertical relationship, RPM is mainly used by the upstream to eliminate double markups and expand quantity to a more efficient level. I also offer suggestive evidence that RPM may facilitate retailer price coordination.

The second contribution is to build an empirically tractable framework to disentangle

these two incentives, show how they interact with market fundamentals. I find that whether RPM aligns with consumer interests depends on which incentives dominate, further depending on whether the inefficiency of the market is from the lack of brand/retailer competition or the conflicts of interests along the vertical chain. I offer a unified framework that incorporates flexible model primitives to evaluate the potential outcomes of RPM and other vertical contracts, which can be applied in broader contexts.

The result also supports the current rule of reason approach to maximum-price and fixed-price RPM in the U.S.. In June 2022, the Chinese legislature revised Article 14 of its antitrust law to revoke RPM's illegal per se status. The findings in this article offer a positive and reassuring note on this policy revision.

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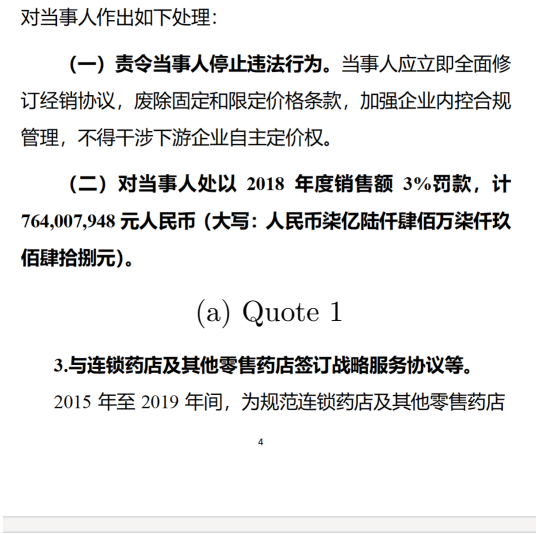
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# Supplemental Appendix

## A Additional Institutional Background

### A.1 Quotes from SAMR Investigation Documents

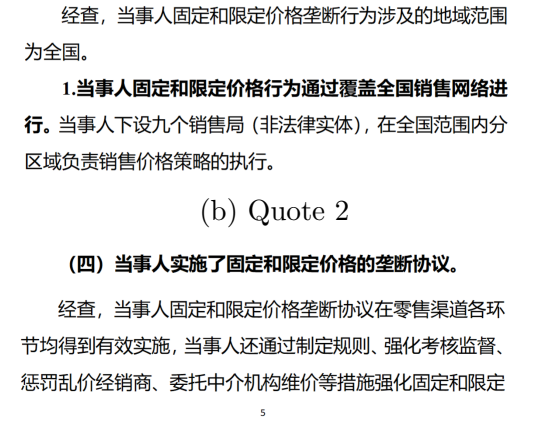

对当事人作出如下处理：

**（一）责令当事人停止违法行为。**当事人应立即全面修订经销协议，废除固定和限定价格条款，加强企业内控合规管理，不得干涉下游企业自主定价权。

**（二）对当事人处以 2018 年度销售额 3%罚款，计 764,007,948 元人民币（大写：人民币柒亿陆仟肆佰万柒仟玖佰肆拾捌元）。**

4

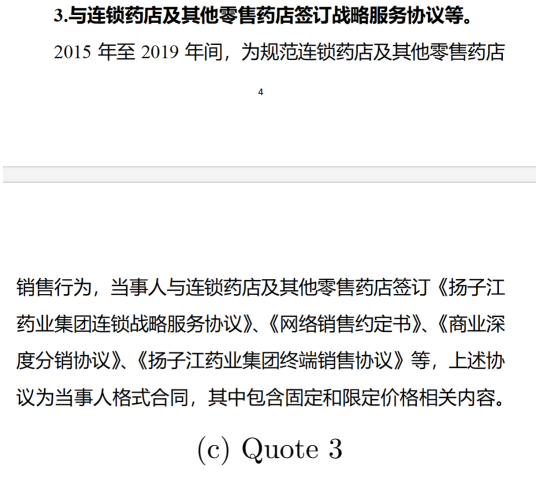
(a) Quote 1


经查，当事人固定和限定价格垄断行为涉及的地域范围为全国。

**1.当事人固定和限定价格行为通过覆盖全国销售网络进行。**当事人下设九个销售局（非法律实体），在全国范围内分区域负责销售价格策略的执行。

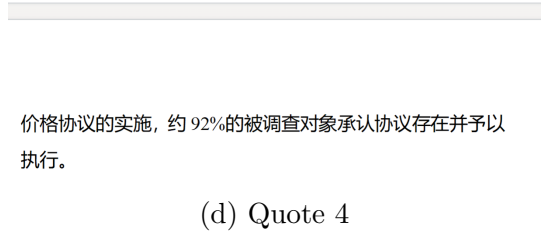
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(b) Quote 2


**3.与连锁药店及其他零售药店签订战略服务协议等。**

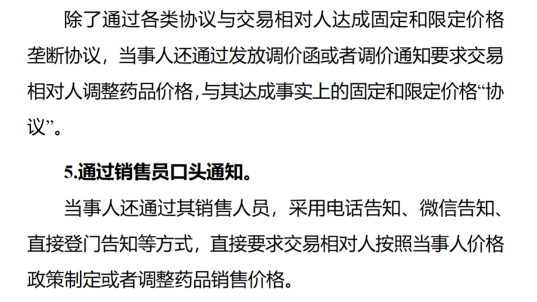
2015 年至 2019 年间，为规范连锁药店及其他零售药店销售行为，当事人与连锁药店及其他零售药店签订《扬子江药业集团连锁战略服务协议》、《网络销售约定书》、《商业深度分销协议》、《扬子江药业集团终端销售协议》等，上述协议为当事人格式合同，其中包含固定和限定价格相关内容。

(c) Quote 3


**（四）当事人实施了固定和限定价格的垄断协议。**

经查，当事人固定和限定价格垄断协议在零售渠道各环节均得到有效实施，当事人还通过制定规则、强化考核监督、惩罚乱价经销商、委托中介机构维价等措施强化固定和限定价格协议的实施，约 92%的被调查对象承认协议存在并予以执行。

(d) Quote 4

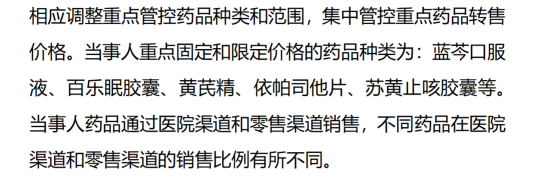

**4.发放调价函或调价通知。**

除了通过各类协议与交易相对人达成固定和限定价格垄断协议，当事人还通过发放调价函或者调价通知要求交易相对人调整药品价格，与其达成事实上的固定和限定价格“协议”。

**5.通过销售员口头通知。**

当事人还通过其销售人员，采用电话告知、微信告知、直接登门告知等方式，直接要求交易相对人按照当事人价格政策制定或者调整药品销售价格。

(e) Quote 5


相应调整重点管控药品种类和范围，集中管控重点药品转售价格。当事人重点固定和限定价格的药品种类为：蓝芩口服液、百乐眠胶囊、黄芪精、依帕司他片、苏黄止咳胶囊等。当事人药品通过医院渠道和零售渠道销售，不同药品在医院渠道和零售渠道的销售比例有所不同。

(f) Quote 6

Figure A.7: Quotes From Original Document (in Chinese)

**Quote 1.** *(1)* ***Ordering the party concerned (YRPG) to stop the illegal act.*** *The*

*parties should immediately and comprehensively revise the agreement, abolish fixed and fixed price clauses, strengthen internal control, and must not interfere with the independent pricing power of downstream retailers. (2)* ***Impose a fine*** *of 3% of the 2018 annual sales volume on the party concerned,* ***totaling RMB 764,007,948****.*

**Quote 2.** *The RPM of the party concerned (YRPG) is carried out through a sale network covering the whole country. The party (YRPG) has set up* ***nine regional sales bureaus (non-legal entities), which are responsible for the implementation of the pricing strategy*** *across the country and by region.*

**Quote 3.** *From 2015 to 2019, in order to control the behaviors of chain pharmacies and other retail pharmacies, the party (YRPG) signed the "YRPG Strategic Service Agreement", "Online Sales Agreement", and "Commercial In-depth Distribution Agreement" etc., with the pharmacy chains and other retail pharmacies. The above agreement is a standard contract between the parties, which* ***includes fixed and limiting price-related content.***

**Quote 4.** *(1) In addition to reaching a fixed price agreement with the retailers through various agreements, the parties sometimes require the retailers to adjust the price of the drug by issuing* ***a price adjustment letter or price adjustment notice*** *to reach a de facto fixed and fixed price "agreement" with them. (2) The party (YRPG) also directly requests the counterparty (retailers) to set or adjust the sales price of the drug in accordance with the price policy of the party (YRPG) through their sales staff, using* ***telephone notification, WeChat notification, and direct door-to-door notification.***

**Quote 5.** *Some of the price adjustment letters mentioned above issued by the party (YTPG) also* ***included threats of cutting supply****, cancellation of selling qualifications, etc. 92% of the interviewed retailers admitted the existence and implementation of the RPM set by YRPG.*

**Quote 6.** *According to the investigation, ...,* ***the types of medicines that the party concerned (YRPG) focused on fixing and limiting prices were: Lanqin Oral Liquid, Bailemian Capsules, Huangqi Jing, Tanglin (Epalrestat Tablets), Suhuang Zhike Capsules, etc.***

## A.2 China's Regulatory Approach toward RPM

As mentioned in the main text, the Chinese "prohibition plus exemptions" approach toward RPM was close to the "per se illegal" approach in the U.S., as the exemptions were never

applied in practice in SAMR-led anti-trust investigations. Table A.8 shows all notable RPM cases (defined by fines > ¥30 million) from 2013 to 2023. Overall, SAMR investigations focus on establishing the legal evidence of RPM conduct rather than the economic analysis of the welfare consequences.

Table A.8: Notable RPM Cases

| Case | Investigation Year | Industry | Fine (in million ¥) | Types of RPM |
|---|---|---|---|---|
| Maotai and Wuliangye | 2013 | Alcohol | 447 | Minimum |
| Biostime and six companies | 2014 | Baby Formula | 670 | Fixed |
| FAW-Volkswagen | 2014 | Automobile | 248 | Fixed |
| Dongfeng-Nissan case | 2015 | Automobile | 123 | Fixed |
| Medtronic | 2018 | Medical Supply | 118 | Fixed |
| Bull | 2021 | Power sockets | 249 | Fixed |
| Yangtze River Pharma | 2021 | Pharmaceutical | 764 | Fixed |
| Straumann | 2022 | Medical Supply | 34 | Minimum |

First, most investigations focused on the legal evidence rather than economics analysis due to the "illegal per se" status of RPM.[48] Second, SAMR usually uses the market shares of the upstream brand to illustrate the brand's dominant positions in the market. As discussed in the main text, focusing solely on brand market share ignores downstream market structure and vertical relations, which is problematic when we study vertical contracts. Third, because of the lack of economic analysis, the expected illegal gains from RPM are unknown. Therefore, the fine in all the cases is set based on the firm revenue (1%-7% of past-year revenues and 2.7% on average.) In some cases, like YRPG, Maotai, and Biostime, only manufacturers were fined, but in other cases, such as Nissan and FAW-Volkswagen, both manufacturers and retailers were fined.

# B Theory Appendix

## B.1 Linear demand system

When I assume a linear demand system, I can obtain closed-form solutions to learn the effects of RPM. For example, suppose that the (inverse) demand function of product $j$,

[48] Most cases did not discuss RPMs alleged anti-competitive effects. More recent reports (for example, Bull, YRPG, and Straumann) mentioned potential anti-competitive effects (dampening intrabrand and interbrand competition) but only touched upon them briefly and did offer evidence of price coordination or exclusion.

defined as $kr$ pair, follows a simple linear form (Dobson and Waterson, 2007):

$$p_{kr} = 1 - (q_{kr} + \beta q_{k,-r}) - \gamma (q_{-k,r} + \beta q_{-k,-r}), \text{where } 0 \leq \beta, \gamma < 1. \tag{16}$$

I can invert the indirect demand equation system to solve for the direct demand function. The demand for brand $k$ at retailer $r$ is:

$$q_{kr}(\mathbf{p}) = \frac{(1-\beta)(1-\gamma) - p_{kr} + \beta p_{k,-r} + \gamma p_{-k,r} - \beta\gamma p_{-k,-r}}{(1-\beta^2)(1-\gamma^2)}.$$

A nice feature of this demand function is that the diversion ratio is captured by parameters $\beta$ and $\gamma$. To see this, note that the within-brand inter-retailer diversion is defined as $D_{A1,A2} = -\frac{ds_{A2}/dp_{A1}}{ds_{A1}/dp_{A1}} = -\gamma$, while the within-retailer inter-brand diversion is defined as $D_{A1,B1} = -\frac{ds_{B1}/dp_{A1}}{ds_{A1}/dp_{A1}} = -\beta$. Therefore larger values of $\beta$ and $\gamma$ imply greater substitutability. For example, $\gamma$ takes a value of one when upstream firms are completely homogeneous, so consumers view different brands as very close substitutes, and zero when upstream firms are differentiated.

I can plug the demand into equation system (11) and (13) to obtain the equilibrium retail and wholesale prices:

$$\begin{aligned}
w^{\text{RPM}} &= \frac{1-\gamma}{2-\gamma}\frac{\tau(1-\gamma)}{\tau(1-\gamma)+(1-\beta)(1-\tau)}. \\
p^{\text{RPM}} &= \frac{1-\gamma}{2-\gamma} \\
w^{\text{non-RPM}} &= \frac{\tau(1-\beta)(2+\beta)(1-\gamma)}{(2-\beta-\beta^2)(2-\tau\gamma)+(1-\tau)\beta^2(2+\beta-\beta^2)} \\
p^{\text{non-RPM}} &= 1 + \frac{w^{\text{non-RPM}} - 1}{2-\beta}
\end{aligned}$$

Based on the solutions, it is easy to prove the following three propositions:

**Proposition 1.** *Final retail price changes induced by RPM ($\Delta p = p^{RPM} - p^{non-RPM}$) increase as $\beta$ increases ($\frac{\partial \Delta p}{\partial \beta} \geq 0$). Further, $\Delta p = \frac{1-\gamma}{2-\gamma} \geq 0$ when $\beta = 1$, $\Delta p \leq 0$ when $\beta = 0$.*

**Proposition 2.** *Final retail prices under both regimes decrease when $\gamma$ increases ($\frac{\partial p^{RPM}}{\partial \gamma} \leq 0$ and $\frac{\partial p^{non-RPM}}{\partial \gamma} \leq 0$). When $\gamma = 1$, $\Delta p = p^{RPM} - p^{non-RPM} = -1 + \frac{1}{2-\beta} \leq 0$.*

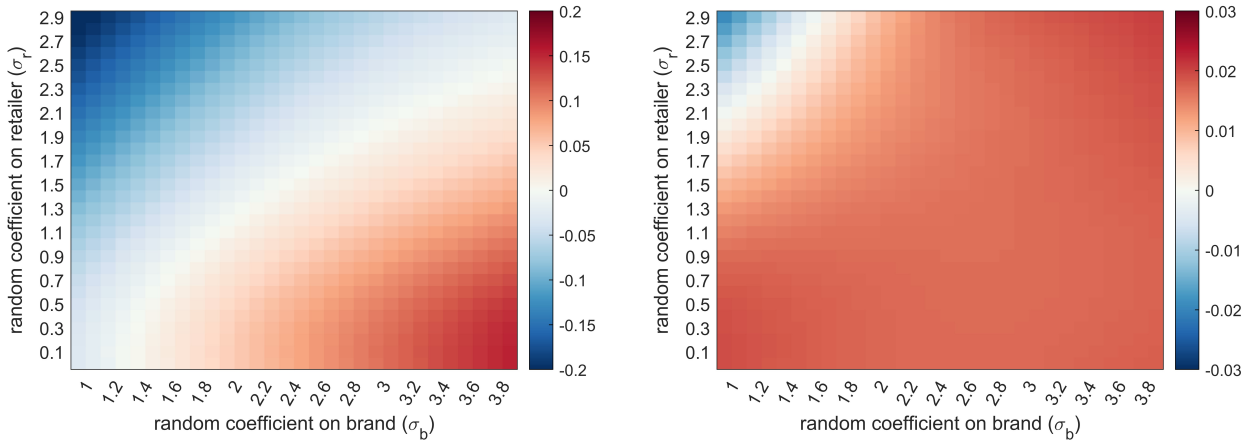
**Proposition 3.** *Final retail price changes induced by RPM ($\Delta p = p^{RPM} - p^{non-RPM}$) decreases as $\tau$ increases ($\frac{\partial \Delta p}{\partial \tau} \leq 0$). Further, $\Delta p = \frac{(\beta-1)}{(2-\beta)(2-\gamma)} \leq 0$ when $\tau = 1$, $\Delta p = \frac{(\beta-\gamma)}{(2-\beta)(2-\gamma)}$ when $\tau = 0$. Note that $sign(\Delta p) = sign(\beta - \gamma)$ when $\tau = 0$.*

## B.2 Discussion of the model solutions and implications

This subsection aims to provide some simulations on how RPM shapes market outcomes in my model and how the predictions of my model change under different market conditions.

**Retail pricing** My model highlights two ways retail prices may differ under RPM versus non-RPM regimes: an incentive to eliminate double markups and an incentive to mitigate downstream competition. To begin with, I abstract away from the discussion of bargaining parameters and fix wholesale prices to focus on the second-stage retail price setting. Intuitively, when interbrand substitution is strong, or when different brands are more or less homogeneous, the intense competition between two brands A and B limits each brand's upstream pricing power; thus the threat of downstream price coordination is minor. At the same time, the gain from eliminating double markups can still be substantial, which drives down the final retail prices. In contrast, when the intrabrand (cross-retailer) substitution is strong, consumers view different retailers as close substitutes. Upstream manufacturers have stronger incentives to use RPM to alleviate downstream competition. Without RPM, downstream firms will fiercely undercut each other, eventually leading to fully competitive prices close to marginal costs in the extreme. Under RPM, the upstream manufacturer can intervene and prevent downstream retailers from pricing against each other, maintaining higher prices. At the same time, double markups are a minor concern when retailers are homogeneous because downstream firms cannot charge a high markup anyway (otherwise, consumers switch to competing retailers). The intuition is confirmed in Figure B.8(a): retail prices tend to increase under RPM when $\sigma_b$ is more significant (so upstream competition is weak) or when $\sigma_r$ is smaller (downstream competition is strong).

**Wholesale pricing** Wholesale prices are characterized by two key forces. First, the passthrough channel is the effect of wholesale prices ($w$) on retail prices ($p$). Second, the bargaining channel splits profits between upstream and downstream firms, since high $w$ indicates the high upstream margin ($w - \mathbf{mc^k}$) and low downstream margins ($p - w$). In non-RPM cases, both effects are active. From an upstream standpoint, raising $w$ leads to higher retail prices $p$, potentially reducing market shares and impacting the collective profits. However, the high $w$ can yield a larger upstream profit. In the presence of RPM, the direct passthrough effect disappears while the bargaining effect persists. Thus, $w$ no longer




(a) $\Delta p_A(\sigma_b, \sigma_r; \tau = 0.5)$ (b) $\Delta p_B(\sigma_b, \sigma_r; \tau = 0.5)$

Figure B.8: Effects of RPM on Own and Rival Retail Prices

*Note*: Simulation based on mixed logit utility function $u_{ij} = \delta_j + \sigma_{ib(j)} + \sigma_{ir(j)} + \varepsilon_{ij}$. Parameter values: $K = 2$ (# of brands), $R = 6$ (# of retailers), $J = 12$ (# of products), $\tau = 0.5$, so upstream and downstream have the same bargaining power. $\alpha = -4, \delta_{ij} = 1, \sigma_{ib(j)} = \sigma_b * \nu_i$, $\sigma_{ir(j)} = \sigma_r * \nu_i'$. $\nu_i$ and $\nu_i'$ are drawn from standard normal distributions (1000 times in the simulation), and I vary values of $\sigma_r$ and $\sigma_b$ in the simulation exercise. Each color square represents a percentage change in retail price after Firm A adopts RPM, i.e., $\Delta p_A = \frac{p_A^{RPM} - p_A^{non-RPM}}{p_A^{non-RPM}}$. Warmer colors denote an increase in retail prices after RPM. Colder colors denote a decrease in retail prices.

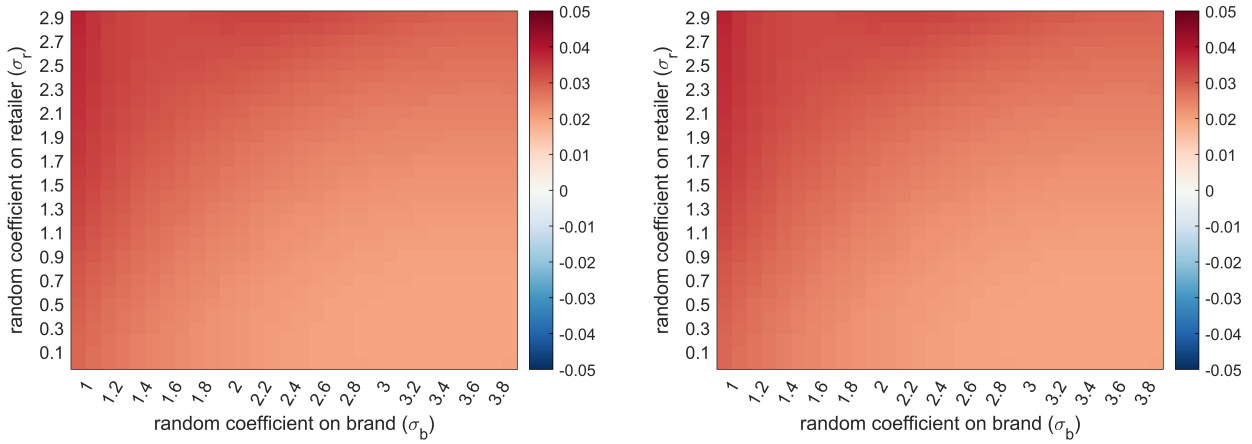
directly impacts $p$.[49] Consequently, given fixed negotiation parameters $\tau$, upstream manufacturers always have incentives to raise $w$ compared to non-RPM cases. The intuition is confirmed in the Appendix Figure B.9(a).

In addition, note that high wholesale prices align with a pronounced double-markup issue. This double-markup issue emerges due to retailers failing to internalize the manufacturer's profit loss when setting retail prices. Such "uninternalized" profit is higher when wholesale prices are higher. Therefore, when upstream bargaining power ($\tau$) rises, wholesale prices increase, accentuating the double-markup issue.[50] Conversely, with full downstream negotiation power, or when $\tau$ approaches zero, double markup vanishes ($w = \mathbf{mc^k}$).

**Rival brands** Note that regardless of whether Firm A imposes an RPM contract, the market structure for B1 and B2 does not change— Firm B still sells its brands to retailers via linear contracts. Therefore, the spillover effects of RPM of rival brands in my model

[49] $w$ still affect $p$ indirectly through general equilibrium effects because rising $w$ for RPM products can still affect the downstream price $p$ of RPM products by affecting the downstream price $p$ of rival brands. In practice, $p_w$ is small but non-zero.

[50] The reason is that high values of $\tau$ must increase upstream profits. The envelope theorem applied to the upstream profit function shows that $w$ has to increase.




(a) $\Delta p_A(\sigma_b, \sigma_r; \tau = 0.5)$ (b) $\Delta p_B(\sigma_b, \sigma_r; \tau = 0.5)$

Figure B.9: Effects of RPM on Own and Rival Wholesale Prices

*Note*: Simulation based on mixed logit utility function $u_{ij} = \delta_j + \sigma_{ib(j)} + \sigma_{ir(j)} + \varepsilon_{ij}$. Parameter values: $K = 2$ (# of brands), $R = 6$ (# of retailers), $J = 12$ (# of products), $\tau = 0.5$, so upstream and downstream have the same bargaining power. $\alpha = -4, \delta_{ij} = 1, \sigma_{ib(j)} = \sigma_b * \nu_i$, $\sigma_{ir(j)} = \sigma_r * \nu_i'$. $\nu_i$ and $\nu_i'$ are drawn from standard normal distributions (1000 times in the simulation), and I vary values of $\sigma_r$ and $\sigma_b$ in the simulation exercise. Each color square represents a percentage change in retail price after Firm A adopts RPM, i.e.: $\Delta w_A = \frac{w_A^{RPM} - w_A^{non-RPM}}{p_A^{non-RPM}}$. Warmer color denotes an increase in retail prices after RPM. Colder color denotes a decrease in retail prices.

come from strategic responses to price changes of products A1 and A2.

The retail pricing behaviors of competing products in response to RPM are ambiguous. On the one hand, considering the strategic complementarity of retail prices in the Bertrand-Nash game, each manufacturer should adjust its price in the same direction as its rivals. This is referred to as the retail competition effect. In particular, when brand A gains a comparative advantage via eliminating double markups by an RPM contract, it also steals business from rival brands, partially excluding rival brands.

However, as a brand A-RPM reduces each downstream retailer's profit from selling product A, the value added by including brand B ($\pi_1(\{A1, A2, B1, B2\}) - \pi_1(\{A1, A2, B2\})$) becomes higher, thereby shifting bargaining leverage toward rival brands. This bargaining leverage effect prompts negotiated wholesale prices, exerting upward pressure on the final retail prices. The relative size of these two incentives will govern how $p_B$ moves. When RPM increases the prices of RPM products, rival brands will unanimously increase prices since the retailer competition and bargaining leverage effects are in the same direction. Otherwise, the responses of rival brands can move in either direction under different parameterizations. This is illustrated by the simulation Figure B.8(b). I observe a decrease in RPM retail prices

but an increase in rival retail prices in some regions of the parameter space (for example, when $\sigma_b = 8$ and $\sigma_r = 1.6$). That is because the bargaining leverage effects dominate the market competition effects.

**Welfare** A full set of welfare results from the simulation analysis can be found in the Appendix (Figure B.10 and B.11). The key insights are as follows. First, the welfare effect of RPM is ex-ante ambiguous and determined by demand primitives and relative negotiation power. RPM tends to be pro-competitive in a market with elastic interbrand substitution, inelastic intrabrand substitution, and large upstream bargaining parameters. [51] Second, consumer surplus is closely tied to the retail prices of all products in the market, including RPM products and rival products. Therefore, ignoring spillover effects on rival responses will bias the welfare estimates. Lastly, there are winners and losers of RPM. While the upstream manufacturers benefit from RPM contracts so long as they hold some bargaining power, these gains often occur at the expense of downstream retailers, potentially also hurting upstream rivals and consumers.

# C Data Appendix

## C.1 Selections of the Control Group

For a product to be an eligible control, I select OTC products that follow each of the following categories: (1) The manufacturer is from one of the top 10 domestic manufacturers in China (YRPG is the 3rd largest producer), (2) The product is not in one of the five investigated category, (3) The product is not in any category that YRPG produces any product, (4) The product's monthly sales ¥> 3 million. This leads to the final 23 products in six categories in the control set. I chose the most popular product in each category as the final control group. Alternatively, I can use all 23 products and the results do not change.

[51] Another way to intuitively understand how market primitives determine the effects of RPM is to ask the following question: when the price of a product increases, what proportion of consumers switches to other brands at the same retailer, and what proportion goes to the same brands at other retailers? If the former is stronger and the latter weaker, retailers are more differentiated than brands. Hence, RPM tends to be pro-competitive and vice versa.

Table C.9: Selection Rule of Control Products

| **Seletion Rule** | **Number of Products** |
|---|---|
| (1) Top 10 Firms | 1614 |
| (2) Sales ¥> 3 million. | 83 |
| (3) Not in RPM category | 55 |
| (4) Not compete with any YRPG products | 23 |

## C.2 Consumer Panel

The consumer panel dataset is sourced from the Sinohealth CMH dataset. In the estimation, I selected 10 representative cities from the dataset to construct the micro-panel that pins down the substitution patterns based on the coverage quality. The summary statistics of the consumers in the dataset are shown in Table C.10:

Table C.10: Summary Statistics of Consumer Panel

| | mean | sd | min | max |
|---|---|---|---|---|
| Age | 46.3 | 12.1 | 20.0 | 80.0 |
| Gender (Male=1) | 0.5 | 0.5 | 0.0 | 1.0 |
| Number of Purchases | 3.4 | 3.6 | 2.0 | 118.0 |
| Spending (¥) | 181.8 | 292.7 | 20.6 | 9017.2 |
| Purchased (Quantity in DDD) | 48.9 | 83.3 | 10.0 | 2877.0 |
| Number of Retailers visisted | 1.4 | 0.7 | 1.0 | 14.0 |
| Number of Brands purchased | 1.1 | 0.4 | 1.0 | 4.0 |
| Multi-brand Buyer % | 13.2 | 33.9 | 0.0 | 100.0 |
| Multi-retailer Buyer % | 27.8 | 44.8 | 0.0 | 100.0 |

Note: This table reports the consumers' spending on the four sleep-disorder drugs in sample pharmacies. The number of observations is 17,336 over the sample period (2018-2022).

# D Solution Algorithm

## D.1 Derivation of Equilibrium Conditions

**Price Derivatives** From Equation (3), I can construct group share derivatives and conditional share derivatives. The group share $\bar{s_g}$ denotes the joint market share of all products in the nest $g$, which is a $R \times J$ matrix, and the conditional share $\bar{s}_{j|g}$ denotes the conditional share of product $j$ conditional on the nest $g$, which is a $J \times J$ matrix (Miller and

Weinberg, 2017).

$$\frac{\partial \bar{s}_g}{\partial \delta_k} = \int \frac{\partial \bar{s}_{ig}}{\partial \delta_k} dF(i) = \begin{cases} \int s_{ik}\left(1 - \bar{s}_{ig}\right) dF(i) & \text{if } k \text{ is in nest } g \\ \int -\bar{s}_{ig} s_{ik} dF(i) & \text{if } k \text{ is not in nest } g \end{cases}$$

$$\frac{\partial \bar{s}_{j|g}}{\partial \delta_k} = \int \frac{\partial \bar{s}_{ij|g}}{\partial \delta_k} dF(i) = \begin{cases} \int \frac{1}{1-\sigma} \bar{s}_{ij|g}\left(1 - \bar{s}_{ij|g}\right) dF(i) & \text{if } j = k \\ \int -\frac{1}{1-\sigma} \bar{s}_{ij|g} \bar{s}_{ik|g} dF(i) & \text{if } j, k \text{ are both in nest } g \\ 0 & \text{if } j, k \text{ are in different nests} \end{cases}$$

The first-order derivatives can be written elegantly into the following matrix, which is computationally easy to construct:

$$\frac{\partial s_j}{\partial p_k} = \int \frac{\partial s_{ij}}{\partial p_k} dF(i) = \int \frac{\partial \bar{s}_{ij|g}}{\partial p_k} \bar{s}_{ig} + \bar{s}_{ij|g} \frac{\partial \bar{s}_{ig}}{\partial p_k} dF(i).$$

Similarly, the second-order derivatives can be written into a $J \times J \times J$ high-dimensional matrix. The $(j, k, l)$ element takes the form:

$$\frac{\partial^2 s_j}{\partial p_k \partial p_l} = \int \frac{\partial^2 \bar{s}_{ij|g}}{\partial p_k \partial p_l} \bar{s}_{ig} + \frac{\partial \bar{s}_{ij|g}}{\partial p_l} \frac{\partial \bar{s}_{ig}}{\partial p_k} + \frac{\partial \bar{s}_{ij|g}}{\partial p_k} \frac{\partial \bar{s}_{ig}}{\partial p_l} + \bar{s}_{ij|g} \frac{\partial^2 \bar{s}_{ig}}{\partial p_k \partial p_l} dF(i)$$

**Passthrough** I assume a sequential game, where choices of retail prices take wholesale prices as given. In the negotiation stage, firms understand that wholesale prices will be passed through to retail prices and affect the market shares and profits. Therefore, to solve for the optimal wholesale prices, it is critical to get the passthrough matrix $p_w$. Solving for $p_w$ requires usage of the implicit function theorem on Equation (11) (retail price FOC) by totally differentiating the retail price's first-order conditions: $p_w = -\left(\wp_w\right)^{-1}\left(\wp_p\right)$ where $\wp \equiv s + \widehat{T^D} \cdot \Delta \times (p - \mathbf{mc^r}) - \hat{T}^D \cdot (1 - \psi) \cdot \Delta \times w - \widehat{T^D} \cdot \psi \cdot \Delta \times \mathbf{mc^k}$. In order to get $\wp_w$, I first define a *product-specific* profit $\pi_j^D = s_j(p_j - \psi mc_j^k - (1 - \psi)w_j - mc_j^r)$, which is the retailer profit created by the product $j$ if $j$ is not under RPM, and the channel profit created by $j$ if $j$ is under RPM. Note that I define this product-specific retailer profit to avoid dealing with the complicated ownership matrix in the elasticities. For simplicity, I additionally define

$m_j^d \equiv p_j - \psi mc_j^k - (1-\psi)w_j - mc_j^r$. Hence, product-specific price elasticities are given by:

$$\begin{aligned}
\frac{\partial^2 \pi_j^D}{\partial p_k \partial p_l} &= \begin{cases} \int \frac{\partial s_{ij}}{\partial p_l} + \frac{\partial m_j^d}{\partial p_l}\frac{\partial s_{ij}}{\partial p_j} + m_j^d \frac{\partial^2 s_{ij}}{\partial p_j \partial p_l} dF(i) \text{ if } j = k \\ \int \frac{\partial m_j^d}{\partial p_l}\frac{\partial s_{ij}}{\partial p_k} + m_j^d \frac{\partial^2 s_{ij}}{\partial p_k \partial p_l} dF(i) \text{ if } j \neq k \end{cases} \\
\frac{\partial^2 \pi_j^D}{\partial p_k \partial w_l} &= \begin{cases} \int -\frac{\partial s_{ij}}{\partial p_j} dF(i) \text{ if } j = k, j = l, \mathcal{K}(j) \notin K_{RPM} \\ \int -\frac{\partial s_{ij}}{\partial p_k} dF(i) \text{ if } j \neq k, j = l, \mathcal{K}(j) \notin K_{RPM} \\ 0 \text{ if } \mathcal{K}(j) \in K_{RPM} \end{cases}
\end{aligned}$$

The last step is to generate joint profit derivatives from the product-specific profit derivatives. Apply this trick:

$$\begin{aligned}
\wp_p(k,l) &= \widehat{T^D}(k,:) \times \frac{\partial^2 \pi_j^D}{\partial p_k \partial p_l}(:,k,l) \\
\wp_w(k,l) &= \widehat{T^D}(k,:) \times \frac{\partial^2 \pi_j^D}{\partial p_k \partial w_l}(:,k,l)
\end{aligned}$$

**Bargaining First Order Condition** First, I show how to derive upstream markup $\mathbf{mk^k}$ in Equation (14) from first-order conditions of Equation (6):

$$\tau \left[\Delta_j \pi_r\right] \frac{\partial \Pi_k}{\partial w_j} + (1-\tau)\left[\Delta_j \Pi_k\right] \frac{\partial \pi_r}{\partial w_j} = 0, \tag{17}$$

where $\frac{\partial \pi_r}{\partial w_j}$ can be written as:

$$\begin{aligned}
\pi_r &= \sum_{l \in J_r} s_l \left(p_l - w_l - mc_l^r\right) \\
\frac{\partial \pi_r}{\partial w_j} &= -s_j + \sum_{l \in J_r} \left( s_l \frac{\partial p_l}{\partial w_j} + \left(p_j - w_j - mc_j^r\right) \frac{\partial s_l}{\partial w_j} \right) \\
&= -s + T^D \cdot B^{Dw} + \left(T^D \cdot Z^w\right) \times \left(p - w - \mathbf{mc^r}\right),
\end{aligned}$$

where $B_{lk}^{Dw} = s_l \frac{\partial p_l^*}{\partial w_j}$, so $B^{Dw} = p_w^T \times s$ ($p_w$ is the passthrough matrix previously defined) in matrix form, and $Z_{jl}^w = \frac{\partial s_l}{\partial w_j}$, $Z^w = (\Delta \times p_w)^T$ in matrix form.

Similarly, $\dfrac{\partial \Pi_k}{\partial w_j}$ can be written in matrix form:

$$\begin{aligned}
\Pi_k &= \sum_{l \in J_k} s_l \left(w_l - mc_l^k\right) \\
\frac{\partial \Pi_k}{\partial w_j} &= s_j + \sum_{l \in J_k} (w_l - mc_l^k) \frac{\partial s_l}{\partial w_j} \\
&= s + \left(T^U \cdot Z^w\right) \times (w - mc^k).
\end{aligned}$$

Lastly, gains from trade can be written in matrix form:

$$S^U \equiv \begin{bmatrix} s_1 & s_2 - s_{2,-1} & \dots & s_j - s_{j,-1} \\ s_1 - s_{1,-2} & s_2 & \dots & s_j - s_{j,-2} \\ \dots & \dots & \ddots & \vdots \\ s_1 - s_{1,-j} & s_2 - s_{2,-j} & \dots & s_j \end{bmatrix} \text{ (exclusion matrix)},$$

where $s_{j,-k} = s_j(G) - s_j(G \backslash \{k\})$ denotes the market share of $j$ if $k$ is excluded. Then I can rewrite $\Delta_j \pi_r$ and $\Delta_j \Pi_k$ into matrix form:

$$\begin{aligned}
\Delta_j \pi_r &= T^D \cdot S^U \times (p - w - mc^r) \equiv T^D \cdot S^U \times \mathbf{mk^r} \\
\Delta_j \Pi_k &= T^U \cdot S^U \times (w - \mathbf{mc^k}) \equiv T^U \cdot S^U \times \mathbf{mk^k}
\end{aligned}$$

Plugging $\frac{\partial \Pi_k}{\partial w_j}$, $\frac{\partial \pi_r}{\partial w_j}$, $\Delta_j \pi_r$, $\Delta_j \Pi_k$ into Equation (17) gets Equation (13):

$$\begin{aligned}
\tau \cdot \underbrace{\left(T^D \cdot S^U \times \mathbf{mk^r}\right)}_{\Lambda} \cdot \left(s + \left(T^U \cdot Z^w\right) \times \mathbf{mk^k}\right) + & \\
\left(T^U \cdot S^U \times \mathbf{mk^k}\right) \cdot (1 - \tau) \cdot \underbrace{\left(-s + T^D \cdot B^{Dw} + \left(T^D \cdot Z^w\right) \times \mathbf{mk^r}\right)}_{\Xi} &= 0 \\
\tau \Lambda s + \left[\left(\tau \Lambda T^U Z^w\right) + (1 - \tau) \Xi T^U S^U\right] \times \mathbf{mk^k} &= 0
\end{aligned}$$

$$\mathbf{mk^k} = -\left[\left(T^U Z^w\right) + \frac{(1 - \tau)\Xi}{\tau \Lambda} T^U S^U\right]^{-1} s.$$

## D.2 Simulation Algorithm

There is no closed-form solution for equilibrium prices when the demand function follows the nested logit (or random coefficient nested logit). I use the following two-step computational program to solve for the fixed point $\{\mathbf{p}, \mathbf{w}\}$:

1. Outer loop: guess a vector of $\{w\}$:

   (a) Solve for fixed points $p(w)$ that satisfies the condition:

   $$p(w) - w - \mathbf{mc^r} = -(\widehat{T^D} \cdot \Delta)^{-1}(s + \widehat{T^D} \cdot \psi \cdot \Delta \times (w - \mathbf{mc^k}))$$

   I adopt the trick to iterate over the following vector $p(w) - w - \mathbf{mc^r}$ instead of $p$, which is proved to be a contraction mapping (Morrow and Skerlos, 2011), and therefore convergence is guaranteed regardless of initial values. I define $(\widehat{T^D} \cdot \Delta) = \Lambda(p) - \Gamma(p)$ where $\Lambda(p) = \int_i Diag(\alpha_i \mathbf{s}_i) dF(i)$ is a diagonal matrix, $\Gamma(p) = \int_i \alpha_i \mathbf{s}_i \mathbf{s}_i' dF(i)$, and $\tilde{s}(p) = s + \widehat{T^D} \cdot \psi \cdot \Delta \times (w - \mathbf{mc^k})$. We have:

   $$p(w) - w - \mathbf{mc^r} \leftarrow \Lambda^{-1} \cdot \Gamma \cdot (p(w) - w - \mathbf{mc^r}) - \Lambda^{-1} \cdot \tilde{s}(p)$$

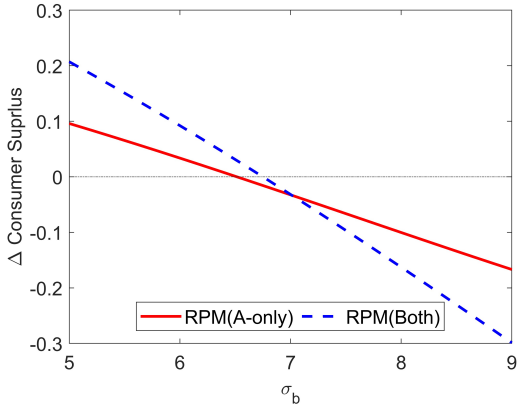
   as a contraction mapping.

   (b) Given $p(w)$ and $w$, find $w'$ that satisfies the Nash-in-Nash first-order conditions:[52]

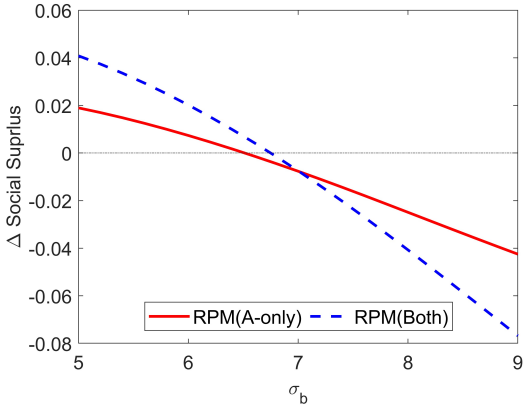
   $$w' - \mathbf{mc^k} = -\left[ \left(T^U Z^w\right) + \frac{(1-\tau)\Xi}{\tau \Lambda} T^U S^U \right]^{-1} s$$

2. Update $w'$. Verify if $||w - w'|| < \epsilon$. If so, the fixed points are found. Set $w = w'$ and go back to the first step otherwise.

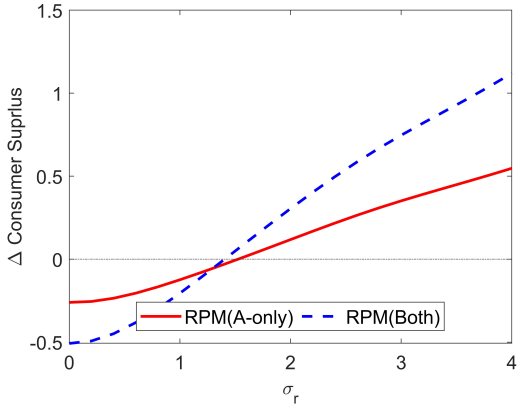
[52] This wholesale price iteration is not necessarily a contraction mapping, and I do not prove the existence or uniqueness of the equilibrium. In practice, I tried extreme initial values (to have $w = mc^k$ so the upstream markup is 0, or $w = mc^k + (T^U Z^w)^{-1} s$ or the biggest possible upstream markup at $\tau = 1$) and confirmed that they converged to the same equilibrium wholesale price vector.



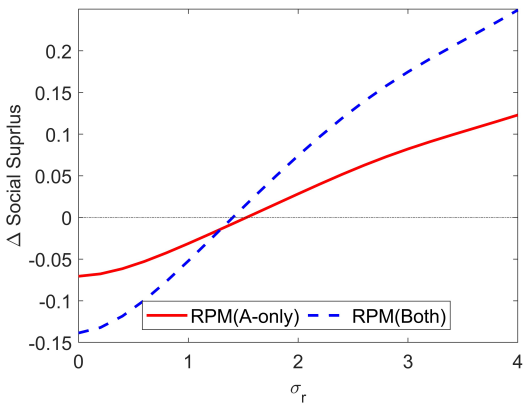

(a) $\tau = 0.5, \sigma_r = 2$



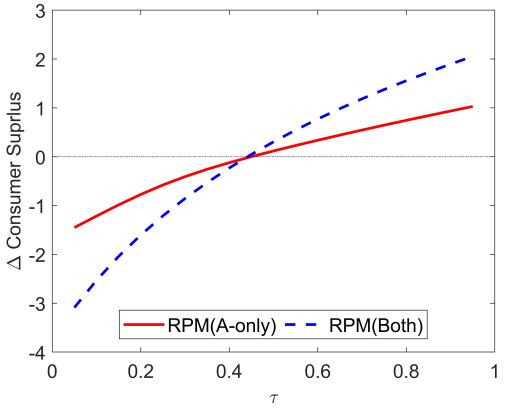

(b) $\tau = 0.5, \sigma_r = 2$



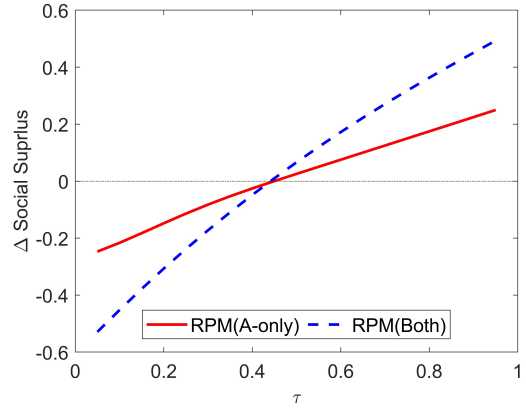

(c) $\tau = 0.5, \sigma_b = 8$




(d) $\rho = 0.5, \sigma_b = 8$



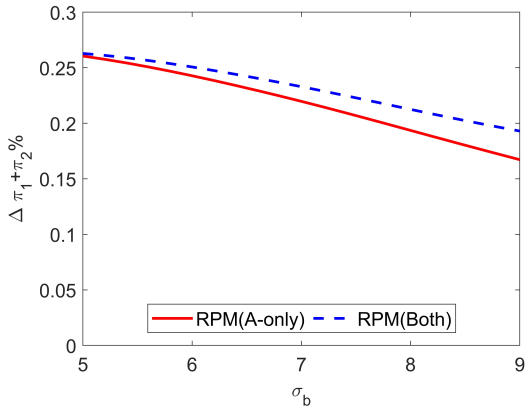

(e) $\sigma_r = 2, \sigma_b = 8$



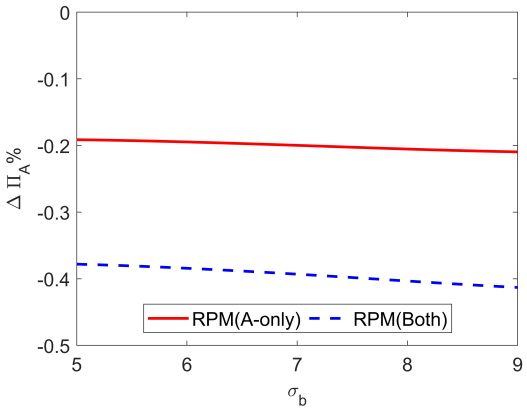

(f) $\sigma_r = 2, \sigma_b = 8$

Figure B.10: Simulation: How Surpluses Change with respect to Model Primitives

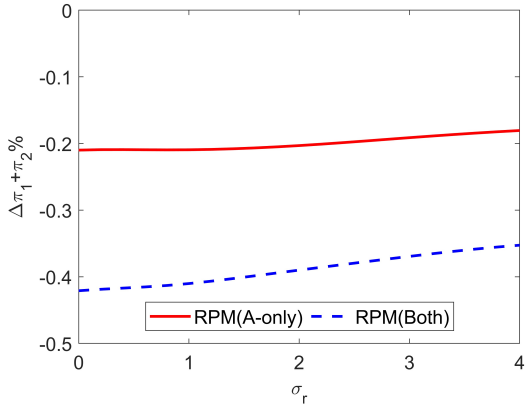
*Note*: This figure plots how the consumer surplus and social surplus change in response to an A-only RPM contract or an industry-wide RPM contract. Consistent with the theoretical results, RPM tends to be more pro-competitive when the diversion ratio to products of the same brand products is low (low $\sigma_b$), the diversion ratio to other products in the same retailers is high (high $\sigma_r$ and when upstream negotiation power is higher (high $\tau$).



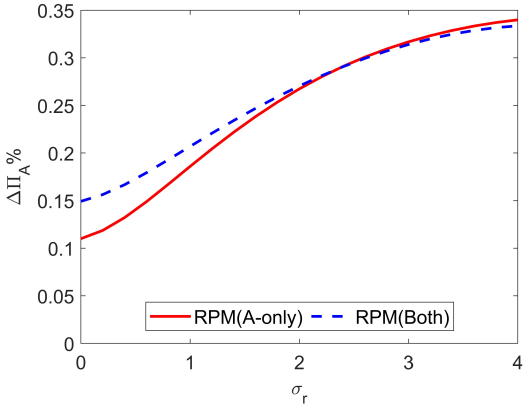

(a) $\tau = 0.5, \sigma_r = 2$



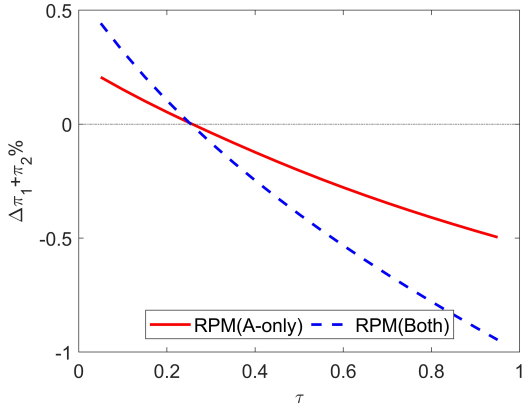

(b) $\tau = 0.5, \sigma_r = 2$



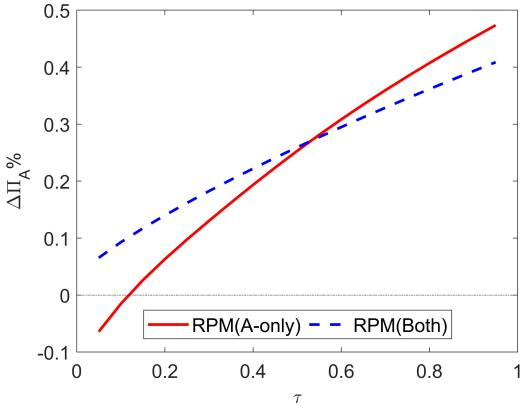

(c) $\tau = 0.5, \sigma_b = 8$




(d) $\rho = 0.5, \sigma_b = 8$




(e) $\sigma_r = 2, \sigma_b = 8$




(f) $\sigma_r = 2, \sigma_b = 8$

Figure B.11: Simulation: How Producer Profit Change with respect to Model Primitives

*Note*: This figure plots how the consumer surplus and firm A's profits change in response to an A-only RPM contract or an industry-wide RPM contract. Consistent with the theoretical results, upstream manufacturers almost always benefit from RPM contracts, and downstream retailers always get hurt by RPM contracts unless the upstream negotiation power $\tau$ is very small (in which case, RPM contracts are most likely to be initiated by downstream retailers).

# E Additional Tables and Figures

Table E.1: Descriptive Evidence on Pricing and Assortment Decisions

| Panel A: Uniform Pricing | | |
|---|---|---|
| Fixed Effects | Retail Price | Wholesale Price |
| $R^2$: | | |
| Chain | 0.718 | 0.808 |
| | (0.065) | (0.053) |
| City | 0.736 | 0.821 |
| | (0.624) | (0.529) |

| Panel B: Assortment Decision | | |
|---|---|---|
| Fixed Effects | 1(Carry) | 1(Carry) |
| $R^2$: | | |
| firm-chain-time | 0.138 | 0.171 |
| firm-store-time | 0.260 | 0.284 |
| brand-chain-time | 0.533 | 0.609 |
| firm-chain | 0.122 | 0.156 |
| firm-store | 0.190 | 0.235 |
| brand-chain | 0.480 | 0.563 |
| brand-store | 0.654 | 0.790 |

*Note*: Panel (A) reports the evidence of uniform pricing. The sample includes the products investigated in this paper. The $R^2$ shows what proportion of store-specific retail and wholesale prices can be explained by chain-uniform pricing. It comes from the regression: $p_{jt} = \eta_{c(j)t} + \epsilon_{jt}$, where $p_{jt}$ denotes price in store j that belongs to chain $c$ at time t for a product. The $R^2$ are averaged over 25 products. Panel (B) reports the carrying decisions of each product-store pair over time by estimating the likelihood that store $i$ carries product $j$ over different fixed effects $\eta$: $1(carry)_{ijt} = \eta + \epsilon_{ijt}$.

Table E.2: Price Dispersion of "RPM" Products Increase after SAMR Investigation

| | Unweighted | | | Weighted | | |
|---|---|---|---|---|---|---|
| | (1) SD | (2) p75-p25 | (3) p90-p10 | (4) SD | (5) p75-p25 | (6) p90-p10 |
| Treated×interim | 0.009 | 0.024*** | 0.013 | 0.007 | 0.016** | 0.014 |
| | (0.006) | (0.008) | (0.013) | (0.006) | (0.007) | (0.013) |
| Treated×post | 0.048*** | 0.060*** | 0.089*** | 0.040*** | 0.042*** | 0.074*** |
| | (0.008) | (0.012) | (0.018) | (0.007) | (0.010) | (0.016) |
| **Base level** | | | | | | |
| $\bar{y}_{RPM}$ | 0.038 | 0.041 | 0.078 | 0.032 | 0.034 | 0.065 |
| $\bar{y}_{non-RPM}$ | 0.11 | 0.122 | 0.21 | 0.099 | 0.105 | 0.192 |

*Note*: All dependent variables are normalized by the average level of price. The regression is at the city-product-month level (N=130k), and the errors are clustered at the city level. I control for city-time and city-product fixed effects. The base level reflects the dispersion of "RPM" and control products before the investigation. Under all three types of measurements, within-city price dispersion of "RPM products" across stores increases substantially after the investigation period. "Weighted" columns weight each observation of retailer by the sale quantity. *** p<0.01, ** p<0.05, * p<0.1.

Table E.3: Price Dispersion of Competing Products after SAMR Investigation

| | Unweighted | | | Weighted | | |
|---|---|---|---|---|---|---|
| | (1) SD | (2) p75-p25 | (3) p90-p10 | (4) SD | (5) p75-p25 | (6) p90-p10 |
| Treated×interim | -0.002 | -0.004 | -0.008 | 0.001 | -0.002 | -0.005 |
| | (0.002) | (0.004) | (0.006) | (0.002) | (0.004) | (0.005) |
| Treated×post | 0.003 | -0.001 | 0.002 | 0.006* | -0.003 | 0.006 |
| | (0.004) | (0.009) | (0.011) | (0.003) | (0.006) | (0.008) |
| **Base level** | | | | | | |
| $\bar{y}_{rival}$ | 0.112 | 0.103 | 0.196 | 0.01 | 0.086 | 0.174 |
| $\bar{y}_{non-RPM}$ | 0.11 | 0.122 | 0.21 | 0.099 | 0.105 | 0.192 |

*Note*: SD= $\frac{se(\cdot)}{mean(\cdot)}$. The regression is at the city-product-month level (N=160k), and the errors are clustered at the city level. I control for city-time and city-product fixed effects. The base level reflects the dispersion of competing and control products before the investigation. Under all three types of measurements, within-city price dispersion of competing products does not significantly change. *** p<0.01, ** p<0.05, * p<0.1.

Table E.4: Frequencies of Downstream Price Adjustment of RPM Products Increase after SAMR Investigation

| | Dependent: $\mathbb{1}$(price adjustment) | | | |
|---|---|---|---|---|
| | $\lvert\Delta p_t/p_{t-1}\rvert > 5\%$ | | $\lvert\Delta p_t/p_{t-1}\rvert > 10\%$ | |
| Variables | (1) | (2) | (3) | (4) |
| Treated×interim | 0.012*** | 0.011*** | 0.016*** | 0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Treated×post | 0.032*** | 0.032*** | 0.031*** | 0.031*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Pre-event mean | 0.197 | 0.197 | 0.096 | 0.096 |
| Store×time FE | Yes | Yes | Yes | Yes |
| Store×brand FE | | Yes | | Yes |

*Note*: The regression is at the store-product-month level (N=1.9 million), and the errors are clustered at the store level. I control for store-time and store-brand fixed effects. In Columns (1) and (2), the dependent variable equals one if the average price change is greater than 5% of the average price in the previous month. In Columns (3) and (4), the dependent variable equals one if the price change is greater than 10%. Under both measurements, pharmacy stores are three percentage points more likely to adjust the price for "RPM products" after the investigation period. *** p<0.01, ** p<0.05, * p<0.1.

Table E.5: Demand Estimates: Linear Parameters

| | (1) All brands | (2) Zuoli | (3) YRPG | (4) Aodong | (5) Rongchang |
|---|---|---|---|---|---|
| Seasonality (base: q1) | | | | | |
| $q2$ | -0.083 | -0.014 | -0.172 | -0.101 | -0.067 |
| | (0.046) | (0.065) | (0.065) | (0.057) | (0.082) |
| $q3$ | -0.155 | -0.033 | -0.231 | -0.151 | -0.194 |
| | (0.046) | (0.065) | (0.065) | (0.057) | (0.081) |
| $q4$ | -0.047 | 0.025 | -0.071 | -0.039 | -0.039 |
| | (0.046) | (0.065) | (0.065) | (0.057) | (0.081) |
| Region (base: northeast) | | | | | |
| *north* | -0.612 | -0.220 | -0.478 | -0.435 | -1.355 |
| | (0.057) | (0.091) | (0.082) | (0.071) | (0.085) |
| *east* | -1.163 | -1.240 | -1.549 | -1.159 | -1.024 |
| | (0.060) | (0.095) | (0.083) | (0.071) | (0.106) |
| *south* | -1.087 | -0.917 | -1.343 | -1.650 | -1.290 |
| | (0.073) | (0.112) | (0.117) | (0.086) | (0.219) |
| *central* | -1.263 | -1.146 | -1.825 | -0.984 | -1.139 |
| | (0.062) | (0.095) | (0.086) | (0.072) | (0.107) |
| *northwest* | -0.885 | -0.899 | -0.757 | -0.625 | -0.407 |
| | (0.077) | (0.113) | (0.112) | (0.105) | (0.130) |
| *southwest* | -0.506 | -1.244 | -1.022 | -0.789 | -1.042 |
| | (0.084) | (0.144) | (0.106) | (0.100) | (0.282) |
| *home province* | 0.109 | 1.363 | 0.253 | 1.449 | -0.262 |
| | (0.079) | (0.131) | (0.162) | (0.121) | (0.103) |
| Chain Size (base: independent) | | | | | |
| *national* | 0.717 | 0.791 | 1.274 | 0.731 | 0.895 |
| | (0.058) | (0.093) | (0.094) | (0.077) | (0.104) |
| *regional* | 0.221 | 0.118 | 0.581 | 0.357 | 0.670 |
| | (0.035) | (0.050) | (0.049) | (0.044) | (0.060) |
| $R^2$ | 0.035 | 0.094 | 0.141 | 0.118 | 0.165 |

*Note*: The estimates of product characteristics are constructed as projections on estimates of fixed effects $\delta_{jt}$ from Column (6) of Table 3. Mean utility estimates for seasonality and regions are constructed as projections of market-time fixed effects $\lambda_j$ onto corresponding characteristics after controlling for price endogeneity. Similarly, mean utility estimates for chains are constructed from brand-retailer fixed effects $\eta_t$. Column (1) reports average effects across brands. I also report the estimates by different brands in Columns (2)-(5). Standard errors are clustered at the market level. The estimates align with expectations: consumers in colder regions (northern and northeast parts of China) and in winter months (the first and last quarter) value sleep disorder drugs more. The region preference is stronger than the quarter-of-year preferences, consistent with the fact that sleep disorder drugs are maintenance drugs. Consumers also prefer brands produced by manufacturers in the same region and prefer buying from chains.

Table E.6: Counterfactual: YRPG-RPM, Zuoli-RPM, and Industry-Wide RPM

| | | Δ from (1) | | | |
|---|---|---|---|---|---|
| | (1) Non-RPM | (2) YRPG-RPM | (3) Zuoli-RPM | (4) Industry-RPM | (5) (4)+ Collusion |
| **Average retail price (¥/DDD)** | | | | | |
| $p_{Zuoli}$ | 3.57 | -0.0001 | 0.22 | 0.23 | 0.24 |
| $p_{YRPG}$ | 4.53 | -0.70 | -0.01 | -0.77 | -0.59 |
| $p_{Aodong}$ | 3.92 | -0.0003 | 0.0002 | -0.27 | -0.25 |
| $p_{Rongchang}$ | 4.42 | -0.14 | -0.003 | -0.85 | -0.42 |
| **Average wholesale price (¥/DDD)** | | | | | |
| $w_{Zuoli}$ | 2.26 | 0.00 | 0.22 | 0.22 | 0.24 |
| $w_{YRPG}$ | 3.30 | 0.09 | 0.002 | 0.07 | 0.25 |
| $w_{Aodong}$ | 2.73 | 0.01 | 0.001 | 0.17 | 0.18 |
| $w_{Rongchang}$ | 3.18 | 0.01 | 0.002 | 0.001 | 0.39 |
| **Total quantity (mil. DDD)** | | | | | |
| $q_{Zuoli}$ | 106 | -0.01 | -7.37 | -7.69 | -8.15 |
| $q_{YRPG}$ | 26 | 18.46 | 0.19 | 18.33 | 13.60 |
| $q_{Aodong}$ | 148 | -0.50 | 0.05 | 26.61 | 25.59 |
| $q_{Rongchang}$ | 7 | -0.76 | -0.02 | 5.14 | 1.76 |
| **Producer surplus (mil. ¥)** | | | | | |
| $\Pi_{Zuoli}$ | 78 | -0.01 | 14.70 | 14.56 | 15.93 |
| $\Pi_{YRPG}$ | 26 | 20.76 | 0.08 | 20.26 | 23.27 |
| $\Pi_{Aodong}$ | 123 | 1.14 | 0.13 | 51.45 | 53.03 |
| $\Pi_{Rongchang}$ | 6 | -0.35 | 0.00 | 3.66 | 5.39 |
| $\sum_r \pi_r$ | 357 | -16.82 | -9.36 | -73.26 | -77.85 |
| **Consumer surplus (mil. ¥)** | | 10.42 | -14.43 | 18.00 | 10.40 |
| **Social welfare (mil. ¥)** | | 15.15 | -8.88 | 34.67 | 30.17 |

*Note*: The counterfactual results are based on estimates from Column (6) of Table 3. Column (1) is based on the 2022 second-half sample with 110 representative markets where the number of observed retailers is >50% of total retailers. Columns (2)-(5) change the market structure and calculate market outcomes regarding retail and wholesale prices, quantities, profits, and surpluses. Column (2) assumes that only YRPG adopts RPM. Column (3) assumes that only Zuoli adopts RPM. Column (4) makes all four upstream brands participate in RPM but not internalize each other's profits. Column (5) additionally allows upstreams to internalize each other's profits, effectively making upstream a single monopolist.




(a) Bailemian
*sleep disorder*




(b) Huangqi
*restorative*




(c) Lanqin
*sore-throat*



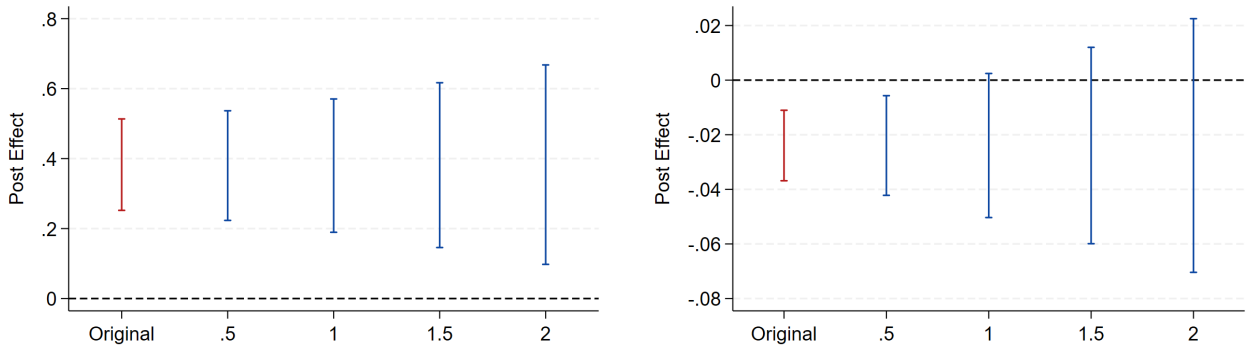

(d) Suhuang
*anti-coughing*




(e) Tanglin
*Diabetes relieving*

Figure E.1: Physical Appearance of Five "RPM" Products

*Note*: This figure shows images of the five investigated products. They are standard products on the shelf in retail pharmacies.

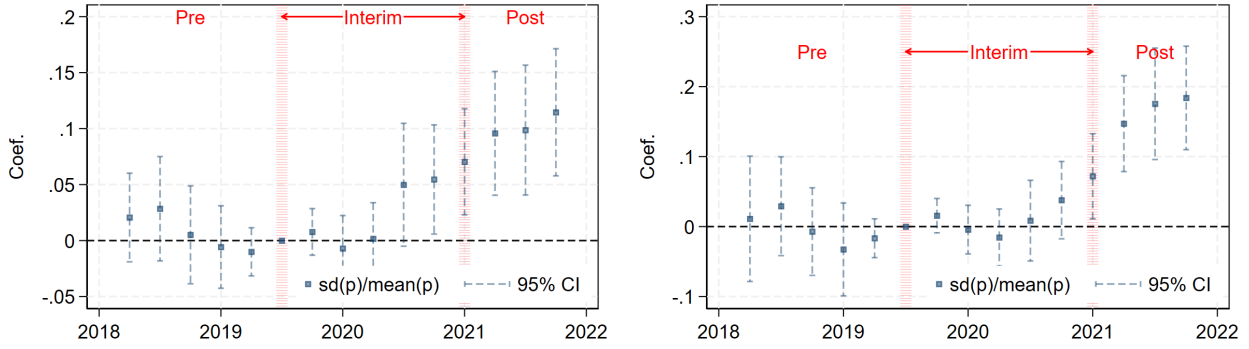



(a) Downstream margin: post effect ($\rho_2$)

(b) Market share: post effect ($\rho_2$)

Figure E.2: Robust inference approach

*Note*: This figure plots the confidence interval for estimated treatment effects in Figure 2 using the pre-trends to infer violations of parallel trends. Different bars plot the 95% confidence interval on estimates, assuming that the post-treatment violation of parallel trends is no worse than $M$ times the pre-treatment violation of parallel trends (between consecutive periods). The post effect is significant even when the trend exists. (as long as the $M < 2$ for margin estimates and $M < 0.9$ for market share estimates.)




(a) Interquartile Range: Retail Price

(b) P90-P10: Retail Price

Figure E.3: Event Study: Alternative Measures of Dispersion

*Note*: This figure plots the time-varying coefficient in Equation (2) for within-city dispersion measure by the interquantile range and p90-p10. The first vertical dashed red line denotes the start of the investigation, and the second dashed line denotes when the final decision was released. The blue dashed lines denote 95 percent confidence intervals around the estimated coefficients based on city-clustered standard errors. Price dispersion increased substantially after the SAMR investigation.

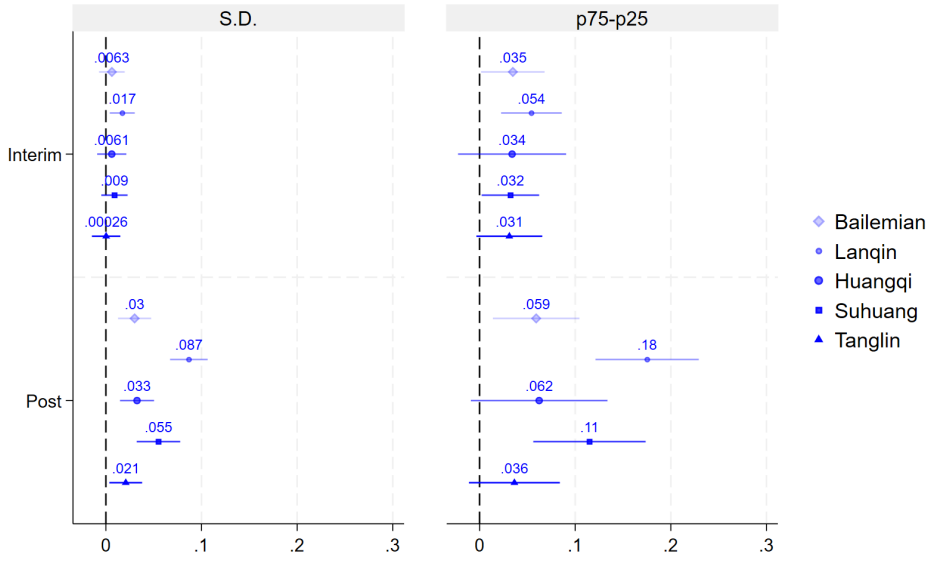



Figure E.4: Price Dispersion changes of each RPM product

*Note*: This figure plots the coefficients of (2) for within-city dispersion measured by the standard deviation and the interquartile range. The bars denote 95 percent confidence intervals of the estimated coefficients based on city-clustered standard errors. The price dispersion increased for all five RPM brands.

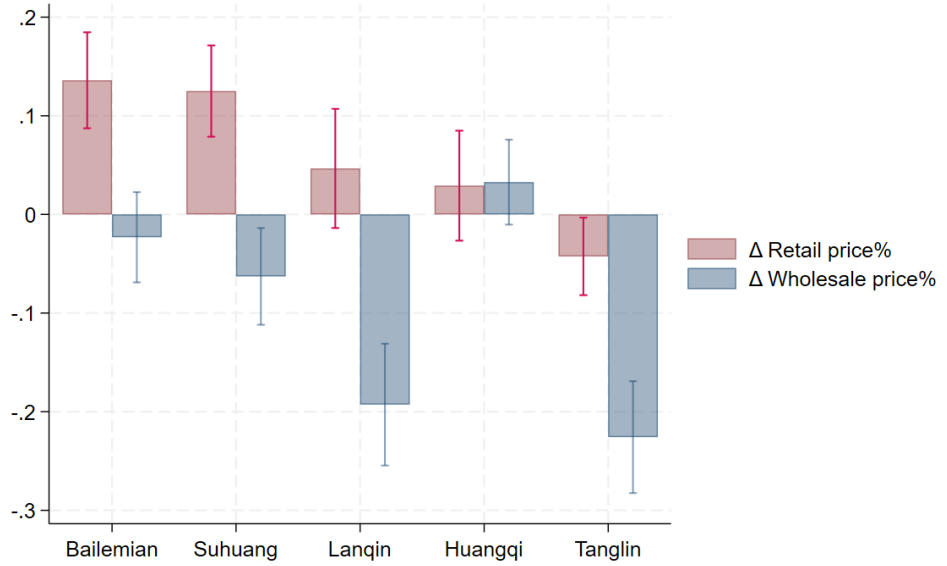
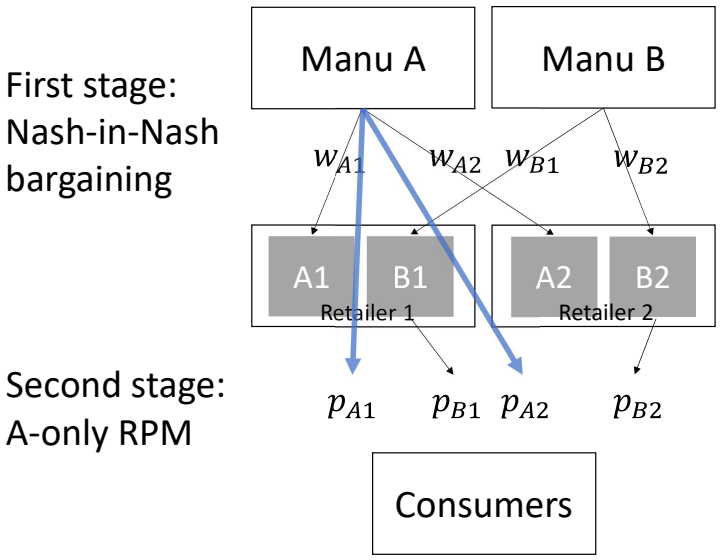
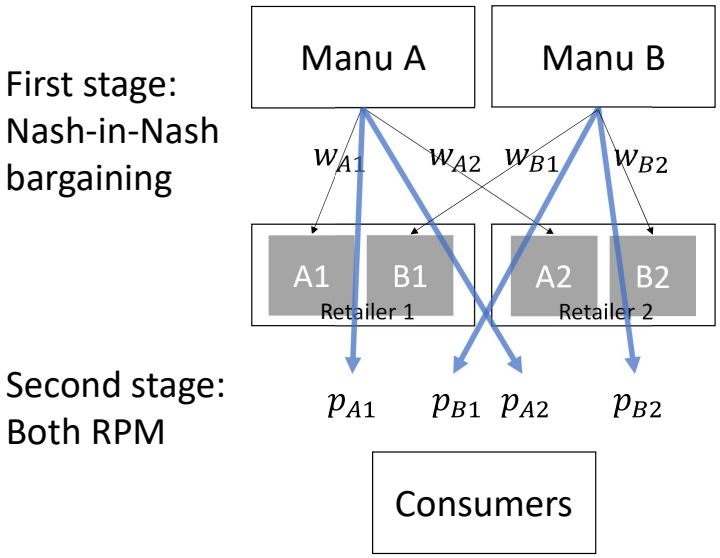



Figure E.5: Market Performance of "RPM" Products After SAMR Investigation: by Product

*Note*: This figure plots the coefficients from a product-specific regression on equation (1). I observe widening gap between retail prices and wholesale prices in four of the five products, consistent with the double markup story as the main motivation for the RPM contract.




(a) A-only RPM




(b) Both A&B RPM

Figure E.6: Diagram Representation of RPM

*Note*: This diagram shows how RPM contracts change the market structure in a 2 (brands) $\times$ 2 (retailers) market. Arrows denote which party is in charge of setting which price. RPM gives the upstream manufacturer to directly set downstream prices (fully as in the fixed price RPM) or partially (as in the one-sided RPM). For instance, if Manu A adopts RPM, it directly controls downstream retail prices of products A1 and A2. Retail 1 only chooses the price for product B1.