A Double Dose of Reform: Insurance and Centralized Negotiation in Drug Markets

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Abstract

Making innovative drugs affordable and accessible is a pressing global challenge. Centralized negotiation is an increasingly popular policy solution, but it remains understudied despite wide variation in implementation. This paper studies China's ongoing National Reimbursement Drug List (NRDL) Reform, which combines centralized drug price negotiation with expanded insurance coverage. The reform reduced retail prices by 48% and out-of-pocket costs by 80%, and increased drug utilization by 350%. At the same time, the insurance design was regressive, and 25% of negotiations failed. Focusing on cancer drugs, we estimate a flexible demand and supply model that features standalone and combination cancer drug regimens, heterogeneous households, bargaining with potential breakdowns, and a government objective function that depends on consumer surplus and insurance spending. We estimate that including innovative cancer drugs in the NRDL generated ¥37 billion ($5.3 billion) in annual consumer surplus gains and increased survival by 1.1 million life-years among Chinese cancer patients each year. Among the counterfactual policies we examined, centralized market-access negotiation with an optimal coinsurance schedule raises social surplus by 29% relative to the observed policy and achieves 93% of the social surplus of an efficient benchmark.

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1 Introduction

Innovative drugs have the potential to generate large social benefits, but high prices place life-saving treatments out of reach for the majority of self-paying patients. Consider Verzenio, a breast cancer therapy approved by the U.S. Food and Drug Administration (FDA) in 2017. While it was shown to improve 5-year survival rates by 12%, its price is prohibitively high: $180,000 per year in the U.S. and an initial annual price of ¥66,000 ($9,430) in China. Prescription drug insurance increases access to these drugs for a wider population, but comes with substantial costs. For instance, the Medicare Part D program for the elderly in the U.S. spends 61% of its budget on the top 100 highest-priced drugs (CMS, 2024). The set of policy interventions commonly deployed to restrain prices include regulation, auctions, and negotiation. Price regulation can be difficult to implement, as it relies on potentially fraught cost and quality data rather than market signals. Successful auctions require multiple close substitutes, which are typically unavailable for innovative drugs. Negotiation is an increasingly popular solution, but it remains understudied despite wide variation in implementation (Kyle, 2025).

In this paper, we examine the economic and policy implications of China's ongoing National Reimbursement Drug List (NRDL) Reform, which began in 2016.[1] Prior to the reform, the NRDL—the national drug formulary that determines drug coverage under China's universal health insurance—provided no coverage for innovative drugs. Patients were required to pay the full cost of these expensive medications out of pocket, in many cases leading to financial hardship or foregoing treatment altogether.[2] The NRDL Reform expanded universal insurance coverage to include an increasing number of innovative drugs, provided that their manufacturers negotiated price reductions with China's National Healthcare Security Administration (NHSA). Once a drug is added to the NRDL, patients can access the drug at a fraction of the negotiated price, with the government paying the balance. In our motivating example of Verzenio, inclusion in the NRDL in 2021 reduced the retail price from ¥66,000 to ¥21,000 and the average out-of-pocket (OOP) price to ¥7,400.

We use the variation generated by the NRDL Reform in China to investigate the welfare implications of observed and counterfactual drug market reforms. For motivation, note two striking features of the environment. First, 25% of negotiations fail, and higher-quality

[1] The program is also referred to as the "National Health Insurance Negotiation," the "Reimbursement-Linked Drug Price Negotiation," and "China's National Negotiation of Drug Prices" (Zhou et al., 2024; Lu and Zhang, 2023).

[2] These challenges were poignantly illustrated in the 2018 film *Dying to Survive*, which is based on the true story of a leukemia patient who resorted to smuggling cancer medicine from India. The film had China's fourth-biggest theatrical opening weekend ever.

drugs are more often successfully negotiated. Second, insurance generosity varies widely. The patient's share of the drug cost (the coinsurance rate) ranges from 20% in higher-income provinces to 45% in lower-income provinces due to provincial subsidies. We incorporate these features into a deep investigation of how key policy choices—regarding negotiating parties' outside options, centralization, and insurance generosity—impact bilateral gains from trade. In turn, gains from trade determine the extensive margin of which drugs are covered, and the intensive margin of negotiated price levels.

The NRDL Reform in China offers a valuable context in which to analyze potential policy instruments aimed at controlling the rising costs of pharmaceuticals. In contrast to the U.S., where drug prices are determined by both administrative and negotiated pricing regimes across a range of public and private payers, China's healthcare system is predominantly public. This simplifies the modeling necessary to evaluate the effectiveness of the insurance expansion. The reform's staggered implementation across drugs, combined with variation in coinsurance rates across provinces, provides ample panel variation in prices and coverage for our research design. Finally, in contrast to many settings where only successful negotiation outcomes are observed, we observe rich market outcomes for both successful and failed negotiations, before and after program eligibility, providing a novel opportunity to infer government preferences and firms' marginal costs separately from bargaining parameters.

We analyze a unique dataset with comprehensive coverage of drug sales across China from 2017 to 2023. The primary data source is SinoHealth, a publicly listed health consulting firm.[3] We supplement the SinoHealth data with additional datasets that detail negotiation outcomes for all participating drugs, approved usage of each drug for different indications, clinical evidence concerning survival improvements, and provincial demographic information.

We present, to our knowledge, the first comprehensive evidence on the price and quantity effects of China's NRDL Reform, which are substantial. The program expanded coverage of 487 innovative drugs to over a billion people during our study period. Negotiations resulted in a 48% drop in retail prices and an 80% reduction in patients' out-of-pocket costs. Utilization of innovative drugs surged, with successful negotiations followed by a 350% increase in quantity on average. These findings contribute to a broad literature examining the effects of prescription drug insurance coverage and generosity on utilization and prices (see, e.g., Abaluck et al. (2018); Dalton et al. (2019); Duggan and Scott Morton (2010); Einav et al. (2015)).

To unpack the economic mechanisms underlying these results, we focus on cancer drugs, which accounted for two-thirds of all NRDL program revenue for negotiated drugs, and de-

[3]SinoHealth's data are widely utilized by major international and domestic pharmaceutical companies, including Pfizer, Roche, Bayer, AstraZeneca, GlaxoSmithKline, Merck, and Eli Lilly, among others.

velop a structural framework. The demand side consists of a random coefficients nested logit model that features patients choosing among standalone and combination drug regimens, and differences in price sensitivity across income groups. The supply side features centralized bargaining between the government and pharmaceutical firms, allowing for bargaining breakdowns and incorporating a government objective function that depends on patient welfare and government expenditure. We estimate several key parameters: income-varying price elasticities of demand, firms' marginal costs of producing and distributing innovative drugs, a bargaining parameter that determines the surplus split between firms and the government, and the relative weights the government places on patient surplus versus government expenditures. Our model shares features with structural work on drug markets (Atal et al., 2022; Cao and Chatterjee, 2022; Chaudhuri et al., 2006; Xia, 2025) and with the recent empirical literature on bargaining in health care markets more broadly (e.g., Gowrisankaran et al. (2015); Grennan (2013); Ho and Lee (2017); see Grennan and Swanson (2022) for a review).

One innovation of our model is its ability to infer how the central government's representatives weigh government expenditures relative to patient surplus. As this weight increases, the set of feasible negotiated prices narrows; eventually, the negotiation fails as including a drug in the NRDL formulary at a price acceptable to the drug company would be too costly for the government.[4] We recover the distribution of this weight using a novel maximum likelihood specification estimated on both successful and failed negotiations. In addition to allowing the government's relative weight on government expenditures to depend upon drug quality (medical benefits), we also allow for bargaining parameters across negotiating pairs to depend on drug characteristics such as foreign/domestic status. In doing so, we extend prior work that models bargaining ability as a function of firm organizational characteristics (Grennan, 2014; Lewis and Pflum, 2015).

Consistent with prior work on global drug markets (e.g., Dubois et al. 2022), price elasticities of demand for cancer drugs are low, around -1.6 for the median patient and -1.8 for patients at the 25^{th} income percentile. The supply-side analyses focus on two classes of innovative cancer drugs: monoclonal antibodies and protein kinase inhibitors. Our estimates indicate that the government assigns roughly equal weight to consumer surplus and government expenditures for the median drug and prefers drugs with larger survival improvements in clinical trials. Finally, the estimated firm bargaining parameter is 0.66, suggesting that

[4] An alternative explanation for the bargaining failures observed in our setting would be incomplete information. See Ausubel et al. (2002) for a review. This is unlikely a key driver of bargaining failures in our setting, as both the government and drug manufacturers observe years of market outcomes prior to negotiations. Moreover, during the pre-negotiation stage, information is exchanged frequently between the parties.

firms hold considerable bargaining power.

The model estimates allow us to evaluate the effectiveness of the NRDL Reform and counterfactual policies. The NRDL Reform, as implemented, combines insurance expansion and negotiation. Insurance expansion alone would reduce price sensitivity, leading to lower out-of-pocket prices but little effect on retail prices; see Cutler and Reber (1998), Jaffe and Shepard (2020), and Liu and Jin (2015).[5] Price negotiation alone would have no impact, as firms receive no gains from trade from participating in the negotiation relative to their outside option of setting profit-maximizing prices on the private market. The combined reform allows the government to discipline prices, while patients benefit from greater drug access. Relative to no reform, the NRDL Reform increases the market share of innovative drugs among all cancer drugs by 19 ppt (694%), far exceeding the gains from insurance alone (7 ppt, or 254%) and negotiation alone (0 ppt). At the same time, it reduces out-of-pocket costs for successfully negotiated drugs by 87% and raises average survival by 3 months per cancer patient. In aggregate, the innovative cancer drugs successfully negotiated under the NRDL reform between 2017 and 2022 generated ¥37 billion ($5.3 billion) in annual consumer surplus gains and contributed to a total survival increase of 1.1 million life-years among Chinese cancer patients each year.

We next turn to counterfactual exercises to shed light on how policy choices impact economic outcomes and welfare, allowing both formularies and negotiated prices to adjust.

First, we examine the role of outside options, contributing to recent work on bargaining with exclusion and formulary tiering (Ho and Lee, 2019, 2024; Prager and Tilipman, 2025). While the observed NRDL reform employs a formulary-access negotiation where a failed negotiation leaves the firm free to sell its drugs in the private market, we model a "market access" negotiation that is more typical in the literature. Here, the government's threat point is to exclude the drug from the Chinese market entirely. This harsher threat point expands the gains from trade for both negotiating parties, allowing more drugs to clear the negotiation threshold but yielding ex-ante ambiguous impacts on equilibrium prices and overall welfare.[6] A key virtue of this market-access framework is its efficacy even in the absence of insurance expansion: if firms must negotiate simply to enter the market, our estimated bargaining parameters imply a 50% reduction in retail prices at zero cost to the government, alongside a 1.61 percentage point (58%) increase in innovative market share relative to the no-reform

[5]This is consistent with classic models of moral hazard, but the fact that many patients could not afford innovative drugs before the reform suggests drug access plays an important role (Nyman, 1999).

[6]The equilibrium price can range from marginal cost (if the government holds all bargaining power and maximizes social surplus) to the profit-maximizing oligopoly price (if the firm has all bargaining power).

baseline. Introducing insurance expansion further reinforces these bargaining dynamics. Compared to NRDL, pairing market-access negotiations with insurance expands drug coverage and generates larger overall welfare gains, despite yielding slightly higher average prices.

Next, we evaluate the role of centralization. There is wide variation in income and price sensitivity across provinces, implying that centralized negotiation may create winners and losers. To investigate this, we contrast the effects of centralized national bargaining with those in which each province negotiates its own prices and formularies. This analysis contributes to recent policy debates and academic research regarding central procurement; see, e.g., Dubois et al. (2021), Dubois and Sæthre (2020), Dubois et al. (2022), Ho and Pakes (2024), and Maini and Pammolli (2023). The driving feature of this comparison is that gains from trade are lower for both firms and the government in low-income provinces than high-income ones. Hence, the effects of centralization vary across regions: while the highest-income provinces would fare better under province-level negotiation, most provinces benefit from more successful negotiations and lower prices under centralized negotiation, making it beneficial on average.

The next set of counterfactual analyses examines the efficiency and equity implications of income-based coinsurance schedules. Public insurance programs often include subsidies tied directly to income, rather than geography. We explore two-tier structures with different coinsurance rates for households above and below the national median income. To evaluate the equity implications of more and less progressive schedules, we follow the public finance literature (e.g., Hendren 2020) and re-weight households' consumer surplus by $income^{-\nu}$ in the government's objective function. When $\nu = 0$, the measure reflects utilitarian preferences, while higher ν indicates a stronger emphasis on equity.

We document a few notable results. First, lower coinsurance rates (more generous insurance) lead to more bargaining failures, which hurt both low- and high-income patients. At the extreme, cutting the coinsurance rate to a flat 20% (down from the 37% national average) would sharply increase government expenditures and cause 64% of negotiations to fail. Second, lowering coinsurance for high-income households is more effective in expanding market demand and increases firms' willingness to grant price discounts in exchange for inclusion in the national formulary. Third, utilitarian social surplus is maximized with a moderately regressive insurance schedule because demand expansion from high-income households offers the government greater bargaining leverage. This in turn leads to more drug coverage and lower prices that also benefit low-income households. However, a stronger preference for equity ($\nu = 2$) yields a nearly flat, high coinsurance schedule as the optimum. Our analyses contribute to the literature on subsidies for privately-supplied products, e.g., Polyakova and

Ryan (2022) and Finkelstein et al. (2019), and on optimal coinsurance given the tradeoff between moral hazard and risk protection (Cutler and Zeckhauser, 2000; Einav et al., 2018; Gowrisankaran et al., 2015).

We conclude by noting that within the broad "Negotiation plus Expansion" regime, centralized, market-access negotiation paired with an optimal coinsurance schedule strikes the best balance in terms of efficiency, access, and equity. In addition, this policy yields a 29% gain in social surplus over the observed policy and achieves 93% of the social surplus of an efficient benchmark.

The rest of the paper proceeds as follows. Section 2 provides institutional background and describes the data. Section 3 presents the model and Section 4 discusses estimation results. Section 5 conducts counterfactual analyses to shed light on policy designs. Section 6 concludes.

2 Institutional Background and Data

2.1 Institutional Features: CHS and the NRDL Reform

The Chinese healthcare system, known as CHS, provides nearly universal coverage to over 95% of Chinese citizens, making it the largest healthcare insurance program in the world (Yu, 2015). It was created in 1999 and has gone through several changes over the years. Today, it consists of two major health insurance plans: the urban employee basic medical insurance plan (UEBMI) for individuals working in (and retirees of) state-owned enterprises and private-sector businesses, and the urban and rural resident basic medical insurance plan (URRBMI) for rural residents and urban residents not covered by the UEBMI. The premiums are low relative to the price of innovative drugs, and vary by plan, province, and other characteristics.[7] A small commercial market for complementary insurance exists, accounting for less than 7% of total health expenditure (National Health Commission of the PRC, 2023).[8] Given the widespread insurance coverage in CHS, we do not model insurance participation decisions and assume all households are enrolled.

A key component of China's health insurance program is its prescription drug coverage,

[7] In 2021, URRBMI enrollees paid ¥320 per person on average after government subsidies. For the UEBMI program, employees pay 2% of salary in premiums, and employer contributions vary by province (The Commonwealth Fund, 2026).

[8] Some provinces have a cap on total annual insurance coverage. Commercial insurance products offer catastrophic coverage, thereby decreasing residents' financial exposure to major health events. In our sample period, coverage caps of the national insurance program are well above the prices of our focal drugs.

which constitutes 40% of total CHS spending (Long et al., 2022).[9,10] Historically, CHS's NRDL excluded innovative drugs due to budget considerations.[11] In recent years, CHS faced criticism due to its lack of coverage for innovative drugs, which resulted in limited access to effective treatments and high out-of-pocket prices.

In response to public pressure, the CHS launched a drug reform in 2016, i.e., the NRDL Reform, that is ongoing today. Each year, the NHSA comes up with an eligible list of innovative drugs that can apply for negotiation. The definition of an "innovative" drug for NRDL inclusion is that it meets *at least one* of the following definitions: new molecules approved within the past five years; new indications approved within the past five years; drugs treating rare diseases; or drugs treating children's diseases. A manufacturer of an eligible drug is then invited to participate in negotiations if its submitted documents pass an initial expert evaluation regarding its clinical value, safety, innovation, etc., as well as a separate assessment of its pharmacoeconomic and budget impact, and if it is classified by the NHSA into the "negotiation" track, which is limited to single-source drugs, rather than the "competitive" track created under the volume-based public procurement policy, which is typically used for multi-source generics. Firms and the NHSA exchange a host of information (including drug effectiveness, sales, and prices, as well as NRDL payment procedures) during the pre-negotiation stage, which can last a few months.

On the day of negotiation, government representatives engage in simultaneous and independent negotiations with delegates from each pharmaceutical company for each drug. Table 1 summarizes the seven rounds of negotiations from 2016 to 2022, which had an average success rate of 76%. Negotiations occur annually, and the number of negotiations has rapidly increased since the pilot year.

The negotiation process has three notable features. First, both parties are well-informed about supply and demand conditions at the time of negotiation. Most eligible drugs have already been sold on the private market, and there is frequent information exchange during the pre-negotiation stage. As a result, the government likely has a good understanding of firms'

[9]Besides prescription drugs, China's health insurance program also covers a range of services including inpatient care, emergency care, and maternity benefits.

[10]China had various price caps and price regulations on pharmaceutical drugs during the 1980s-2000s. In 2015, China removed most price regulations and only retained price controls for anesthetics. See https://www.gov.cn/gongbao/content/2015/content_2901387.htm. The NRDL Reform focuses on improving access to innovative drugs, beginning in 2016. It is part of a suite of reforms targeting drug prices in recent decades, including a mandate that hospitals can only charge drug prices at their procurement cost with zero markup (with a staggered rollout 2009-2013, Fang et al. 2021), and a volume-based public procurement policy targeting off-patent drugs, beginning in December 2018 (Cao et al., 2022; Liu et al., 2024).

[11]In some cases, provincial formularies covered a few innovative drugs, but this practice was ended with the passing of the NRDL Reform in 2016, before the beginning of our dataset.

Table 1: Summary of Each Round of Negotiation 2016-2022

Round	2016	2017	2018	2019	2020	2021	2022	All
# Negotiated Products	5	44	18	150	162	117	147	643
# Successful Negotiations	3	36	17	97	119	94	121	487

Data source: NHSA website. Overall success rate: 75.7%.

production costs, while drug companies likely are well aware of the government's preferences.

Second, the government prioritizes both social benefits and fiscal sustainability. It appoints two expert groups for each negotiation: pharmacoeconomic experts to evaluate potential patient benefits and finance experts to assess the drug's affordability for the insurance fund.

Third, each drug is negotiated independently. Separate government teams meet with company representatives for different drugs in different rooms, without communication across teams. All negotiations are completed by the end of the day. This setup minimizes strategic interactions within and across firms and limits the government's ability to play firms against each other at the time of negotiation, making it an appropriate application for the Nash-in-Nash bargaining model.

If a negotiation is successful, the drug is typically added to the NRDL within one quarter. Negotiated contracts generally last 2–3 years, after which drugs are subject to renegotiation. Contracts are almost always automatically renewed at the originally negotiated price.

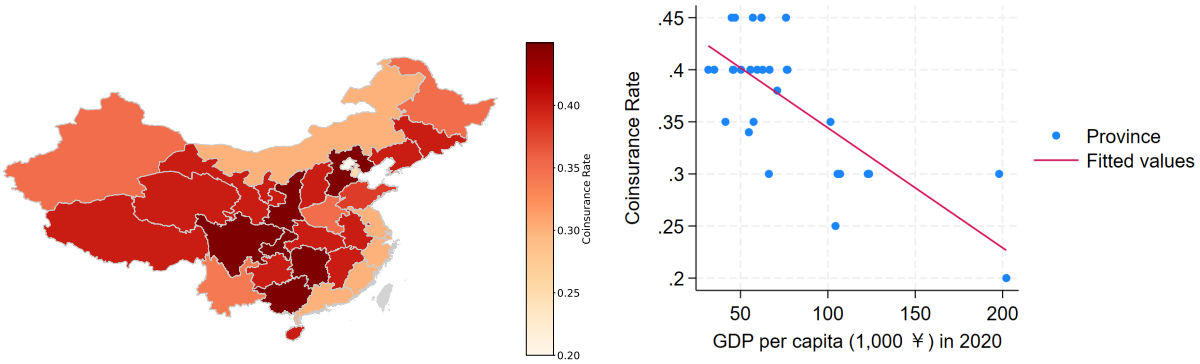
Once a drug is in the NRDL, patients can access it by paying a fraction (the "coinsurance rate") of the retail price. While coverage decisions are centralized, coinsurance rates are determined at the provincial / plan level, resulting in significant variation across provinces. Within each province and plan type, coinsurance rates are uniform for all covered drugs. The URRBMI plan, which covers more than 70% of the country's population, requires 5 ppt higher coinsurance rates than UEBMI on average.[12] We use the coinsurance rate for the larger program (URRBMI) in our analysis.[13] The left panel of Figure 1 presents a map of the URRBMI coinsurance rates across provinces; the right panel presents a scatterplot of the

[12]For a summary of these two types of insurance, see https://www.nhsa.gov.cn/art/2023/7/10/art_7_10995.html.

[13]Some provinces have a deductible that the patient must pay before coverage begins. There may also be a reimbursement maximum, a spending threshold at which the patient no longer receives coverage. We do not observe patient-level data and choose to model OOP as a function only of coinsurance rates. This is a minor limitation, for two reasons. First, annual reimbursement maxima are quite high—e.g., 500,000 RMB across all products and services; or 130,000-400,000 RMB per drug. Given that 95% of drugs have prices below 75,000 RMB upon NRDL inclusion, the reimbursement maximum is unbinding for the vast majority of patients. Second, deductibles are quite low—many provinces apply no deductible at all; others range from 500 RMB-1,200 RMB. This is a modest amount relative to the (post-NRDL) annual price of cancer drugs that ranges from 10,000 to 280,000 RMB.

coinsurance rates against provincial income. Patients in wealthier provinces like Beijing and Shanghai pay 20-30% of the retail price, whereas those in poorer regions like Gansu pay up to 45%.

Figure 1: Coinsurance Rate Design



(a) Coinsurance Rates across Provinces (b) Coinsurance Rates and GDP per Capita

Note: Figure (a) presents provincial coinsurance rates for innovative drugs. Figure (b) presents the relationship between coinsurance and GDP per capita across provinces. Source: Provincial Healthcare and Security Administration.

2.2 Data and Sample Description

Our primary dataset contains comprehensive coverage of drug sales in China from 2017Q1–2023Q2, sourced from SinoHealth. SinoHealth is the only health consulting firm that is publicly listed in China. It supplies data to all major international pharmaceutical companies, including Pfizer, Roche, Bayer, AZ, GSK, Merck, Eli Lilly, etc. Its price and sales data closely match the information posted on NHSA's website and published in China's Statistic Yearbooks. We focus on hospital sales because nearly all innovative drugs are dispensed through hospitals. Data on hospital sales are at the province-quarter level and include total drug sales, quantities dispensed (standardized to years of supply), and retail prices at the SKU level. We merge the SinoHealth data with data on negotiation outcomes from the NHSA, including drug eligibility for negotiation, negotiation success, and negotiated prices; and with data on coinsurance rates from the Provincial Healthcare and Security Administration. Patients' coinsurance rates are determined by their province of residence.

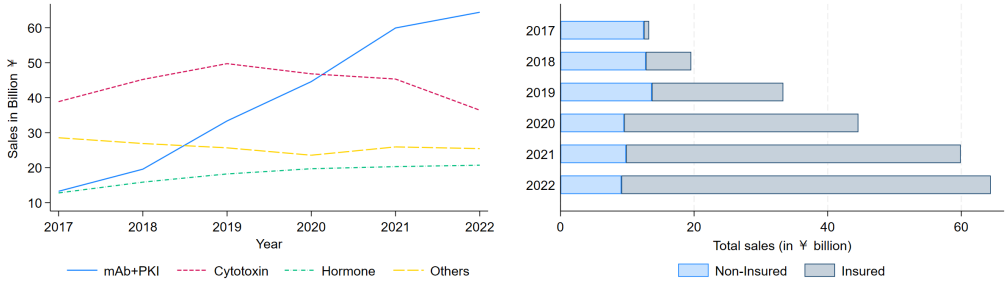
Innovative drugs that are eligible for NRDL negotiations include drugs that treat cancer, hypertension, and diabetes, among others. We focus on cancer drugs in our structural analyses for two main reasons. First, this market is significant from both health and economic

perspectives. In 2020, China had 4.6 million cancer cases and 3 million cancer-related deaths, accounting for 24% of global cancer incidence and 30% of global cancer mortality. China's pharmaceutical market for cancer drugs is growing rapidly, with total sales reaching ¥140 billion (around 0.1% of China's GDP) in 2022. Second, cancer drugs are the most critical category in NRDL negotiations, accounting for more than 60% of revenues among all successfully negotiated drugs.

We constructed several ancillary datasets concerning cancer drug markets. First, we obtained brand-regimen-year-level indications from the Handbook of Innovative Cancer Drugs, which details the approved usage of each cancer drug for different indications by China's National Medical Products Administration, the analog of the U.S. FDA (National Health Commission of the People's Republic of China, 2018, 2019, 2020, 2021, 2022, 2023). Drug regimens can be standalone drugs, or combinations of innovative and/or non-innovative drugs. Second, we collected clinical evidence for all innovative cancer drugs from Phase III clinical trials on ClinicalTrials.gov. Phase III studies are large-scale, double-blind, randomized controlled trials comparing the safety and efficacy of interventions relative to control therapies. Implementing such trials, and registering them on ClinicalTrials.gov, is typically a prerequisite for FDA approval. We use the clinical trial results to measure the quality of each drug. Our preferred measure is the overall survival treatment effect (additional months lived) relative to the standard treatment for the relevant disease. Details of our data collection procedure are available in Appendix A. Third, we collected province-level demographics from each province's Statistics Yearbook, along with cancer incidence data from the National Cancer Center.

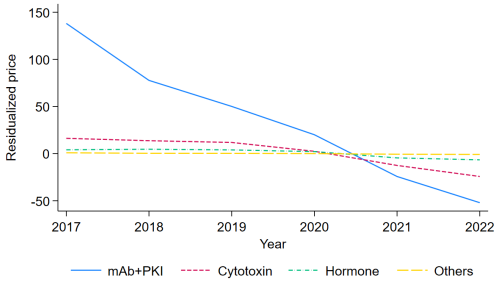
There are four major types of cancer drugs on the market: monoclonal antibodies (mAbs), protein kinase inhibitors (PKIs), cytotoxins (traditional chemotherapy), and hormone drugs. Innovative cancer drugs are typically mAbs or PKIs, and are the primary target of the NRDL Reform. Cytotoxins can be effective in killing cancer cells, but typically have more severe side effects. Hormone drugs are useful for treating certain types of cancers. In addition to these four major types, there are ancillary drugs used for cancer treatments, including traditional Chinese medicine-based products. In the average province-quarter, patients choose among 443 cancer drugs, of which 110 are branded, 84 are innovative, and 70 were eligible for negotiation. Appendix Table A6 presents several key variables on eligible innovative cancer drugs. The most common primary indication—the first indication for which a drug was approved—was lung cancer, and the average drug had 1.9 indications by 2023Q2. Some cancer drugs are used in combination with others: among innovative drugs in our sample, 12% had at least one approved indication for a combination regimen by 2023Q2.

Figure 2: Overview of the Cancer Drug Market

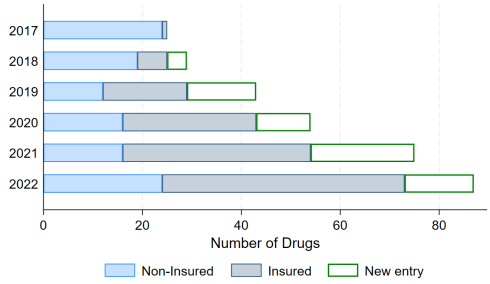


(a) Sales by Cancer Drug Category

(b) Sales for Non/Insured Innovative Drugs



(c) Residualized Retail Price



(d) Num. of Innovative Cancer Drugs in Market

Note: Panel (a) plots the sales of cancer drugs for each major category by year. Panel (b) decomposes sales of the mAb and PKI categories – the innovative cancer drugs – into insured sales and non-insured sales. Panel (c) plots residualized prices by category, after controlling for drug and time fixed effects. Panel (d) reports the number of innovative cancer drugs in the market in each year, with incumbents denoted by the blue and grey solid bars and new entries denoted by the green-bordered bars.

Figure 2 presents key data patterns regarding the cancer drug market. First, the NRDL Reform led to substantial market expansion for innovative cancer drugs.[14] Sales skyrocketed from ¥13 billion in 2017 to ¥64 billion in 2022 (Figure 2(a)). At the same time, sales of traditional chemotherapy drugs declined, suggesting that there was some substitution from cytotoxins to innovative treatments. Figure 2(b) decomposes the sales of innovative cancer drugs into insured and non-insured drugs. In 2017, the innovative cancer drug market was almost entirely uninsured, and patients had to pay the full retail price to receive treatment. By 2022, more than 80% of innovative cancer drug sales were for insured (successfully negotiated) drugs. Meanwhile, the average retail price of innovative cancer drugs declined substantially, as shown in the residualized price plot (Figure 2(c)), after partialing out brand fixed effects to account for price changes driven by drug entry and exit.

This period also saw significant market entry and a growing variety of innovative cancer

[14]In the remainder of the text, we consider mAb and PKI drugs to be the focal innovative drug categories.

drugs. The availability of innovative drugs increased sharply for the most common cancer types between 2017 and 2022, and the total number of innovative cancer drugs available in China nearly tripled over this period (Figure 2(d)). Many drugs newly introduced to the Chinese market were already available in developed countries, suggesting that insurance expansion may have raised the expected profitability of the Chinese market and made it more attractive for multinational pharmaceutical companies to launch their drugs there.[15]

2.3 Descriptive Patterns

In this Section, we present event study evidence regarding the effect of NRDL inclusion on drug prices and quantities, across all innovative drugs and for cancer drugs specifically.

Prices and Quantities Figures 3(a) and 3(b) compare outcomes for successfully negotiated innovative drugs with those of a never-treated group (drugs that appeared on the "eligible list" but were never successfully negotiated). We follow Callaway and Sant'Anna (2021) and implement difference-in-differences regressions allowing for variation in treatment timing and heterogeneous treatment effects. The NRDL program led to a 48% reduction in retail prices and a 350% increase in quantities.[16,17]

The combined effects of the documented price negotiation and insurance expansion reduced patients' out-of-pocket prices by 80%. The price responses are immediate and persistent—retail prices adjust to the negotiated price within one quarter—while the quantity response takes slightly longer to fully materialize. There are no visible pre-trends in prices, indicating that firms did not strategically manipulate retail prices before the negotiation. Appendix Figure A1 shows that the price and quantity treatment effects were large and significant for drugs in all negotiation cohorts, but there is some variation in magnitudes across cohorts due to composition.[18] This supports our use of the method from Callaway and Sant'Anna (2021). We also estimate the treatment effect of successful negotiation using a standard Two-Way Fixed Effects (TWFE) regression, leveraging the staggered timing of negotiation across drugs. The results are similar to those in Figure 3.

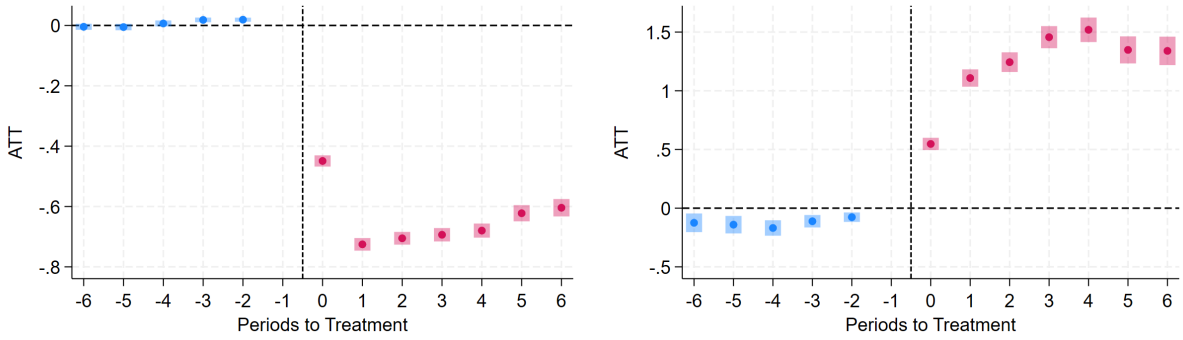
[15]The ratio of new cancer drug indication approvals in China relative to the U.S. was 0.24 between 2001-2016 and more than doubled to 0.5 during 2017-2020.

[16]For each of the reported effect sizes, we present the difference-in-differences estimate in percentage terms. E.g., 48% = 100%*(exp(-0.66)-1).

[17]A few innovative drug companies offered a "Patient Assistance Program" that provided discounts on the retail price to patients in the pre-NRDL period. We have adjusted the retail prices to reflect these discounts.

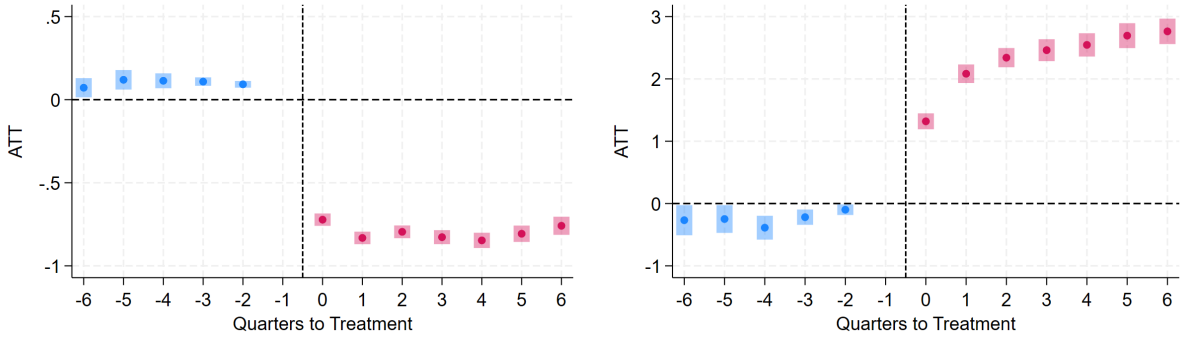
[18]Price reductions and quantity expansions were larger in 2019 and 2022, when a greater proportion of the successfully negotiated drugs were innovative cancer therapies.

Figure 3: Effects of the NRDL Reform on Price and Quantity



(a) Retail Price: All Categories

(b) Quantity: All Categories



(c) Retail Price: Cancer Drugs

(d) Quantity: Cancer Drugs

Note: This figure reports effects of the NRDL Reform on retail prices and quantities of successfully negotiated drugs. The horizontal axis denotes quarters relative to the negotiation period. The vertical axis reports estimated dynamic treatment effects and 95% confidence intervals using the CSDID method from Callaway and Sant'Anna (2021).

Figures 3(c) and 3(d) present the event study estimates of the treatment effects for successfully negotiated *innovative cancer* drugs. The control group consists of innovative cancer drugs that are eligible for negotiation but have either not yet been negotiated or never been included in the formulary.[19] The effect of NRDL inclusion is more pronounced: we estimate a 57% reduction in retail prices and a dramatic 930% jump in quantity. The retail price reduction, combined with insurance, led to an 86% reduction in patients' out-of-pocket price.

Negotiation Successes and Failures Next, we present descriptive evidence on negotiation successes and failures, as motivation for our structural model. By 2022, a total of 89 nego-

[19]Given the greater potential for spillovers (business stealing) across drugs within a single class, these estimates should be interpreted as suggestive.

tiations had taken place covering 70 innovative cancer drugs, with 57 resulting in successful agreements.[20] There are a total of 37 firms, with 16 foreign and 21 domestic.

To examine the factors associated with negotiation outcomes, we regress negotiation success on drug characteristics and present the results in Table 2. Drug quality is positively correlated with success: both lagged sales and expected improvements in patient survival have significant and positive coefficients. For instance, each additional month of expected survival gain increases the likelihood of NRDL inclusion by 2–3 ppt. When all drug attributes are included, drugs that are newer and offer greater clinical benefits are the most likely to be added to the NRDL (Column 7). Perhaps surprisingly, domestic firms are only slightly more likely to be successfully negotiated: Within all eligible drugs, the comparison is 65% for domestic vs. 60% for foreign.

Table 2: Regressions on Bargaining Outcome

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(\text{sales}_{-1})$	0.087***						0.089***
	(0.015)						(0.015)
Δ survival (month)		0.030***					0.022**
		(0.009)					(0.008)
$\mathbb{1}$(1st negot. of an indication)			0.225*				0.099
			(0.117)				(0.104)
log(mortality)				-0.000			-0.010
				(0.013)			(0.011)
International firm					0.008		-0.091
					(0.098)		(0.083)
#Year since entry						-0.057	-0.103**
						(0.046)	(0.041)
Constant	-1.172***	0.404***	0.471***	0.531***	0.523***	0.620***	-1.005***
	(0.290)	(0.060)	(0.054)	(0.158)	(0.076)	(0.088)	(0.300)
R^2	0.245	0.083	0.034	0.000	0.000	0.014	0.353
Independent Variable Mean	19.64	4.13	0.21	11.65	0.60	1.62	

Note: This table presents OLS results of regressing an indicator for negotiation success on various product features. 57 of the eligible drugs, across 89 negotiations, resulted in success. Variable $\log(\text{sales}_{-1})$ denotes the log sales of the drug in the quarter before the negotiation. Δ survival (months) denotes the estimated improvement in overall survival from the drug, compared to standard therapy, based on Phase III clinical trials. $\mathbb{1}$(First negot. of an indication) is an indicator for the drug being the first to be eligible for negotiation in any of its indications; log(mortality) denotes the log of the total deaths in the same year in the drug's approved indications. International firm is an indicator for firms based outside China. Years since entry denotes how long the drug had been sold on the Chinese market as of the negotiation round.

[20] While a quarter of overall negotiations fail, 40% of negotiations involving innovative cancer drugs fail, partly because they are more expensive. Among them, 54 drugs were negotiated once, 13 drugs were negotiated twice, and three drugs were negotiated three times.

3 Model

We now present a model of China's cancer drug market that formulates how key market primitives—such as demand, cost, government objectives, and firm bargaining power—jointly determine equilibrium outcomes. The model also serves two purposes for counterfactual analyses. First, it allows us to decompose the impact of the NDRL reform into effects driven by insurance expansion versus those driven by centralized negotiation. Second, it facilitates simulations of market outcomes under alternative insurance designs and negotiation protocols.

3.1 Model of Patient Demand

A standalone drug is defined by a brand-molecule combination. For innovative drugs, each brand corresponds to a unique molecule.[21] There may be multiple producers of non-innovative cancer molecules. Our sample includes 443 cancer drugs, 84 of which are mAb/PKIs, 70 of which were eligible for negotiation, 57 of which were successfully negotiated. The total market size is the population of cancer patients from the cancer registry, at the province-year level. The outside option is a composite good that may include Chinese traditional medicine, non-drug treatment, or no treatment.

In our preferred specification, patient i's utility from taking cancer drug regimen r in market m (province-quarter) is assumed to take the following form:

$$u_{irm} = \alpha_{im} \times \log(OOP_{rm}) + \mathbf{X}_{rm}\eta + \tilde{\kappa}_r + \log(\rho) * 1\{combo_r\} + \tilde{\xi}_{rm} + \zeta_{ig(r)m} + (1-\lambda)\varepsilon_{irm}, \quad (1)$$

where OOP_{rm} is the out-of-pocket price (OOP) for drug regimen r in market m. "Drug regimen" r may be a standalone innovative drug, a standalone non-innovative drug, or a combination regimen including multiple drugs. For standalone drugs, the out-of-pocket price is defined as $OOP_{jm} = p_{jm} \times [\mathbb{1}(j \in \mathcal{G}) \times \gamma_m + \mathbb{1}(j \notin \mathcal{G})]$, where $\mathcal{G}$ denotes the set of drugs included in the NRDL formulary and γ_m is the coinsurance rate in market m. For combination regimens, the out-of-pocket price for regimen r will be the sum of the out-of-pocket prices across component drugs $\mathcal{D}(r) \equiv \{d_{r1}, d_{r2}, ..., d_{rn}\}$: $OOP_{rm} = \sum_{j \in \mathcal{D}(r)} OOP_{jm}$.

Our preferred specification allows patient i's price sensitivity to depend on income: $\alpha_{im} = \alpha_0 + \alpha_1 \times \log(\text{income})_{im}$, where the empirical distribution of $\text{income}_{im} \sim logN(\mu_m, \sigma_m)$ in each province is observed in the Census data. In alternative specifications, we introduce a random coefficient term in price sensitivity: $\alpha_{im} = \alpha_0 + \alpha_1 \times \log(\text{income})_{im} + \alpha_2 \times \nu_i$, where ν_i follows

[21] None of the innovative drugs have exact generic substitutes, and biosimilars have not yet been eligible for negotiation.

a standard normal distribution.

All specifications control for $\mathbf{X}_{rm}$, which includes province-by-year-quarter fixed effects (year-quarter is quarter-of-the-sample), dummy variables for each of the four major cancer body system indications for the drug regimen-quarter, a total count of other minor cancer indications for the drug regimen-quarter, and a dummy variable for the regimen being past its initial year of entry into the Chinese market.

In the preferred specification, we also include time-invariant preference parameters for each component drug in regimen r, as well as a parameter $\log(\rho)$ that captures the utility weight on an indicator for combination therapies. If the only drug regimens available were standalone drugs, then the preference parameter for drug=regimen j would be captured by the drug-level fixed effect κ_j. However, if regimen r contains more than one standalone drug, then the preference parameter for that combination regimen is the average of drug fixed effects $\tilde{\kappa}_r = \frac{1}{|\mathcal{D}(r)|}\sum_{j\in\mathcal{D}(r)}\kappa_j$.[22] Intuitively, we assume that the perceived quality of a combination regimen equals the average quality of the component drugs in that regimen. By incorporating $\log(\rho)$, we allow for a market share "boost" for therapeutic regimens that combine multiple drugs. This approach is consistent with the increasingly common practice of combining cancer drugs into regimens (Dix and Lensman, 2025; Mokhtari et al., 2017) and the parameterization is analogous to the "complementarity" term in Gentzkow (2007).

Finally, $\tilde{\xi}_{rm} = \frac{1}{|\mathcal{D}(r)|}\sum_{j\in\mathcal{D}(r)}\xi_{jm}$ is an unobservable demand shock at the regimen-market level, $\zeta_{ig(r)m}$ is an idiosyncratic shock common to all regimens in nest g, and ε_{irm} is an idiosyncratic shock specific to regimen r. Both $\zeta_{ig(r)m} + (1-\lambda)\varepsilon_{irm}$ and ε_{irm} are distributed Type 1 Extreme Value. We present results for alternative nesting structures, but our preferred nesting structure includes a separate nest for each primary indication. Drugs may have multiple indications added over time, but a drug's primary indication is the first indication for which it is approved.

We address the correlation between price and the demand unobservable $\tilde{\xi}_{rm}$ using price instruments. Prices are set at the drug level; hence, our instruments are constructed at the drug level. Our preferred price instruments are the predicted probability of negotiation success, and the number of drugs with overlapping indications in the same market. To generate the first instrument, we predict negotiation success in the quarter in which the drug is negotiated. In practice, we set predicted negotiation success equal to zero in all quarters prior to drug negotiation and equal to the predicted success of that negotiation thereafter. The predicted success variable is based on the regression presented in Table 2. We argue that the timing of

[22] This is dictated by the data limitation that we do not observe sales at the regimen level; only at the drug level.

negotiation and the (pre-determined) variables that shift negotiation success in Table 2 are exogenous with respect to demand shocks that vary across markets within drug; however, they are powerful determinants of OOP via the NRDL negotiation. The second instrument is a differentiation instrument in the spirit of Gandhi and Houde (2025), representing the number of substitutable drugs within the same market. For each drug j in market m, we construct a fractional competitive-exposure measure $Z_{jm} = \sum_{j' \neq j, j' \in \mathcal{J}_m} |\mathcal{S}_{j'm} \cap \mathcal{S}_{jm}|/|\mathcal{S}_{jm}|$, where $\mathcal{J}_m$ is the set of drugs in market m and $\mathcal{S}_{jm}$ is the set of approved indications for drug j in market m. This instrument varies within drug over time as new drugs with the same indications enter the market and are approved. Because indication approvals are determined by global regulatory and clinical considerations rather than by Chinese demand shocks, the resulting overlap-based exposure measure provides plausibly exogenous variation in competitive pressure that shifts equilibrium prices but does not directly affect demand conditional on fixed effects. The normalization by $|\mathcal{S}_{jm}|$ prevents drugs with broader indication coverage from being mechanically assigned greater competitive exposure. Because post-negotiation prices are not chosen by firms, we apply this instrument only to the pre-negotiation Bertrand-Nash prices by interacting it with a pre-negotiation dummy. Our results are robust to alternative identification strategies and specifications (Section 4).

3.2 Bargaining Model

We model the negotiation process between the government and pharmaceutical companies using a complete information multi-lateral Nash-in-Nash framework, focusing on the 70 innovative drugs that were eligible for negotiation 2017-2022. Following the empirical bargaining literature for health care and other vertical markets, we assume that bargaining outcomes are binding in all contingencies, and the failure of one negotiation does not influence the outcomes of others (Crawford et al., 2018; Gowrisankaran et al., 2015; Grennan, 2013; Ho and Lee, 2017; Horn and Wolinsky, 1988). These assumptions are supported by the institutional features of the NRDL Reform, in which each group of government delegates negotiates simultaneously and independently over a specific drug with the pharmaceutical company that holds its patent (Section 2.1). Collard-Wexler et al. (2019) provide a microfoundation for this empirical model, which maps closely to our setting. We present the bargaining model at the drug- rather than regimen-level, as all negotiations are for drugs rather than regimens.

Firm Profit Pharmaceutical companies participate in NRDL negotiations to maximize their profits in the Chinese market. While profits from a successful negotiation are standard, the

threat point – firms' profits when negotiations fail – differs from those in most empirical studies of health care bargaining. Typically, negotiation breakdowns would result in the drug being excluded from consumers' choice sets. However, in our context, a failed negotiation means the drug is excluded from the NRDL formulary but remains available in the private market. The key difference is the coinsurance amount: without NRDL inclusion, patients bear 100% of the retail price, compared to the 20%-45% coinsurance if the drug were included. The firm's deviation payoff in the event of a negotiation failure is the maximum achievable profit via Bertrand-Nash (BN) pricing, given the formulary status and prices of other drugs in the market.

For the sake of brevity, we assume single-product firms in the following discussion, though our empirical estimation accommodates multi-product firms.[23] With a slight abuse of notation, we use j to denote the firm producing the drug. Let $\mathcal{G}$ denote all drugs included in the NRDL formulary and m denote a market (province-year-quarter).[24] Under a successful negotiation, firm j's profit at the negotiated price p_j (uniform nationally), given the formulary $\mathcal{G}$ and marginal cost mc_{jm}, is:

$$\Pi_j(p_j; \mathbf{p}_{-j}, \mathcal{G}) = \sum_m (p_j - mc_{jm})\, q_{jm}\,(p_j; \mathbf{p}_{-j}, \mathcal{G})\,.$$

Firm j's payoff from a failed negotiation is the maximal profit achieved from selling the drug without insurance in each private market a la Bertrand-Nash:

$$\Pi_j^{dev}(\mathbf{p}_j^{BN}; \mathbf{p}_{-j}, \mathcal{G} \setminus \{j\}) = \max_{\tilde{p}_{j1},\ldots,\tilde{p}_{jM}} \sum_m (\tilde{p}_{jm} - mc_{jm})\, q_{jm}(\tilde{p}_{jm}; \mathbf{p}_{-j}, \mathcal{G} \setminus \{j\})$$

Crucially, firm j sets different prices across provinces under negotiation failure. Its gain from a successful negotiation at the price p_j and network $\mathcal{G}$ is defined as: $\Delta\Pi_j(p_j; \mathbf{p_{-j}}, \mathcal{G}) \equiv \Pi_j(p_j; \mathbf{p}_{-j}, \mathcal{G}) - \Pi_j^{dev}(\mathbf{p}_j^{BN}; \mathbf{p}_{-j}, \mathcal{G} \setminus \{j\})$. Intuitively, the **gains from trade** come from the quantity expansion induced by the sharp reduction in OOP_{jm} when $j \in \mathcal{G}$.

Government Objective The central government cares about patient welfare but faces constraints on drug spending. We consider several welfare metrics, including the standard

[23]There are 15 cases where a given manufacturer negotiates with the government over multiple drugs in a single year. However, in these cases, negotiation is simultaneous and independent across drugs, with no communication across negotiating teams. Our bargaining model is consistent with this feature of the institutional setting: the gain from trade to a given manufacturer for a given drug allows for cannibalization effects across drugs in that manufacturer's portfolio, but the NRDL inclusion negotiation is otherwise independent across drugs. This is in contrast to the "all-or-nothing" negotiation by hospital systems as in Ho and Lee (2017).

[24]The NRDL formulary varies over time, but we omit the time subscript on $\mathcal{G}$ for simplicity.

measure of consumer surplus, but also more equitable measures, such as an inverse-income weighted consumer surplus measure drawn from the public finance literature and the overall survival from the healthcare literature. The discussions below focus on consumer surplus, though the analyses are similar with other welfare metrics. Let V denote the government objective function, where β captures the government's relative weight on insurance program expenditures:[25,26]

$$V(\mathbf{p}, \mathcal{G}) = CS(\mathbf{p}, \mathcal{G}) - \beta TC(\mathbf{p}, \mathcal{G}),$$

The change in consumer surplus from adding drug j to the NRDL formulary is the aggregate monetized increase in patient utility compared to no insurance coverage for drug j. We calculate this as:

$$\Delta CS(p_j; \mathbf{p_{-j}}, \mathcal{G}) = \sum_m \text{MS}_m \cdot \int_i \int_{\gamma_m p_j}^{p_{jm}^{BN}} \underbrace{\frac{1}{\alpha_i / OOP}}_{\substack{\$ \text{ per} \\ \text{util}}} \cdot \underbrace{\frac{\partial \widetilde{EU}_{im}(OOP; \mathbf{p_{-j}}, \mathcal{G})}{\partial OOP}}_{\substack{\text{change in utils for} \\ \text{a local price change}}} dOOP \cdot dF(i|m), \quad (2)$$

where γ_m is the coinsurance rate in market m, MS_m is the market size (number of patients diagnosed with cancer) in market m, and $\widetilde{EU}_{im} = \mathbb{E} \max_r u_{irm}$ denotes the ex-ante utility of patient i in market m given their choice set. Patient utility u_{irm} is defined in Equation (1). Government spending, TC, consists of insurance program expenditures on all drugs covered by the NRDL formulary:

$$TC(\mathbf{p}, \mathcal{G}) = \sum_j \sum_m \mathbb{1}(j \in \mathcal{G}) (1 - \gamma_m) p_j q_{jm}.$$

The government's gain from covering drug j at the negotiated price p_j is $\Delta V(p_j; \mathbf{p_{-j}}, \mathcal{G}) = \Delta CS(p_j; \mathbf{p_{-j}}, \mathcal{G}) - \beta \Delta TC(p_j; \mathbf{p_{-j}}, \mathcal{G})$.[27]

[25] The assumption that the government values patient surplus and government expenditures is consistent with the government sending pharmacoeconomic experts and health fund experts to each negotiation.

[26] Modeling the government objective as a weighted sum is a reduced form representation of potentially many underlying mechanisms that would generate similar empirical patterns. For example, variation in β could reflect variation in negotiators' perceptions of government priorities across government programs, across diseases, or across patient groups likely to benefit from coverage expansions. An alternative parameterization of the government's objective would be $V(\mathbf{p}, \mathcal{G}) = \lambda CS(\mathbf{p}, \mathcal{G}) - TC(\mathbf{p}, \mathcal{G})$, where $\lambda = \frac{1}{\beta}$ captures the government's preference for (or belief regarding) consumer surplus. This parameterization is isomorphic to our specification.

[27] In principle, both firms and the government care about the discounted sum of future payoffs. We assume that the parties hold passive beliefs about future negotiation outcomes, so the expected gains from successful negotiations are the same in each future period. Therefore, the static payoff is proportional to the discounted sum of future payoffs. Dynamic incentives are an interesting question, but beyond the scope of this paper.

Negotiation A negotiation succeeds if the government and drug company find an *admissible* price such that gains from trade are weakly positive for both parties. This is consistent with the institutional fact that the government and firms negotiate over a linear price without lump sum transfers. The government's relative weight β on expenditure, which we assume is a random variable from a distribution $\beta \sim F_\beta$, serves several purposes. First, it is a parsimonious way to reflect the government's priorities over patient welfare versus fiscal constraints. Second, the parameter helps rationalize negotiation failures observed in our data. As β increases, the government's focus on minimizing expenditure intensifies, exerting downward pressure on the drug prices deemed acceptable. If these prices fall below the threshold where the gains from trade for pharmaceutical firms are zero, negotiations will fail and drug firms will withdraw from the bargaining table. Third, the assumption that β is a random variable helps explain the variability in bargaining outcomes across drugs with similar consumer surplus and expenditure effects. The fact that drugs with similar surplus gains sometimes, but do not always, make it into the NRDL suggests that different government representatives may apply different weights during their negotiations with pharmaceutical firms.

The magnitude of β determines the range of admissible prices that yield positive gains from trade for both negotiating parties. Let $\mathcal{P}_j$ represent the admissible set for drug j:

$$\mathcal{P}_j \equiv \{p_j : \Delta V_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right) \geq 0 \text{ and } \Delta \Pi_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right) \geq 0\}.$$

If β is sufficiently high, such that no mutually agreeable price exists, then the admissible set is empty, $\mathcal{P} = \varnothing$, and the negotiation fails.

For successful negotiations, the negotiated price maximizes the Nash product of gains from trade for both parties. The share of surplus accruing to each party is determined by firm j's bargaining power τ_j:

$$p_j = \arg\max_{p_j} \left(\Delta \Pi_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right)\right)^{\tau_j} \left(\Delta V\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right)\right)^{1-\tau_j}.$$

This implies the following first-order condition for successfully negotiated prices:

$$\sum_m \underbrace{(p_j - mc_{jm})}_{\text{retail margin}} \frac{\partial q_{jm}}{\partial OOP_{jm}} = -\sum_m \underbrace{\frac{q_{jm}}{\gamma_m}}_{\text{expansion effect}} + \underbrace{\frac{1-\tau_j}{\tau_j} \times \frac{\Delta \Pi_j}{\Delta V_j} \frac{d\Delta V_j}{dp_j} \frac{1}{\gamma_m}}_{\text{bargaining effect}}, \ \forall j \in \mathcal{G}. \quad (3)$$

In theory, an unconstrained model of bargaining with insurance expansion could lead to retail price increases due to the rotation of the demand curve. In such a case, it might be appropriate

to impose a cap on negotiated prices (Dubois and Lasio, 2018). In practice, however, the NRDL negotiation/insurance combination always leads to a substantial price decrease, such that a cap would never bind. Figure 4 plots the distribution of retail price discounts across negotiated drugs. For each successfully negotiated drug, we compute the quantity-weighted average retail price in the four quarters immediately before and after the quarter of negotiation. The mean discount is approximately 60%, with a median of 62% and a standard deviation of 13 percentage points.

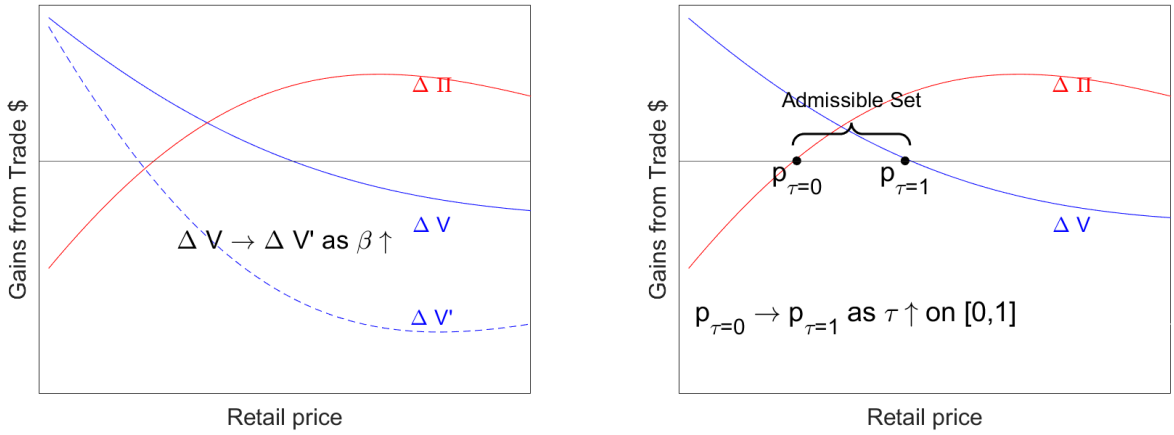
Figure 4: Distribution of Retail Price Discounts at NRDL Negotiation

Note: This figure plots the distribution of retail price discounts (in %) for 56 successfully negotiated cancer drugs. The discount is computed as the percentage decline in quantity-weighted average retail price from the four quarters before to the four quarters after the drug's entry into the NRDL.

To illustrate how the government's preference β and a drug firm's bargaining power τ affect negotiation outcomes, Figure 5 plots each party's gains from trade against the negotiated retail price. The price range where both curves are positive is the admissible set. Ceteris paribus, as β increases, the government's gains from trade shift downward, narrowing or even eliminating the admissible set; conversely, lower β values expand it (Figure 5(a)). The bargaining parameter determines the negotiated price within the admissible region (Figure 5(b)). If the pharmaceutical firm holds all the bargaining power, the negotiated price will be at the upper bound of the admissible set, holding the government to its participation constraint. If the government wields all of the bargaining power, the negotiated price will be at the lower bound, just satisfying the firm's participation constraint. In essence, a negotiation success pins down the upper bound of β, whereas the location of the negotiated price within the admissible set, together with our parametric assumptions, jointly identifies τ and β.

A key advantage of our setting is that we observe prices and quantities both *before* and *after* negotiations, allowing us to directly infer firms' gains from trade, $\Delta\Pi$, from the data,

Figure 5: An Illustration of Model Predicted Bargaining Outcomes



(a) Identification of β

(b) Identification of τ

Note: This figure illustrates the roles of β and τ in determining the bargaining outcomes using a simulated example. Panel (a) plots the government gains from trade with two different β values: the solid blue line represents a low β (ΔV), and the dashed blue line represents a high β ($\Delta V'$). Panel (b) plots changes in the negotiated price as the firm's bargaining power τ increases from zero to one.

demand, and marginal cost estimates. As a result, we can recover $p_{\tau=0}$ (the price at which the firm's participation constraint is binding) after estimating demand. The differences between $p_{\tau=0}$ and observed negotiated prices are informative of τ.

Welfare and Equity Considerations We calculate total surplus as consumer surplus, plus firm profits, minus government expenditures. This approach assumes that demand patterns reveal patients' true preferences over cancer treatments. This would be inappropriate if demand patterns are distorted by behavioral frictions (Baicker et al., 2015) or liquidity constraints (Ericson et al., 2025; Nyman, 1999). An alternative approach to evaluating welfare gains is to use health outcomes, such as overall survival.[28]

The specification of the government's objective function above assumes that the government has utilitarian preferences and values consumer surplus. As a robustness check, we consider alternative specifications that allow for equity considerations, following the public

[28]To do so, we multiply quantity q_{jm} by the estimated gains in overall survival from Phase III clinical trials, as well as a scaling factor $1/\phi_j$, where ϕ_j is the number of years over which patients take drug j in a standard course of treatment. The scaling factor ϕ_j, taken from the drug labels in the SinoHealth data, converts quantities in years of treatment into the number of patients with the standard course of treatment.

finance literature (Hendren, 2020):

$$V(\mathbf{p}, \mathcal{G}) = \frac{1}{H} \int_i \text{income}_i^{-\nu} CS_i(\mathbf{p}, \mathcal{G}) dF(i) - \beta TC(\mathbf{p}, \mathcal{G}) \tag{4}$$

where $\nu \geq 0$ is a scalar and a higher ν indicates a stronger government preference for equity. $H = \int_i \text{income}_i^{-\nu} dF(i)$ is a normalization constant that integrates over all individuals. We examine three cases: $\nu = 0$ (the utilitarian preference above), $\nu = 1$, and $\nu = 2$.

3.3 Estimation

Demand Estimation In the first step of estimation, we recover the demand parameters in Equation (1). Our procedure deviates from standard demand estimation algorithms (Berry et al., 1995; Grigolon and Verboven, 2014) in that we must aggregate predicted regimen-level market shares to the drug level. A patient chooses between drug regimens $\mathcal{R}_m$ available in market m and the outside option, normalized to have utility 0. Define the deterministic part of utility as:

$$V_{irm} \equiv \alpha_{im} \times \log(OOP_{rm}) + \mathbf{X}_{rm}\eta + \tilde{\kappa}_r + \log(\rho) * 1\{combo_r\} + \tilde{\xi}_{rm}, \qquad V_{i0m} \equiv 0.$$

Suppose that $\mathcal{R}_m$ can be partitioned into a set $\mathcal{I}_m$ of mutually exclusive nests, and let $\mathcal{R}_{gm}$ be the set of regimens in nest $g \in \mathcal{I}_m$. Define the following aggregate index for nest g:

$$D_{igm} \equiv \sum_{r \in \mathcal{R}_{gm}} \exp\left(\frac{V_{irm}}{1-\lambda}\right).$$

Then the probability of individual i choosing drug regimen r will be:

$$\tilde{s}_{irm}(.) = \frac{\exp\big(V_{irm}/(1-\lambda)\big)\ D_{i\,g(r)\,m}^{-\lambda}}{1 + \sum_{g \in \mathcal{I}_m} D_{igm}^{1-\lambda}},$$

which in turn yields the aggregate predicted market share for drug regimen r:

$$\tilde{s}_{rm}(.) = \int \tilde{s}_{irm}(.)\, \mathrm{d}F\big(\alpha_{im}\big).$$

We do not observe sales at the regimen level. Instead, we observe total sales for drug j, combining its sales as a standalone therapy and its sales when prescribed as part of combination regimens. The total market share of drug j in market m is therefore the sum of its standalone

market share and its market shares across all combination regimens: $s_{jm} = \sum_{r \in \mathcal{R}(j)} \tilde{s}_{rm}(.)$, where $\mathcal{R}(j)$ denotes the set of all drug *regimens* containing drug j.

We estimate the parameters in Equation (1) by matching observed to predicted drug-market-level shares, using a nested fixed point approach. The inner loop of our algorithm uses a contraction mapping to solve for a vector of linear drug-market-level preference parameters $\delta_{jm} \equiv \kappa_j + \xi_{jm}$. We calculate regimen-level predicted market shares $\tilde{s}_{rm}(\boldsymbol{\delta}; \Phi)$, where $\Phi = (\alpha_0, \alpha_1, \eta, \rho, \lambda)$, then aggregate across standalone and combination regimens $\mathcal{R}(j)$ within each drug j to obtain drug-level predicted market shares $s_{jm} = \sum_{r \in \mathcal{R}(j)} \tilde{s}_{rm}(\boldsymbol{\delta}; \Phi)$.

For a given guess of Φ, our contraction mapping is:

$$\delta_{jm}^{h+1} = \delta_{jm}^{h} + log(s_{jm}) - log(s_{jm}(\boldsymbol{\delta}^h; \Phi)), \forall m.$$

In implementation, we use the SQUAREM fixed point acceleration algorithm of Varadhan and Roland (2008). The outer loop of our demand estimation algorithm searches over $(\boldsymbol{\kappa}, \Phi)$ using a GMM estimator whose empirical moment is $g(\boldsymbol{\kappa}, \Phi) = \frac{1}{M} \sum_{m=1}^{M} \frac{1}{|\mathcal{J}_m|} \sum_{j \in \mathcal{J}_m} Z_{jm} \hat{\xi}_{jm}$.

Supply Estimation For each successfully negotiated drug, we recover the marginal cost in each province using demand parameter estimates and the observed prices and market shares during the quarter before the negotiation. Here, we assume Bertrand-Nash competition among all firm-market pairs whose prices are not yet determined by negotiations.[29] We also assume that marginal costs for drugs under negotiation remain unchanged from their pre-negotiation levels. Note that we can separately identify marginal costs and bargaining parameters (discussed below) because we observe market outcomes in pre-negotiation periods.

In the third step, we assume the government's relative weight on insurance spending β follows an exponential distribution (i.e., β follows T1EV distribution): $\exp(\beta) \sim Exp(X_{\beta j}; \theta_\beta)$. We allow θ_β to be a function of drug attributes $X_{\beta j}$ such as clinical effectiveness. The drug firm's bargaining power may depend on attributes $X_{\tau j}$ such as nationality: $\tau_j = f(X_{\tau j})$.

We then construct the sample log-likelihood function for parameters $\theta = \{\beta, \tau\}$, using the observed negotiation outcomes $\{\mathcal{G}_j \in \{0, 1\}, \forall j\}$ and negotiated prices $\{p_j\}$ for all successful

[29] The marginal cost estimates for non-negotiated drugs change from period to period, though the differences are modest as drug prices change infrequently. Results are similar if we restrict marginal costs to be constant over the entire pre-negotiation period. There are two drugs that enter the Chinese market and NRDL in the same quarter: Ceritinib and Vemurafenib. For these drugs, we do not observe pre-negotiation prices; we apply the average retail price reduction via the negotiation to impute what would have been the Bertrand-Nash price and then infer the marginal cost from that price. There are ten negotiated drugs that could treat cancer but are not mAbs or PKIs. These are included in the demand estimation but excluded from the supply estimation and counterfactual simulations (which focus on mAbs and PKIs).

cases $\mathcal{G}_j = 1$.[30] A negotiation fails if the government's gains from trade are negative at the lowest price acceptable to the drug company, denoted by p_j^l. By construction, p_j^l satisfies:

$$\Delta\Pi_j(p_j^l; \mathbf{p}_{-j}, \mathcal{G}) \equiv \Pi_j(p_j^l; \mathbf{p}_{-j}, \mathcal{G}) - \Pi_j^{dev}(p_j^{BN}; \mathbf{p}_{-j}, \mathcal{G} \setminus \{j\}) = 0,$$

meaning the firm's gains from trade are exactly zero. We then define $\underline{\beta_j}$ as the β value at which the government's gains from trade become zero at price p_j^l:

$$\underline{\beta_j} = \frac{\Delta CS_j(p_j^l; \mathbf{p_{-j}}, \mathcal{G})}{\Delta TC_j(p_j^l; \mathbf{p_{-j}}, \mathcal{G}).} \tag{5}$$

Any β above $\underline{\beta_j}$ results in the government's gains turning negative at p_j^l, leading to bargaining failure. Intuitively, this condition implies that the government is unwilling to include the drug in the formulary, even at the firm's lowest acceptable price. The likelihood of observing a negotiation failure for drug j is thus $Pr_j(\beta > \underline{\beta_j}) = 1 - F_\beta(\underline{\beta_j}; \theta_\beta)$.

For successful negotiations ($\mathcal{G}_j = 1$), β satisfies the interior condition, i.e., β_j and the observed negotiated price p_j must satisfy Equation (3), the bargaining FOC. That equation is invertible with respect to β_j, leading to a closed-form solution of β as a function of the negotiated price and bargaining parameter:

$$\beta_j(p_j; \tau_j) = \frac{\vartheta \Delta CS_j - \Delta\Pi_j \frac{\partial \Delta CS_j}{\partial p_j}}{\vartheta \Delta TC_j - \Delta\Pi_j \frac{\partial \Delta TC_j}{\partial p_j}},$$

where $\vartheta = -\frac{\tau_j}{1-\tau_j}\frac{\partial \Pi_j}{\partial p_j}$. Given the distributional assumption on β, the likelihood of observed price p_j is $\frac{\partial \beta_j}{\partial p_j} f_\beta(\beta_j(p_j; \tau_j); \theta_\beta)$. Putting things together, the joint log-likelihood function is:

$$log\mathcal{L}(\theta_\beta, \tau) = \sum_j \underbrace{\mathbb{1}(\mathcal{G}_j = 1) \log\left(\frac{\partial \beta_j}{\partial p_j} f_\beta(\beta_j(p_j; \tau_j); \theta_\beta)\right)}_{\text{successful negotiations}} + \underbrace{\mathbb{1}(\mathcal{G}_j = 0) \log\left(1 - F_\beta(\underline{\beta_j}; \theta_\beta))\right)}_{\text{failed negotiations}}.$$

We estimate the supply-side parameters via maximum likelihood, using all (successful and failed) negotiations.

[30] Each first-order condition takes as given the prices of non-negotiated drugs, whose prices are set using the Bertrand Nash first-order condition in the same period, and of drugs whose prices are fixed under contracts negotiated in previous periods. Both the government and firms use demand conditions from one quarter before the negotiation to evaluate gains from successful negotiations in future periods.

4 Results

4.1 Demand Estimates

Table 3 reports OLS demand estimates in Column (1) and instrumental variables (IV) estimates in Columns (2)-(5); each column builds flexibility relative to the previous. Column (3) allows price sensitivity to vary with patient income. Column (4) groups drugs into nests by primary indication. Column (5) is our preferred specification as described in Section 3, where combination regimens provide an additional "boost."

Instrumenting for the out-of-pocket price has the anticipated effect of increasing the magnitude of the estimated price elasticity. Drugs with large positive demand shocks tend to have both higher prices and higher demand, biasing the price coefficient toward zero. In Column (2), which instruments for prices, the median own-price elasticity of demand is -1.2, in line with recent studies on global drug markets (Dubois et al., 2022). Across Columns (3)-(5), the interaction between income and price is statistically and economically significant, indicating that higher-income individuals are less price-sensitive; the distributions of price elasticities in these richer specifications are similar. In Columns (4) and (5), the estimated nesting parameter is 0.33-0.35, suggesting that patients and their doctors perceive drug regimens with the same indications as moderately substitutable. In our preferred specification, Column (5), we estimate the combination preference parameter $\rho = 0.012$. To put this value in context, it suggests that the average innovative drug in our sample gets a market share boost of approximately 22% from the introduction of a combination regimen.[31] In this specification, the median own-price elasticity is -1.60, with an inter-quartile range of [-1.76, -1.31]. The distribution of the price elasticity is shown across markets and patients in Appendix Figure A2; the distribution is shifted left (more negative) for low-income regions. The difference in price sensitivity between high- and low-income patients underscores the importance of distributional considerations, especially since the highest-income provinces in our setting have the lowest coinsurance rates.

To demonstrate that the demand model produces sensible substitution patterns, Appendix Table A1 presents own- and cross-price elasticities computed using the preferred random coefficients nested logit specification in column (5) of Table 3. We group drugs in each of the top cancer indications by drug class (Innovative = mAb/PKI, vs. Other), and report cross-

[31] We compute this by comparing each constituent innovative drug's model-implied market share with and without its combination regimens. To compute the model-implied market share without the combinations, we remove the focal drug's combination regimens from the choice set, and calculate market share holding the estimated mean utilities fixed.

Table 3: Demand Estimates for Cancer Drugs

	OLS	IV	IV+RC	IV+RC+Nest	IV+RC+Nest+Combo
	(1)	(2)	(3)	(4)	(5)
log(OOP)	-0.755	-1.189	-4.243	-2.931	-2.902
	(0.023)	(0.042)	(0.625)	(0.448)	(0.411)
log(OOP) × log(income)			0.653	0.448	0.444
			(0.130)	(0.091)	(0.083)
λ (nesting para.)				0.352	0.330
				(0.050)	(0.057)
ρ (combo. pref.)					0.012
					(0.006)
$1\{t > t_{\text{entry}} + 4\}$	1.118	0.845	0.880	0.643	0.615
	(0.055)	(0.054)	(0.058)	(0.050)	(0.060)
Indications					
Lung cancer	0.569	0.342	0.275	0.209	0.198
	(0.081)	(0.085)	(0.091)	(0.063)	(0.065)
Breast cancer	0.383	0.289	0.287	0.151	-0.028
	(0.128)	(0.128)	(0.121)	(0.084)	(0.154)
Colon cancer	0.887	0.872	0.868	0.460	0.489
	(0.101)	(0.100)	(0.099)	(0.088)	(0.108)
Stomach cancer	0.642	0.577	0.492	0.397	0.518
	(0.105)	(0.101)	(0.101)	(0.072)	(0.090)
log(# of Indications)	0.269	0.177	0.121	0.177	0.148
	(0.051)	(0.052)	(0.053)	(0.039)	(0.041)
P75 elasticity	-0.76	-1.19	-1.34	-1.36	-1.31
Median elasticity	-0.76	-1.19	-1.60	-1.67	-1.60
P25 elasticity	-0.76	-1.19	-1.78	-1.84	-1.76
Combinations					Yes
Product FE	Yes	Yes	Yes	Yes	Yes
Province×Time FE	Yes	Yes	Yes	Yes	Yes

Note: Table reports cancer drug demand parameter estimates, as described in the text. N =104,745 observations. All specifications control for drug and province-by-year-quarter fixed effects, a dummy for observations at least four quarters post-entry, dummies for each major cancer indication, and the count of minor indications. Columns (2)-(5) instrument for price with the predicted probability of negotiation success and the count of drugs with the overlapping indications in the same market. Columns (3)-(5) additionally interact the predicted success IV with province-year-level log median income. Columns (4)-(5) also interact the predicted success IV with the count of drugs in the nest, as an IV for the nesting parameter λ. Column (5) includes a dummy for whether the drug has any combination indications in the current market, as an IV for the combination parameter $\log(\rho)$. The reported elasticities are percentiles of individual-level own-price elasticities across all drug-market observations. Standard errors are clustered at the drug-province level.

price elasticities for the average alternative drug, separately for drugs with and without the same cancer indication. The own-price elasticities range from -1.24 to -1.64. The cross-price

elasticities range from 0.016 to 0.16 for drugs in the same indication, and are essentially zero for drugs in different indications.

Robustness The demand specifications above control for drug and province-by-year-quarter fixed effects and exploit variation in the timing of drug negotiation, the probability of negotiation success, and drug differentiation to recover price sensitivity and drug substitution patterns. Appendix Table A2 presents the results of alternative specifications. Column (1) replaces drug fixed effects with drug-year-quarter fixed effects (while retaining province-year-quarter fixed effects). This identification strategy relies on variation in OOP price changes *within* a given drug-year-quarter and *across* provinces, akin to a shift-share design where the shift is negotiation and the share is the provincial coinsurance rate. The implied price sensitivity is essentially identical between Column (1) of Table A2 and its closest analog in Column (2) of Table 3.

Columns (2)-(7) of Table A2 estimate modifications of our preferred specification in Column (5) of Table 3. Column (2) imposes an alternative nesting structure, grouping drugs into nests by their 4th-level Anatomical Therapeutic Chemical (ATC4) classification, as defined by therapeutic, pharmacological, and chemical subgroups.[32] The estimated nesting parameter is small, implying a low within-group preference correlation. ATC4 classifies drugs based on chemical structure, often placing innovative and non-innovative drugs that have the same cancer targets and may be valid substitutes into different nests. We consider the preferred nesting structure of primary indication to be more plausible. Column (3) omits the Gandhi and Houde (2025) differentiation IVs from the IV set; results are essentially unchanged. Column (4) uses realized negotiation success, rather than predicted negotiation success, as an IV. Column (5) instruments the Chinese indication variables using the analogous variables based on U.S. FDA approvals, on the rationale that U.S. regulatory approvals reflect global clinical evidence and are plausibly exogenous with respect to within-drug variation in demand shocks in China.[33] Column (6) generates our OOP variable using an average of the URRBMI and UEBMI coinsurance rates, weighted using the imputed population of urban and employed in each province, rather than the URRBMI coinsurance rates used in our preferred specification. Columns (2)-(6) all result in similar elasticity distributions.

[32]By 2017, there were separate ATC4 groups for PKIs and monoclonal antibodies. In our sample of 443 cancer drugs, there are 67 ATC4 classes total (WHO Collaborating Centre for Drug Statistics Methodology, 2016).

[33]We do not consider this to be our preferred specification, as 23 newly approved cancer drugs in China have not yet gained U.S. approval. When we estimate that specification, we exclude the 23 drugs with missing US indications from the IV moments where indications are treated as endogenous.

Column (7) adds to our preferred specification a pure random coefficient on price. The parameter estimates are similar to those in Column (5) of Table 3, but the median own-price elasticity increases to –2.09. This would imply lower pre-NRDL profit margins than those suggested by industry reports, and that 73% of successfully negotiated drugs have negative profits post-negotiation.[34] For these reasons, we do not use Column (7) of Table A2 as our preferred specification.

4.2 Supply Estimates

Table 4 presents the estimates for β, the government's weight on drug insurance spending, and τ, firms' bargaining power parameter. Column (1) estimates one β and τ for all drugs, while Column (2) allows β to vary with the life-years saved per treatment course and permits domestic and foreign firms to have different bargaining parameters.

Regarding the government's weight on drug spending, the θ_β parameter from the log-exponential distribution implies that β is 0.86 for the average drug and 1.07 for the median drug. The negative coefficient on survival in Column (2) indicates that β is lower for drugs with greater survival benefits. Specifically, a one standard deviation increase in overall survival (6 months) reduces β by approximately 0.13. This implies that, while the government values consumer surplus and drug spending equally for the median drug, it places relatively more weight on consumer surplus for higher-quality drugs, effectively relaxing the budget constraint for these drugs. This finding suggests a policy preference for including high-quality drugs in the NRDL formulary.[35] Our β estimates appear sensible given the estimates in the public finance literature where the social cost of government funds is often assumed to be 1.3 (Ballard et al., 1985).

The bottom panel of the table indicates that firms' bargaining power, τ, is estimated

[34] Accounting estimates of biologic drug marginal costs in the U.S. vary widely; one review article reports a range of 5–19% of price (Chen et al., 2025). Given that pre-reform cancer drug prices in China were lower than those in the U.S.—one study reports a median price ratio of 0.36 (Goldstein et al., 2016)—this would suggest marginal costs ranging from 14–53% of the price in our sample, a range that encompasses our estimate of approximately 20%.

[35] Consumer surplus likely incorporates survival expectations, such that allowing β depend on Δ survival could in principle capture curvature in the relationship between survival and the government's willingness to cover drugs on the NRDL. However, CS may also diverge from Δ survival for other reasons. It may include health outcomes not accounted for by survival gains, like side effects. It may also incorporate errors in patients' perceptions of health benefit, such as overweighting of salient symptoms, present bias, or other behavioral errors as documented in Baicker et al. (2015). In such cases, a reduction in β for higher-quality drugs would counteract the effects of consumers' potential undervaluation of high-quality drugs. In any case, the possibility of such errors leads us to present welfare analyses that highlight both survival outcomes and consumer surplus.

Table 4: Supply-Side Estimation

	Baseline (1)		More Covariates (2)	
Variable	Coef.	S.E.	Coef.	S.E.
Gvt. Budget Constraint				
θ_β (constant)	4.21	0.58	4.66	0.79
θ_β (Δ survival)			-0.13	0.07
Firm Bargaining Power				
τ	0.66	0.01		
τ (Foreign)			0.65	0.01
τ (Domestic)			0.71	0.01

Note: This table presents the supply side estimates. The government's weight on drug spending, β, is assumed to follow a T1EV distribution with the inverse scale parameter determined by θ_β. The mean and median of β are 0.86 and 1.07, respectively. Firms' bargaining power parameter is estimated to be 0.66 and is similar across domestic and foreign firms.

to be 0.66, and is similar for both domestic (0.71) and foreign (multinational) firms (0.65). The magnitude of this bargaining power may have several origins. The empirical bargaining literature often uses the term "bargaining ability" rather than "bargaining power," and it may be that firm representatives are more skilled or persuasive on average than government representatives. It is also possible that the government allows markups in order to provide innovation incentives to firms. Regardless, while firms possess more bargaining power than the government, the government still has enough bargaining power to negotiate prices well below those that would prevail in the private market (i.e., under Bertrand-Nash pricing).

Robustness The baseline estimations assume the government has a utilitarian objective that weights consumer surplus and government expenditures. As a robustness check, we estimate the supply-side parameters assuming the government cares about alternative objects. The results are reported in Appendix Table A3; the preferred specification is in Column (1) and alternative specifications are in Columns (2)-(5). First, we let the government objective value clinical benefits rather than consumer surplus (Column 2). This specification implies a far lower weight on consumer benefits and fits the data substantially less well, as measured by the log-likelihood. Second, we let the government objective function depend on the firm's potential for future innovation, by supposing that the government weights *consumer plus producer* surplus and government expenditure (Column 3). This has the expected effect of increasing θ_β; i.e., the inclusion of $\Delta\Pi$ shifts ΔV everywhere upward, so in order to rationalize the observed prices and successes, the model estimates a larger β. We prefer the baseline supply

model due to its resulting in a distribution of β close to 1. Lastly, Columns (4) and (5) estimate supply under different ν's. The bargaining power parameter τ is essentially unchanged across these specifications. The expenditure-weight parameter θ_β is somewhat smaller under income-weighted CS specifications, but the qualitative ordering and the implications for negotiation outcomes are preserved. We use $\nu = 0$ as our preferred specification for the main analyses, while also reporting welfare results for $\nu = 1$ and $\nu = 2$ to explore equity considerations. We also tried alternative distributional assumptions of β (such as χ^2), and the results are similar.

4.3 Evaluation of the NRDL Reform

The NRDL Reform consists of two policy instruments: (1) insurance expansion, which adds previously uninsured innovative drugs to the NRDL formulary, and (2) central negotiation, where the government and pharmaceutical firms bargain to determine a mutually agreeable price. We first decompose the effects of the NRDL Reform on prices, quantities, and welfare into impacts driven by insurance expansion and those driven by central negotiation. We then explore how these welfare implications vary across provinces and income groups.

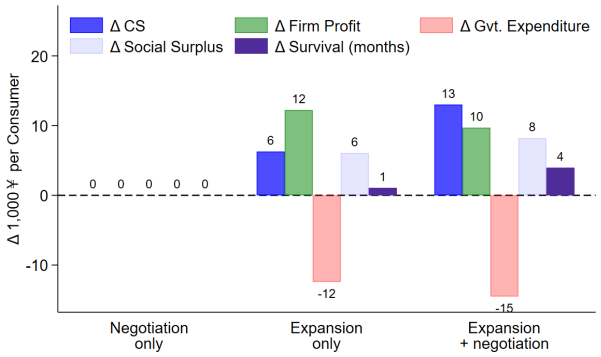
During our study period (2017Q1-2023Q2), 57 drugs were included in the NRDL formulary. The analyses here focus on these drugs with successful negotiation outcomes. We revisit the 13 drugs that failed NRDL negotiations and the issue of bargaining failure in Section 5, where we examine alternative policy designs. We conduct simulations using the second quarter of 2023 as our reference period, holding patient income, preferences, and production costs at their 2023Q2 levels.[36] In each counterfactual simulation, we compute negotiated prices for these 57 drugs, solve for the equilibrium prices for innovative drugs excluded from the formulary and sold in the private market, and then determine the equilibrium quantities for all 443 cancer drugs.

We consider four scenarios. In the **Baseline** scenario, we assume that the NRDL Reform did not occur. There was no insurance expansion, and all 57 successfully negotiated drugs would instead be sold only in the private market. This scenario mirrors the pre-reform conditions in 2016 but accounts for new drugs that entered the market between 2017 and 2023. In the **Negotiation-only** counterfactual, the government negotiates prices with drug firms but does not provide insurance coverage for the negotiated drugs. Firms retain the option to sell in the private market if negotiations fail. In the **Expansion-only** scenario, the government includes the 57 cancer drugs in the NRDL formulary, allowing patients to purchase them at province-specific coinsurance rates, but does not engage in central price negotiations. Phar-

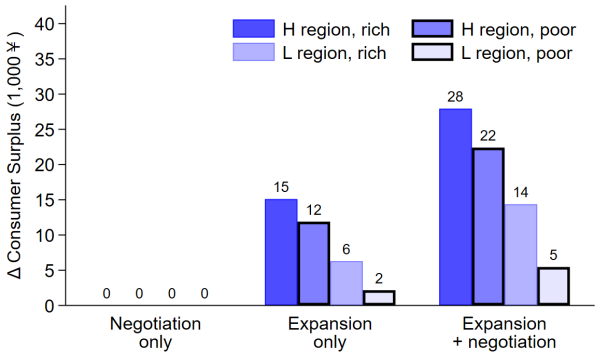
[36] All drugs negotiated during our study horizon (2017-2022) remained on the formulary as of 2023Q2.

Figure 6: Effect of NRDL Reform—Decomposition

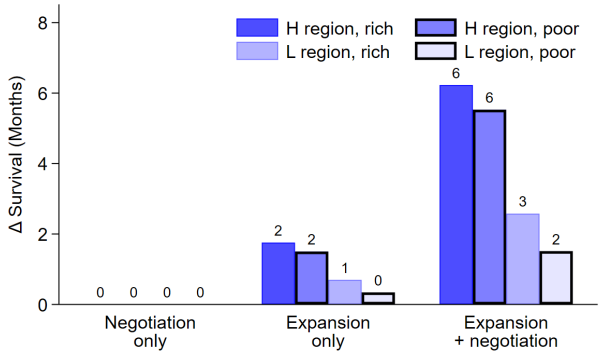
(a) Price and Market Share of Innovative Cancer Drugs



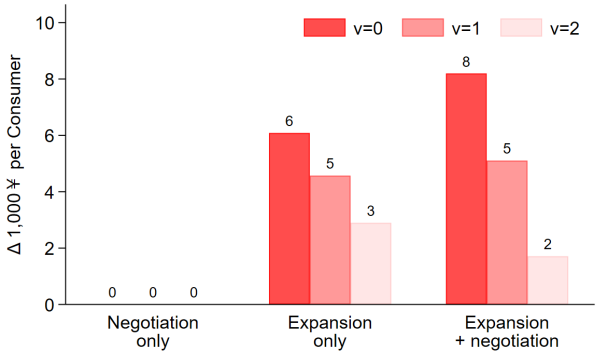
(b) Welfare Effects



(c) Δ Consumer Surplus by Income Group



(d) Δ Survival by Income Group



(e) Alternative Social Surplus Measures

Note: This figure summarizes counterfactual outcomes for the 57 cancer drugs successfully negotiated as of 2023. Panel (a) compares four scenarios. "Baseline" denotes Bertrand-Nash pricing with no insurance coverage. "Negotiation only" assumes the government negotiates lower prices with firms but does not provide insurance coverage. "Expansion only" assumes the government offers insurance coverage without engaging in price negotiations. "Expansion+negotiation" represents the NRDL reform, where the government provides insurance coverage and negotiates prices. Panels (b)-(e) show differences in each scenario relative to the "Baseline" in terms of changes in welfare, consumer surplus by income group, overall survival gains by income group, and alternative social surplus measures that incorporate equity. Appendix Table A4 provides more details.

maceutical firms continue to set prices via Bertrand-Nash competition. Finally, we consider **Negotiation+expansion**, which represents the full NRDL reform as implemented in the data but assumes that all negotiations take place in the 2nd quarter of 2023.

Prices and Quantities The top row of Figure 6(a) reports baseline prices and quantities. Absent the NRDL Reform, both OOP and the retail prices for an annual dosage would average about ¥197,000 per year (equivalent to $28,200), with the focal innovative drugs capturing only 3% of the cancer drug market. Results for the Negotiation-only scenario in the second row of Figure 6(a) are identical to the Baseline. Without insurance, there is no promise of a demand expansion. Thus, the government has no leverage to incentivize firms to participate in negotiations, and firms prefer to sell drugs in the private market at profit-maximizing prices rather than accepting negotiated terms.

The third row of Figure 6(a) presents results for the Expansion-only scenario. These results reflect two countervailing forces. On the one hand, insurance lowers patients' out-of-pocket costs and therefore decreases firms' incentives to decrease retail prices. E.g., for every ¥100 increase in the retail price, patients pay only ¥20–¥45 after insurance. This puts upward pressure on prices. On the other hand, insurance brings more price-sensitive patients into the market. The greater price sensitivity of the marginal patient puts downward pressure on prices. The net result is a 3% decrease in the average retail price to ¥191,000 per year, while patients' OOP spending decreases to ¥68,000 per year (a 65% reduction). Demand surges: the focal innovative drugs' market share increases from 3% to 10% (a 254% expansion).

The fourth row of Figure 6(a) illustrates the combined effect of the full NRDL Reform, with both insurance expansion and central negotiation. Unlike the Expansion-only scenario, the combined reform significantly lowers both retail prices *and* OOP: the average retail price per annual supply decreases by ¥128,000 (a 65% reduction), and the OOP price drops by ¥172,000 (an 87% reduction). These price reductions drive a 694% spike in market share, with the focal innovative drugs capturing 22% of the cancer drug market, a result comparable to the 930% quantity expansion documented in Section 2.3.[37]

[37]We perform all counterfactual simulations in the final quarter of our sample. This choice allows us to isolate the effects of the NRDL elements for all negotiated drugs in the context of a single consistent market. Thus, we do not expect our simulations of the combined reform to replicate the results for cancer drugs in Section 2.3. For example, a drug that entered the NRDL in 2017 would have faced a different competitive environment than it would have in 2023. In practice, our descriptive regressions and counterfactual simulations find similar retail and OOP effects of the combined NRDL for successfully negotiated drugs; however, the aggregate quantity effects in the simulations are somewhat smaller than the drug-specific quantity effects in the descriptive regressions, as the simultaneous price drops across many innovative drugs lead to business stealing.

Overall, these simulation results indicate that the combined effects of insurance expansion and price negotiation are greater than the sum of their individual effects, suggesting complementarity between negotiation and insurance expansion.

Welfare Figure 6(b) illustrates the welfare effects of each scenario relative to the Baseline. Each group of bars represents changes in consumer surplus (CS), firm profit (PS), government spending (GS), total surplus (CS + PS – GS), and overall survival. To emphasize that higher government spending reduces surplus, we plot government expenditures as negative values.

As expected, the Negotiation-only scenario has no welfare impact relative to the Baseline. Expansion-only increases consumer surplus by ¥7,000 per patient-year and firm profit by ¥12,000 per patient-year, but at the cost of an ¥12,000 increase in government spending per patient-year. The Negotiation+expansion reform raises consumer surplus by ¥14,000 per patient-year, more than doubling the gains from Expansion-only due to the larger reduction in OOP costs. Notably, the increase in consumer surplus closely matches the rise in government expenditure, suggesting that the combined reform more effectively achieves the government's goal of improving patient welfare while controlling costs. Firm profit increases by ¥10,000 per patient-year under the combined reform, slightly less than in the Expansion-only scenario.

These results highlight that negotiation alone does not affect welfare, while insurance expansion benefits patients but entails relatively high government spending. In the NRDL Reform, negotiation and insurance expansion are complements: insurance expansion ensures broader access to drugs, while negotiation shifts part of the financial burden from the government to pharmaceutical firms (through lower drug prices), benefiting both the government and patients. Overall, total social surplus is highest under the combined reform, increasing by ¥8,000 per patient-year relative to the Baseline, compared to ¥6,000 under Expansion-only.

An alternative approach to evaluating welfare is to use health outcomes. Enhanced access to innovative cancer drugs under the combined NRDL Reform extends overall survival by 2.99 months per patient, an *846%* increase relative to the survival improvements due to innovative drugs at Baseline. This effect is far larger than the survival benefit of insurance expansion alone, which increases survival by 0.79 months (225% of the Baseline). Note the contrast between CS and survival in Figure 6(b): while gains in CS under the combined NRDL Reform are more than twice those in the Expansion-only scenario, the survival benefits are nearly four times as large. This discrepancy arises because poorer patients contribute less to CS due to their lower willingness to pay, but they experience substantial health benefits.

In aggregate, the innovative drugs successfully negotiated under the NRDL Reform between 2017 and 2022 generated nearly ¥37 billion ($5.3 billion) in annual consumer surplus

gains and contributed a total survival increase of 1.1 million life-years among Chinese cancer patients each year.

Innovation While we abstract away from dynamic considerations such as R&D, our results suggest that the NRDL reform increases firm profits through market expansion, which could spur firm pharmaceutical innovation in the long run and reinforce the short-run welfare gains. This is in contrast to programs that negotiate prices without stimulating demand, as may occur in markets with generous insurance for innovative drugs (Garthwaite, 2025).

Equity Considerations The aggregate welfare effects presented above mask substantial heterogeneity across patients, both by province and income level. To examine these distributional differences, we classify provinces into wealthy and less wealthy regions based on median provincial income. Within each province, we further categorize patients into high-income and low-income groups using each provincial median income as the threshold. This results in four distinct groups: high- and low-income patients in wealthy provinces and high- and low-income patients in less wealthy provinces.

These distributional effects are illustrated in Figure 6(c). Wealthier regions offer lower coinsurance rates; hence, a given reduction in retail drug prices leads to a larger decrease in OOP expenses. In addition, high-income households are less price-sensitive and more likely to purchase innovative drugs. As a result, rich individuals in high-income (low-coinsurance) regions experience the largest dollarized welfare gains under both Expansion-only and Negotiation+expansion, at ¥15,000 and ¥28,000, respectively. In contrast, the welfare gains for poor patients in low-income provinces are significantly lower, at ¥2,000 and ¥5,000, respectively.

A similar, though less extreme, pattern emerges when we measure patient benefits using increases in months survived, as shown in Figure 6(d). While wealthy households in high-income provinces still benefit the most, the disparities in survival gains are much smaller than those in CS gains. This is because survival is a quantity-based measure and is therefore less sensitive to the differences in price sensitivity across income groups. Echoing the discussions above, all income groups experience three to fivefold increases in survival benefits under the combined reform relative to Expansion-only.

Turning to social surplus, both Expansion-only and Negotiation+expansion lead to increases in social surplus compared to the Baseline (Figure 6(e)). However, both scenarios are regressive because wealthier patients benefit more than poorer ones in terms of both CS and survival improvements. The relative ranking of these two policies depends on the government's preference for equity. As the government's weight on equity increases (ν, defined in Equation

(4), increases from 0 to 1 or 2), the social surplus gains associated with each policy decline. This is because both policies entail greater government subsidies for high-income patients than for low-income patients, and a stronger preference for equity penalizes such transfers.

If the government is utilitarian ($\nu = 0$) or has a moderate preference for equity ($\nu = 1$), the efficiency considerations (gains in CS) dominate, making the combined reform the preferred policy. However, if the government has a very strong preference for equity ($\nu = 2$), then the flatter gradient in consumer surplus under Expansion-only becomes more desirable than the steep gradient under Negotiation+expansion.

5 Counterfactual Policy Simulations

In this section, we compare the observed NRDL Reform with several alternative policy designs to evaluate how policy choices impact firms' and governments' gains from trade and, ultimately, the welfare effects of drug market reforms. Section 5.1 examines market access negotiation, Section 5.2 compares centralized negotiation (as in NRDL Reform) with decentralized negotiation, and Section 5.3 investigates optimal coinsurance designs. Each of these scenarios represents a feasible alternative: bundled negotiation for market access and reimbursement occurs in other high-income countries (Dubois et al., 2022; Syversen et al., 2024); the US, EU, and Latin America each have decentralized regimes that are adopting (or proposing to adopt) greater centralization (Duggan and Scott Morton, 2010; Ho and Pakes, 2024; PAHO Executive Committee, 2024); and means-tested coinsurance is the norm in many public insurance models, including several in the US (Commonwealth Fund, 2020).

We discuss both extensive and intensive margins for all alternative policy designs. On the extensive margin, different policy frameworks alter the range of prices that are mutually acceptable to firms and the government, thereby influencing the number of successful negotiations. On the intensive margin, policy variations affect the government's and firms' surplus, which in turn changes negotiated prices, realized quantities, and welfare, conditional on negotiation success. Throughout this Section, we refer to Figure 7 for graphical intuition regarding how policy affects gains from trade and bargaining outcomes.

Our simulations consider all 70 drugs in the 2023Q2 market, including the 13 drugs that failed NRDL negotiations. Since we do not observe the negotiated prices for these drugs, we cannot recover their $\boldsymbol{\beta}$ values. However, we observe the lower-bound thresholds $\underline{\boldsymbol{\beta}}$ (Equation (5)) such that the government's gains from trade equal zero at the price that makes the drug company's gains from trade equal zero. That is, a slight reduction in β would have resulted

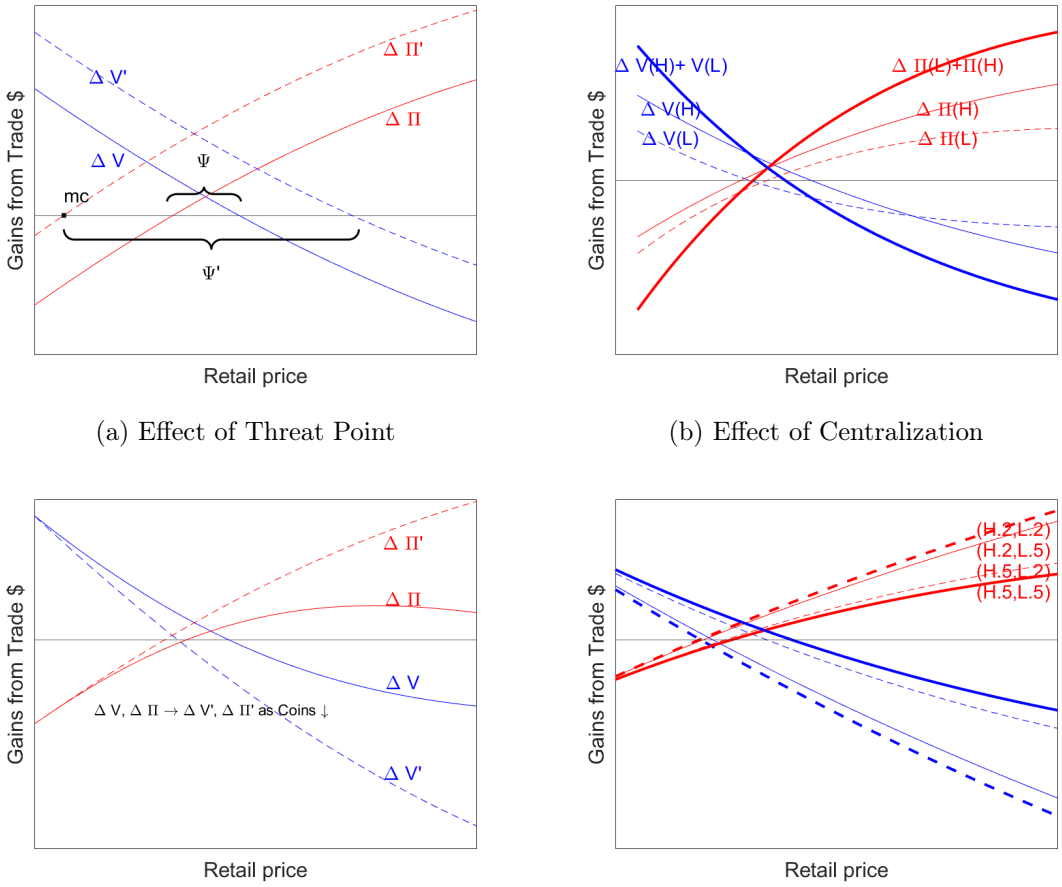
in negotiation success. In the counterfactual simulations presented in the main text, we set $\boldsymbol{\beta} = \underline{\boldsymbol{\beta}}$ for these 13 drugs. In Appendix Section C, we report results under an alternative extreme assumption that these 13 negotiations would always fail ($\boldsymbol{\beta} = \boldsymbol{\infty}$).[38]

Since the success or failure of one drug's negotiation can influence the gains from trade in other negotiations, there could theoretically be multiple equilibria in counterfactual simulations. We detail our algorithm for addressing these concerns in Appendix B.1.[39] Briefly, we use an algorithm similar to the bounding approach in Sabal (2025): in each iteration, we identify drugs that must be in the formulary as those whose narrowest possible admissible price set is nonempty, and drugs that must not be in the formulary as those whose widest possible admissible price set is empty, and iterate this process until convergence.

[38]Since β is a parsimonious representation of the value of government spending for different purposes, across drug markets as well as other government programs, it is unlikely to be infinite. The results reported here and in the Appendix thus provide two meaningful bounds.

[39]In our setting, we do not find evidence of multiple equilibria, as these innovative cancer drugs are sufficiently differentiated from each other. As discussed in Appendix B.1, there is no significant spillover effect of a successful negotiation on other drugs in the same indication.

Figure 7: Effects of Policy Designs on Gains from Trade



(a) Effect of Threat Point

(b) Effect of Centralization

(c) Effect of Coinsurance

(d) Effect of Income-Based Coinsurance

Note: This figure illustrates the effects of policy designs on gains from trade for both firms and the government. Panel (a) compares gains from trade under NRDL (FA-I) ($\Delta\Pi$, ΔV, and range of admissible prices Ψ) with those under the counterfactual MA-I scenario ($\Delta\Pi'$, $\Delta V'$, range of admissible prices Ψ'). Panel (b) contrasts gains from trade in a high-income province $(\Delta\Pi(H), \Delta V(H))$ vs. a low-income province $(\Delta\Pi(L), \Delta V(L))$; the bold line shows $(\Delta\Pi(H) + \Delta\Pi(L), \Delta V(H) + \Delta V(L))$ to illustrate the benefits of centralization. Panel (c) compares gains from trade under insurance expansions with high $(\Delta\Pi, \Delta V)$ vs. low coinsurance rates $(\Delta\Pi', \Delta V')$. Panel (d) plots gains from trade under different income-based coinsurance schedules (γ_H, γ_L), where γ_H and γ_L denote coinsurance rates for high- and low-income patients, respectively. The thick dashed lines represent a uniform coinsurance rate of $(0.2, 0.2)$, thin solid lines represent $(0.2, 0.5)$, thin dashed lines represent $(0.5, 0.2)$, and thick solid lines represent $(0.5, 0.5)$.

5.1 Market Access Negotiation

In Section 4.3, we noted that negotiation has no bite unless paired with insurance expansion. In this section, we model a "market-access" negotiation, where formulary inclusion is bundled with drug entry. Under this policy, a failed negotiation results in the drug being entirely

excluded from the Chinese market. This market-exclusion threat point is commonly used in empirical health economics studies, e.g., Dubois et al. (2022); Gowrisankaran et al. (2015); Grennan (2013); Ho and Lee (2017). We analyze two scenarios: market-access negotiation without insurance expansion (MA-N) and with insurance expansion (MA-I). Additionally, we use the abbreviation FA-N for formulary-access negotiation without insurance and FA-I for formulary-access negotiation with insurance (i.e., the NRDL Reform).

Consider first the MA-N scenario, where government expenditure is always zero regardless of the negotiation outcome, and the government's sole objective is to maximize consumer surplus. Unlike the ineffective Negotiation-only case in Section 4.3, the price in the event of bargaining failure is ∞, as the drug is removed from the patients' choice set. In contrast, under FA-N, the disagreement price is p^{BN}. The higher disagreement price—the harsher threat point—under MA-N increases the gains from trade for both the government and firms. This, in turn, expands the range of admissible prices to be any price between the marginal costs of producing innovative drugs and patients' willingness to pay. Consequently, negotiations always succeed, and the government *does* have leverage in this setting, as shown below.

Now consider MA-I. This policy differs from FA-I (the NRDL Reform) in several key ways. Similar to the discussion above, the price in the event of bargaining failure under MA-I equals ∞, whereas under FA-I, it is p^{BN}. The more severe disagreement payoff expands the set of admissible prices. Firms are willing to accept any price above marginal cost, while the government is willing to pay any price where consumer surplus exceeds government expenditure weighted by β. Thus, switching from FA-I to MA-I increases the likelihood of successful agreements.[40] Figure 7(a) illustrates how the gains from trade for both the government (ΔV) and the drug company ($\Delta\Pi$) shift upward under MA-I compared to the NRDL Reform, thereby widening the admissible set of prices (Ψ).

That said, the effect of switching from FA-I to MA-I on negotiated prices is ambiguous, depending upon the relative magnitudes of the changes in ΔV and $\Delta\Pi$, as well as the bargaining parameter τ. To see this, note that prices are at the bounds of the admissible set Ψ under extreme values of τ. If $\tau = 1$, then $p^{MA-I} > p^{FA-I}$ because the upper bound of the admissible set is higher under MA-I; if $\tau = 0$, then $p^{MA-I} < p^{FA-I}$ because the lower bound of the admissible set is lower under MA-I. Intuitively, if the firm has all the bargaining power, it obtains all of the government's increase in surplus in a move from FA-I to MA-I, and vice versa. Appendix B.2 presents the more nuanced finding for cases where each negotiated price is in the interior of the admissible set: $p^{MA-I} < p^{FA-I}$ if and only if the ratio of the

[40] Negotiation may still fail under MA-I if the coinsurance rate is low (leading to high government spending) and the opportunity cost of government funds, β, exceeds 1, as shown in Section 5.3.

government's inclusion payoff (payoff received upon successful negotiation, which is identical under both MA-I and FA-I) to its deviation payoff under FA-I exceeds the corresponding ratio for the firm. This is more likely to hold when τ is small.

Negotiation Success, Prices, and Quantities Figure 8(a) compares simulated OOPs, retail prices, and quantities under four scenarios (FA-N is discussed in Section 4.3): (1) the Bertrand-Nash Baseline (no negotiation or insurance expansion), (2) MA-N, (3) MA-I, and (4) FA-I (i.e., the existing NRDL Reform). We report the counterfactual results separately for the 13 drugs that failed the NRDL negotiations and the 57 successfully included drugs.

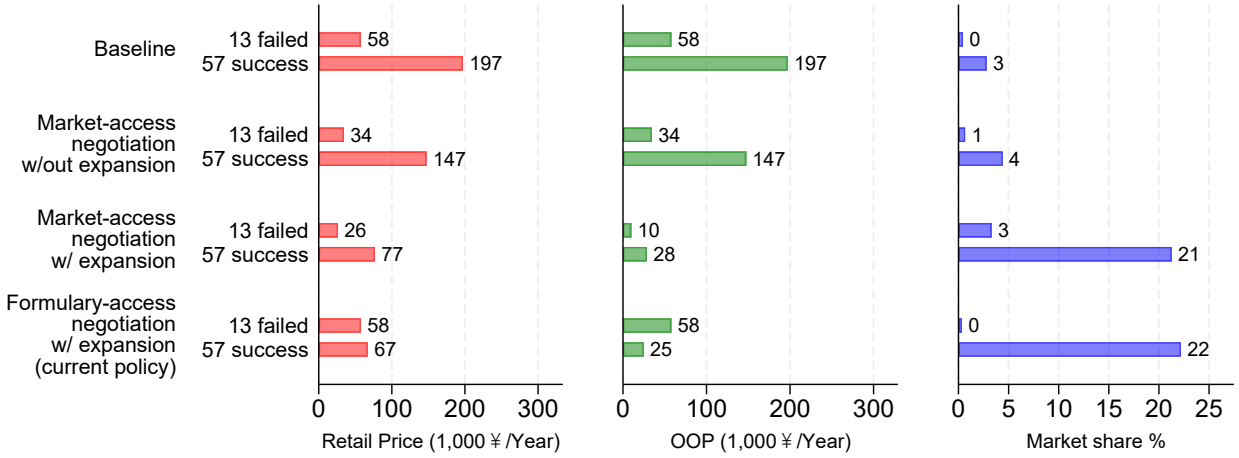
Compared to the baseline, both MA-N and MA-I ensure successful negotiations for all drugs, driving significant market expansion. Under MA-N, the government achieves substantial price reductions by leveraging the threat of market exclusion, even without insurance expansion. The average negotiated price drops by 41% for "failed" drugs and by 25% for "successful" drugs. The OOP prices are the same as negotiated prices. Market shares increase by 1.6 ppt (57%) for the 13 failed drugs and by 0.24 ppt (53%) for the 57 successful drugs. With insurance expansion (MA-I), negotiated and OOP prices decline even further. For failed drugs, retail prices decrease by ¥32,000 (55%), OOPs drop by ¥48,000 (83%), and market share expands by 2.9 ppt (630%). For successful drugs, retail prices fall by ¥120,000 (61%), OOPs decline by ¥169,000 (86%), and market share grows by 18.5 ppt (660%).

As in the NRDL Reform, insurance complements negotiation: MA-I achieves significantly larger price reductions and quantity expansions for both failed drugs and successful drugs than MA-N. However, the price reductions for successful drugs are slightly smaller than those under NRDL Reform, shown in the bottom row. As a result, market expansion for successful drugs is also smaller (18 ppt vs. 19 ppt; 600% vs. 694%). This is because the more severe threat point in MA-I disproportionately impacts the government's gains from trade. However, the result of a smaller price discount depends on firms having high bargaining power. In alternative simulations with $\tau = 0.32$ (where the government holds more bargaining power), we find that MA-I performs as well as NRDL even for the 57 successful drugs.[41]

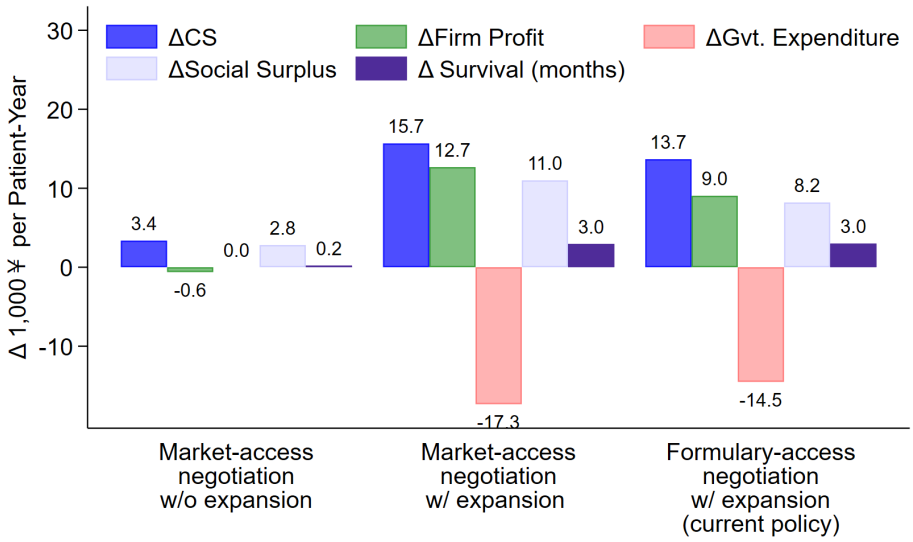
Welfare and Survival Implications Figure 8(b) illustrates changes in welfare in ¥1,000s per cancer patient-year and gains in survival months for the three policy designs relative to the baseline. MA-I generates significantly higher consumer surplus and firm profits than FA-I, but it also increases government expenditure more because more drugs (70 vs. 57) are included in

[41] Results are available upon request.

Figure 8: Counterfactual Results under Alternative Bargaining Formats ($\boldsymbol{\beta}_{failed} = \underline{\boldsymbol{\beta}}$)



(a) Price and Market Share



(b) Welfare Effects

Note: This figure presents results for all 70 innovative cancer drugs from alternative negotiation scenarios, assuming $\boldsymbol{\beta}_{\text{failed}} = \underline{\boldsymbol{\beta}}$ for drugs that failed the NRDL negotiations. For successfully negotiated drugs, β are fixed at their estimated values. Panel (a) compares four scenarios, with results shown separately for the 57 drugs that succeeded in the NRDL reform and the 13 that failed. "Baseline" denotes Bertrand-Nash pricing without insurance coverage. "Market-access negotiation" assumes that drugs are excluded from the Chinese market if negotiations fail. "Market-access negotiation w/ expansion" builds on this by adding insurance coverage at observed provincial coinsurance rates. Finally, "Formulary-access negotiation w/ expansion" corresponds to the NRDL reform. Panel (b) reports changes in welfare relative to the baseline scenario. See Appendix Figure A3 for results with $\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$.

the formulary. Nevertheless, MA-I generates a higher total surplus on net, with similar gains in average survival months.

These analyses highlight three key takeaways. First, in the absence of insurance expansion, market access negotiation is (infinitely) more effective than formulary access negotiation. Second, insurance expansion amplifies the effects of negotiation, making the two policy tools highly complementary. Third, MA-I delivers greater overall welfare gains (higher consumer, firm, and social surplus), and equivalent medical benefits, as FA-I.

5.2 Centralized vs. Decentralized Negotiation

The findings in Section 4.3 on the distributional effects of the NRDL Reform motivate two sets of counterfactual analyses: one examining geographic variation, and the other investigating coinsurance variation. This section addresses the former (with Section 5.3 covering the latter) by comparing centralized national bargaining (the status quo) with a counterfactual scenario in which each province negotiates its own prices. These analyses contribute to ongoing policy debates and academic discussions regarding the costs and benefits of central procurement; see, e.g., Dubois et al. (2021), Dubois and Sæthre (2020), Dubois et al. (2022), and Maini and Pammolli (2023).

In the decentralized negotiation setting, each provincial government independently manages its formulary and negotiates drug prices, with the threat point being exclusion from the provincial formulary rather than from the national list. To ensure comparability, we impose a uniform coinsurance rate across provinces—set at the national average of 0.37—for both decentralized and centralized negotiations. Holding coinsurance rates constant across provinces allows us to isolate the distributional effects of centralized negotiation, separate from those driven by variation in coinsurance rates, which we analyze in Section 5.3. A caveat to this analysis is that we must also hold β, τ, and marginal costs fixed across provinces, as we have no data to shed light on how these parameters (τ in particular) may be different for the national vs. provincial governments. E.g., if provincial governments have lesser bargaining ability, then our simulated retail prices under decentralization would be biased downward.[42]

Potential Mechanisms Prior research has shown that buyer centralization can lead to lower prices when suppliers' cost functions depend on quantities (Chipty and Snyder, 1999; Inderst and Wey, 2007), when there is mutual dependency between buyers and sellers (Inderst

[42]We are also implicitly assuming no cross-province arbitrage: patients cannot travel across provinces to purchase cancer drugs.

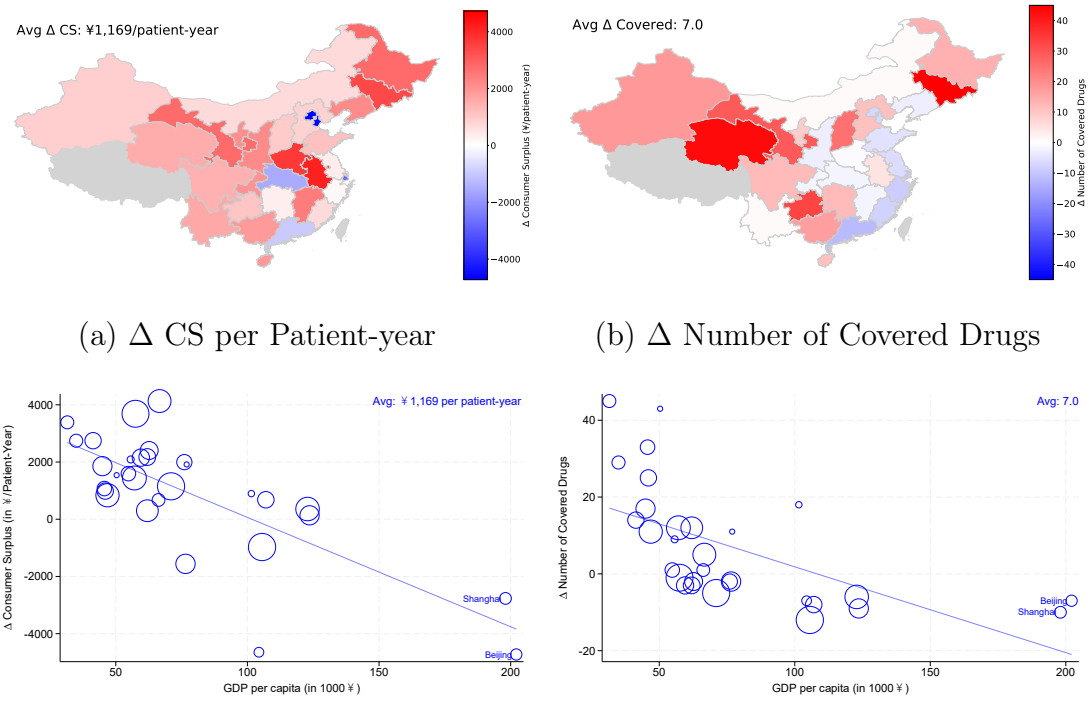
and Montez, 2019), or when buyers compete (Ho and Lee, 2017). These mechanisms do not apply in our setting. Instead, centralization changes equilibrium outcomes through its impact on bargaining failures and regional heterogeneity in willingness-to-pay, as illustrated in Figure 7(b). Intuitively, firms' gains from trade, $\Delta\Pi$, are consistently higher in high-income than low-income provinces. In the price range where firms are willing to negotiate, the government's gains from trade, ΔV, are also higher in high-income provinces because the benefits from market expansion outweigh government costs.[43] The effects of centralization are expected to be heterogeneous across provinces. For low-income provinces, centralization expands the admissible set and, conditional on a successful negotiation, results in higher negotiated prices. For high-income provinces, it shrinks the admissible set and leads to lower negotiated prices. The aggregate effect across provinces is an open empirical question. The simulation results are reported in Figure 9.

Negotiation Success, Prices, and Surplus On average, centralized bargaining results in 7 additional negotiation successes per province compared to decentralized bargaining. Among the 57 drugs included in the actual NRDL formulary, average retail prices would be 23% lower, and the market shares of innovative drugs would rise by 1.6 ppt (a 8% increase). These effects reinforce one another, leading to a net gain in aggregate social surplus of ¥260 (0.9%) per patient-year and an increase in consumer surplus of ¥1,169 (12%) per patient-year under centralized bargaining relative to decentralized negotiations. On net, the expected extensive margin gains in low-income regions, and the intensive margin savings on inframarginal drugs in high-income regions, dominate. Therefore, by aggregating gains from trade across all provinces, centralized bargaining leads to more negotiation successes and lower prices on average.

Variation in Effects of Centralized Negotiation Figure 9 presents additional detail on the distributional consequences of centralized negotiation. Centralization increases the leverage of lower-income provinces at the expense of wealthier ones. Figure 9(a) and 9(b) plot changes in consumer surplus and number of drugs covered in each province when shifting from decentralized to centralized negotiation. Most regions benefit along both dimensions, especially provinces in central and western China with lower income levels. Provinces that experience larger gains in consumer surplus also tend to see greater increases in drug coverage. To put a finer point on this, Figure 9(c) reveals a fairly steep income gradient in the

[43] This no longer holds at higher prices, where higher demand in high-income provinces becomes prohibitively expensive.

Figure 9: Changes in CS and Drug Coverage from Decentralized to Centralized Negotiation



(a) Δ CS per Patient-year

(b) Δ Number of Covered Drugs

(c) Δ CS vs. Income

(d) Δ Number of Covered Drugs vs. Income

Note: Panels (a)-(b) show the geographic distributions of changes in consumer surplus per patient-year and the number of covered drugs across provinces when moving from decentralized negotiation with insurance expansion to centralized negotiation with insurance expansion. Panels (c)-(d) present bubble plots of the same outcomes, with GDP per capita on the x-axis. Each bubble indicates one province, and bubble size scales with the province's population. All the results are based on simulations with $\boldsymbol{\beta} = \underline{\boldsymbol{\beta}}$ for failed negotiations. See Appendix Figure A4 for results with $\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$.

consumer surplus gains, while Figure 9(d) shows a similar gradient in drug coverage. The wealthiest provinces benefit less or even incur losses under centralized negotiation. For example, Beijing and Shanghai would cover 7 to 10 *fewer* drugs under centralization compared to the decentralized scenario.

5.3 Coinsurance Schedule Design

Drug coinsurance rates for China's NRDL range from 0.2 and 0.45 across provinces (Figure 1). This section explores the welfare implications of alternative income-based coinsurance schedules. For simplicity, we consider a two-tier structure where households with income above and below the national median face different coinsurance rates. We simulate equilibrium outcomes while varying coinsurance rates for high- and low-income patients between 20% and

60%.

Potential Mechanisms The effect of higher coinsurance rates on negotiation outcomes is theoretically ambiguous.[44] Holding prices and formularies constant, lower (i.e., more generous) coinsurance rates unambiguously raise consumer demand, consumer surplus, and firms' gains from trade. However, the effect on the government's gains from trade is less clear because lower coinsurance also increases government expenditures. Figure 7(c) presents a case in which the government's gains from trade are lower under a lower coinsurance rate.[45] In such cases, lower coinsurance rates tend to reduce the likelihood of negotiation success, but also tend to reduce retail and OOP prices for drugs that are successfully negotiated. Intuitively, conditional on successful negotiation, lower coinsurance rates increase firms' gains from trade, which in turn strengthens the government's bargaining leverage and makes firms more willing to accept lower negotiated prices.

Importantly, the magnitude and direction of these effects depend on *who* is subject to coinsurance increases. Figure 7(d) extends the example from Figure 7(c), comparing gains from trade under four income-based coinsurance schedules, where high- and low-income patients face either 20% or 50% coinsurance. In this example, as in our empirical exercise, increasing the coinsurance rate for high-income patients has a much larger impact on gains from trade for both parties than increasing it for low-income patients. Note also that a given income group's coinsurance rate has *spillover* effects on the other income group via retail prices and negotiation success, which apply to all patients regardless of income.

Negotiation Success and Prices The effects of alternative coinsurance schedules across all negotiated drugs are presented in Figure 10.[46] Figure 10(a) confirms that lowering coinsurance rates increases negotiation failure, particularly when they apply to high-income patients. For example, when coinsurance equals 20% across all patients, 64% of all negotiations fail.

Figure 10(b) shows the average retail price of innovative cancer drugs, restricted to the 24 drugs that are always successfully negotiated (across different coinsurance levels) to isolate effects on the intensive margin. The diagonal confirms that lowering coinsurance reduces average retail prices. These price reductions are driven by changes in the coinsurance rate

[44] See Appendix B.3 for details.

[45] For a given price, the government's gains from trade are always increasing in the coinsurance rate when $\beta \geq 1$. However, if $\beta < 1$, the effect on ΔV can be positive or negative.

[46] Appendix Figure A5 sets $\boldsymbol{\beta} = \boldsymbol{\infty}$ for drugs that failed to reach agreement under the NRDL Reform, i.e., negotiations for these drugs would always fail regardless of policy designs. The patterns described below hold under both (extremal) assumptions.

for high-income patients, as seen when moving across rows while holding the low-income rate constant. The gradient of prices in the coinsurance rate for low-income patients (moving across columns within each row) is flatter.[47]

Welfare The differential impact of coinsurance changes on high- versus low-income patients generates spillover effects across income groups, shaping the optimal policy design.[48] Figures 10(c)-(d) examine the optimal coinsurance rate under different social welfare criteria. To incorporate the social planner's equity preferences, we weigh consumer surplus by $income^{-\nu}$ as in Section 3.2. The case of $\nu = 0$ corresponds to a utilitarian social planner, while higher values of ν reflect stronger preferences for equity. If the social planner's goal is to maximize total social surplus as in panel (c), welfare is maximized at the schedule (H 0.34, L 0.42)—a moderately regressive structure that resembles the geographic regressivity seen in practice.

However, a more Rawlsian objective ($\nu = 2$), as shown in Figure 10(d), favors higher coinsurance rates for all patients with an optimal rate of (H 0.6, L 0.4). While lowering coinsurance expands drug adoption among marginal patients, it also results in subsidies to inframarginal patients who would have purchased the drug regardless. A Rawlsian social welfare function penalizes such expenditures, making it harder to justify low coinsurance rates for high-income consumers when equity concerns are high. Ultimately, an optimal coinsurance schedule must strike a balance between these competing objectives—ensuring equitable access, managing government expenditures, and preserving effective negotiation leverage.

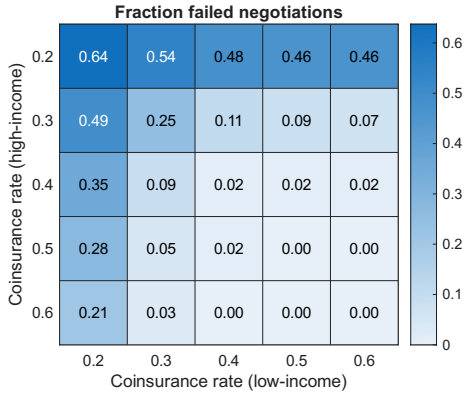
5.4 Toward Optimal Policy Design

To summarize our findings, we consider the welfare implications of policies within the broad "Negotiation plus Expansion" regime. We maintain centralized negotiation, as it has a positive impact on the vast majority of regions and patients. Figure 11 presents the welfare effects of each policy combination, with survival effects on the horizontal axis and total social surplus effects on the vertical axis. Each is relative to the pre-reform Baseline with no insurance or negotiation, and the "×" symbol in the far upper-right defines an ex post efficient benchmark with $OOP = MC$ for each drug.

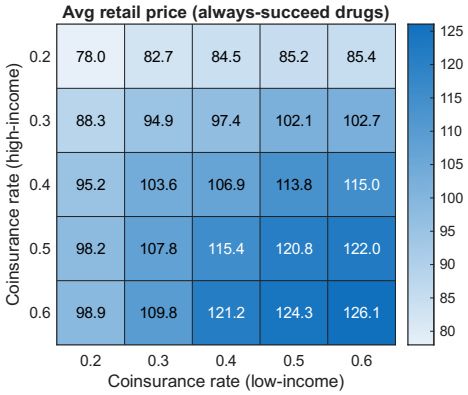
[47] This asymmetry arises because the market expansion effect from lowering coinsurance rates is much larger for high-income patients, which increases firms' gains from trade and strengthens the government's bargaining position. Generally, coinsurance rates affect both the levels and slopes of the gains from trade curves, and lowering coinsurance rates can even lead to higher prices. See Appendix B.3 for details.

[48] We focus on *ex post* optimality, i.e., what coinsurance schedule maximizes social surplus, holding fixed all parameters and ignoring the risk protective value of social insurance? The latter is a key ingredient in optimal insurance design, but requires information about consumers' risk preferences, which we do not have.

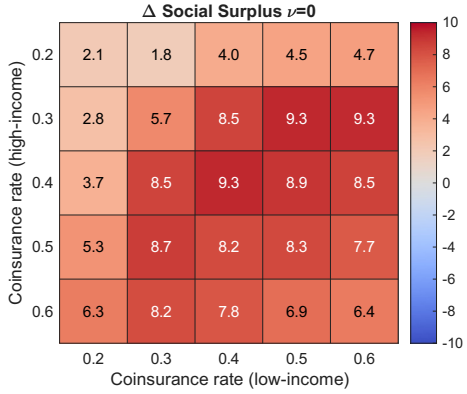
Figure 10: Counterfactual Results under Alternative Coinsurance Schedules



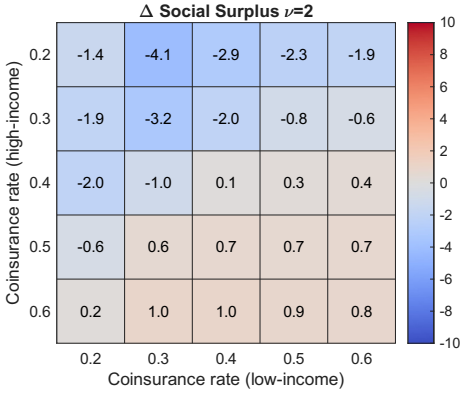
(a) Fraction of Failed Negotiations



(b) Average Retail Prices



(c) Social Surplus ($\nu = 0$)



(d) Social Surplus ($\nu = 2$)

Note: The heatmaps present simulated outcomes under income-based coinsurance schedules for all 70 negotiated drugs (where $\boldsymbol{\beta}_{failed} = \underline{\boldsymbol{\beta}}$ for drugs that failed NRDL negotiations). The horizontal axis and the vertical axis represent the coinsurance rate for low-income (below median) patients and high-income (above median) patients, respectively. "Fraction of failed negotiations" reports the model-predicted percentage of failed negotiations under each coinsurance design. "Average retail price" is the quantity-weighted average retail price across always successfully negotiated drugs. The bottom panel reports social surplus for a utilitarian ($\nu = 0$) vs. a Rawlsian ($\nu = 2$) government, where surplus is measured relative to the baseline with no insurance. See Appendix Figure A5 for results with $\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$.

We make three observations. First, all policies that combine insurance and negotiation are to the upper right of the Baseline (origin), Insurance-only, and Negotiation-only (MA-N) scenarios. Second, at the observed provincial coinsurance schedule γ^{obs}, market-access negotiation improves surplus, and results in similar survival, relative to the NRDL (formulary-access) policy. Third, with optimal income-based coinsurance schedules γ^{opt}, market-access and formulary-access are quite close, with MA-I yielding higher surplus and FA-I yielding higher survival; however, the optimal coinsurance schedule for FA-I is (H 0.34, L 0.42), whereas it is less regressive for MA-I (H 0.30, L 0.45).

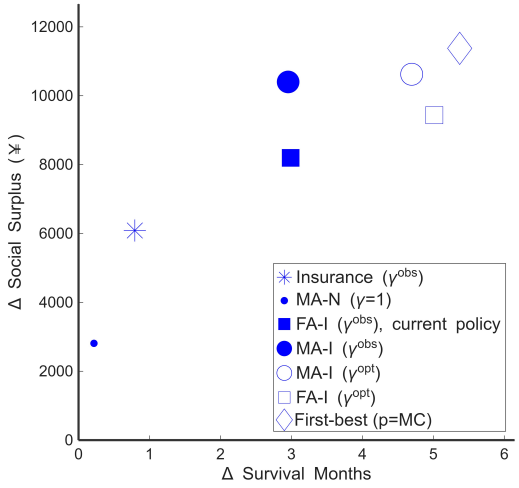
Taken together, we argue that a combined policy of centralization, market access negotiation, and an optimal income-based coinsurance schedule strikes an attractive balance in terms of efficiency, access, and equity. First, MA-I allows for lower coinsurance for low-income patients, which improves equity relative to FA-I. Second, MA-I's advantage over FA-I is even greater in cases where the drug firms have less bargaining power; see discussion in Appendix B.2. Third, it allows for more generous coinsurance on average than FA-I, which reduces financial risk to patients. Lastly, it is worth noting that MA-I may be less demanding in terms of political economy: if it is difficult to deviate from province-based coinsurance subsidies, then MA-I is preferred to FA-I under current coinsurance schedules. Overall, the policy bundle of centralized, market-access negotiation with the optimal coinsurance schedule would yield a 29% gain in social surplus over the observed NRDL, and would achieve 93% of the social surplus and 87% of the survival gains of the short-run efficient benchmark with OOP=MC.

6 Conclusion

Pharmaceuticals accounted for 35% of the increase in U.S. life expectancy from 1990 to 2015 (Buxbaum et al., 2020). Yet many promising treatments remain inaccessible due to high prices, placing heavy burdens on both patients and insurers (CMS, 2024). Against this backdrop, global momentum has grown for centralized drug procurement and similar policy interventions aimed toward expanding access while constraining expenditures. Recent initiatives include the U.S. Inflation Reduction Act of 2022, which authorized Medicare to negotiate prices for selected drugs (The White House, 2023), the European Parliament's 2024 proposal for centralized pharmaceutical pricing (Ho and Pakes, 2024), and joint efforts led by the Pan-American Health Organization (PAHO Executive Committee, 2024).

This paper evaluates the effects of China's NRDL Reform. We estimate that the innovative drugs successfully negotiated under the NRDL Reform between 2017 and 2022 generated

Figure 11: Welfare Comparison of Different Policies



Note: This graph compares the social surplus and extended overall survival per patient due to innovative drugs under seven different policy scenarios. The baseline is without insurance or negotiation. For each scenario, we use the parameter γ to denote the coinsurance rate, which can be the provincial schedule observed in the NRDL Reform (γ^{obs}), the income-based schedule that maximizes social surplus in the relevant bargaining regime (γ^{opt}), or no insurance at all ($\gamma = 1$). See Appendix Figure A6 for details regarding optimal coinsurance with MA-I bargaining.

annual consumer surplus gains of nearly ¥37 billion ($5.3 billion) and increased total survival by 1.1 million life-years among Chinese cancer patients. Counterfactual simulations show that there are substantial health and welfare gains from centralization, that bargaining failures are a consequence of "soft" threat points, and that ignoring bargaining failures would lead us to underestimate the benefits of centralization and the tradeoffs inherent in expanding insurance generosity.

We offer new evidence on the cost, access, health, and welfare consequences of national drug reforms; the distinction between formulary and market-access negotiations; the comparisons between centralized and decentralized negotiation; and optimal coinsurance design. Our framework has broad applicability for evaluating similar reforms across diverse settings. One limitation of our work is that we abstract from dynamic incentives—such as the impact of NRDL inclusion on pharmaceutical innovation—which remains a promising direction for future research.

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Online Appendix

A Data Construction

In our analysis in the main text, we draw on clinical data from ClinicalTrials.gov. All clinical trials involving drugs that are regulated by the FDA must be registered publicly at this site. We focus on Phase III interventional studies. These are large-scale evaluations of the drugs' safety and efficacy relative to a control group. In each trial, the focal innovator drug is the treatment group, and the standard of care, typically an older therapy, is the control group. For sample innovator drugs we could not find on ClinicalTrials.gov, we search for trial results reported in medical journal articles and on trial sponsors' websites.

For each trial, we collect the following fields:

- Innovator drug name
- Indication (cancer type)
- Sample inclusion details, if specified (this might specify an age range for patients, or a requirement that certain treatments were tried previously)
- Treatment therapy (this will include the name of the innovator drug, plus any treatments it's bundled with in the trial)
- Control therapy
- Time units in which outcomes are evaluated; i.e., weeks or months
- For each of the following outcomes (overall survival (OS); overall survival rate (OSR); and progression-free survival (PFS)):
  - Time frame for evaluation; e.g., "up to 43 months"
  - Lower bound of 95% confidence interval of outcome for treatment group, if reported
  - Upper bound of 95% confidence interval of outcome for treatment group, if reported
  - Median outcome for treatment group, if reported
  - Lower bound of 95% confidence interval of outcome for control group, if reported
  - Upper bound of 95% confidence interval of outcome for control group, if reported
  - Median outcome for control group, if reported

- NCTID
- Pub Med ID (PMID)

Using these data, we create an overall survival treatment effect for each innovator drug trial by subtracting the control group median from the treatment group median. We use overall survival directly if reported, then overall survival rate, then progression-free survival. If there are multiple trial results for a given innovative drug, we take a simple average of survival treatment effects across trials.

For some more recent trials, the median survival time for the treatment or control could not be estimated as too few participants had died by the end of the study. If the only trial results available include such cases, we use the study time frame as an informative lower bound on median survival. We do, however, require that an estimate of median survival time be reported for *either* treatment or control therapy. We then take a simple average of imputed survival treatment effects across trials.

See Appendix Table A5 for an overview of key milestones for the top 20 innovative cancer drugs in China, and Appendix Table A6 for a summary table of clinical effects for all cancer drugs eligible for negotiation in our sample.

B Details on Counterfactual Simulations

B.1 Solution Algorithm

This section describes our algorithm to solve for equilibrium formularies and prices in the counterfactual analyses. We apply an iterative Gauss-Seidel method to solve the new equilibrium prices. We assume that negotiated drugs and non-negotiated drugs set prices simultaneously. The contract equilibrium is such that, given the prices, no drug firms have incentives to renegotiate (or change) the retail prices unilaterally.

1. **Outer loop:** In iteration s, start with the old equilibrium price $\mathbf{p}^s = \mathbf{p}^{s-1}$ (or an initial price vector if $t = 0$) and the formulary $\mathcal{G}^s = \mathcal{G}^{s-1}$, initialized as $\mathcal{G}^s \equiv \varnothing$.

2. **Inner loop:** Denote the full set of drugs being negotiated as $\mathcal{J}$. Denote the set of drugs that *must* be included in the formulary at iteration r as $\underline{\mathcal{G}}^r$, initialized as $\underline{\mathcal{G}}^0 \equiv \varnothing$. Denote the set of drugs that *must not* be included in the formulary at iteration r as $\underline{\mathcal{H}}^r$, initialized as $\underline{\mathcal{H}}^0 \equiv \varnothing$. For each iteration $r \geq 1$, let $\underline{\mathcal{G}}^r = \underline{\mathcal{G}}^{r-1}$ and $\underline{\mathcal{H}}^r = \underline{\mathcal{H}}^{r-1}$, then for each $j \in \mathcal{J} \setminus (\underline{\mathcal{G}}^r \cup \underline{\mathcal{H}}^r)$:

(a) Identify the admissible price set $\underline{\mathcal{P}}_j^r \equiv \{p_j : \Delta V_j\left(p_j; \mathbf{p}^{\mathbf{s}}_{-\mathbf{j}}, \mathcal{J} \setminus \underline{\mathcal{H}}^{r-1}\right) \geq 0$ and $\Delta\Pi_j\left(p_j; \mathbf{p}^{\mathbf{s}}_{-\mathbf{j}}, \mathcal{J} \setminus \underline{\mathcal{H}}^{r-1}\right) \geq 0\}$. If $\underline{\mathcal{P}}_j^r \neq \varnothing$, update $\underline{\mathcal{G}}^r = \underline{\mathcal{G}}^r \cup \{j\}$.

(b) If $j \notin \underline{\mathcal{G}}^r$, identify the admissible price set $\overline{\mathcal{P}}_j^r \equiv \{p_j : \Delta V_j\left(p_j; \mathbf{p}^{\mathbf{s}}_{-\mathbf{j}}, \underline{\mathcal{G}}^{r-1}\right) \geq 0$ and $\Delta\Pi_j\left(p_j; \mathbf{p}^{\mathbf{s}}_{-\mathbf{j}}, \underline{\mathcal{G}}^{r-1}\right) \geq 0\}$. If $\overline{\mathcal{P}}_j^r = \varnothing$, update $\underline{\mathcal{H}}^r = \underline{\mathcal{H}}^r \cup \{j\}$.

Iterate until $\underline{\mathcal{H}}^{r*} \cup \underline{\mathcal{G}}^{r*} = \mathcal{J}$. Update $\mathcal{G}^s = \underline{\mathcal{G}}^{r*}$ and return to the outer loop.

3. Solve for the negotiated and non-negotiated prices $\mathbf{p}^s$ given $\mathcal{G}^s$, using the Nash-in-Nash FOC in Equation (3) for $j \in \mathcal{G}^s$ and the Bertrand-Nash FOC for $j \notin \mathcal{G}^s$.

4. The algorithm converges to the equilibrium formulary and price if $|\mathbf{p}^* - \mathbf{p}^s| < \epsilon$ and $\mathcal{G}^s = \mathcal{G}^*$; otherwise reset $\mathbf{p}^{s+1} = \mathbf{p}^*$ and $\mathcal{G}^{s+1} = \mathcal{G}^*$ and move to step 2.

Intuitively, the algorithm rests on the submodularity of gains from trade in our model. When drugs are substitutes, the lowest gain from trade a drug can provide to either firm or government is when the formulary contains all other possible drugs, generating the narrowest admissible set possible for that drug. If the admissible set is nevertheless nonempty, the drug *must* be included in the equilibrium formulary (Step 2a). Conversely, the highest gain from trade a drug can provide to either firm or government is when the formulary excludes all other possible drugs, generating the widest admissible set possible for that drug. If the admissible set is nevertheless empty, the drug *must not* be included in the equilibrium formulary (Step 2b). This approach is similar to the algorithm used for the automobile entry game modeled in Sabal (2025).

Generally speaking, there is no theoretical guarantee that the inner loop condition $\underline{\mathcal{H}}^{r*} \cup \underline{\mathcal{G}}^{r*} = \mathcal{J}$ would ever be met, in which case we would have multiple equilibria. In such a case, we would follow Ho and Lee (2019) in evaluating all possible equilibrium formularies and presenting results for formularies that maximize particular objectives, such as consumer surplus and total surplus. In practice, the condition is always met in our counterfactual analyses because the innovative cancer drugs that are negotiated in our setting are quite differentiated from one another (though they do have non-innovative, and therefore non-negotiated, substitutes that are included in the demand estimation). Indeed, we find that there is no significant spillover effect of a successful negotiation for a drug in a particular indication on the prices or quantities of non-negotiated drugs in the same indication; see Appendix Figure A7.

B.2 Comparisons between MA-I and FA-I

For simplicity of notation, suppose a single-product firm produces drug j. On the extensive margin, MA-I (market access negotiation with insurance expansion)[49] always leads to more bargaining success than FA-I (formulary access negotiation with insurance expansion, or the NRDL). This is because the admissible set is expanded:

$$\Psi^{FA-I} = \{p_j : V_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right) \geq V_j\left(\mathbf{p}^{BN}; \mathbf{p_{-j}}, \mathcal{G} \setminus \{j\}\right) \text{ and } \Pi_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right) \geq \Pi_j\left(\mathbf{p}^{BN}; \mathbf{p_{-j}}, \mathcal{G} \setminus \{j\}\right)\}.$$
$$\Psi^{MA-I} = \{p_j : V_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right) \geq 0 \text{ and } \Pi_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right) \geq 0\}.$$

$\Psi^{FA-I} \subset \Psi^{MA-I}$ if $V_j(p_j; \mathbf{p_{-j}}, \mathcal{G})$ is decreasing in p_j and $\Pi_j\left(p_j; \mathbf{p_{-j}}, \mathcal{G}\right)$ decreasing in p_j.

On the intensive margin, the negotiated price may be higher or lower under MA-I. To see this, assume that j is the only drug negotiated, so we can ignore the prices and formulary status of other drugs and omit j subscripts. For brevity, use F for formulary access and M for market access. In this case, the following proposition holds.

Proposition: The negotiated price under formulary access (p^F) is lower (equal to) [higher] than the price under market access (p^M) if and only if:

$$\frac{V(\mathbf{p}^{BN})}{V(p^M)} > (=)[<]\frac{\Pi(\mathbf{p}^{BN})}{\Pi(p^M)}. \tag{6}$$

Proof: The equilibrium price under either (F/M) negotiation satisfies the first-order condition:

$$\tau\frac{d\Delta\Pi}{dp}\frac{1}{\Delta\Pi} + (1-\tau)\frac{d\Delta V}{dp}\frac{1}{\Delta V} = 0. \tag{7}$$

Rearranging,

$$\frac{\Delta V}{\Delta\Pi} = -\frac{1-\tau}{\tau}\frac{\Delta V'}{\Delta\Pi'}. \tag{8}$$

Suppose price p^M is the negotiated price under MA-I. Then:

$$\Delta\Pi_M = \Pi(p^M) - 0,$$
$$\Delta V_M = V(p^M) - 0,$$
$$\frac{\Delta V_M}{\Delta\Pi_M} = -\frac{1-\tau}{\tau}\frac{V'(p^M)}{\Pi'(p^M)}.$$

We next plug p^M into the formulary access FOC, to see whether the FOC is satisfied at

[49] Under this policy, a failed negotiation results in the drug being entirely excluded from the Chinese market, while a successful negotiation leads to both market and formulary inclusion with insurance.

p^M, and if not, whether we need a bigger or smaller p^F:

$$\begin{aligned}\Delta\Pi_F(p^M) &= \Pi(p^M) - \Pi(\mathbf{p}^{BN}),\\ \Delta V_F(p^M) &= V(p^M) - V(\mathbf{p}^{BN})\\ \frac{\Delta V_F(p^M)}{\Delta\Pi_F(p^M)} &\overset{?}{=} -\frac{1-\tau}{\tau}\frac{V'(p^M)}{\Pi'(p^M)}.\end{aligned}$$

Note that the key differentiating factor across the MA-I and FA-I scenarios is their threat points, which do not directly depend on the price under negotiation. This implies that $V_F(p^M) = V_M(p^M) = V(p^M)$ and $\Delta V_F' = d\Delta V_M'$, and similarly for profits. Therefore, the FOC for FA-I will hold at p^M if and only if:

$$\frac{\Delta V_F(p^M)}{\Delta\Pi_F(p^M)} \equiv \frac{V(p^M) - V(\mathbf{p}^{BN})}{\Pi(p^M) - \Pi(\mathbf{p}^{BN})} = \frac{V(p^M)}{\Pi(p^M)}.$$

Rearranging, the condition simplifies to:

$$\frac{V(\mathbf{p}^{BN})}{\Pi(\mathbf{p}^{BN})} = \frac{V(p^M)}{\Pi(p^M)}.$$

If LHS $>$ RHS, then $p^F < p^M$ and vice-versa.[50] Note also that the RHS is a decreasing function of firm bargaining power, while the LHS is independent of bargaining power. Therefore, when the firm holds more bargaining power, or when the value of the drug on the private market is relatively higher for the government than the firm, $p^{FA-I} < p^{MA-I}$ is more likely to hold. Intuitively, the government may prefer FA-I when the drug is relatively accessible on the private market, the profit for the drug on the private market is relatively low, and when the firm holds more bargaining power.

□

B.3 Effects of Coinsurance Rates on Negotiated Prices

The effects of higher coinsurance on negotiation outcomes are theoretically ambiguous. They depend on how coinsurance affects the levels of gains from trade (GFT), as well as the curvature of the two GFT curves. To see this, recall the bargaining first-order condition, and for simplicity, assume that j is the only drug negotiated, so we can ignore the prices and

[50] We make the weak assumption that $V(p)$ is decreasing in p and $\Pi(p)$ is increasing in p.

formulary status of other drugs and omit j subscripts:

$$\max_p \left(\Delta\Pi\left(p\right)\right)^{\tau}\left(\Delta V\left(p\right)\right)^{1-\tau} \quad \Rightarrow \quad \{g(p(\gamma),\gamma) = \frac{\tau}{\Delta\Pi\left(p\right)}\frac{\partial\Pi\left(p\right)}{\partial p} + \frac{1-\tau}{\Delta V\left(p\right)}\frac{\partial V\left(p\right)}{\partial p} = 0\}$$

Now apply the implicit function theorem:

$$\begin{aligned} p'(\gamma) &= -\frac{\partial g}{\partial \gamma}/\frac{\partial g}{\partial p} \\ &= -\frac{\tau\left(-\frac{\partial\Delta\Pi/\partial\gamma}{\Delta\Pi^2} * \frac{\partial\Pi}{\partial p} + \frac{1}{\Delta\Pi} * \frac{\partial^2\Pi}{\partial p\partial\gamma}\right) + (1-\tau)\left(-\frac{\partial\Delta V/\partial\gamma}{\Delta V^2} * \frac{\partial V}{\partial p} + \frac{1}{\Delta V} * \frac{\partial^2 V}{\partial p\partial\gamma}\right)}{\tau\left(-\frac{\partial\Delta\Pi/\partial p}{\Delta\Pi^2} * \frac{\partial\Pi}{\partial p} + \frac{1}{\Delta\Pi} * \frac{\partial^2\Pi}{\partial p^2}\right) + (1-\tau)\left(-\frac{\partial\Delta V/\partial p}{\Delta V^2} * \frac{\partial V}{\partial p} + \frac{1}{\Delta V} * \frac{\partial^2 V}{\partial p^2}\right)} \end{aligned} \tag{9}$$

First, focus on how the coinsurance rate γ affects GFT: $\partial\Delta V/\partial\gamma$ and $\partial\Delta\Pi/\partial\gamma$. Higher coinsurance unambiguously decreases firms' gains from trade because it increases patients' out-of-pocket prices and reduces demand: $\dfrac{\partial\Delta\Pi}{\partial\gamma} = \dfrac{\partial q}{\partial\gamma}(p - mc) < 0$. However, the government's perspective is more nuanced. High coinsurance rates decrease government expenditure, but also decrease consumer surplus and expected survival. When $\beta \geq 1$, conditioning on the negotiated price p, the government's gains from trade increase with the coinsurance rate γ. This is because:[51]

$$\begin{aligned} \Delta V = \Delta CS - \beta\Delta TC &= \int_{\gamma p}^{p^{BN}} q(OOP)dOOP - \beta(1-\gamma)pq(\gamma p) \\ \frac{\partial\Delta V}{\partial\gamma} = \frac{\partial\Delta CS}{\partial\gamma} - \beta\frac{\partial TC}{\partial\gamma} &= -q(\gamma p)p - \beta(-q(\gamma p)p + (1-\gamma)p^2\frac{\partial q}{\partial OOP}) \\ &= \underbrace{(\beta-1)q(\gamma p)p}_{\geq 0} - \underbrace{\beta(1-\gamma)p^2\frac{\partial q}{\partial OOP}}_{<0} \quad > 0 \quad \text{if } \beta \geq 1. \end{aligned}$$

That is, a higher coinsurance rate shifts the government's gains-from-trade curve upward when the weight on government expenditures is high ($\beta \geq 1$). If the weight is low ($\beta < 1$), it may be the case that $\dfrac{\partial\Delta V}{\partial\gamma} < 0$.

Returning to the bargaining first-order condition, we see that $p'(\gamma)$ depends on both leverage effects (compare $\frac{\partial V}{\partial\gamma}$ and $\frac{\partial\Pi}{\partial\gamma}$) and also curvature effects (compare $\frac{\partial^2\Pi}{\partial p\partial\gamma}$ and $\frac{\partial^2\Pi}{\partial p^2}$ vs. $\frac{\partial^2 V}{\partial p\partial\gamma}$ and $\frac{\partial^2 V}{\partial p^2}$). Intuitively, when γ is small, consumer demand is less elastic, so firms have a particularly strong desire to increase prices, and the government has a particularly strong desire to decrease prices. Ultimately, depending on the magnitude of β, the government's and

[51] Consumer Surplus is defined as the integral under the demand curve between the agreement and disagreement out-of-pocket price, and becomes Equation (2) in the main text under logit demand.

firm's curvature terms may counteract or reinforce one another, and the leverage terms may counteract or reinforce one another. This makes the sign of $p'(\gamma)$ ambiguous:

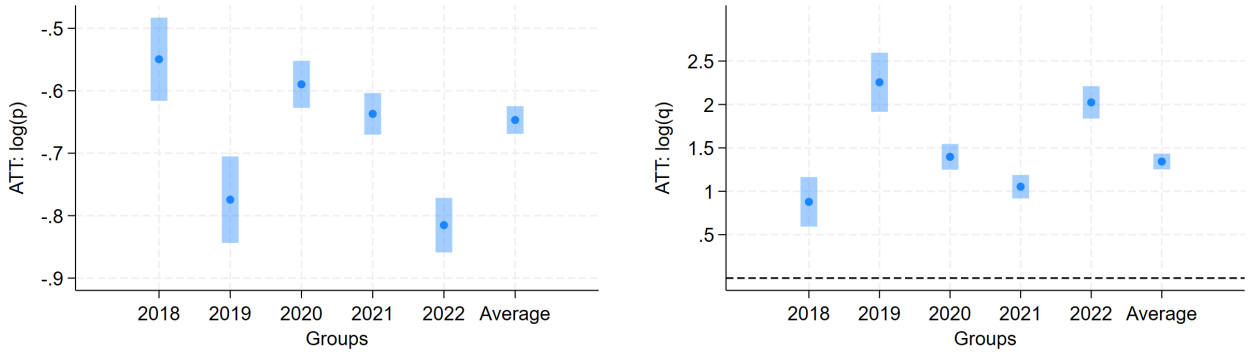
$$p'(\gamma) = -\frac{\tau\left(\underbrace{-\frac{\partial\Delta\Pi/\partial\gamma}{\Delta\Pi^2}}_{>0}\cdot\underbrace{\frac{\partial\Pi}{\partial p}}_{>0}+\underbrace{\frac{1}{\Delta\Pi}}_{>0}\cdot\underbrace{\frac{\partial^2\Pi}{\partial p\partial\gamma}}_{<0}\right)+(1-\tau)\left(\underbrace{-\frac{\partial\Delta V/\partial\gamma}{\Delta V^2}}_{\gtrless 0}\cdot\underbrace{\frac{\partial V}{\partial p}}_{<0}+\underbrace{\frac{1}{\Delta V}}_{>0}\cdot\underbrace{\frac{\partial^2 V}{\partial p\partial\gamma}}_{\gtrless 0}\right)}{\tau\left(\underbrace{-\frac{\partial\Delta\Pi/\partial p}{\Delta\Pi^2}}_{<0}\cdot\underbrace{\frac{\partial\Pi}{\partial p}}_{>0}+\underbrace{\frac{1}{\Delta\Pi}}_{>0}\cdot\underbrace{\frac{\partial^2\Pi}{\partial p^2}}_{<0}\right)+(1-\tau)\left(\underbrace{-\frac{\partial\Delta V/\partial p}{\Delta V^2}}_{>0}\cdot\underbrace{\frac{\partial V}{\partial p}}_{<0}+\underbrace{\frac{1}{\Delta V}}_{>0}\cdot\underbrace{\frac{\partial^2 V}{\partial p^2}}_{>0}\right)}$$

Figure 7(c) illustrates a case with $\beta \geq 1$, where lower coinsurance leads to a smaller admissible set and a lower negotiated price, conditional on negotiation success.

In our empirical application, we find that $p'(\gamma) > 0$ for coinsurance rates of high-income patients, but not always for low-income patients.

C Appendix Figures

Figure A1: Cohort-Specific Effects of the NRDL Reform on Price and Quantity

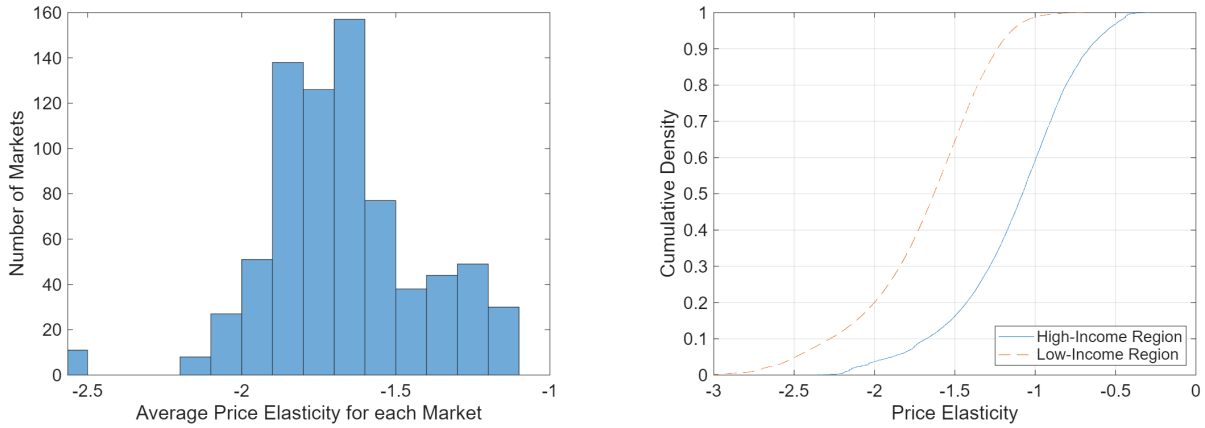


(a) Retail Price: All Categories

(b) Quantity: All Categories

Note: This figure reports the treatment effects of the NRDL Reform on the retail prices and quantities of successfully negotiated drugs, separately for each negotiation cohort. The horizontal axis denotes the year in which the drug was negotiated. The vertical axis reports the pooled post-period treatment effect for each negotiation cohort, estimated using the CSDID package from Callaway and Sant'Anna (2021).

Figure A2: Estimated Income Elasticity across Different Income Levels

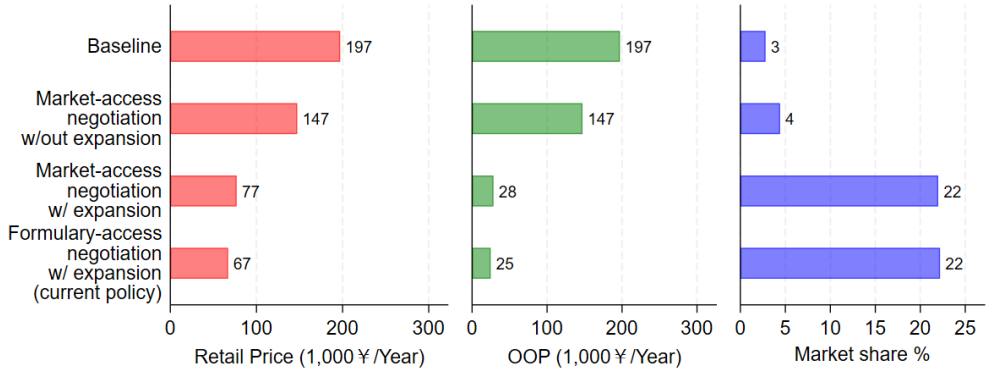


(a) Histogram of Price Elasticity

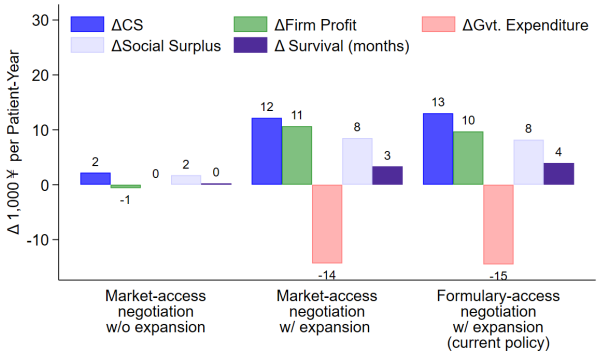
(b) CDF of Price Elasticity

Note: Figure (a) plots the model-implied average drug-level own-price elasticities across different markets and Figure (b) plots the model-implied own-price elasticities across patients, both according to the specification in Column (5) of Table 3. The solid line denotes patients in high-income provinces (Beijing, Shanghai, Guangdong, Tianjin, Zhejiang, Jiangsu, Fujian), and the dashed line denotes patients in low-income provinces.

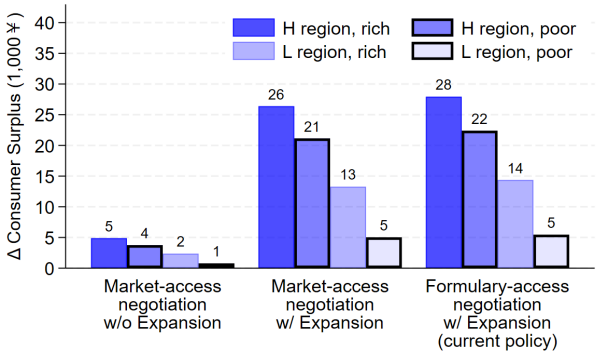
Figure A3: Counterfactual Results: Alternative Bargaining Formats ($\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$)



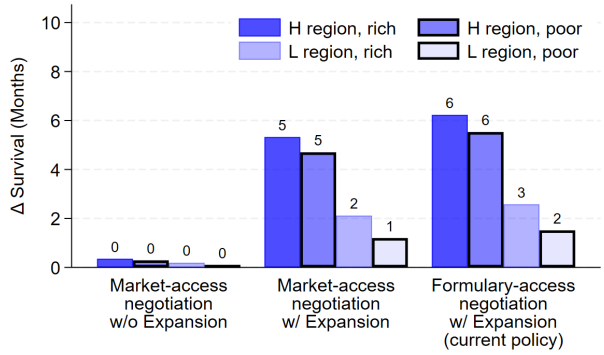
(a) Price and Market Share of Innovative Cancer Drugs



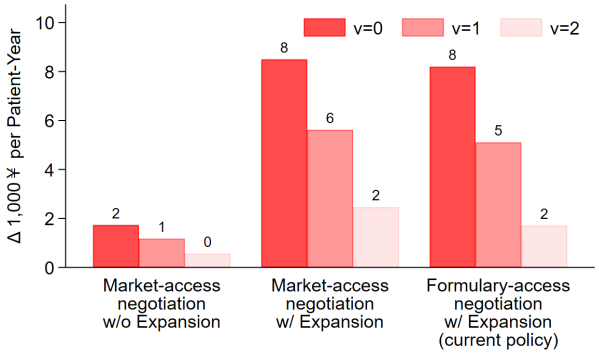
(b) Welfare Effects



(c) Δ Consumer Surplus by Income Group



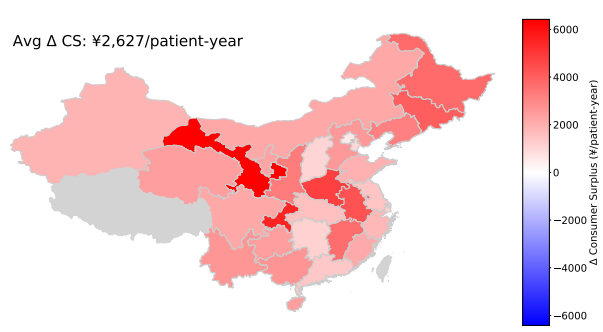
(d) Δ Survival by Income Group



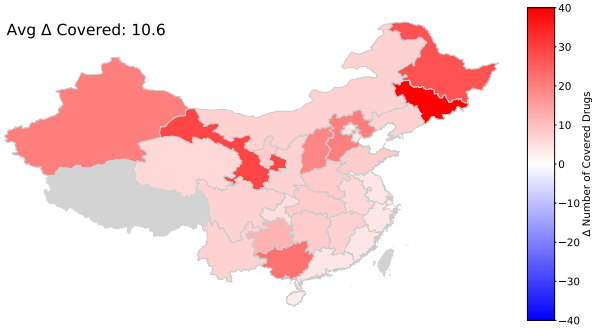
(e) Alternative Social Surplus Measures

Note: Alternative negotiation scenarios allow negotiation for 57 innovative cancer drugs that were successfully negotiated in the NRDL Reform. In panel (a), we compare four scenarios. "Baseline" denotes Bertrand-Nash pricing without insurance coverage. "Market-access negotiation" assumes that, in the event of bargaining failure, the government excludes the drug from the market. "Market-access negotiation w/ expansion" further provides insurance coverage at observed provincial coinsurance rates if the negotiation is successful. "Formulary-access negotiation w/ expansion" is the NRDL Reform. Panels (b)-(e) compare outcomes in each scenario to the "Baseline" scenario.

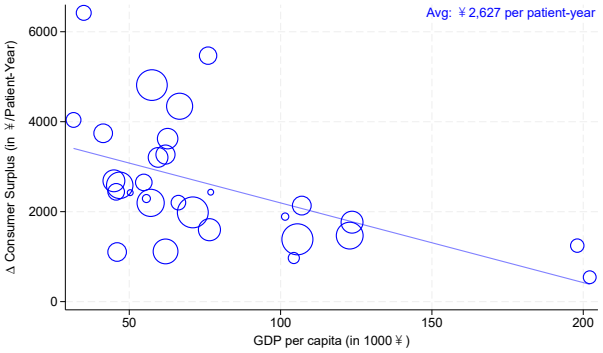
Figure A4: Changes in CS and Drug Coverage from Decentralized to Centralized Negotiation ($\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$)



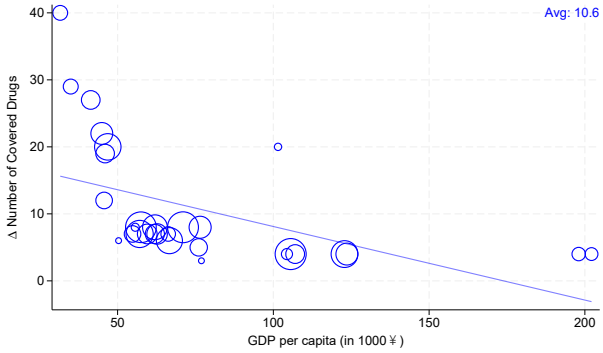
(a) Δ CS (¥/Patient)



(b) Δ Number of Covered Drugs



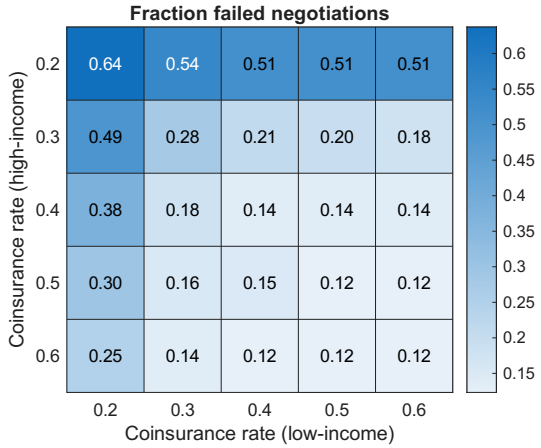
(c) Δ CS vs. Income



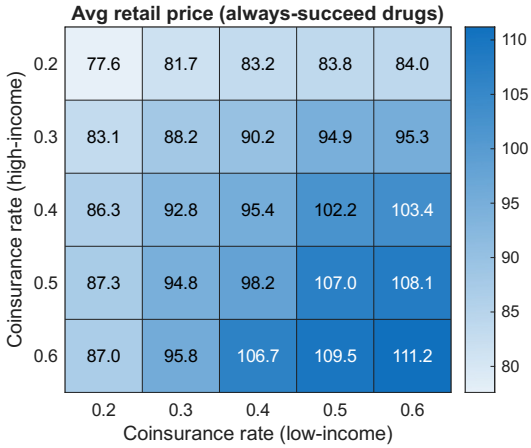
(d) Δ Number of Covered Drugs vs. Income

Note: Panels (a)-(b) show the geographic distributions of changes in consumer surplus per patient-year and the number of covered drugs across provinces when moving from decentralized negotiation with insurance expansion to centralized negotiation with insurance expansion. Panels (c)-(d) present bubble plots of the same outcomes, with GDP per capita on the x-axis. Each bubble indicates one province, and bubble size scales with the province's population. All the results are based on simulations that set $\boldsymbol{\beta} = \boldsymbol{\infty}$ for failed negotiations, so these drugs will always be excluded from the formulary.

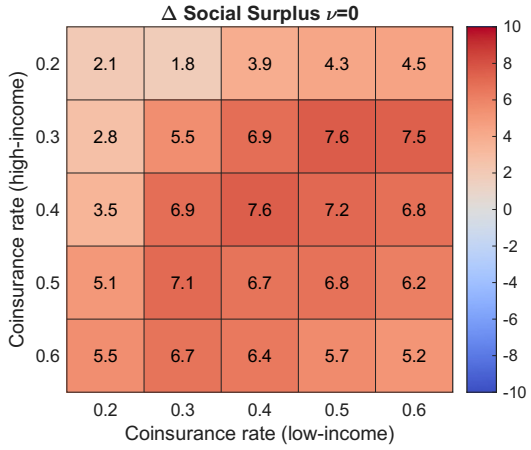
Figure A5: Counterfactual Results under Alternative Coinsurance Schedules ($\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$)



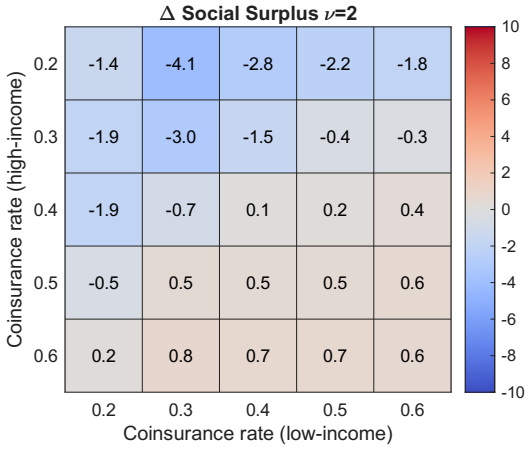
(a) Fraction of Failed Negotiations



(b) Average Retail Prices



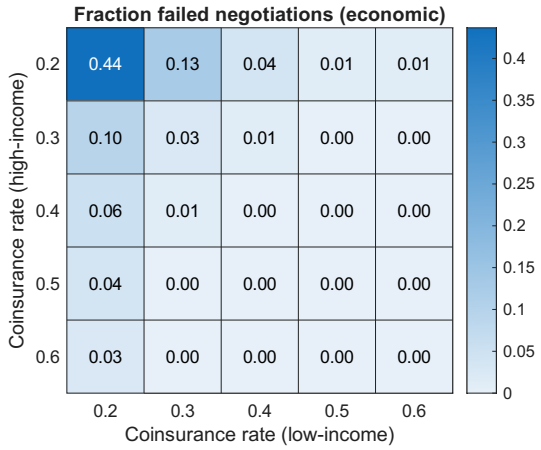
(c) Social Surplus ($\nu = 0$)



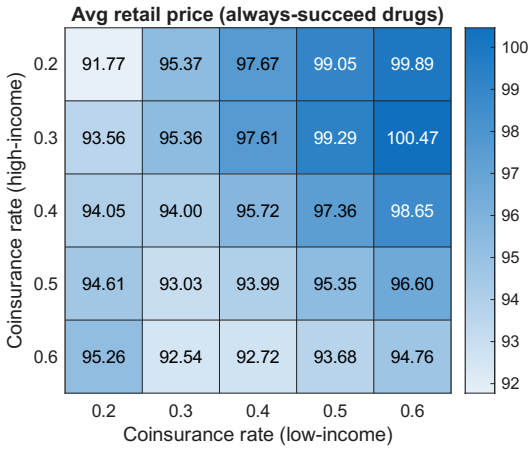
(d) Social Surplus ($\nu = 2$)

Note: These heatmaps present simulated outcomes under income-based coinsurance schedules. Simulations allow negotiation for 57 innovative cancer drugs and assume $\boldsymbol{\beta}_{failed} = \boldsymbol{\infty}$ for drugs that failed the NRDL negotiations. The horizontal axis and the vertical axis represent the coinsurance rate for low-income (below median) patients and high-income (above median) patients, respectively. "Fraction of failed negotiations" reports the model-predicted percentage of failed negotiations under each coinsurance design. "Average retail price" is the unweighted average retail price across the always successfully negotiated drugs. The bottom panel reports social surplus for a utilitarian ($\nu = 0$) vs. a Rawlsian ($\nu = 2$) government, where surplus is measured relative to the baseline without insurance.

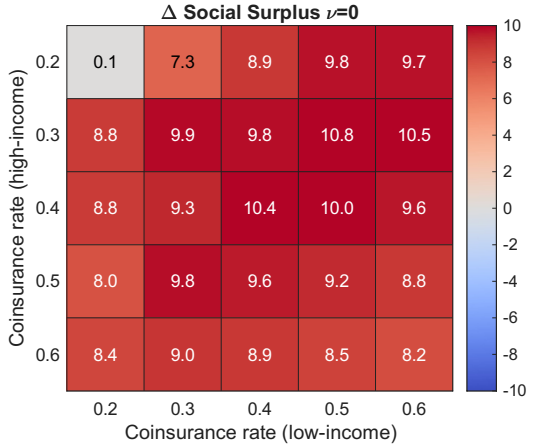
Figure A6: Counterfactual Coinsurance Design for Market-access Negotiation with Insurance Expansion ($\boldsymbol{\beta}_{failed} = \underline{\boldsymbol{\beta}}$)



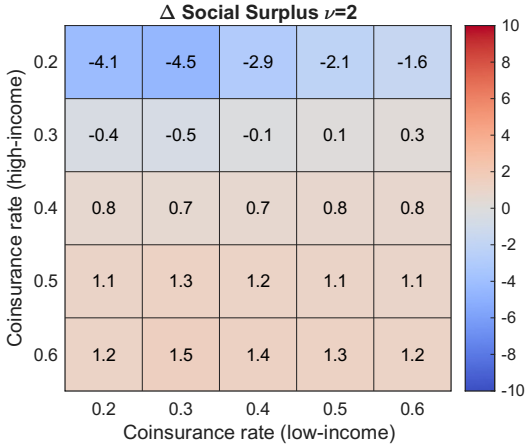
(a) Fraction of Failed Negotiations



(b) Average Retail Prices



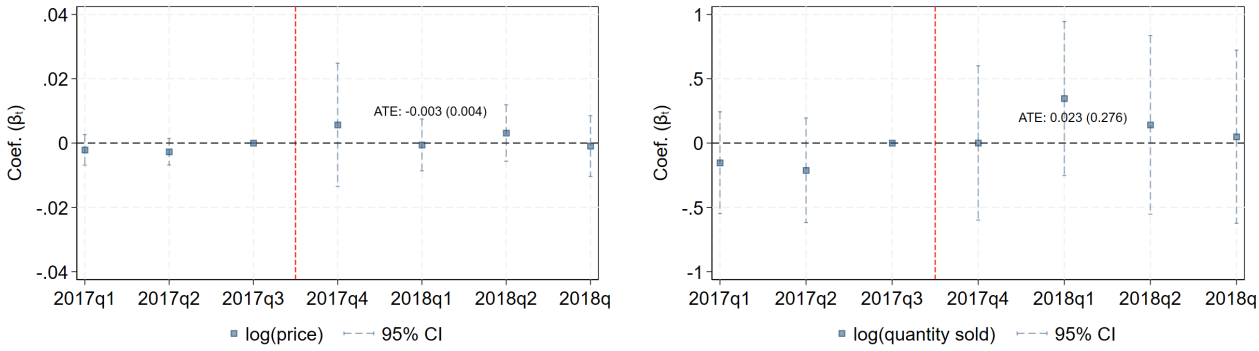
(c) Social Surplus ($\nu = 0$)



(d) Social Surplus ($\nu = 2$)

Note: These heatmaps present simulated outcomes under income-based coinsurance schedules for all 70 negotiated drugs (where $\boldsymbol{\beta}_{failed} = \underline{\boldsymbol{\beta}}$ for drugs that failed NRDL negotiations), in the MA-I scenario. The horizontal axis and the vertical axis represent the coinsurance rate for low-income (below median) patients and high-income (above median) patients, respectively. "Fraction of failed negotiations" reports the model-predicted percentage of failed negotiations under each coinsurance design. "Average retail price" is the quantity-weighted average retail price across the 24 always successfully negotiated drugs defined in Figure 10. The bottom panel reports social surplus for a utilitarian ($\nu = 0$) vs. a Rawlsian ($\nu = 2$) government, where surplus is measured relative to the baseline without insurance.

Figure A7: Spillover Effects of the Negotiation on Competing Drugs



(a) log(Retail Price)

(b) log(Quantity)

Note: This event study examines the potential spillover effects of negotiation on closely competing drugs. All non-included drugs which have at least one overlapping indication with any included drugs from the 2017 negotiation cohort are treated (15 drugs with *lung, liver, breast, kidney, stomach, and ovarian* cancer indications), and other non-included drugs that have zero overlapping indications are in the control group (27 drugs). We compare the prices and quantities of treated vs. control drugs between 2016 and 2018. After 2018, nearly all drugs are treated.

D Appendix Tables

Table A1: Own- and Cross-Price Elasticity Summary by Indication×Class

Indication	Type	Own	Cross (same ind.)	Cross (diff. ind.)
Lung	Innov.	**-1.6130**	0.0156	0.0002
	Other	**-1.6265**	0.0170	0.0002
Breast	Innov.	**-1.5750**	0.0184	0.0002
	Other	**-1.6362**	0.0202	0.0002
Colon	Innov.	**-1.6054**	0.0223	0.0001
	Other	**-1.6298**	0.0223	0.0001
Stomach (GIST)	Innov.	**-1.2397**	0.1638	0.0002
Liver	Innov.	**-1.4991**	0.0807	0.0002
	Other	**-1.2807**	0.0636	0.0001

Note: Mean own-price elasticity and average cross-price elasticities, as described in text. "Own" reports the mean own-price elasticity ε_{kk}; "Cross (same ind.)" averages the cross-price elasticity ε_{jk} over partner drugs k treating the *same* primary indication in the same provincial-quarterly market; "Cross (diff. ind.)" averages over partners treating a *different* indication. All such drugs with primary indication as stomach are innovative PKIs, so no "Other" row appears.

Table A2: Demand Estimates: Robustness

	jt FEs	ATC4 nest	No GHIV	Neg. IV	US FDA IV	Alt. coins.	+Price RC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(OOP)	-1.196	-3.887	-2.999	-3.150	-3.055	-2.822	-3.215
	(0.074)	(0.182)	(0.154)	(0.165)	(0.154)	(0.155)	(0.450)
log(OOP) × log(income)		0.586	0.453	0.486	0.454	0.440	0.430
		(0.038)	(0.030)	(0.032)	(0.030)	(0.031)	(0.033)
log(OOP) × ν							0.354
							(0.288)
λ (nesting para.)		0.010	0.289	0.207	0.298	0.332	0.312
		(0.033)	(0.029)	(0.034)	(0.027)	(0.026)	(0.033)
ρ (combo. pref.)		0.017	0.014	0.024	0.017	0.013	0.011
		(0.005)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
$1\{t > t_{\text{entry}} + 4\}$		0.812	0.626	0.709	0.664	0.615	0.601
		(0.050)	(0.044)	(0.050)	(0.045)	(0.043)	(0.050)
Indications							
Lung cancer		0.270	0.195	0.237	0.098	0.204	0.169
		(0.059)	(0.045)	(0.049)	(0.055)	(0.043)	(0.049)
Breast cancer		0.038	-0.024	-0.005	0.119	-0.049	-0.035
		(0.145)	(0.111)	(0.127)	(0.128)	(0.108)	(0.109)
Colon cancer		0.857	0.536	0.655	0.675	0.470	0.455
		(0.081)	(0.070)	(0.080)	(0.094)	(0.066)	(0.078)
Stomach cancer		0.639	0.531	0.593	0.634	0.527	0.439
		(0.083)	(0.065)	(0.072)	(0.071)	(0.063)	(0.103)
log(# of Indications)		0.104	0.139	0.142	-0.415	0.151	0.144
		(0.036)	(0.023)	(0.025)	(0.073)	(0.023)	(0.023)
P75 elasticity	-1.20	-1.29	-1.32	-1.21	-1.41	-1.23	-1.81
Median elasticity	-1.20	-1.53	-1.60	-1.47	-1.69	-1.52	-2.09
P25 elasticity	-1.20	-1.69	-1.75	-1.62	-1.85	-1.67	-2.24
Nesting level		ATC4	Primary	Primary	Primary	Primary	Primary
Combinations		Yes	Yes	Yes	Yes	Yes	Yes
Product FE		Yes	Yes	Yes	Yes	Yes	Yes
Product×Time FE	Yes						
Province×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table reports alternative cancer drug demand parameter estimates, as described in the text. N =104,745 observations. Column (1) mimics the specification in Column (2) of Table 3, but adds drug-year-quarter fixed effects. Columns (2)-(7) mimic our preferred specification in Column (5) of Table 3, modified as follows: Column (2) groups drugs into nests by ATC4 class rather than indication, and accordingly interacts predicted success with the count of drugs in the ATC4 nest, as an alternative IV for the nesting parameter λ. Column (3) removes the Gandhi and Houde (2025) differentiation IV. Column (4) replaces the predicted success IV and its interactions with a realized success indicator and its interactions. Column (5) instruments the Chinese indication variables using the analogous variables based on U.S. FDA approvals. Column (6) recomputes out-of-pocket prices using an alternative coinsurance measure that blends the URRBMI and UEBMI coinsurance rates in proportion to enrollment. Column (7) includes a pure random coefficient on price; note that the preferred specification is overidentified and the Gandhi and Houde (2025) IV—here, the number of drugs within the same nest and market—is sufficient to identify the additional parameter. The reported elasticities are percentiles of individual-level own-price elasticities across all drug-market observations. Standard errors are clustered at the drug-province level.

Table A3: Robustness Check: Estimation with Alternative Government Objective Functions

	Baseline	Clinical Benefits	CS + PS	Consumer Surplus	
	CS, $\nu = 0$	$\nu = 0$	$\nu = 0$	$\nu = 1$	$\nu = 2$
θ_β	4.21	3.08	8.84	2.67	2.35
S.E.	0.58	0.47	1.34	0.39	0.34
τ	0.66	0.67	0.83	0.64	0.64
S.E.	0.01	0.01	0.01	0.03	0.01
Log-likelihood	-348.95	-425.08	-336.83	-339.03	-350.06

Note: The table shows the supply estimates for alternative specifications. β is assumed to follow a T1EV distribution with inverse scale parameter determined by θ_β, and τ is the firm bargaining power parameter. Column (1): preferred specification. Column (2) replaces CS with clinical benefits, measured as $\Delta Q_j \times \text{VOL} \times \overline{\text{OS}}_j$, where ΔQ_j is the quantity change associated with drug j's inclusion in the NRDL, $\overline{\text{OS}}_j$ is the drug–specific survival gain from j implied by Phase III trials as described in Appendix A, VOL is the value of a life-year (RMB 16,455). Column (3) replaces CS with $CS + \Pi$. Columns (4)-(5) assume the government objective function has different equity considerations $\nu = 1$, or 2.

Table A4: Decomposition of the Effects of Expansion & Negotiation

		(1) Baseline	(2)	(3)	(4)	(5)
			+ Expansion Only		+ Expansion &Negotiation	
		y	Δy	Δy%	Δy	Δy%
Market Outcomes						
Avg. Retail Price	Inno, Success	197.19	-6.64	-3.37	-128.31	-65.07
(¥1,000 per year)	Inno, Others	57.58	-0.02	-0.04	0.06	0.10
	Traditional	13.67	-0.05	-0.37	-0.14	-1.04
Avg. Out-of-pocket Price	Inno, Success	197.19	-128.95	-65.40	-172.38	-87.42
(¥1,000 per year)	Inno, Others	57.58	-0.02	-0.04	0.06	0.10
	Traditional	13.48	-0.07	-0.54	-0.11	-0.84
Market Share	Inno, Success	2.80	7.11	254.48	19.40	694.07
(%|inside)	Inno, Others	0.45	-0.03	-7.70	-0.10	-22.99
	Traditional	96.76	-7.08	-7.32	-19.30	-19.94
Welfare Effects in 1,000 ¥per consumer per year						
Consumer Surplus	H region, Rich	6.57	15.10	229.75	27.93	424.96
	H region, Poor	4.99	11.90	238.27	22.40	448.72
	L region, Rich	3.83	6.30	164.27	14.37	374.99
	L region, Poor	1.10	2.17	196.92	5.46	496.62
	Average	3.28	6.57	200.20	13.67	416.47
Share-weight OS	H region, Rich	0.75	1.76	233.66	6.23	828.74
(months per consumer)	H region, Poor	0.60	1.50	250.64	5.53	922.15
	L region, Rich	0.37	0.70	190.17	2.58	700.51
	L region, Poor	0.13	0.34	267.14	1.51	1178.53
	Average	0.35	0.79	224.72	2.99	845.84
Gvt. Expenditure		1.85	12.43	673.20	14.52	786.49
Variable Profits	Inno, Success	4.69	12.23	260.53	9.70	206.63
	Inno, Others	0.91	-0.03	-3.32	-0.09	-9.65
	Traditional	11.76	-0.20	-1.72	-0.57	-4.85
Welfare	$\nu = 0$	18.80	6.08	32.36	8.20	43.59
	$\nu = 1$	17.92	4.57	25.50	5.10	28.48
	$\nu = 2$	17.00	2.90	17.05	1.71	10.07

Note: This table decomposes the effect of all rounds of policy reform (as of the year 2023) into its two main channels. The baseline scenario excluded all 57 cancer drugs that were included in the program. We report consumer surplus in four groups: "H region, Rich" denotes high-income patients (above median) in high-income (above median) provinces. Total welfare is reported according to different weights on households, as a function of income: $income^{-\nu}$ where $\nu = 0$ is utilitarian and $\nu \to \infty$ is Rawlsian. To compute baseline patient welfare, we calculate the change in consumer surplus between the baseline equilibrium and an alternative equilibrium in which only outside option treatments (i.e., no cancer drugs) are available. Share-weighted overall survival (OS) is based on clinical evidence of increased months of survival collected from Phase III trial data. Results for the market outcomes report the national averages. Δy is the average level change in an outcome relative to baseline across markets, and Δy% is the average percentage change in an outcome relative to baseline across markets. Welfare is reported on a per capita basis, where the denominator includes all patients who seek pharmaceutical cancer treatment.

Table A5: Overview of Top 20 Innovative Cancer Drugs in China

Drug	Success in	Eligible since	Global Entry Time	Local Entry Time	Company	Sales (b ¥)	Type
Bevacizumab	2019	2017		2010	Roche	8.31	mAb
Trastuzumab	2017	2017	1998	2009	Roche	6.00	mAb
Osimertinib	2018	2018	2015	2017.3	AZ	5.56	PKI
Rituximab	2017	2017	1997	2006	Roche	3.82	mAb
Pertuzumab	2019	2019	2011	2018	Roche	3.29	mAb
Anlotinib	2018	2018	2021	2018	Chia Tai*	2.74	PKI
Alectinib	2019	2019	2017	2018.8	Roche	2.38	PKI
Tislelizumab	2020	2020	2019.12	2019.12	Baiji*	2.15	mAb
Cetuximab	2018	2017	2004	2007	Merck	1.85	mAb
Lenvatinib	2020	2020	2019	2018	Eisai	1.85	PKI
Almonertinib	2020	2020	2021	2020.3	Hansoh*	1.78	PKI
Camrelizumab	2020	2020	2019.5	2019	Hengrui*	1.62	mAb
Pembrolizumab		2020	2014	2018.7	Merck	1.53	mAb
Sintilimab	2020	2020	2018.12	2018	Xinda*	1.47	mAb
Imatinib Mesylate			2001	2002.4	Novartis	1.43	PKI
Icotinib	2016	2016	2011	2011.6	Betta*	1.34	PKI
Pyrotinib	2019	2019	2022	2018	Hengrui*	1.18	PKI
Regorafenib	2018	2018	2012	2017.3	Bayer	1.15	PKI
Nimotuzumab	2017	2017	2002	2008	Baitai*	1.07	mAb
Crizotinib	2018	2018	2011	2013	Pfizer	1.01	PKI

Note: This table lists the top 20 cancer drugs by annual sales in China for the year 2022. Eligible denotes the first year the drug appeared on the eligible list for the centralized negotiation program. Success indicates the first year of a successful negotiation. Companies with asterisks are domestic firms. Icotinib has been renegotiated in 2021.

Table A6: Overview of Clinical Effects of Eligible Innovative Cancer Drugs

Drug Name	Year entering NRDL	Effects on survival (months)	Type	Primary indication	# of Indications	Combination (Y/N)
Gefitinib	2016	2.0	PKI	Lung	1	N
Icotinib	2016	1.2	PKI	Lung	1	N
Erlotinib	2017	0.7	PKI	Lung	1	N
Lapatinib	2017	4.2	PKI	Breast	1	N
Nimotuzumab	2017	2.4	mAb	Other	2	N
Rituximab	2017	4.3	mAb	Leukemia	2	N
Sorafenib	2017	1.5	PKI	Liver	3	N
Trastuzumab	2017	4.6	mAb	Breast	2	N
Afatinib	2018	2.1	PKI	Lung	1	N
Anlotinib	2018	2.2	PKI	Lung	5	N
Axitinib	2018	2.2	PKI	Renal	1	N
Ceritinib	2018	8.5	PKI	Lung	1	N
Cetuximab	2018	1.0	mAb	Colorectal	2	N
Crizotinib	2018	3.1	PKI	Lung	1	N
Ibrutinib	2018	11.0	PKI	Leukemia	2	Y
Nilotinib	2018	1.0	PKI	Leukemia	1	N
Osimertinib	2018	3.1	PKI	Lung	1	N
Pazopanib	2018	2.2	PKI	Renal	1	N
Regorafenib	2018	1.6	PKI	Colorectal	3	N
Sunitinib	2018	2.0	PKI	GIST	3	N
Vemurafenib	2018	0.5	PKI	Melanoma	2	N
Alectinib	2019	9.5	PKI	Lung	1	N
Apatinib	2019	2.8	PKI	Gastric	2	N
Bevacizumab	2019	0.6	mAb	Colorectal	5	Y
Pertuzumab	2019	5.9	mAb	Breast	1	Y
Pyrotinib	2019	8.1	PKI	Breast	1	N
Almonertinib	2020	9.4	PKI	Lung	1	N
Camrelizumab	2020	4.5	mAb	Liver	5	Y
Dabrafenib	2020	2.4	PKI	Melanoma	3	N
Daratumumab	2020	9.9	mAb	Myeloma	1	Y
Flumatinib	2020	3.1	PKI	Leukemia	1	N
Inetetamab	2020	3.7	mAb	Breast	1	N
Lenvatinib	2020	4.1	PKI	Liver	3	Y
Ruxolitinib	2020	0.5	PKI	Myeloproliferative Neoplasms	1	N
Sintilimab	2020	3.9	mAb	Lung	5	N
Tislelizumab	2020	5.2	mAb	Lung	9	Y
Toripalimab	2020	4.8	mAb	Melanoma	6	N
Trametinib	2020	6.3	PKI	Melanoma	3	N
Zanubrutinib	2020	9.3	PKI	Leukemia	2	N
Abemaciclib	2021	7.4	PKI	Breast	1	Y
Dacomitinib	2021	2.6	PKI	Lung	1	N
Disitamabvedotin	2021	0.7	mAb	Other	2	N
Donafenib	2021	4.2	PKI	Liver	1	N
Ensartinib	2021	13.1	PKI	Lung	1	N
Furmonertinib	2021	9.7	PKI	Lung	1	N
Neratinib	2021	1.0	PKI	Breast	1	N
Obinutuzumab	2021	18.6	mAb	Leukemia	1	N
Orelabrutinib	2021	21.8	PKI	Leukemia	2	N
Surufatinib	2021	6.3	PKI	Neuroendocrine	1	N
Ado-trastuzumab	2022	2.2	mAb	Breast	1	N
Brentuximab	2022	16.0	mAb	Other	1	N
Brigatinib	2022	12.9	PKI	Lung	1	N
Lorlatinib	2022	23.7	PKI	Lung	1	N
Olverembatinib	2022	18.4	PKI	Leukemia	1	N
Palbociclib	2022	3.3	PKI	Breast	1	N
Ripretinib	2022	6.9	PKI	GIST	1	N
Savolitinib	2022	1.4	PKI	Lung	1	N
Atezolizumab	N/A	2.7	mAb	Lung	2	Y
Avapritinib	N/A	1.8	PKI	GIST	1	N
Blinatumomab	N/A	2.6	mAb	Leukemia	1	N
Cadonilimab	N/A	3.8	mAb	Other	1	N
Durvalumab	N/A	2.9	mAb	Lung	1	Y
Duvelisib	N/A	11.0	PKI	Lymphoma	1	N
Envafolimab	N/A	0.6	mAb	Other	2	N
Inotuzumab	N/A	1.3	mAb	Leukemia	1	N
Ipilimumab	N/A	1.6	mAb	Melanoma	1	N
Nivolumab	N/A	3.3	mAb	Melanoma	7	Y
Pembrolizumab	N/A	3.0	mAb	Lung	12	Y
Pralsetinib	N/A	1.4	PKI	Lung	2	N
Serplulimab	N/A	4.6	mAb	Other	4	N

Note: This table lists the 70 eligible innovative cancer drugs (mAb and PKI) and their survival effects collected from published clinical trials. The number of indications is the number of approved indications at the end of the sample period, and Combination equals Y if the drug is observed in any combination regimen.