Health Insurance Design and the Passthrough of List Prices to Out-of-Pocket Costs*

Josh Feng, Luca Maini†

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Abstract

The cost of U.S. prescription drugs depends on nominal "list" prices and confidential rebates, both of which have grown substantially over time, puzzling regulators. We argue that plans that are constrained in how they set patient cost-sharing have an incentive to cover higher-list-price drugs and pass through those higher prices to patient out-of-pocket costs. Using an instrumental variable approach, we show that increases in list prices pass through one-to-one to increases in out-of-pocket costs in Medicare Part D and commercial high-deductible health plans, where cost-sharing is constrained, but not in commercial PPO and HMO plans that can set cost-sharing freely.

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†Josh Feng: University of Utah Eccles School of Business, josh.feng@eccles.utah.edu. Luca Maini: Harvard Medical School, maini@hcp.med.harvard.edu.

"Cost-sharing is often based on the list price of a drug, even when insurance companies and PBMs are paying a fraction of that price. Our current system [...] incentivizes high list prices and large rebates as a mechanism to keep insurance premiums low."

Kenneth Frazier (Chairman and former CEO, Merck & Co, Inc.)

1 Introduction

Prescription drug prices in the United States have risen sharply in recent years, drawing sustained scrutiny from policymakers concerned about their impact on healthcare spending and patient access. Drug manufacturers usually respond to policy inquiries by arguing that only nominal, "list" prices have grown, whereas net-of-rebate prices—a better reflection of acquisition costs—have remained relatively stable. However, this divergence still matters, because high list prices can translate into higher out-of-pocket costs for patients under the deductible or who owe coinsurance. As evidence mounts that higher cost-sharing can lead patients to discontinue high-value drugs (Brot-Goldberg et al., 2017) and even raise mortality (Chandra et al., 2024; Roberts et al., 2025), understanding why health plans would choose to tie cost sharing to an ever-rising price that is detached from acquisition cost is a question of increasing importance.

We argue that payer incentives created by benefit design constraints are one of the driving forces behind these phenomena.. We begin with a simple observation: caps on coinsurance rates limit the share of a drug's price that a patient pays, but not the price to which that share applies. Health plans facing such caps, therefore, can circumvent them by covering drugs with higher list prices. Coinsurance caps are most prominent in two settings: Medicare Part D, where plans must offer at least the actuarial value of a standard benefit defined by a series of coinsurance rates; and deductibles, where the coinsurance rate is capped at 100 percent.

These incentives imply two predictions. First, that list prices should imply higher patient out-of-pocket costs only in plans whose coinsurance rates are capped. Second, that constrained plans should cover higher-list-price drugs at higher rates than unconstrained plans. We test both predictions using data on U.S. prescription drug claims and plan formularies covering both the commercial and Medicare Part D segments.

To test the first prediction, we estimate the passthrough rate of list prices to out-of-pocket spending across market segments and plan types. A simple comparison of list price and out-of-pocket costs changes across drugs, however, is likely to understate passthrough for two reasons. First, drugs whose prices increase faster may be more valuable, leading plans to improve their coverage and lower the cost sharing patients face. Second, the payments patients make under the deductible or through coinsurance are tied to reimbursement amounts negotiated along the distribution chain, which respond to list price changes with delays.

To address these sources of bias, we use an instrumental variable research design that relies on exposure to the Medicaid segment as a plausibly exogenous shifter for list price growth. The Medicaid reimbursement formula includes an inflation penalty that strongly disincentivizes list price growth above inflation (Feng et al., 2023). Intuitively, our design compares the changes in out-of-pocket costs of drugs with high Medicaid sales, whose list price grows more slowly on average, to those of drugs with low Medicaid sales. The design is valid under the exclusion restriction that other drug characteristics correlated with exposure to Medicaid are not driving the differential trend in out-of-pocket costs for commercial and Medicare patients.

Our estimates confirm that higher list prices lead to higher out-of-pocket costs, but, consistent with our conceptual model, the effects are highly heterogeneous across plan types and market segments. Patients in Medicare Part D plans that follow the standard benefit design or offer actuarially equivalent benefits experience a one-to-one passthrough rate: a 10 percent increase in list price translates to a 10 percent increase in out-of-pocket. The same happens in commercial HDHPs. Conversely, we cannot detect any passthrough among commercial PPO and HMO plans, which face no binding constraint on their benefit design.

To test the second prediction, we compare the coverage of substitutable drugs across different types of plans. Specifically, we estimate the relationship between the average coverage probability at the drug, segment (commercial or Part D), and year level and log list price, controlling for log net price and fixed effects for narrowly-defined therapeutic area interacted with year. We find that coverage is increasing in a product's list price and decreasing in its net price, but much more so in Medicare Part D than among commercial plans. In a related test, we also find that Medicare Part D plans are roughly 37 percentage points more likely than commercial plans to cover originator biologics relative to their biosimilar counterparts, which have lower list and net price.[1]

[1]These results confirm an earlier, more limited analysis in Bertuzzi and Maini (2024).

The main contribution of this article is to provide an evidence-backed explanation for why some U.S. health plans tie patient out-of-pocket costs for prescription drugs to an inflated price that does not reflect true acquisition cost. In doing so, we complement recent empirical advances in the study of U.S. drug pricing, which tend to focus on net prices and treat list prices as exogenous (Olssen and Demirer, 2023; Feng and Maini, 2024; Ho and Lee, 2026). Our work also adds to existing theories related to list prices, which focus on its role as the outside option, by estimating and explaining the connection between list prices and out-of-pocket costs.[2]

More broadly, our model fits within the literature studying how demand for insurance shapes benefit design (Rothschild and Stiglitz, 1976; Cutler and Reber, 1998; Finkelstein, 2004; Abaluck and Gruber, 2016; Weyl and Veiga, 2017; Shepard, 2022; Kreider et al., 2024). Our work is most related to studies showing that Part D drug formularies are shaped by selection incentives (Carey, 2017; Lavetti and Simon, 2018; Geruso et al., 2019). Our novel focus is on how benefit design shapes manufacturers' list price-setting incentives.

Finally, our results contribute to a growing literature on regulatory avoidance in health care markets (Decarolis, 2015; Einav et al., 2018; Eliason et al., 2018; Geruso and Layton, 2020). The closest work to ours is a set of recent papers on "tunneling" in these markets. This line of work has documented firms shifting profits across jointly-owned entities by inflating costs (Gandhi and Olenski, 2024; Yde, 2025; Kakani et al., 2026). Our channel is consistent with the idea of redistributing surplus through nominal prices, but the mechanism is independent of common ownership.

2 Why List Prices Matter Under Constrained Benefit Design

This section provides an intuitive explanation of why a health plan may prefer to cover a drug with a higher list price over a similar drug, holding net price fixed. Appendix A formalizes the argument and derives general conditions under which plans and manufacturers behave as described in this section.

[2]Several existing theories attempt to explain the benefit of higher list prices: (i) some insured patients can still access the drug at those prices (Che, 2025), (ii) they boosts demand for health plans by worsening the outside option of going uninsured, generating profits that both PBMs and manufacturers can share (Conti et al., 2026), and (iii) they could support price discrimination strategies (see, e.g., Grennan and Swanson, 2020).

Consider a health plan deciding which of two clinically identical drugs to cover. Both drugs have a net price of $100. Drug A has a list price of $100, whereas Drug B has a list price of $200 and provides the plan with a $100 rebate. If the plan charges 25 percent coinsurance based on list price, a patient would pay $25 for Drug A but $50 for Drug B. The higher list price therefore shifts an additional $25 of the cost of a fill to the patient, even though the two drugs cost the same to the plan.

Two forces can make Drug B more attractive than Drug A to a health plan. First, healthier patients are more willing to accept higher cost-sharing in exchange for lower premiums, so a plan imposing higher patient cost-sharing may attract patients with lower expected spending (Rothschild and Stiglitz, 1976; Cutler and Reber, 1998). Second, evidence suggests that patients place substantially higher weight on premiums relative to expected out-of-pocket costs when choosing plans (Abaluck and Gruber, 2011, 2016), so financing a $1 decrease in premium through a $1 increase in expected cost-sharing can help plans attract more patients.

Plans that can set coinsurance rates freely do not need to rely on list price to change patient cost-sharing. In our example, if a $50 patient payment were optimal, the plan could set a 50 percent coinsurance on Drug A or a 25 percent coinsurance on Drug B, generating the same patient payment in either case. In this case, the list price is purely an accounting tool.

The list price becomes a relevant tool when plans face coverage restrictions that cap coinsurance rates. Under this scenario, plans can use drugs with higher list prices to achieve the desired patient cost-sharing. For example, suppose the plan in our example was limited to a 25 percent coinsurance rate, capping the patient's payment at $25 on Drug A, but $50 on Drug B. In this case, a higher list price allows the plan to impose higher patient cost-sharing (and use the resulting reduction in claim payments to offer a lower premium) without formally exceeding the cap, making the list price a key strategic element of benefit design.

Two large groups of U.S. health insurance plans face constraints that fall under the umbrella described in the previous paragraph. As noted in the introduction, Medicare Part D plans must provide a minimum standard benefit defined by a series of coinsurance rates.[3] About one half of Medicare beneficiaries with standalone prescription

[3]The pre-IRA standard Part D benefit design (which is what this paper analyzes) consisted of a set deductible, followed by an initial coverage phase with a 25% coinsurance rate, a coverage gap phase with a 100% coinsurance rate, and a catastrophic coverage phase with a 5% coinsurance rate. Post-IRA, the design eliminated the coverage gap phase and capped total yearly patient out-of-pocket costs at $2000.

drug insurance are enrolled in plans that either follow the standard benefit, or are actuarially equivalent (Cubanski and Damico, 2020). The remaining beneficiaries are covered by so-called "enhanced" Part D plans, which offer more generous benefits, but are often identical to standard plans in specific phases.[4] High-deductible plans also face a constraint because coinsurance rates cannot exceed 100%. Conversely, commercial plans with small deductibles, like PPOs and HMOs, generally face limited constraints.

This conceptual model yields two predictions that organize our empirical analysis:

1. *List prices should pass through to out-of-pocket costs only where constraints bind.* Passthrough should be close to zero in plans that can adjust cost-sharing freely (commercial PPO and HMO plans), closer to one where coinsurance rates are capped (basic Medicare Part D plans, high-deductible health plans), and intermediate where constraints bind only in some benefit phases or regions of spending (enhanced Part D plans).

2. *Plans facing constraints should be more likely to cover higher-list-price drugs.* When clinically similar drugs have different list prices, constrained plans should favor the drug with the higher list price as a way to circumvent the restriction.

3 Background, Data, and Empirical Approach

3.1 The Role of List Prices in the Pharmaceutical Supply Chain

The term "list price" generally refers to Wholesale Acquisition Cost (WAC), a public, manufacturer-posted price that serves as the starting point for transactions on the distribution side of the industry. A recent investigation by the U.S. Senate Finance Committee (Senate Finance Committee, 2021), and a 2024 Federal Trade Commission (FTC) public complaint against PBMs (Federal Trade Commission, 2024) both note that contracts between PBMs and manufacturers express discounts as a function of list price, and that increases in list price result in higher patient out-of-pocket costs.

Strictly speaking, however, patients' out-of-pocket costs are tied not to WAC but to the reimbursement price negotiated between the payer (or PBM) and the dispensing pharmacy (also referred to as "allowed amount" in claims data). That price, in turn,

[4] In 2021, even though only 38% of Part D plans offered the standard benefit design, 64% of plans charged the standard deductible amount (Cubanski and Damico, 2020), and many enhanced plans charged the maximum allowable coinsurance under the anti-discrimination provision (Cubanski and Damico, 2021).

can depend on acquisition costs that are negotiated along the drug distribution chain between pharmacies, wholesalers (intermediaries that pick up drugs from manufacturers and deliver them to pharmacies), and the manufacturers themselves.[5]

Because fees along the distribution chain are generally expressed as a percentage of list price (Burns, 2022), WAC does still influence out-of-pocket costs. However, two forces may dampen how this relationship is measured in the data. First, the contracts that affect allowed amount may not update immediately, so allowed amounts can lag posted list prices.[6] Second, the firms negotiating each contract may adjust margins and fees for reasons unrelated to WAC growth, including strategic transfer pricing by vertically integrated plan sponsors (Yde, 2025; Kakani et al., 2026), or regulation affecting patient out-of-pocket costs (Hofmann and Huang, 2025). Therefore, the relationship between list price and patient cost is neither mechanical nor immediate. In the next section, we discuss how our empirical approach addresses these issues.

3.2 Empirical Approach

We estimate the impact of list price on various outcomes tied to patient out-of-pocket cost using the following regression design:

$$\Delta y_{jt} = \alpha_t + \gamma \times \Delta \ln (WAC)_{jt} + \varepsilon_{jt} \tag{1}$$

where j indexes drugs, and t indexes years. Δy_{jt} are changes in a list of dependent variables of interest, α_t are year fixed effects, and $\Delta \ln (WAC)_{jt}$ is the change in log WAC between periods $t-1$ and t. We use a first-difference specification because drug list prices can vary substantially and are often reported in units that are not comparable across drugs, and because both our instrument and our object of interest concern the passthrough of year-over-year price changes.

There are two concerns in estimating this equation. First, as discussed above, contracting lags can attenuate the short-run relationship between the two variables relative to the long-run passthrough.[7] We note that this bias is particularly problematic in regressions using variable *changes*, rather than levels, because changes generally occur on a one-off basis. Therefore accurately capturing the timing of changes is essential to

[5] Appendix B.1 provides more details and a diagram illustrating this market structure.

[6] Appendix C.7 documents lags averaging about 12 weeks in roughly 40 percent of list price increases.

[7] Consistent with this interpretation, correlational evidence comparing list price changes to changes in patient out-of-pocket costs generally finds a weak or no relationship (see, e.g., Yang et al., 2020; Rome et al., 2021; Lalani et al., 2024).

identifying the correct effect.[8]

Second, list price is an equilibrium outcome, which makes a correlation with out-of-pocket cost difficult to interpret. For example, drugs might increase their list (and net) price in response to positive demand shocks (caused, e.g., by new clinical evidence or label extensions). Such a shock is an omitted variable correlated with both price growth and coverage: if plans respond to higher drug value by improving the drug's coverage, a nominal price increase need not translate into higher out-of-pocket costs. The resulting omitted-variable bias is plausibly downward, although its precise sign depends on how the value shock affects allowed amounts, benefit design, and utilization.

Addressing these challenges requires an instrument that affects the incentive to increase or decrease list price, but is not otherwise correlated with other outcomes in the market.

Medicaid Market Share as an Instrument for List Price Growth

The instrument we propose is exposure to the Medicaid program, measured by Medicaid Market Share (MMS)—the share of a drug's sales that are paid for by Medicaid. Evidence from our previous work in Feng et al. (2023) suggests that list prices respond to incentives generated by the formula used by the Medicaid Drug Rebate Program (MDRP) to determine reimbursement for branded drugs.

The MDRP—which all manufacturers must abide by to participate in Medicaid—sets Medicaid's reimbursement for branded drugs as the Average Manufacturer Price (AMP, a proprietary measure of what wholesalers actually pay for drugs that incorporates some small discounts off of WAC) minus the sum of two rebates: a base rebate of 23.1% (or the highest discount granted to a commercial payer) and an inflation rebate consisting of the difference between a drug's current AMP and its inflation-adjusted AMP at launch.[9] The formula implies that the base rebate is expressed as a function of the current AMP. As a result, faster-than-inflation AMP growth *lowers* the overall Medicaid reimbursement.[10]

[8] For example, a list price increase on January 1 whose allowed amount updates on April 1 lowers the measured year-over-year allowed-amount change by 25% relative to WAC.

[9] The statutory minimum rebate was raised from 15.1% to 23.1% in January 2010 by a provision in the Affordable Care Act. Discounts to Medicare Part D plans, the VA, and a few other institutional and public payers are exempt from the calculation of this rebate (42 CFR § 447.509).

[10] In Appendix B.2, we reproduce Figure 2 of Feng et al. (2023), which illustrates graphically this somewhat counterintuitive implication of the formula.

Because high AMP growth lowers Medicaid's reimbursement rates, drugs with a high Medicaid Market Share effectively face a penalty for increasing AMP, so they should, all else equal, exhibit lower AMP growth. Notice that because of this incentive, we should also expect these drugs to have a higher AMP at *launch* (Duggan and Scott Morton, 2006). Therefore, Medicaid exposure will work well as an instrument for changes in list price within drug, rather than level differences across drugs.[11]

While data on AMP is not publicly available, AMP is reportedly very close to WAC (Department of Health and Human Services, 2005; Congressional Budget Office, 2021). Hence, our hypothesis is that changes in WAC will be negatively correlated with a drug's MMS.

3.3 Data

To conduct the analysis outlined in the previous section, we combine data on drug prices and spending, prescription drug claims, and formulary coverage. Data from all sources cover years 2007–2018 unless otherwise noted.

Drug Spending and Price Data. We obtain drug list (WAC) and net prices for approximately 1,000 brand drugs from SSR Health, which calculates estimated US-level quarterly net prices by comparing net sales from SEC filings of publicly traded firms to invoice sales reported by a third-party (Symphony Health).[12] SSR Health data are at the product level, where a product is usually defined by a brand name (e.g., Lipitor). We complement SSR Health with publicly available quarterly data on drug-level Medicaid spending from the Medicaid Public Use Files published by the Centers for Medicare and Medicaid Services (CMS), matched to SSR Health through a map provided by SSR Health, and with the Medicare Spending Dashboard, which reports overall drug-level spending in Medicare Part B and D.

Prescription Drug Claims Data. We use prescription drug claims from MarketScan, covering over 47 million unique lives enrolled in employer-sponsored insurance plans, and from CMS's 20% random sample of Medicare Part D beneficiaries, covering over 90 million unique lives. Each claim includes patient cost-sharing as well as the claim's

[11] Another issue with this instrument is that, as our work in Feng et al. (2023) shows, manufacturers of drugs with a high MMS give lower rebates to commercial payers (though not Medicare Part D plans, which are excluded from the best-price clause). However, since this incentive does not change over time, it should not affect our specification, which focuses on price changes.

[12] See Ippolito and Levy (2022) for a more detailed guide to the SSR Health data.

total allowed amount. MarketScan distinguishes between payments made as copays, coinsurance, and under the deductible, and records each beneficiary's plan type (e.g., HMO, PPO, HDHP). The CMS data do not split cost-sharing across payment types, but the standard benefit design of Medicare Part D means that the vast majority of payments are made as coinsurance or under the deductible; the main exception is enhanced plans, which occasionally cover some drugs using copays and which we isolate from basic plans in some of our analyses. When calculating out-of-pocket costs in Medicare claims, we exclude low-income subsidy (LIS) beneficiaries, who pay no, or limited, cost-sharing.

Formulary Coverage Data. Data on formulary coverage come from MMIT Analytics, a firm that records drug tiering and restrictions from health-plan formularies, along with associated plan enrollment.[13] For each drug–plan pair we observe the formulary tier and any administrative restrictions (e.g., prior authorization or step therapy), which we use to measure whether a plan covers a drug. A plan is coded as covering a product if the product appears on the plan's formulary at a tier and restriction level that leaves it accessible; product-level coverage is then the enrollment-weighted share of lives in plans that cover it, computed separately for commercial and Medicare Part D plans. Our sample for this analysis is an annual panel, covering 2011–2018, which we merge to SSR Health list and net prices at the product–year level.

Therapeutic Classification. We assign each drug to a therapeutic class using the World Health Organization's Anatomical Therapeutic Chemical (ATC) classification. ATC is a hierarchical system that groups drugs from broad anatomical groups (ATC-1; e.g., "cardiovascular system"; 13 groups in our data) down to narrow chemical–therapeutic subgroups (ATC-4; e.g., statins).[14] We use ATC-1 to define broad therapeutic-area fixed effects in robustness checks, and ATC-4 to define drug classes when comparing formulary coverage across drugs competing in the same market. ATC-4 groups direct competitors together, but measures the true set of substitutes with error.

[13] See Geruso et al. (2019) and Dean et al. (2024) for more detailed discussions of the MMIT data.
[14] See, https://www.who.int/tools/atc-ddd-toolkit/atc-classification, accessed June 29th, 2026.

3.4 Sample Selection

We create a core sample of branded, on-patent drugs based on four criteria.[15] First, we exclude products primarily administered by physicians (Medicare Part B sales exceeding 20% of total Medicare sales), because our analysis focuses on the retail and mail channel. Second, following Kakani et al. (2020) and Feng et al. (2023), we exclude drugs whose invoice sales records are most likely to be underestimated in the SSR Health data: injectable drugs, drugs with an indication in oncology, and drugs that record higher net sales than invoice sales. Third, we exclude contraceptives and smoking cessation drugs, which the ACA mandates be covered at no cost to patients. Fourth, we restrict to drug-years within 15 years of launch, because older drugs often accumulate inflation rebates that exceed 100% of AMP, at which point Medicaid caps the rebate and the incentive to restrain list price growth disappears.[16]

After applying these filters, we end up with a core sample of 304 drugs. Panel A of Table 1 provides drug-year level summary statistics for this sample: drugs earn, on average, a little over eight percent of their invoice sales through Medicaid, albeit with significant variation across drugs, and list price growth is about 12 percent per year. WAC and allowed amount are often stated in different units (e.g., price per pill versus price per 30-day supply), but our analysis focuses exclusively on growth rates within a drug, which removes fixed differences in units between WAC and claim-level measures.[17] Medicare and commercial plans have very similar allowed amounts, but Medicare plans—which are known to be less generous—have much higher average out-of-pocket costs.

Panel B of Table 1 reports summary statistics split at the median of Medicaid Market Share: list price growth is 4 percentage points lower for drugs with above-median exposure to Medicaid, previewing our first stage estimates. Growth in allowed amounts displays a similar quantitative difference. Growth in out-of-pocket costs is nearly identical across the two groups in commercial plans, but about 4 percentage points lower for high-exposure drugs in Medicare plans.

[15] We only track drugs through the year before loss of exclusivity (LOE). After LOE, drug sales typically plummet, which means that list prices and cost-sharing are much less relevant. Appendix C.1 provides more details on sample selection.

[16] Appendix C.5 shows that our first stage results do not depend on this restriction, but that our instrument is strongest in the first 15 years after launch.

[17] We note that this approach does not account for time-varying changes in the composition of a drug's claims (e.g., shifts in average days supply, package or strength mix, or retail-versus-mail dispensing), which can move average claim-level amounts independently of list price.

Table 1: Summary Statistics

Panel A. Full Sample

Variables		Mean	SD	N
MMS		8.12%	10.73%	1940
WAC		106.58	574.63	1940
$\Delta \ln(\text{WAC})$		0.12	0.17	1636
Allowed Amount	Commercial plans	1,242.32	3,353.36	1921
	Medicare Plans	1,188.68	3,343.92	1728
$\Delta \ln(\text{Allowed Amount})$	Commercial plans	0.12	0.18	1618
	Medicare Plans	0.13	0.14	1443
Out of pocket cost	Commercial Plans	69.23	61.47	1921
	Medicare plans	163.80	256.29	1728
$\Delta \ln(\text{Out of pocket cost})$	Commercial Plans	0.08	0.20	1618
	Medicare plans	0.07	0.17	1443

Panel B. By Medicaid Exposure

		Below-median MMS			Above-median MMS		
Variables		Mean	SD	N	Mean	SD	N
MMS		1.84%	1.57%	923	13.82%	12.22%	1017
WAC		148.16	804.08	923	68.84	201.15	1017
$\Delta \ln(\text{WAC})$		0.14	0.23	771	0.10	0.08	865
$\Delta \ln(\text{Allowed Amount})$	Commercial plans	0.13	0.22	758	0.10	0.13	860
	Medicare Plans	0.15	0.17	643	0.11	0.10	800
$\Delta \ln(\text{Out of pocket cost})$	Commercial Plans	0.08	0.20	758	0.08	0.20	860
	Medicare plans	0.09	0.18	643	0.05	0.17	800

Notes: Summary statistics for the core sample, limited to drugs 15 years old or younger. Panel A reports statistics for the full core sample. Panel B splits the sample at the median of Medicaid Market Share (MMS). Missing entries for out-of-pocket cost occur for drugs with low sales that do not appear in our claims data in a given year.

Table 2: First-Stage Estimates

	List Price Growth	
	(1)	(2)
MMS	-0.163	-0.158
	(0.033)	(0.033)
Year FE		X
N	1,636	1,636
R^2	0.011	0.047
Kleibergen-Paap F-stat	24.25	22.69

Notes: Estimates of Equation 2, using data from SSR Health on WAC to measure list price growth. Standard errors clustered at the drug level.

4 Passthrough of List Prices to Out-of-Pocket Costs

4.1 The Effect of Medicaid Market Share on List Price Growth

As a first step, we confirm that MMS and WAC growth are inversely correlated. Formally, we run the following regression:

$$\Delta \ln (WAC_{jt}) = \delta_t + \beta \times MMS_{jt} + \varepsilon_{jt} \tag{2}$$

The ideal definition of MMS would be the fraction of a drug's *volume* sales that comes from Medicaid. SSR Health and CMS record units in different ways, making it difficult to compute the MMS directly. Instead, we compute MMS using invoice sales. As both Medicaid and invoice sales are reported at list price levels, the price component should cancel out when we take the ratio. Formally, for any given drug j and period t, we define

$$MMS_{jt} = \frac{\text{Medicaid sales}_{jt}}{\text{Total invoice sales}_{jt}}$$

Table 2 reports estimates from the first-stage regression, with and without year fixed effects. Our findings confirm that drugs with a high MMS increase list price more slowly: with year fixed effects, which we include in our main analysis, the coefficient on MMS is -0.158 (s.e. 0.033), so a standard deviation increase in MMS (approximately 10pp) results in lower list price growth by 1.6 pp each year.

The F-statistic from our first-stage regression indicates a reasonably strong instru-

ment. The inclusion of year fixed-effects absorbs some of the variation in MMS, because the size of the Medicaid program has increased over time as a result of the gradual ACA expansion that began in 2010. Even so, the first-stage Kleibergen-Paap rk Wald statistic, which is robust to heteroskedasticity and within-drug clustering, remains above conventional thresholds (24.25 without and 22.69 with year fixed-effects). Still, to be conservative, we use limited-information maximum likelihood (LIML) estimators and report the Kleibergen-Paap F-statistic throughout our analysis.

4.2 The Effect of List Price Changes on OOP Changes

To estimate the effect of list price growth on changes in out-of-pocket costs, we use MarketScan and CMS data from 2007–2018. We match claims to drugs based on the National Drug Code (NDC) recorded on the claim. Both CMS and MarketScan report patient out-of-pocket costs in separate, clearly identifiable variables. Our main dependent variable is the log change in average claim-level out-of-pocket cost at the drug-year level. We also calculate separate measures of out-of-pocket cost by plan type (PPO, HMO, and HDHP for MarketScan data, and basic vs. enhanced in Medicare data).

Prediction 1 in Section 2 predicts passthrough on the coinsurance and deductible margins and none on copays. Plan labels are therefore best understood as proxies for the mix of binding payment margins faced by a plan's enrollees, rather than as primitives: PPO and HMO enrollees pay disproportionately through copays, HDHP enrollees disproportionately under the deductible, and basic Part D enrollees almost entirely through coinsurance and the deductible.[18]

Table 3 presents our results, with columns reporting estimates for commercial and Medicare Part D plans (overall and separately by plan type). In the OLS regressions (Panel A), we find a significant but weak passthrough rate of WAC to out-of-pocket costs, with little variation across plan types or market segments: across all plan types, a 10 percent increase in list price is correlated with a 0.4 to 2.4 percent increase in out-of-pocket costs. Conversely, our instrumental variable estimates (Panel B), despite being more imprecise, highlight large disparities in passthrough rates that line up with the predictions of the theory.

In commercial PPO and HMO plans, which face no binding constraint on their benefit design, we find limited evidence of passthrough, consistent with the predictions from our conceptual framework. In constrained plans, passthrough is high and

[18] Appendix C.4 provides estimates of passthrough by payment type (deductible, coinsurance, copay) in the commercial segment (payment type data are not available for Medicare Part D).

Table 3: Passthrough of List Prices to Out-of-Pocket Costs and Allowed Amounts

	Commercial $\Delta \log(\text{OOP})$				Medicare Part D $\Delta \log(\text{OOP})$			Commercial $\Delta \log(\text{All. Amt.})$	Medicare Part D $\Delta \log(\text{All. Amt.})$
	All	PPO	HMO	HDHP	All	Basic	Enhanced	All	All
Panel A. OLS Estimates									
$\Delta \ln(WAC)$	0.164	0.181	0.0366	0.197	0.244	0.236	0.187	0.536	0.478
	(0.076)	(0.081)	(0.056)	(0.091)	(0.119)	(0.100)	(0.120)	(0.213)	(0.208)
Panel B. Instrumental Variable Estimates									
$\Delta \ln(WAC)$	-0.107	-0.163	0.197	1.165	0.802	0.874	0.444	1.045	1.089
	(0.321)	(0.340)	(0.394)	(0.345)	(0.182)	(0.330)	(0.180)	(0.263)	(0.188)
Kleibergen-Paap F-stat	22.72	22.73	18.71	20.34	17.69	12.90	13.83	22.72	17.69
Year FE	X	X	X	X	X	X	X	X	X
N	1,618	1,616	1,588	1,586	1,443	1,379	1,414	1,618	1,443

Notes: Estimates of Equation 1. Commercial estimates are based on claims data from MarketScan; Medicare estimates are based on CMS's 20% random sample of Medicare Part D beneficiaries. Basic plans follow the standard Medicare benefit design or offer actuarially equivalent benefits; enhanced plans are more generous, and offer additional coverage. All specifications include year fixed effects. Instrumental variable estimates (Panel B) use Medicaid Market Share as an instrument for list price growth and are estimated by LIML. Standard errors clustered at the drug level.

often indistinguishable from 1. Patients in basic Medicare Part D plans, which follow the standard benefit design or offer actuarially equivalent benefits, experience a passthrough rate of 0.87, while patients in enhanced plans, which are constrained in some benefit phases but not others, experience a passthrough rate of 0.44. In commercial HDHP plans, which face the structural 100% cost-sharing constraint under the deductible, the estimated passthrough rate is 1.17.

One concern with our results is that high- and low-MMS drugs display different trends in out-of-pocket costs for reasons other than their differential list price growth. To partially address this concern, we run robustness checks that control for broad therapeutic area (ATC-1) fixed effects and for the change in the drug's net price (the price directly relevant to plan costs).[19] The estimates (reported in Appendix C.6) are quantitatively similar, albeit more imprecise.

Finally, we also provide some suggestive evidence on the presence of contracting frictions, which we argued could be one of the reasons why OLS estimates of passthrough may be biased downward. To do so, we estimate equation 1 using log change in average claim-level allowed amount as the dependent variable. Allowed amount is the negotiated price between the PBM (or payer) and the pharmacy on which coinsurance and deductible payments are based. For the OLS estimates, we find passthrough rates from list price to allowed amounts of approximately 0.5 in both commercial and Medicare claims. Conversely, both passthrough rates estimated with IV are approximately 1, consistent with contracting frictions and measurement lags dampening the short-run relationship between WAC and allowed amount.

5 Coverage of High-List-Price Drugs

In this section, we provide evidence on the second prediction of our conceptual model: constrained plans prefer to cover higher-list-price drugs within a set of substitutes. This analysis cannot rely on our instrumental variable approach, because the relevant metric is the *relative* list prices within a narrow class of substitutable drugs and Medicaid market share is likely to be highly correlated within such narrow classes. As a

[19] Controlling for net price also partially addresses the potential confounding effect of the Medicaid best-price channel. As discussed in the background section, the best-price clause primarily affects net-price *levels*—high-MMS drugs tend to offer smaller commercial rebates, raising their net price—rather than net-price *growth*, so its first-order effect is differenced out of our specification. This concern also does not apply to Medicare Part D, whose discounts are exempt from the best-price calculation. Because net price is itself an equilibrium outcome, conditioning on it can introduce bad-control bias, so we read this exercise as a robustness bound rather than a definitive adjustment.

result, the evidence in this section is only intended to be suggestive.

Our first test compares the coverage of drugs in our core sample within drug classes, defined by 4-digit ATC codes (ATC-4). Specifically, for each market segment $m \in \{\text{commercial, Part D}\}$ we estimate

$$\text{Coverage}_{jt}^{m} = \beta^{m} \ln(WAC_{jt}) + \gamma^{m} \ln(\text{Net}_{jt}) + \delta_{c(j)t} + \varepsilon_{jt}, \tag{3}$$

where j indexes products, t years, and $c(j)$ the molecule (drug class) to which product j belongs. The molecule-by-year fixed effects $\delta_{c(j)t}$ mean that the specification is a pooled set of cross-sectional comparisons between products in the same therapeutic area. Standard errors are clustered by product.

Panel A of Table 4 shows that, within a molecule and year, plans are more likely to cover the product with the higher list price and less likely to cover the product with the higher net price. The results are consistent with plans preferring to cover drugs with higher list prices, holding acquisition cost fixed. The list-price gradient is three times larger in Part D than in commercial plans, consistent with regulatory constraints as a key factor.[20]

Because the ATC-4 market definition is imperfect, we conduct a second test using originator biologics and their biosimilar counterparts. Biosimilars are copycats of originator biologics that have no clinically meaningful differences, and generally have lower list price and net price (Dean et al., 2024; Feng et al., 2026).

Our analysis sample consists of seven originators that face biosimilar competition during our sample period. Because the SSR Health data does not contain net price data for biosimilars, we use a simplified specification that replaces price with an indicator for biosimilar status. The implicit assumption is that biosimilars have lower list price than their corresponding originator. Formally, our specification is

$$\text{Coverage}_{cbt}^{m} = \beta_1 \text{Medicare}^{m} + \beta_2 \text{Biosimilar}_{b} + \beta_3 (\text{Biosimilar}_{b} \times \text{Medicare}^{m}) + \delta_{ct} + \varepsilon_{cbt}^{m} \tag{4}$$

The coefficient of interest, β_3, captures the originator–biosimilar coverage gap in Part D relative to the same gap in commercial plans. Standard errors are clustered by molecule.

Our results in Panel B of Table 4 show a large relative difference in coverage between commercial and Medicare Part D plans. In commercial plans, biosimilars are covered somewhat less than their reference biologics, but the gap is small and imprecisely estimated. In contrast, Part D plans are 37 percentage points more likely than

[20] The difference is significantly different from zero at the 95% confidence level.

Table 4: Formulary Coverage, List Prices, and Biosimilar Entry

	(1)	(2)
Panel A. Coverage, list price, and net price within molecule-year		
Outcome: share of covered lives	Commercial	Medicare Part D
ln (*WAC*)	0.060	0.174
	(0.028)	(0.057)
ln (Net price)	-0.063	-0.209
	(0.027)	(0.043)
ATC-4 × Year FE	X	X
Clusters (products)	56	56
N	802	802
Adjusted R^2	0.261	0.310
Panel B. Originator versus biosimilar coverage, Part D versus commercial		
Outcome: share of covered lives	Both markets pooled	
Medicare	-0.096	
	(0.015)	
Biosimilar	-0.139	
	(0.072)	
Biosimilar × Medicare	-0.367	
	(0.047)	
Molecule × Year FE	X	
Clusters (molecules)	7	
N	140	
Adjusted R^2	0.706	

Notes: Formulary coverage data are from MMIT Analytics; list (WAC) and net prices are from SSR Health. The sample is the thirteen originator biologics facing biosimilar competition together with their thirty-three biosimilars, 2011–2018. The outcome is the share of enrolled lives in plans that cover the product. Panel A shows estimates from Equation 3 at the product–year level, separately for commercial plans (column 1) and Medicare Part D plans (column 2). Both columns use the same 802 product–year observations but use data from different segments to measure outcomes. Panel B estimates Equation 4 on coverage collapsed to the molecule-by-biosimilar-status level and stacked across the two markets, restricted to the seven molecules for which coverage of both the originator and at least one biosimilar is observed in both markets; the omitted category is the originator biologic in commercial plans. All specifications include class (either ATC-4 or molecule) × year fixed effects, so all comparisons are within a drug class in a given year. Standard errors, in parentheses, are clustered by product in Panel A and by molecule in Panel B. Appendix C.3 plots the underlying coverage rates molecule by molecule.

commercial plans to extend preferential coverage to the more expensive originator over its cheaper biosimilar equivalent.

Taken together, the two panels provide evidence consistent with the second prediction of our conceptual framework: constrained plans appear to have a stronger preference for covering products with high list prices within a set of substitutes.

6 Conclusion

In this article, we provide both a conceptual justification and empirical evidence for why payers pass through list price increases to patients in the form of higher out-of-pocket costs. We argue that health plans facing benefit design constraints can use higher list prices to raise patient cost-sharing, and that such a response can be optimal when facing adverse selection and/or patients that care more about premium costs than expected out-of-pocket costs. Using an instrumental-variables strategy based on incentives generated by Medicaid inflation rebates, we find that: (i) list prices pass through almost one-to-one in percentage terms to patient out-of-pocket spending in plans facing design constraints but have negligible effects on patients enrolled in plans that can set cost-sharing freely; and (ii) constrained plans are more likely to cover drugs with higher list prices within narrow substitution classes.

Our findings have three main implications. First, we confirm that the list-net price divergence is not a harmless accounting artifact (as sometimes argued by pharmacy benefit managers and plan sponsors) but a source of higher out-of-pocket spending relative to true acquisition costs for some patients. Second, our conceptual model suggests that plan-sponsor incentives alone are sufficient to sustain the list-to-net spread, independent of any PBM incentives, which could help explain why the spread has persisted even as PBMs have increasingly integrated with insurers and moved towards full sharing of rebates with payers (Burns, 2022). Third, by bypassing benefit design regulation through the use of list prices, payers are effectively undoing some of the insurance protection guaranteed by the cap. Because higher out-of-pocket costs may allow plans to compete by lowering premiums, this workaround could act as a transfer from sick patients to healthy patients.

Our results also speak to the policy debate over how to contain rising list prices. Measures that restrain list-price growth—such as the inflation rebates that now operate in both Medicaid and Medicare—should mechanically dampen the growth in out-of-pocket costs for the patients most exposed to this channel. However, the quantita-

tive impact of inflation rebates appears modest. Our estimates suggest the Medicaid rebate formula slows annual list-price growth by only about 1.6 percentage points for a standard-deviation increase in Medicaid exposure, against a baseline of roughly 12 percent. More broadly, these rebates do not directly address the incentives that lead constrained plans to exploit the list-net wedge. A more targeted remedy would sever the link between cost-sharing and list prices directly, either by requiring that rebates be passed through at the point of sale, or by restricting cost-sharing to fixed copays.

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Online Appendix

A Formal Model of List Price Setting and Plan Design

A.1 Setup

This appendix presents the formal model summarized in Section 2, states each result, and provides proofs. We incorporate the standard incentives generated by adverse selection as in the seminal model by Rothschild and Stiglitz (1976), and we allow for the possibility that patients care more about premium dollars as shown by Abaluck and Gruber 2011 in the context of Medicare Part D plan choice. All the theoretical results we derive hold whether or not we allow for this behavioral wedge—though they occasionally require slightly different regularity conditions. The results also hold without adverse selection (e.g., with perfect risk-adjustment) as long as the wedge is sufficiently large.

A unit measure of patients is indexed by a risk type θ distributed on $[0, 1]$ according to CDF $F(\theta)$ with continuous density $f(\theta) > 0$. The type θ is the probability that a patient gets sick. If sick, the patient suffers a health shock of dollar value h, which can be fully offset by consuming one unit of a drug.

Patients can purchase insurance to subsidize the cost of the drug. Health insurance plans are characterized by a coinsurance rate α and a premium r. The coinsurance rate is applied to the list price of the drug, w, which is set by the drug manufacturer. Hence, a plan can be characterized as a pair $(\alpha w, r)$, where αw represents the actual out-of-pocket cost paid by patients who consume the drug (we refer to this quantity as "effective cost sharing"). The drug manufacturer also sends a discount d to health plans, so the drug's net price to plans is $p = w - d$, leaving the net cost per fill for the health plan at $p - \alpha w$. We assume that the insurance market is perfectly competitive, so the premium is pinned down by the zero-profit condition

$$r = \mathbb{E}[\theta | \text{enrolled}] \cdot (p - \alpha w) \tag{A1}$$

We assume $h > p$, so there is no scope for moral hazard.[21]

[21] In general, moral hazard would exacerbate the effects we describe in this model by amplifying the cost (and thus premium) differential between more and less generous insurance plans.

Patient utility on a plan $(\alpha w, r)$ is

$$U(\theta, \alpha, w, r) = (1-\theta) \cdot u(W - \kappa r) + \theta \cdot u(W - \kappa r - \alpha w),$$

where W is wealth, $u(\cdot)$ is increasing and concave, and $\kappa \geqslant 1$ is a behavioral parameter allowing for the possibility that patients put extra weight on premium dollars. Setting $\kappa = 1$ recovers the standard expected-utility benchmark. Uninsured patients can purchase the drug at an exogenously set price $\bar{p}$, so the utility of being uninsured is $U^0(\theta) = (1-\theta) \cdot u(W) + \theta \cdot u(W - \bar{p})$.[22] We assume that the cash price faced by the uninsured weakly exceeds the net price paid by plans (i.e., $\bar{p} \geqslant p$), consistent with uninsured patients facing list-based prices at the pharmacy. Because—in equilibrium—effective cost-sharing never exceeds p in the analysis below, this assumption guarantees that insured patients never prefer to bypass their plan and pay the cash price, which simplifies some of our derivations, but has no meaningful implications on the results.

A.2 Irrelevance of List Prices (Proposition 1)

We consider a perturbation from the baseline in which the drug's list price equals its net price ($w = p$, so the rebate is zero) where the manufacturer increases the list price to $w > p$ and pays a rebate $d = w - p$ to plans. This leaves the plan's acquisition cost unchanged. Uninsured patients continue to purchase the drug at price $\bar{p}$.

Proposition 1 ((Irrelevance of List Prices)). *Assume plans are restricted to contracts with positive premiums and effective cost-sharing that does not exceed the net price (i.e., $\alpha w \leqslant p$). Then any solution concept depending only on plans' strategy spaces and payoff functions yields identical predictions about $(\alpha w, r)$ outcomes across all list prices $w \geqslant p$.*

Proof. This Proposition follows from a straightforward substitution. The patient's effective cost-sharing per fill is $c = \alpha w$. By construction, patient utility on a plan with strategy (α, r) and the plan's profit per enrollee both depend on w only through

$$(1-\theta) \cdot u(W - \kappa r) + \theta \cdot u(W - \kappa r - c)$$

[22] We also assume that $h > \bar{p}$, so that uninsured patients also consume the drug. Treating $\bar{p}$ as exogenous shuts down the demand-side channel emphasized in Conti et al. (2026), in which higher list prices reduce the attractiveness of going uninsured and indirectly raise the demand for insurance. Empirically, manufacturers tend to neutralize this channel by expanding patient assistance programs as list prices rise. Treating $\bar{p}$ as exogenous lets us isolate the plan-side incentive without confounding it with the uninsured-demand channel, but does not otherwise affect the implications of the model.

$$\frac{\pi}{n} = r - \mu\,(p - c)$$

where $\mu = \mathbb{E}\,[\theta|\,\text{enrolled in this plan}]$ is the average risk type of the plan's enrollees. Under the restriction $c \leqslant p$, the set of (c, r) pairs feasible to a plan is $[0, p] \times \mathbb{R}_+$ for every $w \geqslant p$, since $\alpha \in [0, 1]$ can always be scaled to reach any $c \leqslant p \leqslant w$. Hence the strategy space and payoff functions in (c, r) space coincide across all $w \geqslant p$, and any solution concept depending only on these objects yields identical predictions. □

A.3 Pooled Equilibrium under Caps (Lemma 2)

We now suppose that α is restricted to the interval $[0, \bar{\alpha}]$, with $\bar{\alpha} < 1$. We begin by analyzing a market with a single drug (drug A) and show that every Nash equilibrium of the free entry plan design game has all plans bunch at the cap $\bar{\alpha}$. For simplicity, we fix $w_A = p$, so that $p - \alpha w_A = (1 - \alpha)\,p$. Setting $w_A > p$ would rescale the feasible effective cost-sharing cap to $\bar{\alpha} w_A$ and the zero-profit premium at the cap to $\mu\,(p - \bar{\alpha} w_A)$. When $\bar{\alpha} w_A < p$, so that effective cost-sharing stays below the net price, this reparametrization leaves the pooling-at-the-cap structure unchanged. We therefore lose no generality by normalizing $w_A = p$.

Lemma 2 ((Pooled Equilibrium under Caps)). *In the single-drug game (drug A with $w_A = p$), and under the assumption that gains to trade exist, together with mild regularity conditions on preferences and the type distribution, every Nash equilibrium has all active plans offering coinsurance $\alpha = \bar{\alpha}$ and a common premium $r^\star = \mu^\star \cdot p \cdot (1 - \bar{\alpha})$, where $\mu^\star = \mathbb{E}\,[\theta|\,\theta \geqslant \theta^\star]$ and $\theta^\star$ is the lowest type preferring this plan to remaining uninsured. If, in addition, the participation condition pinning down $\theta^\star$ admits a unique solution, the equilibrium is unique.*

Intuitively, plans are pushed towards the coinsurance cap by two forces. The first is the standard cream-skim argument of Rothschild and Stiglitz (1976), where any equilibrium with a pool at $\alpha^\star < \bar{\alpha}$ can be broken by a deviator offering $(\alpha^\star + \varepsilon, r^\star - \delta)$ that attracts the healthiest patients out of the original pool. The second is the premium wedge κ. Our formal proof in Appendix A.3 shows that either one of these two forces can generate the pooling result.[23]

[23] In the absence of adverse selection, the premium wedge κ must be large enough to offset the risk aversion of patients near the participation margin—formally, a slope condition ($\kappa\mu^\star > 1$), which holds throughout the empirically relevant range $\kappa \in [2, 5]$. The pooling-at-the-cap conclusion fails without it; Appendix A.3 treats the knife-edge case $\kappa = 1$.

Proof. Since $w = p$, effective cost-sharing at coinsurance α is $c = \alpha p$. Plans choose $\alpha \in [0, \bar{\alpha}]$ and charge a premium r. Free entry imposes a zero profit condition. A plan attracting the set of types $S \subseteq [0, 1]$ charges

$$r = \mathbb{E}[\theta | \theta \in S] \cdot (1 - \alpha) p. \tag{A2}$$

Patient utility on plan (α, r) is

$$U(\theta, \alpha, r) = (1 - \theta) u(W - \kappa r) + \theta u(W - \kappa r - \alpha p),$$

and the outside option is $U^0(\theta) = (1 - \theta) u(W) + \theta u(W - \bar{p})$.

We proceed in six steps.

1. **Single-crossing in α.** We start by establishing the sorting property behind the cream-skim argument: higher-risk types have a stronger preference for lower coinsurance (more generous coverage), so that any deviation raising α attracts a "healthy slice" from the bottom of the pool.

   For any plan (α, r), define the absolute rate of substitution between coinsurance α and premium r as

   $$\text{ARS}(\theta) = \frac{|\partial U / \partial \alpha|}{|\partial U / \partial r|} = \frac{\theta p u'(W - \kappa r - \alpha p)}{\kappa [(1 - \theta) u'(W - \kappa r) + \theta u'(W - \kappa r - \alpha p)]},$$

   which is positive since both $\partial U / \partial \alpha < 0$ and $\partial U / \partial r < 0$. Write $a = u'(W - \kappa r)$ and $b = u'(W - \kappa r - \alpha p)$ with $b > a > 0$ (by strict concavity), so

   $$\text{ARS}(\theta) = \frac{p}{\kappa} \cdot \frac{1}{1 + \frac{(1-\theta) a}{\theta b}}.$$

   The ratio $\frac{(1-\theta) a}{\theta b}$ is strictly decreasing in θ, so $\text{ARS}(\theta)$ is strictly increasing in θ: sicker patients have a higher willingness to pay (in premium) for a marginal reduction in coinsurance.

2. **No equilibrium with a pool at $\alpha^\circ < \bar{\alpha}$.**

   Assume that the Nash equilibrium has all active plans pooling at some $\alpha^\circ \in [0, \bar{\alpha})$ with zero-profit premium $r^\circ = \mu^\circ \cdot (1 - \alpha^\circ) p$, where $\mu^\circ = \mathbb{E}[\theta | \theta \geqslant \theta^\circ]$ and θ° is the marginal type.

   Choose $\varepsilon > 0$ small enough that $\alpha^\circ + \varepsilon \leqslant \bar{\alpha}$. A deviating plan offers $(\alpha^\circ + \varepsilon, r_{\text{dev}})$,

where r_{dev} is set so that a type $\hat{\theta} \in (\theta^\circ, 1)$ is indifferent between the deviating plan and the incumbent pool:

$$U\left(\hat{\theta}, \alpha^\circ + \varepsilon, r_{dev}\right) = U\left(\hat{\theta}, \alpha^\circ, r^\circ\right).$$

By single crossing (Step 1), every type $\theta < \hat{\theta}$ in the original pool strictly prefers the deviating plan. The deviator attracts at least the types in $\left[\theta^\circ, \hat{\theta}\right)$ from the incumbent pool. Some types below θ° who were previously uninsured may also find the deviation attractive, since it offers a lower premium than the plan they rejected (despite higher coinsurance). If any such types enroll, they have $\theta < \theta^\circ < \mu^\circ$, so they further lower the deviator's average risk and strengthen profitability. This set has positive measure since $f(\theta) > 0$. The mean risk of these types is

$$\mu_{dev} = \mathbb{E}\left[\theta | \, \theta \in \left[\theta^\circ, \hat{\theta}\right)\right] < \mu^\circ,$$

strictly below the pool mean. The deviator's zero-profit premium is $r^0_{dev} = \mu_{dev} \cdot (1 - \alpha^\circ - \varepsilon)\, p$, and the premium it can charge (pinned by the indifference condition) satisfies $r_{dev} > r^0_{dev}$ for ε sufficiently small. Because the cost advantage $\mu^\circ - \mu_{dev} > 0$ is bounded away from zero while the premium concession is $O(\varepsilon)$, the deviator earns strictly positive profit, contradicting the assumption that the pool at α° is a Nash equilibrium.

3. **The pool at $\alpha = \bar{\alpha}$ cannot be cream-skimmed.**

   We show that the candidate equilibrium admits no profitable deviation. The regulatory cap rules out an upwards deviation in the coinsurance *($\alpha > \bar{\alpha}$)*. A deviation that keeps the coinsurance but alters the premium is also not relevant. A plan offering $(\bar{\alpha}, r_d)$ with $r_d < r^\star$ attracts the full pool but earns a strictly negative profit. A plan with $r_d > r^\star$ attracts no one.

   Therefore, we focus on downward deviations that attract sicker types ($\alpha_d < \bar{\alpha}$). A plan offering (α_d, r_d) with $\alpha_d < \bar{\alpha}$ provides more generous coverage at a higher premium. By single crossing, a type $\tilde{\theta}$ indifferent between the deviation and the incumbent pool satisfies

   $$U\left(\tilde{\theta}, \alpha_d, r_d\right) = U\left(\tilde{\theta}, \bar{\alpha}, r^\star\right),$$

   and types above $\tilde{\theta}$ (sicker) strictly prefer the deviation. The deviator therefore

attracts types $\theta \in \left(\tilde{\theta}, 1\right]$ with mean risk

$$\mu_d = \mathbb{E}\left[\theta | \theta \in \left(\tilde{\theta}, 1\right]\right] > \mu^\star.$$

The zero-profit premium for this pool is $r_d^0 = \mu_d \cdot (1 - \alpha_d)\, p$. For the deviation to earn positive profit, the premium must satisfy $r_d > r_d^0$.

We show this fails by comparing slopes in (c, r) space, where $c = \alpha p$ is effective cost-sharing. The zero-profit locus for the pool $\left[\tilde{\theta}, 1\right]$ is the line $r = \mu_d (p - c)$ with slope $-\mu_d$. The indifference curve of type $\tilde{\theta}$ through the incumbent point $(\bar{\alpha}p, r^\star)$ has slope $-\text{ARS}\left(\tilde{\theta}\right)/p$ (from Step 1), and since $\text{ARS}\left(\tilde{\theta}\right) < p/\kappa$ for all $\tilde{\theta} < 1$ at every (c, r), the indifference curve is shallower than the zero-profit line whenever $1/\kappa < \mu_d$. Since $\mathbb{E}\left[\theta | \theta \geqslant \tilde{\theta}\right]$ is increasing in $\tilde{\theta}$ and $\tilde{\theta} \geqslant \theta^\star$, the condition $\kappa\mu^\star > 1$ is sufficient.[24]

The slope bound from Step 1 holds pointwise: $ARS(\theta) < p/\kappa$ at every (c, r), not only at the incumbent point, since the factor $\frac{1}{1+((1-\theta)a/\theta b)}$ is strictly below one for every $\theta < 1$. Hence along type $\tilde{\theta}$'s indifference curve through $(\bar{\alpha}p, r^\star)$ the slope satisfies

$$\left|\frac{dr}{dc}\right| = ARS\left(\tilde{\theta}\right)/p < \frac{1}{\kappa} < \mu_d$$

at every $c < \bar{\alpha}p$, where the last inequality uses $\kappa\mu_d \geqslant \kappa\mu^\star > 1$. At $c = \bar{\alpha}p$ the indifference curve passes through $r^\star = \mu^\star(p - \bar{\alpha}p)$, which lies strictly below the deviator's zero-profit line $r = \mu_d(p - c) = \mu_d(1 - \bar{\alpha})\, p$ because $\mu_d > \mu^\star$; and since the line rises strictly faster than the indifference curve as c falls, the curve remains strictly below it for all $c < \bar{\alpha}p$. Therefore the indifference premium r_d is strictly below the break-even premium r_d^0 for any deviation $\alpha_d < \bar{\alpha}$, and the deviator cannot earn positive profit.

Remark on $\kappa = 1$. At $\kappa = 1$, the condition $\kappa\mu^\star > 1$ reduces to $\mu^\star > 1$, which fails since $\mu^\star = \mathbb{E}[\theta | \theta \geqslant \theta^\star] < 1$. The slope comparison must then hold directly. Downward deviations $\alpha_d < \bar{\alpha}$ are unprofitable if and only if

$$\frac{\text{ARS}\left(\tilde{\theta}\right)}{p} < \mathbb{E}\left[\theta | \theta \geqslant \tilde{\theta}\right] \qquad \text{for all } \tilde{\theta} \in [\theta^\star, 1), \tag{R1}$$

[24] The condition $\kappa\mu^\star > 1$ is satisfied throughout the empirically relevant range $\kappa \in [2, 5]$ for any type distribution with $\mathbb{E}[\theta | \theta \geqslant \theta^\star] > 1/\kappa$. At $\kappa = 1$, the bound $\text{ARS}\left(\tilde{\theta}\right) < p$ does not suffice on its own; the argument requires a joint restriction on $u(\cdot)$ and F (condition R1), stated in the Remark below.

a joint restriction on preferences *and* the type distribution. At $\kappa = 1$, $\text{ARS}\left(\tilde{\theta}\right)/p > \tilde{\theta}$ always holds (since $b > a$), so R1 requires the conditional mean to exceed $\tilde{\theta}$ by enough, and it can fail when F concentrates mass just above an interior point, and a deviator targeting that slice breaks the pool.

The limit $\tilde{\theta} \to 1$ (a deviation targeting a thin slice of enrollees) yields a necessary condition. Writing $b/a = u'(W - r^\star - \bar{\alpha}p)/u'(W - r^\star)$ for the marginal utility ratio and expanding to first order in $\varepsilon = 1 - \tilde{\theta}$ gives $\text{ARS}/p \approx 1 - \varepsilon(a/b)$ while $\mu_d \approx 1 - \varepsilon/2$ (for any distribution with continuous, positive density at $\theta = 1$), so the slope condition holds in the limit whenever $a/b > 1/2$, i.e., $b/a < 2$.

For the uniform distribution, this necessary condition is also sufficient: at $b/a = 2$, R1 reduces to $2\tilde{\theta}/\left(1 + \tilde{\theta}\right) < \left(1 + \tilde{\theta}\right)/2$, i.e., $\left(1 - \tilde{\theta}\right)^2 > 0$, which holds for all $\tilde{\theta} < 1$ with the limit $\tilde{\theta} \to 1$ as the unique binding case (and is slack everywhere for $b/a < 2$). For CRRA utility with coefficient γ, $b/a = (1 - \bar{\alpha}p/(W - r^\star))^{-\gamma}$, so the condition $b/a < 2$ is equivalent to $\gamma < \frac{\ln 2}{\ln\left(\frac{1}{1 - \bar{\alpha}p/(W - r^\star)}\right)}$. At a drug-cost-to-income ratio $\bar{\alpha}p/(W - r^\star) = 0.03$, this allows $\gamma \leqslant 22$; at 0.10, it allows $\gamma \leqslant 6.6$. At $\kappa = 1$ we therefore maintain R1, which is satisfied, e.g., by CRRA preferences with empirically standard risk-aversion coefficients ($\gamma \leqslant 5$) together with a uniform (or near-uniform) type distribution.

4. **No separating equilibrium.**

   Suppose a Nash equilibrium features multiple active contracts $\{(\alpha_j, r_j)\}_{j=1}^J$ with $\alpha_1 < \cdots < \alpha_J \leqslant \bar{\alpha}$ and $J \geqslant 2$. By single crossing, each contract attracts a connected interval of types, and less generous contracts (higher α_j) attract healthier (lower-θ) types. The type intervals are therefore ordered opposite to the coinsurance index: contract J (least generous) occupies the healthiest interval at the bottom, and contract 1 (most generous) the sickest types up to $\theta = 1$. Write contract j's interval as $\left[\underline{\theta}_j, \bar{\theta}_j\right]$, with $\underline{\theta}_J \leqslant \bar{\theta}_J = \underline{\theta}_{J-1} \leqslant \cdots \leqslant \bar{\theta}_1 = 1$.

   Consider the least generous sub-cap contract—the active contract with the highest $\alpha_j < \bar{\alpha}$ (it exists because $\alpha_1 < \cdots < \alpha_J \leqslant \bar{\alpha}$ with $J \geqslant 2$ leaves at most one contract at the cap). Apply the Step 2 cream-skim to its pool: a deviator offering $(\alpha_j + \varepsilon, r_{\text{dev}})$, with ε small enough that $\alpha_j + \varepsilon \leqslant \bar{\alpha}$, attracts the healthiest types of $\left[\underline{\theta}_j, \bar{\theta}_j\right]$ at strictly positive profit, breaking it. Hence no active contract can sit strictly below the cap, and all active plans pool at $\bar{\alpha}$ (which, by Step 3, is itself not cream-skimmable), collapsing the menu to a single contract.

5. **Existence.**

   Steps 1–3 establish that any Nash equilibrium must pool at $\bar{\alpha}$. We verify the candidate equilibrium is internally consistent.

   (a) *Participation.* Define $V(\theta) \equiv U(\theta, \bar{\alpha}, r^\star) - U^0(\theta)$. At $\theta = 0$: $V(0) = u(W - \kappa r^\star) - u(W) < 0$. The gains-to-trade assumption implies $V(\theta) > 0$ for θ near 1. By the intermediate value theorem, $\theta^\star \in (0,1)$ exists.

   (b) *Monotonicity.* Since $U(\theta, \bar{\alpha}, r^\star) = u(W - \kappa r^\star) + \theta\,[u(W - \kappa r^\star - \bar{\alpha} p) - u(W - \kappa r^\star)]$ and $U^0(\theta) = u(W) + \theta\,[u(W - \bar{p}) - u(W)]$, $V(\cdot)$ is affine in θ. Combined with $V(\theta^\star) = 0$ and $V(1) > 0$, this gives $V' > 0$. All $\theta > \theta^\star$ strictly prefer the pool to the outside option.

   (c) *Zero profit.* By construction, $r^\star = \mu^\star(1 - \bar{\alpha})\,p$.

   (d) *Fixed-point consistency.* Define the mapping $\theta \mapsto T(\theta)$ as the solution to $U(T, \bar{\alpha}, \mathbb{E}[\theta' | \theta' \geqslant \theta](1 - \bar{\alpha})\,p) = U^0(T)$. The map T is continuous in θ (U, U^0, and the pooled premium $\mathbb{E}[\theta' | \theta' \geqslant \theta](1 - \bar{\alpha})\,p$ all vary continuously, the last because $f > 0$). At $\theta = 0$ the pooled premium is strictly positive while a type-0 enrollee never files a claim, so $U(0, \bar{\alpha}, \cdot) = u(W - \kappa r) < u(W) = U^0(0)$ and the indifferent type is strictly positive: $T(0) > 0$. At $\theta = 1$ the premium is $(1 - \bar{\alpha})\,p$, and the gains-from-trade assumption makes the sickest type strictly prefer the pooled contract to remaining uninsured, so $T(1) < 1$. Writing $g(\theta) \equiv T(\theta) - \theta$, continuity together with $g(0) > 0$ and $g(1) < 0$ yields, by the intermediate value theorem, a fixed point $\theta^\star = T(\theta^\star)$.

6. **Uniqueness of the participation margin.**

   Steps 1–3 imply that any Nash equilibrium pools at $\bar{\alpha}$, so equilibria can differ only in the participation margin, which must solve the fixed-point equation

$$\Psi(\theta) \equiv U(\theta, \bar{\alpha}, \mathbb{E}[\theta' | \theta' \geqslant \theta](1 - \bar{\alpha})\,p) - U^0(\theta) = 0.$$

   Multiple solutions cannot be ruled out in general. Suppose $\theta_0 < \theta_1$ are both solutions, with pools $[\theta_0, 1]$ and $[\theta_1, 1]$, mean risks $\mu_0 < \mu_1$, and zero-profit premiums $r_0 = \mu_0(1 - \bar{\alpha})\,p < r_1 = \mu_1(1 - \bar{\alpha})\,p$. Against the candidate equilibrium at θ_1, an entrant offering $(\bar{\alpha}, r_0 - \varepsilon)$ attracts the pool $[\theta'(\varepsilon), 1]$ with $\theta'(\varepsilon)$ slightly below θ_0, and earns profit per enrollee

$$r_0 - \varepsilon - \mathbb{E}[\theta | \theta \geqslant \theta'(\varepsilon)](1 - \bar{\alpha})\,p = (\mu_0 - \mathbb{E}[\theta | \theta \geqslant \theta'(\varepsilon)])(1 - \bar{\alpha})\,p - \varepsilon,$$

in which both terms are $O(\varepsilon)$. Whether entry is profitable depends on whether the average-cost schedule is flatter or steeper than the demand schedule at the crossing, the typical source of multiple equilibria in selection markets. We therefore impose, as a maintained regularity condition, that Ψ admits a unique root on $(0, 1)$, equivalently that the demand and average-cost schedules cross only once. Under this condition, Steps 1–4 deliver a unique equilibrium. We emphasize that the coverage prediction (pooling at $\alpha = \bar{\alpha}$) holds in *every* equilibrium regardless of this condition. Only the participation margin requires it.

□

A.4 List Prices as a Cap Workaround (Proposition 3)

Next, we consider a game where a second, identical drug is available (drug B) with list price $w_B > p$, but the same net price p as drug A (achieved by sending a rebate $d_B = w_B - p$ to plans). We also assume that both drugs are available to uninsured patients at the same exogenously set price $\bar{p}$.

Plans choose which drug $k \in \{A, B\}$ to cover in addition to their coinsurance $\alpha \in [0, \bar{\alpha}]$. The patient's effective cost-sharing on a plan covering drug k at coinsurance α is αw_k. While the cap restricts $\alpha \leqslant \bar{\alpha}$ uniformly across drugs, it does not restrict the product αw_k. For drug B, effective cost-sharing can reach $\bar{\alpha} w_B$, strictly above the maximum $\bar{\alpha} p$ available on drug A. Drug B therefore expands the set of feasible effective cost-sharing levels beyond what had been allowed by the cap in the single-drug game.

Proposition 3 ((List Prices as a Cap Workaround)). *In the two-drug game with $w_B \in \left(p, \frac{p}{\bar{\alpha}}\right)$ and under the same regularity conditions as Lemma 2, every Nash equilibrium has all active plans covering drug B at $\alpha = \bar{\alpha}$, with effective cost-sharing $c^\star = \bar{\alpha} w_B$ and premium $r^{\star\star} = \mu^{\star\star}(p - \bar{\alpha} w_B)$, where $\mu^{\star\star} = \mathbb{E}[\theta | \theta \geqslant \theta^{\star\star}]$ and $\theta^{\star\star}$ is the marginal enrollee under the new pool. If, in addition, the participation condition pinning down $\theta^{\star\star}$ admits a unique solution, the equilibrium is unique.*

Proof. We reparametrize the two-drug game in terms of effective cost-sharing $c = \alpha w_k$. As established in the proof of Proposition 1, patient utility and plan profit depend on a plan's strategy (k, α, r) only through (c, r), because the rebate $d_k = w_k - p$ offsets the higher pharmacy payment (net cost per fill is $p - c$ regardless of which drug is covered).

The set of c-values feasible to a plan covering drug k at coinsurance $\alpha \in [0, \bar{\alpha}]$ is $[0, \bar{\alpha} w_k]$. Across both drugs, the feasible c-set is therefore $[0, \bar{\alpha} w_A] \cup [0, \bar{\alpha} w_B] = [0, \bar{\alpha} w_B]$, since $w_B > w_A = p$.

For $w_B \in \left(p, \frac{p}{\bar{\alpha}}\right)$, we have $\bar{\alpha} w_B < p$, so the upper bound $c \leqslant \bar{\alpha} w_B$ binds before the zero-profit constraint $c \leqslant p$ (which requires $r = \mu(p - c) \geqslant 0$). The game in (c, r) space is therefore isomorphic to a single-drug game with an effective cap at $\bar{\alpha} w_B$: the feasible set is $[0, \bar{\alpha} w_B] \times \mathbb{R}_+$ and the payoff functions are identical to the single-drug setup with cap $\bar{\alpha} w_B / p$ applied to the net price p.

By Lemma 2, every equilibrium of this reparametrized game pools at the effective cap, $c^\star = \bar{\alpha} w_B$. This pooling level requires $\alpha = \bar{\alpha} w_B / p > \bar{\alpha}$ on drug A (since $w_B > p$), which is infeasible. It is achievable only by covering drug B at $\alpha = \bar{\alpha}$.

The equilibrium premium is determined by the zero-profit condition:

$$r^{\star\star} = \mu^{\star\star}(p - \bar{\alpha} w_B),$$

where $\mu^{\star\star} = \mathbb{E}[\theta | \theta \geqslant \theta^{\star\star}]$ and $\theta^{\star\star}$ is the marginal type indifferent between the pool and the outside option. Existence of $\theta^{\star\star}$ follows from the fixed-point argument in Step 5 of the proof of Lemma 2. Uniqueness holds under the maintained participation-margin regularity condition (Step 6), applied to the reparametrized game. □

A.5 Optimal List Price Setting (Proposition 4)

This subsection states and proves the result that the floor $w = p$ is not an equilibrium of the manufacturers' list-price-setting game. We hold the net price p as constant throughout, and focus on modeling the list price-setting game between the manufacturers of drugs A and B.

Each manufacturer $k \in \{A, B\}$ chooses $w_k \geqslant p$ taking the rival's choice as given. Let $Q_k(w_A, w_B)$ denote the expected number of fills of drug k in the insurance-market equilibrium characterized in Lemma 2 and Proposition 3. Because each type-θ patient fills with probability θ, we have $Q_k = \mu_k \cdot M_k$, where M_k is enrollment and μ_k is the average risk of enrollees in drug-k plans. Manufacturer profits are

$$\pi_k(w_A, w_B) = p \cdot Q_k(w_A, w_B) - \Lambda(w_k - p) \tag{A3}$$

where $\Lambda(\cdot)$ is an institutional penalty on the rebate capturing regulatory, reputational, and negotiation frictions, with $\Lambda(0) = \Lambda'(0) = 0$.[25] We ignore the market for uninsured individuals.[26] At $w_A = w_B$ the two drugs are observationally equivalent (both

[25] The presence of $\Lambda(\cdot)$ prevents list prices from going to infinity—a role similar to the political constraint parameter in Che (2025)—but otherwise does not affect Proposition 4.

[26] This is consistent with our previous treatment of $\bar{p}$ as exogenous. The uninsured revenue stream

deliver the same range of effective cost-sharing), so we assume $Q_A = Q_B$ in this case.

Proposition 4 ((Floor not Nash)). *Under the same regularity conditions as Lemma 2, the symmetric configuration $w_A = w_B = p$ is not a Nash equilibrium of the list-price-setting game. For any sufficiently small $\delta > 0$, either manufacturer can profitably deviate to $w_k = p + \delta$.*

Proof. At $(w_A, w_B) = (p, p)$, the two drugs are observationally equivalent and the insurance-market equilibrium is the Lemma 2 pool at $\bar{\alpha}$ with total expected fills $Q(p) = \mu^\star [1 - F(\theta^\star)]$. By the symmetric tie-breaking convention, each manufacturer captures $Q_k = Q(p)/2$.

Consider a deviation by manufacturer B to $w_B = p + \delta$ for $\delta > 0$. For δ small enough that $p + \delta < p/\bar{\alpha}$, Proposition 3 applies: the unique insurance-market equilibrium has all active plans covering drug B at $\alpha = \bar{\alpha}$.

Revenue gain. Manufacturer B's expected fills jump from $Q(p)/2$ to $Q_B(p, p + \delta)$. Since the new pool covers all insured types (with a marginal type $\theta^{\star\star}$ satisfying $\theta^{\star\star} \to \theta^\star$ as $\delta \to 0$ by continuity of the equilibrium), we have $Q_B(p, p + \delta) = Q(p) + O(\delta)$, where the $O(\delta)$ term reflects the movement of the participation margin; its sign depends on whether the premium reduction or the higher cost-sharing dominates for the marginal type, and is immaterial to the argument. The revenue gain is

$$\Delta\pi_B^{\text{rev}} = p \cdot [Q(p) + O(\delta)] - p \cdot \frac{Q(p)}{2} = \frac{p \cdot Q(p)}{2} + O(\delta),$$

which is bounded away from zero—an $O(1)$ gain from capturing the rival's half of the market.

Penalty cost. The institutional penalty is $\Lambda(\delta)$. By assumption, $\Lambda(0) = \Lambda'(0) = 0$, so Taylor expansion gives $\Lambda(\delta) = O(\delta^2) = o(\delta)$.

Net gain. The change in manufacturer B's profit is

$$\Delta\pi_B = \frac{p \cdot Q(p)}{2} + O(\delta) - o(\delta) > 0$$

for all $\delta > 0$ sufficiently small. A symmetric argument applies to manufacturer A deviating to $w_A = p + \delta$ while holding $w_B = p$. Therefore, (p, p) is not a Nash equilibrium. □

is likely to be second order and the existence of patient assistance programs decouples list prices and the prices faced by uninsured patients. Including profits from uninsured individuals does not alter the implications of the model, but introduces some additional mathematical complexity because increasing list price can affect the number of patients who are uninsured.

A.6 List Price Setting Under Smoother Demand Functions

To move to a less stark setup, we assume that $Q_k(w_A, w_B)$ varies smoothly in list prices.

Define $\Phi(w_A, w_B) = p \cdot \frac{\partial Q_B}{\partial w_B}$ as the marginal revenue gain from a small list-price increase (Φ also depends on the cap $\bar{\alpha}$ through the insurance-market equilibrium; we suppress this argument except where the comparative static in $\bar{\alpha}$ is concerned).

Proposition 5 ((Equilibrium List Price)). *Suppose that*

1. $Q_k(w_A, w_B)$ *is twice continuously differentiable and the game is symmetric under relabeling the two drugs—*$Q_A(w_A, w_B) = Q_B(w_B, w_A)$ *for all* (w_A, w_B)*, with a common penalty* $\Lambda(\cdot)$ *(which implies* $Q_A(w, w) = Q_B(w, w)$ *on the diagonal);*

2. $\Phi(p, p) > 0$*;*

3. $\Phi(w_A, w_B)$ *is non-increasing in each argument, with the own effect dominating the cross effect (*$|\partial\Phi/\partial w_B| \geqslant |\partial\Phi/\partial w_A|$*);*

4. $\Lambda(\cdot)$ *is uniformly strictly convex (*$\Lambda'' \geqslant \underline{c} > 0$ *on* $[0, \bar{d}]$*) with* $\Lambda'(0) = 0$*, and* $\Lambda'(d) \to \infty$ *as* $d \to \bar{d}$ *for some upper bound* $\bar{d}$*, with* $\bar{w} \equiv p + \bar{d}$ *for the corresponding upper bound on the list price;*

Then the list-price-setting game has a unique Nash equilibrium at $w^\star > p$*, characterized by the first-order condition*

$$\Lambda'(w^\star - p) = \Phi(w^\star, w^\star) \tag{A4}$$

Moreover, if $\partial\Phi/\partial\bar{\alpha} > 0$*, then* $w^\star$ *is increasing in the coinsurance cap* $\bar{\alpha}$*.*

Proof. Manufacturer B's profit is

$$\pi_B(w_A, w_B) = p \cdot Q_B(w_A, w_B) - \Lambda(w_B - p).$$

1. *Existence and uniqueness.* The first-order condition for manufacturer B is

$$\frac{\partial \pi_B}{\partial w_B} = \Phi(w_A, w_B) - \Lambda'(w_B - p) = 0 \tag{A5}$$

where $\Phi(w_A, w_B) = p \cdot \partial Q_B/\partial w_B$. By condition (iii), $\Phi(w_A, w_B)$ is non-increasing in w_B for each w_A, and by condition (iv), $\Lambda'(\cdot)$ is strictly increasing. Hence the left-hand side of (A5) is strictly decreasing in w_B: manufacturer B's profit π_B is strictly concave in w_B for each w_A, giving at most one solution. Strict concavity

in own price rules out mixed-strategy equilibria: against any mixed strategy σ_A of the rival, the expected payoff $\int \pi_B(w_A, w_B)\, d\sigma_A(w_A)$ is a mixture of strictly concave functions and hence itself strictly concave in w_B, so manufacturer B has a unique pure best response to any σ_A and cannot randomize in equilibrium. Any symmetric fixed point must satisfy

$$\Lambda'(w^\star - p) = \Phi(w^\star, w^\star).$$

We first show this equation has a unique solution in $(p, \bar{w})$, then show the best-response map is a contraction, so this symmetric fixed point is the unique Nash equilibrium.

At a candidate symmetric equilibrium $w_A = w_B = w^\star$, the condition becomes $\Lambda'(w^\star - p) = \Phi(w^\star, w^\star)$.

At $w^\star = p$: the left-hand side is $\Lambda'(0) = 0$ while the right-hand side is $\Phi(p, p) > 0$ by condition (ii). At $w^\star \to \bar{w}$ (where $\Lambda'(\bar{w} - p) \to \infty$ by condition (iv)): the left-hand side exceeds the right-hand side (since Φ is bounded by smoothness of Q_B). By continuity of both sides and the intermediate value theorem, a solution $w^\star \in (p, \bar{w})$ exists. Since $\Lambda'(\cdot)$ is strictly increasing and $\Phi(w, w)$ is non-increasing in w along the diagonal (by condition (iii), both partial derivatives of Φ are non-positive), the symmetric solution is unique.

Finally, we rule out asymmetric pure-strategy equilibria. Implicit differentiation of (A5) gives the best-response slope

$$\frac{dw_B^\star}{dw_A} = \frac{\partial\Phi/\partial w_A}{\Lambda''(w_B - p) - \partial\Phi/\partial w_B},$$

whose absolute value is uniformly below one. Since the best response is continuous, piecewise continuously differentiable, has slope zero on any lower-corner region, and has derivative bounded in absolute value by $\rho < 1$ wherever interior, the mean-value theorem applied piecewise implies that each best response is globally Lipschitz with modulus ρ. By the uniform strict convexity of Λ (condition (iv)), $\Lambda'' \geqslant \underline{c} > 0$, so the denominator satisfies $\Lambda'' + |\partial\Phi/\partial w_B| \geqslant \underline{c} + |\partial\Phi/\partial w_A|$ using the own-dominance in condition (iii). Hence $|dw_B^\star/dw_A| \leqslant M/(\underline{c} + M) < 1$, where $M = \sup|\partial\Phi/\partial w_A| < \infty$ on the compact set $[p, \bar{w}]^2$ (by smoothness of Q_B).

This bound governs the interior of the best response. Strict concavity of π_B in w_B—from Φ non-increasing in w_B (condition (iii)) and the strict convexity of Λ—

makes the best response $w_B^\star(w_A)$ single-valued and continuous. Where it is interior it obeys the first-order condition and the slope bound above; at the lower corner $w_B = p$ it is locally constant (slope 0); and the upper boundary is never optimal, since $\Lambda'(w_B - p) \to \infty$ as $w_B \to \bar{w}$ forces $\partial\pi_B/\partial w_B < 0$. The joint best-response map is therefore a single-valued contraction on $[p, \bar{w}]^2$ with modulus $M/(\underline{c} + M) < 1$, and admits a unique fixed point; by symmetry of the game (condition (i)), that fixed point is the symmetric profile $(w^\star, w^\star)$.

2. *Comparative static.* Apply the implicit function theorem to the equilibrium condition $G(w^\star, \bar{\alpha}) \equiv \Lambda'(w^\star - p) - \Phi(w^\star, w^\star; \bar{\alpha}) = 0$:

$$\frac{dw^\star}{d\bar{\alpha}} = -\frac{\partial G/\partial\bar{\alpha}}{\partial G/\partial w^\star} = -\frac{-\partial\Phi/\partial\bar{\alpha}}{\Lambda''(w^\star - p) - \left.\frac{d\Phi(w,w)}{dw}\right|_{w=w^\star}}.$$

The denominator is positive: $\Lambda'' > 0$ by condition (iv), and $d\Phi(w,w)/dw = \partial\Phi/\partial w_A + \partial\Phi/\partial w_B \leqslant 0$ on the diagonal since condition (iii) makes Φ non-increasing in each argument. The numerator has sign $\partial\Phi/\partial\bar{\alpha} > 0$ under the additional assumption. Hence $dw^\star/d\bar{\alpha} > 0$.

The conditions in the proposition are stated as reduced-form properties of the expected-fills function $Q_k(\cdot)$ and the penalty $\Lambda(\cdot)$, without committing to a particular model of patient demand for drugs. Condition (ii) requires that a marginal list-price increase generates a positive revenue gain. Intuitively, when a manufacturer raises its list price slightly, plans covering its drug can offer lower premiums. Patients who weight premiums heavily sort toward these lower-premium plans, generating a positive demand response. Condition (iii) ensures diminishing returns from further list-price increases for each fixed rival price, which together with the strict convexity of $\Lambda(\cdot)$ guarantees strict concavity of each manufacturer's objective in its own list price. This yields single-valued best responses, ruling out mixed-strategy equilibria. Finally, the dominance of own over cross effects in condition (iii) makes the best-response map a contraction, which rules out asymmetric pure-strategy equilibria as well.

A leading example is Hotelling demand: patients are uniformly distributed on $[0, 1]$ with transport cost $t > 0$, drug A at 0 and drug B at 1, choosing among plans (and thus drugs) after observing premiums and effective cost-sharing. In this case, $Q_B(\cdot)$ varies smoothly in w_B through the premium channel described above, and a sufficient condition for (ii) is $\kappa\mu^\star > 1$, where $\mu^\star$ is the average risk

type in the pool; we omit the derivation.[27]

□

A.7 List Price Passthrough without Adverse Selection

The main text focuses on the adverse selection channel, but the passthrough prediction can also be consistent with a model without adverse selection and just patients overweighting premiums.

Suppose patient risk types θ are *observable* to plans, so each type receives a type-specific contract. All other primitives are as in Appendix A.1. Plans choose coinsurance $\alpha \in [0, \bar{\alpha}]$ with $\bar{\alpha} < 1$, the drug has net price p and list price $w \geqslant p$, and free entry imposes zero profit on every contract. A plan serving type θ therefore charges

$$r(\theta) = \theta(p - \alpha w),$$

and the patient's utility on this contract is

$$U(\theta) = (1-\theta) \cdot u(W - \kappa r) + \theta \cdot u(W - \kappa r - \alpha w).$$

Substituting the zero-profit premium and writing $c = \alpha w$ for effective cost-sharing, the competitive contract maximizes U over $c \in [0, \bar{\alpha} w]$ subject to $r = \theta(p - c) \geqslant 0$.

Differentiating along the zero-profit locus with $a = u'(W - \kappa r)$ and $b = u'(W - \kappa r - c)$ ($b > a$ by strict concavity):

$$\frac{dU}{dc} = \theta[\kappa(1-\theta)a + (\kappa\theta - 1)b]. \tag{A6}$$

At $\kappa = 1$, this reduces to $\theta(1-\theta)(a-b) < 0$: patients prefer lower cost-sharing, as in the standard model. At $\kappa > 1$, the premium-overweighting channel raises both terms. In particular, $dU/dc > 0$ whenever

$$\kappa > \frac{b}{(1-\theta)a + \theta b} \equiv \kappa^{\star}(\theta), \tag{A7}$$

where $\kappa^{\star}(\theta) > 1$ since $b > a$. With $\kappa \in [2, 5]$ (Abaluck and Gruber, 2011), this threshold is exceeded for all but the lowest-risk types under empirically standard preferences, so the competitive contract sets $\alpha = \bar{\alpha}$ for the bulk of the type distribution.

[27] With $\kappa \in [2, 5]$ from Abaluck and Gruber (2011), this is satisfied for plausible parameter values.

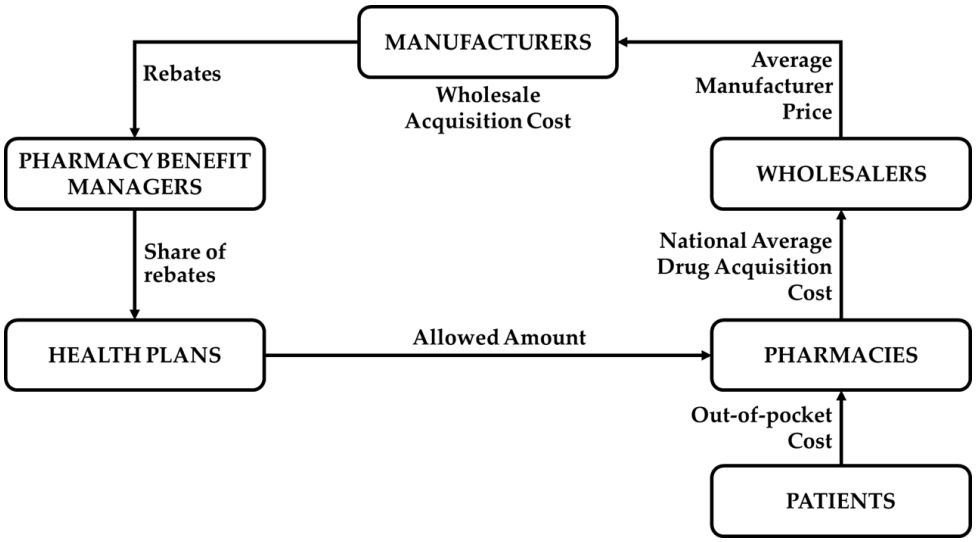

Figure A1: Overview of prices in the market for retail drugs

When $\alpha = \bar{\alpha}$ binds and $w \in (p, p/\bar{\alpha})$, effective cost-sharing is $c = \bar{\alpha}w$ and the zero-profit premium is $r = \theta(p - \bar{\alpha}w) \geqslant 0$. Raising the list price by dw increases out-of-pocket costs by $\bar{\alpha} \cdot dw$, the same passthrough as in Proposition 3. In contrast, unconstrained plans (no cap on α) can adjust α downward to hold c fixed, so list prices remain irrelevant by Proposition 1. The channel shuts off at $w \geqslant p/\bar{\alpha}$, where $r = 0$ and further list-price increases cannot be passed through without violating the non-negative-premium constraint.

The mechanism differs from the main text: the cap binds not because adverse selection drives cream-skimming, but because κ-distorted patients prefer low-premium, high-cost-sharing contracts and competitive plans cater to this preference. The empirical prediction, however, remains identical. List-price increases pass through to patient out-of-pocket costs in cap-constrained plans and not in unconstrained plans.

B Additional Background

B.1 The pharmaceutical distribution chain

Figure A1 shows the steps that transform the WAC into the allowed amount, and the intermediaries involved.

Wholesalers, who pick up drugs from manufacturers and deliver them to pharmacies, are nominally charged the WAC, but typically negotiate small discounts. The aver-

age price paid by wholesalers is called the Average Manufacturer Price (AMP). AMP is reported to the government to comply with several programs (including the Medicaid Drug Rebate Program), but is not disclosed publicly (Peters, 2010). Government reports suggest that the difference between WAC and AMP is small for branded drugs, the focus of our study (between 4-10%), but larger for generics (around 40%) (Department of Health and Human Services, 2005; Congressional Budget Office, 2021).

Pharmacies then buy drugs from wholesalers at a markup above the wholesalers' acquisition cost. Although the acquisition costs for individual pharmacies are unknown, the *average* pharmacy acquisition cost is reported publicly as the National Average Drug Acquisition Cost (NADAC).[28]

Finally, pharmacies and PBMs (or plan sponsors) negotiate a reimbursement price that the pharmacy receives every time a patient fills a prescription. This reimbursement price is what appears under a prescription drug claim's allowed amount.

B.2 The Medicaid Drug Rebate Program

Here, we reproduce Figure 2 of Feng et al. (2023) to illustrate the incentives created by the combination of the basic rebate and the inflation penalty clauses in Medicaid. The scenario represented is the evolution of the Medicaid reimbursement price for a hypothetical drug with a launch list price of $100. In this scenario, the drug's price has doubled since launch, whereas CPI has only increased by 10 percent. As a result, the current Medicaid price is given by $200-$46.2-$90=$63.8, which is lower than the initial Medicaid price of $76.9. This highlights the strong incentives against increasing list price beyond the rate of inflation.

One issue to note is that the inflation penalty introduced as part of the Inflation Reduction Act (IRA) of 2022 creates much weaker incentives. Unlike Medicaid, there is no mandatory rebate rate in Medicare, so the inflation penalty only serves to neutralize any list price increase above the rate of inflation. Of course, Medicare Part B and Medicare Part D prices depend on rebate negotiations by private entities (for Part B through referencing and for Part D through direct negotiations by private insurers and pharmacy benefit managers). If negotiated rebates tend to be a fixed percentage of list price, then the provision would generate similar incentives to those created by the MDRP.

[28] NADAC has been reported since 2013 by the Centers for Medicare and Medicaid Services and is downloadable from https://www.medicaid.gov/medicaid/nadac.

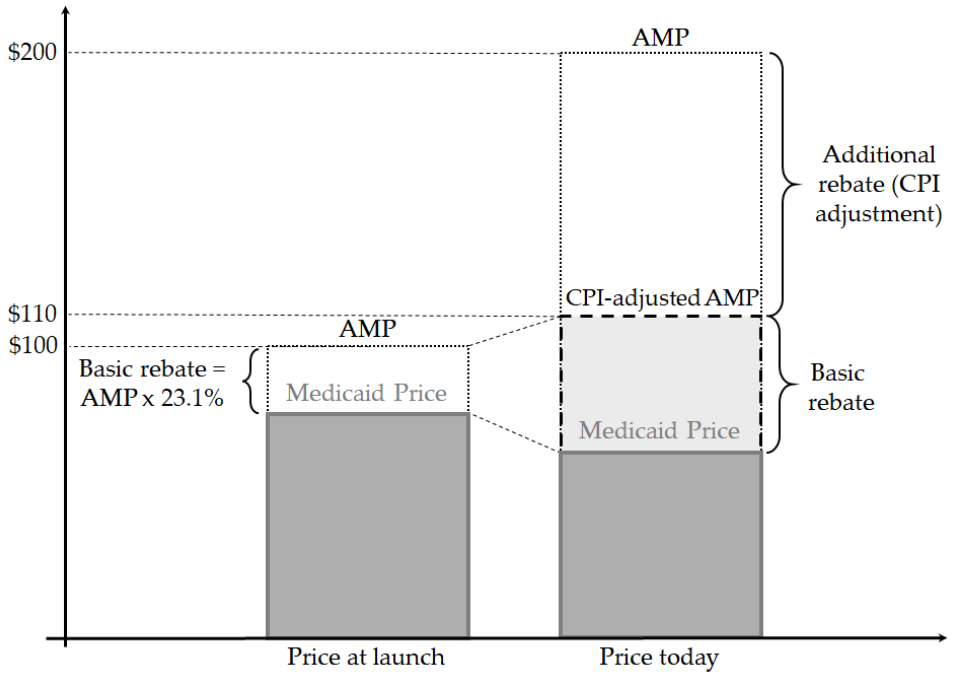

Figure A2: Impact of MDRP on changing list price

Notes: Reproduction of Figure 2 in Feng et al. (2023).

C Additional Results and Robustness Checks

C.1 Drug sample

Table A1: Statistics Related to Sample Selection Criteria

Criterion	Number of excluded drugs	Number of remaining drugs
		941
Part B sales greater than 20%	157	784
Injectables	135	649
Oncology	44	605
Invoice sales less than net sales flag	256	349
Contraceptives and smoking cessation drugs	9	340
Products launched before 1992	12	328
Products with only one year of data	24	304

The table tracks the number of unique drugs remaining after each successive selection criterion. The "invoice sales less than net sales flag" filters out drugs only if their net sales are greater than invoice sales over the entire period in which a drug is in the SSR sample as well as drugs whose net sales are more than 50 percent greater than their invoice sales in any given year other than the launch year and the year before loss of exclusivity. The last two rows implement the market-age restriction at the drug level: we drop products launched before 1992 and products with only one year of data, for which a price change cannot be computed. This yields a core sample of 304 drugs. As described in the main text, the fifteen-year restriction is additionally enforced at the drug-year level: within these 304 drugs we retain only drug-years in which the drug is fifteen or fewer years past launch, so a drug crossing the threshold mid-panel contributes its earlier years but not its later ones. These within-drug exclusions are not reflected in the drug counts above, which is why the estimation sample contains fewer drug-years than the 304-drug core sample alone would imply.

C.2 Market shares of plan types in the MarketScan Data

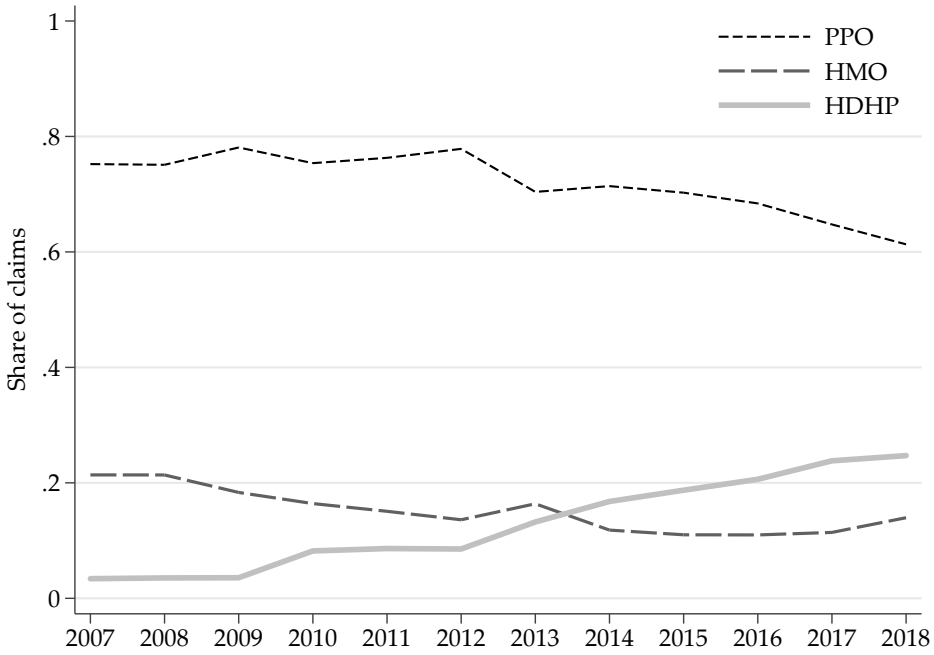

Figure A3: Market shares of plan types in the MarketScan Data

Notes: Plot of share of MarketScan claims from individuals in HMO, PPO, or HDHP plans from 2007 to 2018. A small number of other less common plan types are excluded from this calculation.

C.3 Formulary coverage of biologics and biosimilars, by molecule

Figure A4 plots the coverage rates that underlie Table 4 molecule by molecule, for 2018. The pattern behind the difference-in-differences estimate in Panel B of that table is visible without any regression adjustment: in nearly every molecule, Part D plans cover the biosimilar at a much lower rate than the reference biologic, whereas commercial plans are close to parity between the two. Insulin lispro is the main exception, the one molecule for which commercial coverage of the follow-on product also falls well short of the originator.

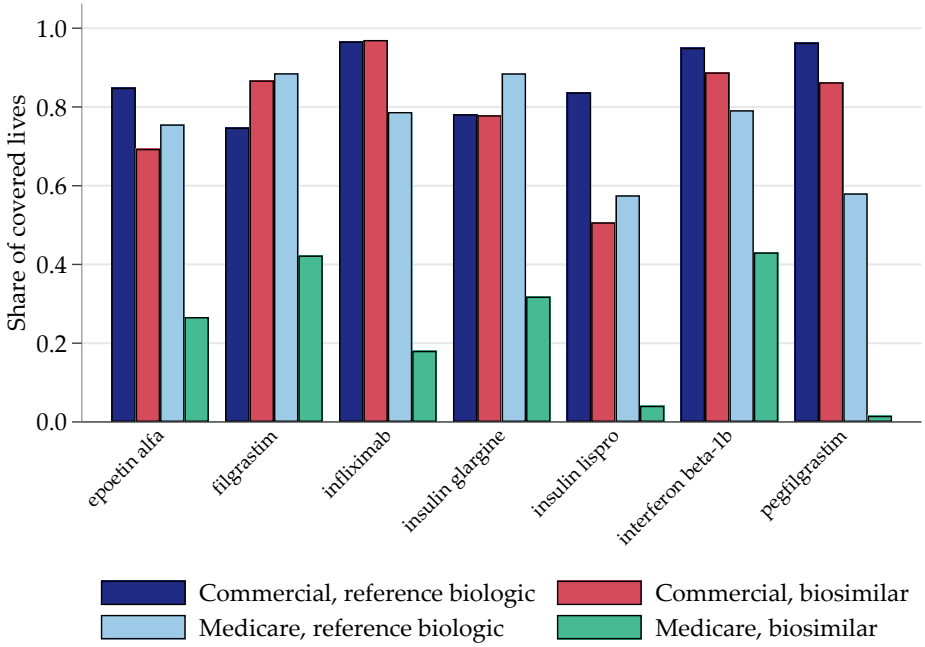

Figure A4: Formulary coverage of biologics and their biosimilars, by molecule and market.

Notes: *Each molecule group reports the share of lives enrolled in plans that cover the originator biologic and the share that cover its biosimilar(s), separately for commercial and Medicare Part D plans. Where a molecule has more than one biosimilar, the biosimilar bar averages coverage across them. Data refer to 2018.*

C.4 Passthrough estimates by payment type (commercial plans)

We report commercial estimates by plan type and, for the full commercial sample, by payment type (deductible, coinsurance, and copay claims) in Table A2.

C.5 Estimates of First-Stage by Age of Drug

Figure A5 presents the estimates of Equation 2, broken down by the age of each drug. The estimates attempt to measure how responsive drugs are to the list price incentives created by the MDRP. As noted in the main text, drugs eventually hit the 100 percent rebate cap, after which the incentives to curb list price growth are nullified. Our estimates for older drugs are consistent with this story.

Table A2: Response in out-of-pocket Costs – Commercial Plans

	$\Delta \log(\text{OOP})$			
	All Plans			
	All claims	Deductible Claims	Coinsurance Claims	Copay Claims
PANEL A. OLS ESTIMATES				
$\Delta \ln(WAC)$	0.164	0.239	0.376	0.134
	(0.076)	(0.120)	(0.162)	(0.062)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES				
$\Delta \ln(WAC)$	-0.107	0.567	0.999	0.000
	(0.321)	(0.327)	(0.406)	(0.301)
Kleibergen-Paap F-stat	22.72	19.14	20.14	22.72
Year FE	X	X	X	X
N	1,618	1,569	1,585	1,618

Notes: Estimates of Equation 1 using claims data from MarketScan. Standard errors clustered at the drug level.

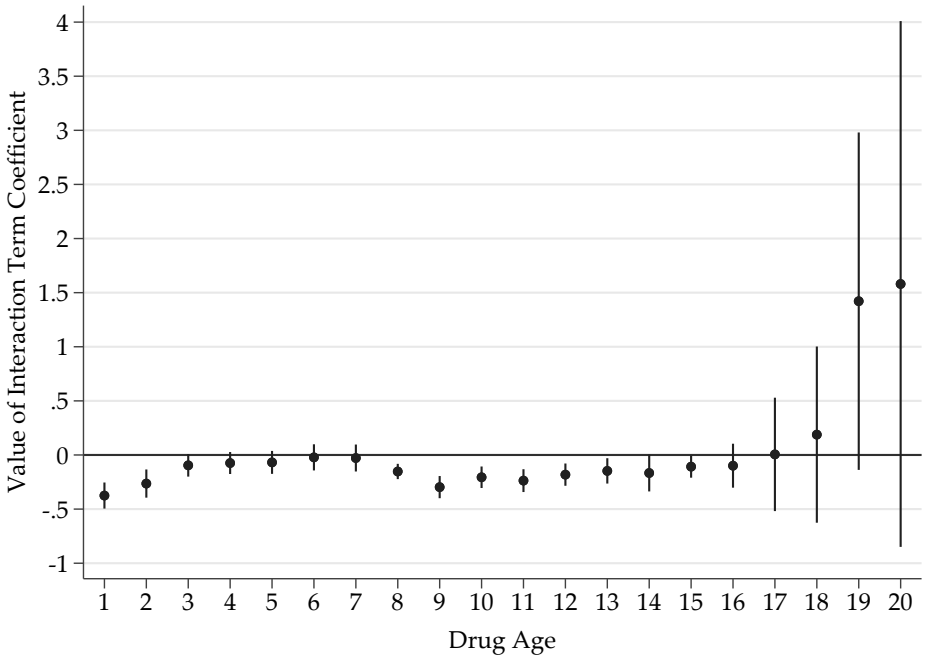

Figure A5: Plot of MMS×Drug-Age FE Coefficients from 1st Stage Model

Notes: Estimates for drug ages above 18 have very large standard errors due to small sample size. For the sake of scale, this plot is restricted to age 20 and under.

C.6 Results including change in net price and therapeutic area fixed effects as controls

We repeat our analysis but add change in net price and broad therapeutic area (ATC-1; see Section 3.3) fixed effects as controls. We find that the results are qualitatively similar, though noisier. This likely reflects a weaker first stage: because Medicaid Market Share is correlated within therapeutic area, the therapeutic area fixed effects absorb much of its variation, leaving less for the instrument to explain.

C.7 Comparison of NADAC and allowed amount increases

We study high-frequency changes in NADAC and allowed amount. NADAC is reported on a weekly basis. Allowed amount can also be calculated on a weekly basis.

Measurement issues: units are potentially not comparable across NADAC and allowed amount. Additionally, allowed amount can vary across pharmacies (e.g., if they are in network or out of network). To minimize these issues we restrict to pills or tablets (where we are reasonably sure that NADAC refers to a single pill and allowed amount

Table A3: First-Stage Estimates (Net Price Control)

	List Price Growth	
	(1)	(2)
MMS	-0.142	-0.137
	(0.0324)	(0.0407)
$\Delta \ln(\text{net})$	0.119	0.117
	(0.0420)	(0.0424)
Year FE	X	X
ATC FE		X
N	1,582	1,574
R^2	0.173	0.194
Kleibergen-Paap F-stat	19.30	11.41

Notes: Estimates of Equation 2, using data from SSR Health on WAC to measure list price growth. Standard errors clustered at the drug level.

per day supply is the comparable number), and to drugs with a sufficiently large number of fills in each week (100 or more). These restrictions limit this analysis to a handful of (potentially unrepresentative) NDCs.

We define a jump in NADAC as

- an increase in NADAC of 2% or more (we do not look at decreases because they are extremely rare)
- that is not preceded by an increase in allowed amount in the previous 4 weeks (we do this in case NADAC increases are reported with a lag)
- and that is permanent (i.e. does not return back to baseline within 4 weeks)

We then identify increases in allowed amount following these jumps in NADAC by applying a similar algorithm *starting with the week in which NADAC jumped*. The time between a NADAC jump and an allowed amount jump is considered a "lag." Figure A6 shows an example of the patterns identified by this algorithm for one of the drugs in the sample.

Figure A7 shows the distribution of lags after each increase in NADAC. We find that in around 60% of cases, the jump is immediately (i.e., in the same week) followed by a jump in allowed amount. However, in the remaining 40% of cases, we find a lag. The average lag (conditional on existing) is about 12 weeks.

Table A4: Response in out-of-pocket Costs – Commercial Plans (Net Price Control)

	$\Delta \log(\text{OOP})$													
	All Plans								PPO		HMO		HDHP	
	All claims		Deductible Claims		Coinsurance Claims		Copay Claims		All claims		All claims		All claims	
Panel A. OLS Estimates														
$\Delta \ln(WAC)$	0.231	0.229	0.254	0.235	0.313	0.291	0.165	0.166	0.201	0.194	0.110	0.121	0.279	0.258
	(0.082)	(0.082)	(0.121)	(0.117)	(0.161)	(0.158)	(0.065)	(0.067)	(0.085)	(0.084)	(0.061)	(0.062)	(0.093)	(0.086)
$\Delta \ln(\text{net})$	-0.051	-0.051	-0.008	-0.014	0.058	0.058	-0.026	-0.024	-0.008	-0.005	-0.076	-0.067	-0.068	-0.071
	(0.031)	(0.031)	(0.027)	(0.027)	(0.019)	(0.019)	(0.024)	(0.024)	(0.019)	(0.019)	(0.040)	(0.039)	(0.025)	(0.025)
Panel B. Instrumental Variable Estimates														
$\Delta \ln(WAC)$	0.057	0.248	0.570	1.124	1.109	1.180	0.076	0.066	-0.025	-0.106	0.431	0.871	1.138	1.365
	(0.310)	(0.400)	(0.364)	(0.633)	(0.442)	(0.603)	(0.329)	(0.422)	(0.352)	(0.482)	(0.377)	(0.570)	(0.379)	(0.545)
$\Delta \ln(\text{net})$	-0.030	-0.053	-0.054	-0.138	-0.052	-0.063	-0.015	-0.013	0.020	0.031	-0.114	-0.155	-0.176	-0.207
	(0.042)	(0.058)	(0.062)	(0.107)	(0.088)	(0.108)	(0.041)	(0.054)	(0.045)	(0.063)	(0.058)	(0.089)	(0.077)	(0.099)
Kleibergen-Paap F-stat	19.61	11.58	18.65	11.62	19.11	12.39	19.61	11.58	19.48	11.27	18.19	10.65	20.87	13.99
Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
ATC FE		X		X		X		X		X		X		X
N	1,568	1,560	1,526	1,520	1,538	1,530	1,568	1,560	1,566	1,558	1,541	1,533	1,540	1,532

Notes: Estimates of Equation 1 using claims data from MarketScan. Standard errors clustered at the drug level.

Table A5: Response in out-of-pocket Costs – Medicare Plans (Net Price Control)

	$\Delta \log(OOP)$					
	All Plans		Basic Plans		Enhanced Plans	
PANEL A. OLS ESTIMATES						
$\Delta \ln(WAC)$	0.245	0.228	0.208	0.184	0.209	0.192
	(0.119)	(0.117)	(0.100)	(0.093)	(0.122)	(0.120)
$\Delta \ln(\text{net})$	0.013	0.013	0.037	0.040	-0.004	-0.004
	(0.016)	(0.016)	(0.021)	(0.022)	(0.018)	(0.019)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES						
$\Delta \ln(WAC)$	0.942	1.229	1.075	0.723	0.558	0.769
	(0.238)	(0.435)	(0.466)	(1.017)	(0.219)	(0.415)
$\Delta \ln(\text{net})$	-0.124	-0.179	-0.161	-0.081	-0.084	-0.133
	(0.099)	(0.148)	(0.164)	(0.254)	(0.085)	(0.134)
Kleibergen-Paap F-stat	16.06	8.10	9.17	2.97	14.02	6.10
ATC FE		X		X		X
Year FE	X	X	X	X	X	X
N	1,410	1,408	1,350	1,348	1,383	1,381

Notes: Estimates of Equation 1 using CMS's 20% random sample of Medicare Part D beneficiaries. Basic plans follow the standard Medicare benefit design or offer actuarially equivalent benefits. Enhanced plans are more generous, and offer additional coverage. Standard errors clustered at the drug level. The first stage is weak in the Medicare sample once therapeutic-area (ATC) fixed effects are included (Kleibergen-Paap F between 2.97 and 8.10), so the ATC-FE columns should be interpreted with caution.

Table A6: Changes in Allowed Amount (Net Price Control)

	Commercial		Medicare	
PANEL A. OLS ESTIMATES				
$\Delta \ln(WAC)$	0.571	0.558	0.486	0.464
	(0.212)	(0.216)	(0.206)	(0.205)
$\Delta \ln(\text{net})$	-0.015	-0.013	0.006	0.007
	(0.018)	(0.018)	(0.017)	(0.017)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES				
$\Delta \ln(WAC)$	1.180	1.237	1.186	1.277
	(0.251)	(0.332)	(0.255)	(0.459)
$\Delta \ln(\text{net})$	-0.087	-0.092	-0.131	-0.149
	(0.062)	(0.071)	(0.116)	(0.152)
Kleibergen-Paap F-stat	19.61	11.58	16.06	8.10
ATC FE		X		X
Year FE	X	X	X	X
N	1,568	1,560	1,410	1,408

Notes: Estimates of Equation 1, using allowed amount as the outcome. Commercial estimates are based on MarketScan claims and Medicare estimates are based on CMS's 20% random sample of Medicare Part D beneficiaries. Standard errors clustered at the drug level. In the Medicare sample, the first stage is weak once therapeutic-area (ATC) fixed effects are included (Kleibergen-Paap F = 8.1), so that column should be interpreted with caution.

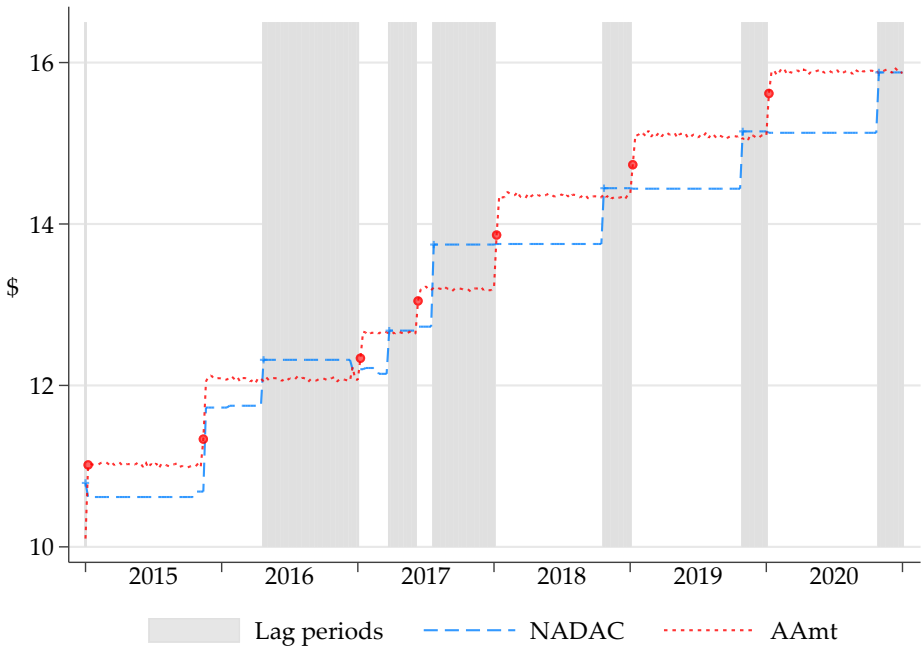

Figure A6: NADAC vs. Allowed Amount in Medicare claims for Januvia 50 MG tablet (NDC: 00006011231)

Notes: Plot of NADAC and average per-claim Medicare allowed amount at the weekly level for NDC 00006011231. Periods shaded in grey represent gaps between changes in NADAC and changes in allowed amount.

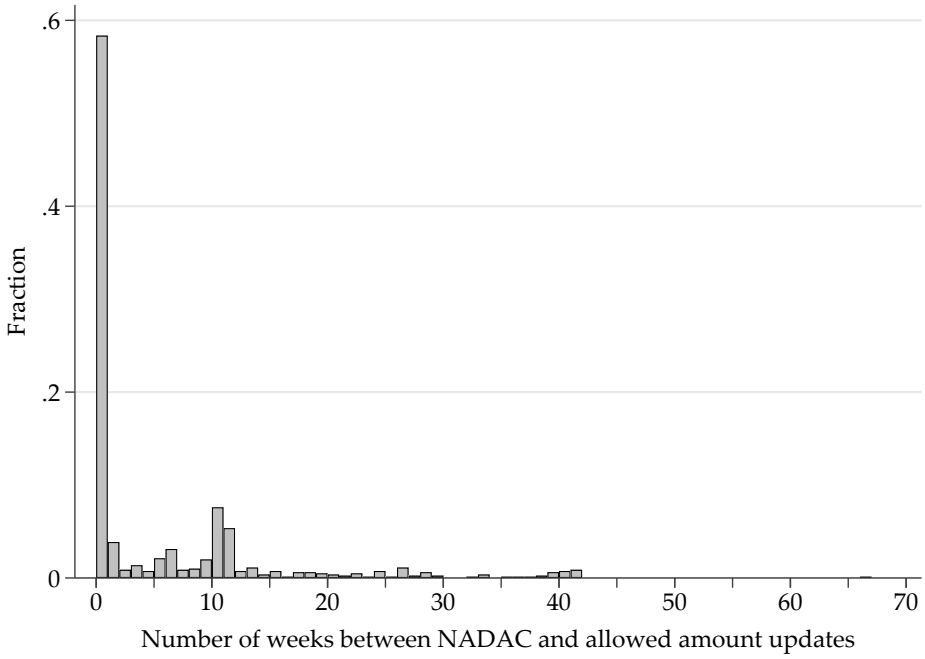

Figure A7: Lag between NADAC and Allowed Amount updates

Notes: Plot of number of weeks between successive NADAC and allowed amount increases.