Insurance Design and the Passthrough of Nominal Drug Prices*

Josh Feng, Luca Maini†

October 31, 2025

Abstract

The cost of prescription drugs to U.S. health plans depends on a nominal "list" price and a hidden rebate. Using a model of health insurance design, we show that when plans must provide a minimum level of coverage, sponsors have an incentive to use list prices to circumvent coverage restrictions and increase patient cost-sharing. Using exposure to the Medicaid market as an instrument, we confirm that higher list prices lead to higher patient out-of-pocket costs. Consistent with the model, pass-through rates are lowest for PPO and HMO commercial plans and highest for more constrained HDHP and Medicare Part D plans.

*We thank Joe Levy, David Ridley, Mark Shepard, and Ben Vatter for providing detailed comments and feedback, as well as conference participants at ASHEcon, Bates White, the Boston Conference on Markets and Competition, and the Southeastern Health Economic Study Group. We thank Richard Evans and Scott Hinds at SSR Health for providing data access and additional feedback. Karishma D'Souza, Hailey Brace, and Katherine Garrett provided excellent research assistance. This research project was supported by Arnold Ventures LLC.

†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

Policymakers in the United States have continually scrutinized increasing prescription drug prices in recent years, concerned about their impact on health expenditures and patient access. When faced with questions about drug price increases, industry stakeholders usually point out that only list prices are growing, and that prices net of rebates grow much more slowly. This response, however, leaves important questions unanswered. If list prices are irrelevant, why do they exist in the first place, and why has their growth outpaced the growth of net-of-rebate prices in recent years?

One clue to the role of list prices comes from the oft-made claim that patient cost-sharing depends on the list price whenever patients face a coinsurance rate or when filling a script under the deductible. This idea is widely held, providing a key motivation behind a 2019 Senate Finance Committee investigation into insulin prices (Senate Finance Committee, 2021), and one of the central theories of harm in a 2024 Federal Trade Commission complaint against Pharmacy Benefit Managers (PBMs)—the middlemen that negotiate drug prices for most private U.S. payers (Federal Trade Commission, 2024). In spite of this, evidence linking the two is scarce, with existing studies finding either a very weak or no correlation (Yang et al., 2020; Rome et al., 2021; Lalani et al., 2024). Moreover, from the point of view of optimal insurance design, it is not clear why cost-sharing would be tied to a price that does not reflect the true cost of care.

In this article, we provide theory and evidence on the connection between list prices and cost sharing. To start, we show theoretically that plans facing minimum coverage requirements have an incentive to tie cost-sharing to list prices rather than net-of-rebate prices. Then, we provide evidence consistent with the theory by using an instrumental variables design to analyze a drug-level panel of list prices and average out-of-pocket (OOP) spending across different types of health plans.

The intuition for the theoretical result is simple: by tying cost-sharing to list prices, plans can reduce their effective generosity while appearing more generous *on paper*. We argue that this is optimal in markets with adverse selection where plans face coverage requirements on their nominal generosity, which are common in government-regulated markets. For a concrete example, consider a Medicare Part D plan, which must provide a minimum standard benefit design consisting of a fixed set of coinsurance rates. By tying these rates to list prices, Part D plans can nominally adhere to the imposed mandate while offering less generous benefits in practice. A key implication of the model is therefore that higher list prices should only result in higher out-of-pocket costs for patients enrolled in such "constrained" plans.

To test the implications of our theoretical model, we combine data on drug list prices with prescription drug claims covering a large set of commercially insured and Medicare patients to create a drug-level panel. Our commercial data covers a range of plan types offered by self-insured employers, and our Medicare data includes a random sample of patients enrolled in both standalone Medicare Part D (PDP) and Medicare Advantage Part D (MA-PD) plans.[1]

In the drug-level panel, we find only a weak correlation between list price growth and growth in OOP costs, consistent with previous research. However, the naive OLS regression presents two potential issues. The first is endogeneity. Drugs whose price increases faster may be more valuable. For example, a drug's price might spike after it obtains a new indication or after the publication of new evidence promoting its effectiveness. In those situations, we might expect plans to improve coverage for those drugs, creating attenuation bias. The second is that the cost-sharing faced by patients paying coinsurance or under the deductible is not based directly on a drug's list price but on an amount negotiated by the health plan with the PBM (or pharmacy). This amount depends on list price, but also on several added fees and discounts negotiated between manufacturers, wholesalers, pharmacies, and the health plans themselves. As a result, changes in list price may not be immediately passed through to patients. Instead, they could be delayed and blunted by contracting frictions along the supply chain, again leading to attenuation relative to the true estimate.

To address these issues, we rely on an instrumental variable research design that uses exposure to the Medicaid segment as a plausibly exogenous shifter for list price growth. Medicaid reimbursement rules strongly disincentivize list price growth above

[1] Both PDPs and MA-PDs cover exclusively retail prescription drug spending, but MA-PDs are attached to privately administered health plan, while PDPs enrollees are covered by Traditional Medicare.

inflation, due to a combination of an inflation penalty and a mandatory rebate that is a fixed percentage of list price. 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. Our design relies on 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.

Estimates from our IV approach confirm that higher list prices lead to higher out-of-pocket costs, but that the effects are concentrated among commercial high deductible health plans (HDHP) and Medicare Part D plans that offer the standard benefit design. Patients in commercial HDHP and basic Medicare plans experience a full pass-through rate (i.e., a 10% increase in list price translates to a 10% increase in OOP costs). Conversely, we find a lower pass-through rate in Medicare plans offering enhanced benefits, and statistically insignificant passthrough in more generous PPO and HMO commercial plans. We interpret these results as consistent with our model, as both Part D plans and HDHPs face minimum coverage constraints. In the case of Part D, these constraints come from regulatory coverage requirements. In the case of HDHPs, the constraints arise from the impossibility of charging more than 100% coinsurance under the deductible.

Our work contributes to several strands of recent theoretical and empirical research on the pharmaceutical market. As noted earlier, existing studies either find no correlation (Lalani et al., 2024) or a minimal pass-through rate of list prices to out-of-pocket costs, ranging from 3–5 cents (Yang et al., 2020) to 14 cents (Rome et al., 2021) per $1 increase in list price. We note two reasons why these correlations may be lower than the true causal effect, and provide estimates based on an instrumental variable approach that aims to account for these issues. These results also complement existing descriptive analyses documenting a growing divergence between list price growth and net price growth (Aitken et al., 2016; Kakani et al., 2020) by showing that list price growth is not merely an accounting curiosity but has real implications for patients on specific plans.

Our results can also help inform models of manufacturer-PBM negotiations. Most existing empirical analyses of drug pricing treat list price as exogenous (Ho and Lee, 2023; Feng and Maini, 2024).[2] Our analysis suggests that list prices may strategically

[2] An important exception is Che (2025), which models price-setting in two separate stages—with manufacturers first setting a list price, and then negotiating a rebate with PBMs. In the model, list prices are pushed upwards for profit-maximizing reasons (because PBMs must cover all drugs for some patients

reflect payer incentives and could affect market outcomes through their impact on demand via increased out-of-pocket costs. Conti et al. (2021) presents a theoretical model where higher list prices make uninsurance less attractive, thus raising demand for insurance and, indirectly, for prescription drugs. This theory does not, however, explain why higher list prices should result in higher OOP costs. We offer a complementary explanation that also explains this fact.

Finally, our results fit within two broader literatures in economics. The first literature studies the effect of adverse selection incentives on insurance benefit design. Although no paper has specifically considered list prices as a tool in plan design, papers showing that drug formulary design is partially shaped by selection incentives are close conceptual neighbors to our work (Lavetti and Simon, 2018; Geruso et al., 2019). More broadly, papers in this space include seminal and recent work on how adverse selection affects strategic health plan design (Rothschild and Stiglitz, 1976; Glazer and McGuire, 2000; Weyl and Veiga, 2017; Kreider et al., 2022; Shepard, 2022). The second literature studies the use of sticker prices and discounts—mostly as tools for price discrimination—and goes back to seminal theoretical work by Pigou (1920) and Holmes (1989) on third-degree price discrimination. More recent empirical work has also shown that transparency can hurt a firm's ability to price-discriminate (see, e.g., Grennan and Swanson, 2020), which can potentially explain why list prices and hidden rebates are used in the pharmaceutical market. Our work uncovers an alternative motivation that applies even under uniform pricing.

2 List Prices: Model and Institutional Details

2.1 A Model of Insurance Plan Design with List Prices and Rebates

WAC, rebates and out-of-pocket costs are all equilibrium outcomes that arise from the interactions of several agents. Although a full treatment of this market is beyond the scope of this paper, we present a simple framework to illustrate the key economic incentives experienced by payers facing changing list prices. In doing so, we focus on plan design and abstract from both optimal list price and rebate setting.

even without rebates), but prevented from growing uncontrollably because of political constraints.

Model

We formalize these effects and their intuition through a simplified version of the Rothschild and Stiglitz (1976) model, adapted to the pharmaceutical setting.

Suppose that we have a measure one set of patients, defined by their type θ, which has CDF $F(\theta)$. θ determines the likelihood that a patient will get sick. If patients are sick, they receive a negative health shock h (measured in dollar terms), but can consume a unit of a drug, at cost w, to completely restore their health. We assume that $h > w$ so there is no scope for moral hazard.[3]

Patients can purchase insurance to subsidize the cost of the drug. Insurance plans are defined as a triple (α, w, r), where α is a coinsurance rate, w is the price to which it applies, and r is premium. Patient's expected utility is given by

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

where W represents wealth, and $u(\cdot)$ is increasing and concave. Uninsurance is equivalent to $\alpha = 1$ and $r = 0$.[4]

Equilibrium

We assume that insurance generosity is exogenously determined (e.g., by government regulation) and that entry is free, so premiums are pinned down by a no-profit condition

$$r = \mathbb{E}\left[\theta | \theta > \bar{\theta}\right] \times (1-\alpha) w \tag{1}$$

where $\bar{\theta}$ is implicitly defined by the indifference condition between purchasing and not purchasing insurance:

$$U(\bar{\theta}, 1, w, 0) = U(\bar{\theta}, \alpha, w, r) \tag{2}$$

[3] In general, moral hazard will exacerbate the effects we describe in this model by amplifying the difference in cost (and, therefore, premium) between more and less generous insurance plans.

[4] We assume fully rational consumers. Empirical analyses of plan choice has shown that patients may in fact place more weight on premium than expected out-of-pocket costs (Abaluck and Gruber, 2011, 2016). These behavioral biases would exacerbate the effects shown in our model, by making less generous plans even more appealing.

The effect of an increase in list price

We analyze the impact of the following perturbation: a drug's list price increases to $w' = w + d$, but insurers also receive a rebate d from the drug manufacturer. This leaves the cost of acquiring the drug unchanged for payers.[5]

We restrict the insurer to two possible responses: (i) pass through the rebate at point of sale, so that enrollees pay αw in cost-sharing (henceforth, contract G); or (ii) do not pass through the rebate at point-of-sale so that enrollees pay $\alpha w'$ (henceforth, contract L).

Given these strategies, there are three potential equilibria:[6]

1. All insurers offer contract G
2. All insurers offer contract L
3. Both contracts are offered

We argue that, under relatively weak regularity conditions on $u(x)$ and $F(\theta)$, and as long as d is not too large, all insurers offering contract G can never be an equilibrium.

Proposition 1. *Under standard regularity conditions for* $F(\theta)$ *and* $u(\cdot)$ *and for a small enough* d*, there exists no equilibrium where all insurers offer contract* G.

Appendix A provides a more formal statement and a proof of Proposition 1. Intuitively, if all insurers offered contract G, an insurer deviating to offer contract L can always set a low enough premium to at least attract the healthier patients among those who would otherwise buy the more generous contract.

Discussion

The result of this model depends on adverse selection and on the presence of an exogenously set limit on benefit design, represented, in this case, by α. If α could be freely chosen by insurers, our result would not apply, because increasing the list price does not expand the choice set of insurers.[7]

[5] When this happens, having no insurance becomes less appealing, raising demand for all insurance contracts. This effect is not necessary for the results of the model, and could be removed by assuming, for example, that manufacturers can also provide copay assistance to uninsured patients (as many of them do).

[6] It's also possible that no equilibrium exists.

[7] An exception to this statement is in cases where insurers wish to set $\alpha > 1$. This does not make sense globally (because $\alpha \geqslant 1$ implies the contract has no insurance value), but may be desirable locally, e.g., in the deductible phase.

Therefore, our model suggests that list price increases are more likely to trickle down to patients who are enrolled in plans that face generosity constraints. The most obvious type of constraint that plans face comes from regulation. For example, Medicare Part D plans must adhere to a minimum standard level of coverage (or provide actuarially equivalent benefits), and plans in the Affordable Care Act Health Exchanges have medical loss ratio requirements tied to their "metal tier." Another, less obvious constraint is faced by plans with a high deductible. Patients under the deductible must cover 100 percent of healthcare costs up to a certain threshold, but cannot normally impose higher than 100 percent cost-sharing. The use of list prices and rebates allows plans to bypass this limit.

2.2 The role of list prices in the pharmaceutical supply chain

To understand our empirical approach, it is necessary to understand what "list prices" actually measure, and how they are set. The term "list price" is informal, but generally refers to Wholesale Acquisition Cost (WAC). We follow this convention in our paper, and use the terms WAC and list price interchangeably throughout. WAC is a public manufacturer-posted price that aims to capture the price paid to drug manufacturers by wholesalers, which serves as a measurable starting point for the price paid on the distribution side of the industry. Moreover, as noted in both recent investigations 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), contracts between PBMs and manufacturers include discounts expressed as a function of WAC. However, patients' out-of-pocket costs are not indexed to WAC, but to the payment that PBMs (or payers) remit to the pharmacy that gives out the prescription. This payment is usually referred to as "allowed amount" in claims data.

Figure 1 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 average 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 fo-

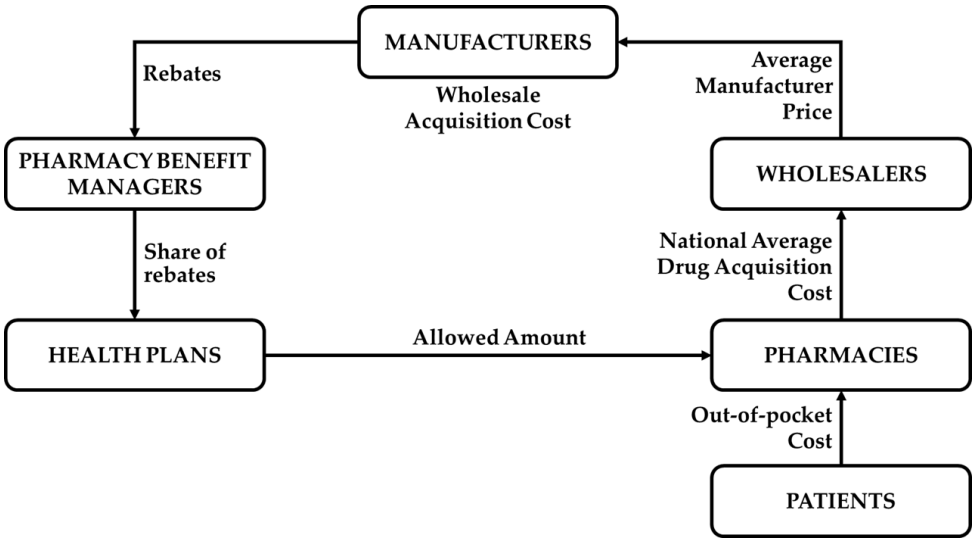


Figure 1: Overview of prices in the market for retail drugs

cus 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 their 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).[8]

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.

A patient's out-of-pocket cost can depend on the allowed amount if it is expressed as a coinsurance rate, or if the payment is made while the patient is under the deductible. Insofar as WAC affects the allowed amount, it can also affect the out-of-pocket cost. However, the extent of this influence depends on the contracts that are in place between manufacturers, wholesalers, pharmacies and payers. These contracts may not update immediately after a raise in WAC.[9] Moreover, plans may also adjust their gen-

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

[9]We show in Appendix C.5 that the timing of WAC, NADAC, and allowed amount increases often do not coincide. The lag between a WAC increase and an allowed amount increase suggests that wholesalers and pharmacies may sometimes sell prescriptions at a loss, an issue which has been flagged in several media reports (see, e.g., https://www.drugchannels.net/2024/04/understanding-cvs-healthmckesson-and.html, accessed October 15. 2025). However, the frequency of these occurrences depends on when each intermediaries acquired the drug, which is not something we can observe in our data.

erosity in response to changes in WAC. Hence, the relationship between what is commonly referred to as list price and patient cost is neither mechanical nor immediate. In the next section, we discuss how our empirical approach addresses these issues.

3 Empirical Approach and Data

3.1 Empirical Approach

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

$$\Delta y_{jt} = \alpha_t + \gamma \times \Delta \ln (WAC)_{jt} + \varepsilon_{jt} \tag{3}$$

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 usually reported in units that are not necessarily comparable across drugs.[10]

There are two concerns in estimating this equation. First, as discussed in the background section, the effect of WAC on out-of-pocket cost is mediated through a series of contracts that may not immediately adjust. These lags generate measurement error that could bias the coefficient of this regression towards zero. 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 identifying the correct effect.[11]

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). In these cases, we may expect price increases to not lead to higher out-of-pocket costs, as the value of these drugs has also increased. This could also bias the coefficient towards zero.

[10] We could have alternatively adopted a specification including drug fixed effects. However, as we argue below, our instrumental variable approach is better suited to this specification.

[11] For example, consider a situation where the list price of a drug increases on January 1st, but allowed amount does not update until April 1st. In that case, the average change in allowed amount relative to the prior year would be 25% lower than the average change in WAC.

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 AMP minus the sum of two rebates: a base rebate of 23.1% (or the highest discount granted to a commercial manufacturer) and an inflation rebate consisting of the difference between a drug's current list price and its inflation-adjusted launch price.[12] 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. Figure A1 illustrates 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.[13]

While data on AMP is not publicly available, changes in WAC are closely tied to changes in AMP. Hence, our hypothesis is that changes in WAC will be negatively correlated with a drug's MMS.[14]

[12]The statutory minimum rebate was equal to 15.1% up until December 2009, but was raised to 23.1% starting 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. See the Code of Federal Regulation (42 CFR § 447.509) for more details.

[13]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.

[14]Note that this result is already reported in Feng et al. (2023), albeit using a slightly different sample and specification.

3.2 Data

To conduct the analysis outlined in the previous section, we combine data on drug prices and spending, and prescription drug claims. 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 a set of approximately 1,000 brand drugs from SSR Health. SSR Health collects net sales on a quarterly basis from SEC filings of publicly traded firms and then calculates estimated US-level quarterly net prices by comparing net sales figures to invoice sales reported by a third-party (Symphony Health).[15] SSR Health data is at the product level, where a product is usually defined by a brand name (e.g., Lipitor).

We complement this main source with data from the Center for Medicare and Medicaid Services (CMS) on Medicaid spending. To calculate Medicaid spending we use publicly available quarter-level data from the Medicaid Public Use Files (PUF), which reports national spending totals at the National Drug Code (NDC) level for all prescriptions filled by Medicaid beneficiaries. These data can be matched to SSR Health data through a map provided by SSR Health. To calculate Medicare spending we use the Medicare Spending Dashboard, which reports overall drug-spending level in Medicare Part B and D.

Prescription drug claims data We use prescription drug claims from MarketScan, covering the commercial market, and from CMS, covering the Medicare market. MarketScan data covers a large sample of patients enrolled in employer-sponsored insurance plans (over 47 million from 2007–2018). Each claim includes patient cost-sharing as well as information on the total allowed amount. Cost-sharing distinguishes between payments made as copays, coinsurance, and under the deductible. The beneficiary information also includes the type of plan they are enrolled in (e.g., HMO, PPO, HDHP).

CMS data comes from the 20% random sample of Medicare Part D beneficiaries (over 90 million unique patients between 2007–2018). As with MarketScan, each claim also includes patient cost-sharing and total allowed amount. Cost-sharing is not split across different types of payments, but the standard benefit design of Medicare Part

[15] Not all drugs are available in all periods. Over time, as more firms have started reporting drug-specific earnings on their SEC filings, the sample has expanded. Occasionally, drugs are also dropped, mainly because of patent expiration. Also see Ippolito and Levy (2022) for more details.

D means that the vast majority of payments are made as coinsurance or under the deductible. The main exception to this rule is for enhanced plans that provide more generous benefits. We isolate these enhanced plans from basic benefit design plans in some of our analyses.

3.3 Sample selection

We create a core sample of branded, on-patent drugs based on four criteria.[16] First, since our analysis focuses on out-of-pocket costs patients face for drugs sold through the retail and mail channel, we exclude products primarily administered by physicians in outpatient settings. To implement this restriction we use Medicare Dashboard Spending data and select drugs whose Medicare sales are concentrated in Medicare Part D. Specifically, we exclude any product whose Medicare Part B sales exceed 20% of total Medicare sales.

Second, we exclude drugs whose invoice sales records are most likely to be underestimated. Undercounting of invoice sales can occur in the SSR Health data because the source of invoice sales consists of surveys that may not have perfect coverage of all sales channels. Undercounting is a particularly prominent issue for products that are sold through less common channels, such as specialty pharmacies. To avoid these issues we follow Kakani et al. (2020) and Feng et al. (2023) in screening out: (i) injectable drugs; (ii) drugs with an indication in oncology and (iii) drugs that record higher net sales than invoice sales.[17]

Third, we exclude contraceptives and smoking cessation drugs, because the ACA mandates that insurance plans cover them at no cost to patients. We confirm that our data reflect these rule changes.

Fourth, and finally, we restrict our sample to drugs that have been on the market for 15 years or less. Older drugs can often accumulate inflation rebates so high that they exceed 100% of AMP. In those cases, the Medicaid program caps rebates at 100%, ensuring that manufacturers don't have to pay money to Medicaid on net, thus removing the incentive to lower list price growth.[18]

[16] 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.

[17] To be conservative, we filter 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. We also exclude drugs whose net sales are more than 50 percent greater than its invoice sales in any given year other than the launch year and the year before loss of exclusivity.

[18] Appendix C.3 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, thus justifying our approach.

After applying these filters, we end up with a core sample of 314 drugs. Panel A of Table 1 provides drug-year level summary statistics for this sample, in order to provide context for our analysis. Drugs, on average, earn a little over seven percent of their invoice sales through Medicaid, albeit with significant variation across drugs. List price growth is about 11 percent per year. We note that WAC and allowed amount are often stated in different units (e.g., price per pill versus price per 30-day supply), which leads to the discrepancy in absolute values but not in growth rates. Our analysis focuses exclusively on growth rates within a drug, which obviates any units-based issues. 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 provides summary statistics broken down by drugs' Medicaid Market Share (MMS). We find that list price growth is 3 percentage points higher in drugs with below median exposure to Medicaid relative to drugs with above median exposure. Growth in allowed amounts also has a similar quantitative difference. Finally, we find minimal differences across the two groups of drugs in average out-of-pocket spending growth for commercial plans, but a 3pp difference for Medicare plans.

4 Results

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:

$$\Delta \ln (WAC_{jt}) = \delta_t + \beta \times MMS_{jt} + \varepsilon_{jt} \tag{4}$$

The ideal definition of MMS would be the fraction of a firm'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.[19] Formally, for any given drug j and period t, we

[19] We estimate invoice sales from the SSR Health data by adjusting net sales by the list-to-net price ratio. In practice, we might still have some residual measurement error because Medicaid data incorporates fees to pharmacies. This may lead us to slightly overestimate MMS. We still prefer this approach to alternatives that have been used in other papers, such as relying on data from the Medicaid Expen-

Table 1: Summary Statistics

Panel A: Overall Statistics

Variables		Mean	SD	N
MMS		7.80%	10.07%	1985
WAC		113.72	589.78	1985
$\Delta \ln$ (WAC)		0.11	0.19	1671
Allowed Amount	Commercial plans	1258.06	3402.58	1962
	Medicare Plans	1204.19	3401.99	1765
$\Delta \ln$ (Allowed Amount)	Commercial plans	0.11	0.18	1651
	Medicare Plans	0.13	0.14	1473
Out of pocket cost	Commercial Plans	69.63	62.40	1962
	Medicare plans	165.63	258.81	1765
$\Delta \ln$ (Out of pocket cost)	Commercial Plans	0.09	0.21	1651
	Medicare plans	0.07	0.17	1473

Panel B: Statistics by Medicaid Exposure

		Below-median MMS			Above-median MMS		
Variables		Mean	SD	N	Mean	SD	N
MMS		1.71%	1.42%	922	13.08%	11.30%	1063
WAC		150.15	822.61	922	82.13	246.64	1063
$\Delta \ln$ (WAC)		0.13	0.27	765	0.10	0.08	906
$\Delta \ln$ (Allowed Amount)	Commercial plans	0.13	0.23	749	0.10	0.13	902
	Medicare Plans	0.15	0.17	631	0.11	0.10	842
$\Delta \ln$ (Out of pocket cost)	Commercial Plans	0.08	0.23	749	0.09	0.20	902
	Medicare plans	0.09	0.18	631	0.06	0.17	842

Notes: Summary statistics for the core sample, limited to 15-year old or less drugs. 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.

define

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

Table 2 shows estimates from the first-stage regression. Our findings confirm that drugs with a high MMS increase list price more slowly. Specifically, a standard deviation increase in MMS (approximately 10pp) results in lower list price growth by 1.6 pp each year.

F-statistics from our first-stage regressions suggest that our instrument may be weak. This issue is particularly prominent in the specification that includes year fixed-effects

diture Panel Survey (e.g., Ippolito and Levy, 2023), which, due to its small sample size, could introduce significant measurement error for less popular drugs.

Table 2: Evidence Related to the Instrument

Panel A – First Stage Estimates,

	List Price Growth	
	(1)	(2)
MMS	-0.161	-0.158
	(0.034)	(0.034)
Year FE		X
N	1,671	1,671
R^2	0.008	0.040
F-stat	22.88	9.008

Notes: Estimates of Equation 4, using data from SSR Health on WAC to measure list price growth. Standard errors clustered at the drug level.

(column 2). Year fixed-effects absorb 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 2012. In our main analysis, we include year fixed-effects, and take care to correct our standard errors to account for weak-IV issues by using a limited-information maximum likelihood (LIML) estimator. Furthermore, following recommendations in Andrews et al. (2019), we report the Kleibergen-Paap F-statistic (and its associated p-value), which accounts for heteroskedasticity when testing for a zero first-stage coefficient in a setting with a single endogenous regressor.

4.2 Estimates of the Impact of List Price Growth on Out-of-Pocket Costs

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 code recorded on the claim. Both CMS and MarketScan report patient OOP in separate, clearly identifiable variables. Our main dependent variable is the log change in average claim-level OOP at the drug-year level. We also calculate separate measures of OOP cost by (i) plan type (PPO, HMO, and HDHP for MarketScan data, and basic vs. enhanced in Medicare data), and (ii) payment type (copay, coinsurance, and deductible—available only in the MarketScan data). When calculating OOP in Medicare claims, we exclude low-income subsidy (LIS) beneficiaries, who pay no, or limited cost-sharing.

The effect of list price growth on patient out-of-pocket costs in commercial plans

We start by focusing on commercial plans. Table 3 presents our results, which include regressions looking only at the claim-level out-of-pocket cost of patients in specific types of plans. In the reduced-form results, we find a significant but weak pass-through rate of WAC to out-of-pocket costs. Across all plans, we find that a 1% increase in list price is correlated with a 0.11% increase in out-of-pocket cost. We also find little variation across plan types.

Conversely, our instrumental variable estimates, despite being more imprecise, highlight large disparities in pass-through rates across plans. We find little evidence of passthrough in more generous PPO and HMO plans, but very high rates of passthrough (statistically indistinguishable from 1) in less generous HDHP plans.

A plausible explanation for these results is that patients in HDHP plans are more likely to make payments under the deductible and with coinsurance. To confirm this intuition we repeat the analysis, but study deductible, coinsurance, and copay claims separately.[20] Once again, we find a relatively low and uniform pass-through rate across all three types of payments. Conversely, our IV estimates reveal large differences in the point estimates, with copay claims having the lowest pass-through rate, followed by deductible and coinsurance claims. Both the coefficients for deductible and coinsurance claims are statistically indistinguishable from 1.

The effect of list price growth on patient out-of-pocket costs in Medicare plans

Next, we study Medicare plans. All Medicare plans must a provide a minimum basic coverage level (or an actuarially equivalent design). Plans can also offer additional benefits, which usually amount to a lower deductible, additional coverage in the coverage gap, or lower coinsurance in the initial coverage phase. Similar to our commercial market analysis, we report average estimates across all plans and also report estimates split by coverage generosity.

Table 4 presents the results, which mimic the patterns seen in the commercial market. OLS estimates are relatively low and uniform across both basic and enhanced plans. The low coefficient on basic plans is particularly surprising in this case because basic Medicare plans rely entirely on coinsurance and deductible payments, which

[20] No claims have non-zero coinsurance and copay recorded spending. 21.48% of deductible claims in our sample are partially paid by copay and 6.41% are partially paid by coinsurance. Claims are counted in a payment type bucket if any amount of the claim was paid with that payment type and therefore can be assigned to multiple payment categories.

Table 3: Response in OOP Costs – Commercial Plans

	$\Delta \log(\text{OOP})$													
	All Plans								PPO		HMO		HDHP	
	All claims		Deductible Claims		Coinsurance Claims		Copay Claims		All claims		All claims		All claims	
Panel A. OLS Estimates														
$\Delta \ln(WAC)$	0.105	0.115	0.199	0.182	0.282	0.283	0.102	0.098	0.119	0.130	0.0107	0.0230	0.100	0.118
	(0.051)	(0.050)	(0.0850)	(0.080)	(0.098)	(0.104)	(0.042)	(0.042)	(0.053)	(0.054)	(0.042)	(0.041)	(0.067)	(0.068)
Panel B. Instrumental Variable Estimates														
$\Delta \ln(WAC)$	-0.177	-0.067	0.809	0.662	1.121	1.005	-0.037	-0.024	-0.148	-0.085	0.042	0.216	1.071	1.026
	(0.333)	(0.325)	(0.356)	(0.351)	(0.420)	(0.427)	(0.321)	(0.316)	(0.335)	(0.338)	(0.405)	(0.402)	(0.351)	(0.353)
Kleibergen-Paap F-stat	11.66	10.05	9.864	8.515	10.44	8.989	11.66	10.05	11.65	10.05	9.765	8.538	10.58	9.209
Kleibergen-Paap p-value	0.0006	0.0015	0.0017	0.0035	0.0012	0.0027	0.0006	0.0015	0.0006	0.0015	0.0018	0.0035	0.0012	0.0024
Year FE		X		X		X		X		X		X		X
N	1,651	1,651	1,601	1,601	1,617	1,617	1,651	1,651	1,649	1,649	1,620	1,620	1,619	1,619

Notes: Estimates of Equation 3 using claims data from MarketScan. Standard errors clustered at the drug level.

Table 4: Response in OOP Costs – Medicare Plans

	$\Delta \log(OOP)$					
	All Plans		Basic Plans		Enhanced Plans	
PANEL A. OLS ESTIMATES						
$\Delta \ln(WAC)$	0.235	0.193	0.240	0.196	0.188	0.142
	(0.072)	(0.078)	(0.059)	(0.065)	(0.073)	(0.077)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES						
$\Delta \ln(WAC)$	0.876	0.908	1.099	1.045	0.467	0.525
	(0.215)	(0.205)	(0.328)	(0.346)	(0.209)	(0.200)
Kleibergen-Paap F-stat	15.68	13.20	14.97	12.65	16.31	13.45
Kleibergen-Paap p-value	0.0001	0.0003	0.0001	0.0004	0.0001	0.0002
Year FE		X		X		X
N	1,473	1,473	1,409	1,409	1,444	1,444

Notes: Estimates of Equation 3 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.

should imply a pass-through rate of 1. Once again, we recover higher, though noisier, pass-through rates in our IV regression, which also shows higher passthrough for basic plans relative to enhanced plans.

4.3 The relationship between list price and allowed amount

As shown above, we find very different estimates when using a standard panel regression versus an instrumental variables approach. We provide some direct evidence on contracting frictions, one of the two potential issues noted earlier.

To do so, we estimate the relationship between changes in list price and changes in the total allowed amount in a claim. As discussed in Section 2, the allowed amount is the negotiated price between the PBM (or payer) and the pharmacy that coinsurance and deductible payments are based on.

Formally, we estimate the specification in equation 3 using as dependent variable the log change in average claim-level allowed amount at the drug-year level. We run separate regressions for commercial and Medicare plans. Table 5 shows that the naive OLS estimates reflect a pass-through rate between 0.35 and 0.42 in both samples. Conversely, our IV approach shows a much larger pass-through rate that is not statistically distinguishable from 1. This suggests that our design is likely isolating predictable

Table 5: Changes in Allowed Amount

	Commercial		Medicare	
PANEL A. OLS ESTIMATES				
$\Delta \ln(WAC)$	0.418	0.405	0.363	0.357
	(0.146)	(0.140)	(0.130)	(0.127)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES				
$\Delta \ln(WAC)$	1.081	1.177	1.119	1.202
	(0.254)	(0.274)	(0.211)	(0.231)
Kleibergen-Paap F-stat	11.66	10.05	15.68	13.20
Kleibergen-Paap p-value	0.0006	0.0015	0.0001	0.0003
Year FE		X		X
N	1,651	1,651	1,473	1,473

Notes: Estimates of Equation 3, 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.

changes in list price rather than changes driven by factors such as demand shocks.

4.4 Discussion and Robustness Checks

Overall, these results are consistent with the predictions of our model. We find that list prices pass through to patient out-of-pocket costs, but only do so in a significant way for patients in plans that are constrained in their design: Medicare Part D plans—which must provide a minimum level of benefits, and commercial high-deductible health plans—which are constrained by the structural 100% coinsurance cap for payments under the deductible. Conversely, plans like commercial PPO and HMO plans appear to leave cost-sharing unchanged.

Although the evidence is consistent with our model, there are alternative explanations that could be consistent with our findings. One explanation could be that plans are simply being managed "passively," i.e., they do not change their deductible, copay, and coinsurance settings over time. Although passive management could be prevalent in the commercial sample (where plans are designed by employers), it seems unlikely that Medicare Part D plans, which are offered directly by insurers, are not designed optimally. Indeed, evidence shows that plan sponsors are sophisticated in how they

design and market these plans (Lavetti and Simon, 2018; Aizawa and Kim, 2018). Moreover, anecdotal evidence suggests that plans passing rebates through to cost sharing are extremely unpopular.[21]

Another possible explanation is that high- and low-MMS drugs display different trends in out-of-pocket costs for reasons other than their differential list price growth. While it is impossible to rule this out, we attempt to address this by adding the change in the actual cost of a drug (i.e., the net price) as a control in the main IV analysis. There are two reasons why this variable might matter. First, and most obviously, net price is what actually affects plan costs. Second, because drugs with a high Medicaid market share are also more affected by the best-price clause, we might expect these drugs to have lower price growth.[22] Appendix C.4 presents the results when controlling for net price. The estimates are quantitatively very similar, albeit slightly more imprecise.[23]

5 Conclusion

In this article, we provide both a theoretical justification for why payers pass through list price increases to patients in the form of higher out-of-pocket costs and empirical evidence showing that this occurs. Our model explains how adverse selection can incentivize payers facing benefit design constraints to use higher list prices to raise patient cost-sharing. Using an instrumental-variables strategy based on incentives generated by Medicaid inflation rebates, we then find that a 10 percent rise in a drug's list price raises average patient out-of-pocket spending by 10 percent among less generous plans.

Our findings are significant for three reasons. First, our empirical results document that higher list prices translate into higher out-of-pocket costs, confirming that the list-net price divergence is not a harmless accounting artifact (as sometimes argued

[21] See, e.g., the case of SilverScript Allure, a Medicare Part D plan that was offered only for one year and immediately terminated due to low take-up (https://californiahealthline.org/news/consumers-rejected-drug-plan-that-mirrors-trump-administration-proposal/, accessed October 15, 2025). We thank David Bradford for pointing out this example to us.

[22] As discussed in the background section, the main effect of the best price clause should be static—higher net prices. Moreover, this concern does not apply to Medicare Part D plans because discounts to Medicare Part D plans are exempted from the Medicaid best price clause.

[23] In additional unreported tests, we also attempt to control for therapeutic area fixed effects. However, adding these controls significantly weakens the first stage F-stat, to an extent that precludes the use of the instrument in subsequent regressions. This pattern is not too surprising, as drugs with high Medicaid market share are concentrated in specific therapeutic areas (mental health and antiinfectives). Because of this, therapeutic area fixed effects capture much of the variation in MMS (though the coefficient on MMS remains negative and significant even in these regressions).

by pharmacy benefit managers and plan sponsors) but a source of real financial burden, which could lower patient access to drugs. These findings support allegations in the Federal Trade Commission's recent complaint against large pharmacy-benefit managers, which argues that steering patients toward high-list-price products can cause harm even when these products cost the same (or less) because of higher rebates.

Second, our theoretical analysis implies that higher list prices provide an advantage in negotiations. To see why, consider two identical competing drugs with the same net price, but different list prices. Sponsors offering plans that are restricted by benefit design regulation will prefer covering the drug with the higher list price because that drug will have higher cost sharing, which in turn will allow them to compete more effectively on premium.

Third, our theory also provides a reason why the list-net spread might benefit plan sponsors—rather than PBMs. If plan sponsors were the primary driver of the list-net price spread, it would explain why this spread has persisted even as PBMs have increasingly integrated with insurers and moved towards full sharing of rebates with payers. Further supporting this theory, our calculations (reported in Appendix C.6) suggest list and net prices initially started diverging after the introduction of Medicare Part D in 2006. Medicare Part D created the first large constraint on U.S. prescription drug benefit design because Part D plans have to adhere to a minimum basic level of coverage. List and net prices have drifted further apart starting in 2014, coinciding with the implementation of Medical Loss Ratio (MLR) requirement rules for Medicare Part D and Medicare Advantage plans through provisions of the Affordable Care Act (the act also introduced MLR requirements for commercial plans in 2011).

References

Abaluck, Jason and Jonathan Gruber, "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program," *American Economic Review*, June 2011, *101* (4), 1180–1210.

_ and _, "Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance," *American Economic Review*, August 2016, *106* (8), 2145–2184.

Aitken, Murray, Ernst R. Berndt, David Cutler, Michael Kleinrock, and Luca Maini, "Has The Era Of Slow Growth For Prescription Drug Spending Ended?," *Health Affairs*, September 2016, *35* (9), 1595–1603.

Aizawa, Naoki and You Suk Kim, "Advertising and Risk Selection in Health Insurance Markets," *American Economic Review*, March 2018, *108* (3), 828–867.

Andrews, Isaiah, James H. Stock, and Liyang Sun, "Weak Instruments in Instrumental Variables Regression: Theory and Practice," *Annual Review of Economics*, August 2019, *11* (Volume 11, 2019), 727–753. Publisher: Annual Reviews.

Che, Catherine, "Do Middlemen Raise Drug Costs? Countervailing Market Power Meets Agency Frictions," 2025.

Congressional Budget Office, "A Comparison of Brand-Name Drug Prices Among Selected Federal Programs," February 2021.

Conti, Rena M., Brigham Frandsen, Michael L. Powell, and James B. Rebitzer, "Common Agent or Double Agent? Pharmacy Benefit Managers in the Prescription Drug Market," May 2021.

Department of Health and Human Services, "Medicaid Drug Price Comparisons: Average Manufacturer Price to Published Prices," Technical Report June 2005.

Duggan, Mark and Fiona M. Scott Morton, "The Distortionary Effects of Government Procurement: Evidence from Medicaid Prescription Drug Purchasing," *Quarterly Journal of Economics*, 2006, *121* (1), 1–30.

Federal Trade Commission, "In the Matter of Caremark Rx, LLC; Zinc Health Services, LLC; Express Scripts, Inc.; Evernorth Health, Inc.; Medco Health Services, Inc.;

Ascent Health Services LLC; OptumRx, Inc.; OptumRx Holdings, LLC; and Emisar Pharma Services LLC.," November 2024.

Feng, Josh and Luca Maini, "Demand Inertia and the Hidden Impact of Pharmacy Benefit Managers," *Management Science*, 2024, *70* (12), 8940–8961.

_ , Thomas Hwang, and Luca Maini, "Profiting from Most-Favored Customer Procurement Rules: Evidence from Medicaid," *American Economic Journal: Economic Policy*, May 2023, *15* (2), 166–197.

Geruso, Michael, Timothy Layton, and Daniel Prinz, "Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges," *American Economic Journal: Economic Policy*, May 2019, *11* (2), 64–107.

Glazer, Jacob and Thomas G. McGuire, "Optimal Risk Adjustment in Markets with Adverse Selection: An Application to Managed Care," *American Economic Review*, September 2000, *90* (4), 1055–1071.

Grennan, Matthew and Ashley Swanson, "Transparency and Negotiated Prices: The Value of Information in Hospital-Supplier Bargaining," *Journal of Political Economy*, April 2020, *128* (4), 1234–1268. Publisher: The University of Chicago Press.

Ho, Kate and Robin Lee, "Contracting over Rebates: Formulary Design and Pharmaceutical Spending," 2023.

Holmes, Thomas J., "The Effects Of Third-Degree Price Discrimination In Oligopoly," *The American Economic Review*, March 1989, *79* (1), 244.

Ippolito, Benedic and Joseph Levy, "Best Practices Using SSR Health Net Drug Pricing Data," *Health Affairs Forefront*, 2022.

Ippolito, Benedic N. and Joseph F. Levy, "The influence of Medicare Part D on the list pricing of brand drugs," *Health Services Research*, 2023, *58* (4), 948–952. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1475-6773.14139.

Kakani, Pragya, Michael Chernew, and Amitabh Chandra, "Rebates in the Pharmaceutical Industry: Evidence from Medicines Sold in Retail Pharmacies in the U.S.," March 2020.

Kreider, Amanda R., Timothy J. Layton, Mark Shepard, and Jacob Wallace, "Adverse Selection and Network Design Under Regulated Plan Prices: Evidence from Medicaid," December 2022.

Lalani, Hussain S., Massimilano Russo, Rishi J. Desai, Aaron S. Kesselheim, and Benjamin N. Rome, "Association between changes in prices and out-of-pocket costs for brand-name clinician-administered drugs," *Health Services Research*, 2024, *n/a* (n/a). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1475-6773.14279.

Lavetti, Kurt and Kosali Simon, "Strategic Formulary Design in Medicare Part D Plans," *American Economic Journal: Economic Policy*, August 2018, *10* (3), 154–192.

Peters, Christie Provost, "Medicaid Payment for Generic Drugs," Issue Brief No. 839, National Health Policy Forum, Washington (DC) September 2010.

Pigou, Arthur C., *The Economics of Welfare*, London: MacMillan and Co., Ltd., 1920.

Rome, Benjamin N., William B. Feldman, Rishi J. Desai, and Aaron S. Kesselheim, "Correlation Between Changes in Brand-Name Drug Prices and Patient Out-of-Pocket Costs," *JAMA Network Open*, May 2021, *4* (5), e218816.

Rothschild, Michael and Joseph Stiglitz, "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information," *The Quarterly Journal of Economics*, 1976, *90* (4), 629–649. Publisher: Oxford University Press.

Senate Finance Committee, "Insulin: Examining the Factors Driving the Rising Cost of a Century Old Drug," Technical Report 2021.

Shepard, Mark, "Hospital Network Competition and Adverse Selection: Evidence from the Massachusetts Health Insurance Exchange," *American Economic Review*, February 2022, *112* (2), 578–615.

Weyl, E. Glen and Andre Veiga, "Pricing Institutions and the Welfare Cost of Adverse Selection," *American Economic Journal: Microeconomics*, May 2017, *9* (2), 139–148.

Yang, Eric J., Emilio Galan, Robert Thombley, Andrew Lin, Jaeyun Seo, Chien-Wen Tseng, Jack S. Resneck, Peter B. Bach, and R. Adams Dudley, "Changes in Drug List Prices and Amounts Paid by Patients and Insurers," *JAMA Network Open*, December 2020, *3* (12), e2028510.

A Proof of Proposition 1

Recall the conditions set in the main text, updated to reflect the presence of a list price w' and a net price $w = w' - d$, where d denotes the discount received by payers. We have a measure one set of patients, defined by their type θ, which follows a distribution $F(\theta)$. θ determines the likelihood that a patient will get sick. If patients are sick, they receive a negative health shock h (measured in dollar terms), but can consume a unit of a drug, at cost w', to completely restore their health. We assume that $h > w'$ so there is no scope for moral hazard.

Patients can purchase insurance to subsidize the cost of the drug. Insurance plans are defined as a triple (α, p, r), where α is a coinsurance rate, p is the price to which it applies, and r is the premium. Then, the expected utility of patient of type θ who purchases plan (α, p, r) is given by

$$U_B(\theta, \alpha, p, r) = (1-\theta) \cdot u(W - r) + \theta \cdot u(W - r - \alpha p) \tag{A1}$$

where W represents wealth, and $u(\cdot)$ is increasing and concave. Uninsurance is equivalent to the contract $(1, w', 0)$, while contract $G = (\alpha, w, r_G)$, with

$$r_G = \mathbb{E}[\theta | \theta \geqslant \underline{\theta}_G] \times (1-\alpha) w \tag{A2}$$

$\underline{\theta}_G$ is implicitly defined by the indifference condition

$$U(\underline{\theta}_G, 1, w', 0) = U(\underline{\theta}_G, \alpha, w, r_G) \tag{A3}$$

In other words, $\underline{\theta}_G$ is the "lowest" type that purchases contract G when it is the only one offered on the market. Finally, to simplify notation in the proof, we also define

$$\mu(\theta') = \int_{\theta'}^{1} \theta f(\theta) \, d\theta = \mathbb{E}[\theta | \theta \geqslant \theta'] \tag{A4}$$

We also make the following assumptions:

Assumption 2. *$u(x)$ is twice continuously differentiable, with $u'(x) > 0$ and $u''(x) < 0$ for all $x \in [W - w', W]$.*

This assumption implies that patients are risk-averse, and is satisfied by virtually all main classes of utility functions used in economic papers (including, e.g., CARA

and CRRA preferences). The fact that $u(x)$ is *continouously* differentiable implies that $u'(x)$ and $u''(x)$ are bounded on the interval $[W-w', W]$.[24] In particular, this implies that there exists $M_1 > 0$ and $M_2 > 0$ such that $\inf_{x\in[W-w',W]} u'(x) = M_1$ and $\sup_{x\in[W-w',W]} -u''(x) = M_2$.[25] We use this fact later on in the proof.

Assumption 3. *The distribution of risk types $F(\cdot)$ is absolutely continuous on $[0,1]$ with $f(\theta) > 0$ for $\theta \in (0,1)$.*

This assumption rules out discrete distributions (e.g., distributions with a finite number of patient types). While these distributions are sometimes used in economic research, in practice they are unlikely to be relevant in real-world situations.

Before moving to the proof of the Proposition, we prove a useful Lemma, which stems from Assumption 2

Lemma 4. *Let $d^{UB} = \frac{2cM_1}{M_2}$, where $c \in (0,1)$ is a constant, $M_1 = \inf_{x\in[W-w',W]} u'(x)$, and $M_2 = \sup_{x\in[W-w',W]} -u''(x)$. Then, for any $d \in \left(0, d^{UB}\right)$ and any $x \in [W-w', W]$,*

$$u(x+d) - u(x) > u'(x)\, d\,(1-c) \tag{A5}$$

and

$$u(x) - u(x-d) < u'(x)\, d\,(1+c) \tag{A6}$$

Proof. We prove inequality A5 first. Write $u(x+d) - u(x)$ using the integral form of Taylor's theorem:

$$u(x+d) - u(x) = u'(x)\cdot d + \int_{t=x}^{t=x+d} (x+d-t)\cdot u''(t)\, dt \tag{A7}$$

The integral on the right-hand side of the equation represents the approximation error of the first-order Taylor expansion of $u(x+d) - u(x)$. Notice that

$$\int_{t=x}^{t=x+d} (x+d-t)\cdot u''(t)\, dt \geqslant -M_2 \times \int_{t=x}^{t=x+d} (x+d-t)\, dt = -M_2 \frac{d^2}{2} \tag{A8}$$

[24] Continuous differentiability does rule out certain common functional forms, though it is unlikely that these functions would apply to the problem at hand. For example, the function $u(x) = \sqrt{x}$ is not twice continuously differentiable at 0, because $u''(x) \to -\infty$ as $x \to 0$. However, as long as $W > w'$, our problem is defined over a range of outcomes that excludes 0. Virtually all utility functions that apply to economic problems are twice continuously differentiable over compact, positive intervals.

[25] Because $u(x)$ is increasing and concave, we actually know that $M_1 = u'(W-w')$, though this does not matter for the proof.

Hence,

$$u(x+d)-u(x) \geqslant u'(x)\cdot d - M_2\frac{d^2}{2} > u'(x)\, d\left(1-\frac{dM_2}{2M_1}\right) \tag{A9}$$

Notice that the last inequality is strict, because $u(x)$ is strictly concave (e.g., non-linear). This implies that $u'(x)$ is strictly decreasing, and therefore $u'(x) < M_1$ for some $x \in [W-w', W]$. The term in parenthesis is a decreasing function of d. Therefore, for all $d \in \left(0, d_1^{UB}\right)$, with $d_1^{UB} = \frac{2cM_1}{M_2}$ we have that

$$u(x+d)-u(x) > u'(x)\cdot d\cdot\left(1-\frac{d_1^{UB}M_2}{2M_1}\right) = u'(x)\cdot d\cdot(1-c) \tag{A10}$$

thus confirming inequality A5. To see that the inequality A6 also holds, we follow analogous steps:

$$u(x-d)-u(x) = u'(x)\cdot(-d) + \int_{t=x-d}^{t=x}(t-x+d)\cdot u''(t)\,dt \tag{A11}$$

Using the bound on the second derivative, we can write

$$u(x-d)-u(x) \geqslant u'(x)\cdot(-d) - M_2\frac{d^2}{2} > u'(x)\cdot(-d)\cdot\left(1+\frac{dM_2}{2M_1}\right) \tag{A12}$$

Therefore, for all $d \in \left(0, d_1^{UB}\right)$, with $d_1^{UB} = \frac{2cM_1}{M_2}$ we have that

$$u(x-d)-u(x) > u'(x)\cdot(-d)\cdot\left(1+\frac{d_1^{UB}M_2}{2M_1}\right) = u'(x)\cdot(-d)\cdot(1+M_2c) \tag{A13}$$

Applying a sign inversion to both sides recovers inequality A6, concluding the proof. □

Finally, define $\bar{d} = \min\left\{\frac{2cM_1}{\alpha M_2}, \frac{1-\alpha}{\alpha}w\right\}$. We now re-state the Proposition.

Proposition 5. *If assumptions 2 and 3 hold, and if* $d \in \left(0, \bar{d}\right)$*, there exists no equilibrium where all insurers offer contract* G.

Proof. We assume that all plans offer a the generous contract $G = (\alpha, w, r_G)$ and provide a proof by contradiction by finding a profitable deviation. Specifically, we prove that a sponsor can offer a contract $L = (\alpha, w', r_L)$ with premium $r_L = r_G - \delta$, where $\delta \in (0, \alpha d)$ can be chosen to be large enough to attract at least some patients who were

previously choosing contract G, but small enough to make positive profits.[26]

The proof proceeds in three steps. First, we find a threshold $\underline{\delta}$ for δ such that if $\delta > \underline{\delta}$, then contract L attracts some patients. Then, we find a threshold $\bar{\delta}$ for δ such that if $\delta < \bar{\delta}$, then contract L makes positive profits. Finally, we show that $\bar{\delta} > \underline{\delta}$.

To find the first threshold, we find the level of δ that induces some patients who would have chosen contract G to choose L instead. The difference in utility between the two contracts for a patient of type θ is given by

$$\begin{aligned}\Delta U(\theta) = (1-\theta)\cdot[u(W-r_G+\delta)-u(W-r_G)]+ \\ \theta\cdot[u(W-r_G-\alpha w-(\alpha d-\delta))-u(W-r_G-\alpha w)]\end{aligned} \tag{A14}$$

Using Lemma 4 and the fact that $\alpha d < \frac{2cM_1}{M_2}$ by assumption,

$$\Delta U(\theta) > (1-\theta)\,u'_H\delta(1-c)+\theta u'_S(\delta-\alpha d)(1+c) \tag{A15}$$

where $u'_H = u'(W-r_B)$ and $u'_S = u'(W-r_B-\alpha w)$, with the subscripts H and S denoting the healthy state and the sick state respectively.[27]

Define

$$\tilde{\theta}_L = \frac{u'_H\delta(1-c)}{u'_S(\alpha d-\delta)(1+c)+u'_H\delta(1-c)} \tag{A16}$$

Hence, $\Delta U\left(\tilde{\theta}_L\right) > 0$, which implies that patients of type $\theta < \tilde{\theta}_L$ prefer contract L to contract G. Notice that $\tilde{\theta}_L$ is an increasing function of δ.

We now prove another lemma.

Lemma 6. *Let*

$$\kappa = \frac{\underline{\theta}_G(1+c)}{(1-c)(1-\underline{\theta}_G)+\underline{\theta}_G(1+c)}.$$

Then, for all $\delta \geqslant \alpha d\kappa$, $\tilde{\theta}_L > \underline{\theta}_G$.

Proof. Applying the bound on δ to the definition of $\tilde{\theta}_L$ in equation A16, yields

$$\tilde{\theta}_L > \frac{u'_H\kappa(1-c)}{u'_S(1-\kappa)(1+c)+u'_H\kappa(1-c)} \tag{A17}$$

[26] The condition $\delta < \alpha d$ must hold otherwise contract L would offer a premium that is lower than G by more than the difference in coinsurance between the two plans. If this were the case, plan L would be universally better than plan G.

[27] Notice that $\alpha d \leqslant \frac{2cM_1}{M_2}$ implies that both $\delta \leqslant \frac{2cM_1}{M_2}$ and $\alpha d-\delta \leqslant \frac{2cM_1}{M_2}$ because $\delta < \alpha d$.

Because $u'(x)$ is concave, $u'_H < u'_S$, further implying

$$\tilde{\theta}_L > \frac{\kappa}{(1-\kappa)\frac{(1+c)}{1-c}+\kappa} = \underline{\theta}_G \tag{A18}$$

□

Lemma 6 implies that contract L will attract some switchers from contract G (because types $\theta > \underline{\theta}_G$ also prefer contract G to no insurance). As an obvious corollary, also notice that type $\underline{\theta}_G$ will also prefer contract L because $\underline{\theta}_B < \tilde{\theta}_L$ and $\underline{\theta}_B$ is indifferent between the generous plan and no insurance.

As a result, we know that if $\delta > \underline{\delta} = \alpha d\kappa$, contract L will attract some patients. We now turn to finding a threshold $\bar{\delta}$ such that contract L always makes positive profits for $\delta < \bar{\delta}$.

Let $\underline{\theta}_L$ and $\bar{\theta}_L$ respectively denote the patient type that is indifferent between no insurance and contract L, and the patient type that is indifferent between contract L and contract G. In other words:

$$(1-\underline{\theta}_L)\cdot[u(W-r_G+\delta)-u(W)]+ \\ \underline{\theta}_L[u(W-r_G-\alpha w-(\alpha d-\delta))-u(W-w')]=0 \tag{A19}$$

and

$$\left(1-\bar{\theta}_L\right)\cdot[u(W-r_G+\delta)-u(W-r_G)]+ \\ \bar{\theta}_L[u(W-r_G-\alpha w-(\alpha d-\delta))-u(W-r_G-\alpha w)]=0 \tag{A20}$$

We can write the profits of contract L as

$$\Pi_L = \mu(\underline{\theta}_G)(1-\alpha)w-\delta-\mathbb{E}\left[|\theta\ \theta\in\left[\underline{\theta}_L,\bar{\theta}_L\right]\right]\times((1-\alpha)w-\alpha d) \tag{A21}$$

Hence, Π_L is positive as long as

$$\delta < \mu(\underline{\theta}_G)(1-\alpha)w-\mathbb{E}\left[|\theta\ \theta\in\left[\underline{\theta}_L,\bar{\theta}_L\right]\right]\times((1-\alpha)w-\alpha d) \tag{A22}$$

Before moving forward, we prove a useful lemma.

Lemma 7. *The average risk type for the deviator will be less than the original average risk type for individuals who prefer contract* G *to no insurance if contract* L *is not offered. In other*

words: $\mathbb{E}\left[|\theta\ \theta \in \left[\underline{\theta}_L, \bar{\theta}_L\right]\right] < \mu\left(\underline{\theta}_G\right)$

Proof. Since $\bar{\theta}_L \leqslant 1$ and $\underline{\theta}_L < \underline{\theta}_G$ (by Lemma 6), we can write

$$\mathbb{E}\left[|\theta\ \theta \in \left[\underline{\theta}_L, \bar{\theta}_L\right]\right] < \mathbb{E}\left[|\theta\ \theta > \underline{\theta}_G\right] = \mu\left(\underline{\theta}_G\right) \tag{A23}$$

□

Now let $\bar{\delta} = \mu\left(\underline{\theta}_G\right)\alpha d$. Then, by Lemma 7, as long as $d < \frac{(1-\alpha)}{\alpha} w$.

$$\bar{\delta} < \mu\left(\underline{\theta}_G\right)(1-\alpha)\, w - \mathbb{E}\left[|\theta\ \theta \in \left[\underline{\theta}_L, \bar{\theta}_L\right]\right] \times ((1-\alpha)\, w - \alpha d) \tag{A24}$$

and therefore $\delta < \bar{\delta}$ satisfies inequality A22, implying that contract L can make positive profits when offered at $r_L = r_G - \delta$ for $\delta < \bar{\delta}$.

To conclude the proof, note that $\bar{\delta} > \underline{\delta}$ because, for absolutely continuous distributions, $\mu\left(\underline{\theta}_G\right) > \underline{\theta}_G$. □

We note that the equilibrium where all plans choose contract L may or may not exist. Under our setting, there may be cases where contract G could be profitable by attracting the upper tail of risk types. However, the analogous argument to the one made here does not work because the more generous plan cannot profitably attract the marginal risk types.

B Additional Background

B.1 The Medicaid Drug Rebate Program

Here, we reproduced 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

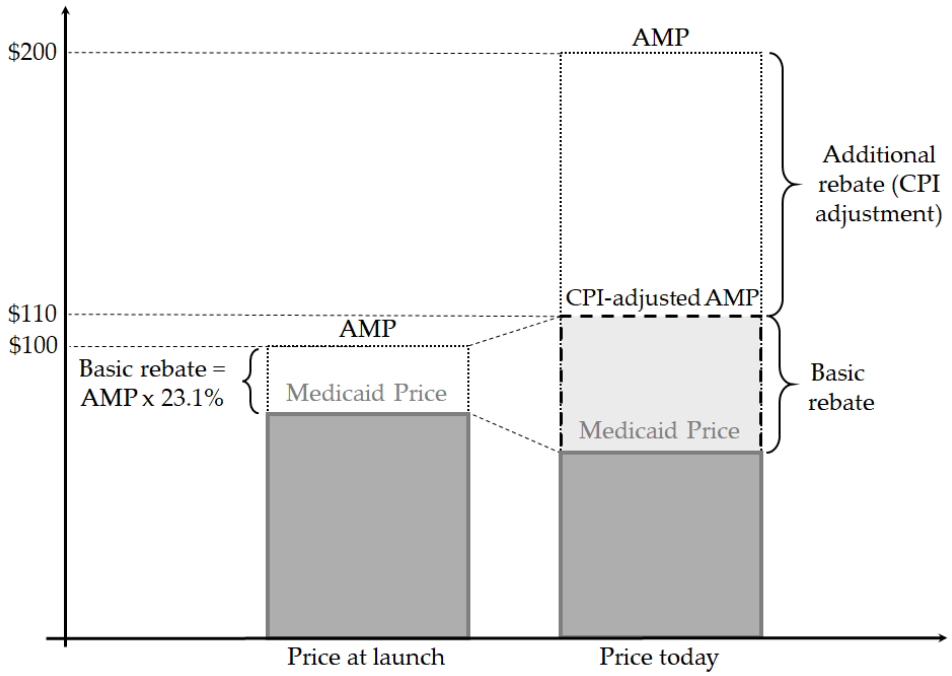


Figure A1: Impact of MDRP on changing list price

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

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.

B.2 Medicare Benefit Design

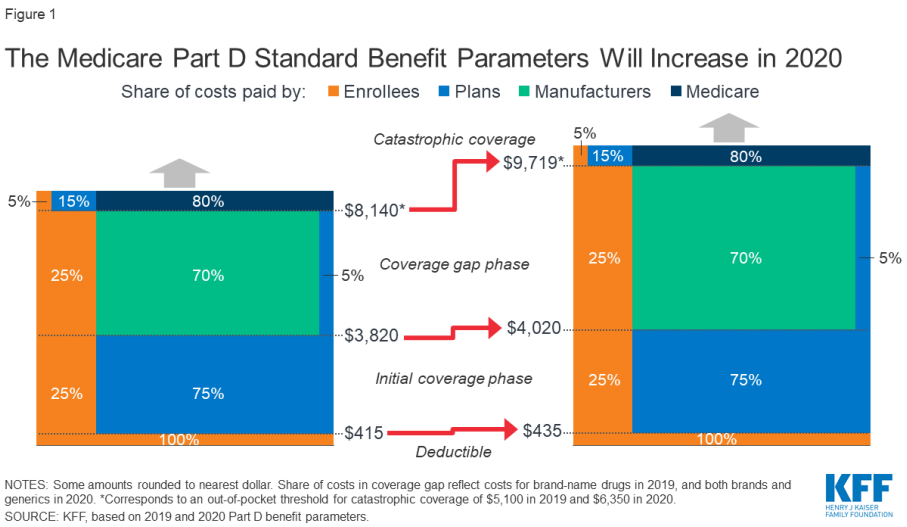


Figure A2: Standard Medicare Part D Benefit Design

Notes: This figure is from an issue brief published online by the Kaiser Family Foundation. The issue can be found here: https://www.kff.org/medicare/issue-brief/how-will-the-medicare-part-d-benefit-change-under-current-law-and-leading-proposals/.

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
		944
Part B sales greater than 20%	163	781
Injectables	134	647
Oncology	45	602
Invoice sales less than net sales flags	234	368
Contraceptives and smoking cessation drugs	9	359
Products launched before 1992	12	347
Products with only one year of data	33	314

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

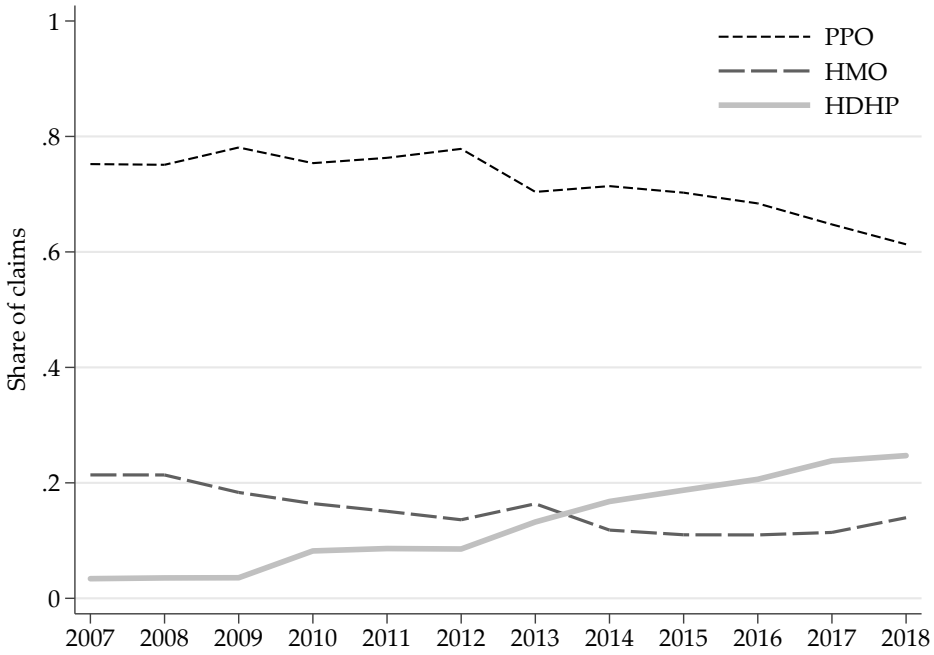


Figure A3: Market shares of plan types in the MarketScan Data

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 Estimates of First-Stage by Age of Drug

Figure A4 presents the estimates of Equation 4, 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.

C.4 Results including change in net price as a control

We repeat our analysis but add change in net price as a control. We find that the results are virtually unchanged. The first stage loses some power after net price is introduced as a control, but all regressions still satisfy the Kleibergen-Paap test thresholds.

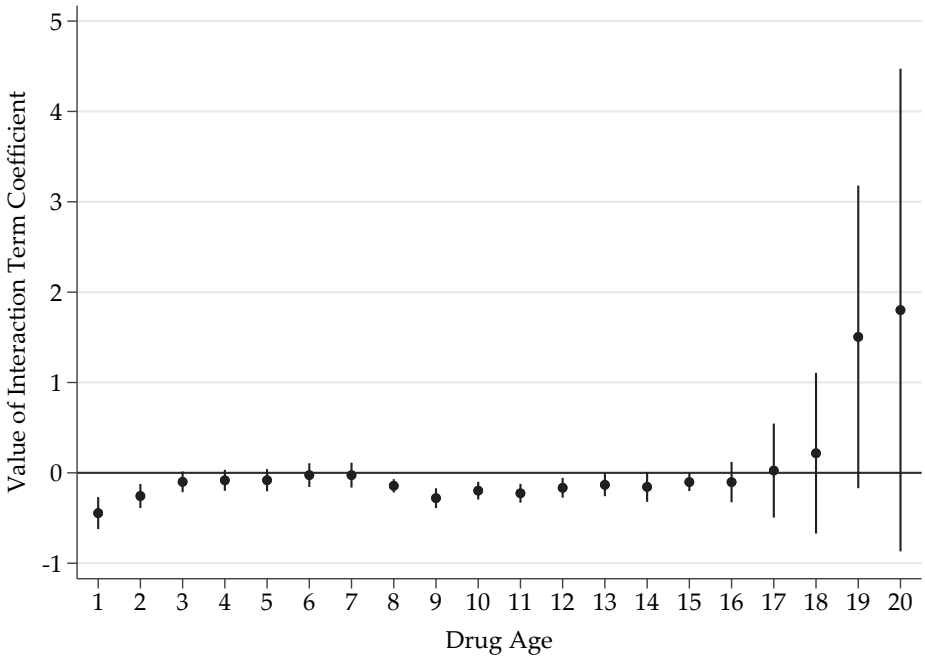


Figure A4: Plot of MMS×Drug-Age FE Coefficients from 1st Stage Model

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.5 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 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)

Table A2: Evidence Related to the Instrument (Net Price Control)

Panel A – First Stage Estimates,

	List Price Growth	
	(1)	(2)
MMS	-0.120	-0.125
	(0.0362)	(0.0345)
$\Delta \ln(\text{net})$	0.207	0.206
	(0.074)	(0.075)
Year FE		X
N	1616	1616
R^2	0.172	0.197
F-stat	18.19	6.187

Notes: Estimates of Equation 4, using data from SSR Health on WAC to measure list price growth. Standard errors clustered at the drug level.

- 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 A5 shows an example of the patterns identified by this algorithm for one of the drugs in the sample.

Figure A6 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.

C.6 Trends in List and Net Prices

To calculate trends in list and net prices, we run a simple regression of log price (both list and net) on product and year fixed effects. Figure A7 plots the year fixed effect coefficients and highlights selected events.

Table A3: Response in OOP Costs – Commercial Plans (Net Price Control)

	$\Delta \log(OOP)$						
	All Plans				PPO	HMO	HDHP
	All claims	Deductible Claims	Coinsurance Claims	Copay Claims	All claims	All claims	All claims
Panel A. OLS Estimates							
$\Delta \ln(WAC)$	0.106	0.183	0.215	0.092	0.125	0.028	0.137
	(0.052)	(0.077)	(0.102)	(0.041)	(0.055)	(0.046)	(0.074)
Panel B. Instrumental Variable Estimates							
$\Delta \ln(WAC)$	-0.014	0.712	1.170	-0.0003	-0.039	0.459	1.022
	(0.388)	(0.416)	(0.506)	(0.403)	(0.414)	(0.422)	(0.432)
Kleibergen-Paap F-stat	7.092	7.527	7.274	7.092	7.081	7.121	7.959
Kleibergen-Paap p-value	0.0077	0.0061	0.0070	0.0077	0.0078	0.0076	0.0048
Year FE	X	X	X	X	X	X	X
N	1,600	1,558	1,570	1,600	1,598	1,573	1,572

Notes: Estimates of Equation 3 using claims data from MarketScan. Standard errors clustered at the drug level.

Table A4: Response in OOP Costs – Medicare Plans (Net Price Control)

	$\Delta \log(OOP)$		
	All Plans	Basic Plans	Enhanced Plans
PANEL A. OLS ESTIMATES			
$\Delta \ln(WAC)$	0.175	0.167	0.146
	(0.075)	(0.062)	(0.073)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES			
$\Delta \ln(WAC)$	1.261	1.544	0.753
	(0.438)	(0.742)	(0.332)
Kleibergen-Paap F-stat	6.968	5.132	8.694
Kleibergen-Paap p-value	0.00830	0.0235	0.00319
Year FE	X	X	X
N	1,440	1,380	1,413

Notes: Estimates of Equation 3 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.

Table A5: Changes in Allowed Amount (Net Price Control)

	Commercial	Medicare
PANEL A. OLS ESTIMATES		
$\Delta \ln(WAC)$	0.424	0.337
	(0.147)	(0.127)
PANEL B. INSTRUMENTAL VARIABLE ESTIMATES		
$\Delta \ln(WAC)$	1.454	1.535
	(0.321)	(0.507)
Kleibergen-Paap F-stat	6.968	13.20
Kleibergen-Paap p-value	0.00830	0.0003
Year FE	X	X
N	1,600	1,440

Notes: Estimates of Equation 3, 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.

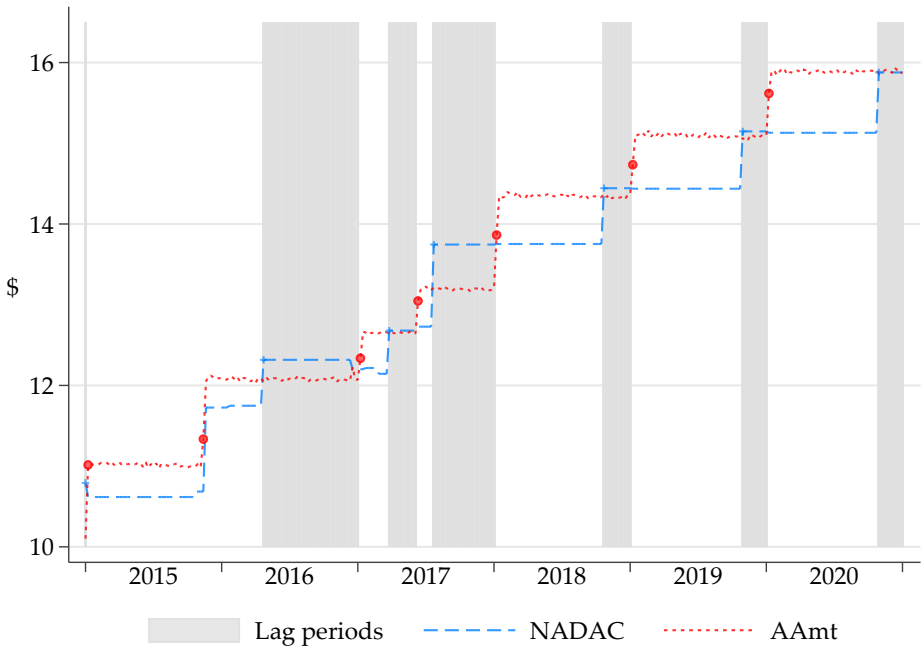


Figure A5: NADAC vs. Allowed Amount in Medicare claims for Januvia 50 MG tablet (NDC: 00006011231)

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

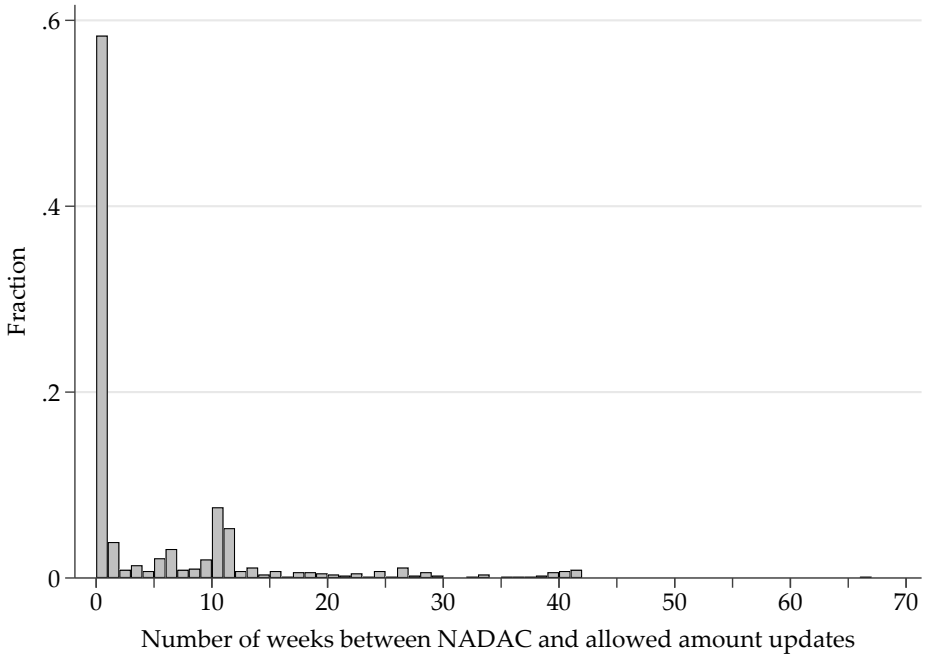


Figure A6: Lag between NADAC and Allowed Amount updates

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

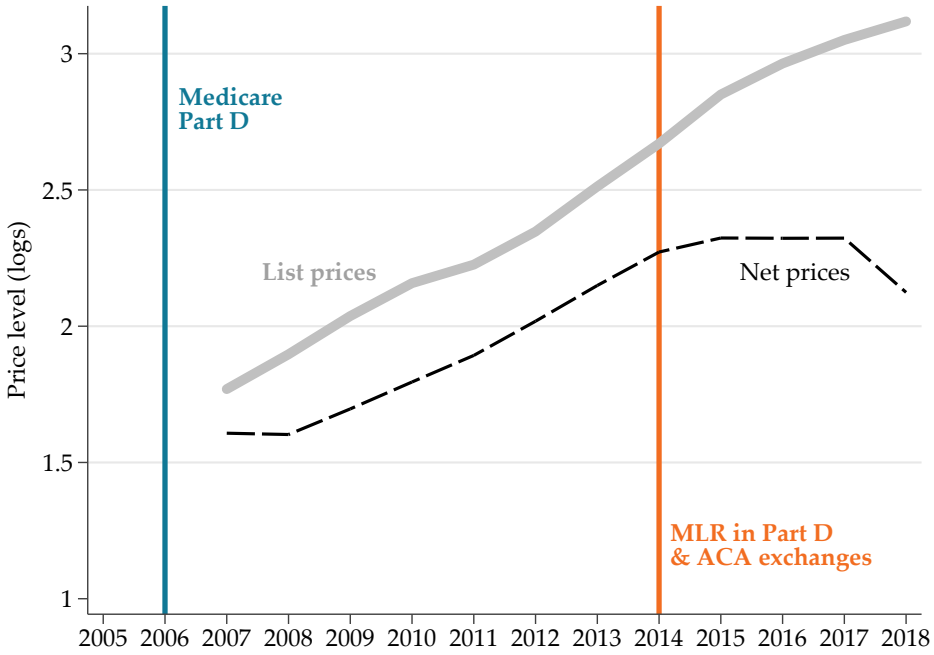


Figure A7: Lag between NADAC and Allowed Amount updates

Notes: Plot of year fixed effects from a regression of log price (list and net) on year and product fixed effects.