

Regulating Vertical Relationships in Prescription Drug Markets: Evidence from Medicaid

Eric Yde*

University of Virginia

December 2023

Abstract

Pharmacy benefit managers (PBMs) are third-party administrators of prescription drug programs for health insurance plans. They play a crucial role in the healthcare system by negotiating drug prices with pharmacies. Consequently, their payment structure can significantly affect the price of prescription drugs. I study the price effects of requiring PBMs and insurers to replace their default fixed-price contracts with cost-plus contracts. Using difference-in-differences methods, I find that Medicaid pre-rebate drug prices declined by an average of 15% in states that prohibited fixed-price contracting, but with heterogeneity across states. I show that these findings are consistent with a bargaining model where, in equilibrium, cost-plus contracting reduces incentives for PBMs to exert effort in negotiating reimbursement with pharmacies, but also reduces their ability to profit off of asymmetric information when negotiating compensation with insurers. In markets where these informational rents are large, cost-plus contracts may be an effective means of reducing drug spending.

JEL Codes: C70, I11, I13, I18, L14, L42

Keywords: pharmacy benefit managers, Medicaid, bargaining, drug pricing, information asymmetry, moral hazard

*edy9g@virginia.edu. I thank Julie Holland Mortimer, Amalia Miller, and Federico Ciliberto for their constant guidance and support. I also thank Gaurab Aryal, Maura Coughlin, Leora Friedberg, Max Schnidman, and workshop participants at the University of Virginia for their valuable comments and insights. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. All errors are my own.

1 Introduction

Like many industries, healthcare is vertically structured and relies on a chain of intermediaries to deliver health services. Gains from specialization by firms can improve the efficiency of supply chains; however, intermediaries may create inefficiencies if they have market power or informational advantages over upstream or downstream firms. Pharmacy benefit managers (PBMs) are intermediary firms that play a crucial role in determining prices and utilization in prescription drug markets. Among other services, PBMs process prescription drug claims, manage formularies, and negotiate prices with both pharmaceutical manufacturers and pharmacies. Their position in the vertical structure may afford them the ability to collect substantial rents, in turn leading to higher healthcare costs. In order to design payment policies and regulations, it is important to understand the incentives faced by PBMs and how they dictate drug spending. Despite their importance, PBMs have received little attention in the economics literature. I advance by studying the price effects of contracts between PBMs and insurers.

In particular, I consider the price effects of forcing PBMs and insurers to switch from default fixed-price contracts to cost-plus contracts. Under a fixed-price (or “spread pricing”) contract, an insurer pays a PBM a pre-set amount for each prescription of a specific drug, and the PBM retains any difference between that amount and what it pays to pharmacies. Under a cost-plus contract, PBMs invoice insurers for the true reimbursement paid to pharmacies plus a pre-set “maintenance fee.” Fixed-price contracts can be very profitable for PBMs: for example, audits of Medicaid programs in Ohio and Kentucky revealed that PBMs retained annual margins of \$225 and \$124 million, respectively (Skoufis and Rivera (2019)). As of 2022, at least 19 states prohibit the use of spread pricing contracts within their Medicaid programs, and a bipartisan Congressional bill proposes to expand this policy nationwide. However, it is unclear whether these profits are rents enjoyed by PBMs or a signal of properly functioning contractual design. I leverage this state-level variation in contracting regulations to study the effects of PBM contract design on drug prices.

Fixed-price contracts often result in lower costs because they create a profit incentive for agents to operate efficiently (e.g., Grossman and Hart (1983); Shavell (1979); Weitzman (1980), chapter 4 of Tirole (1988)). Conversely, cost-plus contracts may induce moral hazard, as the agent (the PBM) reduces effort in negotiating prices with pharmacies because it can pass on higher costs to the principal (the insurer) (Mulligan (2023a,b)). While cost-plus contracts reduce incentives for PBMs to exert negotiating effort, they also reveal the PBM’s true costs to insurers. Insurers are typically unable to observe the true reimbursement rates paid by PBMs to pharmacies under fixed-price contracts, generating an information asymmetry that allows PBMs to collect “informational rents” from insurers. Cost-plus contracts may reduce drug prices through the dissipation of these informational rents, but whether this informational effect dominates the incentive effect is

theoretically ambiguous.

I begin by introducing a model of bargaining between insurers, PBMs, and pharmacies to illustrate how contract design affects drug spending. Using an alternating offers bargaining model (Rubinstein (1982)), I demonstrate that the informational rents obtained by PBMs are largest when insurers enjoy a strong bargaining position relative to PBMs. Asymmetric information serves as a substitute for bargaining power in negotiations between these firms only if insurers have some bargaining power. When PBMs have greater bargaining power, contracting regulations aimed at promoting transparency may be an ineffective means of reducing drug spending, as PBMs can simply extract larger fees from insurers. In the second part of the model, I use a Nash bargaining model to illustrate that PBMs reduce effort in negotiations with pharmacies under cost-plus contracting, which will generally place upward pressure on reimbursement rates. However, both the sign and magnitude of these changes depend on the compensation paid to PBMs by insurers as well as competition and bargaining power in the PBM and pharmacy markets. Thus, the effects of these contracting regulations depend on the scale of the information asymmetries and on countervailing negotiating leverage across trading partners. Ultimately, whether these regulations succeed in reducing prescription drug prices is an empirical question.

Using data on Medicaid drug utilization and pre-rebate prescription prices, I leverage state-level variation in the enactment of policies prohibiting fixed-price contracts in a difference-in-difference (DD) framework to study the effects of contract design on drug prices. The Managed Medicaid pre-rebate price paid per prescription decreased by 21.7% on average in the states that prohibited fixed-price contracting. To address concerns that drug prices in treatment and control states may have not evolved in parallel absent the treatment, I combine data from Managed Medicaid programs with Medicaid “fee-for-service” (FFS) programs (which do not typically rely on PBMs for managing pharmacy networks) in a triple differences (DDD) design and observe decreases in price of 15.4%. Thus, the cost savings from using cost-plus contracts are robust, tangible, and economically significant.

I combine the Medicaid prescriptions data with information on the average acquisition cost paid by pharmacies for each drug to illustrate the magnitude of the policy effects. I find that “excess” Medicaid payments above the National Average Drug Acquisition Cost (NADAC) decreased by \$2.41 per prescription in the treated states, a roughly 65% decrease from pre-treatment levels. The price decreases were largest for generic drugs, for which the excess amount paid by Managed Medicaid programs above the NADAC is typically largest. I do not observe any changes in the utilization of generic drugs in states that initiated the regulations, which suggests that the moral hazard induced by these regulations was minimal.

My findings demonstrate that the primary effect of “spread pricing” bans in many Medicaid markets appears to be the elimination of PBM informational rents, with minimal countervailing

moral hazard effects. Consistent with my model, these effects were heterogeneous across treated states: prices declined by roughly 30% in New York but did not change in Virginia. In a case study of the treated states, I explore possible explanations for this heterogeneity. I detect the largest price decreases in Medicaid markets where PBMs serve as a common agent for competing insurers, which mechanically reduces the number of PBMs operating in the market. PBMs may have greater bargaining leverage over retail pharmacies in markets with few PBMs, as pharmacies lose access to patients if they do not contract with the PBMs that serve their area. I do not detect an effect of the policies in states that rely heavily on insurers that are vertically integrated with a PBM, as these double markups may have already been eliminated.

I contribute to several strands of the economics literature. My primary contribution is to the literature on pharmacy benefit managers. Given the recent increase in public scrutiny of PBMs, there is demand for research that sheds light on the incentives faced by these firms. The few papers that have examined PBMs tend to focus on the “downstream” interactions between PBMs and insurers or “upstream” interactions between PBMs and manufacturers (Brot-Goldberg et al. (2022); Conti et al. (2021); Agha et al. (2022); Lavetti and Simon (2018); Feng and Maini (2019); Olssen and Demirer (2021); Gray et al. (2023)). This paper contributes to the small literature on “upstream” PBM interactions between these firms and retail pharmacies (Starc and Swanson (2021)). As such, I also contribute to the literature on vertical relationships in healthcare markets. My paper relates to the many studies of bargaining between hospitals and insurers (Ho and Lee (2017); Ghili (2022); Ho and Lee (2019)), but also introduces asymmetric information and considers the effects of alternative contractual arrangements on equilibrium outcomes. Relatedly, I contribute to the literature examining “managed competition” markets by examining how contractual arrangements can affect the efficiency of providing public insurance through private firms (Dranove et al. (2021); Geruso et al. (2020)).

I also contribute to our understanding of the effects of vertical contract design. Other empirical papers have studied the effects of specific contractual arrangements on firm behavior, such as rebates (Conlon and Mortimer (2021)), revenue-sharing (Mortimer (2008)), and vendor allowances (Hristakeva (2022)). I add to these papers by studying different but ubiquitous contractual arrangements: fixed-price and cost-plus contracts. Cicala (2015) studies the end of cost-of-service regulation in the energy sector and finds that deregulation led to cost reductions and efficiency gains by coal power plants. In energy markets, the regulators who monitor power plants to determine reimbursement have incomplete information about the true resource costs faced by these firms, but the costs of asymmetric information are amplified when firms are compensated on a cost-plus basis; in the pharmacy benefit industry, cost-plus contracting provides the principal with complete information about the costs faced by the agent, while monitoring by insurers is likely infeasible under a fixed-price contract. My work demonstrates that the efficiency implications of

vertical contract design are likely to be both industry- and market-specific.

Finally, I also contribute to the literature on the role of information in price formation (Grennan and Swanson (2020); Luco (2019)). My bargaining model provides an intuitive prediction on the effects of informational interventions in vertical markets: they will often be ineffective if asymmetric bilateral bargaining power (rather than asymmetric information) is the main distortion in the market. Understanding the relationship between contract design and information is particularly important for analyzing proposed interventions in prescription drug markets, such as the drug pricing provisions of the Inflation Reduction Act, which shift the burden of negotiating Medicare drug prices with manufacturers from PBMs to the federal government.

My paper proceeds as follows. In Section 2, I provide background on the Medicaid pharmacy benefits market and the contracting regulations of interest. In Section 3, I present my model of the pharmacy benefits market and discuss their theoretical implications. Section 4 presents my empirical analysis of the effect of these policy changes on drug prices and utilization, and Section 5 concludes with a discussion and describes paths for future research.

2 Background

Many Americans subscribe to a comprehensive health insurance plan offered by a managed care organization (MCO), which bundles both medical and drug insurance in a single plan. While insurers administer medical insurance themselves, many choose to subcontract with a PBM to manage pharmacy benefits for their enrollees. The PBM's primary responsibilities include processing prescription claims, designing a retail pharmacy network, reimbursing pharmacies for prescription fills, assisting the insurer in establishing a formulary (i.e., tiered lists of covered drugs), and securing rebates from manufacturers. In 2022, three PBMs (Caremark, Express Scripts, and OptumRx) processed roughly 80% of prescription claims (Fein (2023)). Despite the large market share of these three firms, insurers do have several outside options for PBM services. Mulligan (2022) identifies 70 companies that provide PBM services in the US. Furthermore, several insurers have vertically integrated into the PBM market in recent years, either organically or through a merger. Some vertically integrated PBMs may also work with non-integrated insurers.

Medicaid is a joint state-federal sponsored health insurance program that is available to low-income and vulnerable populations living in the United States. As of December 2022, more than 92 million individuals were enrolled in Medicaid, and the program accounts for 10.4% of US drug spending (CMS). While the federal government sets some rules, states have considerable freedom to design their Medicaid programs. The majority of state Medicaid programs provide comprehensive insurance through "Managed Medicaid" programs, in which the state government contracts with private health insurers to provide Medicaid-eligible consumers with insurance. Participating

insurers are typically compensated through lump sum per-enrollee payments from the government and, in some states, through subsidized premium payments by beneficiaries. Other states may choose to administer either benefits themselves rather than through private firms, an arrangement referred to “traditional” or “fee-for-service” (FFS) Medicaid.¹

Medicaid enrollees fill their prescriptions through pharmacies. In FFS Medicaid programs, states compensate pharmacies for each prescription based on the sum of an estimated ingredient cost and a set dispensing fee. In Managed Medicaid programs, insurers are permitted to negotiate reimbursement rates with pharmacies and can leverage their ability to selectively contract with pharmacies to obtain more favorable reimbursement rates. There is considerable variation in drug prices across retail pharmacies (Starc and Swanson (2021)). Additionally, drug prices fluctuate over time and space due to supply chain disruptions, drug shortages, seasonal demand, and other factors.

In commercial insurance markets, manufacturers of therapeutically equivalent drugs compete by offering rebates to PBMs in exchange for preferable placement on the PBMs’ formulary. PBMs share these rebates with their client insurers. Due to the prevalence of rebates, insurers rarely pay the list price for drugs. In 1990, the Medicaid Prescription Drug Rebate Program (MPDRP) mandated that state Medicaid programs receive the maximum rebate for all branded drugs in the market. Initially, insurers that participated in Managed Medicaid were denied participation in this program, but in 2014, the Affordable Care Act extended the federal statutory rebates to drugs covered under Medicaid managed care plans, enticing many states to privatize Medicaid prescription drug benefits (Dranove et al. (2021)). Insurers that participate in Managed Medicaid are permitted to procure additional rebates from drug manufacturers above and beyond the statutory rebates, but I am not aware of any public data that reports these supplemental rebates.

When contracting for pharmacy benefit management, PBMs bill insurers using either a fixed-price or cost-plus contracting model. In the former model, the PBM keeps the difference between the amount paid by insurers and the amount reimbursed to pharmacies for each prescription fill; in the latter, the PBM invoices the insurer for the exact reimbursement paid to the pharmacies for each prescription fill plus a “maintenance fee.” Insurers that are vertically integrated into PBM services presumably pay the exact reimbursement amount charged by the pharmacy with no additional PBM markup.

The use of fixed-price contracts has generated criticism from both pharmacists and policymakers. Pharmacists assert that large PBMs “squeeze” the profits out of retail pharmacies, in some cases reimbursing them for less than what was paid to acquire the drug (Herman (2018)). Several

¹In some states, Medicaid pharmacy benefits are primarily administered through comprehensive insurers, but the state chooses to “carve out” certain drugs from the Managed Medicaid benefit and handle reimbursements for those drugs themselves.

government audits and independent investigations have found that PBMs have earned large spread profits from contracting with Managed Medicaid insurers. An audit by the state of Ohio revealed that PBMs made \$225 million in spread profits during the 2018 fiscal year, accounting for approximately 9% of the state's Managed Medicaid budget. A study commissioned by the Pharmacists Society of the State of New York found that PBMs retained roughly 16% of New York Medicaid MCO spending on generic oral solids in the first quarter of 2018 (Skoufis and Rivera (2019)). Audits of PBMs in Maryland, Florida, and Virginia revealed average Medicaid prescription spreads ranging from 9.4% to 10.4% of prescription prices (Fein (2023)). In 2019, the Congressional Budget Office projected that a nationwide ban of spread pricing contracts in state Medicaid programs (which was proposed in the Prescription Drug Pricing Reduction Act of 2019) would save \$929 million over a ten-year period (Congressional Budget Office (2019)).

PBMs argue that the concerns raised about fixed-price contracts are misguided for several reasons. First, fixed-price contracting shields insurers from risk. The cost of filling a prescription varies across pharmacies and across time; as such, the spread pricing model offers insurers consistency in their pharmaceutical expenditures (Pharmaceutical Care Management Association; Skoufis and Rivera). Second, PBMs argue that the fixed-price model aligns their incentives with those of their insurer clients. The insurers prefer to have prescriptions filled with generic alternatives when possible, as these drugs tend to be cheaper than branded drugs. PBMs tend to make higher spreads from generic drug prescriptions, and thus are incentivized to move volume away from branded drugs as much as possible. Third, PBMs claim that they use profits to fund ancillary services that they provide to consumers, such as drug utilization management (Filipek and Snook (2011)).

As of 2022, at least 19 states have required insurers participating in their Medicaid programs to stop utilizing fixed-price reimbursement models. It is not clear that these policies will result in lower drug prices or spending. Under the fixed-price regime, PBMs have an incentive to negotiate low reimbursement rates with pharmacies. Cost-plus contracts may lack high-powered incentives for PBMs to control costs. Furthermore, with reduced profit incentives, PBMs may exert less effort in steering prescription volume away from expensive branded drugs towards cheaper generic alternatives. This would raise drug spending even if prices remained fixed. PBMs may also recoup their lost spread profits by charging large maintenance fees to insurers.² However, the transparency provided by cost-plus contracting may lessen any informational advantages enjoyed by the PBMs, allowing for insurers to negotiate for reduced compensation. Officials from some PBMs have reported that they retain relatively small spread profits in the Medicare Part D market because CMS

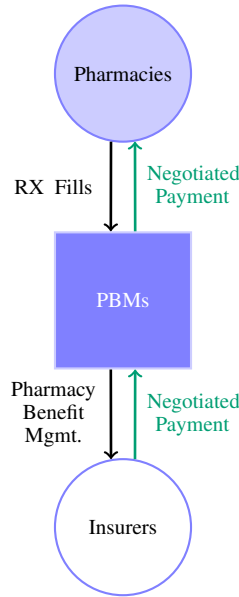
²In commercial markets, PBMs may respond to these policy changes by retaining a larger share of the drug rebates they negotiate with manufacturers. However, because states are entitled to the maximum rebate on all drugs via the MPDRP, and because PBMs do not share in those statutory rebates, that margin is mostly shut down. Thus, in my analysis, I focus on how the policy changes affect pre-rebate drug prices.

requires them to report the true reimbursement rates (United States Government Accountability Office (2019)). This suggests that informational asymmetries may play a large role in determining point-of-sale drug prices.

3 Theoretical Effects

In this section, I formulate a theoretical model of contracting between insurers, PBMs, and pharmacies to examine the effect of contracting regulations on equilibrium outcomes. In the spirit of Ho and Lee (2017), my model features simultaneous “downstream” bargaining between insurers and PBMs over payment terms and “upstream” bargaining between PBMs and pharmacies over reimbursement rates.

Figure 1: **Stylized Pharmacy Benefits Bargaining Model**



3.1 Insurer-PBM Bargaining

I model bargaining between insurers and PBMs using the alternating offers bargaining model introduced by Rubinstein (1982), and I borrow notation from Grennan and Swanson (2020), who use the same framework to examine bargaining between hospitals and their equipment suppliers. The process by which insurers select a PBM is complex and dependent on conditions in many different geographic and product markets (e.g., commercial, Medicaid, Medicare Advantage). As such, I do not model competition between PBMs for the business of a given insurer; instead, I model negotiations between bilateral monopolists to examine how contracting regulations affect the division of surplus.

In my model, a single buyer (the insurer) negotiates with a single supplier (the PBM) over a per-unit surplus $V = WTP - c$, where WTP is the buyer's willingness-to-pay for a unit of the supplier's product and c is the supplier's cost of production. The PBM's cost can be interpreted as the average reimbursement paid to retail pharmacies for a specific drug (e.g., Lipitor), and the insurer's willingness-to-pay represents their valuation of a prescription of that drug for an average use case (e.g., the average per-enrollee hospital expenses avoided through the utilization of Lipitor). In each round, one of the agents proposes a division of the surplus to the other agent, who can either accept or reject this offer; if the receiving agent rejects the offer, they counter with a new offer in the next round. Each agent has their own discount factor $\delta^{PBM} \in (0, 1)$ and $\delta^{insurer} \in (0, 1)$. In the original model presented in Rubinstein (1982), differences in discount factors represent differences in patience, with the agent with a higher discount factor willing to wait longer to come to an agreement; as such, higher discount factors translate to greater bargaining ability. A broader interpretation of the discount factor in the Rubinstein model is that it absorbs many of the different features that contribute to bargaining leverage, including competition, as buyers with few outside supplier options will tend to be "less patient."

The key difference between cost-plus and fixed-price contracting is the insurer's information about the PBM's true costs. Insurers are able to observe the PBM's true costs under cost-plus contracting, but not under fixed-price contracting. I first consider the negotiated price under cost-plus contracting. I assume that the discount factors, the PBM's cost, and the insurer's WTP are common knowledge. I also assume that all of the terms are exogenous and independent of the contracting method. Under complete information, the Rubinstein game has a unique subgame-perfect Nash equilibrium $p^{CI} = [\frac{1-\delta^{PBM}}{1-\delta^{PBM}\delta^{insurer}}] * c + [\frac{\delta^{PBM}(1-\delta^{insurer})}{1-\delta^{PBM}\delta^{insurer}}] * WTP$. Because the information provided via cost-plus contracting eliminates any asymmetries, the equilibrium negotiated price under cost-plus will coincide with the complete information price p^{CI} .

Fixed-price contracts reduce the insurer's information, as they do not observe the true upstream reimbursement rates being paid by their PBM to retail pharmacies. As such, I introduce one-sided asymmetric information into the model: the insurer's WTP remains common knowledge, but the insurer does not know the true value of the PBM's c .³ I assume for simplicity that the PBM's cost can either be a "high type" c_H or a "low type" c_L with $c_L < c_H < WTP$, such that the gains from trade are always positive regardless of the type. The insurer has a subjective probability ω that the PBM is of the low type. Following Rubinstein (1985), I assume that there exists some threshold $\bar{\omega}$

³Grennan and Swanson (2020) follow Rubinstein (1985) and introduce one-sided uncertainty about the discount factors while continuing to assume that both WTP and c are common knowledge. In my context, the important features that underlie the discount factors are likely to be common knowledge (or revealed through repeated interactions), but PBMs obscure the true cost of their services from third parties. Thus, introducing uncertainty with respect to marginal costs permits my model to make predictions about how the effect of incomplete information varies with disparities in PBM and insurer bargaining leverage.

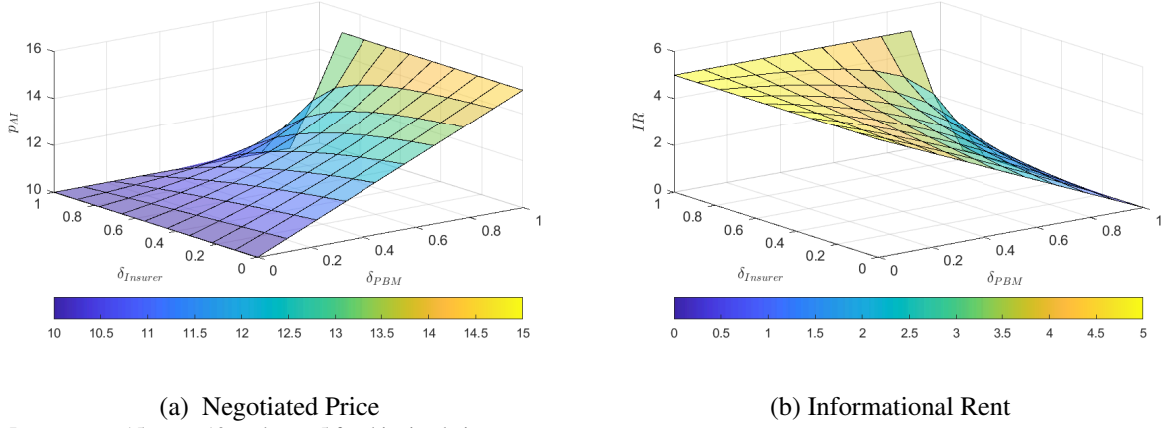
such that for all $\omega < \bar{\omega}$, the insurer is sufficiently pessimistic about the probability that the PBM is of the low type and will offer a price equal to the equilibrium price under complete information when the PBM is of the high type: $p^{AI} = p_H^{CI} = [\frac{1-\delta^{PBM}}{1-\delta^{PBM}\delta^{insurer}}] * c_H + [\frac{\delta^{PBM}(1-\delta^{insurer})}{1-\delta^{PBM}\delta^{insurer}}] * WTP$. The PBM accepts this offer regardless of its true type.

I now consider the case when the PBM is of the low type, such that $c = c_L$. Continuing to assume that $\omega < \bar{\omega}$, the insurer offers p^{AI} under asymmetric information, but would have offered p_L^{CI} if it knew the PBM's true cost. Thus, asymmetric information generates "informational rents" that are retained by the low-type PBM under a fixed-price contract. This informational rent is calculated as $IR = p^{AI} - p_L^{CI} = (c_H - c_L)(\frac{1-\delta^{PBM}}{1-\delta^{PBM}\delta^{insurer}}) \geq 0$. When PBMs and insurers are forced to move from a fixed-price to a cost-plus contract, these informational rents dissipate as the insurer becomes informed and the negotiated price adjusts to the complete information price. Thus, assuming that the PBM's costs are held fixed, mandating cost-plus contracting will result in larger price effects if IR is large.

Figure 2 illustrates how the negotiated price under asymmetric information p_{AI} and the PBM's informational rents IR depend on the relative bargaining leverage of insurers and PBMs. The PBM's informational rent *decreases* as the discount factor of the PBM increases (i.e., as the PBM's bargaining leverage strengthens), and *increases* as the discount factor of the insurer increases. Though this finding may seem counter-intuitive, notice that when the PBM's bargaining leverage increases and the insurer's leverage decreases, the equilibrium price trends towards WTP regardless of whether the insurer is completely informed; that is, when the PBM has all of the bargaining leverage, the PBM will always capture the entire surplus.⁴ The informational rent is largest when the insurer has more bargaining leverage than the PBM because the insurer is able to negotiate prices down towards its subjective perception of the PBM's cost. As a result of the information asymmetry, insurer negotiates price down to the high-type cost when $\omega > \bar{\omega}$ even if the PBM is really of the low-type. The PBM leverages its informational advantage to retain some of the surplus even if insurers have all of the bargaining leverage.

⁴To see this, notice that $\lim_{\delta^{PBM} \rightarrow 1, \delta^{insurer} \rightarrow 0} p_H^{CI} = WTP$ and $\lim_{\delta^{PBM} \rightarrow 0, \delta^{insurer} \rightarrow 1} p_H^{CI} = c_H$.

Figure 2: **Negotiated PBM-Insurer Price and PBM Informational Rent**



Note: I set $WTP = 15$, $c_H = 10$, and $c_L = 5$ for this simulation.

My model confirms the intuitive prediction discussed earlier in this paper that these policies will be ineffective if PBMs have market power over insurers: PBMs would simply recoup lost spread pricing profits through higher maintenance fees. Forcing cost-plus contracting will have greater price effects in markets where informational rents are large, which my model predicts are markets in which insurers have greater bargaining power than PBMs. In these scenarios, asymmetric information serves as a substitute for bargaining power and allows PBMs to obtain rents even if insurers have all of the bargaining power. Based on my model, I predict that fixed-price contracting will cause the greatest price decreases in markets where either (a) insurers have greater bargaining power in negotiations with PBMs, or (b) there is considerable potential variation in drug costs such that $c_H - c_L$ is large.

These two conditions seem somewhat contradictory. One would assume that the bargaining leverage enjoyed by insurers increases with scale, and that large insurers are likely to have invested in information about the true cost of drugs. However, small insurers may have considerable negotiating leverage because of the large number of outside options in the PBM market, and because of the possibility that the insurer could vertically integrate into administering its own pharmacy benefits (Mulligan (2022)).

My model also predicts that the spread pricing bans should result in the largest price decreases for which uncertainty about prices is larger (i.e., $c_H - c_L$ is large). Insurers are less likely to be informed about the pre-rebate prices of generic drugs than they are of popular branded drugs, and thus I expect to see the largest price decreases for generic drugs.⁵ This is consistent with reporting that spread profits are typically largest for generic drugs.

⁵Consistent with this intuition, I observe that Managed Medicaid insurers paid 135% of the NADAC in the first quarter of 2017 for prescriptions of generic drugs, relative to 98% of the NADAC for prescriptions of branded drugs.

3.2 PBM-Pharmacy Bargaining

The model in Section 3.1 assumed that the PBM's costs were independent of the contracting method. However, cost-plus contracts may eliminate the profit incentive for PBMs to negotiate lower reimbursement rates, leading costs to increase. To examine how contract design determines the incentives faced by PBMs in negotiations with pharmacies, I model the bargaining process between these firms using the bilateral Nash bargaining model presented in Ho and Lee (2017). I index pharmacies by h , PBMs by f , and insurers by j . Each PBM maintains a network of pharmacies \mathcal{G}_f at which their enrollees can fill prescriptions, which I take as given. PBMs and pharmacies bargain to determine the price at which retail pharmacies are reimbursed. For simplicity, I assume that the parties bargain over only one drug and one geographic market, and that each PBM f represents just one insurer j .⁶

I assume that profits for pharmacy h are $\Pi_h^H = \sum_{n \in \mathcal{G}_h^H} D_{hn}^H(p_{hn} - c_h)$, where n indexes all of the PBMs for which the pharmacy has “in-network” status (\mathcal{G}_h^H), p_{hn} is the reimbursement price paid by insurer n to pharmacy h , and c_h is the constant marginal cost faced by pharmacy h .

The profit function for PBM f takes one of two forms depending on the contracting method.

- Fixed-price: $\Pi_f^{PBM_{fixed}} = \sum_{h \in \mathcal{G}_f} D_{hj}^H(\phi_{jf}^{fixed} - p_{hj}^{fixed})$
- Cost-plus: $\Pi_f^{PBM_{costplus}} = \phi_{jf}^{costplus} \sum_{h \in \mathcal{G}_f} D_{hj}^H$,

where $\phi_{jf}^{costplus}$ is the per-prescription maintenance fee paid by insurer j to PBM f under cost-plus and ϕ_{jf}^{fixed} is the per-prescription reimbursement paid by insurer j to PBM f under fixed-price.⁷

Under simultaneous bilateral Nash bargaining, each negotiated price per prescription fill p_{hp} between PBM p and pharmacy h maximizes the pair's bilateral Nash product:

$$p_{hf}^* = \underset{p}{\operatorname{argmax}} \underbrace{[\Pi_h^H(\mathcal{G}, \{p, p_{-hf}\}) - \Pi_h^H(\mathcal{G}/hf, p_{-hf})]}_{\text{(i) Pharmacy } h\text{'s GFT}} \underbrace{[\Pi_f^{PBM}(\mathcal{G}, \{p, p_{-hf}\}) - \Pi_f^{PBM}(\mathcal{G}/hf, p_{-hf})]}_{\text{(ii) PBM } f\text{'s GFT}}^{1-\tau_h}, \quad (1)$$

where $\Pi_x^X(\mathcal{G}, \{p, p_{-hf}\})$ is firm x 's profit when pharmacy h is included in PBM f 's network, $\Pi_x^X(\mathcal{G}/hf, p_{-hf})$ is its profit when pharmacy h is excluded, and τ_h is pharmacy h 's Nash bargaining parameter.

⁶In reality, PBMs often work with multiple competing insurers in the same geographic market. I make this assumption strictly for the simplicity of notation.

⁷I assume that the maintenance fees paid under cost-plus are unit fees rather than percentage fees, as I understand this to be common practice in the industry.

I now demonstrate how the different contracting methods affect equilibrium outcomes through a comparative statics exercise. Taking the first order condition of the above with respect to p_{hf} , and abusing notation slightly, gives:

$$\begin{aligned}
\textbf{Fixed-price: } \underbrace{D_{hj}^H p_{hj}^{fixed}}_{\text{Total Pharmacy Payments}} &= \underbrace{\tau_h (D_{hj}^H \phi_{jf}^{fixed} - \sum_{k \in \mathcal{G}/h} \Delta_{hj} D_{kj}^H (\phi_{jf}^{fixed} - p_{kj}^{fixed}))}_{\text{(i) PBM Utilization Effect}} + \underbrace{\sum_{k \in \mathcal{G}/h} \Delta_{hj} D_{kj}^H (\phi_{jf}^{fixed} - p_{kj}^{fixed})}_{\text{(ii) Price Reinforcement Effect}} + \\
&\quad \underbrace{(1 - \tau_h) (D_{hj}^H c_h - \sum_{n \in \mathcal{G}^H/j} \Delta_{hj} D_{hn}^H (p_{hn} - c_h))}_{\text{(iii) Pharmacy Cost Effect}} + \underbrace{\sum_{n \in \mathcal{G}^H/j} \Delta_{hj} D_{hn}^H (p_{hn} - c_h)}_{\text{(iv) Recapture Effect}}
\end{aligned}$$

$$\begin{aligned}
\textbf{Cost-Plus: } \underbrace{D_{hj}^H p_{hj}^{costplus}}_{\text{Total Pharmacy Payments}} &= \frac{\tau_h}{(1 - \tau_h)} \underbrace{(D_{hj}^H \phi_{jf}^{costplus} - \sum_{k \in \mathcal{G}/h} (\Delta_{hj} D_{kj}^H (\phi_{jf}^{costplus})))}_{\text{(i) PBM Utilization Effect}} + \underbrace{\sum_{k \in \mathcal{G}/h} (\Delta_{hj} D_{kj}^H (\phi_{jf}^{costplus}))}_{\text{(ii) Price Reinforcement Effect}} + \\
&\quad \underbrace{(D_{hj}^H c_h - \sum_{n \in \mathcal{G}^H/j} \Delta_{hj} D_{hn}^H (p_{hn} - c_h))}_{\text{(iii) Pharmacy Cost Effect}} + \underbrace{\sum_{n \in \mathcal{G}^H/j} \Delta_{hj} D_{hn}^H (p_{hn} - c_h)}_{\text{(iv) Recapture Effect}}
\end{aligned}$$

For conciseness, $\Delta_{hj} D_{kj}$ is the change in the demand for pharmacy k by insurer j 's enrollees after pharmacy h is dropped from its network, and $\Delta_{hj} D_{hn}$ is the change in the demand for pharmacy h by insurer n 's enrollees after it is excluded from insurer j 's network. Portions (i) and (ii) represent PBM f 's gains from trade from including pharmacy h in their network; portions (iii) and (iv) represent pharmacy h 's gains from trade from being included in PBM p 's network. Borrowing terminology from Ho and Lee (2017), these gains of trade can be decomposed into four different "effects":

- *(i) PBM utilization effect:* the PBM loses revenue when pharmacy h is out-of-network. The more PBM f stands to make more from including pharmacy h in its network, the more pharmacy h is paid in equilibrium.
- *(ii) Price reinforcement effect:* after pharmacy h is dropped from its network, the transactions that previously occurred at pharmacy h are now transferred to the remaining pharmacies in the PBM's network. Some enrollees may choose to switch plans due to the change in PBM f 's network. This term represents PBM f 's opportunity cost of including pharmacy h in its network.
- *(iii) Pharmacy cost effect:* unit increases in the marginal costs of pharmacy h are partially passed through to the reimbursement rate.

- (iv) *Recapture effect*: because some members who were previously enrolled in insurer j 's plan switch as a result of the exclusion, demand changes from other insurers as a result of the change to PBM f 's pharmacy network. This is pharmacy h 's opportunity cost of participating in PBM f 's network. When rival PBMs pay pharmacy h more favorable reimbursement rates, PBM f pays it more in equilibrium.

The PBM faces different incentives under the two contracting regimes, which manifest in the first order conditions derived above. Under a fixed-price contract, the PBM bears the risk of high reimbursement rates. Under a cost-plus contract, the PBM bears no risk and is incentivized to maximize the total number of transactions, since they are compensated based on volume. The cost-plus contract incentivizes PBMs to take a more “laissez-faire” approach to negotiations. Increases in pharmacy marginal costs and in PBM fees charged to insurers are both passed through at a higher rate to pharmacy revenue. The “recapture effect” that represents pharmacy h 's opportunity cost of contracting with PBM f is also passed through at a higher rate, placing an upward pressure on prices.

However, this laissez-faire approach has a double-edged effect on pharmacy revenues. In determining their profits if pharmacy h was excluded from its network, PBM f considers only how many of their consumers would remain in the plan and continue filling prescriptions at in-network pharmacies, not whether they would switch to pharmacies with higher or lower negotiated reimbursements. Thus, in the eyes of the PBM, pharmacies have become less differentiated under cost-plus contracting. This countervailing effect pushes down on pharmacy reimbursements.

It is unclear *ex ante* which of the above effects would dominate. To see this, calculate the difference in the amount paid by PBM f to pharmacy h across the two contracts, holding fixed all other contracts with other partners:

$$\begin{aligned}
D_{hj}^H(p_{hj}^{costplus} - p_{hj}^{fixed}) &= D_{hj}^H(c_h + \frac{\phi_{jf}^{costplus}}{1 - \tau_h} - \phi_{jf}^{fixed}) \\
- \sum_{k \in \mathcal{G}/h} (\Delta_{hj} D_{kj}^H(\frac{\phi_{jf}^{costplus}}{1 - \tau_h} - \phi_{jf}^{fixed} + p_{kj}^{fixed})) &- \sum_{n \in \mathcal{P}/j} \Delta_{hj} D_{hn}^H(p_{hn} - c_h)
\end{aligned} \tag{2}$$

This expression is complex and cannot be easily signed. However, it is apparent that the effects of the contracts will depend on a variety of factors, including the compensation that PBMs negotiate with insurers, the relative bargaining power of upstream pharmacies, and competition in both the upstream and downstream markets. Further, it suggests that the moral hazard effects of cost-plus contracting on negotiated prices will not always be positive as economic theory has typically suggested.

To ease interpretation, assume for the moment that there exists only one insurer, one PBM, and one pharmacy in the market, such that the reinforcement and recapture effects are null. Simplifying Eq. (2), pharmacy h 's revenue increases if $\phi_{jf}^{costplus} > (1 - \tau_h)(\phi_{jf}^{fixed} - c_h) = \phi_{jf}^{fixed} - p_{hj}^{fixed}$. This equation implies that the sign of the change in reimbursement rates will depend on the product of two factors: the pharmacy's bargaining power τ_h , and the surplus created by the formation of a contract between PBM f and pharmacy h . Pharmacy h will receive greater reimbursement rates if the surplus created by that contract is small, which will be true for high-cost pharmacies, or if it has high bargaining power. I understand that only large chain pharmacies may have bargaining power with PBMs, and that these pharmacies tend to operate at lower costs (Starc and Swanson (2021)). Since a pharmacy's marginal costs and bargaining power are likely to be negatively correlated, these two conditions will cover a broad spectrum of pharmacies. My model demonstrates that policymakers should expect these regulations to induce upstream moral hazard which places upward pressure on pharmacy reimbursements.

3.3 Policy Implications

My model delivers two key insights into how PBM contract design influences drug prices. First, cost-plus contracts reduce incentives for PBMs to exert effort in negotiating reimbursement rates with pharmacies, allowing drug prices to rise. Second, the information provided through cost-plus contracting will reduce the end price paid by insurers only if they have bargaining power in negotiations with PBMs. These two forces drive reimbursement rates in different directions, and the ultimate effect of contract design on drug prices will vary across firms and markets. My model suggests that policies which reduce information asymmetries while still maintaining profit incentives for PBMs may be more effective at reducing drug prices than policies which prohibit fixed-price contracting. Some states and insurance markets have already implemented policies like this; for example, CMS requires all PBMs to report how much they earn from spread pricing in Medicare Part D (United States Government Accountability Office (2019)). If the compliance costs with these reporting requirements are sufficiently low, policies requiring transparency may achieve the cost savings that policymakers desire without the upstream moral hazard induced by cost-plus contract requirements.

4 Empirical Analysis

The analysis in Section 3 confirms the intuitive trade-offs in designing compensation for intermediary firms: cost-plus contracts reduce information asymmetries between trading partners, but they also reduce incentives for intermediaries to reduce costs. Whether the information effect or

incentive effect will dominate is ex ante ambiguous and is therefore an empirical question.

4.1 Data

I rely on the publicly available State Drug Utilization Data (SDUD) maintained by the Center for Medicare and Medicaid Services (CMS) for January 2017 through December 2022 (Center for Medicare and Medicaid Services (2017d)).⁸ The SDUD provides the total number of Medicaid prescriptions and dollar amount of pre-rebate spending in each quarter for each state and drug (as defined by the 11-digit National Drug Code). The National Drug Code (NDC) identifies the labeler, product name, and package size of each drug. The SDUD reports these data separately for Managed Medicaid and for FFS programs within each state. While the SDUD is limited in that it groups together all insurers and geographic regions within a state, it also allows for cross-state comparisons.

I supplement the SDUD with drug-level product information available through CMS (Center for Medicare and Medicaid Services (2017c)) and the Food and Drug Administration (FDA) (US Food and Drug Administration), which allow me to identify the generic/branded status and active ingredient of most drugs in the data. I also rely on the CMS National Average Drug Acquisition Cost (NADAC) data, which provides weekly average pharmacy acquisition prices for each drug based on a national survey of retail pharmacies. I use the NADAC data to proxy for pharmacy marginal costs in some analyses (Center for Medicare and Medicaid Services (2017b)). I also use annual Medicaid enrollment data from CMS (Center for Medicare and Medicaid Services (2017a)), and I collected information on insurer-PBM contractual relationships via online research.

I relied on a survey of state Medicaid agencies conducted by the Kaiser Family Foundation (Kaiser Family Foundation (2020)) and also collected information on state legislation related to spread pricing via online research, identifying 19 states that had prohibited fixed-price contracting in their Medicaid programs prior to 2022. Of these 19 states, six were suitable to be studied as a treatment group. Table A.1 provides a more detailed overview of the sample selection. My control group consists of the 16 states that administered pharmacy benefits through comprehensive insurers for the entirety of my study period and for which I am not aware of any spread pricing regulations.

Table 1 presents summary statistics for the first quarter of 2017 separately for the treatment and control states. A common concern with retrospective evaluations of policy changes is the potential endogeneity of the regulations. It is possible that the states which enact regulations on PBMs and insurers suffer from higher drug prices due to their contractual arrangements, which would limit

⁸Economists have used the SDUD to study the effects of Medicaid privatization (Dranove et al. (2021)), Medicaid expansions (Ghosh et al. (2019)), and collusion in generic drug markets (Starc and Wollmann (2022)). I discuss my data cleaning in the appendix.

the external validity of my findings and potentially bias the results of my empirical exercises. The summary statistics presented in Table 1 alleviate those concerns: the treatment and control states are similar on many dimensions, including the use of Managed Medicaid insurers and average pre-rebate drug prices. Following Dranove et al. (2021), I construct two measures of generic drug utilization that I use throughout this paper. The generic share of prescriptions simply measures the share of prescriptions that were filled with a generic. “Generic efficiency” measures the share of prescriptions that were filled with a generic after restricting to drugs for which a generic alternative was available.⁹

For each state, I also compared the average Medicaid pre-rebate prescription prices with the NADAC, which provides a rough estimate of pharmacy marginal costs. The difference between the reimbursement rate and the pharmacy’s acquisition cost is the surplus shared between PBMs and pharmacies. States for which this surplus amount is larger may have greater incentives to introduce spread pricing bans, which would render the interventions endogenous. The treated states paid on average \$3.69 in excess of the NADAC per prescription, or 7.4% above NADAC per prescription. These “excess” amounts are balanced across treatment and control states and do not appear to be correlated with treatment assignment, further easing concerns about the endogeneity of the regulations.

⁹I use the FDA NDC database to identify the active ingredient for 68.7% of drugs in my regression sample, which accounted for 81.1% of total Medicaid drug spending in 2017q1. Of the drugs for which I could identify the active ingredient, 89.9% had a generic alternative available in at least one quarter of the data.

Table 1: **Pre-Treatment State-Level Summary Statistics, 2017**

	Treatment		Control		Difference	
	Mean	SD	Mean	SD	Mean	SD
MCO enrollment share	0.72	0.12	0.72	0.22	-0.01	0.10
MCO prescription share	0.77	0.15	0.80	0.24	-0.03	0.11
MCO drug spending share	0.69	0.26	0.73	0.28	-0.04	0.13
Price per prescription	74.76	22.68	72.80	11.77	1.96	7.30
Price per prescription/NADAC per prescription	1.08	0.07	1.08	0.06	-0.00	0.03
Medicaid Price-NADAC per prescription	3.69	3.28	3.49	2.41	0.20	1.27
Generic share of prescriptions	0.86	0.01	0.85	0.02	0.01	0.01
Generic efficiency	0.92	0.00	0.91	0.02	0.01	0.01
Medicaid expansion 2017-2022	0.83	0.41	0.88	0.34	-0.04	0.17
Observations	6		16		22	

Unit of observation is a state. All values are for 2017q1.

4.2 Empirical Strategy

I leverage spatial and temporal variation in the adoption of contracting regulations to study the effects of these policy changes in a difference-in-differences (DD) framework. My primary unit of analysis is a state-drug-quarter, where a drug is defined as an 11-digit NDC. For state s and drug d in quarter t , let Y_{dst} be the dependent variable of interest, α_{ds} be a state-drug fixed effect, γ_t be a quarter fixed effect, $Policy_{st}$ be an indicator for whether a state has implemented contracting regulations, and $MCExpansion_{st}$ be an indicator for whether the state has expanded Medicaid. Inspired by Dranove et al. (2021), my state-drug level DD specification is

$$Y_{dst} = \alpha_{ds} + \gamma_t + \beta Policy_{st} + \lambda MCExpansion_{st} + \epsilon_{dst}. \quad (3)$$

Let D_{dst}^l be an indicator that is equal to one if and only if state s is l quarters from the policy change in quarter t . My state-drug level event study specification is thus

$$Y_{dst} = \alpha_{ds} + \gamma_t + \sum_{l=-8}^7 \beta^l D_{dst}^l + \lambda MCExpansion_{st} + \epsilon_{dst}. \quad (4)$$

I conduct some analyses at the state-quarter level, for which my DD specification is

$$Y_{st} = \alpha_s + \gamma_t + \beta Policy_{st} + \lambda MCExpansion_{st} + \varepsilon_{st} \quad (5)$$

and my event study specification is

$$Y_{st} = \alpha_s + \gamma_t + \sum_{l=-8}^7 \beta^l D_{st}^l + \lambda MCExpansion_{st} + \varepsilon_{st}. \quad (6)$$

I treat the policy changes as plausibly exogenous with no anticipatory reaction by insurers, PBMs, or pharmacies. The use of long-term contracts between these firms limits their ability to change behavior prior to the policy change. The validity of the “no anticipation” assumption can be visually confirmed by examining the event study plots presented in the following subsection. The event study plots also demonstrate that drug prices were trending similarly in treatment and control states prior to the policy changes, lending additional support to the exogeneity assumption. I assume that absent the regulations, the outcomes of interest in the treatment and control states would have continued to evolve in a similar fashion.

I also assume that the policy changes did not have any spillover effects on the control states. If cost-plus contracts do provide insurers with new information about the costs faced by their PBM in the treatment states, this may cause them to adjust their PBM contracts nationally, which may affect drug prices in the control states. These spillover effects may bias my coefficient estimates in either direction, as the effects of cost-plus contracts are likely to vary across geographies and firms. However, I would expect any spillovers to be small: only three insurers who are not vertically integrated with a PBM offered Managed Medicaid plans in both treatment and control states in 2020.¹⁰ It is unlikely that firms would change their behavior in one state in response to regulatory changes in another state, especially given that Medicaid is a relatively small share of overall business for many participating insurers, PBMs, and pharmacies.

I further assume that the composition of the control and treatment groups are stable during the study period, and control for changes in Medicaid eligibility due to state-level expansions of program eligibility in response to the ACA. For all of my analyses, I use the estimator developed in Callaway and Sant’Anna (2021) to account for heterogeneity in the effects of the policies and the staggered implementation of the contracting regulations across states. I weight all regressions by the number of prescriptions for the given state-drug-quarter and I cluster standard errors by state.

A common concern with DD designs is that post-treatment changes in outcomes may be driven either by unrelated changes in the treatment states that occurred roughly simultaneously with treat-

¹⁰The three insurers are Kaiser Permanente, Molina, and Wellcare. Combined, these firms accounted for 8.6% of total 2020 Managed Medicaid enrollment in my analytic sample.

ment or by changes in the control states rather than in the treatment states. These concerns are prominent in my setting for two reasons. First, states have considerable freedom to design and implement Medicaid pharmacy policies, which may affect drug prices and utilization independently of the contracting regulations. Second, most of the states that adopted the contracting regulations did so shortly before or during the COVID-19 pandemic, which may have affected drug prices and utilization differently across states. I address these potential confounders using data from each state’s “traditional” or “fee-for-service” (FFS) Medicaid program. Many states provide Medicaid pharmacy benefits both through comprehensive insurers and through an FFS program, the latter of which is usually reserved for special populations or drugs.¹¹ FFS programs are required to tie reimbursement rates to publicly available benchmarks, and while FFS programs typically contract with PBMs, most states do not rely on them for pharmacy network contracting. Thus, the policy changes should not directly affect FFS drug prices in the treatment states. However, the FFS prices will be subject to confounding state-level policy changes and other shocks (like COVID-19).

I use the FFS data to estimate “placebo” versions of Eq. (3) to Eq. (4) to demonstrate that my main results are not driven by spurious trends in drug prices and utilization that are unrelated to the policy change. The contracting regulations may have indirect effects on drug prices and utilization for members of same-state FFS programs. To account both for these spillover effects and for unrelated post-treatment trends in the treatment states (e.g., due to heterogeneous effects of the COVID-19 pandemic on drug utilization and prices), I also estimate triple differences (DDD) versions of Eq. (3) to Eq. (4), where I define the outcome variables as $Y_{dst}^{DDD} = Y_{dst}^{MCO} - Y_{dst}^{FFS}$. The DDD regression differences out state-level changes that occur independently of the contracting regulations. I assume that the relative outcome of the Managed Medicaid and FFS programs in the treatment states would trend in the same way as the relative outcome of Managed Medicaid and FFS programs in the control state in the absence of treatment (Olden and Møen (2022)). FFS programs typically provide benefits to small, special populations; as a result, average FFS drug prices at the state level are prone to fluctuations, particularly for states with small FFS enrollments. The DDD parallel trends assumption is thus more credible for state-drug-level regressions, as drug-level prices will be more stable than state-level averages. I report the FFS and DDD state-level results in Table A.2.

There are two main limitations with respect to this paper when considering policy implications. First, due to the aggregated level of the Medicaid SDUD, I am unable to examine effects at a more granular geographic level than is possible with claim-level data, nor am I able to examine firm-level heterogeneity. Second, the effects of these policies may vary across insurance markets because

¹¹For example, when a New York or Virginia resident first enrolls in Medicaid, they receive coverage through the state’s FFS program until they have chosen a Managed Medicaid plan. Other states cover special needs population such as pregnant women or the disabled through their FFS plans.

of differences in regulations. Rebates are an important compensating differential for PBMs in response to policy changes; however, the most-favored-nation status enjoyed by state Medicaid programs from the MPDRP law described in Section 2 essentially shuts down that margin in the Medicaid setting.

4.3 Results

Table 2 presents the drug-level results from Eq. (3). Managed Medicaid pre-rebate prescription prices fell by 21.7% in the treatment states after the policy change. These effects were driven by generic drugs, for which prices declined by 26.6%. This is consistent with the predictions of my model and with anecdotal evidence that PBMs tend to make most of their “spread profits” from prescriptions of generic drugs (Skoufis and Rivera (2019)). I do detect smaller but significant changes in drug prices for the FFS programs in the treated states: pre-rebate prescription prices declined by 2.3% on average. As discussed above, this may be due to within-state spillovers from the policies or confounding state-level trends. Using my DDD specification, I detect significant price decreases that are smaller in magnitude for drugs that were prescribed by both Managed Medicaid plans and FFS programs within the same state: 15.4% for all drugs, and 21.1% for generic drugs.¹² Figure 3 presents the event study estimates for Eq. (4). The event studies demonstrate that outcomes were evolving similarly across the treatment and control groups in the eight quarters preceding the contracting regulations, lending support to the parallel trends and “no anticipation” assumptions.

Table 2: Effect of Contracting Regulations on ln(Avg. Price Per Prescription), Drug-Level

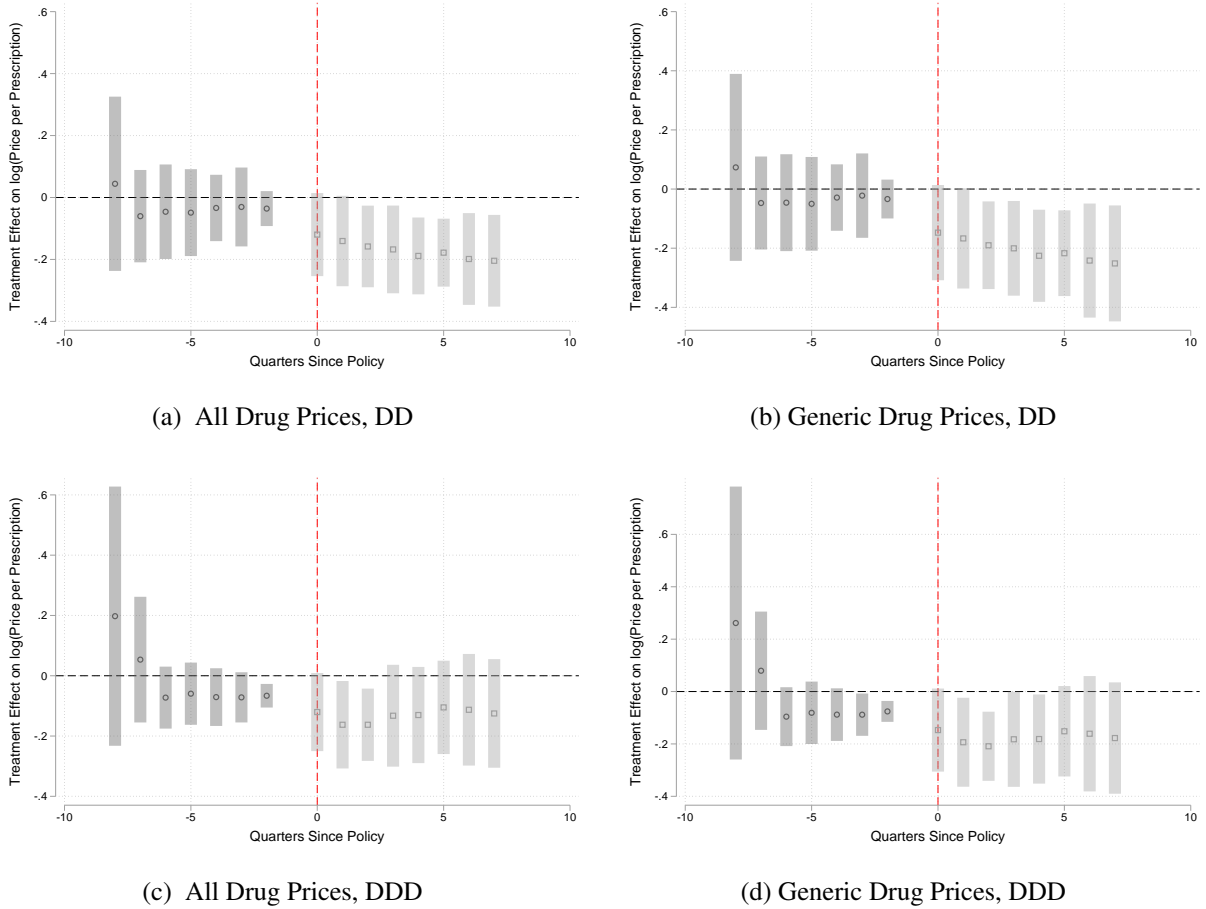
	Managed Medicaid		FFS		DDD	
	All Drugs	Generic Drugs	All Drugs	Generic Drugs	All Drugs	Generic Drugs
Policy	-0.21737*** (0.07784)	-0.26550*** (0.09757)	-0.02289** (0.00995)	-0.03612*** (0.01097)	-0.15379* (0.09171)	-0.21118** (0.10662)
Observations	1,255,320	1,053,816	650,560	530,688	362,344	303,312

Sources: CMS State Drug Utilization Data; CMS Product Data for Drugs in the Medicaid Drug Rebate Program; FDA NDC Database.

Notes: This table presents estimates of Eq. (3). The unit of observation for these regressions is state-drug-quarter, where drug is defined as the 11-digit National Drug Code. I estimate these regressions using a strongly balanced panel of state-drug combinations that appear in all quarters of the data. All specifications include state-drug fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Regressions are weighted by the number of quarterly prescriptions. Standard errors in parentheses are clustered by state. I calculate quarterly prescription prices as the amount reimbursed by the Medicaid program divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS drug data is either NDA Authorized Generic or Abbreviated New Drug Application. I exclude prescriptions of over-the-counter drugs and all observations that were missing the number of prescriptions, the number of units, or the Medicaid reimbursement amount in the SDUD.

¹²Not all drugs are covered by both Managed Medicaid and FFS programs, so the set of observations included in the DDD estimation consists of a smaller number of drugs.

Figure 3: Event Study of Contracting Regulations, Drug-Level



Note: This figure presents estimates of Eq. (4). The unit of observation for these regressions is state-drug-quarter, where drug is defined as the 11-digit National Drug Code. I estimate these regressions using a strongly balanced panel of state-drug combinations that appear in all quarters of the data. All specifications include state-drug fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Regressions are weighted by the number of quarterly prescriptions. Standard errors in parentheses are clustered by state. I calculate quarterly prescription prices as the amount reimbursed by the Medicaid program divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS drug data is either NDA Authorized Generic or Abbreviated New Drug Application. I exclude prescriptions of over-the-counter drugs and all observations that were missing the number of prescriptions, the number of units, or the Medicaid reimbursement amount in the SDUD. The figures presents estimates of treatment effects relative to the quarter before treatment.

To confirm that these results are driven by the contracting regulations rather than drug-specific trends, Table 3 and Figure 4 present estimates of Eq. (3) and Eq. (4) with average Medicaid price per prescription net of NADAC as the dependent variable. Wholesale drug prices may be following secular trends that are independent of the contracting regulations but affect states differently. By differencing out the NADAC, I provide further evidence that the observed price effects are due to the contracting regulations rather than these secular trends. Average Managed Medicaid prices net of NADAC fell by \$2.42 per prescription in the treated states following the contracting regulations. I observe no change in the prices net of NADAC for the FFSU programs of the treated states. Given that my model predicts upstream moral hazard which places upward pressure on pharmacy prices, this effect is consistent with the dissipation of PBM informational rents and unlikely to be driven

by decreases in pharmacy marginal costs in the treated states.¹³

Table 3: Effect of Contracting Regulations on Avg. Price per Prescription Net of NADAC, Drug-Level

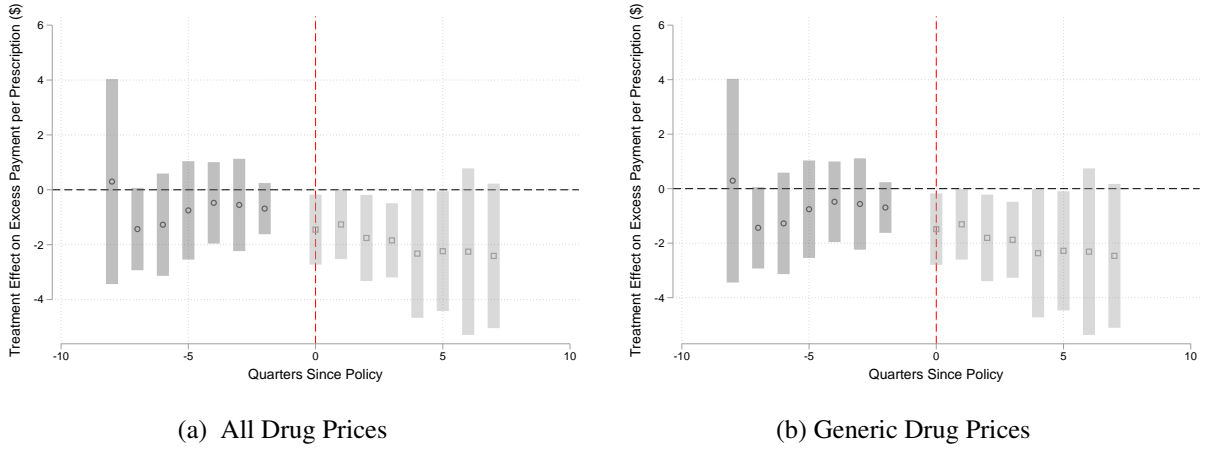
	Managed Medicaid		FFS	
	All Drugs	Generic Drugs	All Drugs	Generic Drugs
Policy	-2.41783** (1.19875)	-2.46681** (1.21073)	0.54752 (0.68112)	0.54363 (0.67646)
Observations	985,488	965,520	505,272	497,040

Sources: CMS State Drug Utilization Data; CMS Product Data for Drugs in the Medicaid Drug Rebate Program; FDA NDC Database; CMS National Average Drug Acquisition Cost Data.

Notes: This table presents DD estimates of Eq. (3), where the dependent variable is the difference between the quarterly average pre-rebate prescription price and the quarterly NADAC. The unit of observation for these regressions is state-drug-quarter, where drug is defined as the 11-digit National Drug Code. I estimate these regressions using a strongly balanced panel of state-drug combinations that appear in all quarters of the data. All specifications include state-drug fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Regressions are weighted by the number of quarterly prescriptions. Standard errors in parentheses are clustered by state. I calculate quarterly prescription prices as the amount reimbursed by the Medicaid program divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS drug data is either NDA Authorized Generic or Abbreviated New Drug Application. I exclude prescriptions of over-the-counter drugs and all observations that were missing the number of prescriptions, the number of units, or the Medicaid reimbursement amount in the SDUD, and drug-quarter combinations that were not present in the NADAC data.

¹³For each drug, the NADAC data provides the national average drug acquisition cost. I do not have access to data that would provide acquisition costs separately by state. As noted in Section 2, these acquisition costs vary across pharmacies and geographies. I use NADAC as a rough proxy of marginal costs.

Figure 4: Event Study of Contracting Regulations on Avg. Price per Prescription Net of NADAC, Drug-Level



Note: This table presents DD estimates of Eq. (4), where the dependent variable is the difference between the quarterly average pre-rebate prescription price and the quarterly NADAC. The unit of observation for these regressions is state-drug-quarter, where drug is defined as the 11-digit National Drug Code. I estimate these regressions using a strongly balanced panel of state-drug combinations that appear in all quarters of the data. All specifications include state-drug fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Regressions are weighted by the number of quarterly prescriptions. Standard errors in parentheses are clustered by state. I calculate quarterly prescription prices as the amount reimbursed by the Medicaid program divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS drug data is either NDA Authorized Generic or Abbreviated New Drug Application. I exclude prescriptions of over-the-counter drugs and all observations that were missing the number of prescriptions, the number of units, or the Medicaid reimbursement amount in the SDUD, and drug-quarter combinations that were not present in the NADAC data. The figures present estimates of treatment effects relative to the quarter before treatment.

Table 4 presents the state-level results from Eq. (5).¹⁴ The dependent variable for the first two columns is logged quarterly average prices per prescription. I do not detect a statistically significant effect of the policy changes at the state-level. However, this level of aggregation is likely inappropriate for analyzing the effects of the contracting regulations. Changes in prices at the state level may be due to changes in the reimbursement rate paid by insurers or due to changes in the mix of prescriptions. The results in Table 2 demonstrate that reimbursement rates did decrease as a result of the contracting regulations. Thus, it is likely that aggregate changes in the mix of drugs consumed by Medicaid populations outweighed the effects of the contracting regulations. This is especially plausible in the Medicaid context, as consumers are mostly shielded from the true cost of drugs due to restrictions on cost-sharing. Furthermore, changes in utilization of brand name drugs and the release of new, expensive products may bias the state-level difference-in-differences estimates. Due to these limitations, I view the drug-level analyses as more reliably identifying the effects of the contracting regulations on drug prices.

Given that generic drug prescriptions may have been more profitable for PBMs under fixed-price contracts, it is possible that PBMs would exert less effort in steering patients towards generic drugs after the policy changes, placing upward pressure on spending. This is of particular concern because PBMs claim to use spread profits to fund programs aimed at managing consumer drug

¹⁴Figure A.1 presents the event study versions of these regressions.

utilization and promoting generic drug utilization (Fein (2023)). Columns 3 and 4 of Table 4 show that these moral hazard effects did not materialize in reduced generic drug utilization: I detect small but insignificant increases in the utilization of generic drugs in the treatment states when measuring utilization as either the overall prescription share of generic drugs or generic efficiency.

Table 4: Effect of Contracting Regulations on $\ln(\text{Avg. Price Per Prescription})$, State-Level

	$\ln(\text{Price Per Prescription})$		Generic Share of Prescriptions	Generic Efficiency
	All Drugs	Generic Drugs		
Policy	-0.03170 (0.03953)	-0.03443 (0.03506)	0.00816 (0.01085)	0.00281 (0.00969)
Observations	528	528	528	528

Sources: CMS State Drug Utilization Data; CMS Product Data for Drugs in the Medicaid Drug Rebate Program; FDA NDC Database.

Notes: This table presents estimates of Eq. (5). The unit of observation for these regressions is state-quarter. All specifications include state fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Standard errors in parentheses are clustered by state. I calculate the average price per prescription in each quarter as the sum of Medicaid spending divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS data is either NDA Authorized Generic or Abbreviated New Drug Application. I define products for which a generic alternative is available as any product for which there is a generic drug with the same listed active ingredient that had non-zero prescriptions in the quarter. I exclude prescriptions of over-the-counter drugs.

4.4 Heterogeneity Across States

Decreases in price that happen after the contracting regulations go into effect are consistent with the dissipation of PBM informational rents. Section 3 demonstrated that this should only occur if insurers have bargaining power in negotiations with PBMs. Whether the informational effects of cost-plus contracts outweigh the costs of upstream moral hazard depends on local market conditions. Table 5 presents the DDD treatment effects for each state along with descriptive statistics on concentration and market structure.¹⁵

¹⁵The Callaway and Sant’Anna (2021) estimator allows me to estimate separate ATTs for each treatment cohort. Some states are part of the same treatment cohort, so I ran separate regressions for those states in order to obtain the ATTs. Table A.3 presents this same table but with the DD treatment effects.

Table 5: **DDD Coefficients with Summary Statistics**

State	DDD Coef.	SE	# of Insurers	Insurer HHI	VI Insurer Share	# of PBMs	PBM HHI	Insurers per PBM
GA	-0.014***	0.004	4	2606	0.515	4	2606	1.0
MD	-0.142**	0.059	9	1709	0.378	5	2696	1.8
MI	0.031	0.053	10	1637	0.431	7	1958	1.4
NY	-0.287***	0.059	17	1805	0.167	6	3815	2.8
PA	-0.065	0.059	8	1900	0.496	4	3034	2.0
VA	0.021	0.060	6	2012	0.604	5	2403	1.2
Avg.	-0.217***	0.078	9	1945	0.431	5.2	2752	1.7

Note: HHIs, shares, and counts are for 2020. The average row presents the pooled DDD estimates and SEs and averages the other statistics across the six treated states.

To understand when cost-plus contracts may be effective at reducing drug prices, I explore correlations between market conditions and the policy effects in a case study fashion. As contracts and market structure are endogenously determined, the purpose of this exercise should be interpreted as descriptive. I focus my analysis on New York, which experienced the largest price decreases of the treated states (28.7% per prescription). The New York Medicaid market is notably different from the other states on a few interesting dimensions:

- *PBM common agency*: PBMs often serve as a common agent for competing insurers. PBMs that are active in the New York Managed Medicaid market serve 2.8 insurers on average, while the average number of insurers per PBM is 1.5 in the other treatment states. PBMs are able to leverage the collective patient volume of their client insurers in negotiating with pharmacies. As patients only visit the pharmacies in their local market, pharmacies must rely on the PBMs that serve their area for patient volume. PBM common agency mechanically reduces the number of PBMs operating in the market, which enhances PBM monopsony power by reducing pharmacies' outside options for customers.
- *Presence of vertically integrated insurers*: As mentioned in Section 2, many insurers have vertically integrated into the provision of PBM services. Standard economic theory suggests that the vertical integration of insurers and PBMs would eliminate the same double markups that these spread pricing bans seek to abolish; as a result, there may be limited pre-existing pharmacy spread in states that rely more heavily on vertically integrated insurers. Only 16.7% of New York Managed Medicaid consumers rely on a vertically integrated plan, relative to 48.5% in the other treatment states. My findings suggest that spread pricing bans may be an ineffective (or perhaps unnecessary) means of reducing drug prices if vertical integration becomes the norm in this market.

Section 3 predicts that prohibiting fixed-price contracts should reduce drug prices when insurers have bargaining power over PBMs. Asymmetric information can substitute for bargaining power as a source of PBM profits only if insurers have some bargaining ability; providing insurers with more information will cause a transfer from PBMs to insurers. My empirical analysis suggests that insurers are in a strong bargaining position with PBMs, but that asymmetric information allows PBMs to profit from transactions with pharmacies, particularly in markets where pharmacies have few outside options for patient volume.

5 Conclusion

Antitrust and health policymakers have proposed a variety of regulations on the behavior of intermediary firms like pharmacy benefit managers. However, because of the lack of transparency in the pharmaceutical industry, proposed interventions often lack empirical support. In this paper, I examined a popular regulation that many states have already implemented: forcing PBMs and insurers to switch from fixed-price to cost-plus contracts. My analysis demonstrates that the price effects of regulations on insurer-PBM contracts will vary based on conditions in local insurer, PBM, and pharmacy markets, and that the effects of these regulations may be counter-intuitive depending on those conditions. Cost-plus contracts are most likely to reduce drug prices in markets where insurers are in a strong bargaining position with PBMs. They will typically (but not always) place upward pressure on the reimbursement rates paid to pharmacies, which may offset savings from resolving information asymmetries. I show empirically that cost-plus contracting mandates by state Medicaid agencies have tended to reduce drug prices, particularly in states that do not rely heavily on vertically integrated insurers.

My analysis suggests that downstream firms in pharmacy markets may have strong outside options and thus greater bargaining power in negotiations with upstream firms. Despite concerns about consolidation in the PBM market, there are many smaller PBMs that are available to managed care organizations. Additionally, insurers have the ability to vertically integrate into pharmacy benefit management. Retail pharmacies do not have attractive outside options to secure patient volume, putting them in a weaker bargaining position with PBMs. On the whole, my theoretical model and empirical findings suggest that the benefits of resolving the informational advantages enjoyed by PBMs typically outweigh the costs generated by upstream moral hazard. More theoretical and empirical work in the pharmaceutical industry is needed to identify potential sources of inefficiencies and evaluate proposed regulations of various pharmaceutical market participants. Further research on PBM behavior can inform policymakers as to how firms may respond to regulations by adjusting on other margins, such as pharmacy network and formulary design. While many details of this market are particular to prescription drugs, the information asymmetries and contracting

incentives that drive these outcomes are ubiquitous across other healthcare and non-healthcare markets. Future research should apply empirical tools to different industries in order to re-examine conventional economic wisdom about vertical arrangements such as cost-plus contracts.

References

- Agha, L., S. Kim, and D. Li (2022, June). Insurance Design and Pharmaceutical Innovation. *American Economic Review: Insights* 4(2), 191–208.
- Brot-Goldberg, Z. C., C. Che, and B. R. Handel (2022, April). Pharmacy Benefit Managers and Vertical Relationships in Drug Supply: State of Current Research. Working Paper 29959, National Bureau of Economic Research.
- Callaway, B. and P. H. Sant’Anna (2021, December). Difference-in-Differences with multiple time periods. *Journal of Econometrics* 225(2), 200–230.
- Center for Medicare and Medicaid Services (2017a). Managed Care Enrollment by Program and Plan.
- Center for Medicare and Medicaid Services (2017b). National Average Drug Acquisition Cost Data.
- Center for Medicare and Medicaid Services (2017c). Product Data for Drugs in the Medicaid Drug Rebate Program.
- Center for Medicare and Medicaid Services (2017d). State Drug Utilization Data.
- Cicala, S. (2015, January). When Does Regulation Distort Costs? Lessons from Fuel Procurement in US Electricity Generation. *American Economic Review* 105(1), 411–444.
- CMS. National Health Expenditure Data.
- Congressional Budget Office (2019, December). Division A - Prescription Drug Pricing Reduction Act of 2019.
- Conlon, C. T. and J. H. Mortimer (2021, December). Efficiency and Foreclosure Effects of Vertical Rebates: Empirical Evidence. *Journal of Political Economy* 129(12), 3357–3404.
- Conti, R. M., B. Frandsen, M. L. Powell, and J. B. Rebitzer (2021, May). Common Agent or Double Agent? Pharmacy Benefit Managers in the Prescription Drug Market. Working Paper 28866, National Bureau of Economic Research.
- Dranove, D., C. Ody, and A. Starc (2021, January). A Dose of Managed Care: Controlling Drug Spending in Medicaid. *American Economic Journal: Applied Economics* 13(1), 170–197.
- Fein, A. (2023). The 2023 Economic Report on U.S. Pharmacies and Pharmacy Benefit Managers. Technical report, Drug Channels Institute.

- Feng, J. and L. Maini (2019, March). Demand Inertia and the Hidden Impact of Pharmacy Benefit Managers.
- Filipek, T. and T. Snook (2011, May). Pharmacy benefit management: Pros and cons of various approaches.
- Geruso, M., T. J. Layton, and J. Wallace (2020, August). What Difference Does a Health Plan Make? Evidence from Random Plan Assignment in Medicaid. Working Paper 27762, National Bureau of Economic Research.
- Ghili, S. (2022, May). Network Formation and Bargaining in Vertical Markets: The Case of Narrow Networks in Health Insurance. *Marketing Science* 41(3), 501–527.
- Ghosh, A., K. Simon, and B. D. Sommers (2019, January). The Effect of Health Insurance on Prescription Drug Use Among Low-Income Adults: Evidence from Recent Medicaid Expansions. *Journal of Health Economics* 63, 64–80.
- Gray, C., A. E. Alpert, and N. Sood (2023, August). Disadvantaging Rivals: Vertical Integration in the Pharmaceutical Market.
- Grennan, M. and A. Swanson (2020, April). Transparency and Negotiated Prices: The Value of Information in Hospital-Supplier Bargaining. *Journal of Political Economy* 128(4), 1234–1268.
- Grossman, S. J. and O. D. Hart (1983, January). An Analysis of the Principal-Agent Problem. *Econometrica* 51(1), 7.
- Herman, B. (2018, April). The pharmacy squeeze.
- Ho, K. and R. S. Lee (2017). Insurer Competition in Health Care Markets. *Econometrica* 85(2), 379–417.
- Ho, K. and R. S. Lee (2019, February). Equilibrium Provider Networks: Bargaining and Exclusion in Health Care Markets. *American Economic Review* 109(2), 473–522.
- Hristakeva, S. (2022, December). Vertical Contracts with Endogenous Product Selection: An Empirical Analysis of Vendor Allowance Contracts. *Journal of Political Economy* 130(12), 3202–3252.
- Kaiser Family Foundation (2020, July). Prohibition of Spread Pricing in Medicaid MCO Contracts.
- Lavetti, K. and K. Simon (2018, August). Strategic Formulary Design in Medicare Part D Plans. *American Economic Journal: Economic Policy* 10(3), 154–192.

- Luco, F. (2019, May). Who Benefits from Information Disclosure? The Case of Retail Gasoline. *American Economic Journal: Microeconomics* 11(2), 277–305.
- Mortimer, J. H. (2008, January). Vertical Contracts in the Video Rental Industry. *Review of Economic Studies* 75(1), 165–199.
- Mulligan, C. B. (2022, July). The Value of Pharmacy Benefit Management. Working Paper 30231, National Bureau of Economic Research.
- Mulligan, C. B. (2023a, September). Ending Pay for PBM Performance: Consequences for Prescription Drug Prices, Utilization, and Government Spending.
- Mulligan, C. B. (2023b, March). Restrict the Middleman? Quantitative Models of PBM Regulations and Their Consequences.
- Olden, A. and J. Møen (2022, September). The triple difference estimator. *The Econometrics Journal* 25(3), 531–553.
- Olssen, A. and M. Demirer (2021). Drug Rebates and Formulary Design: Evidence from Statins in Medicare Part D. *Working paper*.
- Pharmaceutical Care Management Association. Explaining types of PBM Contracts.
- Rubinstein, A. (1982, January). Perfect Equilibrium in a Bargaining Model. *Econometrica* 50(1), 97.
- Rubinstein, A. (1985, September). A Bargaining Model with Incomplete Information About Time Preferences. *Econometrica* 53(5), 1151.
- Shavell, S. (1979). Risk Sharing and Incentives in the Principal and Agent Relationship. *The Bell Journal of Economics* 10(1), 55.
- Skoufis, J. and G. Rivera (2019, May). Final Investigative Report: Pharmacy Benefit Managers in New York. Technical report.
- Starc, A. and A. Swanson (2021, August). Preferred Pharmacy Networks and Drug Costs. *American Economic Journal: Economic Policy* 13(3), 406–446.
- Starc, A. and T. Wollmann (2022, March). Does Entry Remedy Collusion? Evidence from the Generic Prescription Drug Cartel. Technical Report w29886, National Bureau of Economic Research, Cambridge, MA.
- Tirole, J. (1988). *The theory of industrial organization*. Cambridge, Mass: MIT Press.

United States Government Accountability Office (2019, July). Medicare Part D: Use of Pharmacy Benefit Managers and Efforts to Manage Drug Expenditures and Utilization. Technical Report GAO-19-498.

US Food and Drug Administration. National Drug Code Directory.

Weitzman, M. L. (1980, June). Efficient Incentive Contracts. *The Quarterly Journal of Economics* 94(4), 719.

Data Appendix

My primary dataset is the CMS Medicaid State Drug Utilization Data (SDUD). The publicly available version of the SDUD suppresses information for state-drug combinations with fewer than 11 prescriptions. In addition to this suppression, some of the observations appeared to have missing or unreliable information on either the number of prescriptions, the number of units reimbursed (i.e., the number of pills), or the Medicaid amount reimbursed. I exclude all observations for which the number of prescriptions, number of units, or Medicaid amount reimbursed was missing, zero, or less than 0.01. The data for New York appeared to be corrupted for the second and third quarters of 2018. I contacted the New York Medicaid office responsible for reporting the data, but they were unable to update the SDUD. To correct for this issue, I copied the data from the first quarter of 2018 for the second quarter of 2018, and the data from the fourth quarter of 2018 for the third quarter of 2018. For the analyses using the CMS NADAC data, I average the weekly NADAC data across weeks to calculate a quarterly NADAC for each drug.

For the HHI calculations in Table 5, I used data from CMS on Managed Medicaid enrollment by program and plan. I restricted the sample of Managed Medicaid plans to comprehensive insurance plans and exclude other special plans, such as dental plans, behavioral health plans, and children-only plans. I then manually standardized the parent organization for each insurer via online research. To calculate the PBM HHIs, I relied on FOIA'd data from CMS on insurer-PBM contracts and also manually collected information on insurer-PBM relationships for some insurers in the treatment states. I assigned each insurer to my best estimate of their PBM in 2020. I assumed that all insurers who were vertically integrated by 2020 used their own PBM. I was unable to identify the PBM for three insurers, and I assumed that these insurers used a PBM that was not already serving a Managed Medicaid insurer in the same state. This assumption results in PBM HHIs that are weakly lower than the true measure of concentration.

Appendix: Additional Tables and Figures

Table A.1: State Regulations on Insurer-PBM Contracting

State	Date that Regulations Came Into Effect	Included In Study?	Notes
Texas	9/1/2014	No	Outside of data sample
Louisiana	8/1/2018	No	Policy changes in May 2019 affecting drug prices
Michigan	10/1/2018	Yes	
North Dakota	1/1/2019	No	North Dakota carved out Medicaid pharmacy benefits in 2020
Ohio	1/1/2019	No	Ohio shifted to a state-run PBM in 2019
New York	10/1/2019	Yes	
Virginia	7/1/2020	Yes	
Arkansas	7/24/2020	No	Less than 10% of Medicaid population uses an MCO
Georgia	1/1/2021	Yes	
Kentucky	1/1/2021	No	Required one PBM for all payors
Maryland	1/1/2021	Yes	
Pennsylvania	1/1/2021	Yes	Also enacted an “any-willing-provider” law that prohibits PBMs from excluding pharmacists from their network who would otherwise prefer to participate
Delaware	10/26/2021	No	SDUD was unreliable; also prohibited PBMs from paying less than the NADAC or WAC for drugs
Indiana	N/A	No	
Iowa	N/A	No	
Kansas	N/A	No	
Minnesota	N/A	No	
Mississippi	N/A	No	
New Jersey	N/A	No	
Control States			
Arizona, California, Colorado, Washington DC, Florida, Hawaii, Illinois, Massachusetts, Nebraska, New Hampshire, New Mexico, Nevada, Oregon, Rhode Island, South Carolina, Washington			

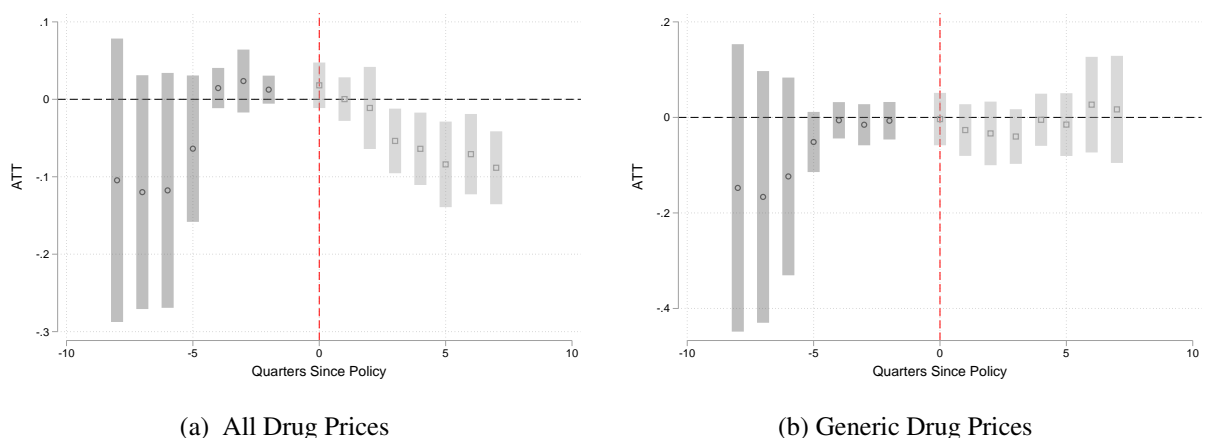
Table A.2: Effect of Contracting Regulations on ln(Avg. Price Per Prescription), State-Level

	Managed Medicaid		FFS		DDD	
	All Drugs	Generic Drugs	All Drugs	Generic Drugs	All Drugs	Generic Drugs
Policy	-0.03170 (0.03953)	-0.03443 (0.03506)	0.06893 (0.08381)	-0.11164 (0.13879)	-0.10063 (0.10332)	0.07643 (0.15689)
Observations	528	528	528	521	528	521

Sources: CMS State Drug Utilization Data; CMS Product Data for Drugs in the Medicaid Drug Rebate Program; FDA NDC Database.

Notes: This table presents estimates of Eq. (5). The unit of observation for these regressions is state-quarter. All specifications include state fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Standard errors in parentheses are clustered by state. I calculate the average price per prescription in each quarter as the sum of Medicaid spending divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS data is either NDA Authorized Generic or Abbreviated New Drug Application. I exclude prescriptions of over-the-counter drugs.

Figure A.1: Event Study of Contracting Regulations on ln(Avg. Price per Prescription), State-Level



Note: This figure presents DD estimates of Eq. (6) and includes state fixed effects, quarter fixed effects, and a post-Medicaid expansion indicator. Standard errors are clustered by state. The unit of observation for these regressions is state-quarter. I calculate prescription prices as the amount reimbursed by the Medicaid program divided by the number of prescriptions. I define generic drugs as drugs for which the covered outpatient drug status listed in the CMS drug data is either NDA Authorized Generic or Abbreviated New Drug Application. I exclude prescriptions of over-the-counter drugs. The pre-period treatment effects for all periods $t < 0$ measure the effects at time t relative to time $t-1$.

Table A.3: **DD Coefficients with Summary Statistics**

State	DD Coef.	SE	# of Insurers	Insurer HHI	VI Insurer Share	# of PBMs	PBM HHI	Insurers per PBM
GA	−0.035***	0.004	4	2606	.515	4	2606	1
MD	−0.163**	0.071	9	1709	.378	5	2696	1.8
MI	−0.116*	0.06	10	1637	.431	7	1958	1.4
NY	−0.342***	0.049	17	1805	.167	6	3815	2.8
PA	−0.117*	0.071	8	1900	.496	4	3034	2
VA	−0.031	0.092	6	2012	.604	5	2403	1.2

Note: HHIs, shares, and counts are for 2020.