Preliminary - Please Do Not Distribute Without Author's Permission

The Incidence of the 340B Program: The Effects of Contract Pharmacies on Part D Premiums and Reimbursements

Charles Gray

The Wharton School, University of Pennsylvania

This Version: October 30, 2023

Click here for latest version

Abstract

Empirical evidence has shown in many contexts that taxes levied against producers are passed through to consumers in the form of higher prices. This paper asks whether a "tax" on drug manufacturers is passed through to insurers and patients enrolled in their plans. The federal 340B Program effectively taxes drug manufacturers by requiring them to provide large discounts on drugs purchased by eligible safety-net providers (e.g., DSH hospitals). I assess to what degree insurer premiums are impacted by drug manufacturer pass-through of 340B discounts by exploiting a major expansion in 340B discounts claimed through contract pharmacies. Historically, a 340B provider could claim discounts for prescriptions its patients filled at a single pharmacy with which it contracted—a so-called *contract pharmacy*. In 2010, a policy change permitted 340B providers to partner with an unlimited number of pharmacies causing exponential growth in the number of contract pharmacies and a massive expansion in the number of prescriptions eligible for discounts. Between 2010 and 2021, the number of contract pharmacies eligible for 340B discounts increased from fewer than 5,000 to 30,000, or one out of every two pharmacies. Using detailed claims and plan-level data for Medicare Part D, I use a two-way fixed effects strategy to estimate the pass-through of 340B discounts to premiums. This strategy leverages changes to the proportion of an insurer's drug expenditures that may be subject to a 340B discount after the 2010 policy change. There is significant geographic variation in contract pharmacy growth across areas over this time period, and insurers are differentially affected by the policy based on their initial enrollment shares across areas. In a second complementary strategy, I use variation in contract pharmacy growth that occurred after the 2014 Medicaid expansions. Both strategies yield evidence that premiums increase in response to expansions in 340B discounts. I find that reducing an insurer's spending that is potentially subject to a 340B discount by 10 percentage points reduces monthly premiums by $3.33 ($\approx$ 6.4 percent). This finding is consistent with the economic theory of pass-through, but challenges the commonly held presumption by 340B advocates that the 340B Program comes at no cost to taxpayers.

Email: chgray@wharton.upenn.edu. I am incredibly grateful to my dissertation committee, Abby Alpert, Guy David, Alex Olssen, and Neeraj Sood for their comments, guidance, and support during this project. I would also like to thank Rena Conti, Adam Fein, Sarah Miller, Sayeh Nikpay, and Rebecca Sachs, as well as seminar participants at the University of Pennsylvania and ASHEcon for their feedback and thoughtful comments. All errors are my own.

1 Introduction

Economists have long recognized that the party who "pays" a tax is not necessarily the one who bears its burden. For instance, gasoline retailers collect sales taxes on fuel and deliver the proceeds to the state, but they may also pass through the burden of the tax to consumers through higher gas prices (Doyle and Samphantharak, 2008). Economic theory predicts that in competitive markets, the degree to which the burden of the tax is passed through depends on the relative elasticities of supply and demand (Fullerton and Metcalf, 2002). By contrast, in differentiated product markets, such as branded pharmaceuticals, where producers possess some amount of market power, producers may pass through a portion of the tax, all of it, or potentially more than one hundred percent. The degree of pass-through in this setting will depend both on the structure of the market and on the form of the tax (Fullerton and Metcalf, 2002; Weyl and Fabinger, 2013).[1]

This paper explores the extent to which a "tax" on drug manufacturers is passed through to insurers and patients enrolled in their plans. Drug manufacturers are statutorily required to provide large discounts on their drugs to purchasers who are enrolled in the 340B Program. These purchasers include certain safety net providers such as hospitals serving a disproportionate share of Medicaid patients (i.e., DSH hospitals), as well as particular kinds of health clinics that receive federal grants to fund their operations (HRSAa, 2021). When a 340B provider claims a discount, it effectively imposes a tax on a drug manufacturer. While proponents of 340B claim that the program comes "at no cost to taxpayers," economic theory predicts that drug manufacturers will likely pass through some of the burden of this tax to downstream participants in the market (Slafsky et al., 2018).[2]

One way in which a manufacturer could pass through the burden is to increase the sticker price of its product to all purchasers—known formally as the *list price* or *gross price*. However, this possibility is unlikely because the 340B law stipulates that the magnitude of the 340B discount is increasing with a drug's list price.[3] In other words, the increase in revenue the drug manufacturer experiences from increasing its list price is offset by the increase in the discount it must pay to a 340B provider.[4]

The other way in which a drug manufacturer could pass through the burden of a 340B discount is to increase the *net price* of its drug to insurers. Specifically, it could reduce the size of the price concession

[1] The market structure includes assumptions about the number of competitors, their cost functions, and the functional form of demand. The form of the tax could be a per-unit tax or an *ad valorem* tax—i.e., a tax which is a fixed percentage of the price (Fullerton and Metcalf, 2002; Weyl and Fabinger, 2013).

[2] Note that I refer to providers enrolled in the 340B Program as "340B providers." They are more commonly referred to as the "covered entities" of the program.

[3] I will primarily use the description "340B discounts" rather than "340B taxes." Note 340B discounts are discounts to 340B providers, but are taxes on drug manufacturers.

[4] Note that the formula to compute the 340B discount is effectively the same formula used to compute Medicaid rebates. Other researchers have found that the Medicaid rebate system has been effective in limiting the growth of list prices for drugs with high Medicaid market shares (Feng et al., 2023).

it offers an insurer, known as a *rebate*.[5] Indeed, a government audit of rebate contracts between drug manufacturers and Medicare Part D insurers found that manufacturers negotiate exemptions for rebates on drug purchases that potentially are subject to a 340B discount (OIG, 2019).[6] Thus, the act of passing through at least some of the incidence of a 340B discount to insurers will result in higher costs for insurers, who may respond by raising their prescription drug premiums to enrollees.

Initially, the 340B Program allowed its providers to claim discounts from drug manufacturers for drugs that they administered inside their own facilities. However, this changed when the program permitted each 340B provider to contract with retail pharmacies—so-called *contract pharmacies*—and claim discounts for prescriptions its patients filled at those pharmacies. For instance, if a 340B DSH hospital contracts with a Walgreens pharmacy, then the hospital can claim a 340B discount on a prescription filled at that Walgreens by a patient of the hospital; as part of the contract, the DSH hospital shares a portion of the discount with the pharmacy.[7]

Prior to 2010, nearly all 340B providers were allowed to contract with only one retail pharmacy, which limited the volume of discounts they could claim via contract pharmacy relationships.[8] In 2010, however, the overseer of the 340B Program, the Health Resources Services Administration (HRSA), issued guidance that allowed 340B providers to engage in an *unlimited* number of contract pharmacy relationships. Since this change in policy, both the number of unique locations serving as contract pharmacies and the number of contractual relationships between 340B providers and pharmacies have grown substantially, thus greatly increasing the volume of discounts claimed by 340B providers through contract pharmacies. In 2012, fewer

[5] While the list price for a patented, brand name drug can be high, most insurers do not pay these list prices. Instead, an insurer typically negotiates a per-unit rebate for the drug that lowers the net price to the insurance plan. In exchange for providing a rebate, an insurer will include the manufacturer's drug on its formulary—a list of drugs that the insurance plan covers—which lowers the out-of-pocket costs for the enrollees of the insurer's plan, thereby increasing demand for the manufacturer's product.

[6] If a Medicaid patient fills a prescription for which a 340B provider claims a discount, then Medicaid is prohibited from also claiming a rebate from the drug manufacturer. The 340B Program stipulates that the 340B provider must have a system in place to prevent these instances of "duplicate discounts." The laws that govern the 340B Program are silent on this issue with respect to commercial insurance or Medicare Part D, but as discussed above, audits of Part D rebate contracts found that they included provisions that prevent drug manufacturers from paying both a rebate and a 340B discount on the same prescription drug claim (OIG, 2019).

[7] 340B providers can employ different methods of remuneration for the pharmacy, but effectively the 340B provider pays the pharmacy some portion of the markup between the 340B-discounted price and the pharmacy's reimbursement paid by the insurer and patient (Fein, 2020). Note that in theory, the reimbursement a contract pharmacy receives from the patient and the patient's insurer is unaffected by whether a prescription qualifies for a 340B discount. However, five states have passed laws prohibiting pharmacy benefit managers (PBMs) and insurers from negotiating lower reimbursements to 340B providers and their contract pharmacies for 340B purchases, suggesting some PBMs or insurers have engaged in this practice (Shafer and David, 2019). That being said, there is reason to believe that the regulations of Medicare Part D prevent this kind of "discriminatory" reimbursement based on 340B contract pharmacy status (see Section 2.2 below).

[8] In 2001, the overseer of the 340B Program, the Health Resources and Services Administration (HRSA), created the Alternative Methods Demonstration Project which enabled some 340B providers to employ multiple contract pharmacies and allowed pharmacies to contract with multiple 340B providers (HRSA, 2007). However, to do so 340B providers had to apply and HRSA had to approve these arrangements. Moreover, the 340B providers and their contract pharmacies had to undergo annual independent audits to ensure that the arrangements did not lead to either diversion—i.e., pharmacies claiming 340B discounts for ineligible patients—or duplicate discounts—i.e., a manufacturer remitting a 340B discount to the pharmacy and a rebate to Medicaid for the same prescription. From 2001 to 2010, only eighteen 340B providers participated in the Alternative Methods project and independent audits did not reveal any issues with diversion or duplicate discounts (HRSA, 2007).

than 5,000 pharmacies participated as 340B contract pharmacies; in the next year, the number had more than doubled to roughly 12,000 pharmacies (Fein, 2019b). Today, almost 30,000, or nearly one out of every two, serve as contract pharmacies, and there exist roughly 150,000 active contractual relationships between 340B providers and contract pharmacies (OPAIS, 2021; Fein, 2021a). In addition, Fein (2021c) estimates that in 2020, the contract pharmacy component of 340B accounted for 30 percent of the $80 billion in total 340B sales that year.[9]

Drug manufacturers have begun to push back against this rapid growth. In the fall of 2020, several large drug manufacturers announced they would stop or limit their sale of drugs to contract pharmacies at 340B-discounted prices (Yood et al., 2021; HRSAb, 2021).[10] In December of 2020, the American Hospital Association and others filed a federal lawsuit against the U.S. Department of Health and Human Services for failing to enforce the requirements of the 340B Program. Litigation over this matter is ongoing and the Biden administration has announced plans to assess fines upon these drug manufacturers for failing to comply with the 340B statute (King, 2021).

Despite the rapid growth in the use of contract pharmacies and the recent legal battles that have ensued, academic research on contract pharmacies has been limited to only a few studies that have chronicled their enormous growth (Clark et al., 2014; Nikpay et al., 2022; Lin et al., 2022; Nikpay et al., 2023). Much of the research on the 340B Program has instead focused exclusively on responses made by 340B hospitals (Alpert et al., 2017; Desai and McWilliams, 2018; Jung et al., 2018; Conti et al., 2019; Nikpay et al., 2020; Desai and McWilliams, 2021; Bond et al., 2023; Han, 2023). The aforementioned studies have provided insight into the behavior of 340B providers and how they have responded to the financial incentives of the 340B Program. However, a clear omission from this literature is research aimed at understanding how *drug manufacturers* respond to providing mandated 340B discounts and how those responses could have unintended consequences on prescription drug costs for insurers and their patients. I aim to fill that gap with this paper by estimating drug manufacturers' pass-through of the costs of providing 340B discounts to insurers and their enrollees. This paper contributes to a large literature in public finance on estimating rates of pass-through from taxes, subsidies, and mandated health benefits[11], as well as literature evaluating the spillover effects of government policies on healthcare prices in the commercial market[12].

[9] This $80 billion figure represents the quantity of products sold at 340B discounts multiplied by the list price of those products. The quantity of these products multiplied by the 340B-discounted acquisition price is roughly $38 billion. Thus, the difference between these two figures gives an approximation of the total dollar value of 340B discounts claimed (Fein, 2021c).

[10] These manufacturers included AstraZeneca, Boehringer Ingelheim, Eli Lilly, Novo Nordisk, Novartis, Sanofi, and United Therapeutics (Yood et al., 2021; HRSAb, 2021). Since then an additional eight manufacturers have restricted 340B sales to contract pharmacies. This second wave include Union Chimique Belge, AbbVie, Bristol Myers Squibb, Amgen, GlaxoSmithKline, Pfizer, Gilead, and Johnson & Johnson (340B Health, 2022).

[11] See, for example, Doyle and Samphantharak (2008); Kowalski et al. (2008); LaPierre et al. (2009); Lahey (2012); Bailey (2014a,b); Fabra and Reguant (2014); Depew and Bailey (2015); Duggan et al. (2016); Miller et al. (2017); Cabral et al. (2018); Carey (2021).

[12] e.g., Dranove (1988); Scott Morton (1997); Cutler (1998); Duggan and Scott Morton (2006); Lakdawalla and Yin (2015);

I begin my analysis by specifying a theoretical model that predicts that drug manufacturers will negotiate lower rebates when an insurer's enrollees fill more of their rebate-eligible prescriptions at contract pharmacies. This, in turn, raises costs to the insurer, leading it to increase its premiums. I then test these predictions using a 20 percent random sample of detailed pharmacy claims and plan-level data for the Medicare Part D market. Part D is a useful setting to study the effects of contract pharmacies because private insurers offer standalone prescription drug plans, which have premiums that reflect only the cost of providing prescription drug coverage and do not include additional medical costs.[13]

While the 2010 policy change expanding the use of contract pharmacies applied nationwide, there was considerable variation across insurers in their exposure to the growth of contract pharmacies over time. Prior to the contract pharmacy policy change, over 95 percent of Part D insurers had fewer than 10 percent of their prescriptions filled by contract pharmacies. By 2015, however, some insurers had the majority of their prescriptions filled at contract pharmacies while other insurers had only a small share of prescriptions filled through these pharmacies. Intuitively, my empirical strategy is to compare how the premiums of insurers with large increases in exposure to contract pharmacies have changed relative to the premiums of insurers with small increases in their exposure to contract pharmacies. Because Medicare beneficiaries tend to use pharmacies near their homes, this variation in exposure to contract pharmacies is primarily determined by the share of an insurer's beneficiaries who live in areas where contract pharmacies happened to become more prevalent.[14] I also demonstrate that the initial shares of an insurer's enrollment across counties are stable over time.[15] Moreover, the prevalence of contract pharmacies in a particular area will largely be determined by contracting between 340B providers and pharmacies, which should be unrelated to competition or other factors that influence Part D enrollment behavior. Thus, changes to an insurer's exposure to contract pharmacies is primarily driven by their initial enrollment shares and is arguably exogenous.

To leverage this plausibly exogenous exposure to contract pharmacies, I use a two-way fixed effects (TWFE) strategy to estimate the possible pass-through of the costs of 340B discounts to insurers. In my preferred specification, I find that a ten percentage point increase in the percentage of an insurer's rebate-eligible drug expenditures at contract pharmacies is associated with an increase of $3.33 in the insurer's premiums. This represents approximately a 6.4 percent effect relative to the average premium of $52 per month during the sample period.

While my TWFE results are robust to a number of specification tests, there may still be unobservables

Clemens and Gottlieb (2017); Ridley and Lee (2020); Feng et al. (2023).

[13] Note that Medicare beneficiaries can enroll in Medicare Advantage plans that bundle medical coverage with prescription drug plans (MA-PDs). However, my analysis will focus solely on the standalone prescription drug plan (PDP) market. See Section 5 for more details.

[14] In Appendix Figure C.2, I show the observed travel distances between patients in my sample and the pharmacies they visit. Around 85 percent of prescriptions are filled within 30 miles of the patient's home zip code.

[15] See Appendix Figure C.3.

that are correlated with insurer premiums and their exposure to contract pharmacies. Thus, I also conduct an instrumental variable (IV) analysis that exploits a plausibly exogenous shock to contract pharmacy growth caused by the 2014 Medicaid expansions that only affected states expanding their Medicaid programs.[16] In particular, because the Medicaid expansions increased the number of Medicaid recipients in expansion states, this led to more hospitals in the expansion states qualifying for and enrolling in the 340B Program. As a result, newly minted 340B DSH hospitals in expansion states were more likely to contract with retail pharmacies in the expansion states—there were about 25 percent more contract pharmacies per capita in the expansion states after 2014. Leveraging this variation, I find the IV methodology yields results almost identical to my TWFE estimates.

These results suggest that insurers and their enrollees bear some incidence of 340B discounts. In addition, I conduct two further analyses whose findings are consistent with the pass-through of 340B discounts to insurers. First, I assess how becoming a contract pharmacy may affect a pharmacy's negotiated reimbursement with insurers. Although the presence of contract pharmacies may increase costs for insurers through reduced rebates, 340B discounts effectively act like subsidies to contract pharmacies. Thus, contract pharmacies may be willing to accept lower reimbursement from insurers because of the subsidies they collect from 340B discounts, which could offset the cost increases insurers experience from reduced rebates. I assess this possibility by using a difference-in-differences design that compares how reimbursements for pharmacies change when they become a contract pharmacy relative to changes in reimbursement for non-contract pharmacies. I find that a pharmacy's reimbursements are unchanged after it becomes a contract pharmacy, suggesting that insurers cannot offset their cost increases by negotiating lower reimbursement to contract pharmacies. This finding is likely due to Medicare Part D regulations that limit the ability of insurers to offer differential reimbursement across pharmacies, which further suggests that the burden of 340B discounts is passed through to insurers and patients.[17]

Second, I compare how the effect of exposure to contract pharmacies may differ across insurers. In particular, insurers that are vertically integrated with pharmacies that also serve as contract pharmacies may not experience the same harm from 340B discounts as non-vertically insurers. For instance, a vertically integrated insurer-pharmacy could utilize profits from its 340B contract pharmacy business to offset any losses its insurance arm experienced from reduced rebates. Indeed, I find that the premiums of prescription drug plans of insurers vertically integrated with a 340B pharmacy are unaffected by exposure to contract pharmacies.

[16] Note that Medicare Part D has markets which consist of either one state or aggregations of small states. For a detailed discussion of how I classify Part D regions as "expansion" or "nonexpansion" regions, please see the Empirical Strategy Section describing the IV strategy (Section 6.1.2).

[17] See Section 2.2 for a detailed discussion of this point.

Collectively, these results suggest that the costs of funding the 340B Program are not borne entirely by drug manufacturers. Rather, insurers bear some of the cost through reduced rebates, resulting in higher premiums for their enrollees. Using a conservative back-of-the-envelope calculation, my TWFE estimate implies that Part D enrollees paid an additional $347 million in premiums per year due to 340B discounts. These findings are of considerable importance because they provide some of the first empirical evidence of how the growth of contract pharmacies may have unintentionally contributed to higher prescription drug premiums. This could bring crucial information to the current debate and ongoing litigation surrounding drug manufacturer's restrictions on the use of contract pharmacies.

The remainder of this paper is organized as follows: Section 2 discusses the institutional details of the 340B Program and Part D. Section 3 discusses findings from related literature and describes my contribution to it. Section 4 presents a stylized model that generates predictions of how exposure to 340B contract pharmacies affects rebates. Section 5 introduces the data used for my analyses. Section 6 details my empirical strategies. Section 7 presents the results. Section 8 concludes and discusses the potential policy implications of this paper's findings.

2 Institutional Setting

2.1 The 340B Program

Established in 1992 under federal legislation, the 340B Drug Pricing Program (aka the 340B Program) was created to provide drugs to safety-net providers at significantly discounted prices.[18] The legislation does not impose any mandates on how 340B providers utilize their savings from these discounts, but the supposition is that 340B providers use them to expand care to individuals who cannot afford it or to subsidize services that would be unprofitable otherwise. The overseer of the program, the Health Resources Services Administration (HRSA), estimates that the discounts vary by drug, but can be between 20 and 50 percent of the drug's list price (GAOa, 2018).[19] These substantial discounts create a strong incentive for participation among providers that qualify for the 340B Program.

340B-eligible providers can be grouped into two broad categories: (1) hospitals, and (2) grantees. The former group consists of six different hospital types, but nearly 90 percent of the hospitals who were enrolled in the program in 2019 were either those that serve a disproportionate share of Medicaid patients (i.e., DSH

[18] The program is called the 340B Program because it was created under Section 340B of the Public Health Service Act—see AHA fact sheet for more details.

[19] More recent analysis from 2020 estimate average rebates across all drugs sold in the 340B Program are 55 percent (Fein, 2021a). However, these average discounts can vary by therapeutic class such that 340B providers receive a 50 percent discount on oncology drugs, but a 90 percent discount on anti-diabetes agents (Vandervelde et al., 2020).

hospitals[20]) or Critical Access Hospitals (CAHs).[21] The grantees of the program are much smaller organizations that receive federal grants to subsidize their services, such as Ryan White HIV clinics or Federally Qualified Health Centers (FQHCs).[22] Despite the wide variety of eligible providers, the overwhelming majority of 340B discounts are claimed by DSH hospitals; Fein (2022) estimates that nearly 80 percent of the $44 billion in 2021 340B-discounted sales originated from the DSH category.

Drug manufacturers are also incentivized to participate in the 340B Program. Any manufacturer who agrees to participate in the Medicaid Drug Rebate Program (MDRP) is also required to participate in the 340B Program. The prospect of losing access to Medicaid enrollees and the optics of manufacturers reducing access to their drugs for Medicaid recipients makes participation in the 340B Program nearly universal. Currently, more than 600 drug manufacturers who produce over 40,000 drug products participate in the MDRP and the 340B Program including all of the top ten drug manufacturers (OPAIS, 2021; Burke, 2021).

To understand how 340B discounts claimed through contract pharmacies operate like taxes on drug manufacturers, it is important to understand a typical pharmaceutical supply chain—Panel C.1a of Appendix Figure C.1 provides a simplified diagram.[23] A patient brings her prescription to a pharmacy and exchanges it for a drug. The pharmacy acquires its inventory of that drug from the manufacturer of the product.[24] The pharmacy is reimbursed for its acquisition cost by a combination of payments from the patient and her insurer.[25] To stimulate demand for its product, the drug manufacturer will often offer the insurer a rebate that lowers the net-price of the drug to the insurance plan. These rebates are not applied at the point-of-sale, but are typically used by the insurer to reduce costs for all of the plan's enrollees by lowering its premiums (MedPAC, 2019; GAO, 2019).

By contrast, if the patient received her prescription from a 340B provider and filled said prescription at a contract pharmacy partner of that provider, then the 340B provider can claim a discount from the drug

[20]Note that the definition of a DSH hospital defined by the 340B Program is different than a hospital receiving DSH payments. Whether or not a hospital qualifies to receive DSH payments depends on federal guidelines and some state-specific rules. In contrast, a hospital can only qualify as a 340B DSH hospital if its adjusted DSH percentage exceeds 11.75 percent. The DSH percentage is the sum of the hospital's percentage of Medicare inpatient days attributable to those who qualify for both Medicare Part A and Supplemental Security Income, and the percentage of total inpatient days attributable to Medicaid patients who are not also eligible for Medicare. This percentage is then adjusted according to a formula that depends on the hospital's size (number of beds) and its urban-rural designation.

[21]A hospital must meet several requirements for the Centers for Medicare and Medicaid Services (CMS) to designate it as a CAH. In short, CAHs tend to be small non-profit hospitals in rural areas serving residents who would otherwise have to travel long distances to seek emergency medial care. The remaining four types of hospitals are Rural Referral Centers (RRCs), Children's Hospitals (PEDs), Sole Community Hospitals (SCHs), and Cancer Hospitals (CANs).

[22]In total, there are 11 different categories of grantees that can qualify for the 340B Program. See the HRSA website for a complete list.

[23]Note that this supply chain applies primarily to branded drug products. Generic products have a similar supply chain, but with a few differences. However, generic drugs do not usually have any manufacturer rebates so they are not relevant for my analysis.

[24]In most cases, there is an additional middleman in this chain. In particular, a wholesaler will acquire the product from the drug manufacturer and distribute it to multiple pharmacies. For simplicity, I have omitted the wholesaler from the diagram because their existence does not materially affect 340B discounts.

[25]The patient's share of this reimbursement could be a copay—a fixed dollar amount—or a coinsurance amount, which is 100 percent of the drug's list price if the patient has a deductible or some fraction of the list price (e.g., 30 percent coinsurance).

manufacturer (Panel C.1b of Appendix Figure C.1). The logistics of how a 340B provider claims a discount for a prescription filled at a contract pharmacy begins in the same way a normal prescription drug is filled and processed. The pharmacy buys its inventory of a drug product from the manufacturer[26] and collects its standard reimbursement from the patient and her insurer. The 340B provider and its contract pharmacy share their historical claims data with a "Third Party Administrator" (TPA) that uses algorithmic software to determine if the 340B provider is entitled to claim a discount on a prescription. In order for a prescription to be eligible for a 340B discount, the 340B provider needs to have some justification that the patient who filled the prescription at a contract pharmacy has received care from the 340B provider relatively recently (e.g., within the last six months). If the TPA determines that a prescription was eligible for a 340B discount, the 340B provider claims a discount from the drug manufacturer by purchasing replacement inventory of the product for the pharmacy at the 340B-discounted price. Finally, the 340B provider and the contract pharmacy share the markup between the pharmacy's standard reimbursement for the drug and the heavily discounted 340B-price; typically the pharmacy's fee is a percentage of this markup. (Martin et al., 2023). This results in a phenomenon where the drug manufacturer makes two payments on one prescription—it pays (1) a rebate to an insurer and (2) a 340B discount to the 340B provider and its contract pharmacy partner. Thus, the 340B discount increases the drug manufacturer's cost, which is likely to cause the manufacturer to reduce the size of the rebate it is willing to offer an insurer.

This arrangement incentivizes 340B providers and pharmacies to form contracts because the 340B-discounted price is considerably lower than a pharmacy's typical acquisition cost. Thus, if a pharmacy's reimbursement for a drug is unchanged, the markup between its reimbursement and the 340B-discounted price will be larger than the markup the pharmacy would earn on its own acquisition cost. The 340B provider can then divide this surplus in a such way that it more than covers its acquisition costs and such that its contract pharmacy partner will earn a larger markup than what it would earn if it had purchased the drug from the manufacturer. Sood et al. (2017) estimate that standard retail pharmacies earn a gross margin of 6 percent on the brand name drugs they dispense; in contrast, Fein (2020) estimates a contract pharmacy can earn a gross margin of 18 to 20 percent.

Lastly, while 340B discounts act like taxes on drug manufacturers, they effectively operate like subsidies to contract pharmacies. Thus, while insurers could be harmed by 340B discounts through reduced rebates, it is theoretically possible that insurers could benefit from them by negotiating reduced reimbursement to contract pharmacies. That is, contract pharmacies may be more willing to accept lower reimbursements since they earn higher margins than non-contract pharmacies. While theoretically possible, Section 2.2 will describe some of

[26] Again, there may be a wholesaler that operates in between the manufacturer and pharmacy, but its presence does not affect how 340B discounts are claimed. See footnote [24].

the institutional details of Medicare Part D that make this kind discriminatory reimbursement challenging for Part D insurers. I will also empirically test this possibility by comparing how reimbursements change for pharmacies after they become contract pharmacies relative to non-contract pharmacies.

2.2 Medicare Part D

Part D is a voluntary benefit that has provided prescription drug insurance to Medicare beneficiaries since 2006.[27] In 2021, nearly 80 percent of the 62 million Medicare beneficiaries were enrolled in a Part D plan (KFF, 2021). These plans are designed and offered by private insurers who compete to enroll Medicare beneficiaries. Broadly speaking, there are two types of Part D plans from which beneficiaries can choose. Beneficiaries who enroll in "Original Medicare" primarily choose from the stand-alone prescription drug plans (PDPs) which provide coverage for drugs typically purchased from the pharmacy. Alternatively, if beneficiaries choose to receive their medical coverage from a Medicare Advantage (MA) plan, they will also receive their prescription drug insurance through that same MA plan (MA-PD).[28] While the Centers for Medicare and Medicaid Services (CMS) specify minimum actuarial standards that every plan must satisfy, an insurer has considerable latitude to differentiate its plans based on financial characteristics such as its monthly premium, annual deductible, as well as copays and coinsurance rates for drugs. Plans can also differentiate themselves based on which drugs they cover—i.e., which drugs are on the plan's formulary—or at which pharmacies their enrollees can fill their prescriptions.[29]

Insurers negotiate rebates from drug manufacturers by threatening to exclude the manufacturer's drug from their formularies. Government reports indicate that insurers use the cost savings they generate from rebates to lower prescription drug premiums for their enrollees (MedPAC, 2019; GAO, 2019). The U.S. Department of Health and Human Services' Office of Inspector General (OIG) issued a report summarizing audits of prescription drug rebate contracts between drug manufacturers and about 25 percent of Part D insurers who offered prescription drug coverage in 2014. OIG found that nearly half of these agreements excused drug manufacturers from paying rebates to Part D insurers on prescriptions that were filled at 340B contract pharmacies, regardless of whether or not a 340B discount was claimed on that fill (OIG, 2019). The OIG estimated that these agreements cost this sample of insurers nearly $75 million in 2014. If we assume this estimate applies to the remaining three fourths of insurers not included in the OIG sample, then this

[27] Although Part D is voluntary for most Medicare beneficiaries, those individuals who are dually eligible for Medicare and Medicaid are automatically enrolled in a subset of Part D plans if they do not make an active plan choice. The subset of plans are those with premiums that fall below a regional benchmark.

[28] In 2018, approximately 48 percent of Part D enrollees were enrolled in a standalone PDP while about 36 percent were enrolled in a MA-PD plan. The remaining 16 percent were enrolled in employer or union sponsored Part D Retiree plans (KFF, 2021). These retiree plans are not available to most Part D beneficiaries and CMS does not publish information on the characteristics of these plans so I do not include them in my analysis.

[29] All plans are required to cover *all* drugs belonging to six "protected" classes: immunosuppressants, antidepressants, antipsychotics, anticonvulsants, antiretrovirals, and antineoplastics (KFF, 2021).

estimate implies that Part D insurers lost about $300 million in rebates in 2014 due to contract pharmacies. I will later use this figure as a benchmark to compare against estimates from my regression analysis.

As mentioned in Section 2.1, some 340B stakeholders have suggested that insurers have responded to this reduction in rebates by engaging in "discriminatory contracting" practices against contract pharmacies. That is, insurers have made up for these lost rebates by offering lower reimbursements to contract pharmacies (Lewis and von Oehsen, 2021). This is a reasonable hypothesis and one that I will empirically test in my analysis. However, it is worth noting that during its audit of rebate contracts OIG remarked that "Part D does not define how rebate agreements should be structured; rather it allows manufacturers and sponsors to negotiate any rebates for drugs" (OIG, 2019). By contrast, OIG found during its audit that "Part D [insurers] ... generally indicated that they did not take [a 340B contract pharmacy's] lower acquisition costs into consideration when negotiating reimbursement rates with 340B pharmacies. Of the 59 sponsors we asked, all but 1 disclosed that they ... did not negotiate lower reimbursement amounts based on a pharmacy's 340B status" (OIG, 2019). The reason why most Part D insurers do not negotiate differential reimbursement to 340B contract pharmacies is likely due to Medicare regulations, which require all plan sponsors to "have a standard contract with reasonable and relevant terms and conditions of participation whereby **any willing pharmacy [my emphasis added]** may access the standard contract and participate as a network pharmacy" (CMS, 2017). Thus, if a 340B contract pharmacy is willing to accept the standard reimbursement that an insurer pays to one of its in-network pharmacies, then the plan sponsor must allow the 340B pharmacy to participate in the insurer's network. In other words, a plan sponsor can neither exclude a pharmacy from the network nor offer the pharmacy different reimbursement simply because said pharmacy contracts with a 340B provider.[30] In short, the available evidence suggests that rebates are more likely to be affected by the presence of 340B contract pharmacies than negotiated reimbursements to pharmacies. However, in my analyses, I will empirically test if reimbursement for contract pharmacies differs from non-contract pharmacies.

[30] Note that insurers are allowed to vary the standard reimbursement terms across different geographies. However, two pharmacies in the same region must be offered the same terms. Additionally, more than 30 states have their own form of any willing provider or any willing pharmacy laws that reinforce the Part D requirements (Fein, 2019a). Part D insurers can also set up preferred pharmacy networks in which pharmacies pay an "entry fee" to join the preferred network—often referred to as a pharmacy direct and indirect remuneration (DIR) fee. Beneficiaries enrolled in plans with preferred pharmacy networks typically have reduced cost-sharing if they fill their prescriptions at pharmacies that are part of their insurer's preferred network. It is possible that insurers use their preferred networks to extract fees from contract pharmacies that would not be captured by claim-level reimbursement data. However, in my discussions with other researchers and industry experts, pharmacies serving as 340B contract pharmacies appear no more likely to join insurers' preferred networks than non-contract pharmacies. Moreover, there are no publicly-available data that track pharmacy DIR fee payments to Part D insurers.

3 Related Literature and Contribution

In this section, I discuss three strands of literature and how my paper contributes to each. These include, (1) the economic incidence of government taxes and subsidies, as well as the incidence of mandated health benefits; (2) the spillover effects of government policies on health care prices and spending in the commercial market; and (3) the 340B Program.

3.1 Incidence of Taxes, Subsidies, & Mandated Health Benefits

There is a sizable economic literature in the field of public finance that estimates the pass-through of government taxes and subsidies to individuals. Economists have used reduced-form methods to estimate pass-through of taxes to gasoline prices (Doyle and Samphantharak, 2008), as well as the pass-through of carbon emissions taxes on electricity and cement prices (Fabra and Reguant, 2014, and Miller et al., 2017, respectively).[31] Most relevant to my context, researchers have estimated the pass-through of various government subsidies to insurance premiums in the Medicare Advantage market (Duggan et al., 2016; Cabral et al., 2018; Chernew et al., 2023), as well as in the Medicare Part D market (Carey, 2021). My paper is similar to these in that it estimates pass-through rates from reduced-form regressions.[32] My study makes a novel contribution to the empirical literature on pass-through because it is the first to consider how a tax on drug manufacturers could be passed through to the insurance market of Medicare Part D. Carey (2021) finds evidence that subsidies to Part D insurers are partially passed through by insurers in the form of lower premiums. Thus, my study will be the first to speak on whether the inverse of a subsidy—that is, a tax—results in higher premiums.

A related literature has evaluated the economic incidence of mandated health benefits. Economists have long been aware that employers can pass through the costs of providing mandated benefits to workers in the form of higher premiums, lower wages, or reduced employment (Summers, 1989). Since then, economists have empirically estimated the pass-through of mandated health benefits for premiums in both the nongroup health insurance market (Kowalski et al., 2008; LaPierre et al., 2009) and the employer-sponsored health insurance market (Bailey, 2014a; Depew and Bailey, 2015). Researchers have also estimated the wage and employment effects of mandated prostate cancer screenings (Bailey, 2014b), maternity benefits (Gruber, 1994), and infertility benefits (Lahey, 2012).[33]

[31] More broadly, economists have also estimated pass-through of cost shocks beyond just subsidies and taxes. For example, Muehlegger and Sweeney (2022) estimate pass-through of cost shocks in the US oil refining business while MacKay and Remer (2022) consider the effects of cost shocks on retail gasoline prices.

[32] Others have taken structural approaches to consider the economic incidence of subsidies in both the MA and standalone Part D market (Miller et al., 2019 and Decarolis et al., 2020, respectively).

[33] A related study also considers how rising health insurance premiums, driven by increased medical malpractice payments, affects wages and employment (Baicker and Chandra, 2006).

Like these previous studies, my paper explores the possibility that the costs of federally mandated drug discounts are not likely to fall squarely on the shoulders of drug manufacturers. Instead, it is quite possible that manufacturers have passed through some of the burden of 340B discounts to insurers in the form of lower rebates, which in turn, may have led to higher prescription drug premiums for enrollees. As far as I am aware, no previous studies have called attention to how 340B discounts operate like taxes on drug manufacturers or attempted to estimate the economic incidence of these discounts.

3.2 Spillover Effects of Federal Programs on Commercial Prices

A related literature has considered how changes in federal policies for public insurance programs (e.g., Medicaid and Medicare) could have spillover effects in the commercial market.[34] These include studies that have evaluated reductions in Medicare payments for hospital services (Dranove, 1988; Cutler, 1998)[35] and physician services (Clemens and Gottlieb, 2017). Others have also found that reimbursement formulas for Medicare Part B can increase drug launch prices (Ridley and Lee, 2020), but the introduction of Medicare Part D expanded the size of insurers, resulting in lower commercial drug prices (Lakdawalla and Yin, 2015)[36].

Most relevant to my paper have been a series of studies on the effects that the Medicaid Drug Rebate Program (MDRP) has had on commercial drug prices. The results of these studies are germane to my setting because the formula used to compute 340B discounts is nearly identical to the formula used to compute Medicaid rebates. The base rebate manufacturers are required to pay Medicaid is the larger of either a percentage of the average private sector price or the best discount the manufacturer offers to any non-Medicaid purchaser.[37] This formula constrains a manufacturer's ability to offer discounts to non-Medicaid buyers, especially for products with a high proportion of use by Medicaid recipients, which, in turn, could result in higher prices in the non-Medicaid market.

Prior research on the MDRP using cross-sectional data has found that drugs with high Medicaid usage have higher list prices when compared to drugs with lower shares of Medicaid users (Scott Morton, 1997; Duggan and Scott Morton, 2006). However, more recent research using a difference-in-differences design finds that manufacturers do not raise list prices for drugs with high Medicaid market shares (Feng et al.,

[34] A related literature also considers how international reference pricing practices affect drug manufacturer's choices of prices and entry across different international markets (Danzon et al., 2005; Kyle, 2007; Brekke et al., 2009; Maini and Pammolli, 2023).

[35] While these studies find some evidence suggesting hospitals raise prices to the commercial market after experiencing cuts from Medicare, the majority of empirical evidence finds that these effects are relatively small or null—see Frakt (2011) for a literature review on this subject.

[36] Duggan and Scott Morton (2010, 2011) find similar results, but their interpretation of the mechanism behind the price decreases was due to cash-paying consumers paying less after gaining insurance coverage through Medicare Part D.

[37] The particular average price is referred to as the average manufacturer price (AMP). The AMP is defined as "the average price paid to the manufacturer for the drug in the United States by wholesalers for drugs distributed to retail community pharmacies and retail community pharmacies that purchase drugs directly from the manufacturer." See Electronic Code of Federal Regulations (e-CFR) 42 CFR §447.504. Note that there are several federal purchasers of drugs that are excluded from the best price provision—see NHPF (2019) for a detailed list.

2023). Feng et al. (2023) posit that the MDRP has likely limited the growth in drug list prices because, in addition to the base rebate, the MDRP requires manufacturers pay an "inflationary" rebate if the drug's list price grows at a faster rate than inflation. This finding supports the supposition of my theoretical model that drug manufacturers cannot simply raise list prices when 340B providers claim higher volumes of discounts.[38] Moreover, Feng et al. (2023) find that manufacturers increase net-of-rebate prices of drugs with more exposure to Medicaid rebates, which supports my hypothesis that drug manufacturers will adjust their rebates in response to paying more 340B discounts.

My paper contributes to this literature as it considers how another federal policy—the 340B Program—can create potential distortions to drug manufacturer behavior that could have unintended effects for consumers. While I cannot observe net drug prices to Part D insurers because rebate data are confidential, my paper considers how distortions to net drug prices could affect a downstream outcome, namely prescription drug premiums. One key difference between my paper and the previous literature in this field is that I am evaluating how drug discounts for private companies can have spillover effects on the costs for a government program (i.e., 340B providers and Medicare Part D, respectively). Not only is this a novel contribution, it is also timely as the Inflation Reduction Act of 2022 has introduced several changes to the Medicare Part D system including "inflationary rebates" and government-led price negotiations that are likely to impact not only Part D premiums[39] but may also have unintended spillover effects to the commercial market.

3.3 340B Program

Much of the research on the 340B Program has focused on whether the program alters the behavior of 340B providers after joining the program. Given that the program was created to supply safety-net providers with savings that they could use to expand services to their low-income patient populations, researchers have used quasi-experimental methods to assess if 340B hospitals increase the amounts of charity care and low-profit services they provide, or if they improve the mortality rates of their low-income patients (Desai and McWilliams, 2018; Nikpay et al., 2020; Desai and McWilliams, 2021).[40] Others have also explored some potential unintended consequences that participation in the 340B Program may have on hospitals such as using high-cost medications (Jung et al., 2018; Bond et al., 2023), or acquiring physician practices that dispense high-cost drugs (Alpert et al., 2017; Desai and McWilliams, 2018).

As far as I am aware, there has been no published research utilizing quasi-experimental methods to explore the potential effects of 340B contract pharmacies. Clark et al. (2014) utilized 2012 data on all prescriptions

[38] See Section 4 for details.

[39] Descriptive research has found that the average enrollee Part D premium has increased from $36 per month in 2023 to $48 per month for 2024 suggesting that these changes may be contributing to higher premiums (Kornfield et al., 2023).

[40] There has also been some work to estimate hospitals profits from participating in the 340B Program (Conti et al., 2019).

filled at the contract and non-contract pharmacy locations of a large retail chain. They find that contract pharmacy locations are more likely to dispense medications treating chronic conditions such as diabetes and HIV/AIDS suggesting the program helps vulnerable patient populations. However, they note that these data are for only one retail pharmacy chain and may not generalize to other contract pharmacies. More recently, there have been two studies that have evaluated the characteristics of the communities that have experienced the largest growth in the number of contract pharmacies since the 2010 policy expansion. Lin et al. (2022) find that higher income and predominantly white zip codes experienced the greatest increase in contract pharmacies between 2011 and 2019. Nikpay et al. (2022) find that a county's uninsured or poverty rate does not predict if pharmacies in that county will contract with 340B hospitals. These results are suggestive that 340B hospitals choose to contract with pharmacies in areas where the residents have more generous insurance coverage that pays higher reimbursement than public programs such as Medicaid.[41],[42]

My paper contributes to this literature since it is the first to ask if the massive growth of 340B contract pharmacies has had unintended consequences outside of the 340B Program—namely, a reduction in rebates and an increase in prescription drug insurance premiums in Part D. Moreover, my study is the first to apply a quasi-experimental research design to the 340B contract pharmacy context.

4 Theory

In this section, I present a stylized Nash bargaining problem that models how a drug manufacturer negotiates the rebate it offers to a Part D insurer. To simplify the exposition and focus our attention on the effect of 340B discounts on rebates, I make the following four assumptions. First, drug manufacturers have a constant marginal cost of production of zero. This assumption approximates reality as manufacturing costs for most drugs are relatively small.

Second, I assume that the drug manufacturer has an exogenous list price of p for its drug. This assumption is consistent with previous work in similar settings.[43] Moreover, prior research has found that list prices for drugs which are subject to high rates of Medicaid rebates have experienced limited list price growth. The reason being that Medicaid rebates contain an inflation penalty that adds any list price growth above inflation to the rebate (Feng et al., 2023). Given that 340B discounts are computed using the same formula as Medicaid rebates, it is reasonable to assume that drugs with high rates of 340B discounts will also experience

[41] This phenomenon is unsurprising given that a majority of states do not permit contract pharmacies to claim 340B discounts on prescriptions filled by Medicaid recipients (see Kaiser Family Foundation survey).

[42] Nikpay et al. (2023) is another recent study that characterizes the number of contracts each contract pharmacy has with 340B providers, the average distance between 340B providers and contract pharmacies, and how the distributions of those metrics have changed between 2009 and 2022.

[43] Feng et al. (2023) assume an exogenous list price in their Nash bargaining problem that models how drug manufacturers and commercial insurers negotiate over commercial rebates.

limited list price growth—that is, drug manufacturers cannot increase their list prices without also increasing their 340B discount.

Third, I assume that the insurer's reimbursement to the pharmacy $\tilde{p}$ is not impacted by the rebate the insurer negotiates with the drug manufacturer. While it is theoretically possible that insurers could negotiate differential reimbursement to contract pharmacies, there are institutional features of Part D that limit an insurer's ability to negotiate differential reimbursement based on contract pharmacy status.[44] Moreover, as I will describe in Section 6.2, I will test this assumption empirically using the Medicare Part D claims data.

Fourth, I assume the manufacturer faces inelastic demand of Q for its product. While this is a simplifying assumption, it is consistent with prior work in this area (Feng et al., 2023). Also note that demand for a drug product will be determined by an enrollee's cost sharing and not necessarily the list price of the drug.[45] Thus, this assumption should reasonably approximate the conditions of this negotiation.

Given these assumptions, the Nash bargaining problem is expressed mathematically as follows:

$$\max_{r} \Big[\Big(b - (\tilde{p} - r)\Big)Q - 0\Big]^{\beta} \times \Big[\Big((p - r - \tau)\sigma + (p - r)(1 - \sigma)\Big)Q - 0\Big]^{1-\beta} \tag{1}$$

The first bracketed term represents the gain for the insurer from successfully negotiating a per-unit rebate of r. The insurer trades off the average clinical benefit the drug (b) provides to a beneficiary with the cost of paying for the drug, which is the difference between the reimbursement it pays to the pharmacy and the rebate it collects from the drug manufacturer ($\tilde{p} - r$). In the event that the two parties fail to come to an agreement, the insurer does not include the manufacturer's drug on the formulary and its enrollees receive a benefit of zero. In contrast, when the parties come to an agreement, the insurer's per-unit cost is reduced by the rebate r and the manufacturer faces demand of Q.

The second bracketed term represents the gain for the manufacturer from a successful negotiation. If the negotiation fails, the manufacturer's drug is excluded from the insurer's formulary and earns zero revenue from this insurer's enrollees. By contrast, if the negotiation succeeds, the manufacturer experiences demand of Q and provides the insurer with a rebate. In addition, for the $\sigma \in [0, 1]$ percent of prescriptions the insurer's beneficiaries fill at 340B contract pharmacies, the manufacturer must also provide a 340B discount ($\tau > 0$) to the contract pharmacy.

The exponents $\beta \in (0, 1)$ and $(1 - \beta)$ are the relative bargaining weights of the insurer and drug manufacturer, respectively. These capture each party's bargaining preferences relative to one another. For instance,

[44] See Section 2.2 for more details.

[45] However, if a patient faces a deductible, her cost-sharing will be equal to the list price of the drug. However, once the deductible is met, her cost-sharing is either a small percentage of the list price or a fixed copayment.

a relatively high β would capture the idea that the insurer had a strong preference to hold out from the negotiation to receive a high rebate.

I will assume the following ordering $b \geq p \geq \tau$. In words, the insurer does not negotiate to include a drug on its formulary if the drug's list price exceeds its average clinical benefit to a patient. The latter assumption, $p \geq \tau$, captures an institutional feature of the 340B Program which caps discounts at a drug's list price.

The negotiated rebate that solves the Nash bargaining problem can be found from the first-order condition of (1). The solution is:

$$r^* = \tilde{p} + \beta(p - \tilde{p}) - b(1 - \beta) - \beta\tau\sigma \tag{2}$$

The equilibrium rebate is positively related to a drug's list price, which suggests that a drug manufacturer cannot unilaterally increase its list price without increasing the rebate to the insurer. From (2), we can also see that the rebate is decreasing in the clinical benefit, but the effect is proportional to the bargaining weight of the manufacturer. That is, a manufacturer with relatively stronger preferences for holding out will negotiate a lower rebate, all else equal.

The term $\beta\tau\sigma$ represents the incidence of the 340B discount that the drug manufacturer can pass through to the insurer. A key implication of this result is that a greater share of prescriptions that an insurer's beneficiaries fill at contract pharmacies will increase the incidence of the 340B discount that is passed through to the insurer. That is,

$$\frac{dr^*}{d\sigma} = -\beta\tau < 0 \tag{3}$$

I will empirically test this implication in the following sections by comparing how a function of rebates—insurers' premiums—respond to greater exposure to 340B contract pharmacies.

5 Data

5.1 340B Data

Data on 340B providers and their contract pharmacy partners come from the Office of Pharmacy Affairs Information Systems (OPAIS) database. The database lists every 340B provider that is or has ever been enrolled in the 340B Program, the effective start date of its enrollment, its effective termination date (if applicable), the criterion under which it qualifies for the 340B Program (e.g. DSH or CAH), as well as the name and street address of the provider. Hospitals are identified by their Medicare Provider number

while grantees are identified by a federal grant number.[46] The database also contains a separate dataset describing every contract pharmacy relationship between 340B providers and pharmacies. The dataset links a 340B provider's unique identifier to each pharmacy with which it currently contracts or has contracted with in the past. The dataset also describes the effective start date of the contract, the effective termination date of the contract (if applicable), as well as the pharmacy name and its street address. One key innovation I have made is that I have matched each contract pharmacy to a national provider identifier (NPI) number that will allow me to identify which pharmacies serve as contract pharmacies in the Part D claims data.[47]

5.2 Part D Data

I use three datasets for Medicare Part D from 2009 through 2018. The first dataset is the CMS Landscape files which list all Medicare plans that offer Part D prescription drug coverage for any given year. The files describe which Part D region each plan is available, the monthly premium, the annual deductible, the name of the insurer offering the plan, the plan type[48], the benefit type[49], as well as if the plan offers gap coverage. As mentioned previously, I limit my sample of plans to include only standalone prescription drug plans (PDPs) since the premiums of Medicare Advantage prescription drug plans reflect both medical and prescription drug costs.

The second dataset I employ from CMS is a 20 percent random sample of prescription drug claims. Each claim describes a prescription for a particular drug product[50] filled by an individual Part D enrollee. Crucially, the claim identifies the pharmacy where the enrollee filled her prescription and the date on which she filled the prescription. Combining these claims with the OPAIS contract pharmacy database, I can identify whether or not any given prescription was filled at a contract pharmacy.

The third dataset from CMS that I use is the Master Beneficiary Summary File (MBSF) which provides demographic characteristics of all Medicare Part D enrollees, including their sex, race, age, the Part D plan in which their enrolled, as well as their zip code and county. The file also describes if the beneficiary is dually eligible for Medicare and Medicaid (i.e., duals) or if she qualifies for low-income cost sharing subsidies

[46] A hospital Medicare Provider number is also known as a CMS Certification Number (CCN).

[47] I used a fuzzy string match algorithm to match the pharmacy's name, street, state, city, and zip code from the OPAIS contract pharmacy dataset to CMS' National Plan and Provider Enumeration System (NPPES) database, which lists all NPIs that submit claims to Medicare. I used annual historical snapshots of the NPPES database going back to 2008 to ensure that my matching algorithm did not miss older pharmacies which may have closed and thus would not appear in current versions of the NPPES database. I then manually reviewed each fuzzy match to ensure accuracy. Of the approximately 45,000 pharmacies in the OPAIS database, I found matches for all but 50.

[48] e.g., a Medicare Advantage Health Maintenance Organization (HMO) or a stand-alone Prescription Drug Plan (PDP).

[49] e.g., the plan uses the Part D defined standard benefit design or it uses an actuarially equivalent design.

[50] The drug products in the Part D claims data are defined by the National Drug Code (NDC). Each NDC is 10 or 11 digits and consists of three segments. The first segment of digits defines the manufacturer of drug. The second segment identifies the product—i.e., the strength, dosage, and formulation of the product. The third segment identifies the package code—i.e., the quantity in the package.

(LIS enrollees). From this file I construct several plan-level variables that will control for differing enrollee characteristics in my regression analyses.

6 Empirical Strategy

In Section 6.1, I describe my empirical strategies to estimate the pass-through of 340B discounts to Part D premiums; these include both a two-way fixed effects estimation strategy, as well as an instrumental variable methodology. In Section 6.2, I outline my empirical strategy to assess the possibility that insurers negotiate lower reimbursement to pharmacies after they become contract pharmacies.

6.1 Contract Pharmacies Effects on Premiums

6.1.1 Two-Way Fixed Effects Strategy

In an ideal world, I could directly test my theoretical model's prediction that insurers with greater exposure to 340B contract pharmacies will face higher pass-through of 340B discounts in the form of lower rebates. Unfortunately, I cannot observe Part D rebates to insurers at either the drug or insurer level because rebates are treated as commercial secrets by insurers and drug manufacturers (Olssen and Demirer, 2021).[51] However, government reports indicate that insurers use the cost savings they generate from rebates to lower premiums (MedPAC, 2019; GAO, 2019). I hypothesize that insurers with higher observed contract pharmacy exposure will likely experience reduced rebates, which could cause them to raise their premiums. Thus, the first strategy I use to test this hypothesis is in a two-way fixed effects regression that leverages both within-insurer and within-Part D region-time variation. Specifically, I estimate the following regression:

$$\text{Premium}_{ijrt} = \eta_{rt} + \gamma_j + X'_{ijrt}\boldsymbol{\psi} + \beta \text{CP}_{jrt} + \epsilon_{ijrt} \tag{4}$$

Premium_{ijrt} is the monthly premium of plan i offered by insurer j in Medicare Part D region r in year t. The primary explanatory variable of interest is CP_{jrt} which measures the percentage of insurer j's Part D region r's expenditures on branded drugs that were made at contract pharmacies in year t. I use this measure because insurers typically only negotiate rebates on branded drugs. Thus, one can think of this variable as measuring the percentage of an insurer's rebate-eligible drug spending that may also be subject to a 340B discount. This approach assumes that insurers set their premiums based on their contemporaneous exposure to contract pharmacies and, consistent with the theoretical prediction of my model, that the magnitude

[51] While there exists one data source (SSR Health) that attempts to estimates rebates at a drug-level, these estimates are not insurer-specific. They are national level estimates of net-prices for drug products.

of their response increases with their exposure to contract pharmacies.[52] I cluster my standard errors at the insurer level and I weight each observation by the Part D region's enrollment from 2008. In robustness analyses, I test the sensitivity of my results by utilizing alternative weights as well as a logarithm version of the dependent variable.

I include a rich set of covariates to control for other determinants of plan premiums. The vector X_{ijrt} includes two groups of time-varying control variables: (1) plan characteristics and (2) enrollee characteristics. Plan characteristics include variables such as the plan's annual deductible and indicators for the generosity of plan coverage (e.g., gap coverage). Enrollee characteristics include the proportion of a plan's enrollees in four different age groups (e.g., 65-74 years old), the proportion of female enrollees, and the proportion of patients in six different racial groups. I also include the proportion of a plan's patients who are dually-enrolled in Medicare and Medicaid, as well as the proportion of enrollees that qualify for low-income cost-sharing subsidies (i.e., LICS enrollees). These enrollee characteristics partially control for the risk profile of each plan's enrollees, and capture, to a degree, the prescription drug preferences of these different demographic groups. The full set of plan control and enrollee characteristics variables are described in detail and summarized in Table 1. Lastly, I include two-way fixed effects that capture time-invariant characteristics of each insurer that may impact premiums (γ_j), and year-by-Part D region fixed effects that control for Part D regional-specific secular trends in premiums (η_{rt}). These year-by-region fixed effects capture important variation that may impact premiums. For instance, suppose an insurer enters region A leading to an increase in insurer competition, but it does not enter region B. These fixed effects would capture any differential changes to premiums across these regions due to the change in insurer competition of region A.

The intuition behind this strategy is to exploit within-insurer variation in exposure to 340B contract pharmacies that arises from differing county-level enrollment patterns within a Part D region over time. Figure 1 displays how the number of contract pharmacies located in each county across the US has changed from 2010 to 2015. In 2010, 80 percent of the 3,143 counties did not have a contract pharmacy. By 2015, about 70 percent of counties had at least one contract pharmacy. However, there is noticeable within-Part D region variation in the growth of contract pharmacies by county. For example, in the Part D region of New Jersey in 2010, Essex County contained six contract pharmacies and Ocean County had one (see Figure 2). By 2015, Essex County had over 60 contract pharmacy locations while Ocean County had only nine. Thus, all else equal, I would expect that an insurer who enrolls more beneficiaries from Essex than Ocean County

[52] A histogram of this variable's distribution (by year) is presented in Appendix Figure C.4. This empirical measure is akin to the theoretical quantity $\tau\sigma$ described in Section 4. Ideally, I would like to be able to measure for each insurer, what percentage of their branded drug spending qualifies for a 340B discount, but there are no claims data that tell whether or not the claim was eligible for a 340B discount. Thus, I proxy for 340B eligibility by assuming that if the pharmacy that filled the prescription was a contract pharmacy, then that branded drug prescription was eligible for a 340B discount. Indeed, Office of Inspector General (2019) found in their audits of Part D rebate contracts between drug manufacturers and insurers that manufacturers were excused from paying rebates on *any* prescription filled at a contract pharmacy even if no 340B discount was claimed.

will face greater 340B contract pharmacy exposure than an insurer with the opposite enrollment pattern. For example, over ten percent of Envision Rx's 2015 enrollment came from Essex County while under 5 percent came from Ocean County. By contrast, more than 12 percent of Horizon Blue Cross Blue Shield of New Jersey's enrollment originated in Ocean County and approximately 7 percent came from Essex. Thus, identification for Equation (4) rests on the assumption that this differential exposure to contract pharmacies, created by differing county enrollment shares for insurers, is conditionally independent of these insurers' potential premiums.[53] This assumption seems plausible given that 340B providers, and not insurers, choose which pharmacies become contract pharmacies. To further support this assumption, I show in Appendix Figure C.3 that insurer's initial shares of enrollment by county are highly predictive of its future county enrollment shares. This is consistent with prior empirical work that finds Medicare Part D enrollees seldom switch plans (Abaluck and Gruber, 2011; Ericson, 2014; Polyakova, 2016; Ho et al., 2017; Heiss et al., 2021).

One potential threat to this assumption is that 340B providers may choose to contract with pharmacies that disproportionately dispense high-cost drugs since the patients of 340B providers may be more likely to need these high-cost medications. Since an insurer's premiums are a function of their enrollees' drug costs, this could result in a spurious positive correlation between premiums and contract pharmacy exposure. Thus, I will also include each plan's spending per beneficiary on branded drugs as a control variable to account for this possibility. Additionally, I utilize a robustness methodology described by Oster (2019) that allows researchers to characterize how sensitive a potential treatment effect is under different assumptions about the degree of omitted variable bias in their regression. I will compare the bounds I derive from this methodology to the 95 percent confidence interval from my two-way fixed effects estimation.[54]

6.1.2 Instrumental Variable Strategy - Medicaid Expansions

While Equation (4) includes a rich set of controls, there still may be unobservables that are correlated with the observed contract pharmacy exposure an insurer experiences and its premiums. Thus, I will also implement

[53] Another way to interpret Equation (4) is that it is a difference-in-differences (DD) strategy with differential timing and a *continuously* varying treatment variable. There has been a considerable amount of new research interest in DD strategies and the use of two-way fixed effects (TWFEs), but nearly all of this published research has focused exclusively on cases where the treatment is a *binary* variable, or in some cases, a discrete value—see De Chaisemartin and d'Haultfoeuille (2022) and Roth et al. (2023) for summaries. Two recently released working papers have begun to diagnose some of the potential issues that can arise from using TWFEs for continuously varying treatment variables (Callaway et al., 2021; De Chaisemartin et al., 2022). Similar to the binary treatment case, Callaway et al. (2021) have shown that in the continuous case, the estimated treatment effect is a weighted average of all possible two-by-two comparisons where some control units may already be treated. This can have the unattractive feature of biasing the TWFE estimated treatment effect towards zero. While researchers have made some progress to develop methods to aid practitioners in avoiding some of the issues associated with TWFE for a binary treatment variable, researchers have not yet developed well-understood methods that deal with a continuously varying treatment variable. For instance, while the Stata command, `did_multiplegt_dyn` can theoretically implement a continuously varying treatment variable as described by De Chaisemartin et al. (2022), there are no well-established guidelines or simulation results to aid practitioners in choices of parameters or diagnostics. Further development of these methods is necessary before researchers can confidentially implement them.

[54] This methodology was first conceived by Altonji et al. (2005a,b) and refined and expanded upon by both Oster (2019) and Basu (2022).

an instrumental variable strategy that exploits plausibly random variation in insurer's exposure to contract pharmacies arising from states' decisions to expand their Medicaid programs following the passage of the Affordable Care Act (ACA). If a hospital's patient population disproportionately is enrolled in Medicaid, then it can join the 340B Program as a disproportionate share (DSH) hospital.[55] Therefore, hospitals in states expanding their Medicaid programs were more likely to qualify for and enroll in the 340B Program than hospitals in nonexpansion states after the expansions. As a result, one can expect that the increase in 340B DSH hospitals in the expansion states led to a commensurate increase in the number of contract pharmacies operating in the expansion states.

Figure 3 displays times series of the number of 340B DSH hospitals per capita in the 2014 Medicaid expansion states versus the states that had not yet expanded their programs by 2020.[56] Prior to 2014, the number of 340B DSH hospitals was trending upward in both expansion and nonexpansion states and these trend lines followed similar patterns of growth. Post the expansions, we observe a clear break in these two trend lines, where expansion states continue to experience upward growth while nonexpansion states experienced a slight decline post-2014.

As suggested above, this differential growth in 340B DSH hospitals also increased the likelihood of pharmacies partnering with newly minted 340B providers as contract pharmacies in the expansion states. Figure 4 displays time series of the number of contract pharmacies per capita in the 2014 Medicaid expansion states versus the states that had not yet expanded their programs as of 2020. In 2014, there were approximately 25 contract pharmacies per million residents in both expansion and nonexpansion states. By the end of 2021, there were about 25 to 30 percent more contract pharmacies per capita in expansion states.

To exploit this cross-regional variation in contract pharmacy exposure brought about by the 2014 Medicaid expansions, I conduct an instrumental variable analysis using two-stage least squares (2SLS). Equation (5) estimates the first-stage relationship between Medicaid expansions and contract pharmacy exposure, while equation (6) estimates the second-stage relationship between contract pharmacy exposure and premiums.

$$\text{CP}_{jrt} = \lambda_t + \alpha_r + \gamma_j + X'_{ijrt}\boldsymbol{\psi} + \theta_1\Big(\mathbf{1}(\text{2014 Expander}_r) \times \mathbf{1}(\text{Year}_t \geq 2014)\Big) + \epsilon_{ijrt} \tag{5}$$

$$\text{Premium}_{ijrt} = \lambda_t + \alpha_r + \gamma_j + X'_{ijrt}\boldsymbol{\psi} + \theta_2\widehat{\text{CP}}_{jrt} + \varepsilon_{ijrt} \tag{6}$$

The instrument is an indicator variable equal to one starting in 2014 if the Part D region r in which the plan

[55] For the details of how a hospital qualifies as a 340B DSH hospital, please see footnote [20].

[56] There were 27 states which expanded their Medicaid programs in 2014; 25 (including DC) expanded on January 1st while, MI and NH expanded on April 1st and August 15th, respectively. There were 10 additional states that expanded their Medicaid programs after 2014 and between 2020. The remaining 14 states had not, as of 2020, expanded their Medicaid programs. See Appendix Table B.1 for a complete list of expansion dates.

i is offered had expanded its Medicaid program by year 2014. The first-stage is effectively a two-way fixed effects difference-in-differences (DD) model where "treatment" begins in 2014 for the Part D regions that expanded their Medicaid programs in that year. Although some Part D regions cross state boundaries, most states that are located in the same Part D region chose either not to expand or to expand their Medicaid programs on the same date.[57] Thus, I designate a Part D region as a 2014 expansion region if all its constituent states expanded their Medicaid programs in 2014 (i.e., the "treated" regions). By contrast, the nonexpansion regions (i.e., the "control" regions) are limited to those where all constituent states had not expanded their program as of Jan. 1, 2019. Thus, my sample consists of 12 treated regions and 13 control regions.[58]

I include the same vector of plan and enrollee controls X_{ijrt} as used in Equation (4) as well as insurer fixed effects. Unlike Equation (4), I can no longer include year-by-region fixed effects because my instrument varies at only the year and region level. Instead, I include year fixed effects that allow for common national trends in plan premiums (λ_t) and Part D region fixed effects (α_r) that allow for constant regional effects on premiums. This specification could lead to a violation of the exclusion restriction that Medicaid expansions affect Part D premiums only through the impact they have on increasing insurer exposure to contract pharmacies. For instance, McInerney et al. (2021) found that Medicaid expansion states experienced an increase in enrollment of individuals with dual eligibility for Medicare and Medicaid—so-called "duals". Duals typically have more severe health problems and chronic conditions than standard Medicare beneficiaries. Therefore, it is plausible that there is a positive correlation between a Part D region's expansion status and their premiums due to the increased presence of duals. However, I directly address this concern by including the proportion of a plan's enrollment that comes from dual enrollees as a control variable in my regressions.

Hudson et al. (2017) refer to the above empirical strategy as an instrumented difference-in-differences design. As with all IV designs, its validity rests on the exclusion restriction, which is a fundamentally untestable assumption. However, we can evaluate the plausibility of this assumption by evaluating if there were parallel trends in premiums between the expansion and nonexpansion regions prior to 2014. To do so,

[57] For instance, Region #30 consists of OR and WA and both states expanded their Medicaid programs on January 1st, 2014. In contrast, Region #12 consists of AL and TN and neither expanded their Medicaid program as of 2020.

[58] There are four Part D regions whose fourteen member states either had far apart expansion years or a mixture of both expansions and nonexpansions. Region #1 which includes ME and NH, Region #6 which includes PA and WV, Region #15 which includes IN and KY, and Region #25, which includes seven small Midwestern states—IA, MN, MT, ND, NE, SD, and WY. Thus, I exclude these fourteen states from my instrumental variable analysis. In addition, I follow the guidance of Carey et al. (2020) by excluding three regions in which some or all of the constituent states already used Medicaid coverage eligibility rules for adults that were comparable to those stipulated by the ACA. MA and VT met this criteria so I exclude their Part D region (i.e., Region #2), which also includes CT and RI. DC and DE also met this criteria so I exclude their Part D region (i.e., Region #5), which also includes MD. Additionally, NY met this criteria so I exclude its region (i.e., Region #3). Lastly, I exclude from my sample of Part D plans the regions where constituent states expanded their programs between 2014 and 2019. This restriction removes two additional Part D regions: AK and LA. Please see the Appendix Table B.1 for a complete description of each state and the inclusion criteria used to determine if it was kept in the sample.

I will run an event study version of the reduced-form effect of Medicaid expansions on plan premiums:

$$\text{Premium}_{ijrt} = \lambda_t + \alpha_r + \gamma_j + X'_{ijrt}\psi + \sum_{t'=2009}^{2012} \omega_{t'} \Big(\mathbf{1}(\text{2014 Expander}_r) \times \mathbf{1}(\text{Year}_t = t') \Big) \sum_{t''=2014}^{2018} \omega_{t''} \Big(\mathbf{1}(\text{2014 Expander}_r) \times \mathbf{1}(\text{Year}_t = t'') \Big) + \varepsilon_{ijrt} \quad (7)$$

While the results of this event study do not directly test the exclusion restriction assumption, they will at least provide us with evidence if there were parallel trends in premiums prior to the expansions.

In addition, prior research has found that Medicaid expansions have had negligible or no impact on Medicare spending. Ghosh et al. (2019) studied the impact of Medicaid expansions on prescription drug utilization of both Medicaid and Medicare Part D recipients after the expansions. Using a DD design, they find that the number of Medicare prescriptions remained constant in the expansion states after the expansions occurred. In a more recent study, Barkowski et al. (2022) also use a DD design to investigate whether Medicaid expansions had spillover effects on the health care consumption of Medicare enrollees. Akin to McInerney et al. (2021), Barkowski et al. (2022) find that Medicaid expansion states experienced a 4 percentage point increase in the percentage of Medicaid-Medicare duals. However, they find that drug spending per Part D beneficiary did not change for enrollees in the expansion states after the expansions.[59] Thus, the available evidence suggests the Medicaid expansions had minimal impact on the Part D market.

Lastly, I will also use an alternative instrument that leverages more granular variation from the Medicaid expansions. In particular, the Medicaid expansions could have differing impacts on the growth of contract pharmacies across different expansion regions depending on pre-expansion variation in the presence of contract pharmacies. For instance, an increase in DSH hospitals caused by a Medicaid expansion in Arizona may not dramatically increase the number of contract pharmacies in that region because over 30 percent of Arizona pharmacies were already serving as contract pharmacies in 2013. In contrast, the Medicaid expansion in New Jersey would likely have a greater impact on the growth of contract pharmacies in that region since only 12 percent of New Jersey pharmacies operated as contract pharmacies prior to the Medicaid expansions. Leveraging this pre-expansion, regional variation in the presence of contract pharmacies, I estimate the first-stage as follows:

$$\text{CP}_{jrt} = \lambda_t + \alpha_r + \gamma_j + X'_{ijrt}\psi + \theta_1 \Big(\mathbf{1}(\text{2014 Expander}_r) \times \mathbf{1}(\text{Year}_t \geq 2014) \times \text{2013 Frac Non-CP}_r \Big) + \epsilon_{ijrt} \quad (8)$$

The instrument is the same as in Equation (5) but it also includes an interaction with 2013 Frac Non-CP$_r$,

[59] These findings are also consistent with previous published research. Carey et al. (2020) found that the ACA Medicaid expansions had no impact on health care utilization by Medicare beneficiaries for primary care services, new patient visits, or physician services expenditures.

which measures the proportion of pharmacies in a Part D region that were *not* serving as contract pharmacies in 2013.[60]

As with my TWFE regression, I cluster my standard errors at the insurer level and I weight each observation by the Part D region's enrollment from 2008. I also test the sensitivity of my results with alternative regression weights and a logarithm version of the dependent variable.

6.2 Effects on Pharmacy Reimbursement

As discussed previously, 340B discounts effectively act like taxes on drug manufacturers. The incidence of those discounts could be borne, at least partially, by insurers if manufacturers reduce the rebates they offer on branded prescription drugs. This phenomenon could increase costs to insurers who may have to raise their premiums to enrollees. By contrast, because contract pharmacies receive a portion of a 340B discount, these discounts operate like subsidies to contract pharmacies, which could reduce their costs. Thus, contract pharmacies may pass through some of their subsidy by accepting lower reimbursement from insurers, which could potentially offset any cost increases an insurer experiences from reduced manufacturer rebates.

To assess this possibility, I estimate the following regression. Effectively, this regression is a difference-in-differences design that compares how reimbursement changes for a pharmacy after it becomes a 340B contract pharmacy relative to changes in reimbursement for non-contract pharmacies.[61]

$$C_{dikt} = \Omega_{dikt} + \mu D_{kt} + \epsilon_{dikt} \tag{9}$$

C_{dikt} is the average reimbursement plan i offered by insurer j in Part D region r paid to pharmacy k on drug product d (i.e., NDC) in year-quarter t.[62] I compute pharmacy reimbursement as the average reimbursement for a 1-day supply of each drug product.[63] The primary explanatory variable of interest is D_{kt} which is an indicator variable equal to one if pharmacy k was operating as a contract pharmacy at time t. The vector Ω_{dikt} includes a rich set of fixed effects to control for any variation across how plans reimburse pharmacies for different drugs. In the baseline specification, I include a pharmacy k fixed effect as well as a drug-by-plan-by-time specific intercept. The former captures any time-invariant differences across pharmacies (e.g., customary dispensing fees), while the latter controls for any plan-specific secular trends in reimbursement

[60] This approach is similar in spirit to Finkelstein (2007) and Finkelstein and McKnight (2008) which both leverage regional variation in the proportion of the elderly that had health insurance coverage prior to the establishment of Medicare to identify the effects of expanding coverage to the elderly.

[61] This regression specification is similar to Starc and Swanson (2021).

[62] To simplify the notation, I omit the insurer j and region r subscripts because the insurer and region are defined by the plan i.

[63] Appendix Section A.1 describes in detail the method for how I compute a standard daily dose for each NDC. Also note that my analysis does not capture the possibility that pharmacies are charged pharmacy DIR fees for joining an insurer's preferred pharmacy network—see Footnote [30] for more details.

for a narrowly defined drug product.

In my preferred specification, I substitute the pharmacy fixed effect for a pharmacy-by-plan fixed effect to control for any time-invariant differences across plan-pharmacy pairs. For example, this term would capture any differences in reimbursement that come from differential dispensing fees negotiated between the plan and pharmacy. Thus, one can think of μ as describing how does the average reimbursement for pharmacy k change when it becomes a contract pharmacy given what it typically receives in reimbursement from plan i for all products and given how much plan i typically reimburses all pharmacies for drug d at time t.

The key identifying assumption is that there are no other shocks to the pharmacy's reimbursement from the plan that coincide with the pharmacy becoming a contract pharmacy. While I cannot test this assumption directly, I will also estimate an event study version of this regression to inspect if there are parallel trends in reimbursement between 340B contract pharmacies and non-contract pharmacies. I cluster my standard errors at the pharmacy level and I weight each observation by the number of claims in each drug-plan-pharmacy-year/quarter cell. For my primary analyses, I estimate these regressions for only brand name drug products since these are the products for which manufacturers typically offer rebates and contract pharmacies claim 340B discounts. I also run identical versions of these regressions for generic drug products to account for the possibility that plans may be negotiating lower reimbursement across all drug products and not just those for which pharmacies claim 340B discounts. Lastly, I limit the sample of contract pharmacies to the three years surrounding the event of the pharmacy becoming a contract pharmacy to assess the short-term effects on reimbursement that are likely attributable to the pharmacy becoming a contract pharmacy.[64]

While the results of the pharmacy reimbursement regressions are interesting in their own right, coupling them with the results from the premium regressions provide a more comprehensive explanation of how contract pharmacies affect Part D insurers. For instance, if we find that Part D premiums do not increase for insurers with greater exposure to contract pharmacies and reimbursement does decrease for contract pharmacies, then this would suggest that contract pharmacies do not result in higher premiums because insurers can negotiate differential reimbursement to contract pharmacies. In contrast, if we find that exposure to contract pharmacies is associated with higher premiums and pharmacy reimbursement is the same for contract and non-contract pharmacies, then this would indicate that insurers (and their enrollees) do bear some of the incidence of 340B discounts because insurers are unable to negotiate lower reimbursement to contract pharmacies.

[64] In robustness analyses, I do not impose this restriction and I find the results are qualitatively the same. Results are available upon request.

7 Results

In Section 7.1, I detail the results from my analysis of the effect of contract pharmacies on Part D premiums. I discuss the results of my TWFE analysis, followed by the IV results. I then provide a back-of-the-envelope calculation to contextualize the magnitude of my estimates. I then summarize various robustness analyses I performed, followed by a heterogeneity analysis to test how the effects of contract pharmacies on premiums may vary for an insurer that is vertically integrated with a contract pharmacy chain. Lastly, Section 7.2 describes the results of my pharmacy reimbursement regressions.

7.1 Effects of Contract Pharmacies on Premiums

7.1.1 Two-Way Fixed Effects Results

In Table 2, I present my two-way fixed effects estimates from Equation (4). Column (1) displays the point estimate of insurer contract pharmacy exposure on plan premiums when I include only the insurer and year-by-Part D region two-way fixed effects as controls. In this specification, a ten percentage point increase in an insurer's contract pharmacy exposure is associated with a statistically significant $3.76 increase in the insurer's plan premiums. Column (2) adds in the full set of plan and enrollee characteristic controls, which reduces the magnitude of the point estimate slightly, but improves its statistical precision. The estimate implies that a ten percentage point increase in an insurer's exposure to contract pharmacies is associated with a statistically significant increase of $3.33 in plan premiums. This represents about a 6.4 percent increase relative to the average monthly plan premium of $52.06 during the sample period.

However, as discussed in Section 6.1.1, this estimate could suffer from omitted variable bias. For instance, suppose there is a region with sick beneficiaries who utilize expensive drugs, which leads to higher drug costs in that area, and thus higher premiums. Because the patients of 340B providers often utilize expensive drugs, these providers may selectively choose to contract with the pharmacies that predominantly dispense those high-cost drugs, thus creating a spurious positive correlation between contract pharmacy exposure and premiums. In other words, the error term of Equation (4) would be positively correlated with both an insurer's exposure to contract pharmacies and its premiums, leading to an upward bias of my estimate.

I address this endogeneity concern in two ways. First, I directly account for this omitted variable concern by including the amount of insurer's branded drug spending per beneficiary as a control variable in my regression. This variable partly captures the degree to which an insurer's enrollees utilize expensive brand medications.

The results of this regression are presented in Column (3) of Table 2. As expected, there is a positive association between high branded drug expenditures per beneficiary and premiums, but this variable does

not materially change the effect of contract pharmacies on premiums; a ten percentage point increase in an insurer's share of branded drug spending at contract pharmacies is associated with a significant increase of $3.31, which suggests the contract pharmacy exposure regressor is not simply proxying for high-cost branded drug spending. I also test to see if expenditures per beneficiary on branded drugs is predicted by contract pharmacy exposure, conditional on the other covariates. Column (4) of Table 2 presents these results. While positively related, the contract pharmacy exposure coefficient is statistically null and the magnitude of its effect is relatively small when compared to the magnitude of the average spending per beneficiary on branded drugs—approximately a 0.3 percent effect relative to the mean.[65]

7.1.2 Instrumental Variable Results

The second way in which I address the endogeneity concern, is by implementing an instrumental variable (IV) strategy that exploits 2014 Medicaid expansions as a plausibly exogenous shock to Part D insurer's exposure to contract pharmacies. In Figure 5, I present an event study version of the reduced-form effect of Medicaid expansions on Part D premiums. Prior to the 2014 expansions, the point estimates are primarily negative, but close to and statistically indistinguishable from zero. There is also no observable differential trend in premiums before the 2014 expansions occur suggesting that premiums in the expansion regions were on similar trends to premiums in the nonexpansion regions prior to 2014. After the expansions, however, we start to observe positive point estimates and a steady upward trend in premiums in the expansion regions. While the post-2014 confidence intervals include zero, there is a noticeable upward trend in the expansion regions that are suggestive of possible positive effects on premiums.

In Column (4) of Table 3, I present both the first-stage and reduced-form effects of the Medicaid expansions. Consistent with Figure 4, there is a strong first-stage effect of Medicaid expansions on contract pharmacy exposure—the F-statistic of excluded instruments is 142.61 (Stock and Yogo, 2002). After the expansions, insurers in Part D regions that expanded their Medicaid programs experienced a statistically significant increase of 5.65 percentage points in their exposure to contract pharmacies, on average. In addition, the reduced-form effect implies that the average insurer monthly premium increased by a statistically significant amount of $1.95 for plans in the Medicaid expansion regions after the expansions. Scaling this reduced-form effect by the first-stage, the 2SLS estimate implies that a ten percentage point increase results in a $3.45 increase in premiums—approximately a 6.6% increase relative to the average premium of $52.09. While the 2SLS estimate is not as statistically precise (i.e., p-value of 0.053) as the TWFE estimates, the magnitude of the effects are very similar. In addition, under the assumption that the Medicaid expansions are a valid instrument for contract pharmacy exposure, I conduct a Wu-Hausman test to compare my IV

[65] i.e., $0.3\% \approx \frac{1.83}{603}$.

estimate to an equivalent two-way fixed effects regression. The Wu-Hausman test finds that we cannot reject the null hypothesis that the IV and TWFE estimates are the same—see Columns (3) and (4) of Table 3.

As described in Section 6.1.2, I also use an alternative instrument that leverages more granular variation from the Medicaid expansions. We should anticipate that the Medicaid expansions should have a larger effect on contract pharmacy exposure in regions where there were fewer contract pharmacies prior to the expansions. Thus, I use the 2013 measure of the proportion of pharmacies in a Part D region that were not already serving as a contract pharmacy interacted with an indicator for if the region expanded its Medicaid program in 2014 and a post-2014 dummy.

Results from this IV analysis are presented in Column (5) of Table 3. Again, the F-statistic is consistent with a strong first-stage effect. The 2SLS estimate with this continuous instrument is slightly larger than the binary instrument. The estimate implies a $3.69 increase in premiums for every 10 percentage point increase in contract pharmacy exposure.

The similar magnitudes of the estimates from both the IV analyses and the TWFE regressions suggest that insurer's increased exposure to contract pharmacies brought about by plausibly exogenous Medicaid expansions or increased exposure caused by plausibly random beneficiary enrollment patterns are both coming from sources of variation that are orthogonal to other sources of premium changes.

7.1.3 Benchmarking the Magnitude of the Effect on Premiums

To give readers a sense of the magnitude of my estimates, I compute how enrollee payments on Part D premiums have changed due to contract pharmacy exposure as implied by my TWFE estimate and then compare it the OIG (2019) estimate of the effect of contract pharmacies on Part D rebates. Consider the following back-of-the-envelope calculation. For the average Part D plan in my sample in 2009, 2.69 percent of their branded prescriptions were filled at contract pharmacies. In 2018, this average was 45.72 percent. Thus, my estimate implies that the monthly premium for a plan facing average contract pharmacy exposure was approximately $14.33 higher in 2018 than 2009 or that each enrollee in the average plan paid an additional $171.95 in annual premiums.[66] Between 2009 and 2018, the average annual number of Medicare Part D PDP enrollees was approximately 18.2 million. This implies that Part D enrollees paid approximately an additional $3.13 billion in premiums in 2019 when compared to 2009 due to 340B discounts. Assuming this average increase in contract pharmacy exposure occurred uniformly over the sample period, this would imply that premiums increased by $347 million per year from 2009 through 2018.[67] Recall from Section 2.2 that the OIG (2019) estimated that drug manufacturers paid Part D insurers approximately $300 million less

[66] $0.333 \times (45.72 - 2.69) \approx \$14.33$.

[67] $\frac{\$3.13 \text{ billion}}{9 \text{ years}} \approx \$347$ million per year.

in rebates in 2014 because of prescriptions their enrollees filled at contract pharmacies. Thus, my estimate of the increase in premiums of Part D insurers seems plausible given what insurers lost in rebates due to contract pharmacies in 2014.

7.1.4 Robustness

In this section, I summarize the sensitivity of both my TWFE and IV results to alternative regression weights and a logarithmic form of the dependent variable. I also use a methodology described by Oster (2019) to create bounds for my TWFE estimate based on different assumptions about the degree of omitted variable bias.

Alternative Regression Weights

Panel C.6a of Figure C.6 displays the point estimates and 95 percent confidence intervals of the TWFE, binary Medicaid instrument, and continuous Medicaid instrument versions of the effect of contract pharmacy exposure on premiums under different weighting choices.[68] The top portion displays the estimates for my preferred choice of weights—the 2008 enrollment of the Part D region in which the plan is offered. Because a plan's enrollment is partially determined by its premium, using 2008 regional enrollment mitigates any endogeneity between the weights and the main outcome variable of plan premiums because the weights are determined prior to my sample period. In addition, by giving more weight to plans located in regions with more Medicare Part D participants, the regression better captures the experience of the average enrollee given that a region such as California has 75 times more Part D enrollees than Alaska.

The middle portion of Panel C.6a displays my three primary estimates if, instead, we treat each plan equally by using no weights. While the magnitude of the TWFE decreases modestly, it is similar in magnitude to my preferred specification and still statistically significant. Similarly, both the binary and continuous instrument point estimates have nearly identical magnitudes to my preferred specification and have tighter confidence intervals. Lastly, the bottom portion of Panel C.6a displays my estimates when I use a plan's contemporaneous plan enrollment as its regression weight. This has the advantage of giving more weight to plans which have higher enrollment, which should better capture the average enrollee's experience. However, as noted above, contemporaneous premiums and enrollment are inextricably linked, which researchers should consider when interpreting these results. Despite this potential issue, my estimates using contemporaneous plan enrollment weights are quite similar to my preferred specification. The TWFE estimate decreases slightly, but both the IV estimates are relatively higher than the estimates using my preferred weights.

Logarithmic Functional Form

The second primary robustness check I consider is if my results are sensitive to my choice of functional form.

[68] The full regression results from these robustness checks can be found in Appendix Tables B.4, B.5, and B.6.

Specifically, my preferred specification uses the dollar or level value of premiums as the primary outcome. The distribution of this variable is slightly right-skewed, which could make it sensitive to outliers.[69] Thus, I re-perform all my premium regressions using the natural log transformation of plan premiums to mitigate this concern. I also transform the contract pharmacy exposure variable to a standard normal variable to ease the interpretation of the coefficient estimates. These results are presented in Panel C.6b of Figure C.6. Using my preferred weights, the TWFE estimate implies that a one-standard deviation increase in exposure to contract pharmacies is associated with a 7.7 percent increase in plan premiums. The magnitude of this effect is similar to the 6.4 percent relative to the average premium increase implied by the results when using the premiums in level form. Additionally, both the binary and continuous IV estimates are comparable to the estimates using levels and actually more statistically precise. In sum, my choice of functional form and preferred choice of weights are relatively conservative given the magnitudes and statistical precision of the effects under these alternative choices of weights and functional form.

Omitted Variable Bias Bounds

Lastly, I employ a methodology that allows researchers to compute an adjusted-treatment effect that adjusts for potential omitted variable bias (Oster, 2019; Basu, 2022). The method requires the researcher to specify two key parameters: (1) an R^2_{max} which describes the hypothetical R-squared the researcher could achieve if all observable and unobservable determinants of the outcome variable were included in the regression model, and (2) a coefficient of proportionality (δ) that characterizes how important the *unobservables* are in explaining the variation in the researcher's main regressor of interest (e.g., contract pharmacy exposure) relative to how well the *observables* explain the variation in the main regressor. Figure C.7 summarizes how the estimated TWFE treatment effect would decrease under a variety of assumptions about R^2_{max} and δ. If we follow Oster (2019)'s suggested parameterization, the bias-adjusted treatment effect would decrease slightly from 0.333 to only 0.316.[70] Even if we make a very conservative assumption that we can fully predict the outcome variable if all unobservables were included in the regression model and that the unobservables were ten times as important as the observables in explaining the variation in the main regressor of interest[71], the bias-adjusted treatment effect would still fall within the 95 percent confidence interval from the primary TWFE estimation.[72] Thus, even if there is omitted variable bias, adjusting the treatment effect for this bias does not dramatically alter the results of my primary analysis.

[69] See Appendix Figure C.5 for kernel density plots of this variable's distribution.

[70] That is, $\delta = 1$ and an $R^2_{max} = 1.3\tilde{R}^2$, where $\tilde{R}^2$ is the R-squared from the regression model that contains all observable controls. In my case, $\tilde{R}^2 = 0.727$.

[71] i.e., $R^2_{max} = 1$ and $\delta = 10$, respectively.

[72] Basu (2022) raises some concerns about the recommendations of R^2_{max} and δ that Oster (2019) suggests. I address his concerns by showing how the bias-adjusted treatment effect varies under a variety of assumptions about R^2_{max} and δ.

7.1.5 Heterogeneity: Vertical Integration between Contract Pharmacies and Insurers

As the previous analyses have suggested, the presence of 340B contract pharmacies is likely to reduce the rebates that insurers collect from drug manufacturers, which in turn, could lead insurers to raise premiums. However, this effect on premiums may not have the same impact across all insurers. In particular, there was one insurer during this sample period—CVS Health—that was vertically-integrated with a chain of pharmacies, many of which served as contract pharmacies.[73] Thus, CVS Health may have been able to use profits it collected from its 340B pharmacy status to subsidize the premiums it offered in the Part D insurance market. For instance, even if CVS's insurance arm cannot collect a rebate on a prescription, it may be able to collect a portion of a 340B discount, which could exceed the value of the rebate.

To test this hypothesis that CVS can subsidize its Part D premiums with revenue earned from its 340B contract pharmacy business, I re-estimate my primary TWFE regression (Equation (4)), but I also include an interaction term between the primary regressor of interest and a dummy variable for if the plan was owned and operated by CVS Health. The results of this regression are presented in Column (2) of Table 4. In this regression, the interpretation is that for all plans, including CVS-owned ones, a ten percentage point increase in exposure to contract pharmacies is associated with about $3.11 increase in premiums. However, for CVS-owned plans we see from the interaction term that there is almost a one-for-one decrease in the premiums of CVS-owned plans. That is, for every ten percentage point increase in exposure to contract pharmacies, CVS-owned plans also experienced a decrease of $2.67 in their premiums. This result is consistent with the possibility that CVS can utilize revenue it earns from its 340B contract pharmacy business to offset cost increases its insurance arm experiences from receiving fewer rebates from drug manufacturers.

7.2 Effects of Contract Pharmacies on Pharmacy Reimbursement

As discussed at the end of Section 6.2, the results of the pharmacy reimbursement regressions are an important component of my analyses that provides a richer description of how contract pharmacies could be impacting Part D insurers. Specifically, since the premium regressions suggest that greater exposure to contract pharmacies results in higher premiums, we should expect that insurers do not negotiate lower reimbursement to contract pharmacies. If, however, we observe that contract pharmacies do receive lower reimbursement from insurers, then this would raise concerns that there are unobserved factors affecting premiums that are positively correlated with, but not actually driven by contract pharmacy exposure.

In Figure 6, I present estimates from an event study version of Equation (9) that compares how reimbursement changes for contract pharmacies after they become contract pharmacies (treated group) relative

[73] CVS merged with another insurer, Aetna, that also offered Part D coverage. This merger was not approved until 2019 which is one year after my sample period ends.

to non-contract pharmacies (control group). Panel (6a) shows the results for the branded drug products while Panel (6b) displays results for generic drugs. The plots show that there are no noticeable changes to a pharmacy's reimbursement after it becomes a contract pharmacy. All of the point estimates in the twelve quarters after the event are clustered around zero. Moreover, there are no disconcerting pre-trend differentials between pharmacies that become contract pharmacies and non-contract pharmacies before the event. Table 5 displays the regression coefficient estimates of Equation (9). Consistent with the event study results, the regression estimates imply no change to a pharmacy's reimbursement for brand-name or generic drugs after becoming a contract pharmacy. For example, in my preferred specification for branded drugs in Column (2), the point estimate implies that contract pharmacies experience a four tenths of a cent increase in reimbursement after becoming a contract pharmacy. This represents about a 0.03 percent increase relative to the average pharmacy reimbursement of $12.49 per day for branded drugs. Similarly, in my preferred specification for generic drugs in Column (4), we see that contract pharmacies experience a six tenths of a cent increase in generic drug reimbursement after joining the 340B Program—approximately a 0.65 percent increase relative to the average generic drug reimbursement of $0.92 per day. Both of these increases are small in magnitude and statistically indistinguishable from zero suggesting that pharmacy reimbursement does not change for pharmacies after they become contract pharmacies.

The lack of a decrease in reimbursement to contract pharmacies is consistent with the prior results of increased premiums for insurers with more exposure to contract pharmacies and suggests that the premium changes are attributable to reduced rebates. That is, if an insurer were experiencing reduced rebates that it could offset by negotiating lower reimbursement to contract pharmacies, then exposure to contract pharmacies should not meaningfully increase insurer premiums. However, given that we observe both higher premiums for insurers with higher contract pharmacy exposure and no change in reimbursements for contract pharmacies, this suggests that insurers do bear some incidence of 340B discounts. While it is theoretically plausible for insurers to negotiate differential reimbursement to contract pharmacies, as discussed in Section 2.2, the institutional details of Medicare Part D make this kind of discriminatory reimbursement based on 340B contract pharmacy status challenging. Specifically, the any willing pharmacy regulations of the Medicare Part D statute requires each insurer to establish reimbursement rates for each drug and an insurer must allow all pharmacies to join its network if the pharmacy is willing to accept those reimbursement rates.

8 Discussion and Conclusion

The 340B Program is a complex and controversial topic. Prior work has primarily focused on how 340B incentives can distort the behavior of the providers that claim 340B discounts. My paper is the first to

consider how the 340B Program may distort drug manufacturer behavior and the potential downstream consequences of those distortions. In particular, I model 340B discounts claimed by contract pharmacies as "taxes" on drug manufacturers who may pass through a portion of those discounts by reducing the rebates they pay to Part D insurers. As a result, this pass-through could impact the premiums these insurers offer. Indeed, I find empirical evidence consistent with this theory. Leveraging plausibly exogenous initial enrollment patterns of beneficiaries within Part D regions, I find that insurers with greater exposure to contract pharmacies have higher prescription drug premiums. My estimates show that a ten percentage point increase in an insurer's percentage of rebate-eligible drug expenditures that are made at contract pharmacies, is associated with a $3.33 increase in its monthly plan premium or a 6.4 percent increase relative to the average premium during my sample. A back-of-the-envelope calculation using this estimate suggests that Part D enrollees paid an additional $347 million per year in premiums due to pass-through of 340B discounts originating from contract pharmacies.

In a set of complementary analyses, I find that insurers do not decrease reimbursement they pay to pharmacies after they become contract pharmacies. This is likely attributable to the fact that Medicare Part D regulations restrict insurers from offering differential reimbursement to pharmacies in their networks. Additionally, I find that the premiums of CVS Health—an insurer that is vertically integrated with a pharmacy chain that generates revenue from the 340B Program—are not adversely affected by exposure to contract pharmacies. This suggests that insurers that have their own pharmacies can countervail the impacts of contract pharmacy exposure by partnering with 340B providers. However, that may raise competition concerns as it would tend to favor only those insurers that are sufficiently large to own and operate a pharmacy business.

Collectively, these findings are consistent with my theory that the cost of 340B discounts are not borne entirely by drug manufacturers and are at least partially passed through to insurers and their enrollees. While these findings are consistent with said theory, it is worth noting two limitations of my analysis. First, I cannot directly measure the impact of contract pharmacies on rebates because insurers, or their pharmacy benefit managers, have been hesitant to share these data with researchers out of concern that publicity of their rebates could hinder their negotiations with drug manufacturers. To this date, some researchers have been granted access to censored rebate data, but for most, these data have been elusive.[74] Second, while my study accurately identifies pharmacies that serve as contract pharmacies, I cannot identify the individual prescriptions filled within those pharmacies for which 340B providers claim discounts. In other words, my estimate of the percentage of drugs subject to a 340B discount may be overstated. However, it is worth noting that the OIG (2019) audit of Part D rebate contracts found that manufacturers were excused

[74] See, for example, Dafny et al. (2022).

from paying rebates to insurers on *any* prescription filled at a contract pharmacy, regardless of whether a 340B discount was claimed. Lastly, my estimates of pass-through are based solely on the standalone prescription plans of Medicare Part D. It is possible that these estimates do not generalize to either the Medicare Advantage market or the commercial insurance market. However, if the costs of 340B discounts are passed through to these other insurance markets, then my back-of-the-envelope estimate may actually understate the magnitude of the impact that contract pharmacies have on premiums.

Despite these limitations, these empirical results have important implications for researchers and policymakers. First, these findings call into question the assumption that no taxpayer dollars are used to fund the program. My analysis shows that the premiums paid by Medicare Part D enrollees may indirectly fund the costs of providing these discounts to 340B providers. Moreover, because the Centers for Medicare and Medicaid Services spent nearly $100 billion subsidizing the costs of the Part D program in 2021 through subsidies for premium and drug costs, this implies that federal tax revenues are partially funding the costs of the 340B Program (CMS, 2021). Second, some of the world's largest drug manufacturers have implemented restrictions on providing discounts to 340B providers claimed through contract pharmacies, which has spurred several lawsuits from 340B stakeholders (King, 2021). My findings could provide these cases with actual empirical evidence that speaks to a potential unintended consequence of the use of contract pharmacies. In addition, there have been several calls for and proposals issued by members of Congress, on both sides of the political aisle, to reform the 340B Program (Grassley, 2018; Lewis, 2019; Winegarden, 2023). The findings of my paper could aid policymakers in their attempt at legislative reform to 340B.

References

340B Health (2022) "Contract Pharmacy Restrictions Represent Growing Threat to 340B Hospitals and Patients: Survey Results,"Technical report, https://www.340bhealth.org/files/Contract_Pharmacy_Survey_Report_FINAL_05-05-2022.pdf.

Abaluck, Jason and Jonathan Gruber (2011) "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program," *American Economic Review*, 101 (4), 1180–1210, 10.1257/aer.101.4.1180.

Alpert, Abby, Helen Hsi, and Mireille Jacobson (2017) "Evaluating The Role Of Payment Policy In Driving Vertical Integration In The Oncology Market," *Health Affairs*, 36 (4), 680–688, 10.1377/hlthaff.2016.0830.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber (2005a) "An evaluation of instrumental variable strategies for estimating the effects of catholic schooling," *Journal of Human resources*, 40 (4), 791–821.

——— (2005b) "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of political economy*, 113 (1), 151–184.

Baicker, Katherine and Amitabh Chandra (2006) "The Labor Market Effects of Rising Health Insurance Premiums," *Journal of Labor Economics*, 24 (3), 609–634, 10.1086/505049.

Bailey, James (2014a) "The effect of health insurance benefit mandates on premiums," *Eastern Economic Journal*, 40, 119–127.

——— (2014b) "Who pays the high health costs of older workers? Evidence from prostate cancer screening mandates," *Applied Economics*, 46 (32), 3931–3941, 10.1080/00036846.2014.948673.

Barkowski, Scott, Dajung Jun, and Yuting Zhang (2022) "Medicaid expansion spillover effects on health care consumption and coverage: evidence from Medicare administrative data."

Basu, Deepankar (2022) "Bounds for Bias-Adjusted Treatment Effect in Linear Econometric Models," *arXiv preprint arXiv:2203.12431*.

Bond, Amelia M., Emma B. Dean, and Sunita M. Desai (2023) "The Role Of Financial Incentives In Biosimilar Uptake In Medicare: Evidence From The 340B Program," *Health Affairs*, 42 (5), 632–641, 10.1377/hlthaff.2022.00812, PMID: 37126754.

Brekke, Kurt R., Astrid L. Grasdal, and Tor Helge Holmås (2009) "Regulation and pricing of pharmaceuticals: Reference pricing or price cap regulation?" *European Economic Review*, 53 (2), 170–185, https://doi.org/10.1016/j.euroecorev.2008.03.004.

Burke, Hannah (2021) "Who are the top 10 pharmaceutical companies in the world? (2021)," https://www.proclinical.com/blogs/2021-7/who-are-the-top-10-pharma-companies-in-2021.

Cabral, Marika, Michael Geruso, and Neale Mahoney (2018) "Do Larger Health Insurance Subsidies Benefit Patients or Producers? Evidence from Medicare Advantage," *American Economic Review*, 108 (8), 2048–87, 10.1257/aer.20151362.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna (2021) "Difference-in-differences with a continuous treatment," *arXiv preprint arXiv:2107.02637*.

Carey, Colleen (2021) "Sharing the burden of subsidization: Evidence on pass-through from a subsidy revision in Medicare Part D," *Journal of Public Economics*, 198, 104401, https://doi.org/10.1016/j.jpubeco.2021.104401.

Carey, Colleen M., Sarah Miller, and Laura R. Wherry (2020) "The Impact of Insurance Expansions on the Already Insured: The Affordable Care Act and Medicare," *American Economic Journal: Applied Economics*, 12 (4), 288–318, 10.1257/app.20190176.

Centers for Medicare and Medicaid Services (2017) "Medicare Program: Contract Year 2019 Policy and Technical Changes to the Medicare Advantage, Medicare Cost Plan, Medicare Fee-for-Service, the Medicare Prescription Drug Benefit Programs, and the PACE Program,"Technical report, Federal Register, https://www.govinfo.gov/app/details/FR-2017-11-28/summary.

——— (2021) "Medicare Trustees Report," https://www.cms.gov/OACT/TR.

Chernew, Michael E., Keaton Miller, Amil Petrin, and Robert J. Town (2023) "Reducing Medicare Advantage Benchmarks Will Decrease Plan Generosity, But Those Effects Will Likely Be Modest," *Health Affairs*, 42 (4), 479–487, 10.1377/hlthaff.2022.01031, PMID: 36947715.

Clark, Bobby L., John Hou, Chia-Hung Chou, Elbert S. Huang, and Rena Conti (2014) "The 340B Discount Program: Outpatient Prescription Dispensing Patterns Through Contract Pharmacies In 2012," *Health Affairs*, 33 (11), 2012–2017, 10.1377/hlthaff.2014.0833.

Clemens, Jeffrey and Joshua D. Gottlieb (2017) "In the Shadow of a Giant: Medicare's Influence on Private Physician Payments," *Journal of Political Economy*, 125 (1), 1–39, 10.1086/689772.

Conti, Rena M., Sayeh S. Nikpay, and Melinda B. Buntin (2019) "Revenues and Profits From Medicare Patients in Hospitals Participating in the 340B Drug Discount Program, 2013-2016," *JAMA Network Open*, 2 (10), e1914141–e1914141, 10.1001/jamanetworkopen.2019.14141.

Cutler, David M. (1998) "Cost Shifting or Cost Cutting?: The Incidence of Reductions in Medicare Payments," *Tax Policy and the Economy*, 12, 1–27, 10.1086/tpe.12.20061853.

Dafny, Leemore, Kate Ho, and Edward Kong (2022) "How do copayment coupons affect branded drug prices and quantities purchased?"Technical report, National Bureau of Economic Research.

Danzon, Patricia M., Y. Richard Wang, and Liang Wang (2005) "The impact of price regulation on the launch delay of new drugs—evidence from twenty-five major markets in the 1990s," *Health Economics*, 14 (3), 269–292, https://doi.org/10.1002/hec.931.

De Chaisemartin, Clément and Xavier d'Haultfoeuille (2022) "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey,"Technical report, National Bureau of Economic Research.

De Chaisemartin, Clément, Xavier d'Haultfoeuille, Félix Pasquier, and Gonzalo Vazquez-Bare (2022) "Difference-in-differences estimators for treatments continuously distributed at every period," *arXiv preprint arXiv:2201.06898*.

Decarolis, Francesco, Maria Polyakova, and Stephen P. Ryan (2020) "Subsidy Design in Privately Provided Social Insurance: Lessons from Medicare Part D," *Journal of Political Economy*, 128 (5), 1712–1752, 10.1086/705550.

Depew, Briggs and James Bailey (2015) "Did the Affordable Care Act's dependent coverage mandate increase premiums?" *Journal of Health Economics*, 41, 1–14, https://doi.org/10.1016/j.jhealeco.2015.01.004.

Desai, Sunita M. and J. Michael McWilliams (2021) "340B Drug Pricing Program and Hospital Provision of Uncompensated Care," *American Journal of Managed Care*, 27 (10), 432–437, https://doi.org/10.37765/ajmc.2021.88761.

Desai, Sunita and J. Michael McWilliams (2018) "Consequences of the 340B Drug Pricing Program," *New England Journal of Medicine*, 378 (6), 539–548, 10.1056/NEJMsa1706475, PMID: 29365282.

Doyle, Joseph J. and Krislert Samphantharak (2008) "2.00 Dollar Gas. Studying the effects of a gas tax moratorium," *Journal of Public Economics*, 92 (3), 869–884, https://doi.org/10.1016/j.jpubeco.2007.05.011.

Dranove, David (1988) "Pricing by non-profit institutions: The case of hospital cost-shifting," *Journal of Health Economics*, 7 (1), 47–57, https://doi.org/10.1016/0167-6296(88)90004-5.

Duggan, Mark G. and Fiona Scott Morton (2011) "The Medium-Term Impact of Medicare Part D on Pharmaceutical Prices," *American Economic Review*, 101 (3), 387–92, 10.1257/aer.101.3.387.

Duggan, Mark and Fiona Scott Morton (2010) "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization," *American Economic Review*, 100 (1), 590–607, 10.1257/aer.100.1.590.

Duggan, Mark and Fiona M. Scott Morton (2006) "The Distortionary Effects of Government Procurement: Evidence from Medicaid Prescription Drug Purchasing*," *The Quarterly Journal of Economics*, 121 (1), 1–30, 10.1093/qje/121.1.1.

Duggan, Mark, Amanda Starc, and Boris Vabson (2016) "Who benefits when the government pays more? Pass-through in the Medicare Advantage program," *Journal of Public Economics*, 141, 50–67, https://doi.org/10.1016/j.jpubeco.2016.07.003.

Ericson, Keith M. (2014) "Consumer Inertia and Firm Pricing in the Medicare Part D Prescription Drug Insurance Exchange," *American Economic Journal: Economic Policy*, 6 (1), 38–64, 10.1257/pol.6.1.38.

Fabra, Natalia and Mar Reguant (2014) "Pass-Through of Emissions Costs in Electricity Markets," *American Economic Review*, 104 (9), 2872–99, 10.1257/aer.104.9.2872.

Fein, Adam J (2019a) "The 2019 Economic Report on U.S. Pharmacies and Pharmacy Benefit Managers," *Philadelphia Drug Channels Institute*.

Fein, Adam J. (2019b) "Walgreens, CVS, and Walmart Lead the 25,000 Pharmacies Now Profiting From the 340B Program," July, https://www.drugchannels.net/2019/07/walgreens-cvs-and-walmart-lead-25000.html.

——— (2020) "How Hospitals and PBMs Profit-and Patients Lose-From 340B Contract Pharmacies," https://www.drugchannels.net/2020/07/how-hospitals-and-pbms-profitand.html.

Fein, Adam J (2021a) "The 2021 Economic Report on U.S. Pharmacies and Pharmacy Benefit Managers," *Philadelphia Drug Channels Institute*.

Fein, Adam J. (2021b) "Exclusive: 340B Continues Its Unbridled Takeover of Pharmacies and PBMs," June, https://www.drugchannels.net/2021/06/exclusive-340b-continues-its-unbridled.html#:~:text=Drug%20Channels%20Institute's%20latest%20review,participate%20in%20the%20340B%20program.

——— (2021c) "EXCLUSIVE: The 340B Program Soared to $38 Billion in 2020—Up 27% vs. 2019," June, https://www.drugchannels.net/2021/06/exclusive-340b-program-soared-to-38.html.

——— (2022) "The 340B Program Climbed to $44 Billion in 2021-With Hospitals Grabbing Most of the Money," August, https://www.drugchannels.net/2022/08/the-340b-program-climbed-to-44-billion.html.

Feng, Josh, Thomas Hwang, and Luca Maini (2023) "Profiting from Most-Favored-Customer Procurement Rules: Evidence from Medicaid," *American Economic Journal: Economic Policy*, 15 (2), 166–97, 10.1257/pol.20200688.

Finkelstein, Amy (2007) "The aggregate effects of health insurance: Evidence from the introduction of Medicare," *The quarterly journal of economics*, 122 (1), 1–37.

Finkelstein, Amy and Robin McKnight (2008) "What did Medicare do? The initial impact of Medicare on mortality and out of pocket medical spending," *Journal of Public Economics*, 92 (7), 1644–1668, https://doi.org/10.1016/j.jpubeco.2007.10.005.

Frakt, Austin B. (2011) "How Much Do Hospitals Cost Shift? A Review of the Evidence," *The Milbank Quarterly*, 89 (1), 90–130, https://doi.org/10.1111/j.1468-0009.2011.00621.x.

Fullerton, Don and Gilbert E. Metcalf (2002) "Chapter 26 Tax incidence," 4 of Handbook of Public Economics, 1787–1872: Elsevier, https://doi.org/10.1016/S1573-4420(02)80005-2.

Ghosh, Ausmita, Kosali Simon, and Benjamin D. Sommers (2019) "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, https://doi.org/10.1016/j.jhealeco.2018.11.002.

Government Accountability Office (GAO), (2018) "Drug Discount Program: Federal Oversight of Compliance at 340B Contract Pharmacies Needs Improvement," *United States Government Accountability Office*, https://www.gao.gov/products/gao-18-480.

——— (2019) "Medicare Part D: Use of Pharmacy Benefit Managers and Efforts to Manage Drug Expenditures," *United States Government Accountability Office*, https://www.gao.gov/products/gao-19-498.

Grassley, Chuck (2018) "Grassley Introduces Bill to Bring Transparency to the 340B Prescription Drug Program," March, https://www.grassley.senate.gov/news/news-releases/grassley-introduces-bill-bring-transparency-340b-prescription-drug-program.

Gruber, Jonathan (1994) "The Incidence of Mandated Maternity Benefits," *The American Economic Review*, 84 (3), 622–641, http://www.jstor.org/stable/2118071.

Han, Dan (2023) "The impact of the 340B Drug Pricing Program on Critical Access Hospitals: Evidence from Medicare Part B," *Journal of Health Economics*, 89, 102754, https://doi.org/10.1016/j.jhealeco.2023.102754.

Health Resources Administration (HRSA), (2007) "Notice Regarding 340B Drug Pricing Program-Contract Pharmacy Services," https://www.federalregister.gov/documents/2007/01/12/E7-334/notice-regarding-340b-drug-pricing-program-contract-pharmacy-services.

Health Resources Services Administration (HRSA), (2021a) "340B Drug Pricing Program," https://www.hrsa.gov/opa/index.html.

——— (2021b) "340B Drug Pricing Program: HRSA Correspondence to Stakeholders 2021," https://www.hrsa.gov/opa/program-integrity/index.html.

Heiss, Florian, Daniel McFadden, Joachim Winter, Amelie Wuppermann, and Bo Zhou (2021) "Inattention and Switching Costs as Sources of Inertia in Medicare Part D," *American Economic Review*, 111 (9), 2737–81, 10.1257/aer.20170471.

Ho, Kate, Joseph Hogan, and Fiona Scott Morton (2017) "The impact of consumer inattention on insurer pricing in the Medicare Part D program," *The RAND Journal of Economics*, 48 (4), 877–905, https://doi.org/10.1111/1756-2171.12207.

Hudson, Sally, Peter Hull, and Jack Liebersohn (2017) "Interpreting Instrumented Difference-in-Differences,"Technical report, https://ucf05cc378f182ac5fd7685b9ed9.dl.dropboxusercontent.com/cd/0/inline2/CDqRjiaUgdB5iiERlAY3WjynZWlj34tnsYaR9nHDGjLeaYd9uWgYXw4vBI9OK0wtqnGgaEy3aoccAYDYxqCJucOdX0ZouLdQm3R4VBgU-XhqomEL3H_8tn4e1oFyH_DrtDF4x-DiiQDT-KJJ4dTDtemXKTPcSwNwIJfilWrG4As0TN6oFfile.

Jung, Jeah, Wendy Y. Xu, and Yamini Kalidindi (2018) "Impact of the 340B Drug Pricing Program on Cancer Care Site and Spending in Medicare," *Health Services Research*, 53 (5), 3528–3548, https://doi.org/10.1111/1475-6773.12823.

Kaiser Family Foundation (KFF), (2012) "States Getting a Jump Start on Health Reform's Medicaid Expansion," April, https://www.kff.org/health-reform/issue-brief/states-getting-a-jump-start-on-health/.

——— (2021) "An Overview of the Medicare Part D Prescription Drug Benefit," October, https://www.kff.org/medicare/fact-sheet/an-overview-of-the-medicare-part-d-prescription-drug-benefit/.

King, Robert (2021) "HRSA intends to fine 6 drugmakers over 340B contract pharmacy violations," https://www.fiercehealthcare.com/hospitals/hrsa-intends-to-fine-six-drug-makers-over-340b-contract-pharmacy-violations.

Kornfield, Tom, Kylie Stengel, Kelsey Lang, and Kelly Brantley (2023) "Part D Premium Increases, Market Disruption Expected in 2024," https://avalere.com/insights/part-d-premium-increases-market-disruption-expected-in-2024.

Kowalski, Amanda E., William J. Congdon, and Mark H. Showalter (2008) "State Health Insurance Regulations and the Price of High-Deductible Policies," *Forum for Health Economics and Policy*, 11 (2), doi:10.2202/1558-9544.1129.

Kyle, Margaret K. (2007) "Pharmaceutical Price Controls and Entry Strategies," *The Review of Economics and Statistics*, 89 (1), 88–99, 10.1162/rest.89.1.88.

Lahey, Joanna N. (2012) "The efficiency of a group-specific mandated benefit revisited: The effect of infertility mandates," *Journal of Policy Analysis and Management*, 31 (1), 63–92, https://doi.org/10.1002/pam.20616.

Lakdawalla, Darius and Wesley Yin (2015) "Insurers' Negotiating Leverage and the External Effects of Medicare Part D," *The Review of Economics and Statistics*, 97 (2), 314–331, 10.1162/REST_a_00463.

LaPierre, Tracey A, Christopher J Conover, James W Henderson, J Allen Seward, and Beck A Taylor (2009) "Estimating the impact of state health insurance mandates on premium costs in the individual market," *Journal of Insurance Regulation*, 27 (3), 3.

Lewis, Jeffrey (2019) "Opinion: Time for Greater Transparency in Critical 340B Federal Drug Pricing Program," August, https://scottpeters.house.gov/2019/8/opinion-time-for-greater-transparency-in-critical-340b-federal-drug-pricing.

Lewis, Jeffrey and William H. von Oehsen (2021) "PBMs and the 340B Program,"Technical report, Legacy Health Endowment, https://www.legacyhealthendowment.org/news/pbms-and-the-340b-program.

Lin, John K., Pengxiang Li, Jalpa A. Doshi, and Sunita M. Desai (2022) "Assessment of US Pharmacies Contracted With Health Care Institutions Under the 340B Drug Pricing Program by Neighborhood Socioeconomic Characteristics," *JAMA Health Forum*, 3 (6), e221435–e221435, 10.1001/jamahealthforum.2022.1435.

MacKay, Alexander and Marc Remer (2022) "Consumer Inertia and Market Power," *Available at SSRN 3380390*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3380390.

Maini, Luca and Fabio Pammolli (2023) "Reference Pricing as a Deterrent to Entry: Evidence from the European Pharmaceutical Market," *American Economic Journal: Microeconomics*, 15 (2), 345–83, 10.1257/mic.20210053.

Martin, Rory, Chuan Sun, and Kepler Illich (2023) "Double Trouble: How Expanding Eligibility Could Double the Size of the 340B Program,"Technical report, IQVIA, https://www.iqvia.com/locations/united-states/library/white-papers/double-trouble-how-expanding-eligibility-could-double-the-size-of-the-340b-program.

McInerney, Melissa, Jennifer M. Mellor, and Lindsay M. Sabik (2021) "Welcome Mats and On-Ramps for Older Adults: The Impact of the Affordable Care Act's Medicaid Expansions on Dual Enrollment in Medicare and Medicaid," *Journal of Policy Analysis and Management*, 40 (1), 12–41, https://doi.org/10.1002/pam.22259.

Medicare Payment Advisory Commission (MedPAC) (2019) "Report to the Congres: Medicare Payment Policy,"Technical report, https://web.archive.org/web/20211116231356/http://www.medpac.gov/docs/default-source/reports/mar19_medpac_entirereport_sec.pdf?sfvrsn=0.

Miller, Keaton S, Amil Petrin, Robert Town, and Michael Chernew (2019) "Optimal Managed Competition Subsidies," Working Paper 25616, National Bureau of Economic Research, 10.3386/w25616.

Miller, Nathan H., Matthew Osborne, and Gloria Sheu (2017) "Pass-through in a concentrated industry: empirical evidence and regulatory implications," *The RAND Journal of Economics*, 48 (1), 69–93, https://doi.org/10.1111/1756-2171.12168.

Muehlegger, Erich and Richard L. Sweeney (2022) "Pass-Through of Own and Rival Cost Shocks: Evidence from the U.S. Fracking Boom," *The Review of Economics and Statistics*, 104 (6), 1361–1369, 10.1162/rest_a_01052.

National Health Policy Forum (NHPF) (2009) "The Basics: The Medicaid Drug Rebate Program," April, https://www.nhpf.org/library/the-basics/Basics_MedicaidDrugRebate_04-13-09.pdf.

Nikpay, Sayeh, Gabriela Gracia, Hannah Geressu, and Rena Conti (2022) "Association of 340B Contract Pharmacy Growith With County-Level Characteristics," *American Journal of Managed Care*, 28 (3), 133–136, https://doi.org/10.37765/ajmc.2022.88840.

Nikpay, Sayeh, Claire C. McGlave, John P. Bruno, Haishan Yang, and Elizabeth Watts (2023) "Trends in 340B Drug Pricing Program Contract Growth Among Retail Pharmacies From 2009 to 2022," *JAMA Health Forum*, 4 (8), e232139–e232139, 10.1001/jamahealthforum.2023.2139.

Nikpay, Sayeh S., Melinda B. Buntin, and Rena M. Conti (2020) "Relationship between initiation of 340B participation and hospital safety-net engagement," *Health Services Research*, 55 (2), 157–169, https://doi.org/10.1111/1475-6773.13278.

Office of Inspector General (OIG), (2019) "Medicare Part D Rebates for Prescriptions Filled at 340B Contract Pharmacies," *Department of Health and Human Services*, https://oig.hhs.gov/oas/reports/region3/31600002.asp.

Office of Pharmacy Affairs (OPA), (2021) "340B OPAIS," https://340bopais.hrsa.gov.

Olssen, Alex and Mert Demirer (2021) "Drug Rebates and Formulary Design: Evidence from Statins in Medicare Part D," working paper, University of Pennsylvania Working Paper, https://faculty.wharton.upenn.edu/wp-content/uploads/2020/07/rebates.pdf.

Oster, Emily (2019) "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 37 (2), 187–204, 10.1080/07350015.2016.1227711.

Polyakova, Maria (2016) "Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D," *American Economic Journal: Applied Economics*, 8 (3), 165–95, 10.1257/app.20150004.

Ridley, David B. and Chung-Ying Lee (2020) "Does Medicare Reimbursement Drive Up Drug Launch Prices?," *The Review of Economics and Statistics*, 102 (5), 980–993, 10.1162/rest_a_00849.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe (2023) "What's trending in difference-in-differences? A synthesis of the recent econometrics literature," *Journal of Econometrics*.

Scott Morton, Fiona (1997) "The Strategic Response by Pharmaceutical Firms to the Medicaid Most-Favored-Customer Rules," *The RAND Journal of Economics*, 28 (2), 269–290, http://www.jstor.org/stable/2555805.

Shafer, Brenda M. and Richard B. David (2019) "New PBM State Laws Indicate a Shifting Battlefront over 340B Program Drug Pricing," https://www.quarles.com/publications/new-pbm-state-laws-indicate-a-shifting-battlefront-over-340b-program-drug-pricing/.

Slafsky, Ted, Samuel Ross, and Bharath Krishnamurthy (2018) "The 340B Drug Discount Program Is Fulfilling Its Original Purpose," *Health Affairs Blog*, 10.1377/hblog20180321.524566.

Sood, Neeraj, Tiffany Shih, Karen Van Nuys, and Dana Goldman (2017) "The Flow of Money Through the Pharmaceutical Distribution System," *University of Southern California: Leonard D. Schaeffer Center for Health Policy and Economics*, https://healthpolicy.usc.edu/wp-content/uploads/2017/06/USC_Flow-of-MoneyWhitePaper_Final_Spreads.pdf.

Starc, Amanda and Ashley Swanson (2021) "Preferred Pharmacy Networks and Drug Costs," *American Economic Journal: Economic Policy*, 13 (3), 406–46, 10.1257/pol.20180489.

Stock, James H and Motohiro Yogo (2002) "Testing for weak instruments in linear IV regression."

Summers, Lawrence H. (1989) "Some Simple Economics of Mandated Benefits," *The American Economic Review*, 79 (2), 177–183, http://www.jstor.org/stable/1827753.

Vandervelde, Aaron, Kevin Erb, and Lauren Hurley (2020) "For-Profit Pharmacy Participation in the 340B Program," *Washington, DC, The Berkeley Research Group*, https://media.thinkbrg.com/wp-content/uploads/2020/10/06150726/BRG-ForProfitPharmacyParticipation340B_2020.pdf.

Weyl, E. Glen and Michal Fabinger (2013) "Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition," *Journal of Political Economy*, 121 (3), 528–583, 10.1086/670401.

Winegarden, Wayne (2023) "A Bipartisan Regulatory Reform Opportunity: 340B," March, https://www.forbes.com/sites/waynewinegarden/2023/03/23/a-bipartisan-regulatory-reform-opportunity-340b/?sh=6e8b2c157e8f.

Yood, Kenneth, Erica Kraus, and Theresa Thompson (2021) "Contract Pharmacies and the 340B Drug Discount Program: New Litigation and an Advisory Opinion Point to Ongoing Skirmishes on the 340B Battlefield," https://www.sheppardhealthlaw.com/2021/01/articles/drug-and-pharmaceutical-law/contract-pharmacies-340b-program-litigation/.

10 Tables

Table 1: Summary Statistics - Sample Means and Standard Deviations

	2010	**2014**	**2018**		**2010**	**2014**	**2018**
N	1,572	1,164	782	% of Dual Enrollees	28.64	28.90	22.42
Monthly Premium ($)	46.58	53.75	52.22		(28.50)	(27.99)	(23.96)
	(19.66)	(31.83)	(32.16)	% of Low-Income Cost Sharing (LICS) Enrollees	37.67	36.40	27.76
% of Branded Drug Spend at CPs	3.97	29.56	49.12		(33.43)	(32.62)	(27.70)
	(3.53)	(9.48)	(10.27)	Proportion of Enrollees, Aged 65-74	0.38	0.41	0.45
Annual Deductible ($)	143	157	245		(0.11)	(0.12)	(0.13)
	(137)	(153)	(191)	Proportion of Enrollees, Aged 75-84	0.24	0.22	0.26
Annual Enrollment	10,790	15,989	26,603		(0.07)	(0.09)	(0.10)
	(24,054)	(33,700)	(45,474)	Proportion of Enrollees, Over 84	0.12	0.11	0.11
Proportion of Plans Offering Gap Coverage	0.20	0.18	0.22		(0.05)	(0.05)	(0.06)
	(0.40)	(0.38)	(0.41)	Proportion of Enrollees - Asian	0.03	0.03	0.03
Initial Coverage Limit ($)	2,822	2,850	3,750		(0.07)	(0.06)	(0.05)
	(37)	(0)	(0)	Proportion of Enrollees - Black	0.10	0.10	0.08
Proportion of Plans - Actuarially Equivalent Standard	0.23	0.40	0.30		(0.11)	(0.11)	(0.08)
	(0.42)	(0.49)	(0.46)	Proportion of Enrollees - Hispanic	0.06	0.06	0.05
Proportion of Plans - Basic Alternative	0.16	0.07	0.16		(0.08)	(0.08)	(0.07)
	(0.36)	(0.26)	(0.37)	Proportion of Enrollees - Native	0.01	0.01	0.01
Proportion of Plans - Defined Standard Benefit	0.11	0.03	0		(0.03)	(0.04)	(0.03)
	(0.31)	(0.17)	(0)	Proportion of Enrollees - White	0.79	0.79	0.81
Proportion of Plans - Enhanced Benefits	0.51	0.50	0.54		(0.16)	(0.16)	(0.13)
	(0.50)	(0.50)	(0.50)	Proportion of Enrollees - Other	0.01	0.01	0.01
					(0.01)	(0.01)	(0.01)
				Proportion of Enrollees - Female	0.59	0.58	0.58
					(0.04)	(0.04)	(0.03)

Note: The first cell in each row displays the sample mean of the variable. The second cell in each row that is bracketed by parentheses shows the standard deviation of the variable. I display sample statistics for three years of my data. My entire sample period is from 2009 through 2018, inclusive.

Table 2: Effects of Contract Pharmacies on Part D Premiums - Two-Way Fixed Effects

Dependent Variable:	**Part D Monthly Premium ($)**			**Expenditures per Beneficiary on Branded Drugs ($)**
	(1)	(2)	(3)	(4)
% of Branded Drug Spend at CPs	0.376**	0.333***	0.319***	1.826
	(0.176)	(0.109)	(0.115)	(1.462)
Expenditures per Beneficiary on Branded Drugs ($)			0.007**	
			(0.003)	
Avg. Monthly Premium ($)			52.06	
1 SD % of Branded Drug Spend at CPs			17.23	
SPB on Branded Drugs ($)			603	
N			10,997	
R^2	0.148	0.727	0.728	0.644
Year-Part D Region FEs	Yes	Yes	Yes	Yes
Insurer FEs	Yes	Yes	Yes	Yes
Plan & Enrollee Controls	No	Yes	Yes	Yes

Note: Columns (1) through (3) display estimates of β from the regression specified in Equation (4). The unit of analysis is at the plan-year level. Each specification includes insurer and year-by-Part D region fixed effects. The regression in column (2) incorporates plan-controls and enrollee-controls. Plan controls include the annual deductible ($), a dummy if the plan offers gap coverage, the initial coverage limit ($), and indicator variables for if the plan is a defined standard benefit plan (DSB), actuarially equivalent standard, basic alternative, or an enhanced plan—DSB is the omitted category. Plan enrollee controls include the proportion of female enrollees, the proportion of enrolles in four different age-bands: under 65, 65-74, 75-84, and over 84—under 65 is omitted category. Lastly, the proportion of enrollees in six different racial groups (Asian, Black, Hispanic, Native American, White, or Other). Column (3) adds the expenditures per beneficiary that each insurer spends on branded drugs as a control variable. By contrast, column (4) uses expenditures per beneficiary on branded drugs as the dependent variable. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. Each observation is weighted by its region's Part D enrollment from 2008. The sample is limited to only standalone prescription drug plans (PDPs).

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 3: Effects of Contract Pharmacies on Part D Premiums - Medicaid Expansion IV

Dependent Variable = Part D Monthly Premium ($)

	All States	Medicaid Expansion Sample			
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	2SLS	2SLS
% of Branded Drug Spend at CPs	0.333***	0.378***	0.283***	0.345*	0.369*
	(0.109)	(0.093)	(0.068)	(0.175)	(0.194)
Avg. Monthly Premium ($)	52.06		52.09		
1 SD % of Branded Drug Spend at CPs	17.23		17.25		
N	10,997		8,150		
R^2	0.727	0.732	0.726	0.682	0.682
F-stat of Excluded Instruments	—	—	—	142.61	121.56
First-Stage	—	—	—	5.649***	6.584***
	—	—	—	(0.005)	(0.007)
Reduced-Form	—	—	—	1.951**	2.432**
	—	—	—	(0.011)	(0.014)
Wu-Hausman Statistic	—	—	—	0.118	0.188
Year by Part D Region FE	Yes	Yes	No	No	No
Year FE	No	No	Yes	Yes	Yes
Part D Region FE	No	No	Yes	Yes	Yes

Note: Columns (1) through (3) display estimates of β from the regression specified in Equation (4). The unit of analysis is at the plan-year level. Column (1) is a reproduction of Column (2) from Table 2. Column (2) is identical to Column (1), but is limited to the sample of plans I use for my instrumental variable analysis, i.e., plans offered in Part D regions whose constituent states expanded Medicaid in 2014 (treated regions) and plans offered in Part D regions whose constituent states never expanded their Medicaid Program as of Jan 1, 2019 (control regions). See Appendix Table B.1 for a full list of states and the category to which they belong. Column (3) is identical to Column (2), but it uses region and year fixed effects instead of region-by-year fixed effects. Columns (4) and (5) contains the results of my 2SLS estimates (i.e., estimates of θ_2 from Equation (6)). The instrument in Column (4) is a binary variable equal to 1 if a plan was offered in a Medicaid Expansion region and the year is 2014 or later (i.e., post expansion). The instrument in Column (5) is a continuous variable equal to the proportion of pharmacies in the Part D region that were not serving as a contract pharmacy in 2013 interacted with a dummy if the region expanded Medicaid as well as a post-2014 dummy variable—i.e., this instrument is equal to 0 in all years for all plans offered in the non-expansion regions. The control variables are the same as the TWFE regressions from Table 2; for a complete list of included control variables, please see the footnote of Table 2. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. Each observation is weighted by its region's Part D enrollment from 2008. The sample is limited to only standalone prescription drug plans (PDPs). The Wu-Hausman test statistic in Columns (4) and (5) compares the potentially endogenous regressor from the OLS regression of Column (3).

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 4: Effects of Contract Pharmacies on Premiums - Heterogeneity by Insurer

Dependent Variable: Part D Monthly Premium ($)		
	(1)	(2)
% of Branded Drug Spend at CPs	0.333***	0.311***
	(0.109)	(0.110)
% of Branded Drug Spend at CPs×**1**(CVS-owned Plan)		-0.267**
		(0.115)
Avg. Monthly Premium ($)	52.06	
N	10,997	
R^2	0.727	0.729

Note: Columns (1) through (2) display estimates of β from the regression specified in Equation (4). The unit of analysis is at the plan-year level. Column (1) is a reproduction of Column (2) from Table 2. Column (2) is identical to Column (1), but contains an interaction term between the share of branded drug spending at contract pharmacies interacted with an indicator variable for if the plan was owned and operated by the insurer CVS Health. For a complete list of included control variables, please see the footnote of Table 2. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. Each observation is weighted by its region's Part D enrollment from 2008. The sample is limited to only standalone prescription drug plans (PDPs).

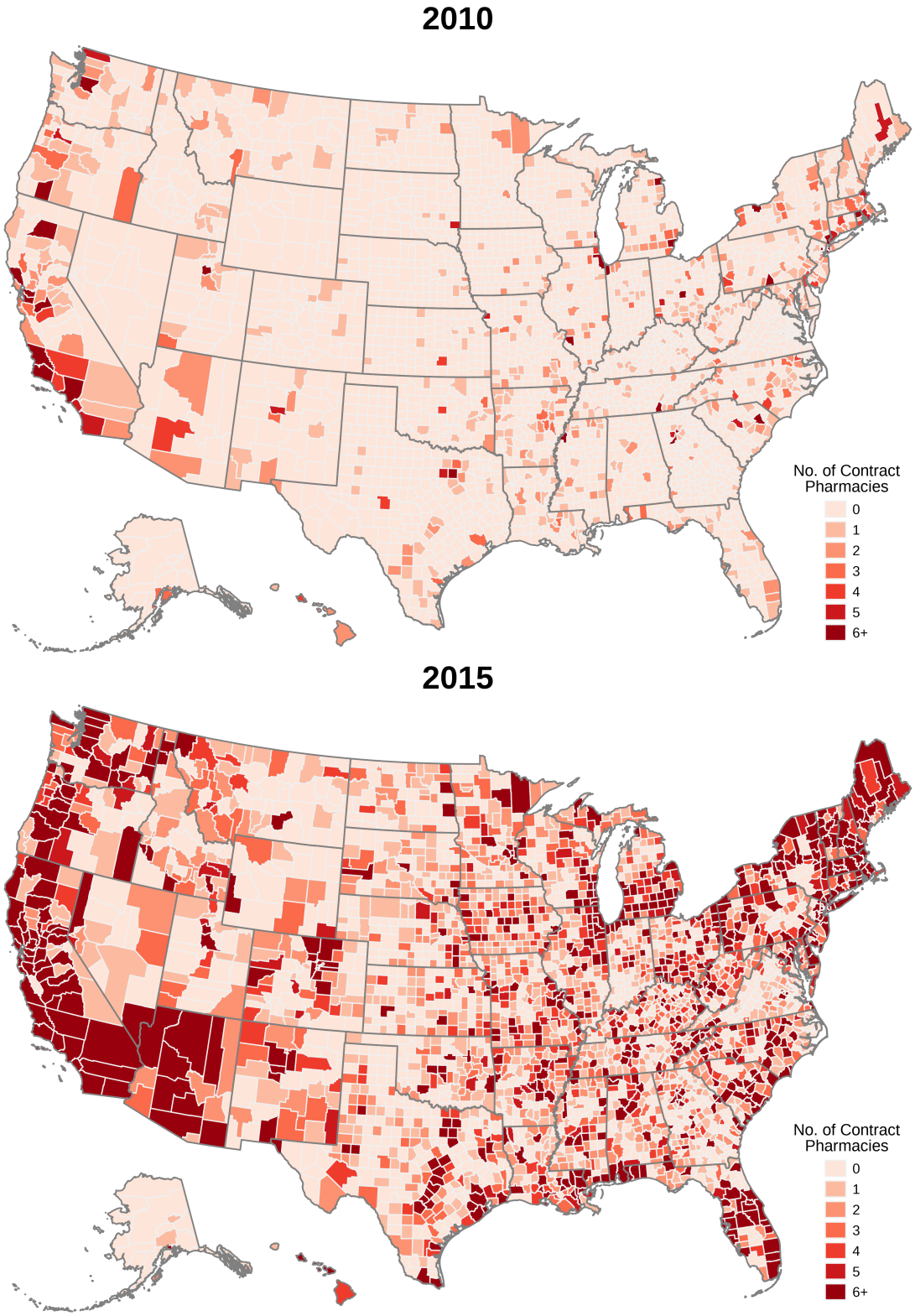
Table 5: Effects of Contract Pharmacies on Pharmacy Reimbursement

Dependent Variable: Pharmacy Reimbursement ($ per day)				
Sample of Drugs	*Brands*		*Generics*	
	(1)	(2)	(3)	(4)
1(Pharmacy is Contract Pharmacy)	0.006	0.004	0.023	0.006
	(0.006)	(0.008)	(0.015)	(0.006)
Avg. Pharmacy Reimbursement ($ per day)	12.49		0.92	
N	30,662,429		157,328,125	
R^2	0.922	0.937	0.725	0.886
Pharmacy FE	Yes	No	Yes	No
Pharmacy-Plan FE	No	Yes	No	Yes
Drug-Plan-Year/Quarter FE	Yes	Yes	Yes	Yes

Note: Columns (1) through (4) display estimates of μ from the regression specified in Equation (9). The sample of drugs in Columns (1) and (2) are branded drug products while Columns (3) and (4) contain generic drugs. The unit of analysis is the drug-plan-pharmacy-year/quarter level. Pharmacy reimbursement is the average reimbursement for a 1-day supply of each drug product. Each specification includes drug-by-plan-by-year/quarter fixed effects. Columns (1) and (3) include a pharmacy fixed effect while Columns (2) and (4) include a pharmacy-by-plan fixed effect. Standard errors are clustered at the pharmacy-level. Regressions are weighted by the number of claims in each drug-plan-pharmacy-year/quarter cell. The pre- and post-period for each contract pharmacy is limited to ± 3 years (12 quarters) around the event of when a pharmacy becomes a contract pharmacy.

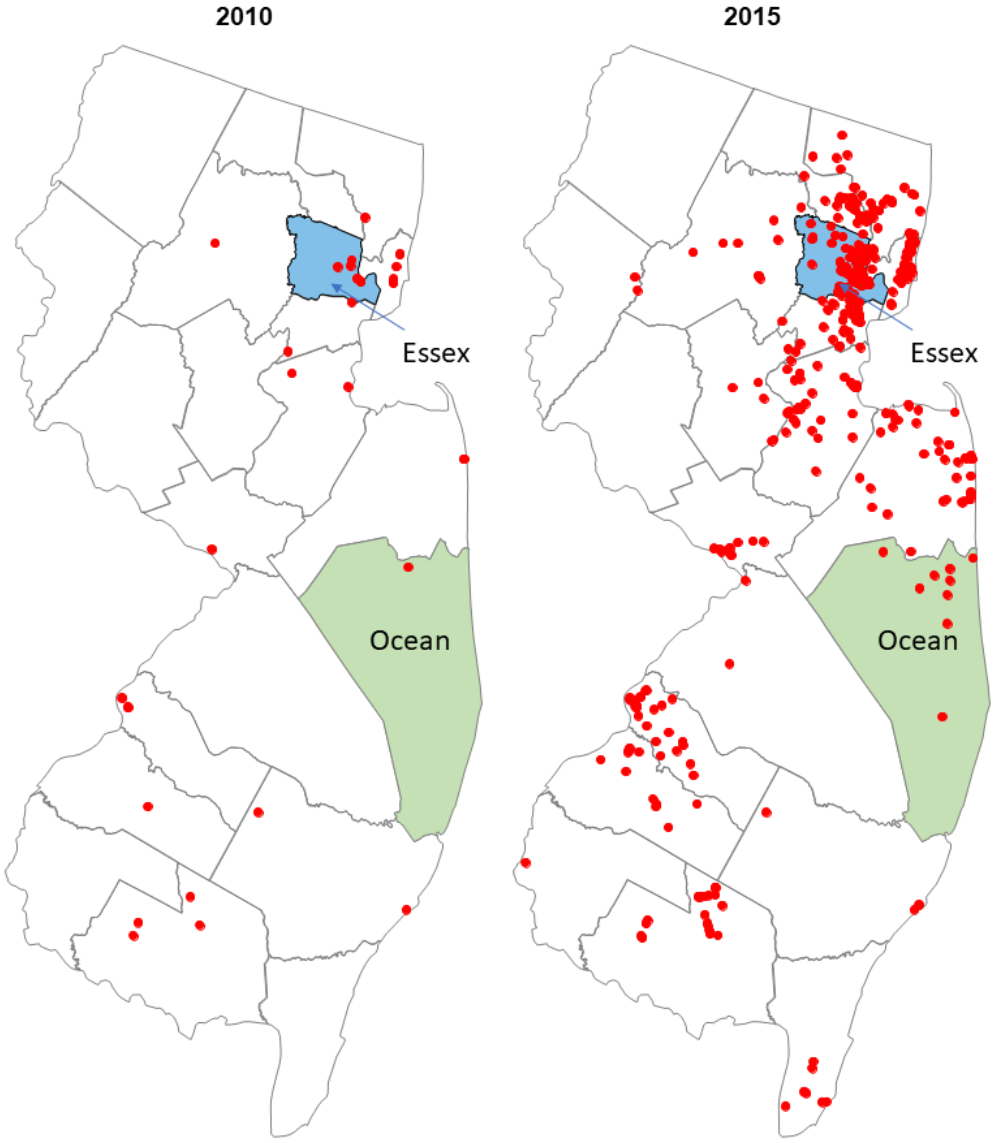
11 Figures

Figure 1: County Level Growth in 340B Contract Pharmacies



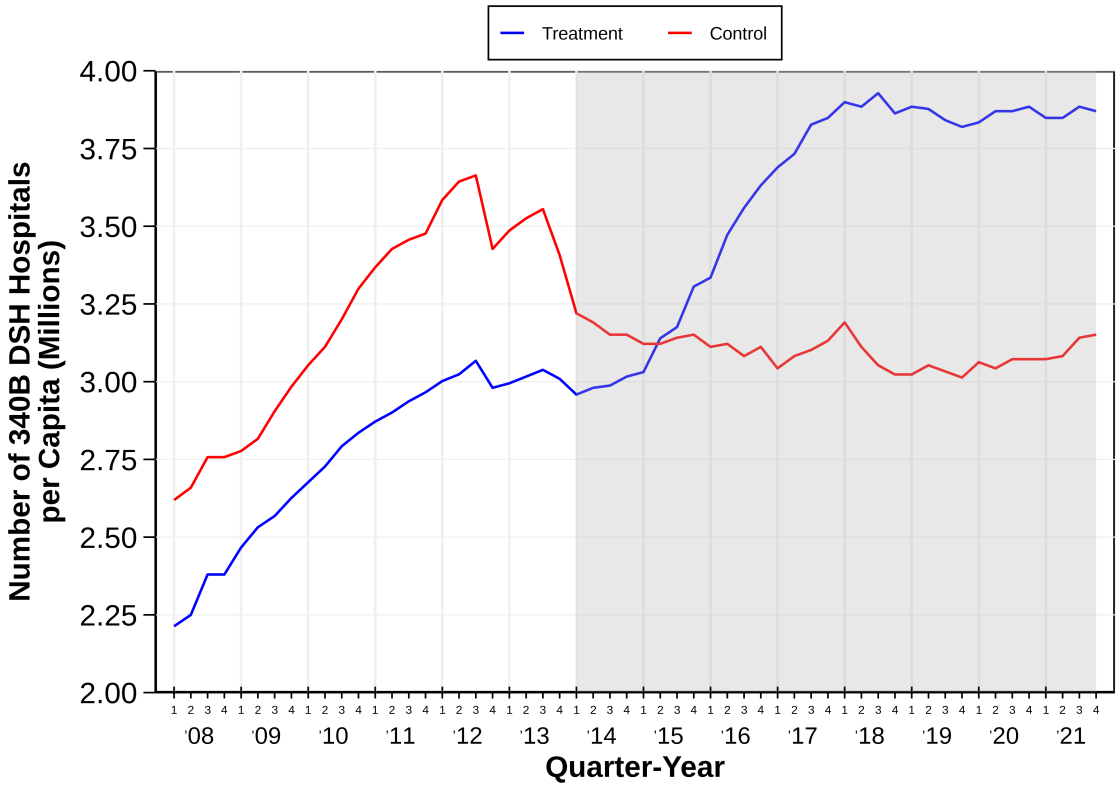
Notes: Data used to generate this graph come from the 340B Office of Pharmacy Affairs Information System (OPAIS) contract pharmacy database and U.S. Census 2010 county shapefile. Address information for each contract pharmacy was geocoded using Google Maps to identify precise latitude and longitude coordinates. Those coordinates were then mapped onto the county shapefile where I used the "points in polygons" tool of QGIS to identify the precise county of each pharmacy. The counts of pharmacies are as of the end of Q1 of the displayed year.

Figure 2: Growth in 340B Contract Pharmacies in New Jersey Counties



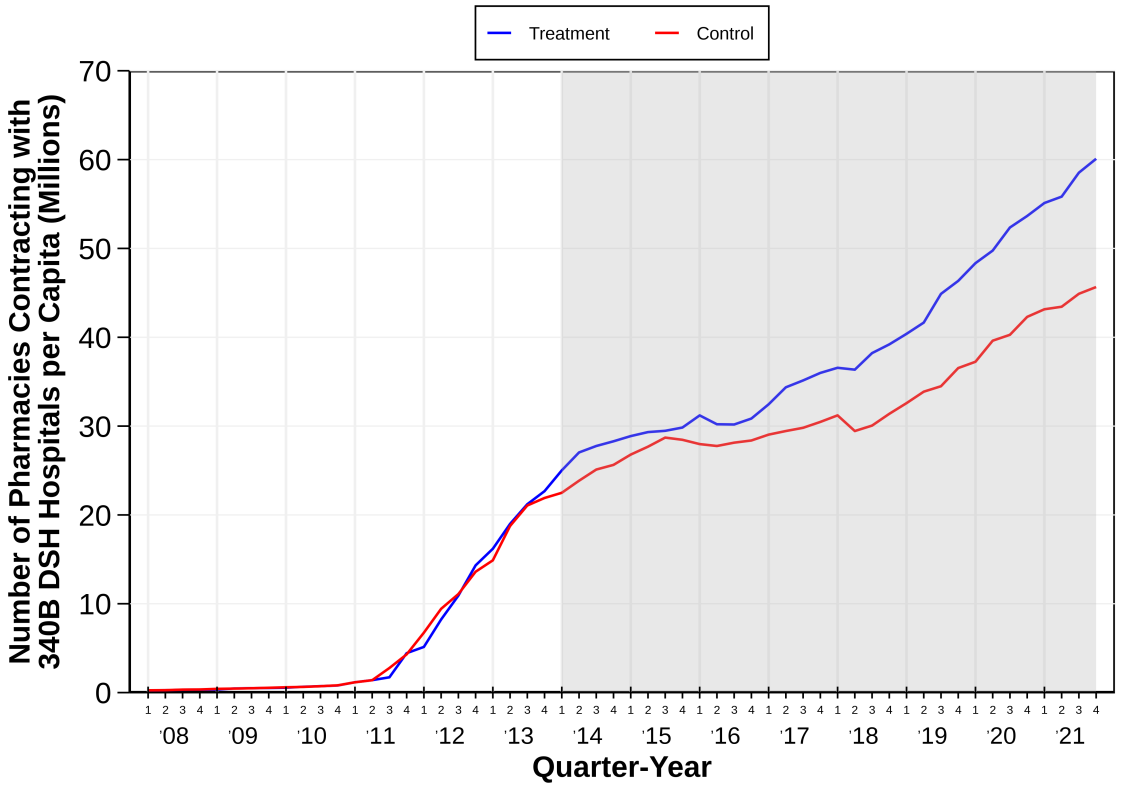
Notes: Data used to generate this graph come from the 340B Office of Pharmacy Affairs Information System (OPAIS) contract pharmacy database and U.S. Census 2010 county shapefile. Address information for each contract pharmacy was geocoded using Google Maps to identify precise latitude and longitude coordinates. Those coordinates were then mapped onto the county shapefile where I used the "points in polygons" tool of QGIS to identify the precise county of each pharmacy. The red dots in this graph represent the latitude/longitude of each contract pharmacy in NJ at the end of Q1 of the displayed year. I have highlighted Essex County in blue and Ocean County in green.

Figure 3: Growth in DSH Hospitals Enrolled in 340B Program by Medicaid Expansion



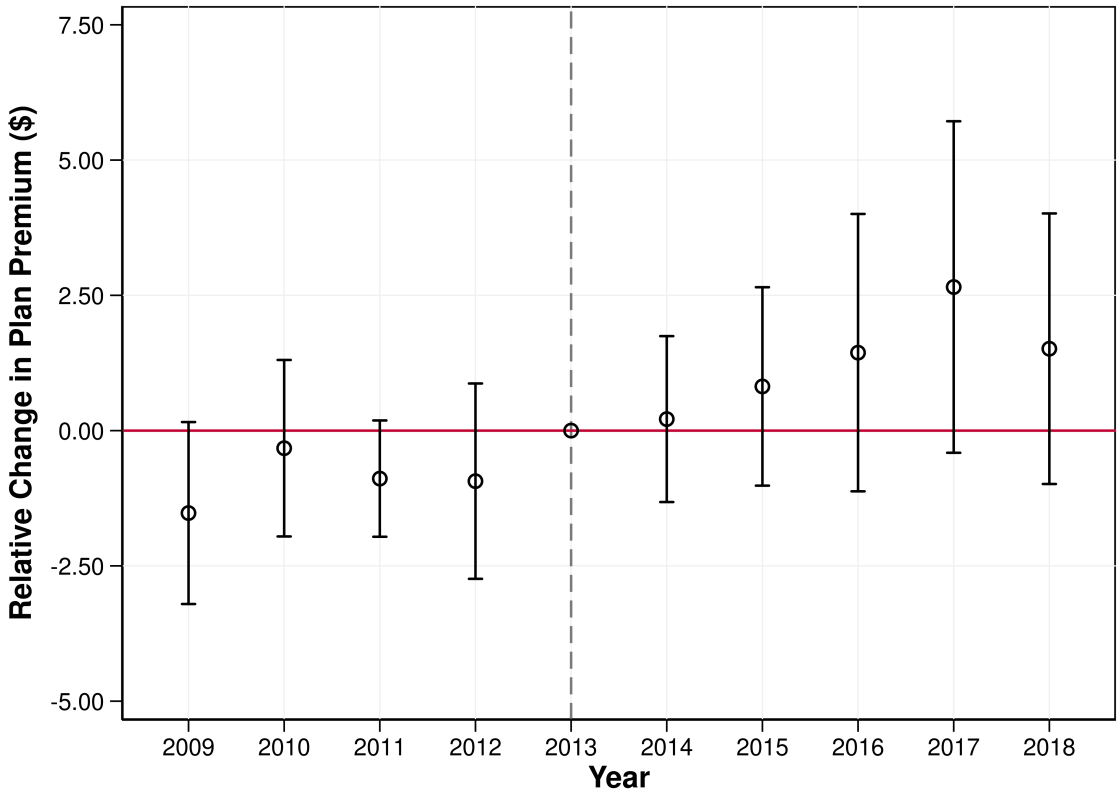
Notes: Data used to generate this graph come from the 340B Office of Pharmacy Affairs Information System (OPAIS) 340B provider database and the U.S. Census of 2010. The graph plots quarterly counts of the number of 340B DSH hospitals in states that expanded their Medicaid programs in 2014 (blue line) vs. those that never expanded their programs (red line). Note that I normalize these two series by population counts reported in the 2010 U.S. Census. To do this, I sum the number of 340B DSH hospitals across all expansion (or nonexpansion) states in a given quarter to get my numerator values. I then divide the numerator series by the 2010 population level in the expansion and nonexpansion states to arrive at the values displayed in the graph. Note that the population data are in units of one million. I have shaded the graph area from 2014Q1 to 2021Q4 to denote when the Medicaid expansions occurred.

Figure 4: Growth in Pharmacies Contracting with 340B DSH Hospitals



Notes: Data used to generate this graph come from the 340B Office of Pharmacy Affairs Information System (OPAIS) contract pharmacy database and U.S. Census of 2010. The graph plots quarterly counts of the number of pharmacies that contract with 340B DSH hospitals and that are located in states that expanded their Medicaid programs in 2014 (blue line) vs. pharmacies that are in states which never expanded their programs (red line). Note that I normalize these two series by population counts reported in the 2010 U.S. Census. To do this, I sum the number of contract pharmacies across all expansion (or nonexpansion) states in a given quarter to get my numerator values. I then divide the numerator series by the 2010 population level in the expansion and nonexpansion states to arrive at the values displayed in the graph. Note that the population data are in units of one million. I have shaded the graph area from 2014Q1 to 2021Q4 to denote when the Medicaid expansions occurred. Note that prior to 2010, nearly all 340B providers were permitted to contract with only one external retail pharmacy. After 2010, HRSA issued guidance allowing 340B providers to contract with an unlimited number of contract pharmacies.

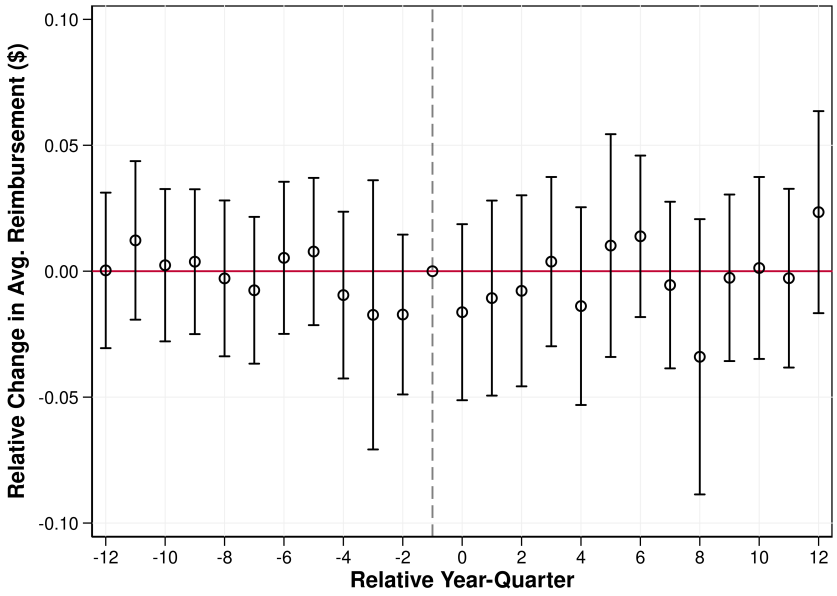
Figure 5: Event Study of Reduced Form Effect of Medicaid Expansions on Premiums



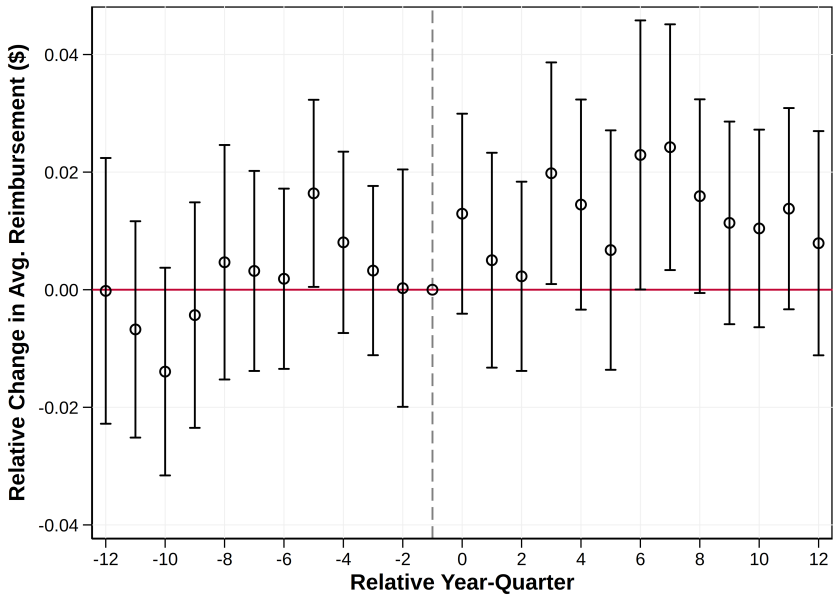
Notes: This figure presents results from the event study specified in Equation (7). These estimates capture the reduced form effect of Medicaid expansions on Part D premiums relative to the omitted year of 2013. The regression includes separate year and region fixed effects, insurer fixed effects, as well as the same plan/enrollee controls specified in Table 2. Standard errors are clustered at the insurer level. Each observation is weighted by its region's Part D enrollment from 2008. The sample is limited to only standalone prescription drug plans (PDPs).

Figure 6: Effects of Contract Pharmacies on Pharmacy Reimbursement - Event Studies

(a) Brand Drugs



(b) Generic Drugs



Notes: This figure presents results from an event study version of Equation (9). The unit of analysis is the drug-plan-pharmacy-year/quarter level. Pharmacy reimbursement is the average reimbursement for a 1-day supply of each drug product. This specification includes drug-by-plan-by-year/quarter fixed effects and a pharmacy-by-plan fixed effect. Standard errors are clustered at the pharmacy-level. Panel (a) is limited to brand-name drug products while Panel (b) is limited to generic drugs. Regressions are weighted by the number of claims in each drug-plan-pharmacy-year/quarter cell. The treatment period for each contract pharmacy is limited to ±3 years (12 quarters) around the event of when a pharmacy becomes a contract pharmacy. The first period in which a pharmacy becomes "treated" is the first full year/quarter in which the pharmacy becomes a contract pharmacy.

A Appendix

A.1 Pharmacy Reimbursement Calculation

In the Part D claims data, there is a variable describing the total cost of the drug to Part D plan (TOT_RX_CST_AMT). There is also a variable that describes the quantity of the drug that was dispensed (QTY_DSPNSD_NUM) and a variable that describes the number of days that that prescription provides to the patient (DAYS_SUPLY_NUM). For instance, a prescription could cost $30 for thirty pills where the patient should take one pill per day. Thus the cost per unit would be $1 per pill and the cost per day would be $1 per day.

One could compute the cost-per-unit of a drug by dividing the total cost of the prescription by the quantity that was dispensed. However, it is challenging to interpret or compare a cost per pill versus a cost per milliliter. As an alternative, one could compute the cost-per-day of a prescription by dividing total cost by the days supplied variable. However, different patients can be prescribed the same quantity of pills, but the daily dosage can differ. For example, suppose a drug costs $10 per pill regardless of the pharmacy that dispenses it. Patient 1 takes one 40MG pill per day for 30 days while Patient 2 is prescribed two 40MG pills per day for 30 days. Thus, Patient 1's cost per day would be $\frac{\$10 \times 30 \text{ pills}}{30 \text{ days}} = \$10$ per day. By contrast, Patient 2's cost per day would be $\frac{\$10 \times 60 \text{ pills}}{30 \text{ days}} = \$20$ per day. However, if one pharmacy happens to dispense primarily to Patient 1 and another pharmacy dispenses to Patient 2, the latter pharmacy would appear to have higher reimbursement, when in reality they are reimbursed the same exact amount per pill.

To deal with this issue, I compute a standardized measure of cost-per-day in the following manner. I collapse down all the claims into every combination of drug-quantity dispensed-days supplied pairs counting the number claims in each cell. I then compute a weighted average using the number of claims in each cell. Consider the example from before:

Dosage Strength	Quantity Dispensed	Days Supplied	Units per Day	Count of Claims	Weight
40MG	30	30	1	10	$\frac{1}{3}$
40MG	60	30	2	20	$\frac{2}{3}$

Thus, in the above example, this drug would have a standardized units per day measure of $1 \times \frac{1}{3} + 2 \times \frac{2}{3} = 1\frac{2}{3}$ units per day. Next, I compute for each pharmacy-drug pair in each quarter, what is the cost-per-unit they are reimbursed. Finally, I multiply each drug-pharmacy's quarterly cost-per-unit by the standardized unit-per-day measure to arrive at each drug-pharmacy's cost-per-day.

B Appendix Tables

Table B.1: Medicaid Expansion Dates and Groups

Part D Region	State	Expansion Date	Group	Part D Region	State	Expansion Date	Group
7	VA	1/1/2019	Control	1	ME	1/10/2019	Exclude
8	NC		Control	1	NH	8/15/2014	Exclude
9	SC		Control	2	CT	1/1/2014	Exclude
10	GA		Control	2	MA*	1/1/2014	Exclude
11	FL		Control	2	RI	1/1/2014	Exclude
12	AL		Control	2	VT*	1/1/2014	Exclude
12	TN		Control	3	NY*	1/1/2014	Exclude
16	WI		Control	5	DC*	1/1/2014	Exclude
18	MO		Control	5	DE*	1/1/2014	Exclude
20	MS		Control	5	MD	1/1/2014	Exclude
22	TX		Control	6	PA	1/1/2015	Exclude
23	OK		Control	6	WV	1/1/2014	Exclude
24	KS		Control	15	IN	2/1/2015	Exclude
31	ID	1/1/2020	Control	15	KY	1/1/2014	Exclude
31	UT	1/1/2020	Control	21	LA	7/1/2016	Exclude
4	NJ	1/1/2014	Treatment	25	IA	1/1/2014	Exclude
13	MI	4/1/2014	Treatment	25	MN	1/1/2014	Exclude
14	OH	1/1/2014	Treatment	25	MT	1/1/2016	Exclude
17	IL	1/1/2014	Treatment	25	ND	1/1/2014	Exclude
19	AR	1/1/2014	Treatment	25	NE	10/1/2020	Exclude
26	NM	1/1/2014	Treatment	25	SD		Exclude
27	CO	1/1/2014	Treatment	25	WY		Exclude
28	AZ	1/1/2014	Treatment	34	AK	9/1/2015	Exclude
29	NV	1/1/2014	Treatment				
30	OR	1/1/2014	Treatment				
30	WA	1/1/2014	Treatment				
32	CA	1/1/2014	Treatment				
33	HI	1/1/2014	Treatment				

Note: Each state's Medicaid expansion status and date were downloaded from the Kaiser Family Foundation website. Note that both Missouri (MO) and Oklahoma (OK) very recently voted to expand their Medicaid programs with expansions set to begin July 1, 2021. Given that my sample period spans from 2009 to 2018, I am including them in the "Never Expanded" group. Note there were five states plus DC that implemented some form of Medicaid expansions between 2010 and 2012. These "early" expanding states included CA, CT, DC, MN, NJ, and WA (KFF, 2012). Carey et al. (2020) suggest that despite these early expansions CA, CT, and MN did not expand eligibility up to 138 percent of the federal poverty line until 2014; the authors do not consider NJ or WA as early expanders and they excluded DC from their analysis. Following Carey et al. (2020), I treat CA, CT, MN, NJ, and WA as expanding their Medicaid programs in 2014. The asterisk (*) denotes states which had, prior to 2014, Medicaid coverage eligibility rules for adults comparable to those stipulated by the ACA. Again, following Carey et al. (2020) I exclude plans in these regions.

Table B.2: Differences in Means: Excluded vs. Included Regions from IV - 2013

	Excluded	Included	Diff.		Excluded	Included	Diff.
N	269	758		% of Dual Enrollees	33.45	29.02	-4.43**
Monthly Premium ($)	54.36	53.21	-1.15		(30.02)	(28.31)	(0.030)
	(28.77)	(28.36)	(0.569)	% of Low-Income Cost Sharing Enrollees	40.40	37.00	-3.40
% of Branded Drug Spend at CPs	18.86	21.14	2.28***		(34.05)	(33.23)	(0.152)
	(5.53)	(7.32)	(0.000)	Proportion of Enrollees, Aged 65-74	0.37	0.39	0.03***
Annual Deductible ($)	162	161	-1		(0.11)	(0.12)	(0.002)
	(156)	(155)	(0.921)	Proportion of Enrollees, Aged 75-84	0.23	0.24	0.01
Annual Enrollment	20,398	16,703	-3,695		(0.09)	(0.09)	(0.126)
	(40,282)	(36,093)	(0.163)	Proportion of Enrollees, Over 84	0.12	0.12	-0.005
Proportion of Plans Offering Gap Coverage	0.34	0.34	-0.003		(0.06)	(0.05)	(0.227)
	(0.47)	(0.47)	(0.924)	Proportion of Enrollees - Asian	0.02	0.03	0.01**
Initial Coverage Limit ($)	2,970	2,970	-0.2		(0.02)	(0.07)	(0.018)
	(0)	(6)	(0.552)	Proportion of Enrollees - Black	0.10	0.10	-0.001
Proportion of Plans - Actuarially Equivalent	0.40	0.41	0.01		(0.13)	(0.11)	(0.936)
	(0.49)	(0.49)	(0.835)	Proportion of Enrollees - Hispanic	0.04	0.07	0.03***
Proportion of Plans - Basic Alternative	0.08	0.06	-0.02		(0.04)	(0.09)	(0.000)
	(0.27)	(0.24)	(0.322)	Proportion of Enrollees - Native	0.02	0.01	-0.01***
Proportion of Plans - Defined Standard Benefit	0.04	0.03	-0.003		(0.06)	(0.02)	(0.004)
	(0.19)	(0.18)	(0.826)	Proportion of Enrollees - White	0.81	0.78	-0.03***
Proportion of Plans - Enhanced Benefits	0.49	0.50	0.01		(0.16)	(0.16)	(0.006)
	(0.50)	(0.50)	(0.714)	Proportion of Enrollees - Other	0.01	0.01	0.0004
					(0.01)	(0.01)	(0.616)
				Proportion of Enrollees - Female	0.59	0.59	-0.001
					(0.04)	(0.04)	(0.714)

Note: The first cell in each row displays the sample mean of the variable. The second cell in each row that is bracketed by parentheses shows the standard deviation of the variable. The difference in means is presented in the "Diff." column and the p-value from a t-test of difference in means is presented below the difference in means. There are 9 excluded regions, which include plans offered in the following 23 states: AK, CT, DC, DE, IA, IN, KY, LA, MA, MD, ME, MN, MT, ND, NE, NH, NY, PA, RI, SD, VT, WV, and WY. The remaining 28 states (representing 25 Part D regions) are included in the Medicaid expansion instrumental variable analysis. See Appendix Table B.1 for more details.

Table B.3: Differences in Means: Excluded vs. Included Regions from IV - 2016

	Excluded	Included	Diff.		Excluded	Included	Diff.
N	226	657		% of Dual Enrollees	30.00	24.35	-5.64***
Monthly Premium ($)	52.59	54.30	1.71		(26.92)	(23.81)	(0.003)
	(26.92)	(29.94)	(0.447)	% of Low-Income Cost Sharing Enrollees	36.11	31.21	-4.91**
% of Branded Drug Spend at CPs	38.62	39.28	0.65		(30.30)	(27.96)	(0.026)
	(9.75)	(11.05)	(0.429)	Proportion of Enrollees, Aged 65-74	0.41	0.43	0.02***
Annual Deductible ($)	224	221	-3		(0.11)	(0.12)	(0.007)
	(163)	(163)	(0.842)	Proportion of Enrollees, Aged 75-84	0.23	0.24	0.01
Annual Enrollment	26,834	21,328	-5,506*		(0.09)	(0.10)	(0.192)
	(47,150)	(40,358)	(0.091)	Proportion of Enrollees, Over 84	0.12	0.11	-0.01*
Proportion of Plans Offering Gap Coverage	0.15	0.16	0.02		(0.06)	(0.06)	(0.095)
	(0.35)	(0.37)	(0.550)	Proportion of Enrollees - Asian	0.02	0.03	0.01**
Initial Coverage Limit ($)	3,310	3,310	0		(0.02)	(0.06)	(0.021)
	(0)	(0)	(.)	Proportion of Enrollees - Black	0.09	0.09	-0.002
Proportion of Plans - Actuarially Equivalent	0.40	0.39	-0.01		(0.11)	(0.09)	(0.788)
	(0.49)	(0.49)	(0.700)	Proportion of Enrollees - Hispanic	0.03	0.06	0.03***
Proportion of Plans - Basic Alternative	0.09	0.11	0.01		(0.03)	(0.08)	(0.000)
	(0.29)	(0.31)	(0.604)	Proportion of Enrollees - Native	0.01	0.01	-0.004
Proportion of Plans - Defined Standard Benefit	0	0	0		(0.05)	(0.02)	(0.120)
	(0)	(0)	(.)	Proportion of Enrollees - White	0.82	0.79	-0.03***
Proportion of Plans - Enhanced Benefits	0.50	0.51	0.002		(0.15)	(0.14)	(0.003)
	(0.50)	(0.50)	(0.950)	Proportion of Enrollees - Other	0.01	0.01	0.001
					(0.004)	(0.01)	(0.194)
				Proportion of Enrollees - Female	0.58	0.58	-0.002
					(0.03)	(0.04)	(0.530)

Note: The first cell in each row displays the sample mean of the variable. The second cell in each row that is bracketed by parentheses shows the standard deviation of the variable. The difference in means is presented in the "Diff." column and the p-value from a t-test of difference in means is presented below the difference in means. There are 9 excluded regions, which include plans offered in the following 23 states: AK, CT, DC, DE, IA, IN, KY, LA, MA, MD, ME, MN, MT, ND, NE, NH, NY, PA, RI, SD, VT, WV, and WY. The remaining 28 states (representing 25 Part D regions) are included in the Medicaid expansion instrumental variable analysis. See Appendix Table B.1 for more details.

Table B.4: Two-Way Fixed Effects - Alternative Regression Weights & Functional Form

Dependent Variable:	**Premium ($)**			ln(**Premium**)		
	(1)	(2)	(3)	(4)	(5)	(6)
% of Branded Drug Spend at CPs	0.333***	0.246**	0.230***	0.077**	0.054**	0.035
	(0.109)	(0.076)	(0.052)	(0.014)	(0.021)	(0.029)
Avg. Monthly Premium ($)			52.06			
1 SD % of Branded Drug Spend at CPs			17.23			
N			10,997			
R^2	0.727	0.715	0.809	0.755	0.743	0.823
Regression Weights	2008 Region Enrollment	None	Contemporaneous Plan Enrollment	2008 Region Enrollment	None	Contemporaneous Plan Enrollment

Note: Column (1) is a reproduction of Column (2) from Table 2. Columns (2) and (3) are identical to Column (1) except for the weights used for the regression. Column (2) is unweighted while Column (3) uses a plan's contemporaneous enrollment as its weight. Columns (4), (5), and (6) are identical to Columns (1), (2), and (3), respectively, except the dependent variable is the natural log of premiums and the main regressor of interest has been transformed to a standard normal variable to ease interpretation of the coefficient. The interpretation of the estimates in Columns (4) through (6) are a 1 standard deviation increase in contract pharmacy exposure is associated with an x percent change in premiums. The control variables are the same as the TWFE regressions from Table 2; for a complete list of included control variables, please see the footnote of Table 2. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. The sample is limited to only standalone prescription drug plans (PDPs).

Table B.5: Medicaid Binary Instrument - Alternative Regression Weights & Functional Form

Dependent Variable:	**Premium ($)**			ln(**Premium**)		
	(1)	(2)	(3)	(4)	(5)	(6)
% of Branded Drug Spend at CPs	0.345*	0.325**	0.536***	0.148***	0.166***	0.250***
	(0.175)	(0.138)	(0.153)	(0.049)	(0.045)	(0.068)
Avg. Monthly Premium ($)			52.09			
1 SD % of Branded Drug Spend at CPs			17.25			
N			8,150			
R^2	0.682	0.666	0.740	0.715	0.700	0.743
First-Stage	5.649***	5.879***	4.770***	0.317***	0.330***	0.268***
	(0.473)	(0.611)	(0.461)	(0.027)	(0.034)	(0.026)
Reduced-Form	1.951**	1.908***	2.557***	0.047***	0.055***	0.067***
	(0.978)	(0.745)	(0.782)	(0.015)	(0.012)	(0.020)
Regression Weights	2008 Region Enrollment	None	Contemporaneous Plan Enrollment	2008 Region Enrollment	None	Contemporaneous Plan Enrollment

Note: Column (1) is a reproduction of Column (4) from Table 3. Columns (2) and (3) are identical to Column (1) except for the weights used for the regression. Column (2) is unweighted while Column (3) uses a plan's contemporaneous enrollment as its weight. Columns (4), (5), and (6) are identical to Columns (1), (2), and (3), respectively, except the dependent variable is the natural log of premiums and the main regressor of interest has been transformed to a standard normal variable to ease interpretation of the coefficient. The interpretation of the estimates in Columns (4) through (6) are a 1 standard deviation increase in contract pharmacy exposure is associated with an x percent change in premiums. The control variables are the same as the TWFE regressions from Table 2; for a complete list of included control variables, please see the footnote of Table 2. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. The sample is limited to only standalone prescription drug plans (PDPs). The sample is also limited to plans offered in Part D regions whose constituent states expanded Medicaid in 2014 (treated regions) and plans offered in Part D regions whose constituent states never expanded their Medicaid Program as of Jan 1, 2019 (control regions). The instrument is a binary variable equal to 1 if a plan was offered in a Medicaid Expansion region and the year is 2014 or later (i.e., post expansion).

Table B.6: Medicaid Continuous Instrument - Alternative Regression Weights & Functional Form

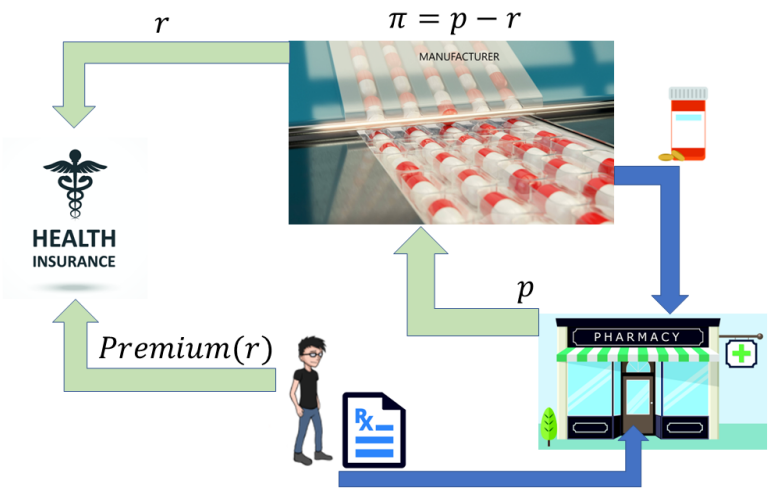
Dependent Variable:	**Premium ($)**			ln(**Premium**)		
	(1)	(2)	(3)	(4)	(5)	(6)
% of Branded Drug Spend at CPs	0.369*	0.346**	0.585***	0.162***	0.181***	0.278***
	(0.194)	(0.168)	(0.176)	(0.055)	(0.056)	(0.079)
Avg. Monthly Premium ($)			52.09			
1 SD % of Branded Drug Spend at CPs			17.25			
N			8,150			
R^2	0.682	0.666	0.738	0.714	0.694	0.738
First-Stage	6.584***	6.556***	5.527***	0.369***	0.368***	0.310***
	(0.597)	(0.819)	(0.605)	(0.034)	(0.046)	(0.034)
Reduced-Form	2.432*	2.271**	3.236***	0.060***	0.067***	0.086***
	(1.271)	(0.994)	(1.033)	(0.020)	(0.016)	(0.026)
Regression Weights	2008 Region Enrollment	None	Contemporaneous Plan Enrollment	2008 Region Enrollment	None	Contemporaneous Plan Enrollment

Note: Column (1) is a reproduction of Column (5) from Table 3. Columns (2) and (3) are identical to Column (1) except for the weights used for the regression. Column (2) is unweighted while Column (3) uses a plan's contemporaneous enrollment as its weight. Columns (4), (5), and (6) are identical to Columns (1), (2), and (3), respectively, except the dependent variable is the natural log of premiums and the main regressor of interest has been transformed to a standard normal variable to ease interpretation of the coefficient. The interpretation of the estimates in Columns (4) through (6) are a 1 standard deviation increase in contract pharmacy exposure is associated with an x percent change in premiums. The control variables are the same as the TWFE regressions from Table 2; for a complete list of included control variables, please see the footnote of Table 2. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. The sample is limited to only standalone prescription drug plans (PDPs). The sample is also limited to plans offered in Part D regions whose constituent states expanded Medicaid in 2014 (treated regions) and plans offered in Part D regions whose constituent states never expanded their Medicaid Program as of Jan 1, 2019 (control regions). The instrument is a continuous variable equal to the proportion of pharmacies in the Part D region that were not serving as a contract pharmacy in 2013 interacted with a dummy if the region expanded Medicaid as well as a post-2014 dummy variable—i.e., this instrument is equal to 0 in all years for all plans offered in the non-expansion regions.

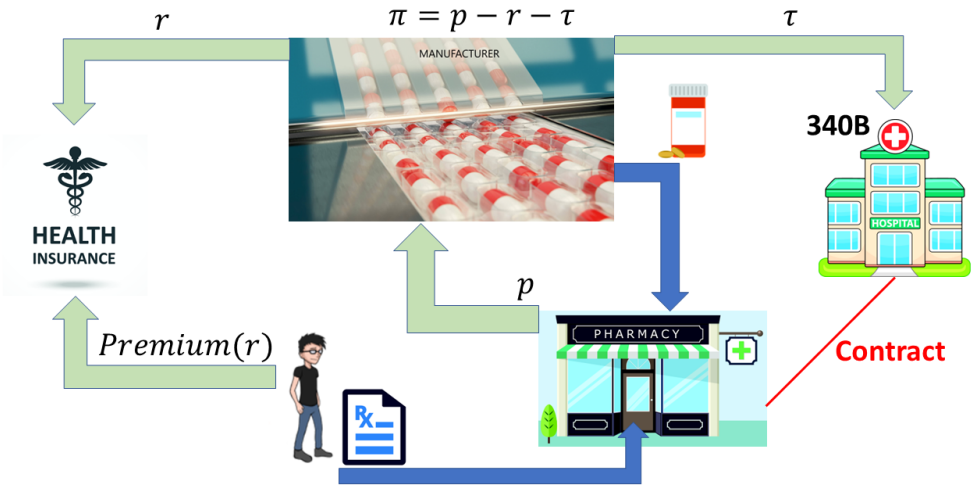
C Appendix Figures

Figure C.1: Pharmaceutical Supply Chain

(a) Traditional Pharmacy

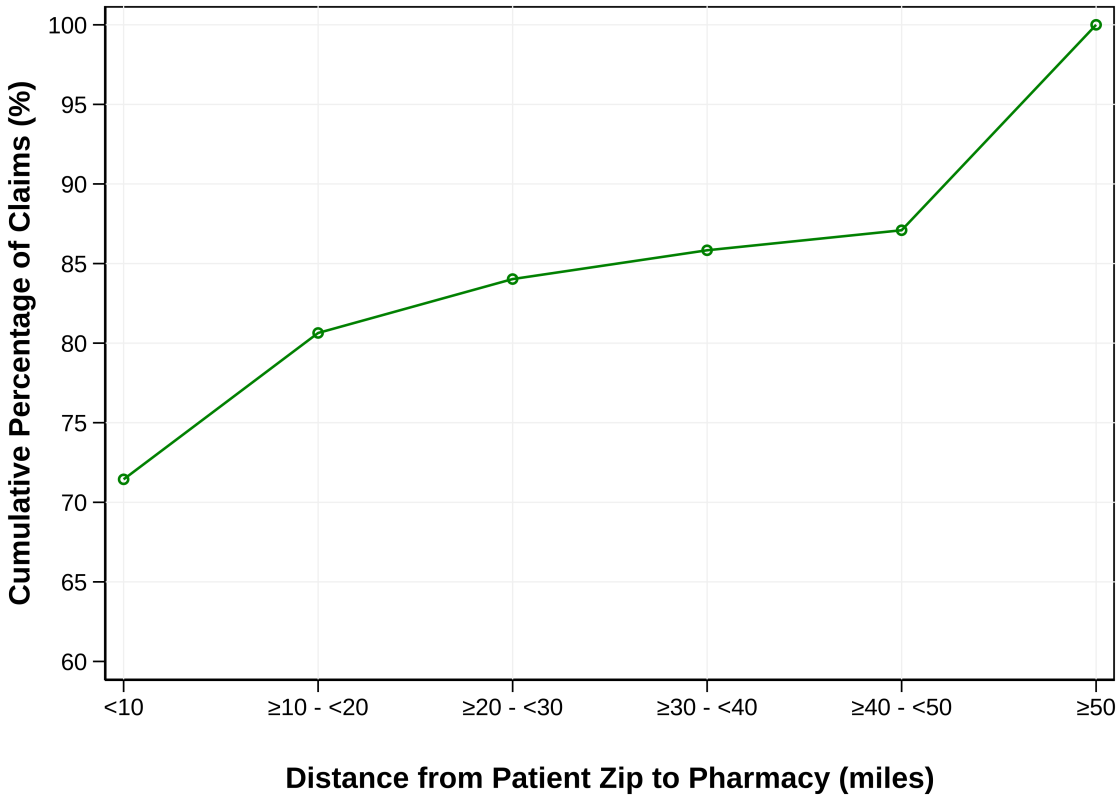


(b) Contract Pharmacy



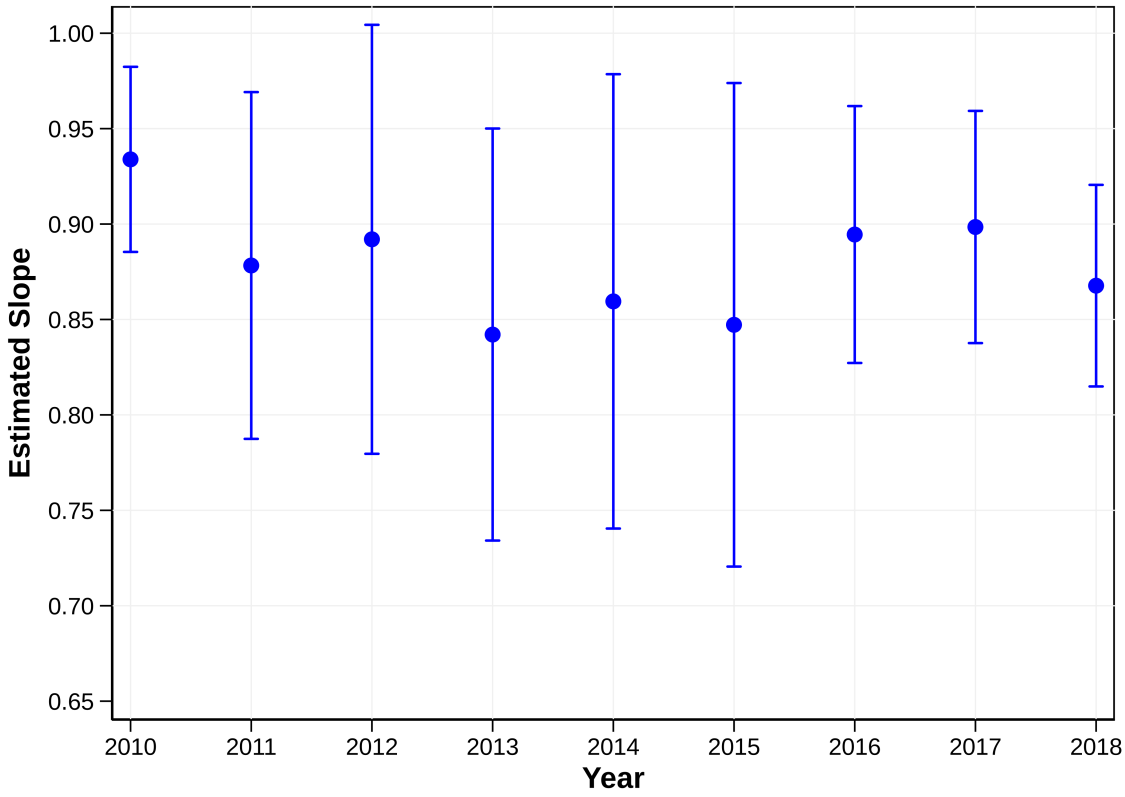
Notes: The above pictures provide simplified diagrams of the pharmaceutical supply chain for a branded drug product. Panel C.1a displays the supply chain for a typical retail pharmacy while Panel C.1b displays the supply chain when the pharmacy operates as a 340B contract pharmacy. Green arrows donate the flow of money while blue arrows denote the flow of goods or prescriptions. The manufacturer's profit is denoted by π. The list price for the drug is p. The rebate the manufacturer pays to the insurer is r. The 340B discount the manufacturer pays to the 340B provider is τ.

Figure C.2: Observed Travel Distances Between Patients and Pharmacies



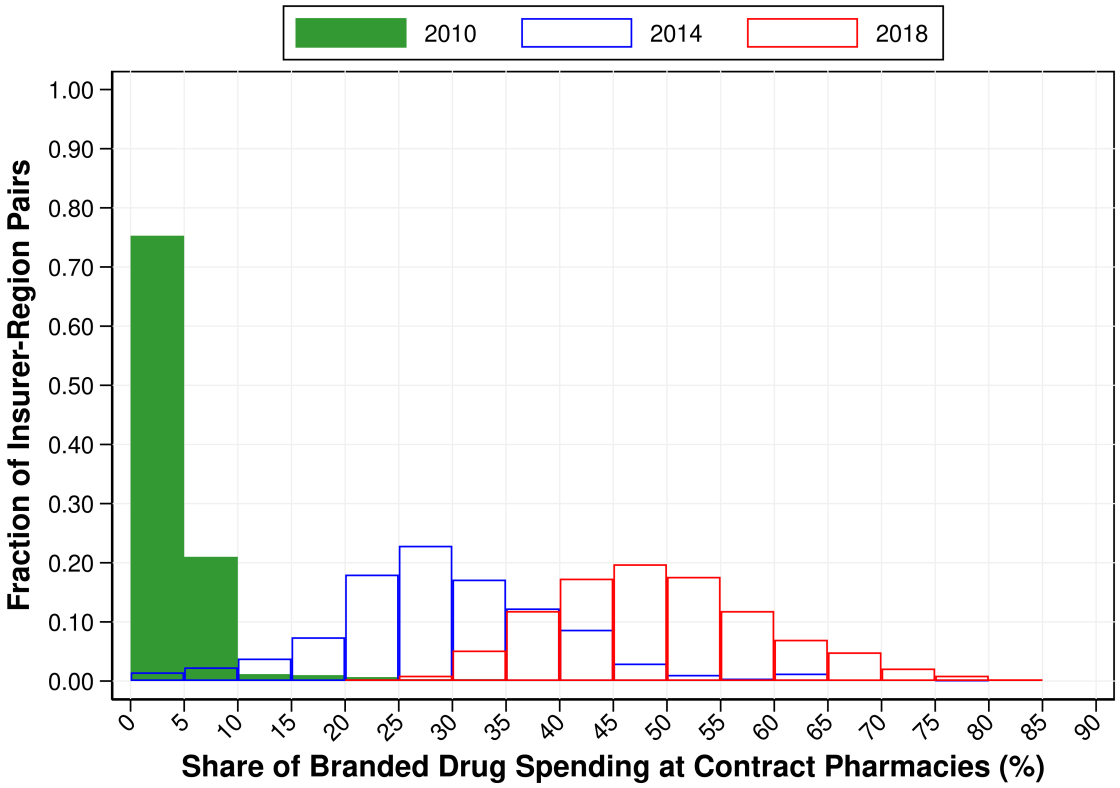
Notes: Data used to generate this graph comes from CMS' National Plan and Provider Enumeration System (NPPES) database, which provides address information for each pharmacy that bills Medicare Part D. I geocoded these addresses using Google Maps API to obtain precise latitude and longitude coordinates of each pharmacy. Patient zip code and counts of claims come from the Medicare Master Beneficiary Summary File (MBSF) and Part D claims data, respectively. I obtained latitude and longitude coordinates for each zip code from the Department of Housing and Urban Development's population-weighted centroids database. I compute distances between each patient zip code and the pharmacy they visit using Stata's `geodist` function.

Figure C.3: Stability of Insurer's Enrollment Shares



Notes: Data used to generate this graph come CMS' Master Beneficiary Summary File (MBSF) and the Part D landscape data. I compute what fraction of an insurer's total enrollment in a Part D regions comes from each county within that region in a given year. For instance, there are 21 counties in the Part D region of New Jersey (NJ). Thus, each insurer offering a plan in NJ will have 21 observations for each year. I then regress this county-level enrollment share variable for $t = 2010, 2011, \ldots, 2018$ on year fixed effects and the county-level enrollment share from 2009 interacted with year fixed effects, i.e., $S_{kjrt} = \sum_{t=2010}^{2018} \psi_t + \theta_t \times S_{kjr,2009}$. Thus, θ_{2010} represents how well enrollment shares from 2009 predict enrollment shares in 2010. The interpretation of the estimate is a 1 pp increase in enrollment shares from 2009 is associated with a 0.93 pp increase in enrollment shares in 2010.

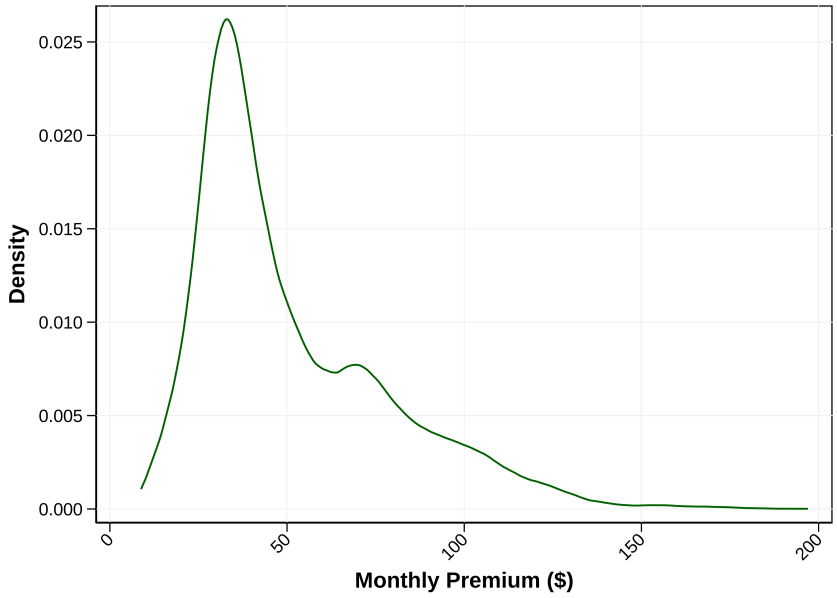
Figure C.4: Distribution of Insurer's Share of Branded Drug Spend at Contract Pharmacies



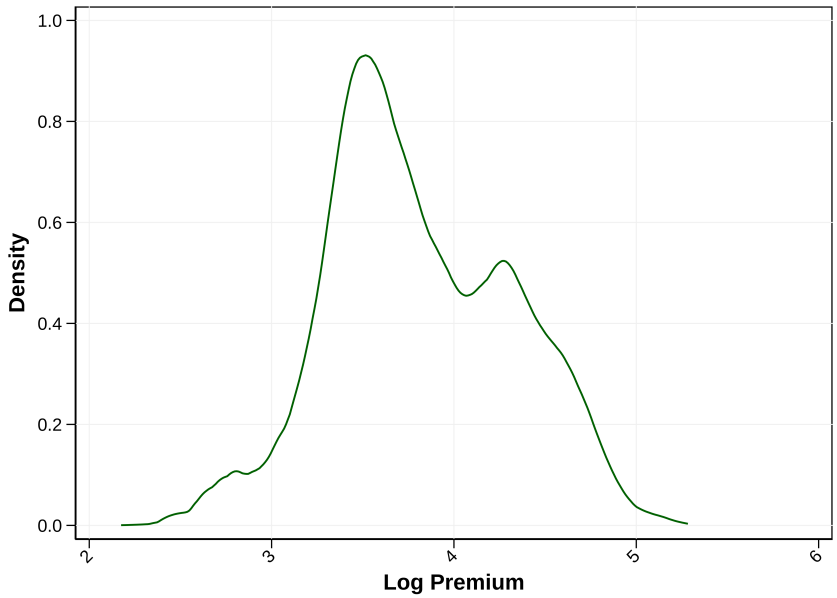
Notes: Data used to generate this graph come from the 340B Office of Pharmacy Affairs Information System (OPAIS) contract pharmacy database and a 20% random sample of Medicare Part D claims. I compute the fraction of insurer-region pairs that fall within 5 percentage point bins of contract pharmacy exposure (CP_{jrt}) for three different years of my sample (2010, 2014, and 2018).

Figure C.5: Distribution of Premiums

(a) Level ($)



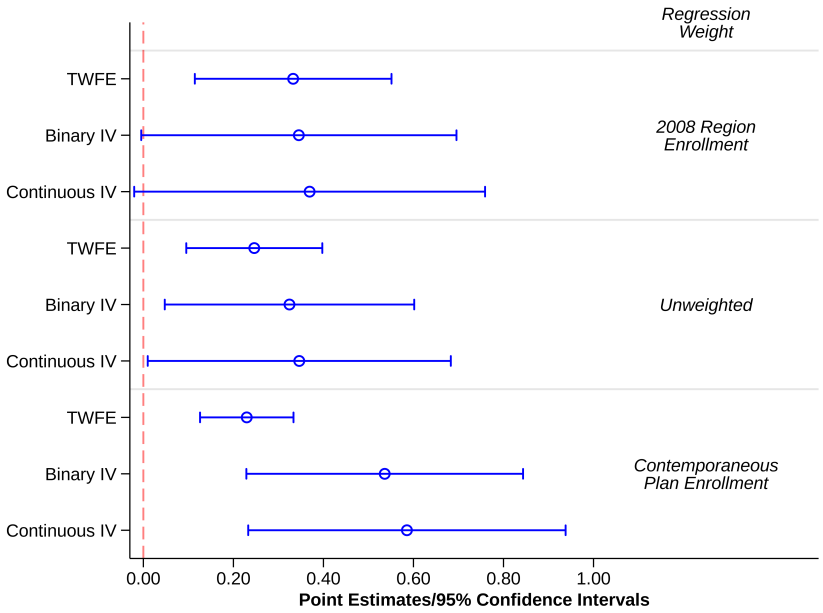
(b) ln(Premium)



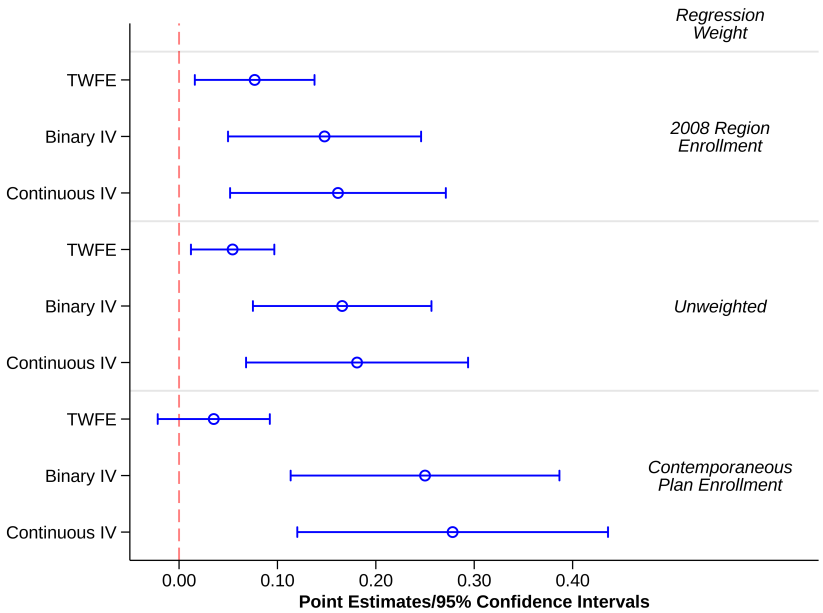
Notes: This figure displays estimated distributions across all plans of the primary outcome variable of interest, monthly Part D premiums. Panel C.5a displays the distribution of the level form of the variable (i.e., US dollars). Note the dollar values are not adjusted for inflation. Panel C.5b displays the distribution of the natural logarithm of the variable. The distributions were estimated using the default kernel density estimation procedure in Stata version 17.0 (i.e., `kdensity`.)

Figure C.6: Effects of Contract Pharmacies on Premiums - Robustness

(a) Dependent Variable = Premiums ($)

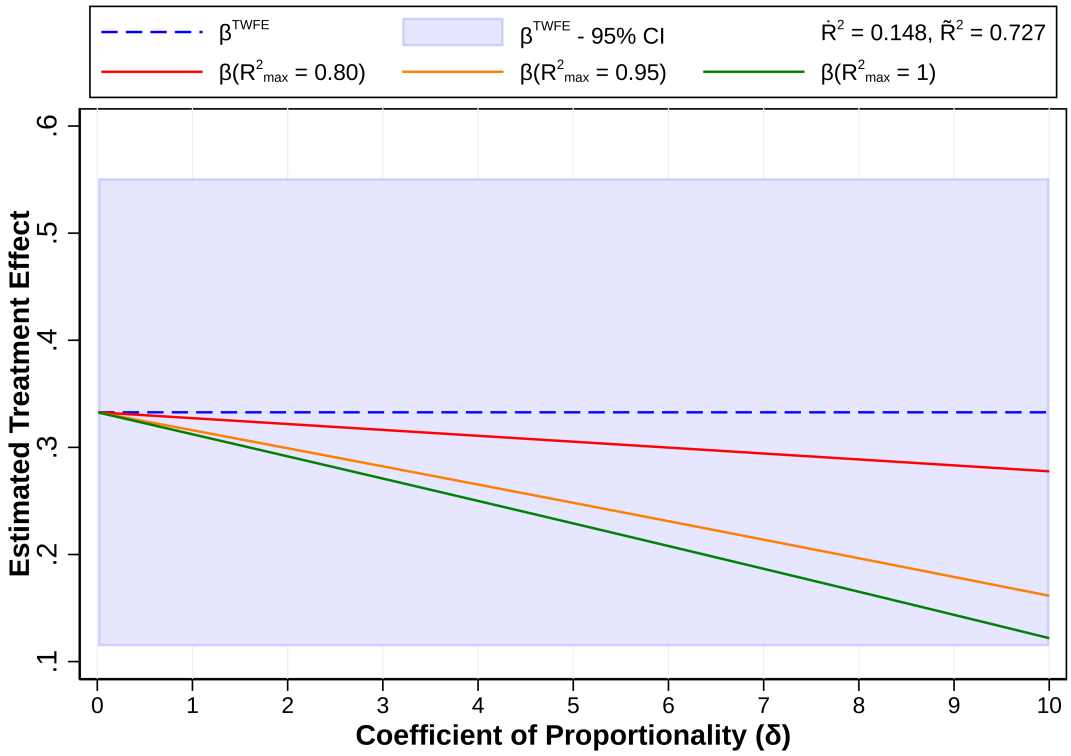


(b) Dependent Variable = ln(Premiums)



Notes: This figure summarizes point estimates and 95 percent confidence intervals of both the two-way fixed effects estimation of Equation (4) and the IV estimation of Equation (6) for different choices of regression weights and different functional form of the dependent variable. Panel C.6a uses the level or dollar value of premiums as the dependent variable while Panel C.6b uses the natural log of premiums. The top portion of each panel uses a plan's 2008 region enrollment as its weight; the middle portion is unweighted; and the bottom portion uses a plan's contemporaneous enrollment as its weight. The control variables are the same as the TWFE regressions from Table 2; for a complete list of included control variables, please see the footnote of Table 2. Standard errors are clustered at the insurer level and are displayed in parentheses below each point estimate. The sample period is from 2009 to 2018, inclusive. The sample is limited to only standalone prescription drug plans (PDPs). Also note that in Panel C.6b, the main regressor of interest has been transformed to a standard normal variable to ease interpretation of the coefficient. The interpretation of the estimates in this bottom panel are a 1 standard deviation increase in contract pharmacy exposure is associated with an x percent change in premiums. These regressions are summarized in tabular form in Appendix Tables B.4, B.5, and B.6.

Figure C.7: Oster/Basu - Omitted Variable Bias Adjusted Treatment Effect



Notes: This figure summarizes results from a robustness methodology described in Oster (2019) and Basu (2022). The dashed blue line displays the two-way fixed effects estimated treatment effect from Column (2) of Table 4 and the shaded blue area displays the 95 percent confidence interval for this estimate. The solid colored lines display how this estimated treatment effect is adjusted for omitted variable bias under different assumptions about the R^2_{max} and how that effect varies under different assumptions about the coefficient of proportionality (δ). The red line assumes an $R^2_{max} = 0.8$; the orange line assumes an $R^2_{max} = 0.95$; and the green line assumes an $R^2_{max} = 1$.