How Do Copayment Coupons Affect Branded Drug Prices and Quantities Purchased?*

Leemore Dafny[1], Kate Ho[2], and Edward Kong[3]

[1]Harvard Business School and Harvard Kennedy School
[2]Princeton University
[3]Harvard University and Harvard Medical School

June 3, 2022

Abstract

We estimate the causal effects of drug copayment coupons, which reduce consumer cost-sharing for branded prescription drugs, on net-of-rebate price and quantities sold. Focusing on drugs without generic substitutes, we show that coupon introductions increase quantity sold by 21-23% for the commercial segment relative to Medicare Advantage, where coupons are banned. To quantify the resulting equilibrium price effects, we estimate a discrete choice model of demand for multiple sclerosis drugs and simulate a model of drug price negotiations. We estimate that net-of-rebate prices are 8% higher due to the availability of coupons for most of these drugs.

*Dafny: ldafny@hbs.edu. Ho: kate.ho@princeton.edu Kong: edwardkong@fas.harvard.edu. We are grateful for comments from Hanming Fang, Alex Olssen, David Ridley, Benjamin Handel, and seminar participants at Wharton, the American Society of Health Economics Annual Meeting, and the American Economics Association Annual Meetings for helpful comments. We thank Amina Abdu, Teresa Rokos, Olivia Zhao, and Ran Zhuo for excellent research assistance. We especially thank Chris Ody for insightful comments and data contributions.

Introduction

The U.S. health care system is well known for its high prices and spending: in 2019, health care absorbed 17 percent of GDP in the U.S., compared to an average of 11.4 percent among the next five highest-spending countries and 8.6 percent among other OECD countries.[1] Comparative analyses find that higher prices for health care products and services are the most significant factor explaining the substantially higher level of spending in the U.S.[2] While higher prices for hospital and physician services have long – and rightly – been critiqued as the primary driver of high spending, in recent years concern about high and rising prescription drug prices has reached a fever pitch.

There are multiple sources for the public outcry over prescription drug prices, including the rise of high-deductible plans in which consumers face higher costs for drugs at the point of purchase, high-profile examples of pharmaceutical manufacturers hiking prices of old drugs abruptly (e.g., Turing Pharmaceuticals and Daraprim) or steadily over time (e.g., Mylan and EpiPen), and the increase in launch prices for new drugs. International comparisons of drug prices have also sparked outrage, culminating in legislation that permits importation of drugs from Canada under certain circumstances, and proposals to link U.S. prices to indices of international prices. In 2021, a RAND study found branded drug prices in the U.S. were 3.4 times higher, on average, in the U.S. than in 32 other countries; generic drug prices were slightly lower (Mulcahy et al., 2021).[3]

In this study, we consider a rarely mentioned potential driver of this pricing phenomenon: drug copayment coupons. These popular programs (also known as "copay cards") defray consumers' out-of-pocket cost-sharing at the point of purchase. Coupon availability has accelerated rapidly since they first appeared in the early 2000s: Dafny et al. (2017) report that the share of branded drug spending with a coupon increased from 26 percent to 54 percent between June 2007 and December 2010. While coupons

[1] Source: OECD 2019 statistics. The next five highest-spending countries are Switzerland (12.1 percent), Germany (11.7 percent), France (11.2 percent), and Japan (11.1 percent).

[2] See, for example, *Accounting for the cost of U.S. health care: A new look at why Americans spend more*, McKinsey Global Institute Report 2008; and *U.S. Health Care from a Global Perspective, 2019: Higher Spending, Worse Outcomes?*, Commonwealth Fund Issue Brief, 2020.

[3] The RAND researchers relied on prices from insurance claims data, which do not reflect manufacturer rebates or discounts. They estimate prices were around 1.9 times higher after applying adjustments based on aggregated published estimates of "the relative differences between manufacturers and net prices." As we discuss later, rebate information is highly proprietary, hence virtually all academic research relies on list prices.

may enable individual consumers to access drugs they couldn't otherwise afford, they may also lead to higher medication prices and insurance premiums. Coupons diminish price competition among drugs and limit insurers' ability to discourage use of certain drugs via tiered formularies. Under tiering, preferred drugs are assigned to lower tiers with lower patient cost-sharing, e.g., $25 for preferred brands in Tier 1 and $50 for non-preferred brands in Tier 2, etc. In the absence of coupons or other copay-assistance programs, insurers can negotiate lower prices with manufacturers in exchange for steering patients toward these drugs by placing them in lower tiers. Insurers can also encourage utilization of generic drugs through tiering, and may offer a lower generic-specific copay, like $5 or $10, further heightening price competition with branded therapeutic alternatives. Finally, tiering enables insurers to contain spending by discouraging utilization of drugs for which cheaper options are available (e.g., two separate generic medications rather than a single, branded combination of the two).

The rise of coupons has reduced the effectiveness of tiering and cost-sharing in general as tools in insurers' arsenal to contain spending. By 2014, the Chief Medical Officer of CVS, one of the largest PBMs, wrote that "traditional tiered formularies are becoming less effective in the face of manufacturers' copayment or coupon programs, which continue to proliferate" (Lotvin et al., 2014). For our analysis, we build a database of coupon introductions spanning a decade, using historical snapshots of multiple online databases supplemented by manual searches. We find that the reach of coupons has increased substantially: by 2017, we estimate over 93 percent of branded spending occurred in couponed drugs. As tiering has become less effective, insurers have increasingly turned to step-therapy programs, which are more onerous and prescriptive, requiring patients to undergo specific regimens or to "fail first" using certain medications or treatments before approving coverage for a drug. Prior authorization requirements and complete exclusion of drugs from formularies are also increasingly common. Indeed, recent research finds that couponed drugs are more likely to be excluded from coverage (Agha et al., 2020).

Although prior researchers have highlighted the mechanisms through which coupons may drive higher prices and spending, there are only two peer-reviewed empirical analyses of coupons, and both consider a specific, limited type of coupon: coupons for branded drugs with bioequivalent generics. Lee (2020) simulates the impact of a single (hypothetical) coupon for Zocor, a branded statin with a bioequivalent generic available during the study period, under the assumption that the effect of the coupon is limited

to its impact on cost-sharing (e.g., there is no advertising or spillover effect of coupons on non-utilizers). In this setting, introducing a single coupon is predicted to soften price competition, and Lee projects significant coupon-induced increases in prices and insurer spending, the magnitude of which vary depending on various modeling assumptions. Consumer welfare (excluding insurer spending and thus the effect of coupons on premiums) can either increase or decrease, again depending on the assumptions.

Dafny et al. (2017) estimate the effects of these types of coupons using a sample of natural experiments generated when branded drugs introduced coupons at the time of generic entry. They compare the "generic efficiency ratio" (i.e., the share of prescriptions for a given drug that are dispensed as generic when both branded and generic options are available) for a set of drugs newly experiencing generic entry in New Hampshire as compared to Massachusetts, where this specific type of coupon is banned.[4] Dafny et al focus on the commercially insured population, as the federal anti-kickback statute prohibits the use of coupons, which are deemed a potential inducement for purchase, by individuals with government health insurance. Using monthly data from 2007-2010, they find that coupons increase branded sales among the non-elderly population by 60+ percent, and this increase comes entirely from reduced sales of bioequivalent generics, i.e. there is no market expansion, only increased cost. In the first five years following generic entry, they estimate couponing increased total spending by $30 to $120 million per drug, where the higher number incorporates the faster observed price growth of branded drugs with versus without coupons. Given the very high rates of generic efficiency in the U.S., however, the aggregate impact of coupons is likely to be greater for drugs without bioequivalent generics. No states ban coupons for these medications, necessitating a different identification strategy.

In this paper, we study the impact of copay coupons on prices and quantities of branded drugs without bioequivalent generics using two distinct and complementary approaches: (1) estimating a difference-in-differences model that quantifies the impact of coupon introductions by comparing pre vs. post-coupon prices and quantities for the commercially insured vs. the Medicare Advantage population, which is ineligible to use coupons and (2) building and calibrating a stylized model of demand and pricing for a specific drug segment (medications for multiple sclerosis), and using the model to predict the equilibrium effect of coupons on list prices. The model shows that the effect

[4]When the study was published, Massachusetts was the only state with such a ban. California passed a similar ban in 2017.

on price of introducing coupons for drugs without perfect substitutes is theoretically ambiguous. The difference-in-differences analysis is performed using proprietary data at the drug-month-segment level (where segment is commercial or Medicare Advantage) from one of the largest PBMs, for the period January 2014–June 2017. The price variable we use is net of rebates and discounts, a significant advantage relative to the vast majority of prior studies analyzing drug prices. We limit attention to drugs that do not experience generic entry during the study period, and which have been on the market without a coupon for at least 9 months. Medicare Advantage enrollees, who are not permitted to redeem coupons, serve as a natural control group for each drug. This analysis yields a relatively clean estimate of the *short-term* effect of coupons because data constraints limit the post-period to 12 months. Moreover, this effect may be conservative. Branded drugs typically have coupons at launch. Drugs with relatively late coupon introductions may be those for which coupons are expected to have the least impact on manufacturer revenues. We find substantial quantity effects: couponing is followed by an almost immediate quantity surge on the order of 20 percent. We do not find changes in relative net-of-rebate prices, which may be due to the use of a control group as well as the short time series used in this analysis. Because list prices are the same for both customer segments, a relative change in net-of-rebate price for the commercial versus the Medicare Advantage segment would require a renegotiation of segment-specific rebates within the first 12 months of a coupon introduction.

The second analysis explores the equilibrium effect of coupons on drug prices by estimating a demand model and using it to calibrate a bargaining model between insurers and manufacturers. We make use of claims data over the period 2009 through 2017 from the Health Care Cost Institute, which includes claims for roughly 25% of commercially insured individuals and 35% of Medicare Advantage enrollees in the U.S. The analysis incorporates rich detail on a specific drug category – disease-modifying therapies for multiple sclerosis (MS) – and incorporates a fully-specified model of demand as well as insurer-manufacturer negotiations over prices, allowing for simulations of a key policy option: banning coupons. Rather than modeling the determination of list prices and rebates separately, we collapse the problem to a single dimension by specifying a model of bargaining over net-of-rebate prices. The simulations indicate that prices of MS drugs are around 8% higher during the 2015-2017 period due to the availability of coupons, which drive demand through two mechanisms: (1) reducing patients' price elasticity and (2) an advertising effect. We document the distributional

impacts of a ban, which lowers out-of-pocket spending for those whose cost-sharing varies with price and lowers premiums for all, but increases out-of-pocket spending for commercially insured individuals who previously used coupons. We predict that total savings (for the MS drug market) would outweigh the increase in out-of-pocket payments by 4 to 1. We discuss potential mechanisms to address the distributional consequences of a ban.

The paper proceeds as follows. Section 1 provides background information on copay coupons, multiple sclerosis, and related literature. Section 2 presents our difference-in-differences analysis of the impact of coupon introductions on drug utilization. In Section 3, we build a model that serves as the foundation for our demand estimation and counterfactual simulations. Section 4 presents our data and demand estimates for the effects of coupons on multiple sclerosis drugs. Section 5 presents counterfactual simulations for a policy that bans coupons and examines the sensitivity of the predictions to several different assumptions. We discuss the implications of our findings in Section 6.

1 Background

1.1 Drug Coupons

A copay coupon is an offer by a manufacturer to pay some or all of a consumer's copay for the manufacturer's drug. By offering a copay coupon, a manufacturer can reduce the out-of-pocket price for its drug, as well as any difference between the out-of-pocket price for its drug and competing drugs, thereby encouraging consumers to buy the manufacturer's drug. Manufacturers' coupons pertain to specific (branded) drugs, and may not be utilized by individuals purchasing drugs with public health insurance such as Medicare. The federal Anti-Kickback Statute prohibits manufacturers from providing anything of value that may induce a purchase or service financed by a federal health care program. (However, manufacturers may donate to independent charitable foundations that offer copay assistance programs to publicly insured enrollees with certain health conditions (e.g., multiple sclerosis), provided the manufacturers abide by certain restrictions, including not earmarking their donations specifically for their own medications.)

Copay coupons (also called "copay cards") may apply to only a subset of a drug's formulations, e.g., the extended release version but not the immediate release version, and may contain caps on the total amount the manufacturer will pay for a given pre-

scription or on behalf of an individual in a given time period. A recent study by Sen et al. (2021) used a proprietary dataset of prescription drug transactions from U.S. pharmacies over 2017–2019 and finds that manufacturer-sponsored "offset" programs, such as coupons, reduce out-of-pocket cost sharing by a median of 87 percent.[5] Manufacturer offset programs insulate consumers not only from high out-of-pocket spending, but also from price variation across therapeutic substitutes.

1.2 Multiple Sclerosis

In the second of our two analyses, we focus on medications to treat multiple sclerosis. Multiple sclerosis (MS) is a disease characterized by inflammation of the brain and spinal cord. It usually onsets between 20 and 40 years of age and affects over 850,000 individuals in the United States (Wallin et al., 2019). While MS does not usually result in decreased life expectancy, it can cause substantial disability through impacts on sensation and motor, autonomic, and neurocognitive function. MS initially presents in a relapsing-remitting form (RR-MS, which accounts for 85-90% of cases) or a steadily progressing form (primary progressive MS, or PP-MS, which accounts for 10-15% of cases). Relapsing-remitting MS usually progresses to secondary progressive SP-MS (Sospedra and Martin, 2005). In RR-MS, relapses are characterized by one or more new neurological symptoms or a worsening of prior symptoms.[6]

We study the market for drugs called "disease modifying therapies" (DMTs), which are currently the best available treatment for slowing the course of MS. The majority of DMTs (and all of the DMTs that we study) have been approved for treating relapsing forms of MS (RR-MS) and some cases of secondary progressive MS (SP-MS).[7] DMTs for MS are expensive, and prices have increased significantly over time. Estimates for actual spending range significantly across sources. One recent study estimated that total Medicaid spending on DMTs has increased from $172 million in 2008 to $1.3 billion in 2018 (Elsisi et al., 2020). Using data on individuals covered through both commercial and Medicare Advantage plans, The Health Care Cost Institute estimated spending on DMTs per person diagnosed with MS increased from $9,400 per year to

[5] The data do not reflect payments made by the charitable foundations described above, as these payments are not made at the point of service.

[6] See *Disease-Modifying Therapies for MS*, National Multiple Sclerosis Society, 2020. http://www.nationalmssociety.org/NationalMSSociety/media/MSNationalFiles/Brochures/Brochure-The-MS-Disease-Modifying-Medications.pdf

[7] *Ibid.* DMTs are ineffective for patients with disabilities, patients with PP-MS, and patients with SP-MS without relapses (Lonergan et al., 2009; Torkildsen et al., 2016).

nearly $21,000 per year between 2009 and 2015.[8] Both sources find that increases in the list price of DMTs were the largest component of cost increases. Neither study was able to adjust for rebates. However, a study performed by the Massachusetts Attorney General's office, which used subpoena authority to obtain rebate information, concluded that net-of-rebate prices for DMTs per commercially-insured patient in the state nearly doubled between 2011 and 2015, from approximately $3000 to $5-6000 per month.[9] Consistent with these high prices, pharmacy claims data suggest that up to 75% of commercially insured MS patients use coupons when they are available (see Starner et al. (2014) and Appendix Section B.7 for details). In sum, DMTs for multiple sclerosis are very expensive and becoming more so, and patients utilizing these medications rely heavily on copay coupons and assistance programs.

1.3 Related Literature

In previous work, Dafny et al. (2017) find that copay coupons increase branded drug sales at the expense of newly released bioequivalent generics. That paper focused exclusively on "multi-source" drugs, i.e. branded drugs for which bioequivalent generics were also available. Our paper extends this work by considering the impact of coupons on "single-source" branded drugs without generic equivalents. Branded drugs account for roughly three-quarters of U.S. prescription drug spending. In light of the fact that the "generic efficiency ratio" – the rate at which generics are dispensed in place of a brand when both are available – exceeds 95 percent, assessing the impact of coupons on single-source drugs is of critical policy interest. Coupons may have a greater impact on the volume of sales for single-source as compared to multi-source drugs, as consumers lack access to an inexpensive bioequivalent substitute. While Dafny et al. (2017) did not find an increase in aggregate molecule-level demand as a result of coupons, coupons for single source drugs may result in both share shifts (i.e., business-stealing among therapeutic substitutes) as well as market expansion.

Our paper is also related to the previous industrial organization literature that models price negotiations in vertical settings. Our simulations apply the Nash-in-Nash model of price negotiations that has been extensively used in previous empirical work studying insurer-hospital negotiations (e.g. Gowrisankaran et al. (2015), Ho and Lee (2017)), negotiations between hospitals and device manufacturers (Grennan (2013)),

[8] *The Rising Cost of Specialty Drugs Drove Spending Increases for People with Multiple Sclerosis*, Health Care Cost Institute Issue Brief, 2018.

[9] *Examination of Health Care Cost Trends and Cost Drivers Pursuant to G.L. c. 12C, §17*, Commonwealth of Massachusetts Office of the Attorney General, October 7, 2016.

and also in non-health care settings (Draganska et al. (2010), Crawford and Yurukoglu (2012)).

2 Difference-in-Differences Analysis

2.1 Data Sources

Drug Coupon Data We construct a dataset spanning 2009 through 2018 using historical snapshots of three online databases of drug coupons: InternetDrugCoupons.com, RxPharmacyCoupons, and NeedyMeds.org.[10] We record the earliest date a copay coupon is observed on any site for any given drug. The unit of observation is the drug name, where drug names reflect those appearing on coupons (e.g., Effexor and the extended release version, Effexor XR, are unique observations). Coupons may become available prior to being posted on the websites, or there may be gaps in the data during which snapshots are unavailable. For the subset of drugs we ultimately include in our estimation sample, we manually verify coupon dates using historical snapshots of manufacturer websites as well as press releases. Appendix Section A contains additional details on the coupon dataset. Appendix Section B.1 describes our process for harmonizing drug names across sites and over time, and Appendix Section B.2 provides additional details on the manual verification process. In general, we find that prior to these manual checks, the drug coupon database captures coupons with a median lag of 10 months.[11]

Pharmacy Benefits Manager Data We leverage a proprietary dataset from a large pharmacy benefits manager (PBM) for January 2014 through June 2017. The unit of observation is the NDC9-month-customer segment, where the customer segments are commercial insurance and Medicare Advantage plans. NDC9 codes are highly granular, 9-digit drug codes that identify the drug labeler (typically a manufacturer) and product (a unique combination of strength, dose, and formulation). The data include a field for the common name of the drug, which differs for branded and generic manufacturers of the same molecule, e.g. Lipitor is the branded version of atorvastatin. For each

[10] Historical snapshots of both sites were scraped from https://web.archive.org/

[11] We do not assemble data on when/whether coupons are withdrawn. Our understanding is that coupon withdrawal for branded drugs is rare, although it may occur particularly when a drug manufacturer is seeking to shift users of one formulation toward another. Unfortunately, identifying coupon removal is very difficult. We revisit this issue in our analysis of multiple sclerosis drug utilization (see Appendix 4.1).

observation, the data include the average net-of-rebate price per day supplied, total days supplied, total out-of-pocket spending, an indicator for whether the drug is a generic, and the major condition treated (out of 101 categories constructed by the PBM). Rebates negotiated by PBMs are closely-held, hence the data source masked the actual net-of-rebate prices. The masking obscures price levels but allows us to study relative prices and price growth over time.

The price data are highly unique as they reflect net-of-rebate prices, whereas most pharmaceutical research has relied on list prices, wholesale acquisition cost (WAC), or allowed amounts from claims data. Recent exceptions are Sood et al. (2020) and Kakani et al. (2020), who make use of rebates for a subset of drugs estimated by a private company, SSR Health. Kakani et al. (2020) estimate that average rebates increased from 32 to 48 percent of list prices between 2012 and 2017, although they exclude many products owing to limitations in the SSR Health data. Notably, their analysis excludes injectable drugs, which account for the majority of MS DMTs we study in our structural analysis. The authors generously provided us with their estimated rebates for MS drugs, however, which decline from a share-weighted average of 24% in 2012 to a low of 7% in 2014 before rising again to 18% in 2017. We make use of these estimates in our stylized model in Section 3.

Additional Data We obtained data on drug approval dates and active pharmaceutical ingredients from FDA databases, for the time period 1939 through October 2018. The unit of observation is the NDC9, which enables us to merge these data directly to the PBM data. Below, we describe how we use the two data sources to identify (1) which drugs are generic and (2) which drugs have generics. Additional details on the FDA data are in Appendix B.3.

2.2 Sample Construction and Descriptive Statistics

To construct our estimation sample, we begin by merging together the PBM and FDA data using the NDC9 codes in both, and dropping observations lacking an FDA match.[12] The combined data account for more than 97 percent of total PBM spending in each segment; unmatched items include medical supplies, vaccinations, and other miscellaneous items billed to the PBM but not listed in the FDA data. Details are

[12] We applied an additional filter for branded drugs, dropping the NDC9s that correspond to a given brand if at least half of the PBM spending for that brand occurs in NDC9s that do not have a direct match in the FDA data. See Appendix for details.

available in Appendix Figure B1.

We use the combined data to construct two key indicator variables. The indicator *is generic* takes a value of 1 if a drug was approved through an Abbreviated New Drug Application (ANDA) or is designated as a generic in the PBM data.[13] For branded drugs (i.e., drugs not defined as generic), we construct the indicator *has generic*, which takes a value of 1 if a bioequivalent generic is available for that drug at any point during the study period, i.e. by June 2017. We define a bioequivalent generic as an NDC9 code with *is generic* = 1 and the same active ingredient list, dosage form, dosage strength, route of administration, and extended-release status as its branded counterpart.

We collapse the resulting data to the drug-month-segment level, where drug is defined by the common name included in the PBM data.[14] Using fuzzy text matching techniques supplemented by manual checks, we merge in the coupon data, creating an indicator for "coupon" that takes a value of 1 beginning in the relevant drug-month in which it is first observed.[15] Only branded drugs are observed to have coupons.

The merged PBM-FDA-coupon dataset contains 1,854 unique drugs. About half of the drugs (906) are branded. Of all spending in the original PBM dataset (and matched to FDA codes), total spending on these branded drugs accounts for 65 and 66 percent of commercial and Medicare Advantage spending, respectively. These figures are net of rebate, hence the share of spending on branded drugs is lower than that reported elsewhere using gross spending data. For example, the Health Care Cost Institute reports that in 2017, spending on brands for the under-65 employer-insured population was nearly 76 percent; however they note this figure is gross of any rebates.[16]

In Figure 1, we plot the share of monthly branded spending accounted for by couponed drugs, separately by segment. Because Medicare enrollees are not permitted to redeem coupons, and therefore manufacturers should be less likely to release coupons for drugs primarily targeting Medicare enrollees, we expect to see somewhat lower shares for the Medicare population.[17] The data reveal this to be the case, although the difference between the two data series narrows substantially by the end of the

[13] One reason these definitions are not equivalent is that so-called "authorized generics" are unbranded but manufactured under NDAs.

[14] Price is constructed as the cost per day supplied by dividing the total cost by the total number of days supplied.

[15] Drugs that do not merge to an observation in the coupon data are assigned a 0 for coupon status throughout the study period.

[16] *2017 Health Care Cost and Utilization Report*, Health Care Cost Institute, 2019.

[17] The expectation of different couponed shares assumes (1) different utilization levels across the two segments; and (2) non-trivial cost of introducing a coupon program.

study period, when coupons are virtually ubiquitous for branded drug spending in both segments (94 percent of commercial, and 92 percent of Medicare).

Figure 1 also includes a time series labeled "Medicare Part D," obtained by combining our coupon data with annual Medicare Part D spending by drug, limited to the same set of drugs present in our merged PBM-FDA data. For this time series, we use coupon status as of June in the relevant year. The additional time series shows that the share of Part D spending potentially impacted by coupons is similar to that observed for the Medicare segment of our PBM data, suggesting the PBM data are likely to be representative of Medicare spending.[18]

[Figure 1 Here]

The sharp increases in the couponed share of spending in late 2014 for both the commercial and Medicare segments can mostly be accounted for by the new introduction of a coupon for Revlimid, a cancer drug with high spending, the approval of Harvoni for hepatitis C[19] and large spending increases for Levemir (a couponed insulin). The subsequent decline in couponed spending share that occurs only in the commercial segment in early 2015 is driven by a concurrent decrease in the spending share of Harvoni and an increase in the spending share of Viekira, a non-couponed alternative.

Our empirical analysis explores the impact of coupons on single-source drugs, so we eliminate branded drugs with generics at any point in the study period, which leaves 589 branded drugs but retains the vast majority of spending: net-of-rebate spending for single-source drugs accounts for 86 percent of branded spending in the commercial population and 83 percent in the Medicare population. Next, we exclude drugs without utilization in both populations, or which have very different utilization levels in the commercial and Medicare populations (e.g., drugs for attention deficit hyperactivity disorder). Including these drugs may result in a violation of the parallel trends assumption for commercial and Medicare populations absent coupons. Further details, and a summary of the impact of all sample restrictions on the share of PBM spending included in the estimation sample, are provided in Appendix B.4.

[18] While the time series plotted using our data reflect net-of-rebate spending shares, the time series plotted using Part D drug spending is not net of rebates. Nevertheless, the trends illustrate the similarity in the relative utilization of couponed drugs included in our Medicare Advantage data and in Medicare Part D.

[19] Like many drugs, Harvoni's coupon coincided with its introduction.

After applying the utilization restrictions, there are 366 drugs remaining. Of these, 263 are always observed to have a coupon during the study period ("always-couponed"), 35 are not couponed at any point in the study period ("never-couponed"), and 68 introduce a coupon during the study period ("switchers"). Table 1 contains summary statistics for these drugs, separately by coupon status. The top panel contains aggregate statistics for each category of drugs, including the distribution of total spending across the three coupon categories. Always-couponed drugs account for around 80 percent of spending in both the commercial and Medicare Advantage segments in this sample. Drugs with new coupon introductions during the study period account for 9-10 percent of spending in each segment, while never-couponed drugs account for less than 2 percent of spending. The major condition treated by switchers is cancer.

The second panel of Table 1 presents drug-level statistics. The average annual list price (obtained from the first year a drug is observed in the Medicare Part D data) is highest for switchers and lowest for never-couponed drugs.[20] The average compound annual growth rate (CAGR) in price is fairly similar across all three groups. There is wide variation in the volume of drug utilization across categories, as well as in utilization growth. Average monthly days supplied per always-couponed drug is around 66,000 as compared to 16,000 per switcher and 8,700 per never-couponed drug. The CAGR for days supplied is largest among switchers, at 101 percent (as compared to 29 percent for always-couponed and 14 percent for never-couponed drugs, on average).

Table 1 also lists the leading medical conditions for drugs included in each category. Diabetes drugs appear frequently in all three groups. HIV drugs, which have very high prices, are common in the "always couponed" group. Taken together, these summary statistics suggests that always-couponed or never-couponed drugs are not ideal control groups for switchers. Hence, our analysis and identification strategy focuses on switchers only.

[Table 1 Here]

2.3 Empirical Specifications

To assess the impact of coupon introduction on net-of-rebate prices and quantities, we pursue a difference-in-differences approach, comparing the change in outcomes before

[20] As previously noted, the PBM data include only a normalized price measure, and the normalization differs by segment, so price levels from the PBM data are uninformative. For this reason we rely on list prices from Medicare Part D for these general summary statistics. The analyses below use net-of-rebate prices from the PBM data.

vs. after coupon introduction for the treatment group (the commercial segment) with that of the control group (the Medicare segment). The key identifying assumption is that the trends in outcomes absent the coupon would have been similar in the two groups. The ability to include drug-specific control groups (rather than to rely on a simple pre vs. post comparison for the treatment group) is particularly valuable given that coupons may not be exogenously introduced, and may in fact be introduced when current or future price or quantity growth is expected to decline.[21] As long as any omitted factors impacting utilization or price have a common proportional effect on commercial and Medicare enrollees, the differences-in-differences estimate will capture the short-term effect of coupons. We expect the estimates to be conservative, however, as Medicare enrollees may utilize patient assistance programs, which cover cost-sharing for all drugs used to treat eligible conditions, in lieu of coupons, and such programs may be contemporaneously introduced or expanded for the same reasons underlying a coupon introduction. Moreover, price effects may not be captured by this identification strategy if list prices are jointly determined for both market segments.

We estimate the following specification using observations at the drug-month-segment level:

$$\begin{aligned} Y_{jkt} = & \sum_{q \in \{-3,3\} \setminus -1} \gamma_q \mathbf{1}(quarter = q) \cdot \mathbf{1}(commercial)_k \\ & + \sum_{q \in \{-3,3\} \setminus -1} \eta_q \mathbf{1}(quarter = q) + \alpha_{jk} + \delta_t + \varepsilon_{jtk} \end{aligned} \tag{1}$$

where Y_{jtk} is either log quantity (defined as the number of days supplied) or log net-of-rebate price for drug j in period t and segment k. The data are monthly, with t reflecting each month from January 2014 through June 2017. The variable *quarter* denotes the number of quarters before or after coupon introduction, with $quarter = 0$ for the first 3 months a coupon exists for drug j. γ_q are the coefficients of interest: they capture the difference in outcomes in the commercial segment relative to

[21] The recent literature on difference-in-differences and event study estimation highlights potential problems that may arise if treatment effects are heterogeneous (Borusyak et al., 2021; Sun and Abraham, 2021; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020). With staggered treatment introductions, control groups may contain a mix of pre- and post-treatment periods of other treated units, and treatment effects for certain units may receive negative weight. Our setting avoids these issues by including a natural *drug-specific* control group: each drug's Medicare outcomes. Our estimator can thus be interpreted as recovering an average of these drug-specific commercial vs. Medicare differences.

Medicare before and after coupon introduction. The η_q coefficients capture common changes in Y_{jtk} leading up to, and following coupon introductions. (We use quarters rather than months to gain precision in our estimates of interest, and because there is some uncertainty around the exact timing of coupon introduction.) The α_{jk} and δ_t coefficients denote drug-segment and year-month fixed effects. The former control for time-invariant differences within drugs across segments, and the latter allow us to control more flexibly for trends in outcomes. The results are very similar if we include year and month fixed effects in place of year-month fixed effects, or if we include a higher-order set of interactions: drug-year-month fixed effects. For parsimony, we present specification with year-month effects. We cluster standard errors at the drug level.

The estimation sample includes drugs denoted as "switchers" in Table 1 above, restricted to those observed at least 9 months before and after the quarter of coupon introduction. The panel is balanced so each drug is included for 21 months in total, although the calendar months vary across drugs. Descriptive statistics for this sample are included in Column 4 of Table 1.

2.4 Results

Table 2 presents the coefficients of interest from estimating equation (1) on the balanced switchers sample, using either logged quantity (Columns 1-2) or logged price (Columns 3-4) as the dependent variable. We estimate equation (1) by unweighted and weighted OLS, weighting each observation by the share of within-segment spending accounted for by the relevant drug in the 6 months prior to coupon introduction.[22] The weighted specifications (Columns 2 and 4) may better represent the average impact of coupons on spending, as coupon effects for drugs that account for a larger share of total spending receive more weight.

Figure 2 plots the corresponding estimated coefficients from the unweighted and weighted models, with results for quantity in the top panel and price in the bottom panel. The figure plots the point estimates and 95% confidence intervals for the quarterly interaction terms with the commercial segment indicator (i.e., $\hat{\gamma}_q$) in equation 1 above). The figures confirm that for 3 of the four specifications, there is no differential trend in quantity or price for commercial relative to Medicare enrollees in the quarters

[22] The masking procedure applied by the PBM data source affects relative spending between segments. To account for this, we normalize the average weight across drugs to be the same for Medicare and commercial segments.

prior to coupon introduction. However, there is a modest increase in relative price for commercial enrollees (2 percent) in the 3 quarters preceding coupon introduction in the weighted model, suggesting for this outcome the parallel trends assumption may not be satisfied.

The quantity graphs show clear and large increases in quantity beginning in the second quarter after coupon introduction (i.e., months 4-6 after the month of introduction). The magnitude of the quantity effect increases over time, perhaps due to coupon introductions that occur mid-year but primarily affect demand in the following year as deductibles and out-of-pocket maximums reset. Both the unweighted and weighted specifications imply increases in the relative quantity of couponed drugs used in the commercial segment of 21-23 percent by the third quarter after coupon introduction. The relative similarity of the results for weighted and unweighted models suggests similar responses across drugs with different revenue levels.

To determine whether this quantity effect is driven by increases in commercial utilization, decreases in Medicare utilization, or both, we estimate specifications that include separate quarter interactions for each segment. This illuminates absolute changes in segment-specific quantity for newly couponed drugs. The results show that demand for newly couponed drugs is increasing in both segments prior to coupon introduction, but post-introduction demand surges upward only for the commercially insured population (see Appendix C.1 for more details).

[Table 2 Here]
[Figure 2 Here]

In contrast, the price specifications do not show post-coupon increases in net-of-rebate prices for drugs supplied to the commercial versus the Medicare population. The lack of a price response may be due to the fact that list prices are common to all segments, so that changes in price for a specific segment would require changes in segment-specific rebate arrangements with the PBM. While the source of PBM data reports that segment-specific rebates do occur, so that manufacturers could attempt to negotiate lower rebates for the commercial sector after introducing a coupon–or propose smaller increases in rebates for the commercial sector as compared to the Medicare sector–we do not find evidence of such renegotiations within the 12 months following a coupon introduction.

2.5 Robustness and Extensions

As a robustness check, we re-estimate both the weighted and unweighted regressions for quantity responses, dropping drugs from our sample one at a time, and pooling the post-coupon period into a single indicator variable. The pooled quantity effect for the full 33-drug sample is 16.6% for the unweighted specification and 17.7% for the weighted specification.[23] The unweighted estimates obtained when dropping one drug at a time all lie between 14.8% and 18.7% with similar standard errors. With the exception of dropping Revlimid (an oral chemotherapy approved to treat various blood cancers), the weighted estimates all lie between 15.2% and 18.9%. Dropping Revlimid, a high-revenue coupon-switcher drug, leads to a slightly smaller weighted estimate of 14.3%.

We also estimated models that attempted to discern whether the coupon-induced utilization growth arises primarily from market expansion or from "business stealing" by newly couponed drugs. However, due to significant difficulties in identifying therapeutic substitutes for all 33 index drugs, as well as the fact that many couponed drugs accounted for a very small share of their respective drug markets (as defined using drug-level data), the effort was not fruitful. See Appendix C.2 for details.

In sum, the reduced-form analysis of coupon introductions suggests that coupons can induce a significant increase in the volume of prescription drugs sold, consistent with studies showing a high elasticity of consumer demand for prescription drugs with respect to out-of-pocket cost-sharing. The analysis does not find that coupons are associated with relative price changes; however, list prices do not vary across segments and rebates (which *can* differ across segments) may take more time to adjust than we observe in our one-year post-coupon study period. In the next section, we estimate a model of demand and parameterize a stylized model of supply that enables us to quantify the extent to which the optimal pooled price is likely to change (for the drugs in question) in the presence of coupons.

3 Model for Estimation

In this section, we present a framework for drug demand and manufacturer-insurer bargaining that accounts for the existence of coupons. We apply this framework to the

[23] While the specification with a pooled post-period is convenient for performing robustness checks, our preferred specification is equation (1), which disagreggates the post period into quarters. Coupon effects are likely to build over time, at least within the year after introduction.

market for multiple sclerosis drugs, and estimate the model using claims data for both commercially insured and Medicare Advantage enrollees included in the Health Care Cost Institute (HCCI) dataset.

We assume that, prior to the stages we model, insurers set coinsurance and copays, consumers decide which insurance plans to purchase, and drug manufacturers make decisions about whether to offer coupons. Insurers are responsible both for non-drug benefits and for drug benefits, which may be outsourced to a PBM. We assume that all coupons fully offset consumer cost-sharing. Because we do not observe plan formularies, we assume that no drugs are excluded from any formulary in equilibrium; however, the threat of exclusion impacts negotiated prices. Taking these attributes as pre-determined, a model of price-setting and demand in this market has the following stages:

1. Drug manufacturers choose list prices and negotiate rebates with insurers
2. Insurers set premiums for the following year
3. Consumers choose a drug from the set of options available for their diagnosis. A subset of consumers redeem a coupon for their purchase.

We allow coupons to increase demand in two ways. First, they directly reduce the out-of-pocket prices of patients who use them. Second, coupons may have an advertising effect on all individuals, regardless of whether they actually redeem a coupon.[24] In particular, physicians may be aware that a drug is couponed - as sales representatives typically advise them of this fact and may share coupon cards to distribute - and the knowledge that a drug can be obtained at a low out-of-pocket cost may increase the likelihood that a physician prescribes it and therefore gains experience with the drug. This increased propensity to prescribe couponed drugs may therefore impact all of the physician's patients, even those who do not ultimately use coupons. Both demand effects are likely to exert upward pressure on drug prices and premiums.[25] However, there are offsetting effects, largely due to the impact of negotiations with insurers,

[24] Our empirical analysis allows for the advertising effect of coupons to differ across Medicare and commercial enrollees. The effect for Medicare enrollees is captured through the coupon indicator, which applies to both market segments and also addresses the potential endogeneity of coupon introduction, which may occur in response to demand shocks. Our focus in the model is on the incremental advertising effect for commercial enrollees.

[25] It is possible that, by attracting new consumers through the advertising effect, coupons could increase the price elasticity of the marginal consumer and hence reduce the optimal markup. This seems unlikely, particularly in our setting where all diagnosed patients are assumed to take a drug.

that make both the magnitude and the direction of the overall price effect of coupons theoretically ambiguous. [26]

Our model is designed to tease out these effects and allow us to quantify the impact of coupons on prices and spending in equilibrium. The model relies on a number of simplifying assumptions necessitated by data constraints. First, we assume that consumer selection into plans takes place in an initial step before our model begins: that is, consumers do not switch plans based on changes in out-of-pocket drug prices or the impact of drug price changes on premiums.[27] Second, we assume insurance plan markups and non-pharmaceutical costs are invariant to the introduction of coupons. Third, we combine the setting of list prices and negotiation over rebates into a single step in which the insurer and manufacturer negotiate over net-of-rebate price.

In the following subsections, we work through the stages of the model in reverse order, introducing our assumptions and explaining how we bring each stage to the data. We begin with a model of drug demand (Stage 3), then specify how insurers set premiums (Stage 2), and finally show how net-of-rebate prices are determined in a model of insurer-manufacturer negotiations (Stage 1). We use the resulting model to clarify the mechanisms through which coupons affect prices. Then we combine our demand estimates with the pricing model to conduct counterfactual simulations that show how prices change when coupons are banned. We present our demand estimates in Section 4 and simulation results in Section 5.

3.1 Drug Demand

We model each consumer's choice of drug as a discrete choice among options available to treat a particular condition. This choice varies based on individual characteristics, including the individual's insurance segment (i.e., commercial or Medicare Advantage). Medicare enrollees are prohibited from utilizing coupons, however as previously noted we allow for the possibility that their choices are affected by an "advertising effect" of

[26] Corts (1998) shows that, even without price bargaining, coupons may generate either lower or higher list prices because they allow firms to price discriminate, sorting customers into multiple groups, only some of which use coupons. If consumer preferences across firms are not symmetric then coupons can generate reduced list prices for some firms.

[27] This assumption is plausible for enrollees in employer-sponsored health insurance, as employers typically offer a limited selection of plans. Even when multiple plans are offered, they often utilize the same PBM and hence the same drug benefit design (i.e., set of drugs that are covered and copay tier associated with each), so that their enrollees effectively have a single option for drug insurance. For Medicare enrollees, plan switching is uncommon: a prior literature argues that enrollees rarely switch between Part D plans, in part because of inattention regarding changes in plan coverage and premiums. See, for example, Ho et al. (2017).

coupons. The utility of a Medicare Advantage enrollee i choosing drug j in year t can be written:

$$u_{ijt}^{MA} = \delta_{jt} + \gamma \text{coupon}_{jt} + \alpha p_{ijt}^{OOP} + X_{ijt}'\beta + \varepsilon_{ijt} \tag{2}$$

where drug-year fixed effects δ_{jt} allow the mean utility of each drug to vary flexibly over time. The indicator $coupon_{jt}$ equals 1 when a coupon is in place for a particular drug; γ measures the change in utility upon coupon introduction for Medicare Advantage enrollees. It combines the effect of any within-year demand shocks that coincide with coupon introduction[28] with potential advertising effects of coupons for these enrollees. It is common for all couponed drugs and time periods. Out-of-pocket prices p_{ijt}^{OOP} depend on consumers' coinsurance rates or copay amounts. The variables X_{ijt} denote drug time-since-approval bins and their interactions with gender, which capture the ramp-up of each drug's sales in the months after its introduction.[29] The error term ε_{ijt} is distributed Type 1 extreme value.

We assume that there are two types of commercially insured consumers. With probability λ a particular consumer will redeem coupons for drug purchases and face no cost-sharing, while with probability $1-\lambda$ she does not use them. All commercially-insured consumers are affected by coupons' commercial advertising effect, which might be different from the effect for Medicare Advantage enrollees.[30] The utility specification for commercially insured consumer i who chooses drug j in year t is therefore

$$u_{ijt}^{com} = \begin{cases} u_{ijt}^{c} = \delta_j^{com} + \delta_{jt} + (\gamma + \gamma^{com})\text{coupon}_{jt} + X_{ijt}'\beta + \varepsilon_{ijt} & \text{with proba. } \lambda \\ u_{ijt}^{nc} = \delta_j^{com} + \delta_{jt} + (\alpha + \alpha^{com})p_{ijt}^{OOP} + (\gamma + \gamma^{com})\text{coupon}_{jt} + X_{ijt}'\beta + \varepsilon_{ijt} & \text{with proba. } 1-\lambda \end{cases} \tag{3}$$

where δ_j^{com} allows the mean utility of each drug to vary by segment; this captures any fixed differences in drug preferences between segments. The parameters γ^{com} and α^{com} allow the coupon advertising effect and the effect of price to differ between commercial

[28] While the reduced form analysis suggests that coupons are not, on average, introduced to coincide with negative demand shocks, we still allow for the possibility in this particular sample of drugs.

[29] We define drug age as the time since FDA approval. To capture the non-linear increase in adoption of a drug over time, we specify the time since FDA approval using indicators for under 6 months (omitted category), 6-12 months, 1-2 years, 2-3 years, 3-5 years, and 5+ years. We find adoption trends vary by gender, hence we include gender interactions. The results are insensitive to the inclusion of these terms.

[30] We also test alternative specifications where the commercial advertising effect is larger for coupon users, which may reflect the scenario where the advertising effect and coupon usage are both linked to knowledge of a coupon's existence. See section 5.3 for details.

and Medicare Advantage enrollees.

In practice, since we do not observe coupon usage at the individual or drug level, we fix $\lambda = 0.75$ based on estimates of coupon utilization for MS drugs reported in Starner et al. (2014) and estimate the remaining parameters of equations (2) and (3) jointly by maximum likelihood. Appendix Section D.1 provides additional details, including the likelihood function. In Section 5.3 we discuss alternative assumptions for λ, including allowing it to vary depending on the magnitude of the patient's cost-sharing. We assume that every diagnosed consumer chooses a drug, i.e., there is no outside option in this specification. This assumption is necessary because we do not reliably observe patients with MS who never take a drug, as an MS diagnosis without an associated medication claim may not appear in our claims data. Moreover, we do not observe the timing of individuals' decisions to forgo any MS drug. Thus, our analysis does not allow for market expansion effects of coupons.

3.2 Insurance Premiums

The average premium for a plan in segment k and period t is the marginal cost per enrollee plus a markup:

$$\text{Premium}_{kt} = \frac{1}{N_{kt}^I} \sum_{i \in I_{kt}} \left[\mu_{ikt} + \omega_{ikt} + \sum_{j \in J_t} s_{ijkt} \left[p_{jt} - p_{ijkt}^{OOP} \right] \right] \tag{4}$$

where $N_{k,t}^I$ is the total number of enrollees in segment k and year t and $I_{k,t}$ is that set of enrollees, μ_{ikt} is the markup for consumer i (measured in dollars) which might vary across consumers and across plans, ω_{ikt} is the insurance plan's non-drug cost of enrolling that consumer, s_{ijkt} is the probability that patient i chooses drug j (determined by the demand model outlined above), and p_{jt} is the negotiated net-of-rebate price for drug j.

A full premium-setting model would require a framework of consumer plan choice as an input into insurers' choice of profit-maximizing premiums. We simplify by assuming that the insurer markup and non-pharmaceutical costs in the premium expression are determined by broader factors outside the pharmaceutical market; they are unaffected by the introduction of coupons and can be held fixed in our simulations. We normalize them to zero and consider the component of premiums that covers the insurer's drug costs.

3.3 Drug Pricing

A full model of drug pricing would distinguish between two components: list prices—which manufacturers set—and rebates, which manufacturers negotiate with insurers and which may depend on the formulary placement of each drug relative to its substitutes. The manufacturer's payment (the net-of-rebate price) is the list price after applying the negotiated rebate rate. Because we lack insurer identifiers and information on each drug's formulary placement, we do not develop and estimate such a model.

Instead, we use a simpler framework that focuses attention on the impact of coupons on net-of-rebate prices without requiring the additional assumptions or data that would be needed for a fully-specified model. We collapse the problem into a single dimension by assuming that drug manufacturers and insurers engage in Nash-in-Nash bargaining over net-of-rebate prices.[31] This allows us to focus on the pricing incentives due to coupons' effects on manufacturer revenues and insurer costs, which (as shown in the equations below) are functions of this net-of-rebate price. The impact of coupons on net-of-rebate prices that is predicted by our model reflects both list price effects (e.g. due to the reduction in out-of-pocket prices for consumers redeeming coupons) and effects on the insurer's ability to steer consumers to lower-priced drugs, which might operate via rebates and drug tiering. To compute consumer out-of-pocket prices, we need to recover the list price separately from the net-of-rebate price. We do so by applying a rebate percentage that is informed by external data. In our counterfactual simulations, we explore robustness to different rebate percentages and alternative assumptions over whether and how much rebates adjust when coupons are removed.

Our approach has the additional advantage that the bargaining framework is a simple way to account for sources of insurer leverage that would be difficult to capture in the more fully-specified model. These include the insurer's ability to require prior authorization, increase hassle costs, and/or alter copay and coinsurance parameters in response to very high list prices.[32]

[31] One could alternatively model price-setting using a Nash Bertrand pricing assumption, where manufacturers choose prices to maximize profits given the estimated demand model. This approach leads to implausibly high prices, as manufacturers are able to charge very high markups in the face of inelastic demand.

[32] Note that this last channel is also impacted by coupons: insurer responses that threaten to increase cost sharing are weakened by the existence of coupons. Because we do not include this insurer response in our model, our simulations may understate the impacts of coupons.

Consumer Cost-Sharing Insurer cost-sharing requirements are an important input into the pricing equilibrium: consumer price sensitivity constrains equilibrium prices only if consumers pay some portion of the price. Cost-sharing in our setting takes the form of a percentage coinsurance rate or a fixed copay. If the consumer pays a coinsurance rate ρ_i, she pays a fixed percentage of the list price, so the out-of-pocket price is $p_{ijkt}^{OOP} = \rho_i p_{jt}/(1 - r_{jt})$ where p_{jt} is the net-of-rebate price and r_{jt} is the rebate percentage. Other consumers pay a fixed copay, which we assume is invariant to changes in list prices. As previously noted, we assume that consumers who use coupons have zero out-of-pocket costs. Details on how we construct out-of-pocket prices from our data are provided in Appendix Section B.6.

The impact of a change in the net-of-rebate price on the out-of-pocket price paid by the consumer, $\frac{\partial p_{ijt}^{OOP}}{\partial p_{jt}}$ is therefore given by:

$$\frac{\partial p_{ijkt}^{OOP}}{\partial p_{jt}} = \begin{cases} \rho_i/(1 - r_{jt}) & \text{if } i\text{'s plan uses coinsurance rate } \rho_i, \text{ no coupon} \\ 0 & \text{if } j \text{ has a coupon and } i \text{ uses coupons} \\ 0 & \text{if } i\text{'s plan uses copays.} \end{cases} \tag{5}$$

Only the minority of enrollees who face a coinsurance rate actually pay a portion of the negotiated price. Coupon introduction reduces this proportion of enrollees still further, leading to upward pressure on prices.

Manufacturer-Insurer Price Negotiations We assume that the net-of-rebate price of every drug, p_{jt}, is determined via simultaneous bilateral Nash bargaining between the manufacturer and insurer. Given our limited data, we simplify by assuming that a single insurer covers the entire market through an array of plans, and that all branded MS drugs are included on its formulary in equilibrium. A single price for a particular drug applies jointly to both commercial and Medicare Advantage markets.

We make the common simplifying assumption (e.g., Capps et al. (2003), Gowrisankaran et al. (2015)) that our single insurer maximizes consumer surplus (net of consumer cost-sharing for drugs) less total pharmaceutical costs. The insurer's objective function is then:

$$V(J_t, p_t) = CS(J_t, p_t) - TC(J_t, p_t) \tag{6}$$

where J_t is the complete set of MS drugs available to enrollees from all manufacturers

at time t, p_t is the vector of their net-of-rebate prices, $CS(\cdot)$ denotes consumer surplus and $TC(\cdot)$ denotes total drug costs.[33] Both consumer surplus and total costs depend critically on the predicted drug choices of both commercial and Medicare Advantage enrollees as a function of prices and coupon availability, obtained from the demand model. Details are provided in Appendix Section D.2.

The manufacturer's objective function is its profit:

$$\pi_{j,t}(p_{j,t}) = \sum_{k} \sum_{i \in I_{k,t}} s_{ijkt}\big(p_{jt} - c_{jt}\big) - \lambda coupon_{j,t} \sum_{i \in I_{com,t}} s^{c}_{ijt} p^{OOP}_{ijt} \tag{7}$$

where $I_{k,t}$ denotes the enrolled population for segment k in period t, c_{jt} is the manufacturer's marginal production cost for drug j in period t, and the last term reflects the additional cost to the manufacturer (of a couponed drug) from paying the out-of-pocket costs of commercially insured individuals who redeem coupons.

The negotiated price for product j maximizes the Nash product:

$$p_{j,t} = \arg\max_{p} \big(\pi_{j,t}(p)\big)^{\eta} \big(V(J_t, p) - V(J_t \setminus j, p)\big)^{1-\eta} \tag{8}$$

where η is the Nash bargaining parameter (assumed constant across all manufacturers).

Predicted price without coupons. Consider first the case where no coupons are offered. Taking logs and setting the first order condition to zero yields:

$$p^{nocoupon}_{jt} = c_{jt} + \frac{\bar{s}_{jt}}{-\Big(\big[\frac{1-\eta}{\eta}\big]\frac{V'(J_t,p_t)}{\Delta V(J_t,p_t)}\bar{s}_{jt} + \frac{\partial \bar{s}_{jt}}{\partial p_{jt}}\Big)} \tag{9}$$

where $V'(J_t, p_t) = \frac{\partial V(J_t,p_t)}{\partial p_{jt}}$, $\Delta V(J_t, p_t) = V(J_t, p_t) - V(J_t \setminus j, p_t)$, and $\bar{s}_{jt}$ indicates a weighted sum of s_{ijt} across Medicare Advantage and commercially insured enrollees.[34]

The model nests the Nash Bertrand model of manufacturers setting prices (the case with $\eta = 1$). The solution differs from Nash Bertrand only through the denominator of the second (markup) term, which now accounts for the insurer's gains from trade as well as those of the manufacturer. While the impact of a change in price on consumer

[33] Our measure of consumer surplus accounts for consumer out-of-pocket payments but does not include premiums paid. We account for the disutility from high premiums by including insurer total costs in the objective function.

[34] That is: $\bar{s}_{jt} \equiv \sum_{i \in \bar{I}_{MA,t}} s^{MA}_{ijt} + \sum_{i \in \bar{I}_{com,t}} (\lambda s^{c}_{ijt} + (1-\lambda) s^{nc}_{ijt})$ and $\frac{d\bar{s}_{lt}}{dp_{jt}} \equiv \sum_{i \in \bar{I}_{MA,t}} \frac{\partial s^{MA}_{ilt}}{\partial p_{jt}} + (1-\lambda) \sum_{i \in \bar{I}_{com,t}} \frac{\partial s^{nc}_{ilt}}{\partial p_{jt}} + \lambda(1 - coupon_{jt}) \sum_{i \in I_{com,t}} \frac{\partial s^{c}_{ilt}}{\partial p_{jt}}$.

out-of-pocket prices—and hence consumer choices—may be small, the insurer's costs increase almost one-for-one with prices. This is reflected in the much lower equilibrium markups under this model than under Nash Bertrand. The term $\Delta V(J_t, p_t)$ is an important input into prices: it is the change in consumer surplus when drug j is added, less the change in insurer costs. It measures the net gain to the insurer from including the drug in its formulary: all else equal, the higher this term, the higher the price.

Unpacking the markup term further, we see that three bargaining-related factors have important effects on price. First, if the drug is particularly attractive to consumers, $\Delta CS(J_t, p_t)$ will be high, implying a sizeable loss to the insurer from excluding the drug and a relatively high price. Second, if excluding a drug prompts enrollees to substitute to more expensive alternatives, then $\Delta TC(J_t, p_t)$ will be negative, and the equilibrium price will be higher. This "reinforcement effect" implies that the prices of substitute drugs tend to move together in equilibrium; see Ho and Lee (2017). Finally, there is an effect due to coinsurance. As in Gowrisankaran et al. (2015), insurers can use coinsurance rates to steer consumers to low-priced products; this may reduce the downwards pressure placed on prices by the insurer, particularly for relatively costly drugs.

Prices when coupons are offered. The first order condition defining the net-of-rebate price is different when coupons are offered:

$$p_{jt}^{coupon} = c_{jt} + w(.)\lambda coupon_{j,t} \sum_{i \in I_{com,t}} s_{ijt}^{c} p_{ijt}^{OOP} + \frac{\bar{s}_{jt} - \lambda coupon_{j,t} \sum_{i \in I_{com,t}} s_{ijt}^{c} \frac{\partial p_{ijt}^{OOP}}{\partial p_{jt}}}{-\left(\left[\frac{1-\eta}{\eta}\right] \frac{V'(J_t,p)}{\Delta V(J_t,p_{j,t})} \bar{s}_{jt} + \frac{\partial \bar{s}_{jt}}{\partial p_{jt}}\right)} \quad (10)$$

Comparing the two equations allows us to unpack the predicted change in price in response to coupon introduction. There are two new terms that reflect the manufacturer's cost of offering a coupon. First, a portion of this cost is passed through to prices (the second term of the equation): the fraction passed through, denoted $w(.)$, is a function of model primitives including the Nash bargaining weights.[35] Second, the manufacturer now accounts for the fact that an increase in list price generates an increased out-of-pocket price for consumers whose plans charge a coinsurance rate, inflating the manufacturer's own costs when consumers redeem coupons. This is the

[35] The weight is defined as: $w(.) \equiv 1/[\bar{s}_{jt} + \frac{\eta}{1-\eta} \frac{\Delta V(J_t,p_{j,t})}{V'(J_t,p)} \frac{\partial \bar{s}_{jt}}{\partial p_{jt}}]$.

second part of the numerator in the markup term; it exerts a new downward pressure on price.

Now consider the elements of the markup that are common to the two equations. They are functions of variables that change in response to coupon introduction. First, coupon availability increases the product's market share $\bar{s}_{jt}$ and reduces $\frac{\partial \bar{s}_{jt}}{\partial p_{jt}}$. These two effects have a positive impact on manufacturer markups and they may dominate the others: the larger the consumer response to the coupon, the larger the price increase. The first term in the markup denominator will also change. ΔCS increases for the newly-couponed drug, generating a further upwards pressure on price. Offsetting this, coupons reduce the effectiveness of steering through coinsurance, implying a greater cost to the insurer of offering relatively high-priced drugs and generating increased downwards pressure on price. Finally, the change in the reinforcement effect, operating through ΔTC, is difficult to sign because it is affected by changes in demand in response to coupons and is also a function of the equilibrium prices of all drugs.

Overall, the net effect of coupons on negotiated prices is an empirical question. As detailed in Section 5, our simulations predict that a coupon ban would reduce the prices of all drugs.

4 Demand Estimation

4.1 Claims Data

We use claims data from the Health Care Cost Institute (HCCI) to derive individual-level drug choices from 2009 through 2017. We focus on the market for multiple sclerosis (MS) drugs. In particular, we restrict to choices over disease-modifying therapies (DMTs), believed by experts to be the best strategy currently available for slowing the natural progression of MS.[36] We focus on this set of drugs because the choice set is well-defined, there is a good deal of coupon variation, and there are no generic versions of most of these drugs during our sample period.[37] Generic drugs can have significant

[36] *Disease-Modifying Therapies for MS*, National Multiple Sclerosis Society, 2020. http://www.nationalmssociety.org/NationalMSSociety/media/MSNationalFiles/Brochures/Brochure-The-MS-Disease-Modifying-Medications.pdf

[37] Another benefit of studying MS drugs is that, unlike categories such as cancer drugs and antidepressants, they are not a "protected class" for Medicare Part D prescription drug plans. Medicare Advantage insurers are required to cover all drugs within a protected class; this would complicate our model of price negotiations because Medicare Advantage plans would not have the option of dropping a particular drug from the formulary. Further, DMTs for MS are costly specialty medications; the DMTs that we study account for 0.058% of all prescriptions but 4.6% of the total prescription

impacts on market shares and prices of therapeutic substitutes, so the limited role of generics in this segment during our study period helps us to isolate coupon effects.[38]

Over the course of our study period, eleven DMTs are offered.[39] Of these, six are introduced midway through the sample period (these are Aubagio, Copaxone 40mg, Glatopa, Plegridy, Tecfidera, and Gilenya). See Appendix Table B2 for more details on these drugs. All of these products are branded drugs without generic equivalents, except for Copaxone 20mg, for which a generic (Glatopa) was approved later in our sample.[40]

Two of the DMTs introduce a coupon during our sample period (Copaxone 20mg and Gilenya), five are never couponed during our sample period, and the remaining drugs are always observed with a coupon.[41] More modern drugs (approved after 2011) are almost invariably couponed at introduction. Older drugs (approved in the 1990s or early 2000s) tend to introduce coupons around 2010 or not at all. Copaxone 20mg and Gilenya are somewhat older drugs[42] that chose to introduce coupons.

Inferring Out-of-Pocket Prices The prices that enter our demand model are the out-of-pocket prices paid by patients, which are usually only a small fraction of list prices. These out-of-pocket prices are not directly observed in the claims data except for the enrollee's actual spending on their chosen drug. In addition, we lack fields containing information on plan copays and/or coinsurance rates, and plan identifiers are not included, so we cannot aggregate observations within a specific plan to infer the out-of-pocket price of other drugs in the enrollee's choice set. To address this issue, we impute cost-sharing using each patient's annual history of claims data for all drugs,

drug costs in the HCCI data. (These statistics exclude Tysabri, which is usually reimbursed via medical insurance, rather than prescription drug insurance.)

[38]The only generic drug in our sample is Glatopa, which is the generic version of Copaxone 20mg.

[39]These are Aubagio, Avonex, Betaseron, Copaxone 20mg, Copaxone 40mg, Gilenya, Glatopa, Plegridy, Rebif, Tecfidera, and Tysabri. Of these, Avonex, Plegridy, Rebif, Betaseron, and Tysabri are biologic drugs delivered via infusion (Tysabri) or injection (all others); Copaxone 20mg, Copaxone 40mg, and Glatopa are formulations of Glatiramer Acetate (a small-molecule drug delivered via injection); and Gilenya, Aubagio, and Tecfidera are small-molecule drugs delivered orally.

[40]Glatopa was introduced in April 16, 2015. Its list price is only around 20% percent lower than its branded reference product (Copaxone 20mg), whose price increased significantly after generic entry. Glatopa is only 5% cheaper than Copaxone 40mg during our study period, and its share is minimal (less than 1%).

[41]The never-couponed drugs are Avonex, Plegridy, Betaseron, Tysabri, and Glatopa. The always-couponed drugs are Aubagio, Copaxone 40mg, Rebif, Tecfidera.

[42]Copaxone was first approved by the FDA in January 1996, but Gilenya is a newer oral medication that was first approved in September 2010.

assigning the same fixed copays to all MS drugs when fixed copays are relevant, and applying the same coinsurance rate to the average allowed amount for each drug-year when an individual appears to face coinsurance.

A small fraction of individuals are classified to either pay no cost sharing (i.e., to have reached their out-of-pocket maxima) or full cost sharing (to have not yet hit their deductible). Approximately 76 percent of the commercially insured sample and 27 percent of the Medicare Advantage sample face fixed co-pays. Around 16 percent of the commercially insured and 68 percent of the Medicare Advantage sample have coinsurance when making their first MS drug purchase. See Appendix Section B.6 and Appendix Table B3 for further details.

[Table 3 Here]

Estimation Sample Our estimation sample consists of patients who have filled a prescription for any MS drug in our choice set. Because we observe that individuals' DMT choices are very persistent over time, we limit the data to choices that are likely to be active choices, defined as cases where we observe that a patient is enrolled in a plan for at least 180 days before filling their first multiple sclerosis prescription. Limiting the sample to these "active choices" enables us to abstract away from dynamic concerns such as patient inertia or learning.[43] To mitigate concerns about unobserved differences between individuals who are commercially insured or in Medicare, we limit the sample to the age groups immediately before Medicare eligibility (ages 55-64) and immediately after Medicare eligibility (ages 65-74). We are unable to condition on finer age groups (e.g. age 64 vs. 65) because our version of the HCCI dataset only includes 10-year age bins. Moreover, the population prevalence of multiple sclerosis is low, especially among the older population, so conditioning on finer age groups would substantially reduce statistical power.

Table 3 shows descriptive statistics for the estimation sample. From 2009 to 2017, average allowed amounts (our measure of list prices) increased substantially for all drugs in the choice set, from about $3,000 in 2009-2011 to about $6,000 in 2015-2017. Out-of-pocket costs also approximately doubled over the same period, averaging

[43]Because MS typically onsets at earlier ages, many individuals in our sample may have prior experience – which we are unable to observe – with a drug in the choice set. However, recurrence of symptoms can prompt an active choice and a potential switch to a different drug. *Source: Interview with Joshua P. Klein, MD, PhD, Chief, Division of Hospital Neurology, Brigham and Women's Hospital,* March 2019.

about $250 per prescription for commercially insured patients and $550 for Medicare Advantage enrollees in 2015-2017.

4.2 Demand Estimation Results

We estimate the parameters of equations (2) and (3) jointly by maximum likelihood, setting λ to 0.75 based on reported estimates of coupon utilization for MS drugs (Starner et al., 2014). Our primary identifying assumption for the effect of coupons on demand is that individuals just above and below the age 65 threshold for Medicare eligibility have preferences over MS drugs that evolve similarly over time in the absence of coupons.

We estimate three specifications, the results of which are shown in Table 4. Our main specification (Column 3 of Table 4) includes drug-by-year fixed effects, which allow preferences for each drug to vary flexibly over time, and drug-segment fixed effects, which allow commercially insured patients to systematically prefer different drugs than Medicare patients. Thus, identifying variation in our main specification primarily comes from drugs that we can observe before and after they introduce a coupon, specifically Copaxone 20mg and Gilenya. Changes in the choice set when new drugs are introduced, with or without coupons, also generate useful variation. Our second demand specification (Column 2 of Table 4) omits drug-segment fixed effects, allowing identifying variation for the estimated coupon effect to come from comparisons of always- vs. never-couponed drugs across segments, since fixed differences in demand across segments are no longer netted out. Medicare enrollees cannot redeem coupons, so greater attractiveness of a drug for commercial enrollees just below the Medicare age threshold would—in this specification—imply a positive effect of coupons on demand. Our last specification (Column 1 of Table 4) omits both drug-segment fixed effects and the X_{ijt} terms, which are the drug time-since-approval bins and their interactions with gender.

The drug-year and drug-segment fixed effects in our main specification also absorb demand shocks that could confound our estimates of the price coefficient. We estimate a price coefficient using variation in out-of-pocket prices across consumers: enrollees with a relatively high coinsurance rate face greater differences in out-of-pocket prices across products than do enrollees with a low coinsurance rate. That is, the identifying price variation comes from coinsurance variation across plans, which we assume to be exogenous.[44] As noted above, many individuals do not pay coinsurance rates but

[44]Recall that the menu of insurance plans offered by each employer often uses a single PBM, addressing

instead pay a fixed copay amount per prescription. Because copays vary across individuals but not across drugs for a given individual, copay variation does not contribute to estimation of the price coefficients. However, individuals with fixed copays provide useful variation to estimate other model parameters.[45]

[Table 4 Here]

Across specifications, we find that demand for MS drugs is highly inelastic with respect to out-of-pocket price. The price sensitivity of Medicare enrollees is not significantly different from zero. Recall that commercially insured enrollees who use coupons do not face cost sharing, and are thus assumed to be unresponsive to price. The price sensitivity of commercially insured enrollees who do not use coupons has the expected sign and is highly significant ($p = 0.001$ for the *Price X Commercial* interaction term), illustrating that coupons reduce the price elasticity of demand.

However, even commercially insured enrollees who do not use coupons are relatively price inelastic. In our preferred specification, a $100 increase in a drug's out-of-pocket price leads to only a 4.2% drop in market share on average.[46] The overall own-price elasticity for commercially insured individuals is -0.104. This is within the range of other estimates in the literature, albeit at the low end. Using data on retirees in the California Public Employees Retirement System (CalPERS), Chandra et al. (2010) estimate arc-elasticities for prescription drug consumption of -0.03 to -0.15. Using data on Medicare Part D enrollees, Abaluck et al. (2018) and Dalton et al. (2020) estimate price elasticities of -0.13 and -0.38, respectively.[47] Einav et al. (2018) show that elasticity varies across drugs: they find a mean elasticity of -0.24, with a standard deviation is 0.49. Given their sample consists of the most commonly purchased drugs, for which substitutes (including generics) are more readily available, it is unsurprising that elasticity for MS drugs would be on the low side.

the potential concern that enrollees select plans with low coinsurance for their preferred drug. Medicare enrollees have a choice of prescription drug plans, but a prior literature documents low switching rates across plans that is largely due to consumer inattention (Ho et al., 2017).

[45] Copays may vary between preferred and non-preferred drugs in a given plan, but our data do not allow us to observe these within-plan copay differences for MS drugs.

[46] We compute this by, for each drug, increasing out-of-pocket prices by $100 and using the estimated demand equation to predict how the share of that drug changes for commercially insured individuals who do not use coupons. Then, we take the average of these effects across all drugs in the choice set. The effect of a $100 out-of-pocket price increase is similar across drugs, ranging from -3.2% to -4.8% with a standard deviation of 0.5%.

[47] Dalton et al. (2020) report an elasticity of -0.54 in their estimation sample, and an elasticity of -0.38 in a nationally representative sample.

The estimated effect of coupon introduction on overall demand (common to Medicare and commercial segments, Row 3 of Table 4) is not statistically significant in any specification. In our preferred specification, the point estimate is -.263 and noisy ($p = 0.284$). This estimate is likely to be downward-biased, however, as coupons may be introduced to stem a decrease in demand or in anticipation of a competitive threat. For this reason, we do not rely on the time-series impact of coupons on demand to estimate our coupon effect; rather, we focus on the differential effect for commercial and Medicare enrollees.[48]

The positive estimated coefficient on *Coupon X Commercial* indicates that coupon introduction is associated with an increase in demand for the commercial segment, consistent with a causal advertising effect of coupons that goes beyond the price effect of coupons on the demand elasticity. This point estimate is large and similar in magnitude whether we include drug-segment fixed effects (Column 1) or not (Columns 2-3). When drug-segment fixed effects are omitted, the estimated advertising effect coefficient is highly significant at $p < 0.001$. The estimate is noisier when drug-segment fixed effects are included and identification comes from the only two drugs that introduce a coupon midway through the sample period ($p = .073$). The estimated coefficient on *Coupon X Commercial* is quite large; it implies that removing a drug's coupon causes a 30.6% decrease in the market share of that drug, ceteris paribus.[49] The effect of removing all coupons at once results in smaller decreases in shares for couponed drugs, on the order of 9.7%.

As previously noted, these estimates are subject to several caveats. Coinsurance rates and copays are imperfectly observed, and we do not know which consumers choose to redeem coupons nor their exact redemption values. Our measure of consumer out-of-pocket prices is based on various assumptions, including that no branded MS drug is excluded from consumers' formularies and that all branded MS drugs are placed on the same formulary tier for a given consumer. However, fixed effects do account for differences in formulary exclusion across drugs and over time, as well as any time-

[48] Because we interpret this coefficient to reflect the timing of coupon introductions rather than a causal effect of coupon introduction, we will hold this effect constant when simulating the removal of coupons in Section 5.

[49] We compute this comparative static using our main specification by removing the coupon for each ever-couponed drug in the sample one-by-one, observing how this affects the market share of the drug in question, and then taking the average of these effects across all ever-couponed drugs. The effect of coupon removal is similar across drugs, with effects ranging from -28.5% to -33.2% and a standard deviation of 2.0%.

invariant drug-specific differences across segments.

5 Counterfactual Simulations

We use the demand estimates from Section 4 as an input to simulations that quantify the potential price effects of coupon introduction. We follow the framework of the model outlined in Section 3. As noted there, since coupons reduce consumer sensitivity to out-of-pocket prices, they generate upward pressure on list prices for couponed drugs. However, there are offsetting effects due to bargaining, and the overall effects on equilibrium prices are an empirical question. The estimated demand model allows us to quantify these effects and the resulting changes in consumer out-of-pocket spending and premiums.

To generate counterfactuals, we simulate consumer demand following Equations (2) and (3) with a coupon user share for commercial enrollees of $\lambda = 0.75$, inferred from the literature. We estimate demand coefficients via maximum likelihood conditional on this choice of λ, as described in Section 4 and further in Appendix Section D.1. Given this framework for consumer demand, we simulate net prices by solving the system of Nash-in-Nash first order conditions introduced in Section 3.3. To compute out-of-pocket prices, our simulations assume a constant rebate percentage $r = 0.15$ across all drugs and both segments, which is based on unpublished data from Kakani et al. (2020).We then compute insurer drug costs, premiums, and cost-sharing following Section 3.2.

In the following subsections, we report predictions for the effect of coupons on net prices and patients' out-of-pocket costs. We also provide predictions for the impact of coupons on insurer costs and hence (under reasonable assumptions) on average premiums. In Section 5.3 and Appendix Section E.2, we explore how our predictions vary with changes in the rebate magnitude and in the proportion λ of consumers who use coupons when available.

5.1 Impact of Coupons on Prices and Market Shares

Table 5 shows the predicted impact of coupons on prices and market shares. We calibrate $\eta = 0.69$ to provide a reasonable match of observed prices (Column 2) to their predicted values in the presence of coupons (Column 4). Appendix E.1 outlines our method for calibrating this parameter; note that values closer to 1 imply a greater share of surplus accrues to the pharmaceutical manufacturer. We assume the marginal production cost $c_{j,t}$ is zero for all drugs and that each manufacturer produces a single

product. Our simulation sample is restricted to the time period where all drugs in our choice set are available, April 2015 through December 2017. Baseline simulated shares (Column 5) are close to the observed shares (Column 3). These baseline simulations include the observed set of coupons, shown in Column 1.

[Table 5 Here]

Columns 7-10 of the table provide the predicted equilibrium net prices and market shares of MS drugs in the scenario where all coupons are banned. The market shares of previously couponed drugs fall by 6-9% as consumers substitute to never-couponed drugs, whose shares increase by about 25-37% (these increases are larger due to the smaller baseline shares of non-couponed drugs). Prices decline for all drugs, with previously couponed drugs typically experiencing larger declines in price when coupons are banned. The share-weighted average price reduction is 7.4%.[50]

5.2 Impact on Premiums and Out-of-Pocket Costs

Table 6 summarizes the predicted impact of the coupon ban on insurer costs and consumer out-of-pocket prices. Columns 5-7 report effects on out-of-pocket costs for different types of consumers, categorized by segment, coupon use, type of cost-sharing, and drug choice.[51] Coupon removal would have sizeable distributional implications. Note first that out-of-pocket costs are higher on average for individuals in Medicare Advantage, whose plans often use coinsurance rather than copays. Medicare Advantage enrollees are predicted to experience a decrease in their out-of-pocket costs when coupons are banned as a result of lower list prices and hence lower coinsurance payments.[52] In contrast, individuals with commercial insurance have lower initial out-of-pocket costs but the coupon ban increases these costs on average, as individuals who previously redeemed coupons must now pay their full copay or coinsurance amount.

[50] Removing coupons for some drugs leads to reductions in all drugs' prices because of the substitution effects already noted. If a drug's price is higher than those of its substitutes, the insurer's total cost decreases when that drug is dropped, and this puts downwards pressure on the drug's equilibrium markup. This reinforcement effect means that prices of substitute drugs tend to move together (Ho and Lee (2017)).

[51] We only model consumer cost sharing for the first MS drug prescription filled, and we do not account for out-of-pocket maxima. Hence, our results may overstate the impact of a coupon ban on out-of-pocket payments, as some consumers will reach their out-of-pocket maximum in subsequent prescriptions.

[52] Note that Medicare Advantage enrollees who face copays in their prescription drug coverage may pay coinsurance rates in their medical insurance, which is utilized for the infused drug, Tysabri. This leads to small decreases in out-of-pocket costs for individuals who are listed as paying copays.

The increases are especially large for commercially insured individuals who pay coinsurance rather than copays. Appendix Figure E7 presents the distribution of the change in cost-sharing for each segment. Among commercially insured enrollees, those who do not use coupons and those who take non-couponed drugs experience reductions in their out-of-pocket expenses when coupons are removed.

We also consider the impact of coupons on premiums. As discussed above, a full premium-setting model would require a framework for consumer plan choice as an input into insurers' choice of premiums to maximize their profits. Instead, we simplify by assuming that the insurer markup and non-pharmaceutical costs in the full premium expression from Section 3 (equation (4)) are held fixed when coupons are introduced and hence not relevant for our analysis; we normalize them to zero and consider the component of premiums that covers the insurer's drug costs. For MS drugs, this component is simply the average of TC_t across enrollees. Our predictions for the effect of coupons on insurer costs (and hence premiums) are set out in Columns 2-4 of Table 6. Insurer costs decline substantially in both commercial and Medicare Advantage markets when coupons are removed. The average cost reduction is approximately $385 per enrollee per month, or 7.6% of total costs. The decline is primarily caused by lower list prices and applies to all subgroups of individuals regardless of coupon use or type of cost-sharing. The shift in market share towards never-couponed drugs, whose prices are lower than couponed drugs, also contributes to the reduction in insurer costs and hence premiums.

[Table 6 Here]

Overall, under our assumptions, we find that banning coupons leads to premium reductions from reduced insurer costs that are nearly 4 times as large as the increases in out-of-pocket payments. A coupon ban therefore has the potential to reduce costs for all enrollees, and if an appropriate redistributional mechanism can designed, may be both politically feasible and Pareto-optimal, at least in a static sense (i.e. not accounting for any effects of reduced manufacturer profits on pharmaceutical innovation, profits, and social surplus). We estimate net savings from a coupon ban would amount to $287 per prescription. Given annual net-of-rebate U.S. spending on multiple sclerosis drugs of around $15.9b, this translates into savings of about $950 million *per year* from banning coupons on this category of drugs alone.[53]

[53]We estimate net-of-rebate spending as 85 percent of total invoiced spending on MS drugs in 2017,

5.3 Robustness to Modeling Assumptions

To explore the sensitivity of our results to our modeling assumptions, we conduct analyses that vary the share of coupon users (λ), including versions where consumers with higher out-of-pocket expenses are more likely to use coupons. We also assess the effect of varying the fixed rebate percentage and evaluate the implications of an upward rebate adjustment that could occur in response to a coupon ban. Lastly, we consider the impact of assuming that the advertising effect of coupons has a greater impact on users than non-users (rather than an equal effect, as in the baseline). Our results are qualitatively unchanged across these sensitivity analyses, as we summarize below. See Appendix Section E.2 for further details.

In our baseline simulation, we assumed a $\lambda = 0.75$ share of commercially insured individuals use coupons when they are available. This assumption affects both our demand estimates and simulation results. We assess the robustness of our results to the alternative assumptions of $\lambda = 0.60$ and $\lambda = 0.90$. Because λ may not be fixed in the population, we also evaluate two versions where λ is heterogeneous and correlated with out-of-pocket expenses. This matches the empirical observation that the likelihood of coupon use increases with the magnitude of pre-coupon cost sharing (see, for example, Brouwer et al. (2021)). In version 1, we assume that $\lambda = 0.7$ for consumers whose average OOP amount is less than \$150 and 0.9 for consumers whose OOP amount exceeds \$150. In version 2, we assume that $\lambda = 0.5$ for OOP amounts below \$75, 0.7 between \$75 and \$150, and 0.9 above \$150. These values allow us to introduce heterogeneity in λ while maintaining an average λ of similar magnitude to our baseline assumption of $\lambda = 0.75$, given the observed distribution of out-of-pocket expenses we observe in the data.

Our demand estimates are similar across all specifications for λ, although the estimated price elasticity for commercial individuals who do not use coupons is larger when λ is smaller. A larger demand elasticity corresponds to a larger coupon price effect, which is necessary to fit the data when the assumed share of coupon users is smaller. The average simulated effect of a coupon ban on prices is therefore slightly larger when $\lambda = 0.60$ (-7.7%) and slightly smaller when $\lambda = 0.90$ (-6.6%). The versions where λ is correlated with OOP expenses are similar to the latter case, with price effects of -6.6% and -6.5%. Moreover, a larger value of η is required to match baseline simulated

which was \$18.7 billion. Source: *Medicines Use and Spending in the U.S. A Review of 2016 and Outlook to 2021. Report by the Quintiles, IMS Institute. May 2017*

prices to observed prices, which also tends to increase the price effect of coupons, as the $\frac{\partial s_{jt}}{\partial p_{jt}}$ becomes a greater determinant of the markup in Equation 10. Reducing λ also reduces the number of individuals who use coupons, which exerts an opposing effect that tends to reduce the price effect of coupons. But this effect is outweighed by the higher estimated price elasticity. The opposite situation applies when λ is higher (or heterogeneous): η and the demand elasticity are both smaller, and the resulting price effect of coupons is smaller in magnitude.

Changing λ also affects the distributional effects of a coupon ban. When $\lambda = 0.60$, the increase in out-of-pocket prices is smaller and cost savings are larger. In this case, savings outweigh out-of-pocket increases by 5.5 to 1. When $\lambda = 0.90$, nearly all consumers use coupons, so out-of-pocket prices increase by a larger amount. That said, savings still outweigh out-of-pocket increases by nearly 3 to 1. Results are similar when λ is heterogeneous, with a ratio of savings to out-of-pocket increases of 2.8 to 1.

Assuming a larger fixed rebate r increases the price effects of coupons, but this effect is small. Rebate shares of 0.10, 0.15 (our baseline results), 0.2, and 0.25 correspond to average coupon price effects of -7.2%, -7.4%, -7.6%, and -7.7%. For a fixed net price, higher rebates imply higher list prices, greater cost sharing, and thus increased importance of coupons.

Our baseline simulations assume rebates remain fixed when coupons are banned. However, in fact this change may lead to increased rebates as insurers' ability to use tier placement as a negotiation device increases (Ho and Lee, 2022). As mentioned previously, we lack the data on formulary placement and rebates necessary to simulate bargaining over both rebates and prices. That said, we can test robustness to the existence of a rebate response by assuming that rebates increase after coupons are banned. We simulate the impact of increasing the rebate rate from 15% to 20% at the same time as (i.e., in response to) a coupon ban. This exercise yields a similar average change in net price of -7.6%. Because this price reduction is partially due to increased rebates, out-of-pocket prices increase more when coupons are banned. The ratio of savings to out-of-pocket price increases is 3.6 to 1, compared to a baseline of about 4 to 1.

Lastly, we tested the sensitivity of our results to the assumption in our demand model that the advertising effect of coupons affects all commercially insured enrollees equally, regardless of whether they use coupons. We re-estimated demand under alternative assumptions where the advertising effect is 1.5x larger for coupon users, 2x

larger for coupon users, and where the advertising effect only affects coupon users. As the advertising effect becomes more restricted to coupon users, its magnitude (as estimated by maximum likelihood) increases, from 0.373 when both coupon users and non-users are equally affected to 0.693 when only coupon users are affected. The simulated average price effect of coupons also increases, from -7.4% to -8.7% when only coupon users are affected.

6 Discussion and Conclusions

As branded drug prices continue to rise and new drugs are launched at ever higher prices, consumers and policymakers are intensifying their opposition to the status quo. However, current market prices reflect, among other things, the willingness of patients and insurers to pay the going rate. Lowering prices would require greater elasticity of downstream demand, more bargaining leverage on the part of insurers/PBMs, greater supply-side competition, regulation, or some combination of all four.

In this paper, we consider the role of manufacturer-sponsored coupons in contributing to higher spending through the channels of price as well as quantity. We pursue two complementary approaches. Our difference-in-differences analysis quantifies the short-term impact of coupon introduction by comparing responses of the commercially insured and Medicare-Advantage populations. Using a novel proprietary dataset with monthly data on drug quantities and net-of-rebate prices by enrollee segment, and focusing on drugs without bioequivalent generics, we find new coupon introductions between 2014 and 2016 led to an average increase in drug volume (as measured by days supplied) of more than 20 percent within 12 months post-coupon. We do not find any differential change in net-of-rebate prices, although theoretically coupons should enable manufacturers to offer lower rebates, ceteris paribus, for commercially-insured enrollees (or, similarly, to raise list prices and to offer higher rebates for the Medicare Advantage segment). Unfortunately, the post-coupon period of analysis is short, which may explain why we do not observe a differential effect on prices.

We supplement the difference-in-differences analysis by developing and estimating a model of drug choice, characterizing the bargaining between insurers and pharmaceutical manufacturers, and using the results of the drug choice model together with estimated rebate information to calibrate the bargaining model. We use data on "first choices" of multiple sclerosis drugs by individuals in the HCCI claims data, over the period 2009 through 2017. Two of the drugs experience coupon introductions during

our study period. The estimation does not allow for a change in market size, an assumption that is necessary given the data available to us and likely less restrictive for this condition than for many others given the medical benefit and limited availability of substitute products. Our simulations indicate that prices of MS drugs are about 8 percent higher than they would be if coupons were banned. A coupon ban would raise out-of-pocket spending for MS patients who currently use coupons, but we estimate the savings for insurers would be nearly 4 times as large. Net savings for MS drugs alone would amount to nearly a billion dollars annually. The estimates are robust to a wide set of changes in assumptions, ranging from the rate of coupon utilization to rebate levels as well as changes in these levels in the wake of a coupon ban.

A coupon ban would restore the ability of downstream insurers to use cost-sharing to steer patients toward preferred therapies, and in so doing, provide insurers with leverage to negotiate lower drug prices. Our findings imply that utilization of couponed drugs, and prices of both couponed and non-couponed drugs, would decline. However, the distributional effects of such a ban – which we assume would apply uniformly to branded drugs – are significant. Many patients who currently utilize coupons would face higher cost-sharing for their medications. To mitigate the distributional effects of a coupon ban, a ban could be accompanied by a mechanism to transfer savings from removing coupons to consumers who would be made worse off. This could be achieved via fixed lump-sum contributions to the health savings accounts of enrollees with conditions treated by costly drugs, or through targeted premium reductions. The objective would be to preserve price incentives to utilize cost-effective therapies, while nevertheless minimizing the financial burden for patients with high drug costs. Notably, our results suggest that popular policy proposals such as capping cost-sharing, or requiring plans to shift from coinsurance to fixed (and low) copays are likely to lead to drug price inflation. These reforms would likely exacerbate the underlying problem of high prices while addressing a symptom (high patient cost-sharing).

Drug copay coupons are but one form of manufacturer-backed assistance to alleviate OOP costs. There are a number of additional programs, ranging from free samples to discount cards, that facilitate both price discrimination as well as patient access. Additional research on all of these programs would be helpful in developing comprehensive solutions to enable downstream drug demand to play a role in disciplining upstream prices.

References

Abaluck, Jason, Jonathan Gruber, and Ashley Swanson. 2018. "Prescription drug use under Medicare Part D: A linear model of nonlinear budget sets." *Journal of Public Economics*, 164: 106–138.

Agha, Leila, Soomi Kim, and Danielle Li. 2020. "Insurance Design and Pharmaceutical Innovation." National Bureau of Economic Research, Cambridge, MA.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2021. "Revisiting Event Study Designs: Robust and Efficient Estimation."

Brouwer, Elizabeth, Kai Yeung, Douglas Barthold, and Ryan Hansen. 2021. "Characterizing patient assistance program use and patient responsiveness to specialty drug price for multiple sclerosis in a mid-size integrated health system." 27(6): 732–742.

Callaway, Brantly, and Pedro H. C. Sant'Anna. 2020. "Difference-in-Differences with Multiple Time Periods."

Capps, Cory, David Dranove, and Mark Satterthwaite. 2003. "Competition and Market Power in Option Demand Markets." *RAND Journal of Economics*, 34(4): 737–763.

Chandra, Amitabh, Jonathan Gruber, and Robin McKnight. 2010. "Patient Cost-Sharing and Hospitalization Offsets in the Elderly." *The American economic review*, 100(1): 193.

Corts, Kennth S. 1998. "Third-degree price discrimination in oligopoly: all-out competition and strategic commitment." *RAND Journal of Economics*, 29(2): 306–323.

Crawford, Gregory S., and Ali Yurukoglu. 2012. "The Welfare Effects of Bundling in Multichannel Television Markets." *American Economic Review*, 102(2): 643–685.

Dafny, Leemore, Christopher Ody, and Matt Schmitt. 2017. "When discounts raise costs: The effect of copay coupons on generic utilization." *American Economic Journal: Economic Policy*, 9(2): 91–123.

Dalton, Christina M, Gautam Gowrisankaran, and Robert J Town. 2020. "Salience, Myopia, and Complex Dynamic Incentives: Evidence from Medicare Part D." *The Review of Economic Studies*, 87(2): 822–869.

Draganska, Michaela, Daniel Klapper, and Sofia Villas-Boas. 2010. "A Larger Slice or a Larger Pie? An Empirical Investigation of Bargaining Power in the Distribution Channel." *Marketing Science*, 29(1): 57–74.

Einav, Liran, Amy Finkelstein, and Maria Polyakova. 2018. "Private provision of social insurance: Drug-specific price elasticities and cost sharing in Medicare Part D." *American Economic Journal: Economic Policy*, 10(3): 122–153.

Elsisi, Zizi, Ana L Hincapie, and Jeff Jianfei Guo. 2020. "Expenditure, Utilization, and Cost of Specialty Drugs for Multiple Sclerosis in the US Medicaid Population, 2008-2018." *American health & drug benefits*, 13(2): 74–84.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Gowrisankaran, G., A. Nevo, and R.J. Town. 2015. "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry." *American Economic Review*, 105(1): 172–203.

Grennan, Matthew. 2013. "Price Discrimination and Bargaining: Empirical Evidence from Medical Devices." *American Economic Review*, 103(1): 147–177.

Ho, Kate, and Robin S. Lee. 2017. "Insurer Competition in Health Care Markets." *Econometrica*, 85(2): 379–417.

Ho, Kate, and Robin S. Lee. 2022. "Contracting Over Rebates: Formulary Design and Pharmaceutical Spending." *working paper*.

Ho, Kate, Joseph Hogan, and Fiona Scott-Morton. 2017. "The Impact of Consumer Inattention on Insurer Pricing in the Medicare Part D Program." *RAND Journal of Economics*, 48(4): 877–905.

Kakani, Pragya, Michael Chernew, and Amitabh Chandra. 2020. "Rebates in the Pharmaceutical Industry: Evidence from Medicines Sold in Retail Pharmacies in the U.S." National Bureau of Economic Research Working Paper 26846.

Lee, Chung Ying. 2020. "Pricing strategy and moral hazard: Copay coupons in pharmaceuticals." *International Journal of Industrial Organization*, 70(May 2017): 102611.

Lonergan, Roisín, Katie Kinsella, Marguerite Duggan, Sinead Jordan, Michael Hutchinson, and Niall Tubridy. 2009. "Discontinuing disease-modifying therapy in progressive multiple sclerosis: can we stop what we have started?" *Multiple sclerosis (Houndmills, Basingstoke, England)*, 15(12): 1528–31.

Lotvin, Alan M., William H. Shrank, Surya C. Singh, Benjamin P. Falit, and Troyen A. Brennan. 2014. "Specialty medications: Traditional and novel tools can address rising spending on these costly drugs." *Health Affairs*, 33(10): 1736–1744.

Mulcahy, Andrew W, Christopher M Whaley, Mahlet G Tebeka, Daniel Schwam, Nathaniel Edenfield, and Alejandro U Becerra-Ornelas. 2021. *International Prescription Drug Price Comparisons: Current Empirical Estimates and Comparisons with Previous Studies.* Santa Monica, CA:RAND Corporation.

Sen, Aditi P, So-Yeon Kang, Emaan Rashidi, Devoja Ganguli, Gerard Anderson, and G Caleb Alexander. 2021. "Characteristics of Copayment Offsets for Prescription Drugs in the United States." *JAMA internal medicine*.

Sood, Neeraj, Rocio Ribero, Martha Ryan, and Karen Van Nuys. 2020. "The Association Between Drug Rebates and List Prices." University of Southern California, Leonard D. Schaeffer Center for Health Policy and Economics.

Sospedra, Mireia, and Roland Martin. 2005. "Immunology of Multiple Sclerosis." *Annual Review of Immunology*, 23: 683–747.

Starner, Catherine I., G. Caleb Alexander, Kevin Bowen, Yang Qiu, Peter J. Wickersham, and Patrick P. Gleason. 2014. "Specialty drug coupons lower out-of-pocket costs and may improve adherence at the risk of increasing premiums." *Health Affairs*, 33(10): 1761–1769.

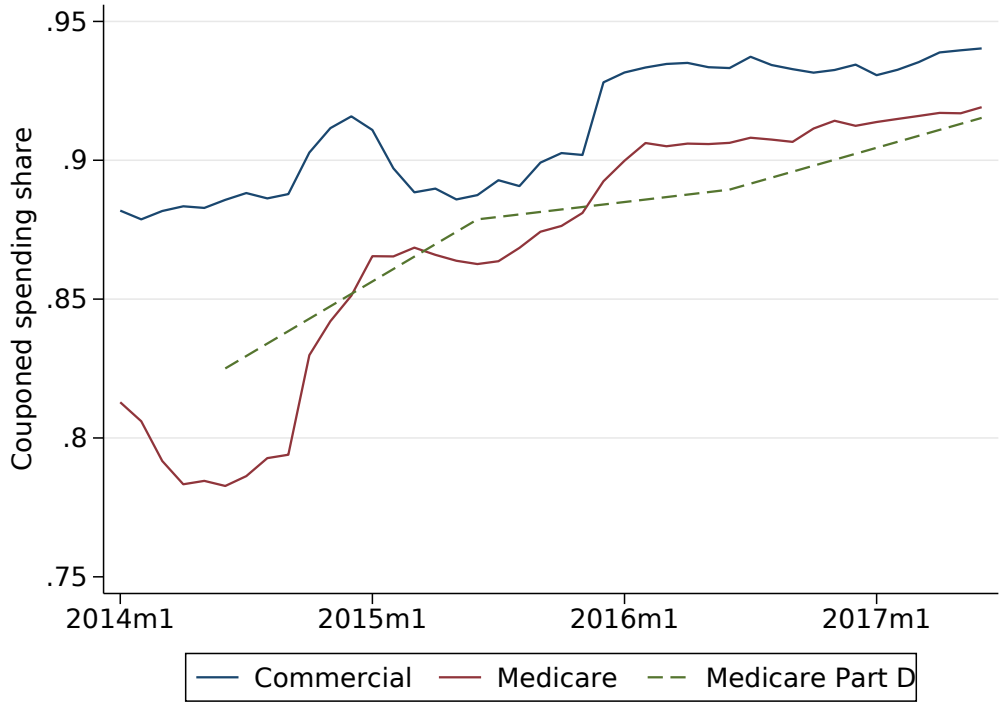
Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.

Torkildsen, O., K. M. Myhr, and L. Bø. 2016. "Disease-modifying treatments for multiple sclerosis - a review of approved medications." *European Journal of Neurology*, 23: 18–27.

Wallin, Mitchell T., William J. Culpepper, Jonathan D. Campbell, Lorene M. Nelson, Annette Langer-Gould, Ruth Ann Marrie, Gary R. Cutter, Wendy E. Kaye, Laurie Wagner, Helen Tremlett, Stephen L. Buka, Piyameth Dilokthornsakul, Barbara Topol, Lie H. Chen, and Nicholas G. Larocca. 2019. "The prevalence of MS in the United States: A population-based estimate using health claims data." *Neurology*, 92(10): E1029–E1040.

Exhibits

Figure 1: Share of branded drug spending with a copay coupon



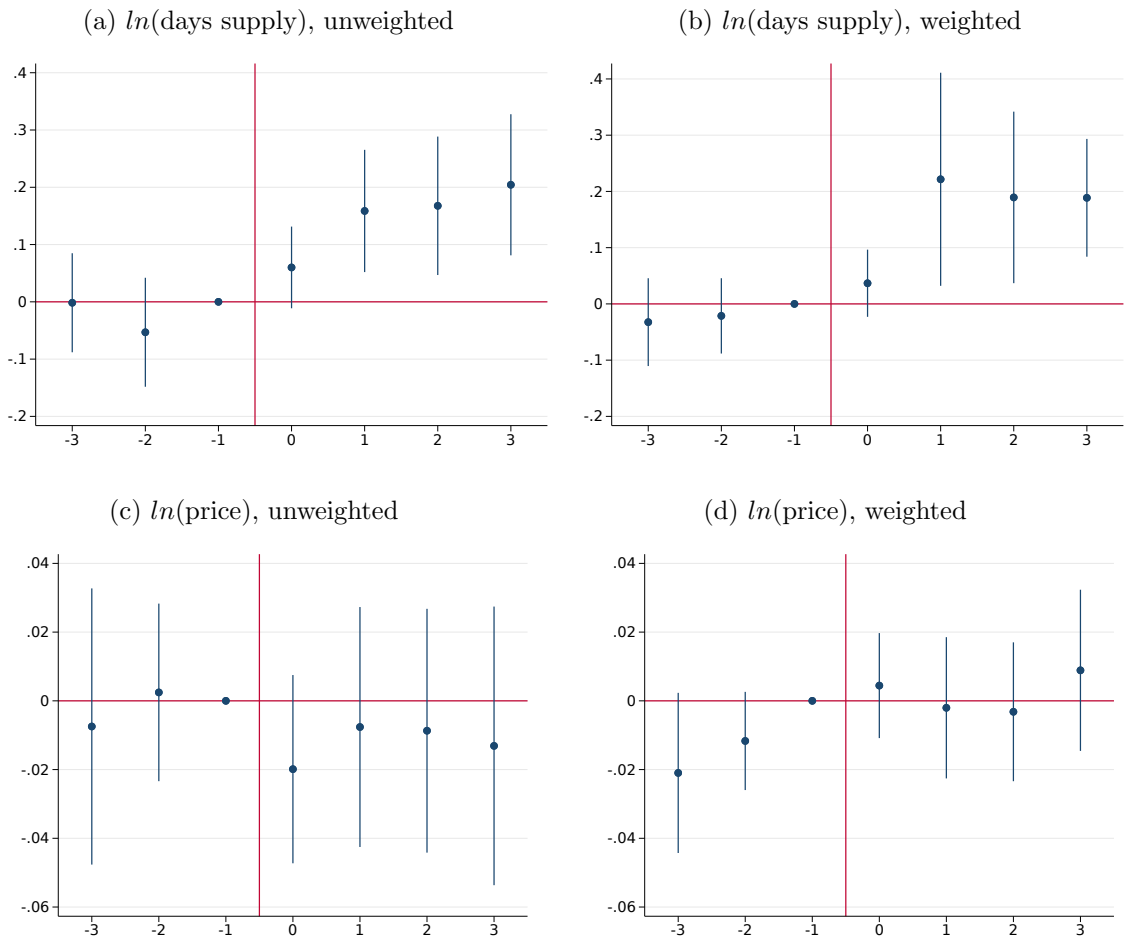
Notes: Figure shows the share of total spending on branded drugs accounted for by drugs with a copay coupon. Data are shown separately for commercial and Medicare segments in the monthly PBM data, as well as for annual Medicare Part D spending. Part D spending is derived from authors calculations using CMS Part D Prescriber data:
Centers for Medicare and Medicaid Services. 2014-2017. "Medicare Provider Utilization and Payment Data: Part D Prescriber." https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Part-D-Prescriber (accessed February 20, 2019).

Table 1: Descriptive Statistics (Drug-Month Sample)

	Always	Never	Switch (all)	Switch (estimation sample)
	(1)	(2)	(3)	(4)
A. Statistics by Category				
Number of drugs	263	35	68	33
% commercial spending	83.38	1.13	9.77	5.72
% Medicare spending	82.64	1.49	8.97	6.90
Top MCI (number of drugs)	Diabetes (25)	Diabetes (5)	Cancer (7)	Cancer (7)
Second MCI (number of drugs)	HIV (22)	Asthma (3)	Diabetes (6)	Ophthalmic (4)
Third MCI (number of drugs)	Asthma (19)	HBP/Heart Disease (2)	Ophthalmic (5)	Blood Cell Deficiency (2)
N (drug-month observations)	19,212	2,402	4,972	2,700
B. Statistics by Drug				
Average list price (2014$)	1,672	369	1,788	2,585
	(3,841)	(367)	(2,873)	(3,482)
Monthly average days supplied	66,012	8,657	15,829	13,284
	(183,093)	(16,779)	(28,243)	(20,352)
Average CAGR in price (%)	7.15	9.02	6.80	10.18
	(10.02)	(10.50)	(10.67)	(10.92)
Average CAGR in days supplied (%)	28.87	14.00	100.74	24.01
	(71.63)	(58.27)	(162.21)	(62.78)

Notes: Panel A shows statistics at the drug category level, for drugs that are always couponed in our sample (Column 1), never couponed in our sample (Column 2), introduce a coupon (switchers) during our study period (Column 3), and introduce a coupon during our study period and are observed for 9 months before and after the quarter of coupon introduction (i.e., our estimation sample, in Column 4). Panel B shows drug-level statistics and standard deviations (in parentheses) for the set of drugs in each category. For both panels, the sample is limited to branded drugs utilized in both commercial and Medicare populations and with no generic equivalent available as of July 2017. Average list price is from the 2014 Medicare Part D data (or the first year the drug appears in Part D data). The compound annual growth rate (CAGR) in net-of-rebate price for each drug is computed from the first quarter to the last quarter that the drug is observed in the PBM data.

Figure 2: Effects of Coupons on Utilization and Price



Notes: Each graph plots coefficient estimates and 95% confidence intervals from a regression of ln(*days supply*) or ln(*price*) on quarter relative to coupon introduction. Coefficients plotted reflect the response in the commercial segment relative to the response in Medicare. All specifications are estimated on a balanced panel of data for switchers, including monthly observations from 9 months prior to coupon introduction through 12 months after coupon introduction. The quarter prior to introduction is omitted. Panels (a) and (c) show unweighted results, while Panels (b) and (d) show results weighted by each drug's share of spending in each segment in the 6 months prior to coupon introduction.

Table 2: Difference-in-Differences Estimates

	ln(quantity)		ln(price)	
	(1)	(2)	(3)	(4)
Commercial ×				
$Q = -3$	-0.002	-0.032	-0.007	-0.021*
	(0.042)	(0.038)	(0.020)	(0.011)
$Q = -2$	-0.053	-0.021	0.002	-0.012
	(0.047)	(0.033)	(0.013)	(0.007)
$Q = -1$	0	0	0	0
	(-)	(-)	(-)	(-)
$Q = 0$	0.060*	0.037	-0.020	0.004
	(0.035)	(0.029)	(0.013)	(0.008)
$Q = 1$	0.159***	0.222**	-0.008	-0.002
	(0.052)	(0.093)	(0.017)	(0.010)
$Q = 2$	0.168***	0.189**	-0.009	-0.003
	(0.059)	(0.075)	(0.017)	(0.010)
$Q = 3$	0.204***	0.189***	-0.013	0.009
	(0.060)	(0.051)	(0.020)	(0.012)
Weights	N	Y	N	Y

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Notes: Standard errors are clustered at the drug level. Weights are defined as the share of within-segment spending accounted for by the drug in the 6 months before coupon introduction, normalized so that average weights in each segment are equal. Q = 0 represents the first three months after coupon introduction. For each drug, we include only observations for the 9 months prior and 12 months after coupon introduction. The unit of observation is the drug-month-segment. All specifications include drug-segment and year-month fixed effects. N=1,386.

Table 3: Descriptive Statistics for HCCI Estimation Sample

Panel A: Commercial

Drug	Share		Avg. OOP Price ($)		SD ($)		Avg. Allowed Amt. ($)	
	2009-2011	2015-2017	2009-2011	2015-2017	2009-2011	2015-2017	2009-2011	2015-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aubagio	-	0.126	-	243	-	559	-	5,742
Avonex	0.211	0.078	126	248	354	576	2,706	5,900
Betaseron	0.121	0.036	128	259	361	609	2,750	6,260
Copaxone20	0.399	0.031	135	275	391	655	2,998	6,765
Copaxone40	-	0.311	-	237	-	543	-	5,567
Gilenya	0.086	0.083	210	259	571	612	3,798	6,267
Glatopa	-	0.008	-	234	-	548	-	5,415
Plegridy	-	0.026	-	247	-	574	-	5,873
Rebif	0.159	0.056	124	260	346	612	2,634	6,275
Tecfidera	-	0.230	-	262	-	618	-	6,345
Tysabri	0.074	0.015	284	671	518	1,058	3,251	5,908

Panel B: Medicare

Drug	Share		Avg. OOP Price ($)		SD ($)		Avg. Allowed Amt. ($)	
	2009-2011	2015-2017	2009-2011	2015-2017	2009-2011	2015-2017	2009-2011	2015-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aubagio	-	0.168	-	515	-	488	-	5,672
Avonex	0.331	0.101	260	508	221	482	2,839	5,584
Betaseron	0.071	0.140	263	548	222	521	2,882	6,040
Copaxone20	0.396	0.028	297	599	253	570	3,235	6,592
Copaxone40	-	0.237	-	490	-	463	-	5,376
Gilenya	0.054	0.014	359	550	286	525	3,755	6,072
Glatopa	-	0.008	-	470	-	482	-	5,122
Plegridy	-	0.026	-	512	-	487	-	5,634
Rebif	0.130	0.057	253	544	214	517	2,760	5,998
Tecfidera	-	0.211	-	558	-	532	-	6,155
Tysabri	0.039	0.014	218	393	481	965	2,831	5,494

Note: Table shows descriptive statistics by drug for the HCCI estimation sample, separately by market segment. Statistics for the first and last three years of the sample are shown. No new drugs were approved between 2009 and 2011. Only Glatopa (approved in April 2015) enters the market between 2015 and 2017. Columns 1-2 show market shares for each drug; Columns 3-4 show average out-of-pocket costs; Columns 5-6 show the standard deviation of out-of-pocket costs across enrollees; and Columns 7-8 show average allowed amounts (a measure of list prices) The estimation sample contains N = 3,483 commercially insured enrollees and N = 1,098 Medicare Advantage enrollees.

Table 4: Maximum Likelihood Estimates

	(1)	(2)	(3)
OOP Price	0.036	0.037	0.049 $^{+}$
	(0.023)	(0.023)	(0.026)
OOP Price X Commercial	-0.081 **	-0.084 **	-0.099 **
	(0.027)	(0.027)	(0.029)
Coupon X Commercial	0.376 **	0.357 **	0.373 $^{+}$
	(0.085)	(0.085)	(0.208)
Coupon	-0.134	-0.223	-0.263
	(0.193)	(0.193)	(0.246)
Drug Age (6-12 mo)		0.635 $^{+}$	0.632 $^{+}$
		(0.268)	(0.269)
Drug Age (1-2 yr)		1.328 **	1.300 **
		(0.280)	(0.280)
Drug Age (2-3 yr)		1.562 **	1.518 **
		(0.322)	(0.322)
Drug Age (3-5 yr)		1.843 **	1.821 **
		(0.353)	(0.354)
Drug Age (5+ yr)		1.850 **	1.816 **
		(0.420)	(0.420)
Drug Age (6-12 mo) X Female		-0.366	-0.351
		(0.288)	(0.288)
Drug Age (1-2 yr) X Female		-0.508 $^{+}$	-0.493 $^{+}$
		(0.257)	(0.257)
Drug Age (2-3 yr) X Female		-0.640 $^{+}$	-0.624 $^{+}$
		(0.263)	(0.263)
Drug Age (3-5 yr) X Female		-0.844 **	-0.836 **
		(0.261)	(0.261)
Drug Age (5+ yr) X Female		-0.319	-0.315
		(0.231)	(0.231)
Drug FE	Yes	Yes	Yes
Drug-Year FE	Yes	Yes	Yes
Drug-Segment FE	No	No	Yes

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Notes: Table shows maximum likelihood estimates of Equations 2 and 3 for N = 4,581 enrollees. Column 1 shows estimates with drug fixed effects, drug-year fixed effects, and drug-segment fixed effects. Column 2 shows estimates omitting drug-segment fixed effects. Column 3 additionally omits controls for the age of each drug (relative to its approval date) when each choice is made and interactions between drug age and patient gender.

Table 5: Impact of a Coupon Ban on Prices and Shares

		Data		Simulation: Baseline		Simulation: Coupons Banned			
Drug	Coupon Status	Net Price ($)	Share	Net Price ($)	Share	Net Price ($)	Share	Δ Price (%)	Δ Share (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Aubagio	Always	4941	0.148	5077	0.139	4704	0.130	-7.4	-6.4
Avonex	Never	5071	0.076	4940	0.082	4646	0.103	-5.9	26.6
Betaseron	Never	5395	0.044	4937	0.055	4635	0.068	-6.1	24.8
Copaxone20	Aug 2011	5787	0.030	4873	0.029	4569	0.037	-6.2	28.5
Copaxone40	Always	4753	0.308	5198	0.303	4799	0.280	-7.7	-7.7
Gilenya	Oct 2011	5420	0.066	4989	0.067	4563	0.061	-8.5	-8.8
Glatopa	Never	4538	0.008	4848	0.008	4544	0.011	-6.3	31.0
Plegridy	Never	5060	0.028	4870	0.027	4567	0.035	-6.2	29.2
Rebif	Always	5390	0.054	4998	0.056	4616	0.053	-7.6	-6.7
Tecfidera	Always	5486	0.224	5135	0.222	4738	0.205	-7.7	-7.5
Tysabri	Never	5011	0.015	4499	0.013	4120	0.017	-8.4	36.6

Notes: Table shows observed prices (computed as 0.85 × the average allowed amount) and market shares in the simulation sample (Columns 2-3). Columns 4-5 show simulated net prices and shares at baseline, where coupons are as observed in the data (Column 1). Columns 6-10 show results from a simulation where all existing coupons are banned. Columns 6-7 show the resulting net prices and market shares; Columns 8-9 express the effects of the coupon ban as a percent of baseline simulated values. The average change in net price is -7.4%, weighting by the baseline simulated shares in Column 5.

Table 6: Impact of a Coupon Ban on Insurer and Out-of-Pocket Costs

Group	N (1)	Insurer costs with coupons (2)	Insurer costs coupon ban (3)	Δ Insurer Costs (4)	OOP Cost with coupons (5)	OOP Cost coupons ban (6)	Δ OOP Costs (7)
Commercial	1,104	5,081	4,690	-391	86	232	146
Coupon Users	828	5,082	4,690	-392	33	232	199
Non-users	276	5,077	4,690	-387	245	232	-14
Copay	910	5,080	4,692	-388	31	76	45
Coinsurance	194	5,086	4,683	-403	343	961	618
Couponed Drugs	895 → 806	5,127	4,731	-396	57	240	183
Non-couponed Drugs	209 → 298	4,888	4,584	-304	234	225	-9
Medicare	388	5,065	4,698	-367	542	503	-38
Copay	120	5,066	4,698	-368	164	154	-10
Coinsurance	268	5,064	4,697	-367	711	659	-51
Couponed Drugs	282 → 282	5,127	4,736	-391	550	509	-41
Non-couponed Drugs	106 → 106	4,901	4,598	-302	521	490	-31
Overall	1,492	5,077	4,692	-385	204	302	98

Notes: Table shows insurer and out-of-pocket costs with and without coupons, separately for selected subgroups. Insurer costs are expressed in $ per member per month; out-of-pocket costs are expressed in $ per prescription for enrollees' first observed choice. Results average over coupon users and non-users (except where otherwise indicated) based on our assumption that 75% share of commercially insured patients use coupons. Copay/coinsurance designations apply at the patient level. Patients are coded as paying copays or coinsurance based on the nature of their prescription drug insurance (see Appendix Section B.6). Patients facing prescription drug copays may have medical insurance requiring coinsurance. The number of individuals choosing couponed drugs may change after coupons are banned; this is reflected in Column 1 in the format [number of individuals when coupons are available] ⟶ [number of individuals when coupons are banned].

Online Appendix

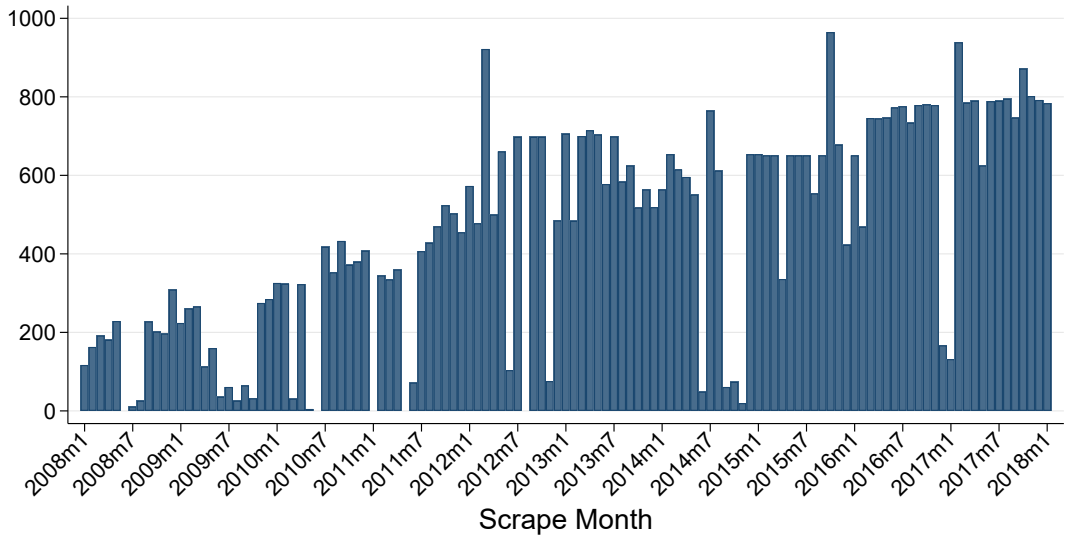
A Coupon Data

We combine data from InternetDrugCoupons.com, RxPharmacyCoupons.com, and NeedyMeds.org to code coupon introduction dates from January 2009 through January 2018. The data were assembled using historical snapshots of the three websites stored on the Internet Archive (webarchive.org). No single source is available and reliable for the entire time period. The quality of InternetDrugCoupons data, the source used in Dafny et al. (2017) and extended to encompass the period from January 2008 to October 2017, decreases after June 2015 due to a change in website structure that resulted in fewer snapshots. Snapshots from RxPharmacyCoupons.com are available between March 2012 and October 2017, but the website does not appear to be updated frequently. Data from NeedyMeds.org is available for the entire study period, but its quality is best from January 2015 onward.[54]

By combining all three sources, we are able to obtain at least one snapshot for most of the year-months over this time frame, as depicted in Appendix Figure A1) below. In some months, only a small number of drugs have archived snapshots. The main gap in coverage that overlaps with our study period occurs between September 2014 and November 2014. When the same drug has a coupon in multiple datasets, we use the earliest coupon introduction date. We manually verify coupon introduction dates for all drugs are included in our difference-in-differences analysis, using the method described in Appendix Section B.2.

[54] Webpages on NeedyMeds.org are arranged in alphabetical order, which leads to fewer snapshots for drugs beginning with letters other than "A." However, we are still able to obtain a reasonable density of snapshots for other letters starting in January 2015.

Appendix Figure A1: Coupon Data Availability



Notes: Figure shows availability of coupon data scraped from InternetDrugCoupons.com, RxPharmacyCoupons.com, and NeedyMeds.org. Blue bars indicate the maximum number of drugs observed in each year-month across the three websites.

B Data Construction

B.1 Harmonizing Drug Names

The coupon data contain coupon availability by drug name but do not include other standardized drug identifiers such as National Drug Codes (NDCs). Drug names may differ across datasets; for example, the drug name is sometimes followed by its salt (e.g. hydrochloride, phosphate, acetate, etc.) or dosage form (e.g. Tablet, Capsule, etc.).

To enable merging across various datasets, we remove special characters, company names, and other extraneous words. The first word of what remains is the "standardized drug name" for each drug.

B.2 Manual Verification of Coupon Introduction Dates

We manually verify the coupon introduction dates for the subset of drugs that underpin our identification strategies in the difference-in-differences analysis (Section 2) and demand estimation (Section 4).

For the difference-in-differences analysis, the drugs that contribute identifying variation to our estimates are branded drugs without generic equivalents (defined as in Appendix Section B.3) for which we can observe at least a 9-month pre-period prior to coupon introduction and a 12-month post-period.[55]

[55]This corresponds to drugs that introduced a coupon at least 9 months after a drug is approved and

We first established a set of drugs to manually verify. Because manually verified coupon introduction dates may be earlier but not later than scraped introduction dates, we limited to drugs with scraped introduction dates no earlier than 10 months after we first observe the drug in the PBM data (this accommodates the need for at least a 9-month pre-period). We included drugs with scraped introduction dates that occur through July 2017, a year past the July 2016 cutoff required for a 12-month post-period. This yielded 66 drugs. Then, we attempted to manually verify the date of coupon introduction by locating historic snapshots of manufacturer websites.[56] Of the 66 drugs, we were able to manually verify and adjust the introduction dates for 52 of them.[57] One of these drugs did not actually introduce a coupon, leaving 65 remaining drugs. Of these, coupon introduction dates were revised earlier by a median of 10 months (mean 11.5 months). This includes 17 drugs that were not revised to an earlier introduction date. Appendix Figure B2 shows the distribution of the revisions applied to the coupon introduction dates originally scraped from the Internet Archive.

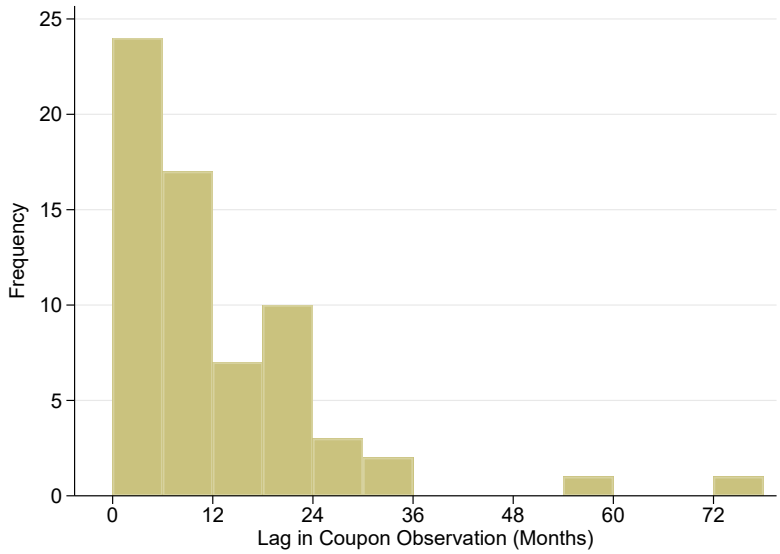
These results imply that the scraped coupon database prior to manual verification reflects coupon introductions with a lag. However, all regression analyses use coupon dates that are revised via the above manual verification process. Appendix Section B.5 describes additional detail from our verification process for the drugs used in our demand estimation.

appears in our data, and where coupon introduction occurs between October 2014 and July 2016 so that we can observe a 9-month pre-period and 12-month post-period.

[56] For drugs where the scraped introduction date is within several months of the initial FDA approval date, we also search for press releases for the drug approval. In a number of cases, a coupon program is mentioned in the press release, indicating that coupon introduction actually occurred at the same time that the drug was approved, rather than a few months after FDA approval as sometimes indicated by the coupon database.

[57] For the remaining 14 drugs, we were unable to locate informative archived snapshots of manufacturer websites, in many cases because archived snapshots were not available far enough back in time. For these drugs, we kept the original scraped coupon introduction dates. For one additional drug (Xenical) we determined that no coupon in fact existed and removed this drug from consideration.

Appendix Figure B2: Lags in Scraped Coupon Dataset



Notes: Figure shows lags between coupon introduction dates in the scraped dataset and manually collected introduction dates. Data are shown for the 65/66 drugs fitting our sample criteria that are confirmed to introduce a coupon (1 drug is excluded as it did not actually introduce a coupon).

B.3 FDA data

We use the Drugs@FDA database of FDA-approved drugs to obtain drug-specific characteristics such as application approval date, application type (New Drug Application or Abbreviated New Drug Application), active ingredient at the FDA application level, and whether or not a drug is an extended-release formulation.[58] We use the application type to help define generic status (all drugs approved via an Abbreviated New Drug Application are generic drugs). We merged the Drugs@FDA data with the National Drug Code Directory (also maintained by the FDA) by application number. This allows us to ultimately merge the Drugs@FDA data with our PBM dataset, which defines a drug product by its 9-digit National Drug Code (NDC). Below, we provide further details on how we obtained and merged these data sources.

We obtained yearly copies of the Drugs@FDA database for 2009–2018 from the FDA website.[59] We appended these yearly datasets, keeping the most recent information for each FDA application number. The database contains information on all drugs currently manufactured, prepared, propagated, compounded, or processed for sale in

[58] We classify drugs as extended release based on whether their Drugs@FDA dosage form includes words like "extended," "release," or "delayed."

[59] U.S. Food and Drug Administration. 2009–2018. "Drugs@FDA: FDA-Approved Drugs." U.S. Department of Health and Human Services. https://www.accessdata.fda.gov/scripts/cder/daf/ (last accessed November 6, 2018).

the U.S. Each drug product is identified by a unique National Drug Code (NDC). The first 9 digits of the NDC code (NDC9) identify the drug labeler and drug product, while the remaining 1 or 2 digits denote the package size. We defined drug products at the NDC9 level, keeping the most recent information for each NDC9 code. We obtained yearly copies of the National Drug Code Directory[60] for 2009-2018, using the Web Archive to obtain data prior to 2011. Using yearly snapshots ensures that we observe NDC codes that may have been changed or discontinued over time. The NDC9 data also contain FDA application numbers, which allows us to merge the NDC9 codes with the Drugs@FDA data.[61]

Using the merged Drugs@FDA and NDC data, we determine whether there are generic equivalents for a given NDC9 code, where generic equivalents are defined as generic NDC9 codes that share the same active ingredient, dosage form, route of administration, and extended-release status.

B.4 Dataset for Reduced Form Analysis

The unit of observation for the PBM data is the 9-digit NDC (NDC9)- year-segment-month. The NDC9 codes uniquely identify a drug product by a 4-digit labeler name (which usually denotes the manufacturer, e.g. Biogen, but can also refer to a repackager or distributor), a 4-digit product code (which denotes the drug product, which is a unique combination of strength and dosage form, e.g. "Tecfidera 240mg oral capsule"), and a 2-digit package code (which identifies the package size and type, e.g. "bottle of 30 tablets"). The PBM data also includes the name corresponding to each NDC9; multiple NDC9 codes may map to the same name. The same molecule may have a branded name as well as a generic name (which correspond to different NDC9 codes). The PBM data also assigns an indication to each NDC9, corresponding to how that drug product is most often used.

For our analysis, we use the standardized name in the PBM data as the unique drug identifier (see Appendix Section B.1 for the construction of the standardized drug name), but we first merge the PBM and FDA datasets using the more granular NDC9 codes. We are able to match 98% and 97% of the total PBM costs for the commercial and Medicare segments respectively to an NDC9 code in the FDA data. The drugs for which we were not able to find matches in the FDA data consist primarily of lower-cost and distinct indications that are billed to the PBM but are not listed in the FDA drug data, including vaccinations, medical supplies, alternative therapies, topical antiseptics, diagnostic aids, and nutrition-related products. We eliminate indications where more than 50% of the PBM's costs for that indication consist of NDC9s that we are unable to match in the FDA data. These indications include: vaccinations, alternative therapies, and medical supplies, among others. In total, these indications account for 1.6% of total costs in the PBM data.

[60] U.S. Food and Drug Administration. "National Drug Code Directory." U.S. Department of Health and Human Services. https://www.fda.gov/drugs/drug-approvals-and-databases/national-drug-code-directory (last accessed November 8, 2018)

[61] Multiple NDC9 codes may map to a single FDA application number.

After the above merge process, we standardize the drug names (following the process described in Appendix Section B.1) and arrive at a sample of 1,608 (1,656) unique drugs in the Medicare (commercial) segment with both FDA and PBM data. Next, we drop generic drugs as well as branded drugs with generic equivalents. At this point, only 496 (507) unique branded drugs in the Medicare (commercial) segment without generic equivalents remain.

Because our main analysis relies on comparisons across commercial and Medicare segments, we further limit the sample in two ways. First, we limit the sample to drugs that are observed in both segments for at least one month. Second, we limit the sample to drugs with similar utilization in both segments. To do this, we first calculate the average utilization share s_{jk} for each drug d and segment k, defined as

$$s_{jk} = \frac{1}{|T_j|} \sum_{t \in T_j} \frac{ds_{jmk}}{\sum_{j \in J_m} ds_{jmk}},$$

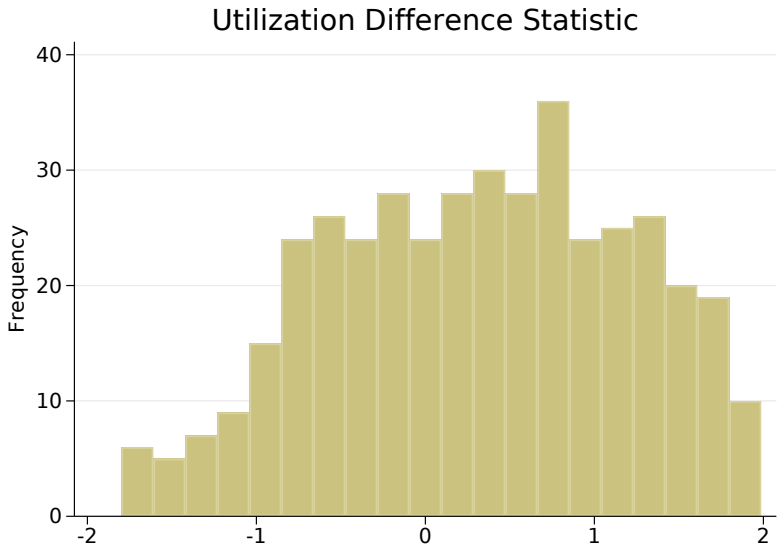
where T_j is the set of months where drug j is marketed in the data, ds_{jmk} is days supplied in the relevant year-month, and J_m is the set of drugs marketed in each month m. This gives us a measure of the average share of overall utilization (measured by days supplied) accounted for by each drug in a given segment. For each drug, we then construct the following measure of how utilization differs between segments:

$$\Delta u_j = \frac{s_{j,commercial} - s_{j,Medicare}}{\frac{1}{2}(s_{j,commercial} + s_{j,Medicare})}$$

This measure reflects the degree to which a drug makes up a larger share of prescriptions in the commercial segment as compared to the Medicare Advantage segment. For example, if a drug has $s_{j,commercial} = 7\%$ and $s_{j,Medicare} = 1\%$, then $\Delta u_j = (7-1)/(0.5 * (1+7)) = 6/4 = 1.5$. The distribution of this statistic is provided below. We exclude drugs with a difference greater than 1.5 in absolute value; this excludes 48 drugs. Of these excluded drugs, 40 are used disproportionately more in the commercial segment, with the most common MCIs being skin conditions or infections, diabetes, growth deficiency, and hormonal supplements. The drugs disproportionately utilized in Medicare are medications to treat diabetes, asthma, and inflammatory conditions.

After applying all of these restrictions, the sample contains 364 drugs.

Appendix Figure B3: Distribution of Segment Utilization Difference Statistic Δu_j



Next, we manually verified coupon introduction dates for the 66 drugs that appear to introduce a coupon in the scraped data between October 2014 and July 2017, inclusive.[62] We manually verified these drugs following the procedure outlined in Appendix Section B.2. After manual verification, the sample contains 68 "switchers" that introduced a coupon during our study period (i.e., between January 2014 and June 2016).[63] Of these, a subset of 33 drugs have a sufficient number of pre- and post-periods for our regression.[64]

Table B1 presents the sequential list of sample restrictions we apply, beginning with the original PBM data and ending with the estimation sample. The table contains the number of unique drug names and total spending on all in-sample drugs by segment, relative to total PBM spending by segment.

[62] Setting the minimum month to October 2014 allows for at least a 9-month pre-period. Because coupon introductions are often observed with a lag in the scraped data, using a July 2017 cutoff allows us to include coupon introductions that are observed with up to a 12-month lag. For example, a drug with a scraped coupon introduction date of July 2017 could have a revised coupon date of June 2016. This drug would then have at a 12-month post-period and could be included in our estimation sample.

[63] These 68 drugs are a different set compared to the set of 66 drugs that we manually verify as the former are identified *after* manual verification and have coupon introduction dates in a different time period (January 2014–June 2016 vs. October 2014–July 2017).

[64] We require a 9-month pre-period and 12-month post-period.

Appendix Table B1: Effect of Sample Restrictions

	Medicare Advantage		Commercial	
Step	Share of spending after step	Unique Drugs	Share of spending after step	Unique Drugs
Original PBM data	100%	1,929	100%	1,999
Exclude drugs not present in FDA data	97.5%	1,608	97.9%	1,656
Exclude generics	64.7%	758	63.7%	762
Exclude brands with generic equivalents	53.8%	496	54.6%	507
Exclude brands with dissimilar utilization across segments	48.3%	366	47.1%	366
Restrict to switchers only	4.6%	68	4.9%	68
Restrict to switchers with sufficient pre and post period for regression	3.6%	33	2.9%	33

Notes: "Drugs" are defined by our drug name standardization process and may correspond to multiple NDC9 codes. Drugs "not present" in FDA data include any drug for which at least 50 percent of spending for the drug's category lacks a match in the FDA data.

B.5 Dataset Construction for Demand Model Estimation

Selecting the drugs in the choice set

We use National Drug Code (NDC) and HCPCS codes to identify prescription drug and medical claims for MS drugs. The 11 MS drugs we include in our choice set are the most common MS drugs in the HCCI data and account for 99.9% of spending on DMTs during our study period. We excluded MS drugs with very few observed prescriptions, including Extavia, Lemtrada, Ocrevus, Novantrone, and two additional Copaxone generics (Glatiramer 20mg and Glatiramer 40mg).

Defining coupon status for each drug

Taking the scraped coupon data as a starting point, we manually verified the coupon status of all MS drugs in our choice set using snapshots of each drug's website from the Internet Archive. In some cases, we determined whether a drug had a coupon at the time of FDA approval based on contemporary press releases, which usually mention a coupon or copay assistance program if one exists.

Among the interferon-based therapies, only Rebif is coded to have a coupon. Rebif (interferon beta-1a) is the earliest drug to introduce a coupon (October 2007) and is always couponed during our sample period. Avonex (another drug containing interferon beta-1a) introduced a free trial program in October 2011, but this program saw very little use ($< 3\%$ of scripts according to a contemporary industry report[65], and we code Avonex as having no coupon during our sample period. Plegridy, a longer-acting

[65] Avey, Steve and Alaina Sandhu. 2014. *Copay Coupons for Specialty Drugs: Strategies for Health Plans and PBMs.* Atlantic Information Services, Inc.

version of Avonex approved in August of 2014, also lacks a coupon in our scraped coupon database. Betaseron (interferon beta-1b) is the oldest MS drug (approved July 1993), but our coupon dataset only shows a coupon starting in December 2017. The above industry report suggests that there may have been a copay program for Betaseron, but that it had low utilization ($< 5\%$). Hence, we code Betaseron as not having a coupon in our analyses.

Copaxone 20mg was approved January 1996 and couponed starting in August 2011. In the second quarter of 2012, Teva increased the coupon benefit of Copaxone 20mg from \$500 to \$2,500 per prescription and from \$6,000 to \$12,000 per year. Because coupon databases do not always distinguish between Copaxone 20mg and 40mg, one concern is that we do not know precisely if or when the coupon for Copaxone 20mg expires. Researchers with access to coupon redemption data verified that the coupon was still redeemed at least until April 2015, when the generic version of Copaxone 20mg (Glatopa) entered the market. Thus, we assume that the coupon for Copaxone 20mg shuts off starting April 2015. Our estimates are robust to lengthening the lifespan of the Copaxone 20mg coupon, including the case where the coupon never expires.

Soon after this increase in coupon generosity for Copaxone 20mg, the oral medication Aubagio was approved and launched with a 3-month free trial plus a coupon that reduced out-of-pocket costs to \$35. Hence, we code Aubagio as being couponed at approval (September 12, 2012). In the first quarter of 2013, the Aubagio coupon was revised to reduce out-of-pocket costs to \$10 per prescription. Like Aubagio, the other oral medications in our choice set are also couponed. Gilenya introduced a coupon in October 2011, a year after the drug's approval in September 2010. Tecfidera was approved and launched with a coupon in March 2013.

Tysabri is the only drug in our choice set that must be infused at a physician's office. Because it is usually covered by medical insurance rather than prescription drug insurance, it is not couponed.

According to msfocus.org, all of the above drugs are first line therapies for MS except for Gilenya and Tysabri. Table B2 shows characteristics for the MS drugs in our choice set.

Constructing average allowed amounts

As a proxy measure of the list price of a drug, we use the average allowed amount for a given drug, market segment (commercial vs. Medicare), and year-quarter. We compute this using all MS drug claims (across all patients in the HCCI database). First, we extract all claims from the HCCI database for MS drugs based on National Drug Code (NDC) and Healthcare Common Procedure Coding System (HCPCS) codes, restricting to claims with a positive allowed amount. This yields N = 2,540,002 claims. For each NDC/HCPCS code, we filter out claims where the days supply does not match the modal value (this excludes 264,547 observations). We also drop NDC/HCPCS codes that comprise <= 1000 claims or <= 2% of claims for a given drug (this excludes an additional 479 observations). Next, we drop claims with allowed amounts <= \$100 (2,907 observations), which are likely to represent errors given the high prices of MS

Appendix Table B2: Drug Characteristics

Drug	**Form**	**US Approval**	**Firm**	**Coupon status**
Aubagio	Daily pill	2012 Sept 12	Sanofi	Always
Copaxone 20mg (Glatiramer Acetate)	Daily injection	1996 Jan 28	Teva	8/2011–4/2015
Copaxone 40mg (Glatiramer Acetate)	Thrice-weekly injection	2014 Jan 29	Teva	Always
Glatopa (Glatiramer Acetate; generic for Copaxone 20mg)	Daily injection	2015 Apr 16	Sandoz (Novartis)	Never
Avonex (Interferon Beta-1a)	Weekly injection	1996 May 17 2012 Feb 28 (in pen form)	Biogen	Never
Plegridy (Interferon Beta-1a)	Biweekly injection	2014 Aug 15	Biogen	Never
Tecfidera	Twice-daily pill	2013 March 27	Biogen	Always
Tysabri	1-hour infusion per month	2004 Nov 23	Biogen	None
Betaseron (Interferon Beta-1b)	Injection every other day (usually by physician)	1993 July	Bayer	None
Rebif	Thrice-weekly injection	2002 March 8	Merck	From 10/2007 (Always for study period)
Gilenya	Daily pill	2010 Sept 21	Novartis	From 10/2011

Notes: Table provides summary characteristics for all of the MS drugs in our choice set. Column 1 gives the drug brand name, with non-proprietary (generic) name in parentheses. Column 2 describes the dosage form and route of administration. Column 3 shows the first U.S. FDA approval date. Column 4 shows the drug manufacturer. Column 5 provides coupon information for each drug.

drugs.

Next, we exclude claims with extremely low or high values for the allowed amount relative to other claims for the same drug, plan characteristics, and time period. For each drug, we perform a claim-level regression of allowed amount on dummies for year-quarter, NDC/HCPCS code, segment, specialty drug status, mail order status, insurance plan type, and whether the insurance plan is a high-deductible plan. We treat missing values for specialty and mail-order status as separate bins. For each drug, we exclude claims where the residual from this regression is below the 1st percentile or above the 99th percentile.

For some drugs in the choice set, the number of pills in a single prescription varies between 28 and 30. This occurs when a manufacturer changes the number of pills or doses in a single prescription. To establish a single allowed amount for these drugs, we rescale the allowed amounts to correspond to the most common prescription size. For example, allowed amounts for Gilenya prescriptions for a 30-day supply of pills are rescaled by 28/30 to correspond to the more common 28-day supply. After applying these cleaning steps, we found that for each drug, most of the variation in allowed amount can be accounted for by year-quarter and NDC/HCPCS fixed effects. This suggests that we can treat average allowed amounts as a proxy measure of the list price charged to insurers, and that this allowed amount predominantly varies over time rather than across insurance plans or across segment.[66]

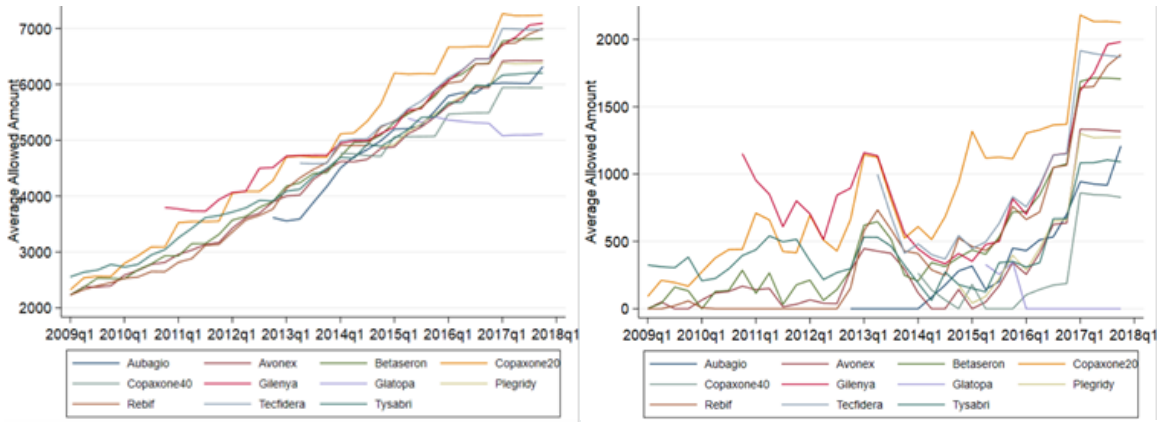
Figure B4 demonstrates how average allowed amounts for MS drugs have evolved over time. Although there is some price variation across drugs, average allowed amounts for MS drugs have generally increased in lock-step, from about $2500 in 2009 to about $6500 in 2017.

[66]Note, this does not include rebates, which may vary across insurers.

Appendix Figure B4: Average Allowed Amounts for MS Drugs Over Time

(a) Average Allowed Amounts

(b) Relative Allowed Amounts



Notes: Panel (a) shows average allowed amounts over time. Panel (b) shows the same, but subtracting the lowest price in each period to better visualize relative prices. Note that the price of Copaxone20 rises quickly after the introduction of Copaxone40, to facilitate the product hop. Also notice that the price of the Glatopa generic is initially pretty high (right below Copaxone40), but it doesn't grow along with the other drugs, so it ends up being quite a bit cheaper (nonetheless, Glatopa is not very popular as a result of the product hop to Copaxone 40)

B.6 Defining out-of-pocket prices

The prices that enter our demand model are the out-of-pocket prices paid by patients, which are usually only a small fraction of list prices. These out-of-pocket prices are challenging to infer from the HCCI data since neither plan copays and coinsurance rates for MS drugs nor plan identifiers are available. Moreover, most individuals only take one or two different drugs throughout their enrollment period, so it is not possible to directly observe copays or coinsurance rates at the patient-drug level. To surmount this issue, we make assumptions on how out-of-pocket prices vary.

For each patient-year, we first infer whether a patient's plan uses copays or coinsurance, using the complete set of RX and medical claims filled in each patient-year. Importantly, this includes both claims for MS drugs and claims for all other drugs and medical services.

We first categorize each claim as on deductible, no cost sharing, copay, or coinsurance. Claims on deductible are those where the deductible column in the data is greater than zero or where the total patient cost sharing is equal to the allowed amount.[67] Claims where patient cost sharing is \$0 are coded as such. Copay claims are those where total patient cost sharing is a multiple of \$1, no more than \$300 in

[67] The data contains columns for copay, coinsurance, and deductible amounts, but these fields are not reliable, since coinsurance and deductible payments are frequently entered in the "copay" field.

total, and not already coded as a deductible claim. Coinsurance claims are those that are not already coded as a deductible claim, and where patient cost sharing is not a multiple of $1 or greater than $300. The coinsurance rate for a claim is defined as patient cost sharing divided by the total allowed amount, rounded to the nearest 5%. We re-classify claims with coinsurance rates greater than 40% as deductible claims.

After classifying each claim, we calculate the share of coinsurance claims out of the total number of coinsurance or copay claims (excluding deductible claims and those with $0 cost sharing). We calculate this share at the patient-year level, separately by plan type (i.e. prescription drug insurance or medical insurance), and over all claims (i.e. not only those for MS drugs).[68] Patient-year-plan type combinations with a share of coinsurance claims $\geq 50\%$ are classified as using coinsurance, where the coinsurance rate is defined as the median coinsurance rate for all claims in that patient-year-plan type.

This method relies on the supposition that plans either operate on a coinsurance or copay basis, such that MS drugs would not be on coinsurance if all other drugs were on a copay basis, and vice versa. Moreover, it supposes that coinsurance rates do not vary within plan across different drugs. This is necessary to guarantee that we can define both RX and medical coinsurance rates for all drugs for all individuals. To the extent that these assumptions do not hold, measurement error will be introduced into our estimates of the price coefficient.

For patient-year-drug combinations that use coinsurance rates, we define the out-of-pocket price as the coinsurance rate times the average allowed amount, where the coinsurance rate is defined as the median coinsurance rate on all RX scripts in the patient-year. We allow the average allowed amount to vary by drug, segment, and year-quarter.[69] For individuals whose plan charges copays for MS drugs, we assume that the copay amount is the same across all MS drugs in the choice set. Hence, copays only vary across individuals and thus do not contribute to pinning down the price sensitivity parameters in our demand estimates.[70]

For patient-year-plan types that use copays, we set p_{ijkt}^{OOP} to the average copay on all DMT prescriptions for that patient-year. If the average DMT copay is missing, we assign the average copay across all drugs.

Of the remaining observations that lack an out-of-pocket price, some can be inferred to have $0 cost sharing, if at least 50% of DMT claims or 50% of all claims have no cost sharing. These individuals are likely those with enough costs to hit their out-of-pocket maximums.

The remaining patients are assumed to be making their choice at a time when their spending is lower than their deductible, and hence their out-of-pocket price for each drug is set equal to the minimum of the average allowed amount (as a proxy for the

[68] We must consider medical insurance because Tysabri is typically delivered at a physician office and hence appears in medical rather than prescription drug claims.

[69] Using the weighted average acquisition cost (WAC) instead of the average allowed amount yields similar results.

[70] This is because the conditional logit model implicitly controls for patient fixed effects.

list price) and estimated deductible.[71] In practice, most patient-drug out-of-pocket price observations (98.4%) are coded as coinsurance, copays, or $0 cost sharing (see Appendix Table B3 for more details).

Appendix Table B3: Source of Out-of-Pocket Prices by Segment

Type of price	Medicare Advantage	Commercial
Avg DMT copay (MD)	-	0.1%
Avg DMT copay (RX)	6.5%	58.6%
Avg copay (MD)	8.3%	6.0%
Avg copay (RX)	12.2%	11.6%
List price (MD)	0.3%	0.3%
List price (RX)	0.2%	0.6%
No CS on DMTs (MD)	-	0.1%
No CS on DMTs (RX)	3.4%	5.0%
No CS on all drugs (MD)	0.4%	0.9%
No CS on all drugs (RX)	-	0.2%
Deductible (RX)	-	0.1%
Deductible (RX + MD)	0.2%	1.0%
Coinsurance (MD)	2.3%	4.9%
Coinsurance (RX)	66.1%	10.7%
Total Observations	9,733	29,419

Notes: Table shows the source of out-of-pocket prices in the HCCI demand estimation sample, separately by segment.In Column 1, *Avg DMT copay* refers to the average copay on all DMT prescriptions for a given patient-year. *Avg copay* refers to the average copay on all prescriptions for a given patient-year. *Coinsurance* reflects cases where $\geq 50\%$ of claims in a patient-year are classified as coinsurance, where the median coinsurance rate is used to define the out-of-pocket price. Cost-sharing under the deductible is captured by *Deductible*; *List price* covers cases where the average allowed amount is used as the out-of-pocket price. *No CS on DMTs* and *No CS on all drugs* reflects cases where individuals have reached their out-of-pocket maximums and are observed to have no cost sharing. (MD) denotes medical insurance, which covers Tysabri, and (RX) denotes prescription drug insurance, which covers all other drugs in the choice set. *Deductible (RX+MD)* refers to a common deductible across prescription drug and medical insurance.

B.7 Share of Coupon Users

We derive our baseline value for the share of commercial enrollees who use coupons (λ) using pharmacy claims data reported by (Starner et al., 2014). Starner et al. find that 46% of prescriptions for MS drugs among commercially insured patients are associated with a coupon. Their sample of MS drugs included Gilenya (fingolimod), Copaxone 20mg (glatiramer acetate), interferon beta-1a (Avonex and Rebif), interferon beta-1b

[71] We estimate the total deductible in a patient-year by summing together all medical and RX deductible claims.

(Betaseron), and Tysabri (natalizumab). Their sample period was from July 2010 to December 2012.

To calibrate λ from the estimates in Starner et al 2014, we first note that not all of the drugs in their sample have a copay coupon: we do not observe coupons for Avonex, Betaseron, and Tysabri. This suggests that, for the drugs where a coupon was available, the usage rate λ was higher than 46%. The share of commercial prescriptions in our data that correspond to a couponed drug between July 01, 2010 and Dec 31, 2012 was 61.3%. This suggests that of the 61.3% of prescriptions that could have had a coupon, 75% of them were associated with a coupon. Assuming that coupon users and non-users fill a similar number of prescriptions per person, we can calibrate $\lambda = 0.75$. That is, 75% of commercially insured individuals taking a couponed MS drug will use the coupon.

Thus, our preferred specification sets $\lambda = 0.75$. We also test robustness of our estimates and simulation results to $\lambda = 0.60$ and $\lambda = .90$.

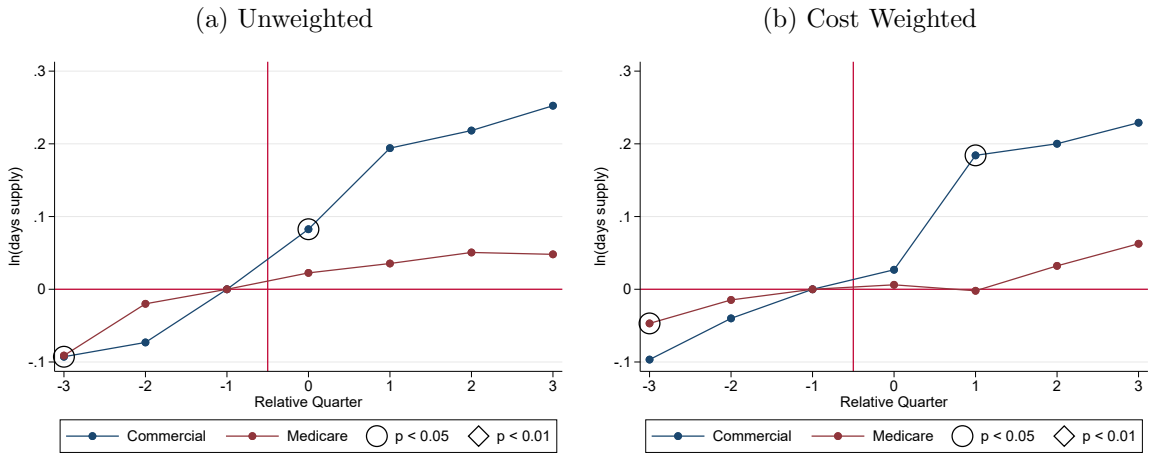
C Details for Difference-in-Differences Analysis

C.1 Segment-specific Trends

To examine absolute trends in quantity for the treatment (commercially insured) and control (Medicare Advantage enrollees) groups, we estimate a variant on equation (1) that shows the segment-specific time trends before and after coupon introduction. Figure C5 below shows the results from this specification for quantity.[72]

[72] We do not find any changes in time trends relative to coupon introduction for prices.

Appendix Figure C5: Segment-specific Trends in Utilization



Notes: Figure shows segment-specific trends in drug utilization relative to coupon introduction. Panel (a) shows results without weights; Panel (b) shows cost-weighted results. The estimated specification regresses log(days supply) on relative-quarter fixed effects interacted with dummies for each segment. As in specification (1) in the main text, we include drug-segment fixed effects; however, we exclude year-month fixed effects to allow us to interpret the time trend *levels* for both segments around coupon introduction (rather than just the between-segment differences, as in our main specification).

The results show that for the set of drugs in our estimation sample, days supplied is increasing prior to coupon introduction for both the commercial and Medicare Advantage segments, but demand surges up for the commercial segment after coupon introduction. Table C4 below presents coefficient estimates from a specification that pools the post-coupon period, and confirms that the increase in quantity after coupon introduction is statistically significant at $p < 0.01$ for the commercially insured population.

Appendix Table C4: Segment-specific Trends Pooled Specification

	Unweighted (1)	Cost Weighted (2)
Medicare × Post	0.076	0.045*
	(0.061)	(0.026)
Commercial × Post	0.242***	0.206***
	(0.058)	(0.048)

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Notes: Table shows coefficient estimates from a pooled regression of log days supply on a post coupon introduction indicator, separately by segment. Standard errors are clustered at the drug level. Column (1) and (2) show unweighted and cost-weighted results respectively.

C.2 Challenges in Distinguishing Between Market Expansion and Business Stealing in the Differences-in-Differences Analysis

The welfare effects of coupons cannot be deduced from the reduced form analyses for a range of reasons, including the fact that we do not evaluate whether the coupons resulted in a net increase in drug utilization.

To the extent that coupons induce substitution toward the couponed drug in lieu of therapeutic substitutes ("business stealing"), rather than growth in overall utilization ("market expansion"), coupons are less likely to be welfare-enhancing (assuming more is better for prescription drug utilization). (Even if the increase in demand were entirely due to market expansion, however, this analysis would not enable us to definitively assess the welfare implications of coupons as we lack an estimate of the benefit from incremental utilization net of its price.)

We attempted to discern between business stealing and market expansion effects by defining markets around each index drug in our PBM analysis sample. Following prior research on pharmaceutical markets, we began by including the therapeutic substitutes for each drug as those with the same ATC4 code, and then we used the PBM designation of "medical indication" for each drug to restrict the market to drugs with the same broad medical indication. In addition, we manually reviewed all 219 substitute—index drug pairs, excluding cases where the candidate substitute drug does not treat the same specific medical indication (and thus should not be included in the index drug's market). For instance, we further separated rescue inhalers from long-acting inhalers (both may share the same ATC4 code and treat COPD but are not substitutable). Similarly, many cancer medications share the same ATC4 code but are used to treat different specific types of cancer. Using this methodology, we classified some of our index drugs as monopoly markets, for which coupon effects likely reflect market expansion, however the majority of drugs have substitutes.

In principle, differential decreases in commercial utilization relative to Medicare Advantage utilization among substitutes following coupon introduction for the index drug would suggest business stealing effects, whereas differential increases in overall market quantity (without decreases for substitutes) would reflect market expansion. However, we concluded this analysis was not appropriate due to ill-defined markets and small expected effect sizes.

For instance, potential substitute drugs often treat multiple indications that only partially overlap with an index drug. This is especially true for cancer drugs. Gleevec can be used to treat the same indications as the index drug Stivarga, but Gleevec also treats other cancer indications that Stivarga does not, and Gleevec's quantity sold swamps that of Stivarga. Thus, searching for quantity effects of a Stivarga coupon on aggregate Gleevec sales, or on sales of all therapeutic substitutes in the relevant market using the data available to us, is not likely to be an effective approach to assessing which mechanism prevails.

In addition, the expected size of business stealing or market expansion effects are small, as index drugs often account for only a small share of the overall market. Thus, even if our estimated coupon effect of 20% were entirely due to business stealing, this would only lead to a 1-2% decrease in the quantity of substitutes for index drugs with a 5-10% market share (which is approximately their actual median market share using the market definitions described above). The expected magnitude of any market expansion effects would be similarly small.

In summary, high variance in the outcome variable due to ill-defined markets, coupled with small expected effect sizes, severely limit our statistical power to assess market-level outcomes and thus to differentiate between business stealing and market expansion.

D Further Model Details

D.1 More Detailed Demand Framework

We estimate the demand model introduced in Section 3.1 via maximum likelihood, taking the share of commercially insured enrollees who use coupons (λ) as given. The log likelihood function is:

$$\ln \mathcal{L}(\theta) = \sum_{i \in \bar{I}_{MA,t}} \ln \big(\sum_{j \in J_t} s_{ijt}^{MA} \big) \times 1[chosen_i = j] + \sum_{i \in \bar{I}_{com,t}} \ln \big(\sum_{j \in J_t} \lambda s_{ijt}^{c} + (1-\lambda) s_{ijt}^{nc} \big) \times 1[chosen_i = j].$$

The shares s_{ijt}^{MA}, s_{ijt}^{c}, and s_{ijt}^{nc} are given by:

$$s_{ijt}^{g} = \frac{\exp(u_{ijt}^{g})}{\sum_{l \in J_t} \exp(u_{ilt}^{g})}, \text{ for } g = MA, c, \text{ and } nc,$$

where the utilities u_{ijt}^{MA}, u_{ijt}^{c}, and u_{ijt}^{nc} are as defined in Section 3.1.

D.2 Further Details of Price Negotiation Model

This appendix provides details of the terms determining markups in the Nash Bargaining model. Recall from Section 3.3 that we model the insurer's objective function as:

$$V(J_t, p) = CS(J_t, p) - TC(J_t, p)$$

The total consumer surplus in period t is modeled as:

$$CS_t(J_t, p) = \frac{1}{\alpha_{com}} \Big[\sum_{i \in \bar{I}_{MA,t}} \ln \big(\sum_{j \in J_t} \exp(u_{ij,MA,t}) \big) + \sum_{i \in \bar{I}_{com,t}} \ln \big(\sum_{j \in J_t} \exp(u_{ij,com,t}) \big) \Big],$$

where the factor $\frac{1}{\alpha_{com}}$ ensures that $CS_t(\cdot)$ is in dollar units.

The total drug cost to the insurer for MS drugs is:

$$TC_t(J_t, p) = \sum_{j \in J_t} \Big[\sum_{i \in \bar{I}_{MA,t}} s^{MA}_{i,j,t} \big(p_{jt} - p^{OOP}_{ijt} \big) + \sum_{i \in \bar{I}_{com,t}} (\lambda s^{c}_{ijt} + (1-\lambda) s^{nc}_{ijt}) \big(p_{jt} - p^{OOP}_{ijt} \big) \Big]$$

where p_{jt} is the negotiated net-of-rebate price, and $p^{OOP}_{ijkt} = f_i(p_{jt})$ is the out-of-pocket price paid by the enrollee, which is related to p_{jt} in a way that depends on the cost-sharing rules faced by each individual i, and the rebate, as in equation (5).

For each drug j, we can write the first order condition:

$$p^{coupon}_{jt} = c_{jt} + w(.)\lambda coupon_{j,t} \sum_{i \in I_{com,t}} s^{c}_{ijt} p^{OOP}_{ijt} + \frac{\bar{s}_{jt} - \lambda coupon_{j,t} \sum_{i \in I_{com,t}} s^{c}_{ijt} \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}}}{-\big([\frac{1-\eta}{\eta}] \frac{V'(J_t,p)}{\Delta V(J_t, p_{j,t})} \bar{s}_{jt} + \frac{\partial \bar{s}_{jt}}{\partial p_{jt}} \big)}$$

where the weight $w(.)$ is defined as $w(.) \equiv 1/[\bar{s}_{jt} + \frac{\eta}{1-\eta} \frac{\Delta V(J_t, p_{j,t})}{V'(J_t,p)} \frac{\partial \bar{s}_{jt}}{\partial p_{jt}}]$. The terms $V'(J_t, p)$ and $\Delta V(J_t, J_t \backslash j, p_{j,t})$, shown below, provide additional constraints on markups relative to the Nash Bertrand price-setting model. The second term reflects the portion of the manufacturer's cost of offering coupons that is passed through to prices.

The term $V'(J_t, p)$ captures the effect of increasing list price on the insurer's objective, which can be broken down into how changes in price affect consumer surplus and total costs.

$$
\begin{aligned}
V'(J_t,p) &= \frac{\partial V(J_t,p)}{\partial p_j} = \frac{\partial CS}{\partial p_j} - \frac{\partial TC}{\partial p_j} \\
&= \underbrace{\sum_{i\in I_{com,t}} [\text{coup avail}_j] \times (1-\lambda) s^{nc}_{ijt} \frac{\partial \tilde{u}^{nc}_{ijt}}{\partial p^{OOP}_{ijt}} \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}} + [\text{no coup avail}_j] \times s^{com}_{ijt} \frac{\partial \tilde{u}^{com}_{ijt}}{\partial p^{OOP}_{ijt}} \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}}}_{\partial CS/\partial p_j} \\
&\underbrace{- \Big[\sum_{i\in I_{MA,t}} s^{MA}_{ijt} (1 - \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}}) + \sum_{i\in I_{com,t}} s^{com}_{ijt} (1 - \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}}) }_{} \\
&\underbrace{+ \Big(\sum_{l\in J_t} \sum_{i\in I_{com}} [\text{no coup avail}_j] \times \frac{\partial s^{com}_{ilt}}{\partial p^{OOP}_{ijt}} \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}} (p_{lt} - p^{OOP}_{ilt}) + [\text{coup avail}_j] \times \left((1-\lambda) \frac{\partial s^{nc}_{ilt}}{\partial p^{OOP}_{ijt}} \frac{\partial p^{OOP}_{ijt}}{\partial p_{jt}} (p_{lt} - p^{OOP}_{ilt}) \right) \Big) \Big]}_{\partial TC/\partial p_j}
\end{aligned}
$$

The first line of this expression is $\partial CS/\partial p_j$. The second line is the first-order effect of a small change in p_j on TC: a direct effect on insurer costs, net of rebates and consumer out-of-pocket payments. Line three contains terms allowing a change in p_j to affect market shares through an effect on out-of-pocket prices. These terms are non-zero only for commercial enrollees (because MA enrollees are insensitive to price) and only for those who do not use a coupon.

The term $\Delta V(J_t, J_t \setminus j, p_{j,t})$ captures how excluding a drug j affects the insurer's objective. Removing a drug from the choice set decreases consumer surplus, but it may also decrease total costs if consumers substitute to cheaper alternatives.

$$
\begin{aligned}
&\Delta V(J_t, J_t \setminus j, p_{j,t}) = \Delta CS(J_t, J_t \setminus j, p_{j,t}) - \Delta TC(J_t, J_t \setminus j, p_{j,t}) \\
&= \sum_{i\in I_{MA,t}} \left[\ln \sum_{l\in J_t} \exp(\tilde{u}^{MA}_{ilt}) - \ln \sum_{l\in J_t\setminus j} \exp(\tilde{u}^{MA}_{ilt}) \right] \\
&+ \sum_{i\in I_{com,t}} \lambda \left[\ln \sum_{l\in J_t} \exp(\tilde{u}^{c}_{ilt}) - \ln \sum_{l\in J_t\setminus j} \exp(\tilde{u}^{c}_{ilt}) \right] + (1-\lambda) \left[\ln \sum_{l\in J_t} \exp(\tilde{u}^{nc}_{ilt}) - \ln \sum_{l\in J_t\setminus j} \exp(\tilde{u}^{nc}_{ilt}) \right] \\
&- \Big(\sum_{l\in J_t} \left[\sum_{i\in I_{MA,t}} s^{MA}_{ilt} (p_{lt} - p^{OOP}_{ilt}) + \sum_{i\in I_{com,t}} (\lambda s^{c}_{ilt} + (1-\lambda) s^{nc}_{ilt}) (p_{lt} - p^{OOP}_{ilt}) \right] \\
&- \sum_{l\in J_t\setminus j} \left[\sum_{i\in I_{MA,t}} s^{MA}_{ilt}(j) (p_{lt} - p^{OOP}_{ilt}) + \sum_{i\in I_{com,t}} (\lambda s^{c}_{ilt}(j) + (1-\lambda) s^{nc}_{ilt}(j)) (p_{lt} - p^{OOP}_{ilt}) \right] \Big)
\end{aligned}
$$

where $s^k_{ilt}(j)$ indicates the share when drug j is excluded from the choice set.

The final two lines in the above equation reflect $\Delta TC(J_t, J_t \setminus j, p_{j,t})$ and the preceding two lines reflect $\Delta CS(J_t, J_t \setminus j, p_{j,t})$.

Note that the derivative $\frac{\partial s_{ilt}}{\partial p_{jt}}$ is with respect to the net price p_{jt}, and can be written

as

$$\frac{\partial s_{ilt}}{\partial p_{jt}} = \frac{\partial s_{ilt}}{\partial p_{ijt}^{OOP}} \times \frac{\partial p_{ijt}^{OOP}}{\partial p_{jt}} = \begin{cases} \frac{\partial s_{ilt}}{\partial p_{ijt}^{OOP}} \times \frac{\rho_i}{1-r} & \text{if } i\text{'s plan uses coinsurance rate } \rho_i \text{ and } j \text{ is not couponed} \\ 0 & \text{otherwise,} \end{cases}$$

where $\frac{\partial p_{ijt}^{OOP}}{\partial p_{jt}}$ is also with respect to the net price. However, because coinsurance rates for drugs are applied to list prices, we evaluate this derivative with respect to list price using a change of variables: the coinsurance ρ_i is multiplied by $1/(1-r)$, where r is the fixed rebate percentage, which we take from outside data on rebates from Kakani et al. (2020).

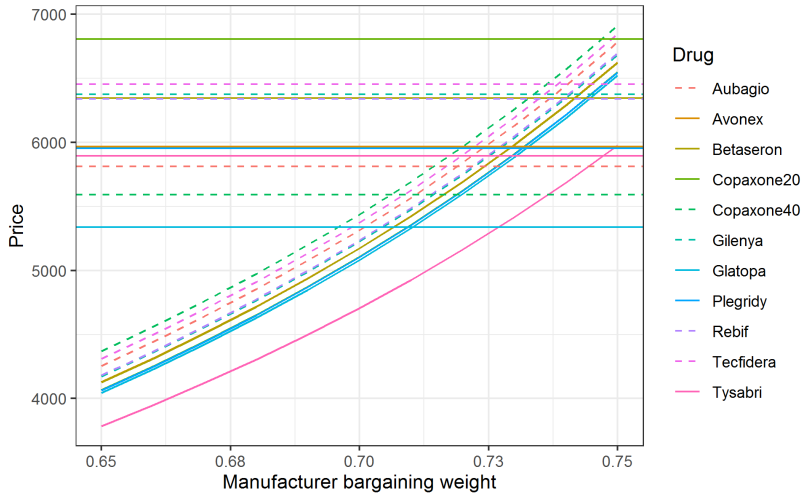
E Details of Counterfactual Simulations

E.1 Calibration of the bargaining parameter

The bargaining parameter η describes the weight placed on manufacturer profits versus the insurer's objective in the Nash Product (Equation 8). Bargaining nests Nash Bertrand pricing (this is the case when $\eta = 1$). When $\eta < 1$, the insurer has additional leverage in constraining list prices or increasing rebates, since the insurer can threaten to exclude a drug from its formulary. Thus, the value of η captures the degree to which the insurer can constrain prices beyond consumer cost sharing.

Because the value of η is not observed, we calibrate η to match the simulated net prices (Equation 9) to net prices that we infer from the simulation data, assuming zero marginal costs of drug manufacturing. We calculate inferred net prices from the data by multiplying the allowed amounts (a proxy for list prices) by 1 - r, where r is the fixed rebate share that we assume to be 0.15. Figure E6 shows how simulated net prices vary with η, and how these prices compare to the observed prices (defined as $(1-r)$ times the average allowed amount for each drug). As expected, increasing η results in higher simulated prices. We calibrate η to minimize the mean squared distance between the vectors of simulated and observed prices.

Appendix Figure E6: Calibrating the Manufacturer Bargaining Weight η



Notes: Figure shows how we calibrate the manufacturer bargaining weight to approximately match the prices observed in the data. Line colors represent different drugs; dashed lines indicate couponed drugs. Y-axis shows simulated and observed prices. X-axis shows the manufacturer bargaining weight η.

E.2 Sensitivity of simulation results to parameter choices

Our simulation results depend on the assumed values of the share of eligible consumers who use a coupon λ and the magnitude of the fixed rebate share r. Recall that the bargaining parameter η is calibrated conditional on λ and r to match the share-weighted average simulated and observed prices. Below, we demonstrate that the broad conclusions from our simulations are robust to a range of different values of these parameters.

Robustness to λ: To assess how our assumption of $\lambda = 0.75$ affects our results, we consider $\lambda = 0.60$ and $\lambda = 0.90$ while holding r constant at 0.15. In addition, we estimate specifications where λ is assumed to vary with cost sharing. In one version, we set $\lambda = 0.7$ for individuals whose cost sharing amount (averaged across drugs) is less than \$150 and $\lambda = 0.9$ for individuals whose average cost sharing exceeds \$150. In another version, we set $\lambda = 0.5$ for cost sharing below \$75, 0.7 for cost sharing between \$75 and \$150, and 0.9 for cost sharing above \$150. Given each specification for λ, we re-estimate demand (Sections 3.1 and D.1) and re-calibrate η to arrive at new simulation results. Table E5 below shows demand estimates under these alternative specifications for λ.

Appendix Table E5: Maximum Likelihood Estimates, Varying λ

	$(\lambda = 0.60)$	$(\lambda = 0.75)$	$(\lambda = 0.90)$	$(\lambda = (0.7, 0.9))$	$(\lambda = (0.5, 0.7, 0.9))$
OOP Price	0.049 $^{+}$	0.049 $^{+}$	0.049 $^{+}$	0.049 $^{+}$	0.049 $^{+}$
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
OOP Price X Commercial	-0.121 **	-0.099 **	-0.080 **	-0.079 **	-0.079 **
	(0.030)	(0.029)	(0.028)	(0.028)	(0.028)
Coupon X Commercial	0.367 $^{+}$	0.373 $^{+}$	0.388 $^{+}$	0.390 $^{+}$	0.390 $^{+}$
	(0.208)	(0.208)	(0.209)	(0.208)	(0.208)
Coupon	-0.261	-0.263	-0.264	-0.264	-0.263
	(0.246)	(0.246)	(0.245)	(0.245)	(0.245)
Drug Age (6-12 mo)	0.634 $^{+}$	0.632 $^{+}$	0.633 $^{+}$	0.633 $^{+}$	0.633 $^{+}$
	(0.269)	(0.269)	(0.269)	(0.269)	(0.269)
Drug Age (1-2 yr)	1.303 **	1.300 **	1.299 **	1.299 **	1.300 **
	(0.280)	(0.280)	(0.280)	(0.280)	(0.280)
Drug Age (2-3 yr)	1.522 **	1.518 **	1.516 **	1.516 **	1.517 **
	(0.322)	(0.322)	(0.322)	(0.322)	(0.322)
Drug Age (3-5 yr)	1.826 **	1.821 **	1.818 **	1.818 **	1.818 **
	(0.354)	(0.354)	(0.353)	(0.354)	(0.354)
Drug Age (5+ yr)	1.825 **	1.816 **	1.809 **	1.809 **	1.809 **
	(0.420)	(0.420)	(0.420)	(0.420)	(0.420)
Drug Age (6-12 mo) X Female	-0.352	-0.351	-0.352	-0.352	-0.351
	(0.288)	(0.288)	(0.288)	(0.288)	(0.288)
Drug Age (1-2 yr) X Female	-0.495 $^{+}$	-0.493 $^{+}$	-0.493 $^{+}$	-0.494 $^{+}$	-0.494 $^{+}$
	(0.257)	(0.257)	(0.257)	(0.257)	(0.257)
Drug Age (2-3 yr) X Female	-0.625 $^{+}$	-0.624 $^{+}$	-0.623 $^{+}$	-0.623 $^{+}$	-0.624 $^{+}$
	(0.263)	(0.263)	(0.263)	(0.263)	(0.263)
Drug Age (3-5 yr) X Female	-0.838 **	-0.836 **	-0.834 **	-0.834 **	-0.834 **
	(0.261)	(0.261)	(0.261)	(0.261)	(0.261)
Drug Age (5+ yr) X Female	-0.316	-0.315	-0.314	-0.314	-0.314
	(0.231)	(0.231)	(0.231)	(0.231)	(0.231)
Drug FE	Yes	Yes	Yes	Yes	Yes
Drug-Year FE	Yes	Yes	Yes	Yes	Yes
Drug-Segment FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Notes: Table shows maximum likelihood estimates of Equations 2 and 3 across different assumptions for the share of coupon users λ. All columns include drug, drug-year, and drug-segment fixed effects. Columns 1, 2, and 3 show estimates assuming $\lambda = 0.60$, 0.75, and 0.90 respectively. Columns 4 and 5 show results when λ is assumed to vary with cost sharing.

Table E6 below shows the simulated price effects of coupons under alternative specifications for λ. When $\lambda = 0.60$, banning coupons coupons results in a slightly larger average decrease in list prices of 7.7%. In contrast, when $\lambda = 0.90$, banning coupons results in a smaller decrease in prices of 6.7%. Assuming that λ varies with out-of-pocket costs (Columns 9-10 and 11-12) gives similar results, with average price decreases of 6.6% (under the specification $\lambda = 0.7$, 0.9) and 6.5% (under the specification $\lambda = 0.5$, 0.7, 0.9).

Appendix Table E6: Sensitivity of Coupon Price Effect to λ

		$\lambda = 0.60$		$\lambda = 0.75$		$\lambda = 0.90$		$\lambda = (0.7, 0.9)$		$\lambda = (0.5, 0.7, 0.9)$	
Drug	Coupon Status	ΔPrice (%)	ΔShare (%)	ΔPrice (%)	ΔShare (%)	ΔPrice (%)	ΔShare (%)	ΔPrice (%)	ΔShare (%)	ΔPrice (%)	ΔShare (%)
Aubagio	Always	-7.6	-6.5	-7.4	-6.4	-6.7	-6.4	-6.6	-6.4	-6.5	-6.4
Avonex	Never	-6.7	26.5	-5.9	26.6	-4.6	26.7	-4.4	26.7	-4.4	26.6
Betaseron	Never	-6.9	24.6	-6.1	24.8	-4.8	24.9	-4.7	24.8	-4.6	24.7
Copaxone20	Aug 2011	-7.0	28.4	-6.2	28.5	-4.9	28.6	-4.7	28.5	-4.7	28.4
Copaxone40	Always	-7.8	-7.7	-7.7	-7.7	-7.2	-7.6	-7.1	-7.6	-7.0	-7.6
Gilenya	Oct 2011	-8.6	-8.9	-8.5	-8.8	-8.1	-8.7	-7.9	-8.7	-7.9	-8.7
Glatopa	Never	-7.1	30.9	-6.3	31.0	-5.0	31.1	-4.8	31.0	-4.8	30.9
Plegridy	Never	-7.0	29.0	-6.2	29.2	-4.9	29.3	-4.7	29.2	-4.7	29.1
Rebif	Always	-7.8	-6.8	-7.6	-6.7	-7.1	-6.6	-6.9	-6.6	-6.8	-6.6
Tecfidera	Always	-7.9	-7.6	-7.7	-7.5	-7.2	-7.4	-7.1	-7.4	-7.0	-7.4
Tysabri	Never	-10.0	39.8	-8.4	36.6	-5.8	32.8	-5.6	32.5	-5.6	32.3

Notes: Table shows how simulated changes in net price and shares vary across assumptions of λ. The average change in net price, weighting by baseline simulated shares, is -7.7%, -7.4%, and -6.7% for λ=0.60, 0.75, and 0.90 respectively. Columns 4 and 5 show results when λ is assumed to vary with cost sharing. For these cases, the average change in net price is -6.6% and -6.5% for these cases respectively.

The effect of changing λ comprises two different effects. A lower value of $\lambda = 0.60$ results in a larger estimated price coefficient. This case requires a higher value of η to match simulated and observed baseline prices. The higher inferred bargaining power of the drug manufacturer reduces the importance of the insurer objective in the negotiated price (Equation 10) and increases the impact of coupons, which directly affect the $\frac{\partial \bar{s_{jt}}}{\partial p_{jt}}$ term. This tends to increase the effect of coupons on price. On the other hand, the lower value of λ means that fewer individuals use coupons, which tends to reduce the effect of coupons on price. On net, the first effect outweighs the second, leading to a somewhat larger price effect of coupons for $\lambda = 0.60$ and a somewhat smaller price effect of coupons when $\lambda = 0.90$.

The distributional consequences of a coupon ban also depend on the specification for λ, as shown in Table E7 below. When $\lambda = 0.60$, there are fewer coupon users who would be negatively affected by a coupon ban, so the average increase in out-of-pocket costs is lower at \$73, compared to \$98 when $\lambda = 0.75$. Cost savings are also larger at \$402 compared to \$385 when $\lambda = 0.75$, due to a larger coupon effect on prices. Taken together, assuming $\lambda = 0.60$ implies that banning coupons would result in cost savings that are 5.5 times larger than the increase in out-of-pocket costs.

Assuming $\lambda = 0.90$ has the opposite effects, resulting in lower cost savings of \$361 and a larger increase in out-of-pocket costs of \$126, for a ratio of savings to out-of-pocket cost increases of 2.9. Assuming that λ varies with out-of-pocket costs (Columns 9-10 and 11-12) gives similar results, with a ratio of insurer savings to out-of-pocket cost increases of 2.8.

Appendix Table E7: Sensitivity of Distributional Effects to λ

Group	N	λ=0.6		λ=0.75		λ=0.90		λ=0.7, 0.9		λ=0.5, 0.7, 0.9	
		Δ Insurer Costs ($)	Δ OOP Costs ($)	Δ Insurer Costs ($)	Δ OOP Costs ($)	Δ Insurer Costs ($)	Δ OOP Costs ($)	Δ Insurer Costs ($)	Δ OOP Costs ($)	Δ Insurer Costs ($)	Δ OOP Costs ($)
Commercial	1,104	-408	112	-391	146	-369	183	-350	175	-350	175
Coupon Users	994	-410	196	-392	199	-369	205	-351	201	-351	202
Non-users	110	-403	-13	-387	-14	-365	-13	-347	-12	-347	-12
Medicare	388	-387	-40	-367	-38	-339	-35	-321	-34	-321	-34
Overall	1,492	-402	73	-385	98	-361	126	-342	121	-343	120
Ratio		5.5		3.9		2.9		2.8		2.8	

Notes: Table shows how a coupon ban would affect insurer costs (i.e., premiums) and out-of-pocket costs, separately for commercially insured consumers (separately for coupon users and non-users) and Medicare enrollees. Insurer costs are expressed in $ per member per month; out-of-pocket costs are expressed in $ per prescription for enrollees' first observed choice. Results average over coupon users and non-users (except where otherwise indicated) based on our assumed specification for the share of commercially insured individuals who use coupons λ.

Robustness to different values of the fixed rebate share r: Varying our assumed fixed rebate percentage (holding $\lambda = 0.75$ fixed) does not significantly affect our conclusions. Our baseline specification assumes a rebate percentage of 15%. Assuming a lower rebate percentage of 10% results in a small decline in the effect of coupons on net price, from -7.4% to -7.2%. Assuming higher values of 20% and 25% results in slight increases in the coupon price effect to -7.6% and -7.7% respectively.

Allowing the rebate share to adjust when coupons are banned: Rebates may adjust when coupons are banned. To account for this possibility, we simulate the impact of a coupon ban under the assumption that rebates adjust when coupons are removed, increasing from 15% to 20%. This results in a similar coupon effect on net price of -7.6%, as shown in Table E8 below.

Appendix Table E8: Price Effect of Coupons when Rebates Adjust

		Data		Simulation: Baseline		Simulation: Coupons Banned			
Drug	Coupon Status	Net Price ($)	Share	Net Price ($)	Share	Net Price ($)	Share	Δ Price (%)	Δ Share (%)
Aubagio	Always	4941	0.148	4805	0.137	5014	0.129	-7.6	-5.8
Avonex	Never	5071	0.076	4676	0.086	4952	0.105	-6.2	22.1
Betaseron	Never	5395	0.044	4672	0.058	4939	0.070	-6.4	20.6
Copaxone20	Aug 2011	5787	0.030	4614	0.030	4870	0.038	-6.5	23.4
Copaxone40	Always	4753	0.308	4912	0.298	5110	0.278	-7.9	-6.9
Gilenya	Oct 2011	5420	0.066	4723	0.066	4860	0.061	-8.8	-7.9
Glatopa	Never	4538	0.008	4590	0.009	4842	0.011	-6.6	25.6
Plegridy	Never	5060	0.028	4611	0.029	4866	0.036	-6.5	24.0
Rebif	Always	5390	0.054	4734	0.056	4922	0.052	-7.9	-6.0
Tecfidera	Always	5486	0.224	4856	0.218	5047	0.203	-7.9	-6.7
Tysabri	Never	5011	0.015	4248	0.013	4317	0.018	-10.0	32.7

Notes: Table shows how net prices and shares change when coupons are banned, assuming rebates adjust from 15% to 20% after the ban. Columns 3-4 show observed prices (computed as 0.85 × the average allowed amount) and market shares in the simulation sample. Columns 5-6 show simulated net prices and shares at baseline, where coupons are as observed in the data (Column 2). Columns 7-11 show results from a simulation where all existing coupons are banned. Columns 7-8 show the resulting net prices and market shares; Columns 9-10 express the effects of the coupon ban as a percent of baseline simulated values. The average change in net price is -7.6%, weighting by the baseline simulated shares in Column 6.

Insurer cost savings are slightly larger, but so is the increase in out-of-pocket expenses. This is because a portion of the decrease in net prices operates through rebates, which does not help reduce cost sharing, since coinsurance rates are applied to list prices not net prices. Table E9 below shows how insurer and out-of-pocket costs change for various groups of individuals.

Appendix Table E9: Distributional Effects when Rebates Adjust

Group	N	Insurer costs with coupons ($)	Insurer costs coupon ban ($)	Δ Insurer Costs ($)	OOP Cost with coupons ($)	OOP Cost coupons ban ($)	Δ OOP Costs ($)
Commercial	1,104	5,102	4,700	-402	88	240	153
Coupon Users	828	5,103	4,700	-404	35	240	205
Non-users	276	5,098	4,700	-398	245	240	-4
Copay	903	5,101	4,702	-399	30	69	40
Coinsurance	201	5,107	4,690	-418	348	1,009	661
Couponed Drugs	895 → 806	5,151	4,743	-409	57	251	195
Non-couponed Drugs	209 → 298	4,916	4,593	-323	234	233	-1
Medicare	388	5,090	4,709	-381	544	535	-9
Copay	117	5,091	4,710	-381	123	122	-2
Coinsurance	271	5,090	4,709	-381	726	714	-12
Couponed Drugs	282 → 282	5,152	4,748	-404	553	541	-11
Non-couponed Drugs	106 → 106	4,928	4,609	-319	524	521	-3
Overall	1,492	5,099	4,702	-397	206	317	111

Notes: Table shows average premiums and out-of-pocket costs with and without coupons, separately for selected subgroups. Rebates adjust from 15% to 20% when coupons are banned. Premiums are expressed in $ per member per month; out-of-pocket costs are expressed in $ per prescription for enrollees' first observed choice. Results average over coupon users and non-users (except where otherwise indicated) based on our assumption that $\lambda = 0.75$ share of commercially insured patients use coupons. Copay/coinsurance designations apply at the patient level. Patients are coded as paying copays or coinsurance based on the nature of their prescription drug insurance (see Appendix Section B.6) Patients with copay-based prescription drug insurance may have medical insurance that is coinsurance based. The number of individuals choosing couponed drugs may change after coupons are banned; this is reflected in Column 2 in the format [number of individuals when coupons are available] $\longrightarrow$ [number of individuals when coupons are banned].

Assuming that the coupon advertising effect selectively affects coupon users

Our baseline specification assumes that the advertising effect of coupons on demand affects all commercially insured individuals, regardless of whether they redeem coupons or not. This would be the case if coupons induce physician offices to prefer prescribing couponed drugs to all patients, with the expectation that many patients will have reduced out-of-pocket costs via coupons. However, the advertising effect of coupons may also affect coupon users to a larger degree than non-users, if knowledge that a coupon exists for a drug drives both coupon use and the advertising effect.

To test the sensitivity of our results to this assumption, we estimate versions of the demand model where the coefficient representing the advertising effect is 1.5 times larger for coupon users, 2 times larger for coupon users, and where the advertising effect only affects coupon users.

Our results are qualitatively similar under these alternative assumptions. The maximum likelihood demand estimates corresponding to these versions are shown below in Table E10. (Note that for the 1.5x and 2x cases, the reported *coupon X com* coefficient

applies to coupon non-users). When only coupon users have the advertising effect, the corresponding coefficient is 0.693, compared to 0.373 in the baseline case. The price effect of coupons is somewhat larger, at 8.7% compared to a baseline of 7.4%. Table E11 below reports the price effects of coupons when we assume that only coupon users have an advertising effect.

Appendix Table E10: Demand Estimates Under Alternative Advertising Effects

	Equal Ad Effects	Users 1.5x	Users 2x	Only Users
OOP Price	0.049 $^{+}$	0.049 $^{+}$	0.049 $^{+}$	0.049 $^{+}$
	(0.026)	(0.026)	(0.026)	(0.026)
OOP Price X Commercial	-0.099 **	-0.101 **	-0.102 **	-0.107 **
	(0.029)	(0.029)	(0.029)	(0.029)
Coupon X Commercial	0.373 $^{+}$	0.301 *	0.251 *	0.693 *
	(0.208)	(0.151)	(0.119)	(0.275)
Coupon	-0.263	-0.297	-0.318	-0.386
	(0.246)	(0.246)	(0.246)	(0.248)
Drug Age (6-12 mo)	0.632 *	0.633 *	0.632 *	0.634 *
	(0.269)	(0.269)	(0.269)	(0.269)
Drug Age (1-2 yr)	1.300 **	1.300 **	1.301 **	1.301 **
	(0.280)	(0.280)	(0.280)	(0.280)
Drug Age (2-3 yr)	1.518 **	1.518 **	1.519 **	1.520 **
	(0.322)	(0.322)	(0.322)	(0.322)
Drug Age (3-5 yr)	1.821 **	1.821 **	1.821 **	1.824 **
	(0.354)	(0.354)	(0.354)	(0.354)
Drug Age (5+ yr)	1.816 **	1.816 **	1.816 **	1.818 **
	(0.420)	(0.420)	(0.420)	(0.421)
Drug Age (6-12 mo) X Female	-0.351	-0.351	-0.350	-0.353
	(0.288)	(0.288)	(0.288)	(0.289)
Drug Age (1-2 yr) X Female	-0.493 $^{+}$	-0.494 $^{+}$	-0.493 $^{+}$	-0.494 $^{+}$
	(0.257)	(0.257)	(0.257)	(0.257)
Drug Age (2-3 yr) X Female	-0.624 *	-0.624 *	-0.624 *	-0.624 *
	(0.263)	(0.263)	(0.263)	(0.263)
Drug Age (3-5 yr) X Female	-0.836 **	-0.835 **	-0.835 **	-0.836 **
	(0.261)	(0.261)	(0.261)	(0.261)
Drug Age (5+ yr) X Female	-0.315	-0.315	-0.314	-0.315
	(0.231)	(0.231)	(0.231)	(0.232)
Drug FE	Yes	Yes	Yes	Yes
Drug-Year FE	Yes	Yes	Yes	Yes
Drug-Segment FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Notes: Table shows maximum likelihood estimates of Equations 2 and 3 across different assumptions for how coupon users and non-users are affected by the coupon advertising effect. Column 1 shows estimates assuming that both coupon users and non-users are equally affected by the advertising effect. Columns 2 and 3 show estimates assuming that the advertising effect coefficient (on Coupon X Commercial) is 1.5 or 2 times as large for coupon users (Note: the reported coefficient estimates are for non-users in these columns). Lastly, Column 4 shows estimates assuming that only coupon users are affected by the advertising effect. The advertising effect coefficient in Column 4 corresponds to coupon users. All columns include drug, drug-year, and drug-segment fixed effects.

Appendix Table E11: Price Effects of Coupons Under Alternative Advertising Effects

		Equal Ad Effects		Users 1.5x		Users 2x		Only Users	
Drug	Coupon Status	ΔPrice	ΔShare	ΔPrice	ΔShare	ΔPrice	ΔShare	ΔPrice	ΔShare
Aubagio	Always	-7.4	-6.4	-7.6	-7.1	-7.9	-7.5	-8.6	-8.4
Avonex	Never	-5.9	26.6	-6.2	29.3	-6.5	30.9	-7.2	34.9
Betaseron	Never	-6.1	24.8	-6.4	27.2	-6.7	28.7	-7.4	32.4
Copaxone20	Aug 2011	-6.2	28.5	-6.5	31.1	-6.8	32.7	-7.5	36.4
Copaxone40	Always	-7.7	-7.7	-8.0	-8.4	-8.2	-8.9	-9.0	-10.0
Gilenya	Oct 2011	-8.5	-8.8	-8.8	-9.7	-9.1	-10.2	-9.8	-11.5
Glatopa	Never	-6.3	31.0	-6.6	34.2	-6.9	36.1	-7.5	40.5
Plegridy	Never	-6.2	29.2	-6.5	32.0	-6.8	33.8	-7.5	38.1
Rebif	Always	-7.6	-6.7	-7.9	-7.4	-8.2	-7.8	-8.9	-8.7
Tecfidera	Always	-7.7	-7.5	-8.0	-8.2	-8.3	-8.7	-9.0	-9.8
Tysabri	Never	-8.4	36.6	-8.9	40.1	-9.3	42.6	-10.2	48.1

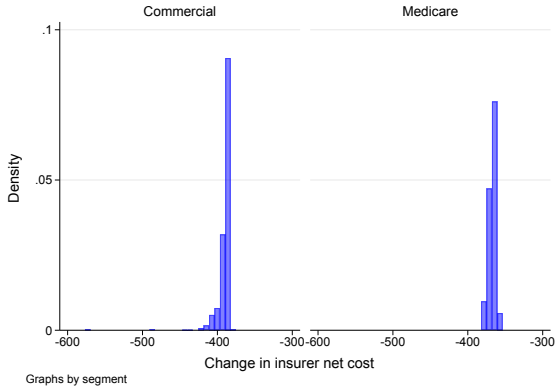
Notes: Table shows how simulated changes in net price and shares vary across assumptions on the advertising effect. Columns 3–4 show results when both coupon users and non-users are equally affected by the coupon advertising effect (our baseline specification). Columns 5–8 show results when the advertising effect is assumed to be 1.5x or 2x larger for coupon users. Columns 9-10 show results when we assume that only coupon users are affected by the advertising effect. The corresponding average changes in net price, weighting by baseline simulated shares, are -7.4%, -7.7%, -8.0%, and -8.7%.

E.3 Distributional Implications of a Coupon Ban

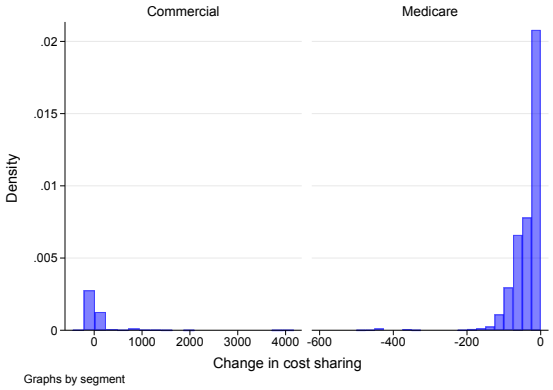
As noted in the text, the distributional implications of a coupon ban vary across individuals and segments. Panel (a) of Appendix Figure E7 below shows the effects of a ban on per-enrollee insurer expenditures. Insurers' costs decline across all enrollees due to the reduction in list prices for all medications. Panel (b) shows the effects on per-enrollee out-of-pocket costs per claim, which weakly decline for all Medicare Advantage enrollees, who were not able to redeem coupons so can only benefit from list price reductions, and can be large and positive for commercial enrollees who relied heavily upon coupons.

Appendix Figure E7: Distribution of Coupon Effects on Insurer and Out-of-Pocket Costs

(a) Coupon effect on insurer costs



(b) Coupon effect on cost sharing



Notes: Figures show the distribution of effects of banning coupons on insurer costs (Panel (a)) as well as enrollee out-of-pocket costs (Panel (b)) per prescription.