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HOW DO COPAYMENT COUPONS AFFECT BRANDED DRUG PRICES AND
QUANTITIES PURCHASED?

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ABSTRACT

Drug copayment coupons to reduce patient cost-sharing have become nearly ubiquitous for high-priced brand-name prescription drugs. Medicare bans such coupons on the grounds that they are kickbacks that induce utilization, but they are commonly used by commercially-insured enrollees. We estimate the causal effects of coupons for branded drugs without bioequivalent generics using variation in coupon introductions over time and comparing differential responses across enrollees in commercial and Medicare Advantage plans. Using data on net-of-rebate prices and quantities from a large Pharmacy Benefits Manager, we find that coupons increase quantity sold by 21-23% for the commercial segment relative to Medicare Advantage in the year after introduction, but do not differentially impact net-of-rebate prices, at least in the short-run. To quantify the equilibrium price effects of coupons, we employ individual-level data to estimate a discrete choice model of demand for multiple sclerosis drugs. We use our demand estimates to parameterize a model of drug price negotiations. For this category of drugs, we estimate that coupons raise negotiated prices by 8% and result in just under \$1 billion in increased U.S. spending annually. Combined, the results suggest copayment coupons increase spending on couponed drugs without bioequivalent generics by up to 30 percent.

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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

¹Source: 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).

²See, 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.

³The 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

⁴When 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

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

⁶See *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

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

¹¹We 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

¹²We 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

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

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

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

¹⁶2017 *Health Care Cost and Utilization Report*, Health Care Cost Institute, 2019.

¹⁷The 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 C¹⁹ 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.

¹⁸While 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.

¹⁹Like 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

²⁰As 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

²¹The 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

²²The 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

²³While the specification with a pooled post-period is convenient for performing robustness checks, our preferred specification is equation (1), which disaggregates 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,

²⁴Our 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.

²⁵It 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

²⁶Corts (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.

²⁷This 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:

$$u_{ijt}^{MA} = \delta_{jt} + \gamma \text{coupon}_{jt} + \alpha p_{ijt}^{OOP} + X'_{ijt} \beta + \varepsilon_{ijt} \quad (2)$$

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 introduction²⁸ 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

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

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

²⁸While 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.

²⁹We 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.

³⁰We 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:

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

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 rates 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

³¹One 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.

³²Note 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, $\frac{\partial p_{ijkt}^{OOP}}{\partial p_{jt}}$ is therefore given by:

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

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:

$$V(J_t, p_t) = CS(J_t, p_t) - TC(J_t, p_t) \quad (6)$$

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:

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

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:

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

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:

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

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

³³Our 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.

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

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:

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

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 $w(\cdot)$, 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

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

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>

³⁷Another 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 drugs⁴² 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.)

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

³⁹These 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

⁴⁰Glatopa was introduced in April 16, 2015. Its list price is only around 20% percent lower than its branded equivalent (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%).

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

⁴²Copaxone 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

⁴³Because 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

⁴⁴Recall 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](#)).

⁴⁵Copays 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.

⁴⁶We 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-

⁴⁸Because 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.

⁴⁹We 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.

⁵⁰Removing 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)).

⁵¹We 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.

⁵²Note 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 redistributive mechanism can be 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

⁵³We 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.

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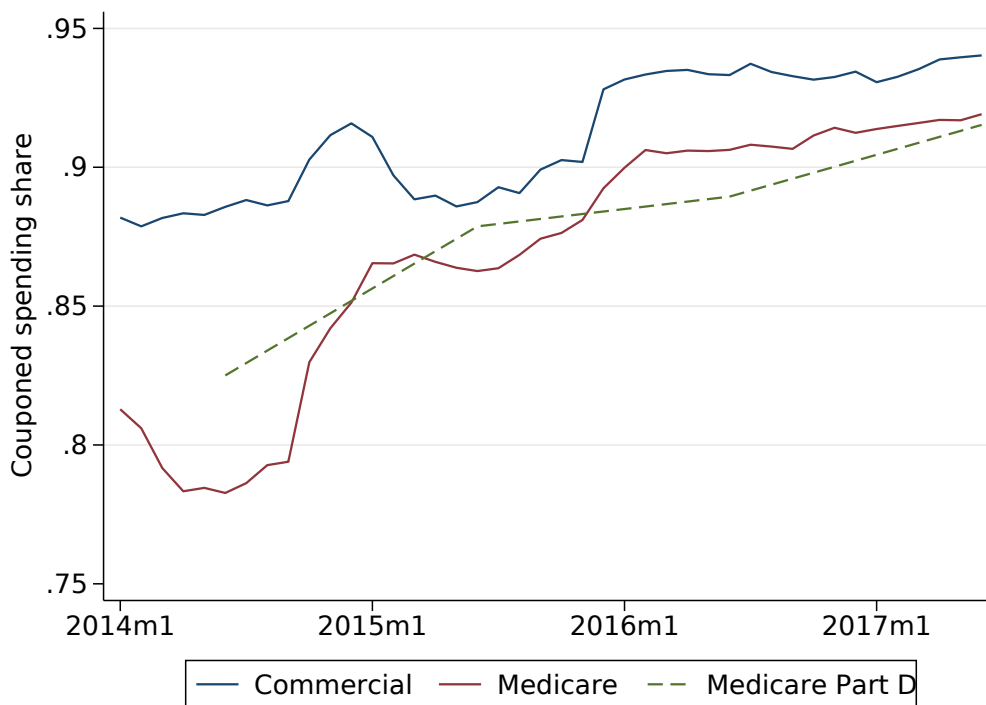
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Exhibits

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:

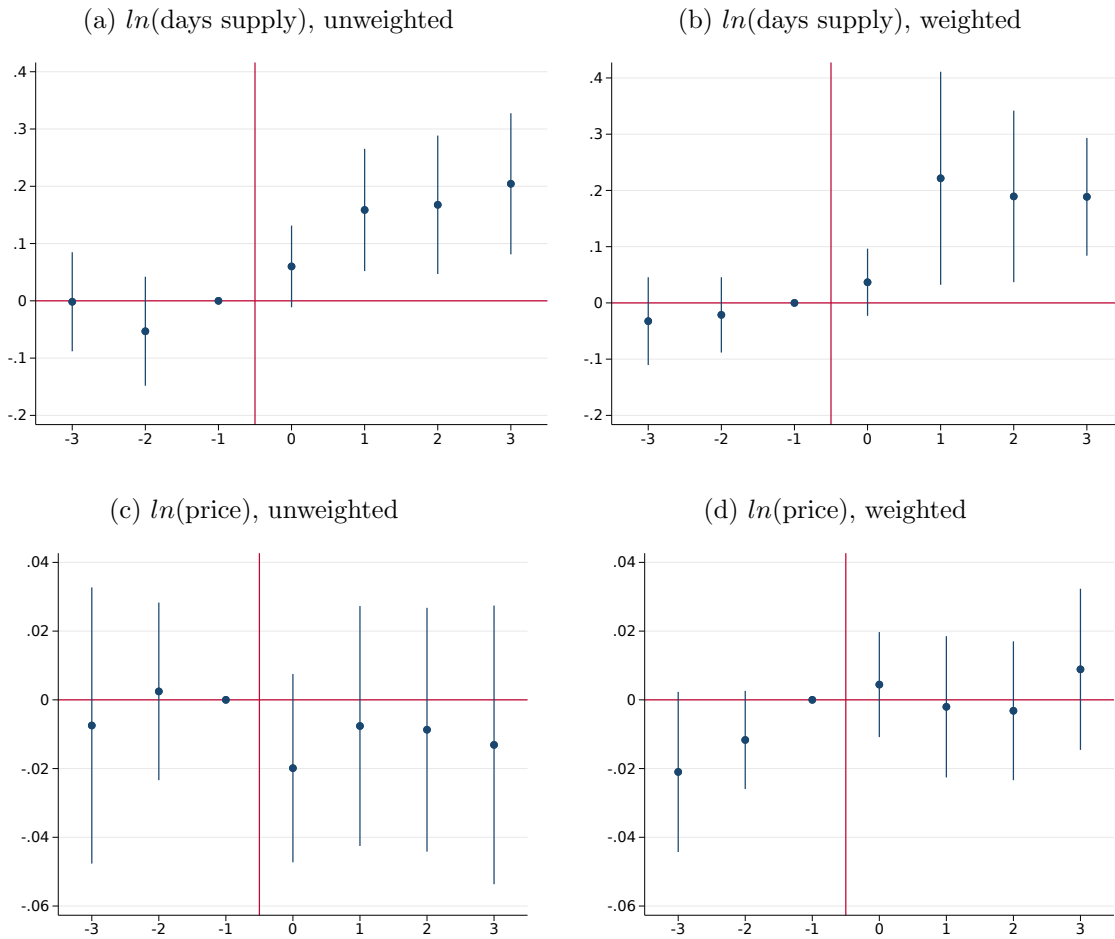
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Table 1: Descriptive Statistics (Drug-Month Sample)

	Always (1)	Never (2)	Switch (all) (3)	Switch (estimation sample) (4)
<i>A. Statistics by Category</i>				
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
<i>B. Statistics by Drug</i>				
Average list price (2014\$)	1,672 (3,841)	369 (367)	1,788 (2,873)	2,585 (3,482)
Monthly average days supplied	66,012 (183,093)	8,657 (16,779)	15,829 (28,243)	13,284 (20,352)
Average CAGR in price (%)	7.15 (10.02)	9.02 (10.50)	6.80 (10.67)	10.18 (10.92)
Average CAGR in days supplied (%)	28.87 (71.63)	14.00 (58.27)	100.74 (162.21)	24.01 (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 $\ln(\text{days supply})$ or $\ln(\text{price})$ 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)
<i>Commercial</i> ×				
$Q = -3$	-0.002 (0.042)	-0.032 (0.038)	-0.007 (0.020)	-0.021* (0.011)
$Q = -2$	-0.053 (0.047)	-0.021 (0.033)	0.002 (0.013)	-0.012 (0.007)
$Q = -1$	0 (-)	0 (-)	0 (-)	0 (-)
$Q = 0$	0.060* (0.035)	0.037 (0.029)	-0.020 (0.013)	0.004 (0.008)
$Q = 1$	0.159*** (0.052)	0.222** (0.093)	-0.008 (0.017)	-0.002 (0.010)
$Q = 2$	0.168*** (0.059)	0.189** (0.075)	-0.009 (0.017)	-0.003 (0.010)
$Q = 3$	0.204*** (0.060)	0.189*** (0.051)	-0.013 (0.020)	0.009 (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 (0.023)	0.037 (0.023)	0.049 + (0.026)
OOP Price X Commercial	-0.081 ** (0.027)	-0.084 ** (0.027)	-0.099 ** (0.029)
Coupon X Commercial	0.376 ** (0.085)	0.357 ** (0.085)	0.373 + (0.208)
Coupon	-0.134 (0.193)	-0.223 (0.193)	-0.263 (0.246)
Drug Age (6-12 mo)		0.635 + (0.268)	0.632 + (0.269)
Drug Age (1-2 yr)		1.328 ** (0.280)	1.300 ** (0.280)
Drug Age (2-3 yr)		1.562 ** (0.322)	1.518 ** (0.322)
Drug Age (3-5 yr)		1.843 ** (0.353)	1.821 ** (0.354)
Drug Age (5+ yr)		1.850 ** (0.420)	1.816 ** (0.420)
Drug Age (6-12 mo) X Female		-0.366 (0.288)	-0.351 (0.288)
Drug Age (1-2 yr) X Female		-0.508 + (0.257)	-0.493 + (0.257)
Drug Age (2-3 yr) X Female		-0.640 + (0.263)	-0.624 + (0.263)
Drug Age (3-5 yr) X Female		-0.844 ** (0.261)	-0.836 ** (0.261)
Drug Age (5+ yr) X Female		-0.319 (0.231)	-0.315 (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

Drug	Coupon Status	Data		Simulation: Baseline		Simulation: Coupons Banned			
		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 $0.85 \times$ 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 \rightarrow 806	5,127	4,731	-396	57	240	183
Non-couponed Drugs	209 \rightarrow 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 \rightarrow 282	5,127	4,736	-391	550	509	-41
Non-couponed Drugs	106 \rightarrow 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] \rightarrow [number of individuals when coupons are banned].