Online Appendix

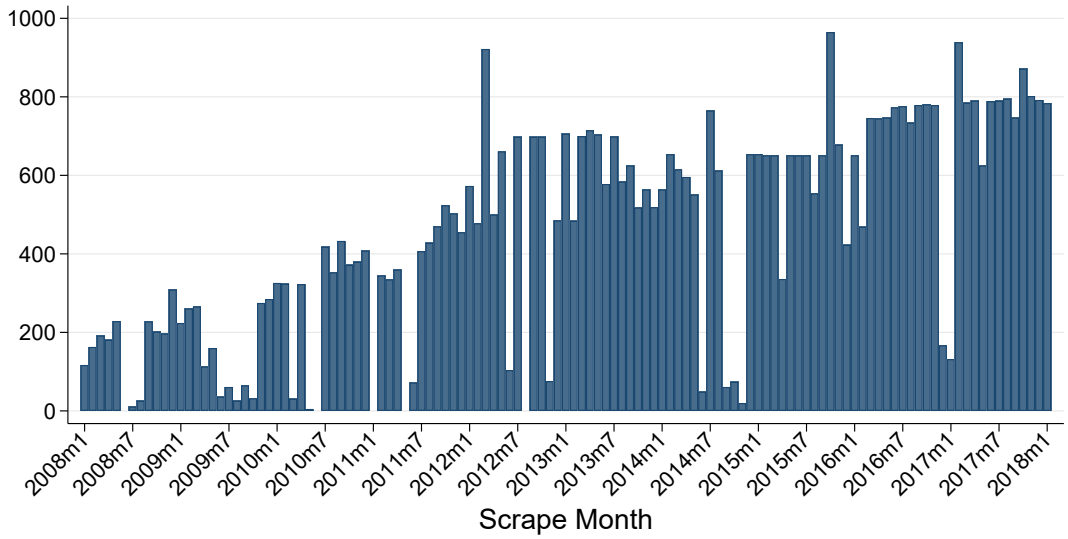
A Coupon Data

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

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

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

Appendix Figure A1: Coupon Data Availability



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

B Data Construction

B.1 Harmonizing Drug Names

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

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

B.2 Manual Verification of Coupon Introduction Dates

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

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

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

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

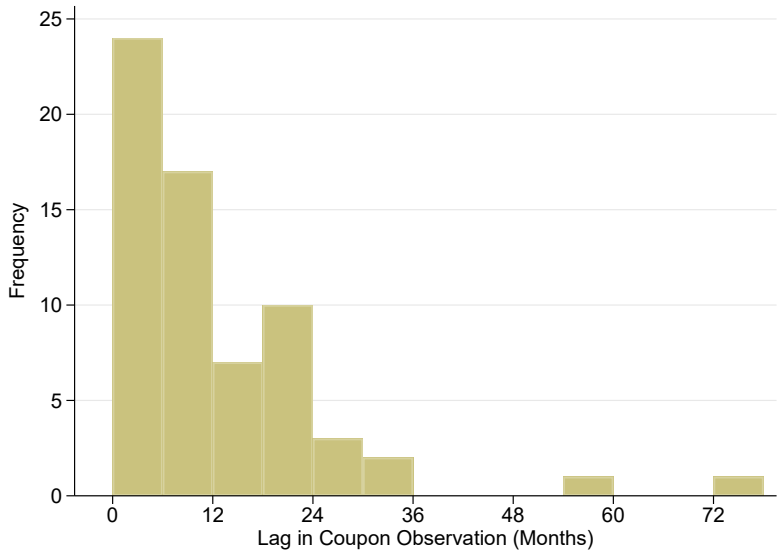
These results imply that the scraped coupon database prior to manual verification reflects coupon introductions with a lag. However, all regression analyses use coupon dates that are revised via the above manual verification process. Appendix Section B.5 describes additional detail from our verification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

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

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

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

Appendix Figure B2: Lags in Scraped Coupon Dataset



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

B.3 FDA data

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

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

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

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

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

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

B.4 Dataset for Reduced Form Analysis

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

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

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

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

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

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

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

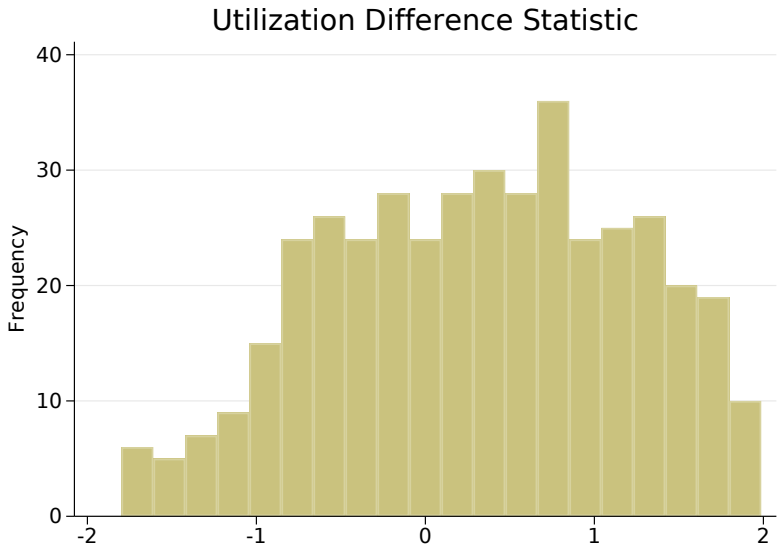
where T_j is the set of months where drug j is marketed in the data, ds_{jmk} is days supplied in the relevant year-month, and J_m is the set of drugs marketed in each month m. This gives us a measure of the average share of overall utilization (measured by days supplied) accounted for by each drug in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

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

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

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

Appendix Figure B3: Distribution of Segment Utilization Difference Statistic Δu_j



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

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

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

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

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

Appendix Table B1: Effect of Sample Restrictions

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

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

B.5 Dataset Construction for Demand Model Estimation

Selecting the drugs in the choice set

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

Defining coupon status for each drug

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

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

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

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

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

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

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

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

Constructing average allowed amounts

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

Appendix Table B2: Drug Characteristics

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

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

drugs.

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

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

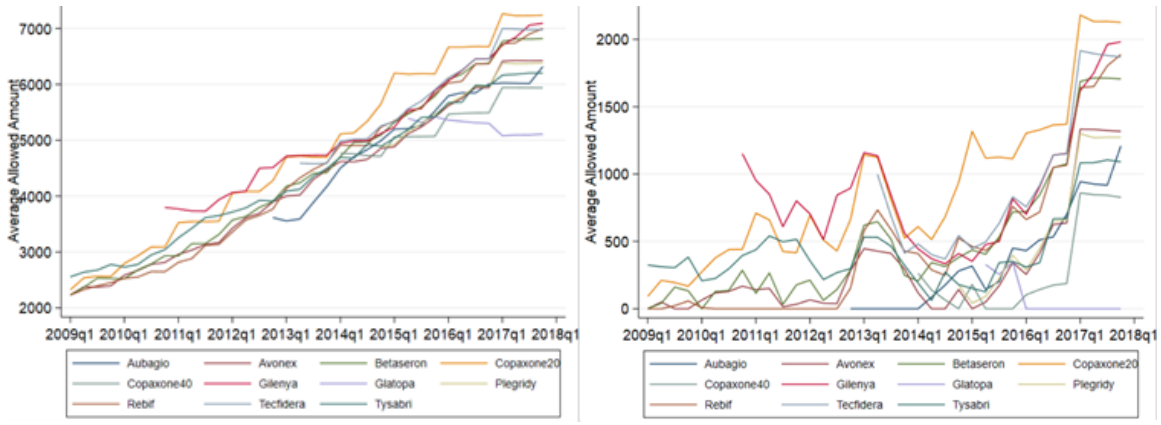
Figure B4 demonstrates how average allowed amounts for MS drugs have evolved over time. Although there is some price variation across drugs, average allowed amounts for MS drugs have generally increased in lock-step, from about $2500 in 2009 to about $6500 in 2017.

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

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

(a) Average Allowed Amounts

(b) Relative Allowed Amounts



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

B.6 Defining out-of-pocket prices

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

B.7 Share of Coupon Users

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

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

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

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

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

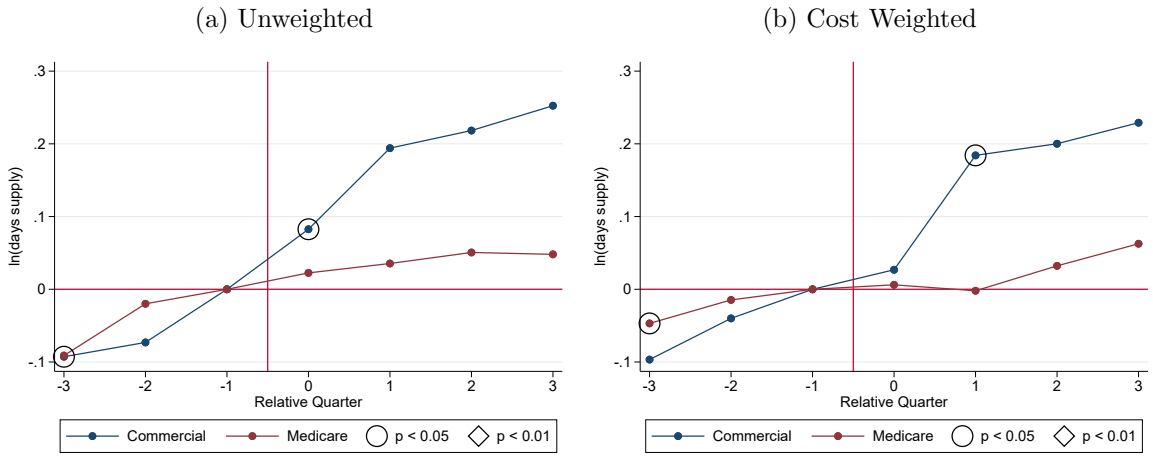
C Details for Difference-in-Differences Analysis

C.1 Segment-specific Trends

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

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

Appendix Figure C5: Segment-specific Trends in Utilization



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

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

Appendix Table C4: Segment-specific Trends Pooled Specification

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

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

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

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

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

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

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

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

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

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

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

D Further Model Details

D.1 More Detailed Demand Framework

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

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

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

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

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

D.2 Further Details of Price Negotiation Model

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

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

The total consumer surplus in period t is modeled as:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

as

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

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

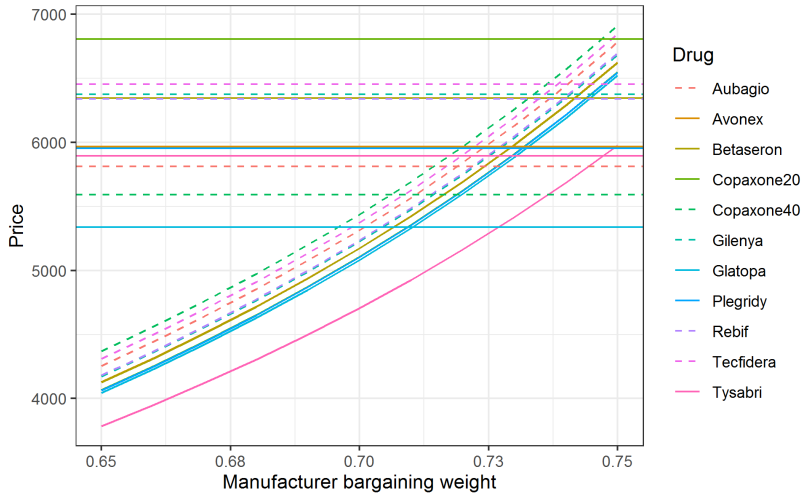
E Details of Counterfactual Simulations

E.1 Calibration of the bargaining parameter

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

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

Appendix Figure E6: Calibrating the Manufacturer Bargaining Weight η



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

E.2 Sensitivity of simulation results to parameter choices

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

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

Appendix Table E5: Maximum Likelihood Estimates, Varying λ

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

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

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

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

Appendix Table E6: Sensitivity of Coupon Price Effect to λ

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

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

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

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

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

Appendix Table E7: Sensitivity of Distributional Effects to λ

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

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

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

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

Appendix Table E8: Price Effect of Coupons when Rebates Adjust

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

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

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

Appendix Table E9: Distributional Effects when Rebates Adjust

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

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

Assuming that the coupon advertising effect selectively affects coupon users

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

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

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

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

Appendix Table E10: Demand Estimates Under Alternative Advertising Effects

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

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

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

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

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

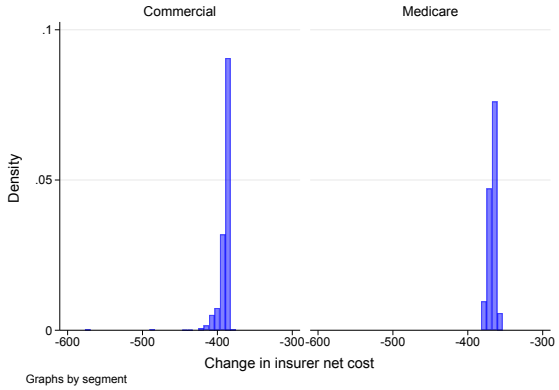
Notes: Table shows how simulated changes in net price and shares vary across assumptions on the advertising effect. Columns 3–4 show results when both coupon users and non-users are equally affected by the coupon advertising effect (our baseline specification). Columns 5–8 show results when the advertising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

E.3 Distributional Implications of a Coupon Ban

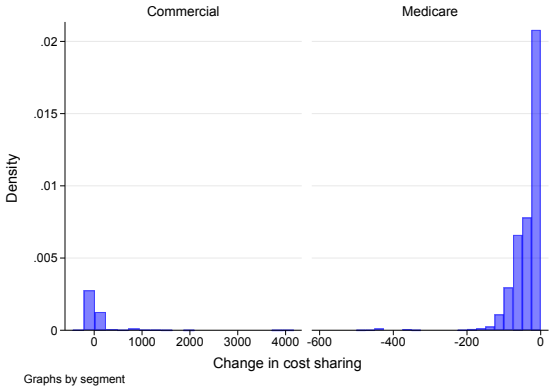
As noted in the text, the distributional implications of a coupon ban vary across individuals and segments. Panel (a) of Appendix Figure E7 below shows the effects of a ban on per-enrollee insurer expenditures. Insurers' costs decline across all enrollees due to the reduction in list prices for all medications.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

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

(a) Coupon effect on insurer costs



(b) Coupon effect on cost sharing



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