Online Appendix

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

Leemore Dafny, Kate Ho, Edward Kong

Code and public data are available in the AEA Data and Code Repository, see Dafny et al. (2023)

A Coupon Data

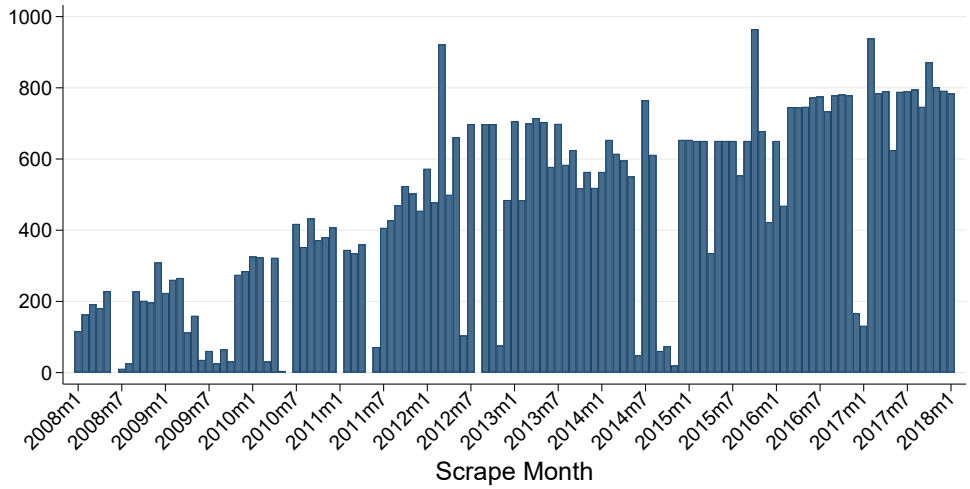
We combine data from InternetDrugCoupons.com, RxPharmacyCoupons.com, and NeedyMeds.org to code coupon introduction dates from January 2009 through January 2018. The data were assembled using historical snapshots of the three websites stored on the Internet Archive (webarchive.org). No single source is 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. A large share of 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.

By combining all three sources, we are able to obtain at least one snapshot for most of the year-months over this time frame. Appendix Figure A1) shows the number of coupons in our dataset by scrape month; each bar represents the *maximum* number of coupons observed in that month across the three datasets. In some months, low bars indicate that only a small number of drugs have archived snapshots that month (for example, if only the webpage corresponding to drugs starting with the letter "A" is archived in a given month, that month will have a significantly smaller number of coupons). 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. Spikes in the data reflect months were there were a high number of coupons observed, which may be due to multiple temporary offers per drug (e.g., a free trial offer as well as a separate copay coupon). 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.

Appendix Figure A2 demonstrates the rapid increase in the significance of coupons for branded drugs. This figure merges the coupon data with public data on drug

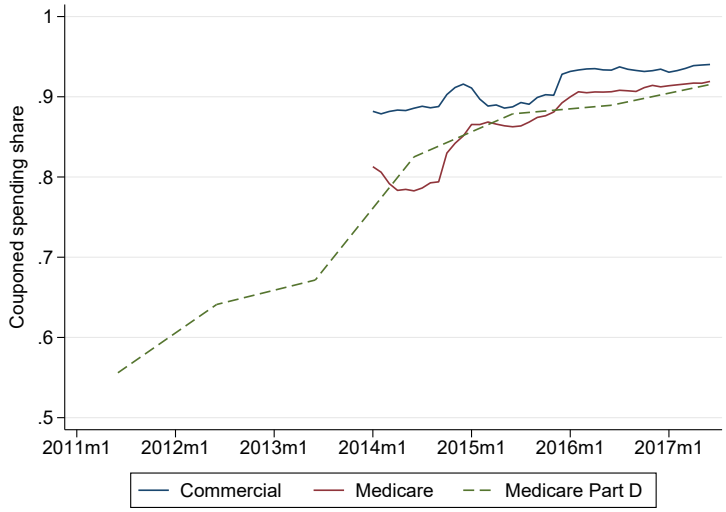
spending from Medicare Part D (2011–2017) and shows that the share of spending with a coupon increased from 55% in 2011 to over 90% in 2017 for drugs used in Medicare (with the corresponding commercial share likely being higher). This corresponds to a doubling in the number of coupons over the same period, from about 400 coupons in 2011 to 800 in 2017 (Appendix Figure A1). Appendix Figure A2 also confirms that the PBM Medicare Advantage data in our analysis matches the public Medicare Part D data (although the public data is gross of rebates, and the PBM data are net of rebates).

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.

Appendix Figure A2: 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 (gross of rebates). Part D spending is derived from authors calculations using CMS Part D Prescriber data: Centers for Medicare and Medicaid Services. 2011-2017. "Medicare Provider Utilization and Payment Data: Part D Prescriber." https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Part-D-Prescriber (accessed February 20, 2019).

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.[53]

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.[54] Of the 66 drugs, we were able to manually verify and adjust the introduction dates for 52 of them.[55] 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 B3 shows the distribution of the revisions applied to the coupon introduction dates originally scraped from the Internet Archive.

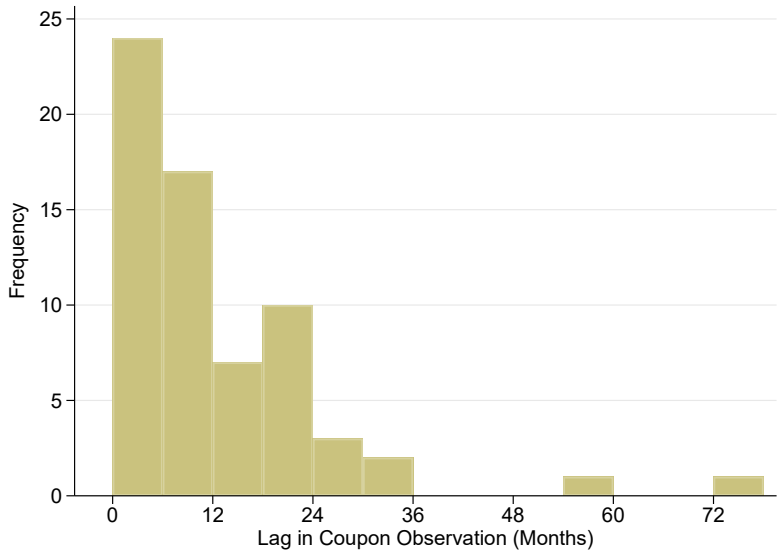
These results imply that the scraped coupon database prior to manual verification reflects coupon introductions with a lag. However, all regression analyses use coupon dates that are revised via the above manual verification process. Appendix Section B.6 describes additional detail from our verification process for the drugs used in our demand estimation.

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

[54] 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.

[55] 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 B3: 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.[56] 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 (U.S. Food and Drug Administration, 2009-2018*a*). 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 the U.S. Each drug product is identified

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

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 (U.S. Food and Drug Administration, 2009-2018*b*) 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.[57]

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. This is called the most common indication (MCI).

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.

After the above merge process, we standardize the drug names (following the process

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

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.

Drugs are identified as generic if they are manufactured under an ANDA (per the FDA data) or are designated as a generic in the PBM data. Among the branded drugs, we create an indicator for which has a bioequivalent generic, defined as another drug with the same active ingredient, dosage form, strength, route of administration, and extended-release status.

Our definition accords with the requirements of a bioequivalent generic described by the FDA.[58] Per the FDA, to establish bioequivalence, a "generic version must deliver the same amount of active ingredients into a patient's bloodstream in the same amount of time as the pioneer drug." Other studies in the literature (e.g., Dusetzina et al. (2020)) identify generics using all but one of our criteria (extended-release status). However, coding extended release status is a manual exercise based on drug names; we undertook this exercise because our focus is on couponed drugs, and branded drug manufacturers often introduce extended-release versions of their drugs in advance of generic entry of the immediate-release version, together with a coupon to promote switching to the extended-release version. Some studies adopt a coarser definition of a generic product, aggregating over different strengths of the same molecule and dosage form (e.g., Berndt et al. (2017)).

We drop generic drugs as well as branded drugs with bioequivalent generics. At this point, only 496 (507) unique branded drugs in the Medicare (commercial) segment without bioequivalent generics 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:

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

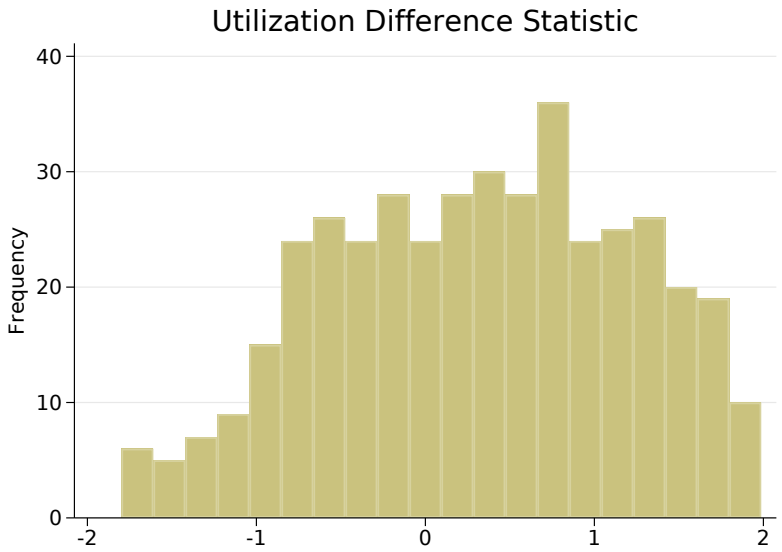
This measure reflects the degree to which a drug makes up a larger share of prescriptions in the commercial segment as compared to the Medicare Advantage segment. For example, if a drug has $s_{j,commercial} = 7\%$ and $s_{j,Medicare} = 1\%$, then

[58] https://www.fda.gov/drugs/resources-you-drugs/fda-ensures-equivalence-generic-drugs

$\Delta u_j = (7-1)/(0.5*(1+7)) = 6/4 = 1.5$. 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 B4: 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.[59] We manually verified these drugs following the procedure outlined in Appendix Section B.2. For our unbalanced event study analysis, we manually verify an additional 35 potential switchers that appear to introduce a coupon with at least 1 month of pre-period and 1 month of post-period. After these manual verifications, the sample contains 56 "switchers" that introduced a coupon during our study period (i.e., between January 2014 and June 2016). Of these, a subset of 33 drugs have a sufficient number of pre- and post-periods for our baseline balanced specification.[60]

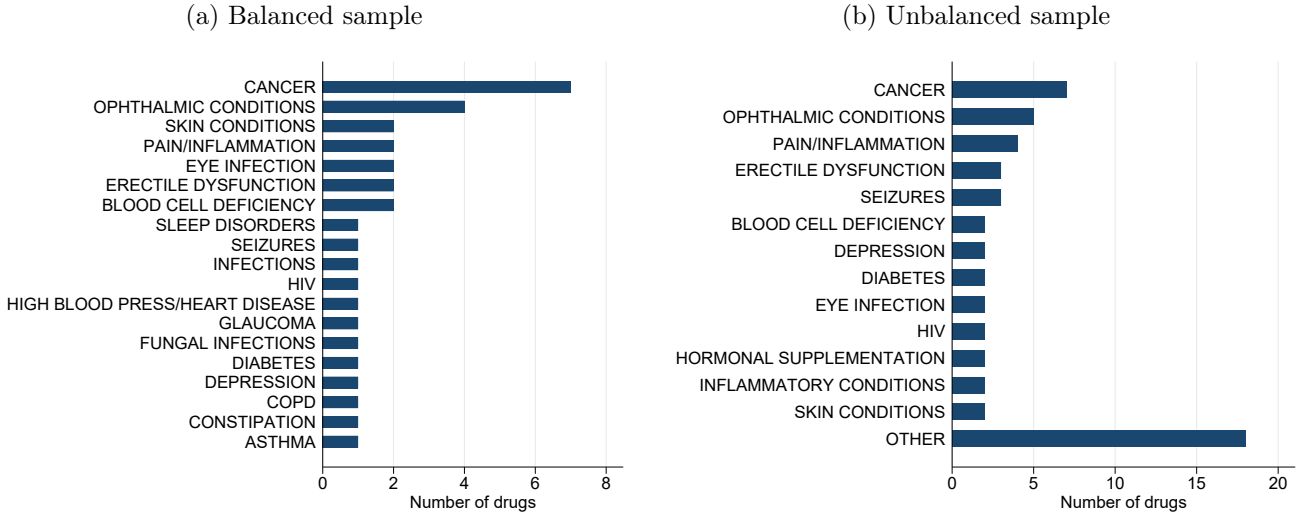
[59] Setting the minimum month to October 2014 allows for at least a 9-month pre-period. Because coupon introductions are often observed with a lag in the scraped data, using a July 2017 cutoff allows us to include coupon introductions that are observed with up to a 12-month lag. For example, a drug 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.

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

Table 1 in the main text 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.

B.5 Drug Indications

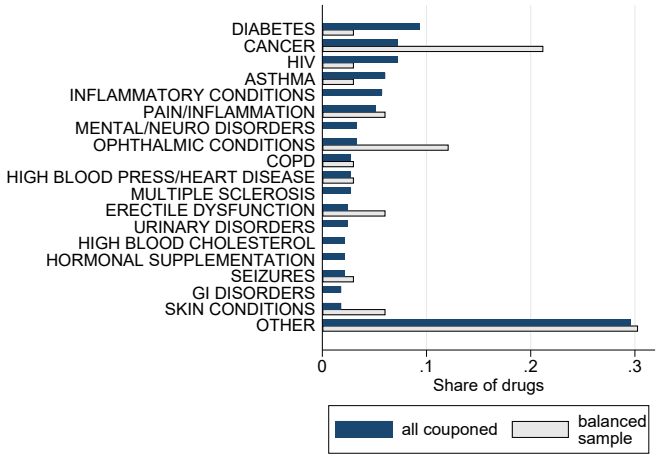
Appendix Figure B5: Drug Indications by Estimation Sample



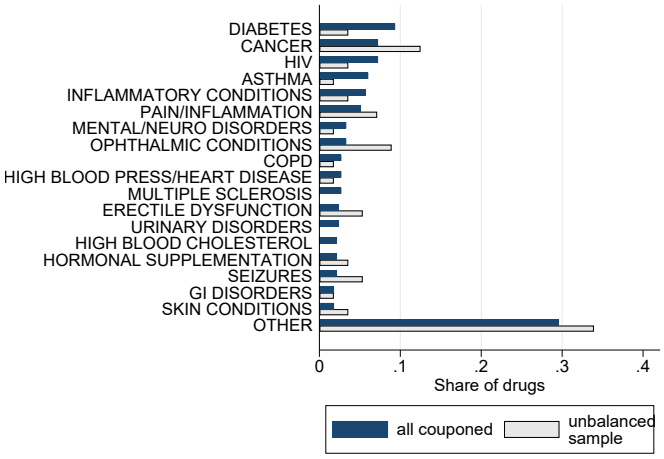
Notes: Figure shows the distribution of drug indications in each estimation sample, ranked by the number of drugs in each indication. Panel (a) shows the distribution of drug indications for our baseline specification (balanced sample of N=33 switchers). Panel (b) shows the distribution of drug indications for the unbalanced sample of switchers (N=56). The "Other" indication includes many indications with only 1 drug.

Appendix Figure B6: Comparison of Drug Indications Across Samples

(a) All drugs vs. balanced sample



(b) All drugs vs. unbalanced sample



Notes: Panel (a) compares drug indications for the overall sample of couponed drugs (N = 275 always + 56 switch = 331 total) with our baseline balanced sample of N=33 drugs. Panel (b) compares drug indications for the overall sample with our extended unbalanced sample of N=56 drugs.

B.6 Dataset Construction for Demand Model Estimation

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.[61] 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.[62] Generic drugs can have significant 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.[63]

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.[64]

Over the course of our study period, eleven DMTs are offered.[65] Of these, six are introduced midway through the sample period (these are Aubagio, Copaxone 40mg, Glatopa, Plegridy, Tecfidera, and Gilenya). See Appendix Table B1 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.[66]

[61] *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

[62] Another benefit of studying MS drugs is that, unlike categories such as cancer drugs and antidepressants, they are not a "protected class" for Medicare Part D prescription drug plans. Medicare Advantage insurers are required to cover all drugs within a protected class; this would complicate our model of price negotiations because Medicare Advantage plans would not have the option of dropping a particular drug from the formulary. Further, DMTs for MS are costly specialty medications; the DMTs that we study account for 0.058% of all prescriptions but 4.6% of the total prescription drug costs in the HCCI data. (These statistics exclude Tysabri, which is usually reimbursed via medical insurance, rather than prescription drug insurance.)

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

[64] We excluded MS drugs with very few observed prescriptions, including Extavia, Lemtrada, Ocrevus, Novantrone, and two additional Copaxone generics (Glatiramer 20mg and Glatiramer 40mg).

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

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

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[67], and we code Avonex as having no coupon during our sample period. Plegridy, a longer-acting 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

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

except for Gilenya and Tysabri. Table B1 shows characteristics for the MS drugs in our choice set.

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.[68] More modern drugs (approved after 2011) are almost invariably couponed at introduction. Older drugs (approved in the 1990s or early 2000s) tend to introduce coupons around 2010 or not at all. Copaxone 20mg and Gilenya are somewhat older drugs[69] that chose to introduce coupons.

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.[70] Moreover, each individual only takes one disease-modifying therapy at any given time.

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). Those below the threshold may utilize coupons or manufacturer-sponsored patient-assistance programs; those above the threshold are not permitted to redeem coupons or to receive aid from manufacturer-sponsored assistance programs, although they may receive charitable assistance. 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.

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

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

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

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

Appendix Table B1: 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	8/2011–3/2015
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.

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 drugs.

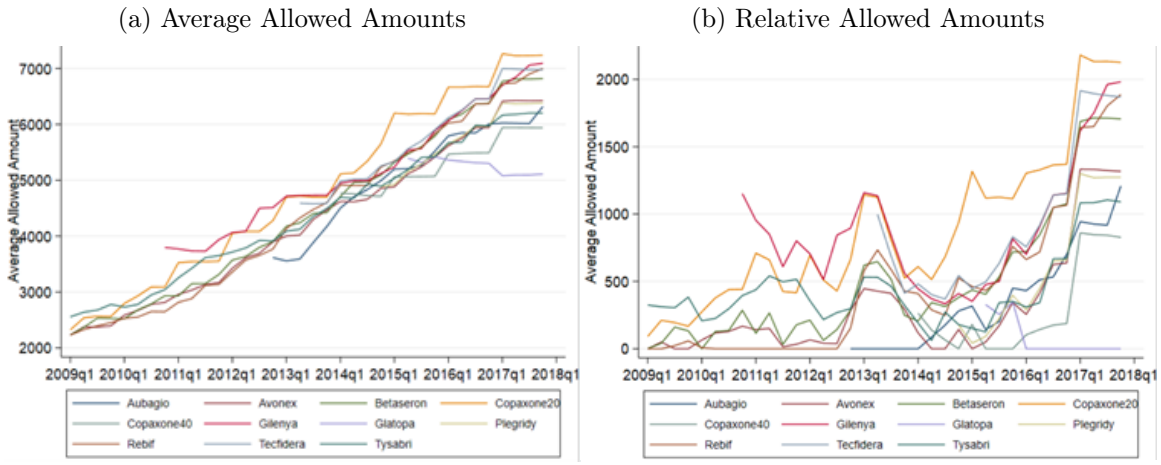
Next, we exclude claims with extremely low or high values for the allowed amount relative to other claims for the same drug, plan characteristics, and time period. For each drug, we perform a claim-level regression of allowed amount on dummies for year-quarter, NDC/HCPCS code, segment, specialty drug 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.[71]

Figure B7 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.

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

Appendix Figure B7: Average Allowed Amounts for MS Drugs Over Time



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)

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 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, 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.

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.[72] 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 total, and not already coded as a deductible claim. Coinsurance claims are those that

[72]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.

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).[73] 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.

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.[74] 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.[75]

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 list price) and estimated deductible.[76] In practice, most patient-drug out-of-pocket price observations (98.4%) are coded as coinsurance, copays, or $0 cost sharing (see Appendix Table B2 for more details).

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

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

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

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

Appendix Table B2: 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.

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 (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.

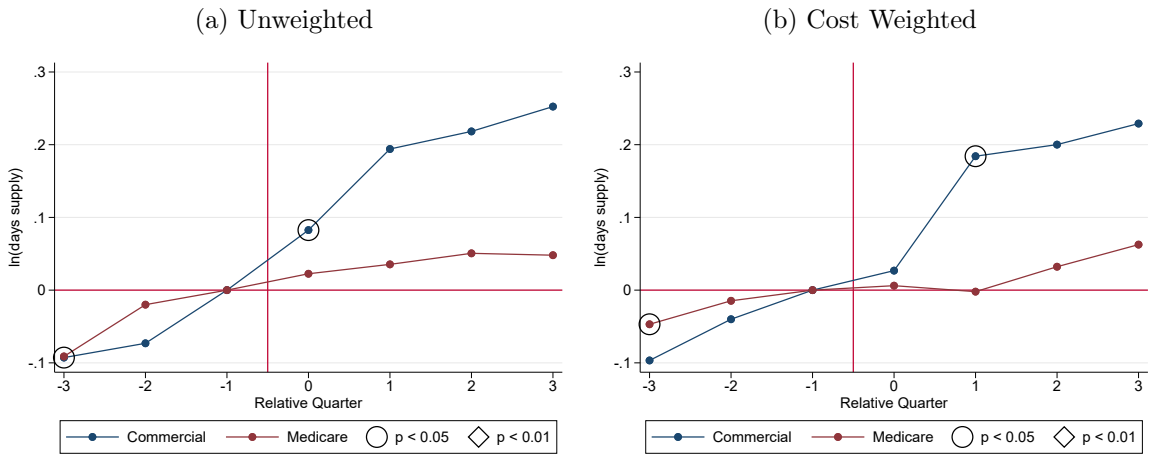
Thus, our preferred specification sets $\lambda = 0.75$. We also test robustness of our estimates and simulation results to $\lambda = 0.60$ and $\lambda = .90$.

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 of equation (1) that shows the segment-specific time trends before and after coupon introduction. Figure C8 below shows the results from this specification for quantity.[77]

Appendix Figure C8: 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 C3 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.

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

Appendix Table C3: 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 * $p < 0.10$.

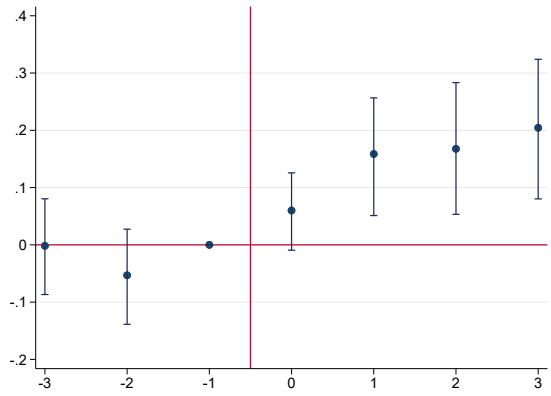
Notes: Table shows coefficient estimates from a pooled regression of log days supply on a post coupon introduction indicator, separately by segment. Standard errors are clustered at the drug level. Column (1) and (2) show unweighted and cost-weighted results respectively.

C.2 Inference Using Cluster Wild Bootstrap

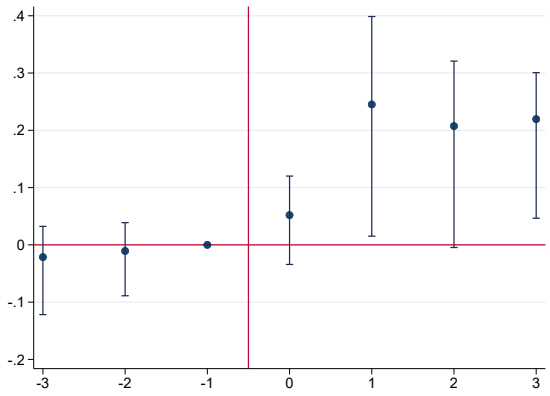
In Appendix Figure C9 below, we show a version of the results in Figure 2, where the 95% confidence intervals are derived using the cluster wild bootstrap.[78]

Appendix Figure C9: Effects of Coupons on Quantity and Price (cluster wild bootstrap)

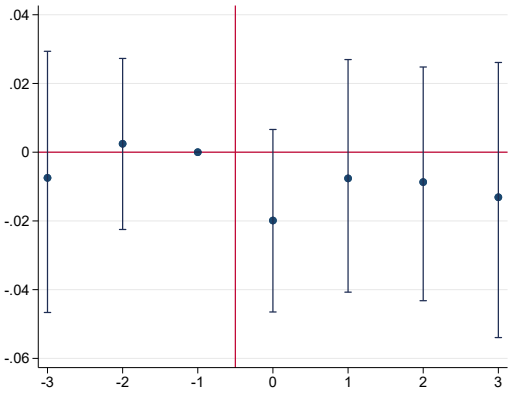
(a) *ln*(days supply), unweighted



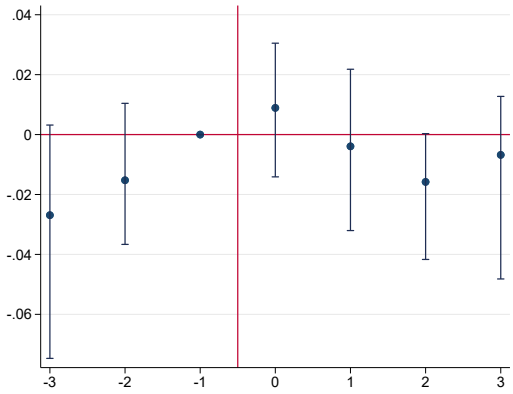
(b) *ln*(days supply), weighted



(c) *ln*(price), unweighted



(d) *ln*(price), weighted



Notes: Each graph plots coefficient estimates from a regression of ln(*days supply*) or ln(*price*) on quarter relative to coupon introduction. Graphs show 95% confidence intervals derived from a cluster wild bootstrap.[79] 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.

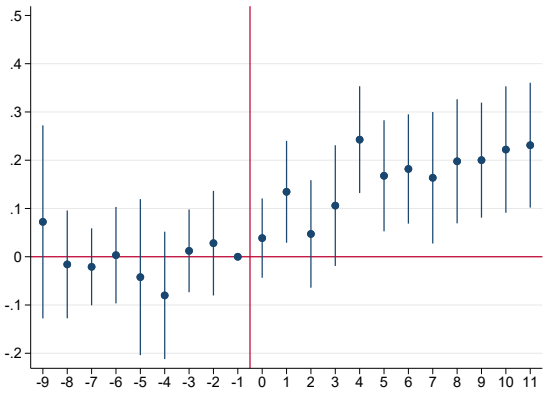
[78] Implemented using the *boottest* stata module:
David Roodman, 2015. "BOOTTEST: Stata module to provide fast execution of the wild bootstrap with null imposed," Statistical Software Components S458121, Boston College Department of Economics, revised 19 Jul 2022.

C.3 Month-Level Event Studies

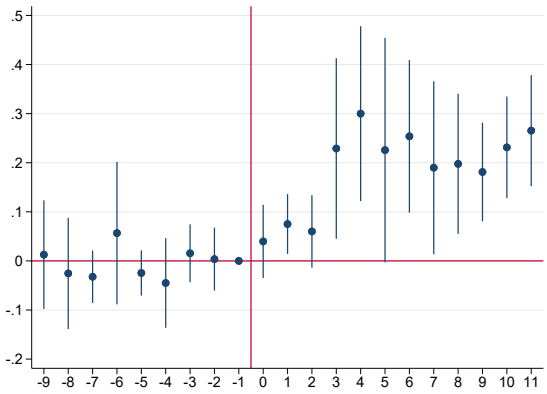
Figure C10 shows versions of our main specification in Figure 2 at the month level. We see that the coefficients in the months prior to coupon introduction are flat in most specifications, supporting our identifying assumption that coupon introductions are not correlated with unobserved factors affecting commercial-segment-specific demand or price.

Appendix Figure C10: Effects of Coupons on Utilization and Price (month-level effects)

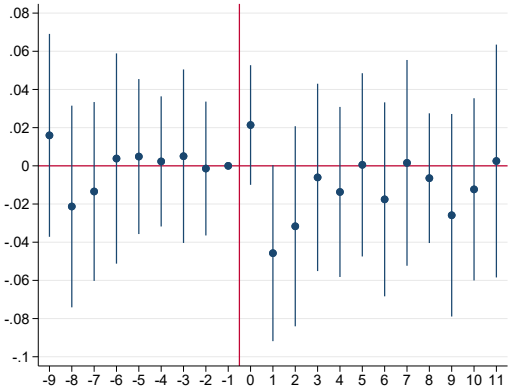
(a) *ln*(days supply), unweighted



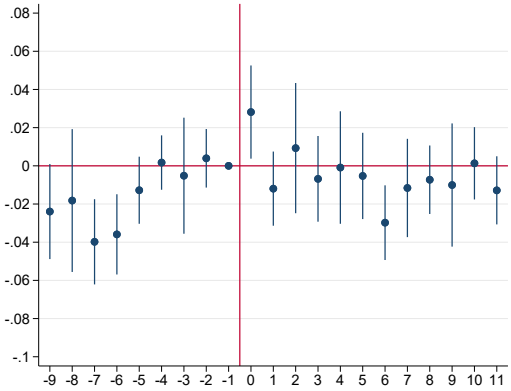
(b) *ln*(days supply), weighted



(c) *ln*(price), unweighted



(d) *ln*(price), weighted



Notes: Each graph plots coefficient estimates and 95% confidence intervals from a regression of ln(*days supply*) or ln(*price*) on month relative to coupon introduction for the commercial segment relative to 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 month prior to coupon 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.

C.4 Unbalanced Panel Event Studies

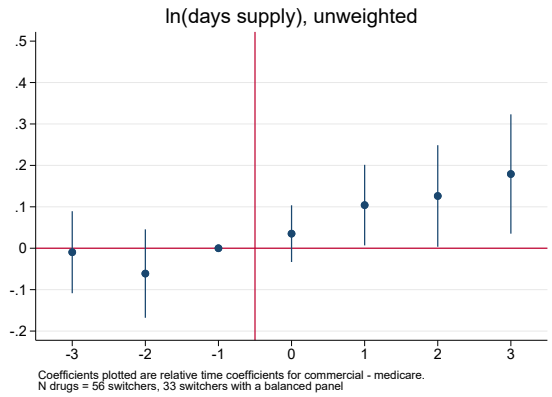
As a robustness test, we estimated a version of Equation 1 using the sample of all drugs where we observe a coupon introduction and at least 1 month pre-introduction and 1 month post-introduction. We manually verified coupon introduction dates for these additional drugs following the process outlined in Appendix Section B.2.[80] Out of 35 candidate drugs, 10 were determined to have introduced a coupon at the exact time of entering the market. An additional 2 drugs did not actually have a valid coupon and were excluded. This version increases our sample size by 23 drugs to $N = 56$ total drugs that switch coupon status.

We then added these drugs to our original estimation sample, for a total unbalanced sample of $N = 56$ drugs. As shown in Appendix Figure C11 and Appendix Table C4, the quantity effect in the weighted specification is nearly identical to our baseline results, whereas the results for the unweighted specification are somewhat attenuated. Overall, our conclusions are unchanged.

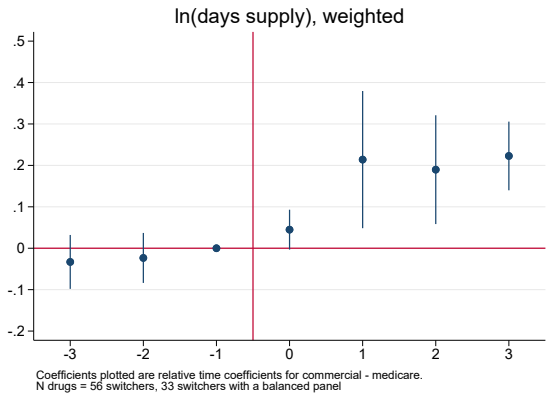
[80] Some of these were not manually checked previously, as their pre- or post-periods were already too short to be included in our main analysis.

Appendix Figure C11: Effects of Coupons on Utilization and Price (unbalanced panel)

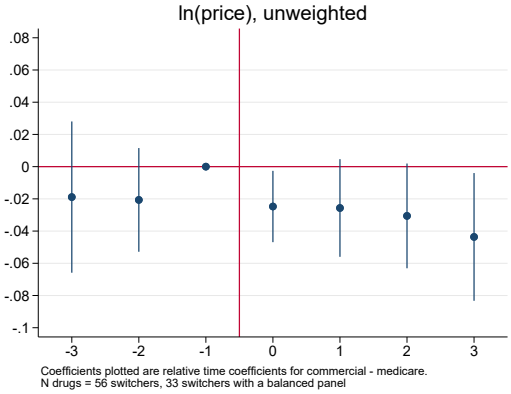
(a) ln(days supply), unweighted



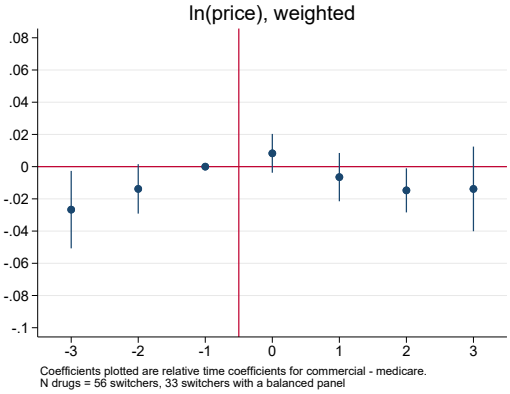
(b) ln(days supply), weighted



(c) ln(price), unweighted



(d) ln(price), weighted



Notes: Each graph plots coefficient estimates and 95% confidence intervals from a regression of ln(*days supply*) or ln(*price*) on the quarter relative to coupon introduction for the commercial segment relative to Medicare. All specifications are estimated on an unbalanced panel of all $N = 56$ switchers, including observations from up to 9 months prior to coupon introduction and up to 12 months after coupon introduction. The month prior to coupon introduction is omitted. Panels (a) and (c) show unweighted results, while Panels (b) and (d) show results weighted by each drug's average pre-period share of segment-specific spending.

Appendix Table C4: Difference-in-Differences Estimates (unbalanced panel)

Commercial ×	ln(supply)		ln(price)	
$Q = -3$	-0.010	-0.033	-0.019	-0.0267**
	(0.049)	(0.033)	(0.023)	(0.012)
$Q = -2$	-0.061	-0.023	-0.021	-0.0138*
	(0.053)	(0.030)	(0.016)	(0.008)
$Q = -1$	0	0	0	0
$Q = 0$	0.0352	0.0448*	-0.0247**	0.008
	(0.034)	(0.024)	(0.011)	(0.006)
$Q = 1$	0.104**	0.214**	-0.0257*	-0.007
	(0.049)	(0.083)	(0.015)	(0.007)
$Q = 2$	0.126**	0.190***	-0.0306*	-0.0147**
	(0.061)	(0.066)	(0.016)	(0.007)
$Q = 3$	0.179**	0.223***	-0.0436**	-0.014
	(0.072)	(0.041)	(0.020)	(0.013)
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.

C.5 Drugs Couponed at the Time of Market Entry

Our difference-in-differences approach is not able to assess coupon effects for drugs where coupons are introduced at the exact time of launch (because these drugs lack a pre-period entirely). To assess the effects of coupons for these drugs, we adopt an alternative approach that compares commercial vs. Medicare quantities for drugs that enter the market with a coupon versus *never-couponed* drugs. To ensure that we are comparing drugs during similar parts of their life cycle, we restrict the sample to drugs where we can observe prices and quantities for the first 12 months on the market. This leaves us with N=42 always-couponed drugs and N=10 never-couponed drugs. Because there is no pre-period with which to compute cost weights, all estimates are unweighted.

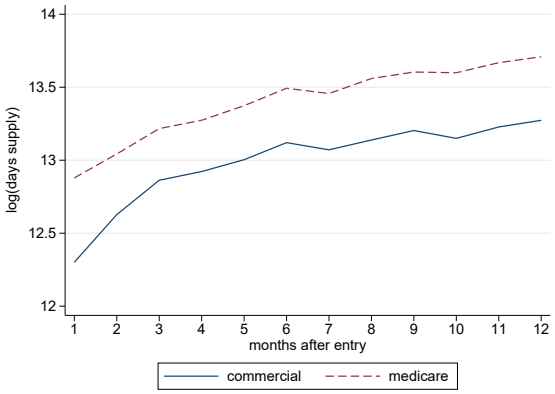
The raw data, graphed in Appendix Figure C12 below, show that drugs that

are launched with a coupon have higher commercial utilization compared to never-couponed drugs. We confirm this result by regressing ln(quantity) on an indicator variable for being always couponed, an indicator variable for the commercial segment, their interaction, and drug fixed effects. This yields a coefficient of 0.70 (SE=0.10) on the interaction term. This corresponds to an increase of exp(0.7)-1 = 101%. The same regression with ln(price) as the outcome variable yields a coefficient estimate of -0.03 (SE=0.02) that is not statistically significant.

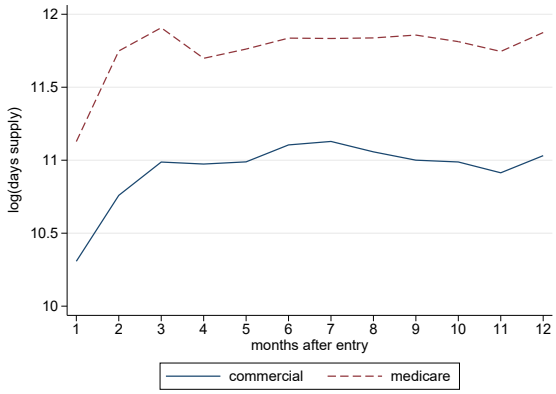
This quantity effect is much larger than the 23-25% estimated in our main specifications. This could indicate that always-couponed drugs benefit more from coupons than switchers, but it could also reflect fixed differences in expected commercial utilization between always-couponed and never-couponed drugs (always-couponed drugs may treat conditions that are more prevalent among individuals less than 65 years old and thus have larger potential utilization among commercially insured enrollees).

Appendix Figure C12: Utilization and price for always-couponed vs never-couponed drugs

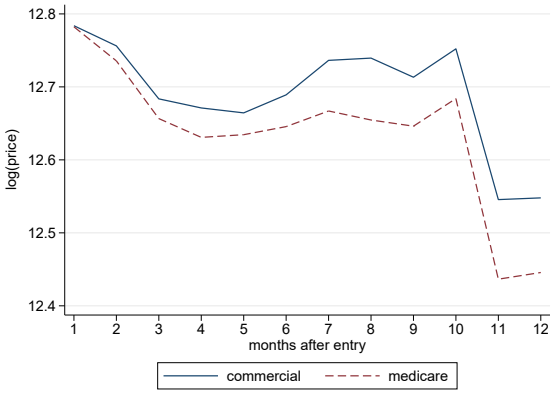
(a) ln(days supply), always-couponed



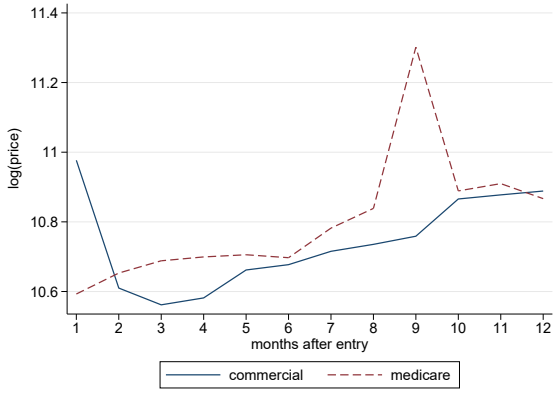
(b) ln(days supply), never-couponed



(c) ln(price), always-couponed



(d) ln(price), never-couponed



Notes: Figure plots averages of ln(days supply) or ln(price) for always-couponed and never-couponed drugs against the relative month after the drug enters the market, limited to the set of drugs that are introduced within our sample period with at least 12 months of data.

C.6 Coupon Effect Heterogeneity

We estimated several new analyses to explore heterogeneous effects by different drug characteristics. To do this, we re-estimated specification 1 in the text, adding an additional interaction term for the above-median group to allow for heterogeneous effects by group. This new specification is shown below:

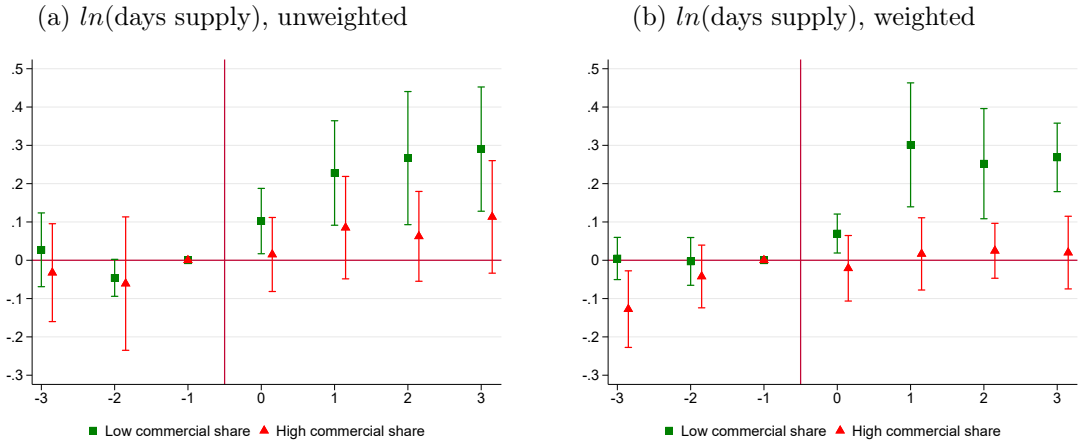
$$\begin{aligned} Y_{jkt} = & \sum_{q \in \{-3,3\} \setminus -1} \hat{\gamma}_q \mathbf{1}(quarter = q) \cdot \mathbf{1}(commercial)_k \cdot X_j \\ & + \sum_{q \in \{-3,3\} \setminus -1} \hat{\eta}_q \mathbf{1}(quarter = q) \cdot \mathbf{1}(commercial)_k + \hat{\alpha}_{jk} + \hat{\delta}_{jt} + \varepsilon_{jtk} \end{aligned} \tag{7}$$

where Y_{jtk} is either log quantity for drug j in month t and segment k. 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. $X_j \in \{0, 1\}$ is an indicator variable encoding a particular dimension of heterogeneity. The $\hat{\eta}_q$ coefficients denote the coupon effect for the group $X_j = 0$, and the $\hat{\gamma}_q$ coefficients denote the difference in the coupon effect between group $X_j = 1$ and $X_j = 0$. The coupon effect for group $X_j = 1$ is therefore $\hat{\eta}_q + \hat{\gamma}_q$. The $\hat{\alpha}_{jk}$ and $\hat{\delta}_{jt}$ coefficients denote drug-segment and drug-year-month fixed effects.

Heterogeneity by relative size of commercially insured market Using this specification, we first looked at the relative size of the commercial vs. Medicare market for each drug. We computed the ratio of commercial to Medicare pre-coupon spending for each of the N=33 drugs in our main estimation sample. Then, we split the drugs into two groups based on whether they fell above or below the median of this measure.

We find that the quantity effect of coupons is larger for drugs below the median commercial:Medicare spending ratio. That is, drugs with relatively smaller commercial markets appear to have larger percentage increases in quantity due to a coupon, and this increase is more precisely estimated. The estimated coupon effect is smaller and more noisily estimated among drugs above the median commercial:Medicare spending ratio, as shown in the graphs below:

Appendix Figure C13: Heterogeneity By Commercial:Medicare Spending Ratio



Notes: Each graph plots coefficient estimates and 95% confidence intervals from Equation 7. Coefficients plotted reflect the response in the commercial segment relative to the response in Medicare, separately for drugs with below-median commercial spending (green squares) and above-median commercial spending (red triangles). 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. Panel (a) shows unweighted regression results, while panel (b) shows results weighted by each drug's share of spending in each segment in the 6 months prior to coupon introduction.

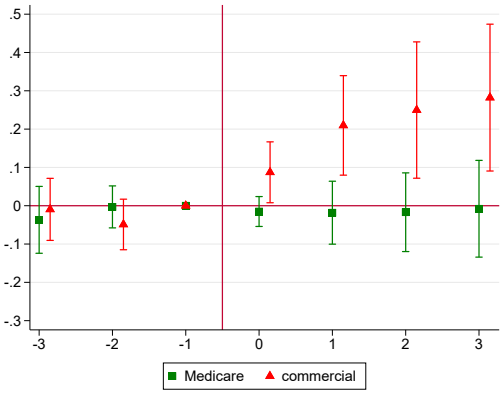
One possible explanation is that spillover effects from coupon introduction (from the commercial segment to Medicare) may be stronger when a drug is commonly used among commercial enrollees, and this in turn attenuates the apparent coupon effect for drugs with a high commercial share. That is, for drugs where a high percentage of patients are commercially insured, introducing a coupon may induce doctors to prescribe the drug more often to all patients (including Medicare enrollees). Because our estimates are based on commercial vs. Medicare differences, this will attenuate the estimated coupon effect for drugs with a high commercial share, even if there are no true heterogeneous treatment effects. This spillover effect is less likely to occur for drugs where commercial enrollees comprise a small share of patients, explaining the larger (and more accurate) estimate of the coupon effect for these drugs.

Consistent with this explanation, we find that for drugs with an above-median commercial share, Medicare quantities are increasing along with commercial quantities after coupon introduction (consistent with commercial to Medicare spillovers), whereas this is not the case for drugs with a below-median commercial share. Appendix Figure C14 below shows that commercial quantities are increasing in for both below-median commercial share (Panels a, c) and above-median commercial share (Panels b, d). However, Medicare quantities are also increasing specifically for above-median commercial share drugs (reflecting spillovers), whereas Medicare quantities are flat for below-median

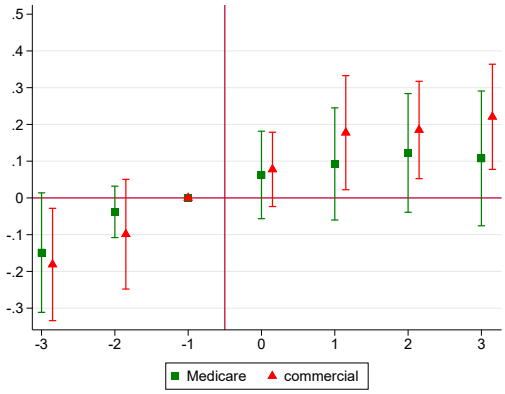
commercial share drugs (no spillovers). This explains the smaller estimated coupon effects for above-median commercial share drugs shown in Appendix Figure C13.

Appendix Figure C14: Segment-specific Trends By Relative Commercial Share

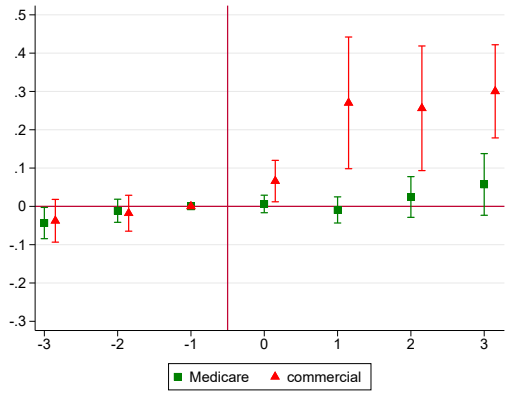
(a) below-median commercial share



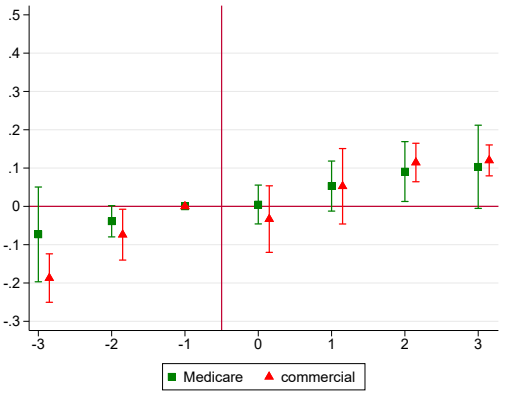
(b) above-median commercial share



(c) below-median, weighted



(d) above-median, weighted



Notes: Each graph plots coupon effects on ln(days supply). Coefficient estimates and 95% confidence intervals use the same specification as in Appendix Section C.1, but separating the sample into drugs with below-median commercial share (Panels a, c) and above-median commercial share (Panel b, d). Regressions in (a) and (b) are unweighted; regressions in (c) and (d) are weighted by drugs' average costs prior to coupon introduction. 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.

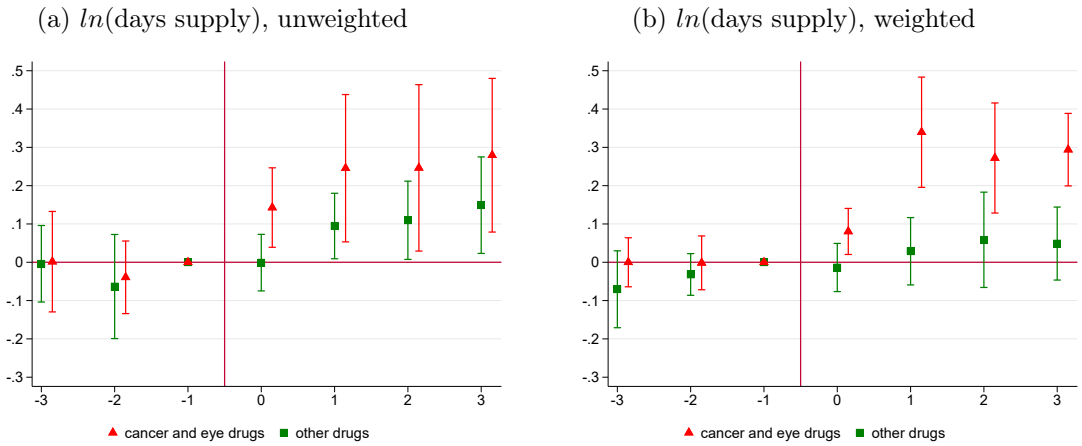
An additional explanation may be differential selection into introducing a coupon. A high relative commercial market presence is correlated with introducing a coupon at the time of FDA approval (consistent with our findings comparing always vs. never couponed drugs in Appendix Section C.5). Hence, drugs that have a high commercial presence but wait at least 9 months before introducing a coupon are likely drugs for which coupons are relatively less impactful.

Lastly, as shown below, cancer and eye medications have larger coupon effects. This may help explain the larger coupon effects observed for low commercial presence drugs, since most of the cancer and eye drugs are concentrated in the low commercial presence group (which contains 9 out of 14 cancer or eye drugs).

Heterogeneity by indication To explore potential heterogeneity by the condition treated by a drug ("indication"), we began by examining graphs for each of six major groupings of indications: cancer, psychiatric conditions (Depression, sleep disorders, seizures), inflammatory conditions (asthma, COPD, Pain/Inflammation), anti-infectives (HIV, eye infection, fungal infection, infections), eye conditions, and other chronic conditions (diabetes, blood cell deficiency, high BP/Heart disease, erectile dysfunction). We used groupings of indications as individual indications often contained no more than two drugs. We found the most pronounced impacts in two categories: cancer and eye medications, which account for 14/33 (42%) of drugs, with 7 drugs each.

We then estimated specifications with interaction terms between the coefficients of interest and an indicator for cancer or eye drugs. (We also estimated versions with separate indicators for cancer drugs and for eye medications, and the results are similar.) As shown in Appendix Figure C15, coupon effects are larger for cancer and eye medications.

Appendix Figure C15: Heterogeneity by Drug Indications



Notes: Each graph plots coefficient estimates and 95% confidence intervals from Equation 7. Coefficients plotted reflect the response in the commercial segment relative to the response in Medicare, separately for cancer and eye drugs (red triangles) vs. other drugs (green squares). 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. Panel (a) shows unweighted regression results, while panel (b) shows results weighted by each drug's share of spending in each segment in the 6 months prior to coupon introduction.

Appendix Table C5 below summarizes the significant heterogeneity results discussed above by displaying estimates of the between-group difference in coupon effects ($\hat{\gamma}_q$ in Equation 7). The table also shows estimates from specifications that pool the periods before vs. after coupon introduction.

Appendix Table C5: Heterogeneity of coupon effects

Commercial ×	Above-median commercial share		Cancer and eye drugs	
$Q = -3$	-0.060	-0.132**	0.005	0.0704
	(0.082)	(0.058)	(0.084)	(0.061)
$Q = -2$	-0.015	-0.039	0.024	0.0303
	(0.092)	(0.052)	(0.085)	(0.045)
$Q = -1$	0	0	0	0
$Q = 0$	-0.087	-0.091*	0.144**	0.094**
	(0.066)	(0.051)	(0.065)	(0.044)
$Q = 1$	-0.143	-0.285***	0.151	0.311***
	(0.097)	(0.096)	(0.107)	(0.086)
$Q = 2$	-0.204*	-0.227***	0.137	0.214**
	(0.107)	(0.082)	(0.122)	(0.097)
$Q = 3$	-0.177	-0.248***	0.130	0.245***
	(0.112)	(0.067)	(0.121)	(0.069)
Pooled	-0.128	-0.156**	0.131	0.182***
	(0.096)	(0.061)	(0.105)	(0.054)
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.

Drug price level We separated the drugs into above-median and below-median price groups, based on average commercial net-of-rebate prices in pre-period before coupon introduction. We found larger coupon effects in the above-median group; however, this result was not statistically significant in both specifications. Moreover, it is difficult to independently distinguish whether this effect is driven by indication, as all of the cancer drugs are in the above-median price category.

Heterogeneity by cost-sharing We also explored whether effects were heterogeneous by the degree of cost sharing (either expressed as a percentage of the net price

or as a dollar amount) but did not find statistically significant differences.

Summary of coupon effect heterogeneity Overall, the exploration of heterogeneous effects yields two main conclusions. First, drugs with relatively smaller commercial share have larger estimated coupon effects. The data suggest this may be due to larger spillover effects onto Medicare (the control group) when a drug has heavy commercial share relative to Medicare. Second, coupon effects vary by drug indication; in our sample, the effects are largest for drugs treating cancer or eye conditions.

The last result implies coupons can impact volume for drugs that might typically be considered inelastically demanded (e.g., cancer drugs). This is not too surprising given the research that cost-sharing impacts utilization across a wide range of drugs (e.g. Chandra et al. (2021)). Of course, there are a range of cancer treatments, and coupons might shift utilization toward more expensive therapies.

C.7 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:

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

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.

MS Drug Coverage Assumption In our demand estimation, we assume that all MS drugs are covered for all individuals. Accordingly, in our simulations, we assume that, in equilibrium, all MS drugs are covered. To support this assumption, we manually collected MS drug coverage information for the three insurers that comprise the HCCI data, by drug X insurer X segment X year (N = 299 individual cells of formulary information).

For each cell, we defined *Coverage* = 1 if the drug is covered under at least some plans (for example, for a given drug and insurer, *Coverage* = 1 for Medicare Advantage in 2016 if we could locate at least one MA plan formulary from that insurer that includes the drug in 2016). We set *Coverage* = 0 if the drug was excluded from formularies we located. *Coverage* = missing if we were not able to locate any formularies for that cell (or if the drug had not yet entered the market).

We averaged over all non-missing observations for our simulation period (2015-2017), weighting by the insurers' national market shares in 2016 and MS drug shares in our simulation sample. This resulted in an overall coverage rate of 87%, suggesting that for MS drugs, the assumption of complete coverage is not overly strong.

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 Section 3.3.

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

$$p^{nocoupon}_{jt} = c_{jt} + \frac{\bar{s}_{jt}}{-\Big(\big[\frac{1-\eta}{\eta} \big] \frac{V'(J_t, p_t)}{\Delta V(J_t, p_t)} \bar{s}_{jt} + \frac{\partial \bar{s}_{jt}}{\partial p_{jt}} \Big)} \tag{8}$$

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.[81]

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 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

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

equilibrium price will be higher. This "reinforcement effect" implies that the prices of substitute drugs tend to move together in equilibrium; see Ho and Lee (2017). Finally, there is an effect due to coinsurance. As in Gowrisankaran et al. (2015), insurers can use coinsurance rates to steer consumers to low-priced products; this may reduce the downwards pressure placed on prices by the insurer, particularly for relatively costly drugs.

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

$$p_{jt}^{coupon} = c_{jt} + w(.)\lambda coupon_{j,t} \sum_{i \in I_{com,t}} s_{ijt}^{c} p_{ijt}^{OOP} + \frac{\bar{s}_{jt} - \lambda coupon_{j,t} \sum_{i \in I_{com,t}} s_{ijt}^{c} \frac{\partial p_{ijt}^{OOP}}{\partial p_{jt}}}{-\left(\left[\frac{1-\eta}{\eta}\right] \frac{V'(J_t,p)}{\Delta V(J_t,p_{j,t})} \bar{s}_{jt} + \frac{\partial \bar{s}_{jt}}{\partial p_{jt}}\right)} \quad (9)$$

Comparing the two equations allows us to unpack the predicted change in price in response to coupon introduction. There are two new terms that reflect the manufacturer's cost of offering a coupon. First, a portion of this cost is passed through to prices (the second term of the equation): the fraction passed through, denoted $w(.)$, is a function of model primitives including the Nash bargaining weights.[82] 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 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.

Assumption of zero marginal production costs Given high list and net prices of MS drugs and data suggesting small production costs, we believe that the our assumption of zero marginal costs is reasonable for our setting. Six of the 11 drugs in

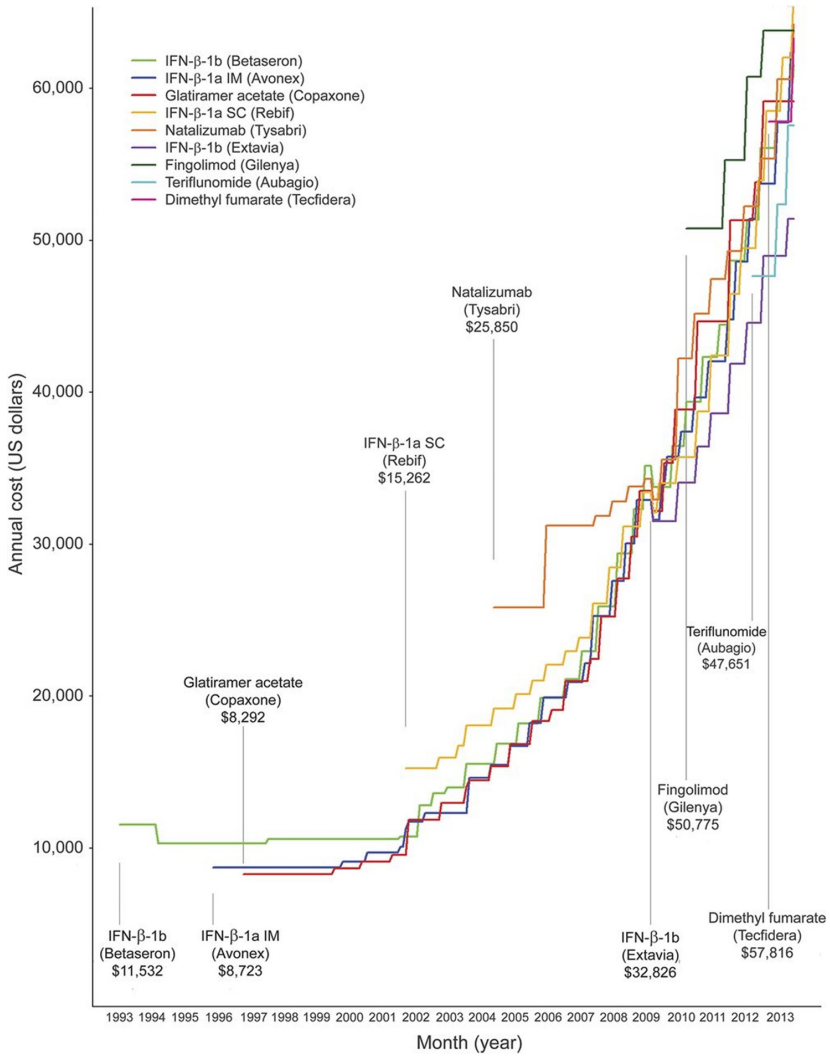
[82] The weight is defined as: $w(.) \equiv 1/[\bar{s}_{jt} + \frac{\eta}{1-\eta} \frac{\Delta V(J_t,p_{j,t})}{V'(J_t,p)} \frac{\partial \bar{s}_{jt}}{\partial p_{jt}}]$.

our sample are small molecule medications, both oral solids and injectables (which are usually somewhat more expensive to produce). According to internal data obtained by a US House of Representatives investigation,[83] the injectable MS drug with the greatest market share, Copaxone, has a marginal cost less than 3% of its net price. This is consistent with production cost estimates in the literature[84] for injectable drugs, which are on the order of <$1 to $20 per vial, i.e., <1% of list prices for MS drugs (MS drug prices are on the order of $5000 in our data between 2015-17.)

We do not have marginal cost estimates for the 5 biologic drugs, however based on their initial launch prices (which presumably reflect price well above marginal cost), it appears their production costs are also very low. The chart below includes most of the drugs in our sample. To pick one example, Avonex – the second most popular drug in the choice set, and a biologic – was introduced at an annual price of $8723 in 1996. Assuming a gross margin of 75% yields an estimated marginal cost of $2181/year. In our data, the annual average allowed amount for Avonex was $70,800/year in 2015-2017, implying marginal cost of around 3 percent. (Granted, these prices do not exclude rebates, but based on SSR health data, Avonex rebates are low, averaging 9% in 2015-17) The most recently-introduced biologic in the sample, Plegridy, relies on the same molecule type (interferon beta-1a), suggesting marginal costs of production are likely to be a similar order of magnitude.

[83] *Drug Pricing Investigation Teva – Copaxone.* Staff report, Committee on Oversight and Reform. US House of Representatives. September 2020. https://oversight.house.gov/sites/democrats.oversight.house.gov/files/Teva%20Staff%20Report%2009-30-2020.pdf Accessed 5/24/2022

[84] for example, Gotham, D., Barber, M. J., & Hill, A. M. (2019). Estimation of cost-based prices for injectable medicines in the WHO Essential Medicines List. *BMJ Open, 9*(9). https://doi.org/10.1136/BMJOPEN-2018-027780



Reproduced from "The cost of multiple sclerosis drugs in the US and the pharmaceutical industry, Too big to fail?," Daniel M. Hartung, Dennis N. Bourdette, Sharia M. Ahmed, Ruth H. Whitham. First published April 24, 2015, *Neurology*, DOI: https://doi.org/10.1212/WNL.0000000000001608

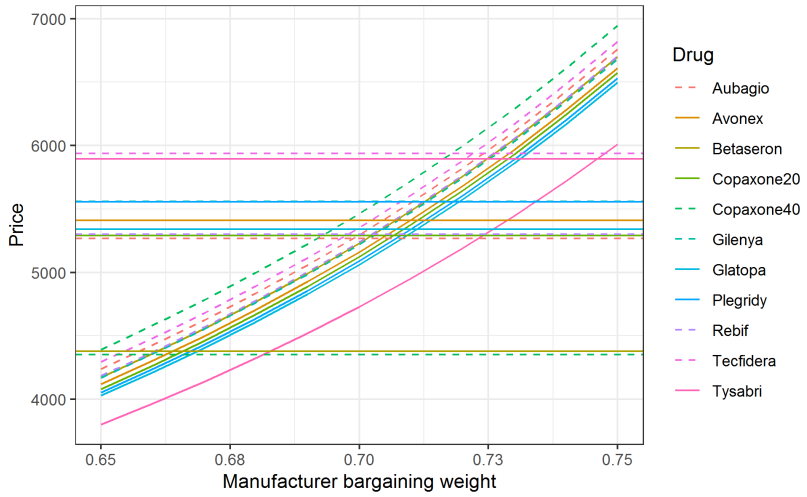
E Details of Counterfactual Simulations

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 6). 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 8) 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 E16 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 E16: 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 net prices. X-axis shows the manufacturer bargaining weight η.

E.2 Robustness to Modeling Assumptions

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 and re-calibrate η to arrive at new simulation results. Table E6 below shows demand estimates under these alternative specifications for λ.

Appendix Table E6: 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 E7 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 E7: 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 9) and increases the impact of coupons, which directly affect the $\frac{\partial s_{\bar{j}t}}{\partial p_{jt}}$ 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 E8 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 E8: Sensitivity of Distributional Effects to λ

Group	N	λ=0.6 Δ Insurer Costs ($)	λ=0.6 Δ OOP Costs ($)	λ=0.75 Δ Insurer Costs ($)	λ=0.75 Δ OOP Costs ($)	λ=0.90 Δ Insurer Costs ($)	λ=0.90 Δ OOP Costs ($)	λ=0.7, 0.9 Δ Insurer Costs ($)	λ=0.7, 0.9 Δ OOP Costs ($)	λ=0.5, 0.7, 0.9 Δ Insurer Costs ($)	λ=0.5, 0.7, 0.9 Δ OOP Costs ($)
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.

Using estimated rebates from SSR Health: Rebates are likely to vary *across* drugs, and this may affect our simulation results. To account for heterogeneous rebates, we test the sensitivity of our simulations to using estimated rebates from SSR Health. Broadly, our simulation results are not changed (details below).

Table E9 below shows rebate estimates from SSR Health. These estimates derive from combining data on drug quantities sold with financial documents from public drug manufacturers, which do not report revenues separately by drug. Thus, rebates are estimated at the national level (combining many payors with potentially different rebates) with some error, and some estimates may be negative. Over the 2015–2017 simulation period, estimated rebates for MS drugs ranged from 0—31% across drugs. Glatopa is not available in the SSR Health dataset. Because it is a generic (of Copaxone 20mg), we assume that it has rebates of 0%. We also assume that Tysabri's rebate is 0% to avoid negative rebates.

Appendix Table E9: Estimated Rebates from SSR Health

Product	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Average 15-17
Aubagio							-.02	.02	.10	.12	.06	.08	.09
Avonex	-.31	-.13	.38	.34	.52	.30	.21	.09	.04	.18	.06	.11	.09
Betaseron	.00	.03	.26	.25	.37	.16	.01	.17	.28	.31	.34	.43	.31
Copaxone 20	-.12	-.15	.00	-.07	.04	.26	.11	.12	.20	.19	.29	.48	.22
Copaxone 40								.12	.19	.19	.29	.48	.22
Gilenya					.36	.18	.01	-.00	.06	.14	.19	.22	.13
Plegridy									.05	.12	.04	.24	.07
Rebif	-.14	-.00	.03	-.08	.07	.12	.06	.05	.11	.17	.21	.26	.16
Tecfidera								.02	.07	.07	.10	.18	.08
Tysabri	-1.06	-.81	-.31	-.26	.04	-.03	.00	-.15	-.10	-.01	.08	.06	-.01

Notes: Table shows average estimated rebate shares by drug-year for MS drugs from SSR Health.

Using SSR rebates does not significantly change our results, as shown by Table E10 below. We find the a nearly identical overall coupon price effect of -7.4%. This is likely because the average SSR Health rebate is about 15%, which matches our assumption of a fixed 15% rebate across drugs.

Appendix Table E10: Coupon Price Effects with SSR Health Rebates

		Data		Simulation: Baseline		Simulation: Coupons Banned			
Drug	Coupon Status	Net Price ($)	Share	Net Price ($)	Share	Net Price ($)	Share	Δ Price (%)	Δ Share (%)
Aubagio	Always	5266	0.148	5059	0.139	4690	0.130	-7.3	-6.2
Avonex	Never	5411	0.076	4927	0.086	4636	0.104	-5.9	26.8
Betaseron	Never	4379	0.044	4992	0.058	4676	0.067	-6.3	24.2
Copaxone20	Aug 2011	5290	0.030	4889	0.030	4581	0.037	-6.3	28.3
Copaxone40	Always	4351	0.308	5223	0.298	4811	0.278	-7.9	-8.0
Gilenya	Oct 2011	5560	0.066	4985	0.066	4562	0.061	-8.5	-8.7
Glatopa	Never	5339	0.008	4830	0.009	4530	0.011	-6.2	31.5
Plegridy	Never	5554	0.028	4857	0.029	4556	0.035	-6.2	29.5
Rebif	Always	5301	0.054	5003	0.056	4618	0.053	-7.7	-6.8
Tecfidera	Always	5938	0.224	5116	0.218	4727	0.206	-7.6	-7.2
Tysabri	Never	5895	0.015	4522	0.013	4145	0.018	-8.3	36.8

Notes: Table shows observed prices (computed as $(1 - r_j)\times$ the average allowed amount, where r_j is the 2015–17 average SSR Health rebate estimate for drug j from Appendix Table E9) 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.

Varying the bargaining weight: We could alternatively vary the bargaining weight η, which is the only model parameter affected by our assumptions on the value of rebates (i.e., net prices). A higher value of η corresponds to higher net prices earned by manufacturers (i.e., lower rebates). Varying η directly does slightly change our results, but the magnitudes are small (see details below).

Our baseline sets the manufacturer bargaining weight $\eta = 0.69$. As we describe in Section E.1, this is the value of the bargaining weight that best fits the observed prices in the data, assuming a 15% fixed rebate. As shown in Appendix Table E11 below, coupon price effects are directly proportional to the manufacturer's bargaining weight: higher manufacturer bargaining power corresponds to greater coupon effects (as well as higher net prices in general).

Appendix Table E11: Coupon Price Effects: Varying the Bargaining Weight η

Manufacturer bargaining weight	Net price with coupons	Price effect when coupons are banned
0.5	2329	-5.6% ($130)
0.6	3458	-6.2% ($215)
0.65	4257	-6.8% ($288)
0.69 (baseline)	5077	-7.4% ($375)
0.75	6778	-8.7% ($587)

Notes: Table shows how the price effect of a coupon ban varies across assumptions on the manufacturer bargaining weight η (Column 1). Column 2 shows the average simulated net price of MS drugs in the baseline case when coupons are allowed. Column 3 shows the average price effect when coupons are banned as a percentage of the net price in Column 2, and also as a dollar amount in parentheses.

Varying insurer weight on drug costs: We have assumed that insurers place equal weight on consumer surplus and drug costs. However, this may not necessarily be the case. Below is a modified equation for the insurer objective function, where τ encodes the relative weight that insurers place on consumer surplus (versus drug costs). For example, Gowrisankaran et al. (2015) estimate a value of $\tau = 2.79$ but with a standard error of 2.87, such that the welfare weight is not distinguishable from 0 or 1 (the value we assume at baseline).

$$V(J_t, p_t) = \tau \times CS(J_t, p_t) - TC(J_t, p_t)$$

To assess the sensitivity of our coupon price effect to the assumption of $\tau = 1$, we run simulations under alternative values of τ. We find that higher values of τ (i.e., the insurer places more weight on consumer surplus and less weight on keeping drug costs low) correspond to larger price reductions under a coupon ban (-9.1% with $\tau = 2$ compared to -7.4% in our baseline case where $\tau = 1$). Also, when the insurer cares less about costs ($\tau = 2$), a smaller manufacturer bargaining weight ($\eta = .53$ vs. $.69$) rationalizes the observed prices.

Conversely, when insurers have a lower value of $\tau = 0.5$ (prioritizing lower drug costs), coupons have smaller price effects (-6.7%), and a larger manufacturer bargaining weight $\eta = 0.82$ is necessary to rationalize observed prices.

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 E12 below.

Appendix Table E12: 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	5105	0.137	4719	0.129	-7.6	-5.8
Avonex	Never	5071	0.076	4969	0.086	4660	0.105	-6.2	22.1
Betaseron	Never	5395	0.044	4964	0.058	4649	0.070	-6.4	20.6
Copaxone20	Aug 2011	5787	0.030	4903	0.030	4584	0.038	-6.5	23.4
Copaxone40	Always	4753	0.308	5219	0.298	4809	0.278	-7.9	-6.9
Gilenya	Oct 2011	5420	0.066	5018	0.066	4574	0.061	-8.8	-7.9
Glatopa	Never	4538	0.008	4877	0.009	4557	0.011	-6.6	25.6
Plegridy	Never	5060	0.028	4899	0.029	4580	0.036	-6.5	24.0
Rebif	Always	5390	0.054	5029	0.056	4632	0.052	-7.9	-6.0
Tecfidera	Always	5486	0.224	5159	0.218	4750	0.203	-7.9	-6.7
Tysabri	Never	5011	0.015	4513	0.013	4063	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 E13 below shows how insurer and out-of-pocket costs change for various groups of individuals.

Appendix Table E13: 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 non-price or "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.

Appendix Table E14: 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 E15: 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%.

Our results are qualitatively similar under these alternative assumptions. The maximum likelihood demand estimates corresponding to these versions are shown below in Table E14. (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 E15 below reports the price effects of coupons when we assume that only coupon users have an advertising effect.

Assuming that the coupon advertising effect remains after coupons are banned: We also test the effects of a modified coupon ban that eliminates coupons' price discounts but maintains the estimated advertising effect (γ^{com} in Equation 3). This reflects a scenario where manufacturers maintain advertising but are no longer able to provide discounts. With persistent advertising, drug shares shift less as a result of a coupon ban. The coupon price effect is only slightly lower: 6.6% vs. 7.4% in our baseline case, see Appendix Table E16.

Appendix Table E16: Coupon Price Effect: Advertising Effect Remains Post-ban

		Data		Simulation: Baseline		Simulation: Coupons Banned			
Drug	Coupon Status	Net Price ($)	Share	Net Price ($)	Share	Net Price ($)	Share	Δ Price (%)	Δ Share (%)
Aubagio	Always	5812	0.148	5973	0.139	5569	0.137	-6.8	-1.0
Avonex	Never	5966	0.076	5811	0.086	5505	0.085	-5.3	4.0
Betaseron	Never	6347	0.044	5808	0.058	5500	0.057	-5.3	3.9
Copaxone20	Aug 2011	6808	0.030	5733	0.030	5424	0.030	-5.4	4.3
Copaxone40	Always	5592	0.308	6116	0.298	5704	0.299	-6.7	-1.3
Gilenya	Oct 2011	6376	0.066	5869	0.066	5410	0.066	-7.8	-1.2
Glatopa	Never	5339	0.008	5704	0.009	5396	0.008	-5.4	4.5
Plegridy	Never	5953	0.028	5730	0.029	5419	0.028	-5.4	4.5
Rebif	Always	6341	0.054	5880	0.056	5462	0.056	-7.1	-1.0
Tecfidera	Always	6454	0.224	6041	0.218	5624	0.219	-6.9	-1.2
Tysabri	Never	5895	0.015	5293	0.013	4880	0.014	-7.8	11.0

Notes: Table shows observed prices (computed as 0.85 × the average allowed amount) and market shares in the simulation sample (Columns 2-3). Columns 4-5 show simulated net prices and shares at baseline, where coupons are as observed in the data (Column 1). Columns 6-10 show results from a simulation where all existing coupon discounts are removed, but the coupon advertising effect is allowed to remain. 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 -6.6%, weighting by the baseline simulated shares in Column 5.

Using quantitative coupon values: We manually checked for dollar amounts for MS coupons (from 2009 through 2017), and then applied these rules in our demand estimation and simulations. Appendix Table E17 below shows the specific coupon offers we impute using archived manufacturer websites and coupon databases.

Drug manufacturers tend to pay slightly less for coupons in the earlier period, since early versions of the coupons had limits on the monthly amount they would pay (e.g. by limiting discount amounts to $500 per or only reducing copays to $35 instead of $0). In the later years relevant to our simulations (2015-17), all coupons are $0 copay coupons (although the coupon for Gilenya still has a $1000 maximum for the amount of out-of-pocket costs covered by the coupon per month). Thus, our simulations are only affected insofar as the measured coupon values affect the estimated demand coefficients.

Appendix Table E17: Quantitative Coupon Values Over Time

Drug	Date Range	Coupon Description
Aubagio	Sept 2012 – Dec 2012	3 month free trial ($0 copay) at time of drug launch
	Jan 2013 – Mar 2013	Pay no more than $35 out of pocket
	Apr 2013 – Nov 2014	Pay no more than $10 out of pocket
	Dec 2014 – Dec 2017	Pay $0 out of pocket
Copaxone 20mg	Aug 2011 – Jun 2012	Pay no more than $35 out of pocket (maximum $500/month)
	Jul 2012 – Mar 2015	Pay no more than $35 out of pocket (maximum $2500/month)
Copaxone 40mg	Feb 2014 – Dec 2017	Pay $0 out of pocket
Gilenya	Oct 2011 – Apr 2013	Pay $0 out of pocket (maximum $800/month)
	May 2013 – Dec 2017	Pay $0 out of pocket (maximum $1000/month)
Rebif	Jan 2009 – Mar 2013	Pay no more than $50
	Apr 2013 – Dec 2017	Pay $0 out of pocket
Tecfidera	Mar 2013 – Sept 2014	Pay no more than $10
	Oct 2014 – Dec 2017	Pay $0 out of pocket

Notes: Table shows coupon values over time for MS drugs in our sample that introduce a coupon. Coupon values are manually verified through December 2017.

Both the demand estimates (see Appendix Table E18) and simulation results (Appendix Table E19) are very similar to our baseline case.

Appendix Table E18: Demand Estimates with Quantitative Coupon Values

	Estimates with measured coupon values
OOP Price	0.049 $^{+}$
	(0.026)
OOP Price X Commercial	-0.096 **
	(0.029)
Coupon X Commercial	0.394 $^{+}$
	(0.208)
Coupon	-0.245
	(0.245)
Drug Age (6-12 mo)	0.630 *
	(0.269)
Drug Age (1-2 yr)	1.295 **
	(0.280)
Drug Age (2-3 yr)	1.511 **
	(0.322)
Drug Age (3-5 yr)	1.814 **
	(0.354)
Drug Age (5+ yr)	1.809 **
	(0.420)
Drug Age (6-12 mo) X Female	-0.350
	(0.288)
Drug Age (1-2 yr) X Female	-0.493 $^{+}$
	(0.257)
Drug Age (2-3 yr) X Female	-0.622 *
	(0.263)
Drug Age (3-5 yr) X Female	-0.834 **
	(0.261)
Drug Age (5+ yr) X Female	-0.313
	(0.231)
Drug FE	Yes
Drug-Year FE	Yes
Drug-Segment FE	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 where coupon discounts are given by the measured value of each coupon in Appendix Table E17. Specification includes drug, drug-year, and drug-segment fixed effects.

Appendix Table E19: Coupon Price Effects with Quantitative Coupon Values

		Data		Simulation: Baseline		Simulation: Coupons Banned			
Drug	Coupon Status	Net Price ($)	Share	Net Price ($)	Share	Net Price ($)	Share	Δ Price (%)	Δ Share (%)
Aubagio	Always	5817	0.140	6076	0.141	5621	0.129	-7.5	-8.3
Avonex	Never	5983	0.075	5911	0.086	5551	0.104	-6.1	37.6
Betaseron	Never	6353	0.045	5910	0.058	5538	0.069	-6.3	34.8
Copaxone20	Aug 2011	6825	0.030	5831	0.030	5458	0.037	-6.4	40.5
Copaxone40	Always	5600	0.308	6233	0.298	5738	0.279	-7.9	-9.8
Gilenya	Oct 2011	6389	0.069	5954	0.066	5452	0.062	-8.4	-11.3
Glatopa	Never	5290	0.009	5800	0.009	5427	0.011	-6.4	44.4
Plegridy	Never	5953	0.029	5826	0.029	5455	0.035	-6.4	41.6
Rebif	Always	6364	0.055	5979	0.056	5514	0.052	-7.8	-8.6
Tecfidera	Always	6471	0.224	6152	0.218	5663	0.204	-7.9	-9.6
Tysabri	Never	5815	0.015	5396	0.013	4942	0.017	-8.4	48.7

Notes: Table shows coupon price effect results when measured coupon values (Appendix Table E17) are used in the demand estimation and simulations. Columns 2-3 show observed prices (computed as 0.85 × the average allowed amount) and market shares in the simulation sample. 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 coupon discounts are removed, but the coupon advertising effect is allowed to remain. 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 -7.6%, weighting by the baseline simulated shares in Column 5.

Robustness of the coupon price effect to varying the price elasticity: Because we do not observe coupon use and must impute out-of-pocket prices, our estimate of price sensitivity may be too small (for example, due to attenuation bias from measurement error). Therefore, we tested the sensitivity of the coupon price effect to increasing or decreasing the price coefficient by one times the standard error of $\alpha^{\hat{com}}$ in Equation 3. We find that greater price sensitivity leads to larger coupon price effects: if the price coefficient increases in magnitude by 1 standard error, a coupon ban reduces prices by 9.8% compared to our baseline of 7.4%. Conversely, if that coefficient is reduced by one standard error, then the coupon ban reduces prices by 4.8%.

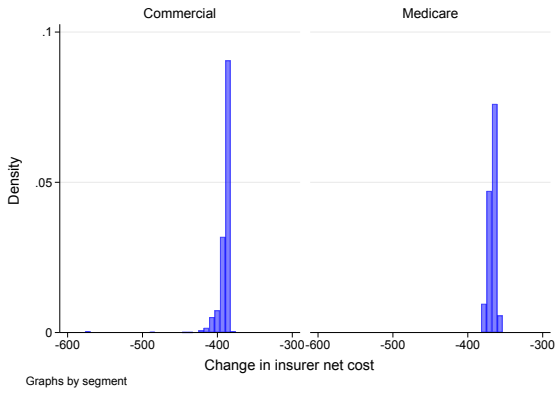
Accounting for variation in demand parameter estimates: In addition to varying the price elasticity, we test the sensitivity of our price simulations to variation in all of the parameters in the demand model. To do this, we take draws from the joint sampling distribution of the parameter estimates, simulate the resulting price effect, and repeat this 200 times to capture uncertainty in the simulated price effect. The 2.5 and 97.5 percentiles of this distribution generate price effects of 5.5% and 9.7% respectively.

E.3 Distributional Implications of a Coupon Ban

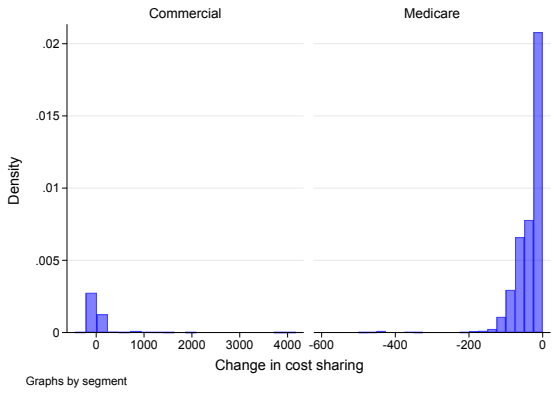
As noted in the text, the distributional implications of a coupon ban vary across individuals and segments. Panel (a) of Appendix Figure E17 below shows the effects of a ban on per-enrollee insurer expenditures. Insurers' costs decline across all enrollees due to the reduction in list prices for all 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 E17: 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.

References

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

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

Anonymous PBM. 2017. "Confidential Pharmacy Benefits Manager dataset." (accessed December 1, 2018).

Baker, Andrew C., David F. Larcker, and Charles C.Y. Wang. 2022. "How much should we trust staggered difference-in-differences estimates?" *Journal of Financial Economics*, 144(2): 370–395.

Berndt, Ernst, Rena Conti, and Stephen Murphy. 2017. "The Landscape of US Generic Prescription Drug Markets, 2004-2016."

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

Bureau of Labor Statistics U.S. Department of Labor. n.d.. "Prescription drugs in U.S. city average, all urban consumers, not seasonally adjusted." (accessed March 3, 2021).

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

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

Centers for Medicare and Medicaid Services. 2011-2017. "Medicare Provider Utilization and Payment Data: Part D Prescriber." (accessed February 20, 2019).

Chandra, Amitabh, Evan Flack, and Ziad Obermeyer. 2021. "The Health Costs of Cost-Sharing." *NBER Working Paper Series No. 28439.*

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

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

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

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

Dafny, Leemore, Kate Ho, and Edward Kong. 2023. "Data and Code for: How Do Copayment Coupons Affect Branded Drug Prices and Quantities Purchased?" *American Economic Journal: Economic Policy. http://doi.org/10.3886/E185842V1*.

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

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

Dusetzina, Stacie B., Juliette Cubanski, Leonce Nshuti, Sarah True, Jack Hoadley, Drew Roberts, and Tricia Neuman. 2020. "Medicare Part D Plans Rarely Cover Brand-Name Drugs When Generics Are Available." *https://doi.org/10.1377/hlthaff.2019.01694*, 39(8): 1326–1333.

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

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

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

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

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

Grennan, Matthew, Kyle Myers, Ashley Swanson, and Aaron Chatterji. 2022. "No Free Lunch? Welfare Analysis of Firms Selling Through Expert Intermediaries." *NBER Working Paper 24864*.

Hartman, Micah, Anne B. Martin, Joseph Benson, and Aaron Catlin. 2020. "National health care spending in 2018: Growth driven by accelerations in medicare and private insurance spending." *Health Affairs*, 39(1): 8–17.

Health Care Cost Institute. 2009-2017. "HCCI Commercial Claims Data." (last accessed September 22, 2022).

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

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

Jordan, Matthew, Bouke Klein Teeselink, Nicholas Adolph, and Shane Frederick. 2020. "Discounts Shift the Demand Curve for Life-Saving Medications." *SSRN Electronic Journal*.

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

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

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

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

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

Rambachan, Ashesh, and Jonathan Roth. 2023. "A More Credible Approach to Parallel Trends*." *The Review of Economic Studies*. rdad018.

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

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

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

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

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

Tunçel, Tuba. 2020. "Should We Prevent Off-Label Drug Prescriptions? Empirical Evidence from France." *SSRN Electronic Journal*.

U.S. Food and Drug Administration. 2009-2018*a*. "Drugs@FDA: FDA-Approved Drugs." (last accessed November 6, 2018).

U.S. Food and Drug Administration. 2009-2018*b*. "National Drug Code Directory." (last accessed November 8, 2018).

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