Pharmaceutical Copay Assistance Programs and Patient Drug Choice: Biological Specialty Drugs

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Abstract

In an effort to manage prescription drug spending, health insurers design tiered copay schemes that steer patients towards buying lower-price drugs. In response, pharmaceutical companies issue coupons (called copay cards) that can lower the high copayments insurers assign to non-preferred drugs. This paper exploits the lifting of a ban on coupons in Massachusetts effective July 2012. The paper examines the effect of the ban lift on patients' choice of drug brand as well as changes in the cost burden shared by insurers and patients. I use pharmacy claims data for biological specialty drugs that treat Multiple Sclerosis and Rheumatoid Arthritis to examine the effect of copay cards on insurers' costs and patients' purchasing behavior. I find that brand names that introduced coupons following the ban lift saw a 16% increase in the number of prescriptions (scripts) and patients per quarter relative to brand names that did not offer coupons. Moreover, I find evidence that the likelihood that a transaction had a coupon increases with the copayment. Lastly, I find that for a given drug brand, following the ban lift, transactions with a coupon also had higher copayments. This fact suggests that the introduction of coupons in Massachusetts was offset by a decrease in the share of the drug cost covered by the insurer, resulting in no change in the patient's out-of-pocket payment.

Keywords: Tiered co-pay schemes, co-pay offset programs, prescription drug choice, pharmaceutical pricing, and coupons

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1 Introduction

Unlike in perfectly competitive markets, pharmaceutical prices are set well above marginal cost to compensate for high research and development (R&D) costs. Additionally, demand for healthcare products is distorted because consumers only face a small portion of the drug cost. In particular, consumers might pay a fixed amount called a copay for the drug, and the insurer will cover the rest of the cost. The copay of the drug depends on the copay scheme of the insurer, which is often segmented into tiers. A typical tier structure might look as follows: generics, preferred brands, and off-patent and non-preferred brands. Drug manufacturers that can negotiate lower prices for the insurer are placed in the first two tiers. In order to incentivize patients to buy favorably tiered drugs, insurers will make the copays for drugs in those tiers lower. For example, the out-of-pocket (OOP) cost for a generic statin to lower cholesterol will be lower than that of a brand name drug.

In an effort to circumvent the tiered copay system, drug manufacturers can directly offer insured patients a coupon, sometimes called a copay card, to lower their OOP cost. For example, consider a brand name drug that costs \$150 and a generic alternative that costs \$100. A patient's copayments for the two drugs are \$50 and \$30, respectively. Without the coupon, a patient who is indifferent between the brand and generic drug will choose the generic medication. This scenario results in the insurer paying \$70 for the prescription. If the branded drug manufacturer gives the patient a coupon that reduces the OOP cost to \$30, he is more likely to choose the brand name drug and the insurer will pay \$100. In this case, the branded drug manufacturer helps the patient to pay for $20 of copayment and earns $100 from the insurer. This illustrated example shows how manufactures of non-preferred drugs can use coupons to steer patients to buy their product.

According to Zitter Health Insights Co-Pay Offset Monitor, about 700 brand-name drugs offered coupon programs in 2014, constituting an increase of 61% in less than two years. Even though coupon programs accounted for less than 5% of all dispensed prescriptions, more than one-third of biological specialty drug [2] transactions used a copay card in 2014. The use of copay cards, however, varies drastically by therapeutic class. For Rheumatoid Arthritis (RA), which accounted for about half of specialty pharmacy scripts, the percentage of prescriptions with a copay offset was 56% in the third quarter of 2013. Without a coupon, the average copay for an RA script was $60 while with a coupon, the copay is only $0-$5. For Multiple Sclerosis (MS), which accounted for about a quarter of specialty scripts, 28% of prescriptions had a copay offset. The average co-pay for an MS script was $76, but coupons reduced patients' OOP cost to about $10.

The rising prevalence of coupon programs may be partially explained by the rise in high copay and coinsurance tiers. According to the Kaiser/HRET Survey of Employer-Sponsored Health Benefits (2013), the distribution of covered workers facing different cost-sharing formulas for prescription drug benefits has seen a

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[2] Specialty pharmacy scripts refer to medications that require special handling and auxiliary services to treat diseases such as: cancer, cystic fibrosis, immune deficiency, multiple sclerosis, osteoarthritis, and rheumatoid arthritis.

significant increase in the number of plans with four or more tiers[3]. In 2013, the share of such plans was 23%, up from 14% in 2012. The shift towards fourth-tier copay tiers requires patients to cover a larger portion of the cost. In this sense, pharmaceutical copay cards can help lower patients' OOP cost for biological specialty drugs that are not covered by their insurance. If tiered copay schemes depend on copay differentials, however, then it is important to assess the effect of this rise in drug coupons on insurers' costs and patients' purchasing choices.

The main debate surrounding pharmaceutical coupons concerns their potential to undermine the tiered copay system. Critics of copay programs claim that coupons induce consumers to purchase more expensive drugs, thereby making insurers charge higher premiums and increasing total healthcare costs. On the other hand, proponents of copay cards assert that coupons make medications more affordable to consumers and improve drug compliance. This paper tests the hypotheses of whether coupons induce purchases and whether they change how the cost of the drug is allocated across patients and insurers. Towards this end, I present an empirical evaluation of the effect of coupons on the number of scripts sold and the cost covered by the patient and the insurer. The central question is if coupons actually reduce patients' out-of-pocket cost or do insurers simply rearrange copay amounts so that consumers end up paying the same as without coupons.

I rely on pharmaceutical data for biological specialty drugs that treat Multiple Sclerosis and Rheumatoid Arthritis provided by a healthcare research

[3] Among workers with three or-more tier plans, the average copayments in these plans are $11 for first-tier drugs, $31 for second-tier drugs, $53 for third-tier drugs, and $83 for fourth-tier drugs.

company called Zitter Health Insights. In the data, I observe national retail dollars and unit sales of each script at quarterly frequency from January 2012 to June 2014. My data set includes information on over 2,056,557 prescriptions and 1,421,127 patients. This data set contains information on the medication, including its trade name, whether it is brand or generic, the disease it is used to treat, and whether it is a refill; it also includes the zip code of the pharmacy where the drug was sold, the specialty of the prescribing physician, the total cost of the drug, and the amount covered by insurance, patient, and coupon.

My empirical strategy exploits a policy change that repealed the ban on using coupons to purchase biological specialty drugs in Massachusetts. Figure 1 shows the mean portion of transactions that used a coupon in Massachusetts and the rest of the U.S. over each quarter. The data demonstrates that before the ban is lifted, the average share of transactions involving a coupon was zero whereas after the ban lift, the number steadily increases in a similar fashion to the rest of the United States. If a similar chart is plotted for comparison states like New Hampshire or Rhode Island, no such trend is found (see Appendix section 9.1). This paper exploits this change in policy to isolate the effect of coupons on health spending in Massachusetts. Using sources of variation in the offering of coupons by drug companies after the ban lift in a differences-in-differences method, I can estimate the ban lift's effect on the number of scripts sold. Moreover, the variation among coupon use in transactions for the same brand name allows me to also examine whether coupons change the share of the drug cost covered by insurers.

I find that companies that distributed coupons in Massachusetts after the ban lift saw an increase of 1,339.6 in the number scripts sold per quarter, corresponding to a 15.8% increase relative to companies that did not offer coupons. Similarly, companies that distributed coupons had an increase of 866.3 patients per quarter, corresponding to a 15.9% increase. Based on changes in copay structures, my analysis finds that the redeemable coupon amount is offset by an increase in copays. This indicates that on net there is almost no change in patients' out-of-pocket costs.

This paper is organized into the following sections. Section 2 provides a brief overview of the Massachusetts copay ban and biological specialty drugs. In Section 3, I review the relevant literature in three sections: papers that study the impact of tiered copay structures on healthcare costs, papers that examine company advertising strategies, and a paper that conducts a welfare analysis of drug coupons. Section 4 discusses the data set, how I construct my sample, and how I define variables of interest. Section 5 describes my empirical methodology, particularly the differences-in-differences strategy and other econometric models. In Section 6, I explain the results of the regressions and show the effects of the Massachusetts coupon ban lift on drug sales and patient cost. Section 7 concludes with a discussion of copay cards and directions for further research.

2 Background

This paper exploits a recent overturn of an amendment in Massachusetts that outlawed the use of coupons in pharmacy transactions. Before 2012, Massachusetts was the only state to outlaw the use of drugs coupons. "The Massachusetts statute (Mass. Gen. Laws ch. 175H, § 3) contains a broad prohibition on soliciting, receiving, offering, or paying remuneration in return for purchasing, or to induce a person to purchase, any good, facility, service, or item for which payment may be made by a healthcare insurer." On July 8, 2012, Governor Deval Patrick signed the Massachusetts budget bill, which contained a provision lifting the state's anti-kickback law. The new law allows for the limited use of copay cards and other coupons with the purchase of biologicals and brand name drugs with no generic alternatives. This new provision, effective July 1, 2012, applied to all Massachusetts residents except for those enrolled in Medicare, Medicaid, and other federal health care programs that are still subject to federal anti-kickback laws.

At this point, it is worth mentioning why biological specialty drugs are given special treatment under the law. Unlike other drugs, biological specialty drugs lack generic alternatives because an FDA review and approval procedure for biosimilars is still in the process of being developed. This means that Massachusetts's residents suffering from illnesses like Rheumatoid Arthritis (RA) or Multiple Sclerosis (MA) could have experienced a significant drop in their out-of-pocket costs for drugs in the third quarter of 2012. This exogenous policy change serves as a natural experiment to examine the effect of copay cards on insurers' costs. In particular, this paper will test the hypothesis that insurers in Massachusetts absorbed the shock of the ban lift by simply raising the copay band of patients whose net OOP expense remained constant. The paper also examines the change in the composition of patients' purchasing behavior to see if they substitute drugs that do not offer coupons for those that do.

The data in this paper focuses exclusively on medications for two diseases, which deserve a brief discussion. The first is Multiple Sclerosis (MS), which is considered to be an immune-mediated disease in which the body's immune system attacks the central nervous system. In particular, the immune system attacks myelin, which is the fatty substance that surrounds and insulates the nerve fibers, distorting nerve impulses traveling to and from the brain and spinal cord and producing a variety of symptoms. The second disease is Rheumatoid Arthritis (RA), which is also considered to be an autoimmune disorder in which the immune system mistakenly attacks a patient's joints causing painful inflammation and damage.

Multiple Sclerosis does not have a cure, but there are treatment options that slow down the course of the disease. Taken on a long-term basis, medications can reduce the severity of relapses and the accumulation of lesions. The majority of MS medications are biologicals, which means that they are genetically engineered drugs that provide patients with substances that are naturally produced by the body's immune system. So far, experts have found that the immune system protein interferon beta is effective in treating MS. My data set contains four drugs of this form: Avonex, Betaseron, Extavia, and Rebif. Table 1.1 compares the mode of administration and administration intervals for drugs that treat MS. The table shows that drugs are taken in intervals that range from twice a day to every four weeks, administered by mouth or by injection. The main takeaway from this table; however, is that there is no clear winner for ease of use and that medication choice largely depends on physicians' advice and individual preference. Nevertheless, it is worthwhile to note that since these medications take a few months to work, switching drugs leaves patients unprotected for long periods of time.

Rheumatoid Arthritis also has no cure. Medications can only reduce inflammation in joints to relieve pain and prevent or slow joint damage. Patients have four main medication options: anti-inflammation drugs, steroids, disease-modifying antirheumatic drugs, and biologicals. As noted earlier, the majority of drugs in my data set are biologicals, which interfere with biologic substances that cause or worsen inflammation. Similar to Table 1.1, Table 1.2 compares routes of delivery and frequency of medications that treat RA. Because drugs vary wildly across these two factors, there are no direct substitutes and drug choice rests heavily on doctors' orders. Clinical research and experience suggest that these drugs also exhibit meaningful differences in their efficacy and safety, and that switching between biological therapies is not advisable. The fact that consumer drug choice is relatively sticky and that patients can incur switching costs means that coupons that induce purchases can have a significant effect on pharmaceutical companies' profits and insurers' costs.

3 Related Literature

3.1 Multi-tiered copay schemes

The first section of the literature review contains papers that assess the extent to which tiered copay schemes are successful at managing consumer behavior. The relevance of tiered copay structures to drug coupons rests on the following conjecture: if the success of insurance cost-sharing programs relies on copay differentials, then the introduction of coupons could undermine their effect. Rector et al. (2003) develops an empirical framework to study whether tiered prescription copayments affect patients' use of preferred brand medication. In particular, the paper tests whether financial incentives in drug formularies are effective in getting patients to buy preferred drugs. The authors employ a longitudinal logistic regression analysis of pharmacy claims from 1998 and 1999 comparing concurrent groups that were or were not exposed to tiered copayments. The study focuses on enrollees in four independent physician practices across three main therapeutic classes: ACEI, PPI, and STATIN drugs. The study showed that tiered prescription copayments correspond to a statistically significant increase in the use of preferred brands of ACEI, PPI and STATIN over time.

In a similar study, Gilman and Kautter (2008) assess the impact of multitiered copayments on the use and cost of prescription drugs among Medicare beneficiaries. The paper compares individuals enrolled in retirement health plans with one tier with those enrolled in plans with three tiers, and finds that the latter group had lower total drug expenditures, fewer prescriptions filled, and higher out-of-pocket costs than individuals in lower tiered plans. The portion of generic prescriptions was also higher among the three-tiered group. Additionally, the authors look at the effect of cost sharing on the use of medications that treat chronic conditions. They find that while tiers are effective at lowering drug expenditures among Medicare beneficiaries, they are less effective in influencing the behavior of patients who have chronic conditions. The implication of these papers is that copay differentials are an important determinant in consumer purchasing behavior. This means that coupon programs bear the potential of steering patients towards non-preferred brands, thereby, circumventing the tiered copay scheme.

Dickstein (2014) develops a model of physician and patient incentives in prescription drug choice. The paper addresses two main distortions in the market for prescription drugs: (i) consumer moral hazard problem stemming from the fact that patients do not face the full cost of the drug, (ii) asymmetric information as physicians know more about the severity of patients' condition. The paper seeks to resolve whether the benefits of higher cost sharing, which come in the form of lower short-term costs, outweigh the unintended potential consequence of lower adherence rates, which can raise health costs in the long run. Dickstein uses variation in three plan types, PPO, HMO, and Capitated HMO, to identify the effect of different cost sharing structures on physician prescribing choices between brand and generic medications that treat depression.

To address the problem of self-selection bias, Dickstein restricts the sample to patients who are newly diagnosed with depression, and as a result are less likely to select a health plan based on copay amounts. He finds that physicians facing capitation elect psychotherapy at higher rates and are more likely to prescribe generic brands. However, plans with high degrees of cost sharing also have the poorest rates of adherence, which may lead to costly relapse. This paper serves as a good starting point for understanding the tradeoffs between higher cost sharing, in the absence of coupons, and potentially lower compliance rates that are associated with patients not being able to afford their medications. Unlike this paper which focused on the prescribing behavior of physicians, my paper will address the purchasing behavior of patients through variation not in plan structure but in coupon use.

3.2 Pharmaceutical pricing strategy

The next section of the literature review surveys papers that examine company-advertising decisions. The first paper focuses on the advertising cycle of pharmaceutical companies in the face of patent expiry. The second paper assesses the empirical validity of theories for why manufacturers offer coupons. Bhattacharya and Vogt (2003) propose a dynamic model to explain why branded pharmaceutical prices rise after their patents expire and generics enter the market. The model predicts a pattern of rising prices and diminishing advertising over a drug's life cycle. The logic behind this is that initially pharmaceutical firms build the public's stock of knowledge about their drug, and then they take advantage of it and of physicians' sticky prescribing habits. Even though generic entry should force the price of branded drugs down, the model of knowledge diffusion predicts that a brand's knowledge stock will outweigh the competitive force on prices. The author test the predictions of the model using data on beta-blockers, using time to expiry as an instrument that affects pricing and advertising but is not correlated with demand. They find confirmation for price dynamics based on the accumulation of knowledge stock for branded drugs. The patent life of drugs is an important factor to consider when assessing a firm's decision to offer coupons. Specifically, if the patent on a brand name drug is close to expiry and the company is worried about competition from generics, it might be willing to offer coupons to compensate for the copay differential to stop consumers from switching to the generic version.

Expanding on the question of companies' advertising strategies, Nevo and Wolfram (2002) explore the question of why do manufacturers issue coupons. The paper is an empirical analysis of the market for breakfast cereals, a highly concentrated stable oligopoly. The authors seek to assess the empirical validity of four major explanations: (i) price discrimination, (ii) fluctuating demand, (iii) retailers' objectives and costs, and (iv) cross-brands effects. To do so, they compare shelf prices in given cities and quarters for which a coupon was distributed for a particular brand and other cities in which a coupon was not distributed.

Nevo and Wolfram find that shelf prices are lower during periods when coupons are available. This is in support of models of price discrimination in oligopoly settings that suggest inter-brand competition that causes all prices to be lower than the uniform (nondiscriminatory) price. They also find that coupons are used most intensely at the end of manufacturers' fiscal years when brand managers are trying to meet sales targets. Finally, they find a positive correlation between lagged coupon use and current sales, suggesting that coupons are used to encourage purchases. In addition to providing a useful way to think about the return on coupon marketing campaigns, this paper raises questions about the long-term implication of drugs coupons. In particular, can copay card programs result in price discrimination if consumers self-select into groups that do and do not use coupon? Are drug coupons a "foot-in-the-door" loyalty program to get patients on drugs and prevent them from switching when a generic alternative becomes available? While the scope of this paper does address these broader questions, these questions should still be raised when discussing the welfare implication of coupons.

3.3 Contribution

Though coupons in retail markets have received considerable attention from economists, there has been no significant study on the effect of pharmaceutical coupon programs. One paper that seriously addresses this question is by Lee (2013) who presents a welfare analysis of coupons in pharmaceuticals. His paper seeks to address two questions: (i) how do coupons impact the agency problem of consumers not facing the full cost of drugs? (ii) how does the ability of drug manufacturer to target coupons to particular types of consumer affect their profitability? Using data from the IMS Health on dollars and unit sales of different molecule/form/strength combinations at monthly frequency from January 2003 to August 2011, Lee compares outcomes under random versus targeted distribution of coupons and allows pharmaceutical companies to change their prices in response to coupons.

After running counterfactual simulations, Lee finds a net drop in welfare because the increase in insurance costs exceeds the increases in consumer surplus due to lower copayments. Additionally, the paper concludes that pharmaceutical companies that distribute coupons can rely on consumers to self-select into groups to achieve price discrimination and increase profits.

This paper contributes to the existing literature by exploiting an exogenous policy change that presents opportunities to compare treatment and control observations across multiple periods. This differences-in-differences strategy, which will be explained in detail in section five, allows me to isolate the effect of coupons on each drug's total number of scripts and patients per quarter. Additionally, this paper exploits variations in coupon use for the same trade name to determine how coupons change the cost burden of insurers and patients. This setup of a natural experiment provides more causal evidence on the effect of coupons on consumer copayments and insurers' health costs.

4 Data

4.1 Summary of Data: Description of Sample Construction and Variables of Interest

<u>What I observe in the data:</u>

This paper uses claims data for biological specialty drugs that treat Multiple Sclerosis (MS) and Rheumatoid Arthritis (RA). The data was obtained from Zitter Health Insights, a healthcare research firm that consults life science companies. In, the data, I see transactions associated with 27 drug brands from across the country, but the time stamp on each transaction is only associated with the quarter and the year to preserve privacy. At the prescription level, I am able to observe the drug name, whether it is brand or generic, the disease it is used to treat, whether it is a refill, the zip code of the pharmacy where the drug was sold, the specialty of the prescribing physician, the total cost of the drug, and the amount covered by insurance, patient, and the coupon.

The data set described above does not provide a way to identify individuals so it is not possible to track purchasing decisions longitudinally. Because individuals are de-identified, the data also does not include information on patients' general health status. Even though there is a variable to indicate whether the consumer involved in the transaction is insured, there is no detailed information on the insurance type or extent of coverage. As such, there is no way of telling which tier a drug is classified under, though usually drugs in high copay bands are considered to be in higher tiers. As can be seen in the last row of Table 2, the data set has 495,940 observations for MS and 842,042 observations for RA, resulting in a total of 1,337,982 transactions from across the United States. Some of these transactions involve multiple scripts and patients. Table 1 provides a breakdown of transactions on the patient and script level across time for each drug class.

<u>How I construct the subsample:</u>

The results in this paper come from a sample of 63,736 transactions with zip codes in Massachusetts. In addition, I restrict my attention to individuals with insurance. Table 3 categorizes transactions by coverage type. As can be seen from the second row fourth column, 99.25% of the data is composed of individuals with insurance. The reason I exclude people without health insurance is because coupons are only offered people with health insurance. Including noninsured in the non-coupon users "control" group will bias the results because the characteristic of having insurance is not orthogonal to health spending.

Variables of interest:

Table 4 shows basic statistics for the main variables in the data set. The unit of observation is the transaction, which may involve more than one script and patient. The first string variable is the name of the drug. The next two variables are indicators that equal one if the drug sold in the transaction is brand (versus generic) or if the drug is used to treat MS (as opposed to RA) and zero otherwise. As can be seen from the second row third column of Table 4, 99.8% of transactions involved brand name drugs, as expected in the case of biological specialty drugs. Row 3 column 3 shows that 37% of transactions involved medication used to treat MS while the remaining 63% of transactions involved drugs that treat RA. The next string variable specifies the zip code of the pharmacy where the transaction took place from all across the nation. The zip code variable proves to be extremely important in the ensuing analysis because it provides a way to separate observations from Massachusetts in the pre- and post- ban period.

The fifth row is a dummy variable that equals one if the transaction is for a refill prescription. As can be seen from the fifth row third column of Table 3, 61% of the transactions involved refills as opposed to new prescriptions. The variable in row six of table 4 specifies the specialty of the prescribing physician, which varies across 140 categories. The next two variables indicate the number of scripts and patients involved in every transaction. In order to get cost information on a per unit basis, I divide the total cost variables (rows 9-13 of Table 4) by the product of the total number of patients and scripts per transaction. For example, when I do this operation on the variable total_spend ($) from row 9, I obtain the variable total_spend_per script in row 14, the average of which was $4,425 for a one-month supply of drugs that treat MS and RA. I do the same procedure to the rest of the cost variables (rows 10-13), which specify the amount covered by the insurance, the consumer, the coupon, and a charitable subsidy in that order.

Out of the $4425 average total cost for a one-month supply of both medication types, the insurer covers on average $4141 per script. The standard deviation for both of these numbers is roughly $3000. The maximum drug cost is $142,815 while the maximum insurance payment is $135,674. While the insurer pays an average of about $4000 per script, the patient's average out-of-pocket is only $109 (with a standard deviation of $340 and a maximum of $75,133). The average amount of coupon assistance from the drug manufacturer is $42 (with a standard deviation of $270 and a maximum of $13,252), which constitutes roughly half of the patient's copay. Lastly, row 19 of table 4 gives summary statistics for the dollar amount that patients receive in the form of subsidies from charitable organizations. The average assistance from non-pharmaceutical companies is only $3. Because the magnitude of donations is insignificant compared to the total cost of the drug (on the order of $4000), it will not be featured in the ensuing analysis.

Variables I constructed:

In addition to per unit cost variables, I create the following aggregate variables: Total_Scripts is the sum of the number of scripts (can be found in Table 4 row 8) per quarter for each drug, classified into two groups of brands that offered coupons after the ban lift and those that did not. Total_Patients is the sum of the number of patients (can be found in Table 4 row 7) per quarter for each drug, split into the same two groups as above. To run to the differences-in-differences regression, I also needed to create the following dummy variables: Treat signifies that the transaction involves a brand that offered coupons after the ban lift, Post signified that the transaction took place in MA after the ban lift, and Treat*Post is the interaction variables that equals one if the brand offered coupons and the transaction occurred after the lift.

Another important discrete random variable is Copay_Band, which takes on seven possible values copay range from $0 - $25 to $1000 AND UP as detailed in table 5. Even though Copay_Band is a truncated variable, there is a separate copay variable that allows us to observe the exact copay amount the patient was expected to pay out-of-pocket in each transaction.

Lastly, I construct variables to quantify the cost burden of each party. Each variable equals the amount paid by the player divided by the total cost of the drug as detailed in the Appendix section 9.2.

4.2 Summary Statistics

Figures 2.1 and 2.2, which show the average price for a one-month supply of Multiple Sclerosis and Rheumatoid Arthritis drugs, demonstrate that drug brands can vary significantly in prices. The average price of a one-month supply of MS medication is $4,726, while the average price of a one-month of RA medication is $3,529. The high price of these biological drugs emphasizes the importance of insurance coverage and the potential role for coupons to influence patients' choices. Charts 3.1 and 3.2 group drug brands into two groups: those with prices above the average and those below. In this case the two drug treatments exhibit different behaviors. For MS, the drugs with above-average prices issued fewer coupons in Massachusetts after the ban lift, while for RA drugs with above-average prices issued slightly more coupons.

Despite their high costs, most biologicals have copays that are less than $100. The last rows of Tables 6.1 and 6.2 show the percentage of transactions that fall across the copay bands. Adding the percentages for each column, we see that for Multiple Sclerosis, 88% of transactions fell within the $0 - $100 copay range and for Rheumatoid Arthritis, the cumulative share of transactions that fell within that range is 83%. The main takeaway from this table is that the majority of copays are less than $100, meaning that the insurance company covers almost the entire cost of the drug. However, the next tables show that coupons start to play a major role precisely when copays exceed $100.

Tables 7.1 and 7.2 show the breakdown of dollar amount spent on coupons by pharmaceutical companies across these copay bands. Over the period of 2012Q1-2014Q2, pharmaceutical companies spent $21,728,771 on coupons for MS medication, constituting 1% of total transaction costs. Alternatively for RA drugs, pharmaceutical companies spent $95,702,287 on coupons, which represented 2% of total transaction costs over the period. It is important to note that more coupons are redeemed in transactions that involve drugs with copays of $101 and up. In particular, the last rows of tables 7.1 and 7.2 show that for MA, 83% of the total amount spent on coupons fell in this range and for RA it was 76%. Lastly, tables 8.1 and 8.2 show the share of the drug cost born by insurers and patients by copay band. The second to last row in both tables show that the insurer's coverage of drug cost significantly drops in extreme copay categories of $500 or more, where the majority of coupons are redeemed.

Table 9.1 and 9.2 show which pharmaceutical companies spent the most on coupons in 2013. In addition, it lists the companies' sales and relative market share ranking for that year. Both tables show that there is discernable variation among the brand names in the percent of national transactions with a coupon. Secondly, we see that for MS, the biggest market player Copaxone is also the one with the highest percentage of coupons, but that other big players like Avonex and Gilenya had very few transactions with coupons in the 2013 data. Meanwhile Tecfidera and Ampyra, who had large percentage of transactions with coupons, had relatively low sales figures in 2013. For RA, the correlation between coupon offering and market size seems clearer. Specifically, the two biggest players Humira and Enerbal are also the ones whose transactions had the most coupons redeemed, while the rest of the brands had less coupons and lower sales figures.

In order to exploit the variation in coupon offering in Massachusetts after the ban lift, I had to first identify which brands offered coupon and which ones did not. Table 10 shows the percent of transactions in Massachusetts with coupons from 2012Q1 to 2014Q2 for each drug brand. As can be seen from the first three rows of the first table, the three MS brands that began to offer coupons after the ban lift are Ampyra, Aubagio, and Tecfidera. By contrast, for RA, all but the last three brand names, Acterma, Kineret, and Methotrexate, started offering coupons after the ban was lifted.

5 Empirical Methodology

This paper uses three main identification strategies that will be discussed in turn. First, I employ a differences-in-differences approach that only uses insured individuals in Massachusetts because coupons are only offered to people with insurance. This approach relies on the fact that some pharmaceutical firms did not offer coupons even after the ban was lifted, at least not in the time frame of the study (see Table 10). This variation in coupon offering presents a natural division between control and treatment firms. The following equations were used to analyze the effect of coupons on two dependent variables of interest:

$$Total\_Scripts_{it} = \alpha_0 + \alpha_1 Drug\_Brand_i + \alpha_2 Quarter_t + \alpha_3 Treat_i * Post_t + \xi_{it} \qquad (1)$$

$$Total\_Patients_{it} = B_0 + B_1 Drug\_Brand_i + B_2 Quarter_t + B_3 Treat_i * Post_t + \varepsilon_{it} \qquad (2)$$

Where Total_Scripts is sum of scripts for drug i in quarter t, Total_Patients is sum of patients for drug i in quarter t, Drug_Brand are fixed effects to pick up characteristics of drug brands that are constant over time period, Quarter are fixed effects to capture time trends, Treat is a binary variable that equals one if the drug company offered coupons after the ban lift and zero otherwise, and Treat*Post is an interaction term and the variable of interest.

Note that this strategy relies on the assumption that firms that started offering coupons after the ban lift and those that did not exhibit parallel trends in the period before the ban was lifted. The diff-in-diff approach isolates the effect that offering coupons had on the sales of pharmaceutical companies, both in terms of number of scripts and number of patients per quarter. In essence, this approach subtracts the change in the number of scripts and patients experienced by brands that did not offer coupons (the first difference) from the change experienced by those that did offer coupons (the second difference) in order to not attribute the effect of time passage to the introduction of coupons.

The second estimation strategy exploits variation in coupon use among transactions for the same drug. Even for a drug that had a coupon program after the ban lift, not all patients redeemed a coupon in transactions involving that drug. This portion of the analysis is restricted to observations of insured patients in Massachusetts after the lifting of the ban. The comparison of transactions with and without a coupon allows me to assess how the cost burden shouldered by the insurer and the patient changes after the introduction of coupons.

In order to estimate the effect of coupons on patients' copay band, I first employ a multinomial logit model to estimate the probability that a transaction with a coupon will land in one of the following seven copay bands. The corresponding regression equation is:

$$\Pr(\text{Copay\_band} = z) = \gamma_0 + \gamma_1 \text{Coupon}_i + \gamma_2 \text{MS}_i + \gamma_3 \text{Refill}_i + \varepsilon_i \tag{3}$$

Where Copay band is a discrete dependent variable that takes on seven possible values (see Table 5), i stands for transaction that occur in Massachusetts after the ban lift, Coupon is binary variable that equals one if the transaction had a redeemable coupon amount that is greater than zero, MS is an indicator variable for whether the medication treats Multiple Sclerosis (as opposed to Rheumatoid Arthritis), and Refill is dummy for whether that prescription was a refill.

We are interested in the coefficient on the coupon dummy, γ_1. In the data section, we observed the trend that the highest coupon amounts are redeemed at high copay bands (see Table 7), so we should expect the coefficient on the coupon dummy to increase relative to the baseline as we increase the copay band.

Finally, in order to examine how the cost of medications with coupons gets allocated across insurers and patients, I run the following set of regressions:

$$Y_i = \alpha_0 + \alpha_1 \text{Coupon}_i + \alpha_2 \text{MS}_i + \alpha_3 \text{Refill}_i + \alpha_4 \text{Tradename}_i + \alpha_5 \text{MD\_specialty}_i + \xi_{it} \tag{4}$$

Where Y stands for one of six variables: Total drug cost, Insurance cost, Insurance cost share (see Appendix 9.2 for explanation), Patient cost share, Copay amount, and Patient out-of-pocket. Additionally, i stands for transaction that occur in

Massachusetts after the ban lift, Tradename is the fixed effect for each drug brand, and MD_specialty is the fixed effect for the specialty of the prescribing physician. The results from this regression could go one of two ways: it is possible that coupons reduce the out-of-pocket cost of patients and that the insurance company ends up carrying a larger cost burden. It is also possible, however, that the coupon amount is offset by an increase in the copay amount, resulting in a zero net change in the OOP spending of the patient. If the latter is true, then coupons do not result in a change in the cost of the patient, but a change in the framing of who is paying for it.

6 Results

6.1 Comparing brands that did not introduce coupons to those that did

Before I ran the differences-in-differences regressions, I plotted the raw data to verify that the two groups exhibit different trends after the ban lift. Chart 4.1 shows that the portion of transactions with coupons is significantly different across the treatment and the control group whose percentage is flat at zero. Chart 4.2 shows the divergence in the total number of scripts across the two groups. It can be seen that before the ban lift both groups were relatively flat, with the control group (drugs that did not introduce coupons after ban lift) having slightly more scripts. However, after the ban is lifted, the number of scripts for brand names that offered coupons increased even though it decreased for brands that did not offer coupons. Similarly, Chart 4.3 shows the same story but with total number of patients. Both groups start out at roughly the same level and growth rate, but after the ban lift the number of patients for brands that offered coupons increased by more than for brands that did not offer them.

Table 11 shows the results from the diff-in-diff regression assessing the effect of coupons on total scripts and patients and confirms the story from the figure 5. The results present the coefficient from regression specified in equations (1) and (2) in the empirical methodology section. The coefficients were obtained by aggregating the unit transaction level data into quarterly buckets and the results should thus be interpreted as quarterly averages. As can be seen in Table 11, both coefficients on the interaction term are positive and statistically significant at the 99% level. In particular, the first row of Table 13 shows that the introduction of coupons for specific brands was associated with an increase of 1,339.6 scripts per quarter, which corresponds to a 15.8% increase relative to the starting level. Moreover, those drug brands that introduced coupons following the ban lift saw an increase of 866.3 patients per quarter, corresponding to a 15.9% increase relative to drug brands that did not offer coupons.

6.2 Assessing the impact of coupons on copay bands

Table 12 shows the results from the multinomial logit regression of copay band categories on whether a coupon was used in the transaction. In particular, it presents the coefficients from running the regression specified by equation (3) in the empirical methodology section. In my regression, the first copay band of \$0-\$25 is omitted due to multicollinearity. As such, all coefficients should be interpreted relative to this baseline. In addition, this regression is restricted to transactions of insured patients in Massachusetts after the ban lift.

The coefficients on the coupon dummy in Table 12 show that the presence of a coupon in the transaction increases the multinomial log-odds for a higher copay band relative to the omitted category. In other words, the likelihood that a transaction had a coupon increases as the copay band rises. For example, the cell in the second row first column of Table 12 shows that redeeming a coupon at purchase increases the likelihood that the transaction had a copay between \$26-\$50 by 1.3 relative the baseline. Similarly, for copay band \$251-\$500 (row two column two) the coefficient is 3.3. The coefficient on the coupon dummy increases monotonically with copay range until it reaches \$500. While the first four coefficients are statistically significant at the 99% confidence level, the last two coefficients are not statistically significant perhaps because there are fewer observations in that range. Focusing on the negative coefficients on the refill dummy that are statistically significant is also revealing. Specifically, we see that refill prescriptions are more likely to belong to the cheapest \$0-\$25 copay range.

6.3 Do coupons change the share of the cost covered by insurance?

The third and final portion of the analysis exploits variation in coupon usage among transactions for the same brand name in Massachusetts after the ban lift. It is illustrative to start with a case example that appears multiple times in the data. Chart 5 presents a four-panel story that starts by plotting the average coupon redeemable amount for transactions with and without a coupon. Obviously for those without a coupon, the amount is constant at zero. However, for transactions with a coupon, the average redeemable starts at around \$20 and steadily increases until it reaches \$220. The total price of the drug steadily increases over time, for both coupon and non-coupon transactions. What is interesting to note, though, is how the sharp rise in coupon amount is matched by a steep decline in the share of the drug cost covered by insurance and, consequently, a sharp rise in the share covered by the patient. This sequence of events suggests that on net, the patient did not benefit from the coupon because it was used to cover a higher copay.

Even though it is tempting to generalize this story to the rest of the data, doing so would be seriously misleading as figure 5 was based on one drug, Orencia and its 1482 observations. These figures do, however, serve as a good starting point to hypothesize about what we could expect to see once we use all 63,736 observations from Massachusetts. Now that the motivation for this section has been laid out, Table 13 presets the results from regressing total price and the share covered by insurer and patient on the presence of a coupon in the transaction. The regression also includes fixed effects for brand name and the specialty of the prescribing physician (see equations 4 in the empirical methodology section).

Table 13 shows that the story is not as clear as it seems. In particular, the first column has the total drug cost as the dependent variable, and the coefficient on the coupon dummy is not statistically significant. The same holds for the dollar amount paid by the insurer to cover the cost of the medication, which is dependent variable in the second column. The rest of the coefficients are statistically significant. In particular, the drop in the portion of the cost covered by the insurer is almost exactly matched by the increase in the copay's percentage of total cost. Specifically, the third column regresses the insurance share of the cost on the coupon dummy and results in a negative coefficient of 0.02 while the fourth column regresses the copay share of the cost on the same dummy and results in a positive coefficient of 0.02. In addition, the fifth column regresses the dollar amount the insurance expects the patient to pay for the drug and shows that this amount increases by $57.4 dollars when a coupon is used in the transaction. Nevertheless, the sixth column shows that the actual amount paid by the patient out-of-pocket (which equals the copay amount minus the value of the coupon) decreases by less than one dollar. This means that even though consumers have a coupon, because they are now required to cover a greater portion of the drug's cost, the net change in OOP expense is about zero.

As an exercise to further test this hypothesis, I ran the same set of regressions on four subsamples: (1) MS drugs whose price is above average (2) MS drugs whose price is below average (3) RA drugs whose price is above average and (4) RA drugs whose price is below average. I do not present the full results in a table because most of the coefficients turn out to be statistically insignificant. The only dependent variable for which the coefficient on the coupon dummy is statistically significant is the share of the drug cost covered by the copay. Table 14 summarizes the results. For Rheumatoid Arthritis, the coefficient is not significantly different across the two groups. However, the last two rows show that for Multiple Sclerosis drugs that are priced above average, having a coupon increase the share of total cost covered by the copay (0.014 percentage points) by a significantly lower amount than for MS drugs that priced below average price (0.032 percentage points).

7 Conclusion

I examine the economic consequences of the lift on coupons for bio-specialty drugs in Massachusetts in the third quarter of 2012. The advantages of evaluating this policy change is that (a) its timing was well defined and (b) differences across brand names and transactions allow for a treatment/control design. I find that brand names that started introducing coupons following the ban lift saw close to a 16% increase in the total number of scripts and patients per quarter relative to brand names that did not offer coupons. Moreover, I find support that coupons are more likely to be used to pay for drugs that have high copays. Lastly, I find that the introduction of coupons in Massachusetts was associated with a corresponding decrease in insurers' share of the drug cost, resulting in no change in patients' out-of-pocket cost.

A key outstanding issue is what causes insurance companies to raise the copay for drugs that offer coupons. If patients with coupons are expected to cover a larger portion of the drug cost, then their total out-of-pocket cost stays the same. Because the effect of coupons on total drug price is inconclusive, it remains unclear whether insurance companies pay more to cover patients who use coupons.

Possibly, insurance companies try to keep their patients' out-of-pocket cost the same as without coupons in order to maintain the tiered structure, which incentivizes patients to buy preferred drugs by giving them lower copayments.

This analysis of the use of coupons by pharmaceutical companies provides several directions for further research. First, future researcher might study whether coupons give pharmaceutical companies the power to price discriminate because consumers self-select into customer segments that do and do not use coupons. Further research should also explore paths by which drug coupons can be used in loyalty programs or foot-in-the-door advertising campaigns. If physician-prescribing habits are sticky as Bhattacharya claims, then targeted campaigns to physicians' offices can have long-lasting effects. In addition to studying the validity of this statement, researchers could look at the interplay between asymmetric information and drug coupons. In particular, they could test if patients' limited medical knowledge makes them more likely to use a coupon given to them by a doctor even when a cheaper generic alternative is available. Thirdly, future research could exploit variations in the number of times a drug coupon can be redeemed to determine if consumers switch drugs when their coupon expires. Finally, further research could characterize the extent to which coupons create barriers to entry in the pharmaceutical industry. This question is especially relevant for smaller players who compete with established brand names that employ coupons to keep consumers from switching over to substitutes. These ideas underscore the importance of investigating pharmaceutical companies' decision to issue coupons.

Overall, my analysis provides a valuable starting point for further research to understand how coupons affect sales and the out-of-pocket cost of patients.

8 References

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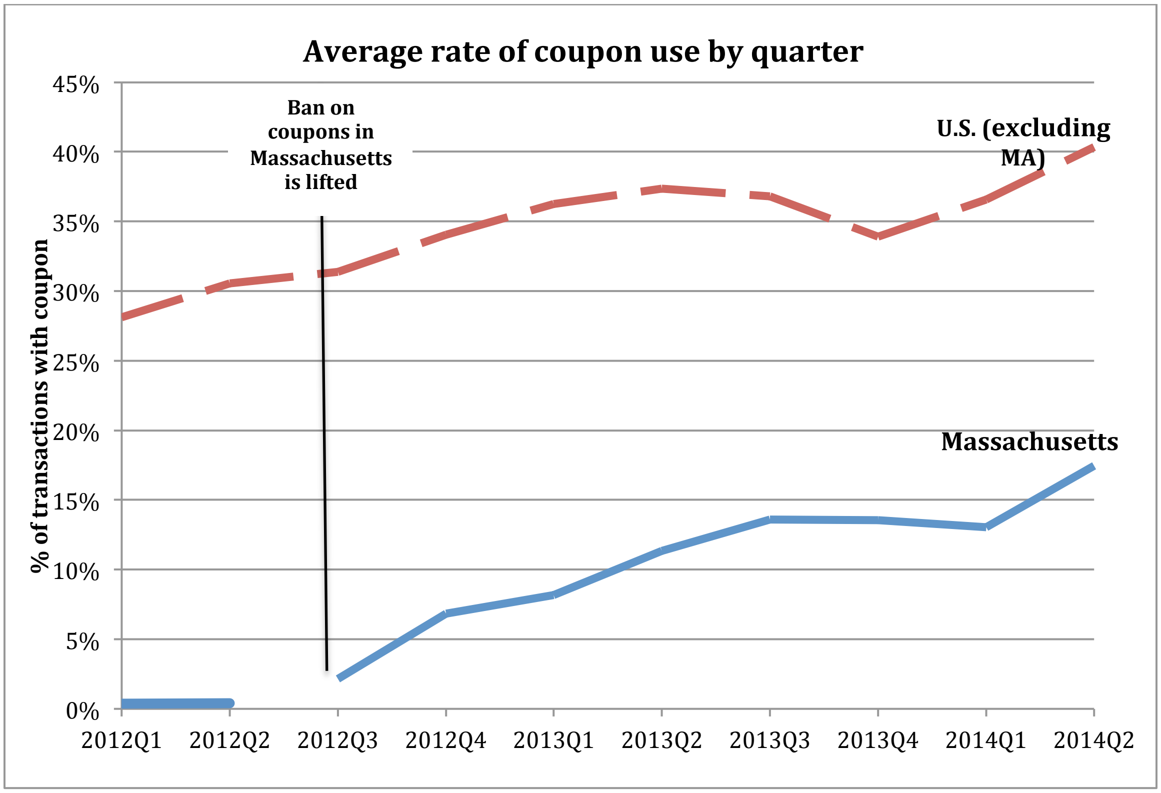
9 Tables and Figures

Figure 1 Average rate of coupon use by quarter



Notes: Percent of transactions with coupon equals the sum of transactions where the patient had a coupon amount that was greater than zero divided by the total number of transactions that quarter. Discontinuity reflects the lifting of the ban on coupons in Massachusetts. Unless otherwise noted, all data comes from Zitter Health Insights, Copay Offset Monitor, Pharmaceutical Transaction Data.

Table 1.1 Multiple Sclerosis medications: mode of administration and administration intervals

Brand Name	Must be repeated	Administration
AMPYRA	Twice a day	By mouth
AUBAGIO	Daily	By mouth
AVONEX	Every week	Intramuscular injection
BETASERON	Every other day	Subcutaneous injection
COPAXONE	Daily	Subcutaneous injection
EXTAVIA	Every other day	Subcutaneous injection
GILENYA	Daily	By mouth
REBIF	3 times / week	Subcutaneous injection
TECFIDERA	Twice a day	By mouth
TYSABRI	Every 4 weeks	Intravenous infusion

Notes: Note that some drugs may have alternate routs of delivery. Information about drugs is taken from the National Multiple Sclerosis Society.

Table 1.2 Rheumatoid Arthritis medications: mode of administration and administration intervals

Brand Name	Must be repeated	Administration
ACTEMRA	Every 4 weeks	Intravenous infusion
CIMZIA	Every other week	Subcutaneous injection
ENBREL	Weekly	Subcutaneous injection
HUMIRA	Every other week	Subcutaneous injection
KINERET	Daily	Subcutaneous injection
ORENCIA	Every 4 weeks or weekly	Intravenous infusion or Subcutaneous injection
SIMPONI	Once a month	Subcutaneous injection

Notes: Note that some drugs may have alternate routs of delivery. Information about drugs is taken from Consumer Reports Best Buy DrugsTM.

Table 2 Sample size in terms of transactions, patients, and scripts

Multiple Sclerosis

Year	Rows	Patients	Scripts
2012	181,816	188,986	292,761
2013	207,389	219,961	343,480
2014	106,735	113,144	170,227
Total	495,940	522,091	806,468

Rheumatoid Arthritis

Year	Rows	Patients	Scripts
2012	315,416	333,447	464,529
2013	350,204	377,451	530,738
2014	176,422	188,138	254,822
Total	842,042	899,036	1,250,089

Notes: Sample consists of all transactions from across the U.S. for all patients, including non-insured individuals, from 2012Q1-2014Q2.

Table 3 Data cross-section by type of insurance coverage

Coverage Type	**Freq.**	**Percent**	**Cum.**
Insured	878,615	65.67	65.67
Insured and used coupon	449,283	33.58	99.25
Uninsured	2,676	0.2	99.45
Insured and used subsidy from charity	7,408	0.55	100
Total	1,337,982	100	

Notes: Sample consists of all transactions from across the U.S. for all patients, including non-insured individuals, from 2012Q1-2014Q2.

Table 4 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
1. Tradename	1337982		string variable		
2. Brand dummy	1337982	0.998	0.05	0	1
3. Multiple Sclerosis dummy	1337982	0.37	0.48	0	1
4. Zipcode	1337958				
5. Refill	1337982	0.61	0.49	0	1
6. MD_specialty	1337982		categorical variable		
7.total_patient	1337982	1.06	0.31	0	17
8. total_script	1337982	1.54	0.93	1	41
9. total_spend ($)	1337982	6,314.66	4,473.51	0	142,815
10. total_insur ($)	1156166	5,918.89	4,425.31	0	135,674
11. total_copay ($)	1337982	138.05	412.92	0	75,133
12. total_coupon_amt ($)	314124	54.76	339.04	0	20,076
13. total_fdt_subsidy ($)	1337982	3.49	74.44	0	18,756
14. total_spend per script	1337979	4425.00	3229.12	0	142,815
15. total_insur per script	1156166	4141.64	3141.91	0	135,674
16. total_copay per script	1337979	108.91	340.53	0	75,133
17. total_coupon_amt per script	314124	42.64	269.57	0	13,252
18. total_fdt_subsidy per script	1337979	2.94	61.92	0	4,866

Notes: Table 4 only shows variables that were provided in the original dataset. Sample consists of all transactions from across the U.S. for all patients, including non-insured individuals, from 2012Q1-2014Q2.

Table 5 Possible values that the Copay_Band variable can take and their corresponding value

Value of Copay Band variable	Corresponding copay rang
1	\$0 - \$25
2	\$26 - \$50
3	\$51 - \$100
4	\$101 - \$250
5	\$251 - \$500
6	\$501 - \$1000
7	\$1000 AND UP

Note: While Copay_Band is a discrete random variable, the data set also contains a non-truncated version that specifies the exact copayment for each transaction.

Figure 2.1 Average prices of Multiple Sclerosis drugs

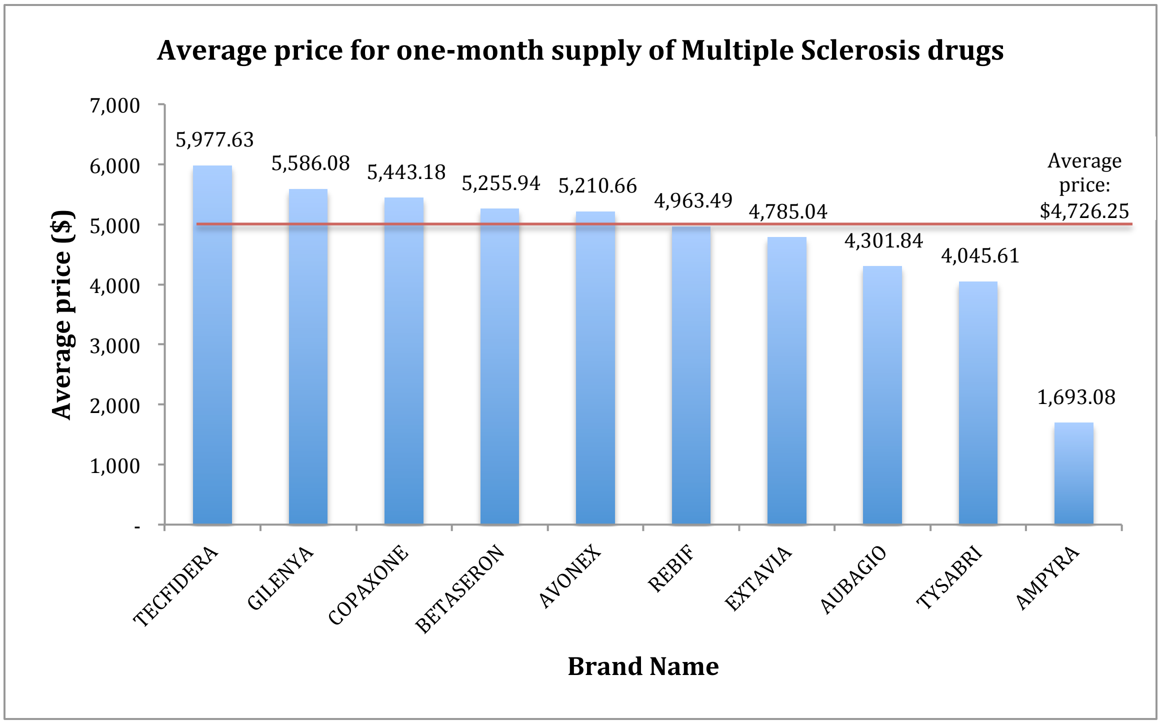


Figure 2.2 Average prices of Rheumatoid Arthritis drugs

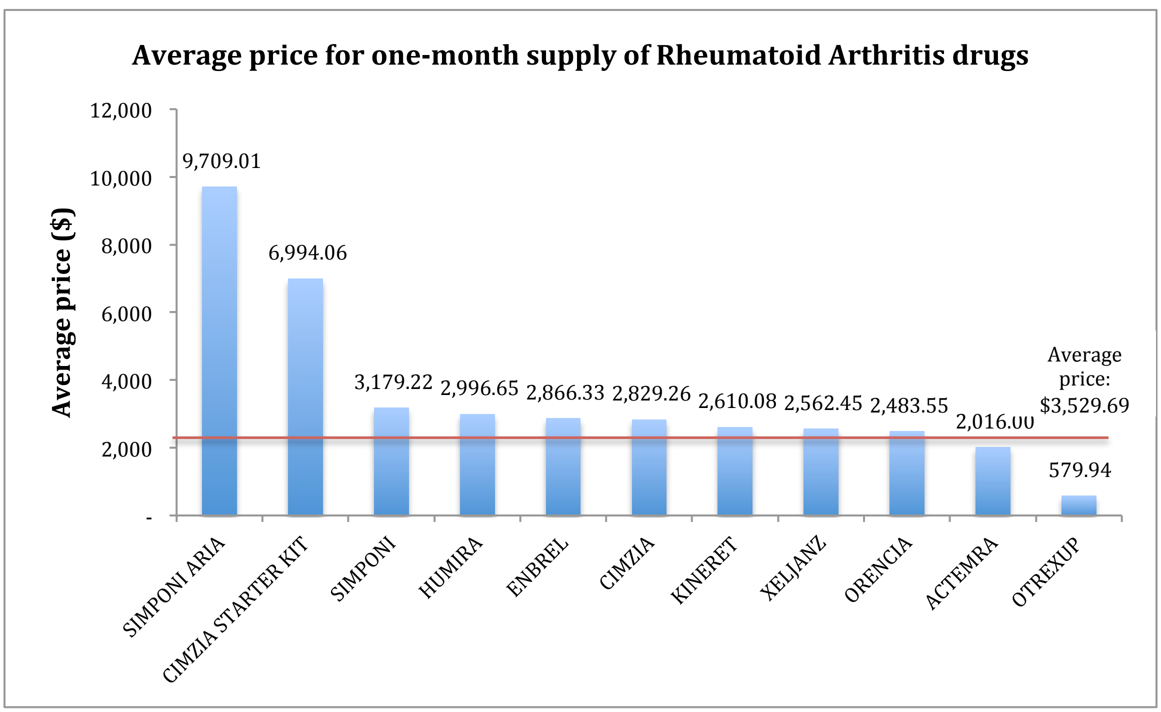


Figure 3.1 Rate of coupon use in MA for Multiple Sclerosis by drug price

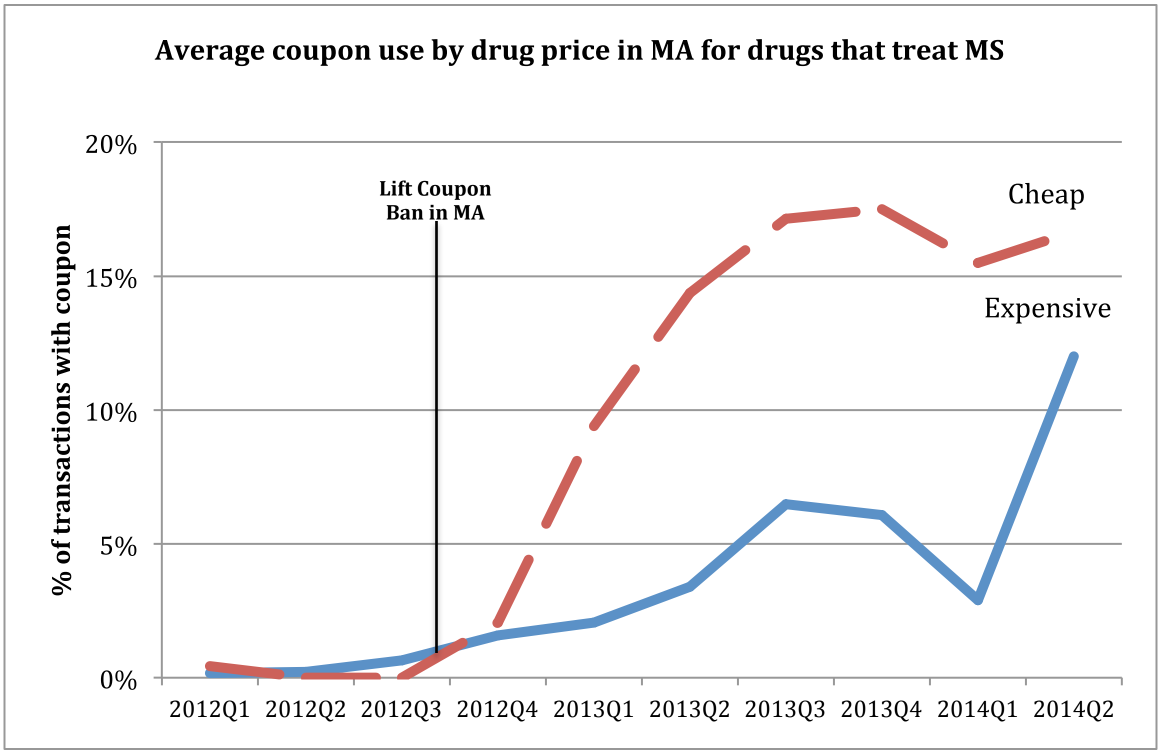
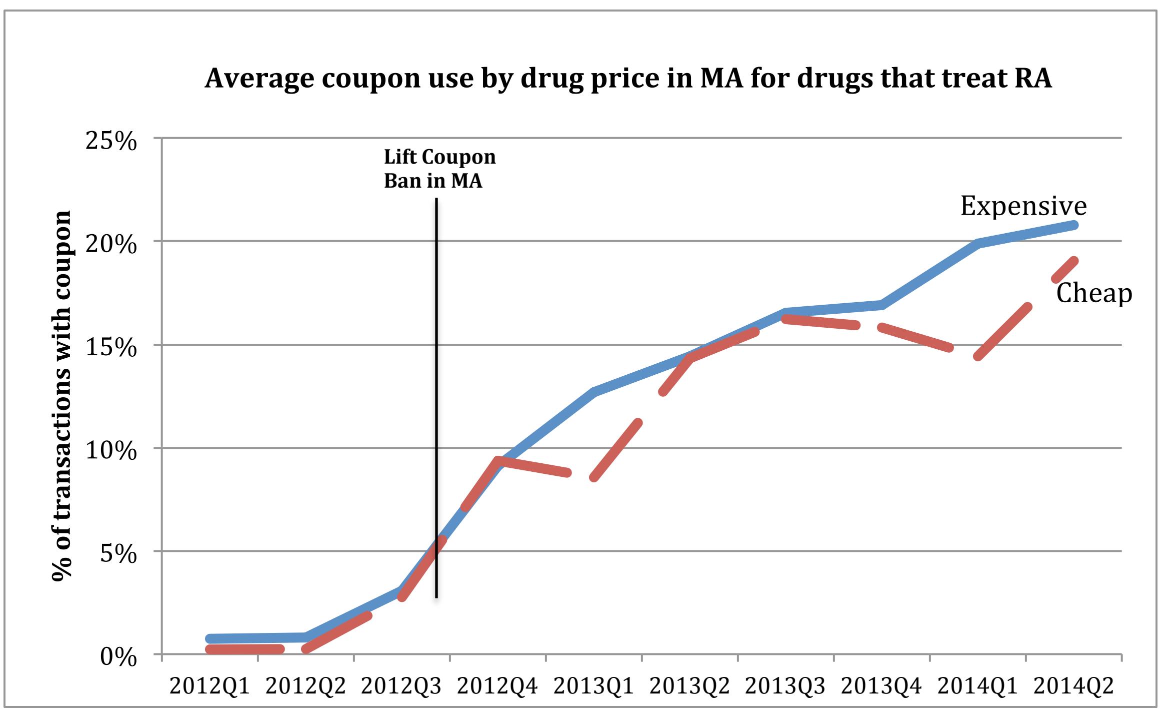


Figure 3.2 Rate of coupon use in MA for Rheumatoid Arthritis by drug price



Notes: Drug brands whose average price was above the mean price for all trade names is considered expensive and those with below average price are classified as cheap.

Table 6.1: Distribution across copay bands for transactions involving Multiple Sclerosis (MS) drugs

	COPAY BAND 2012Q1 - 2014Q2						
Percent of total cost	**$0 - $25**	**$26 - $50**	**$51 - $100**	**$101 - $250**	**$251 - $500**	**$501 - $1000**	**$1001 AND UP**
AMPYRA	42%	19%	26%	9%	3%	1%	1%
AUBAGIO	44%	17%	22%	10%	2%	2%	3%
AVONEX	40%	23%	25%	9%	1%	1%	1%
BETASERON	60%	12%	20%	6%	1%	0%	1%
COPAXONE	36%	24%	24%	11%	2%	1%	2%
EXTAVIA	72%	10%	11%	6%	0%	1%	1%
GILENYA	88%	4%	5%	2%	0%	0%	0%
MITOXANTRONE	100%	0%	0%	0%	0%	0%	0%
REBIF	47%	21%	20%	9%	1%	0%	1%
TECFIDERA	38%	21%	24%	11%	2%	1%	2%
TYSABRI	66%	15%	14%	3%	1%	1%	1%
Grand Total	48%	19%	21%	8%	1%	1%	1%

Table 6.2: Distribution across copay bands for transactions involving Rheumatoid Arthritis (RA) drugs.

	COPAY BAND 2012Q1 - 2014Q2						
Percent of total cost	**$0 - $25**	**$26 - $50**	**$51 - $100**	**$101 - $250**	**$251 - $500**	**$501 - $1000**	**$1001 AND UP**
ACTEMRA	57%	18%	17%	6%	2%	0%	1%
CIMZIA	21%	21%	35%	15%	5%	2%	2%
CIMZIA STARTER KIT	22%	27%	36%	8%	1%	2%	3%
CYCLOPHOSPHAMIDE	9%	0%	0%	91%	0%	0%	0%
CYCLOSPORINE	100%	0%	0%	0%	0%	0%	0%
ENBREL	32%	24%	27%	11%	3%	2%	2%
HUMIRA	33%	24%	27%	11%	3%	1%	1%
KINERET	35%	19%	24%	13%	6%	2%	1%
METHOTREXATE	99%	1%	0%	0%	0%	0%	0%
METHOTREXATE SODIUM	99%	1%	0%	0%	0%	0%	0%
ORENCIA	29%	20%	32%	12%	4%	2%	2%
OTREXUP	26%	50%	20%	4%	1%	0%	0%
SIMPONI	23%	21%	33%	14%	4%	2%	2%
SIMPONI ARIA	39%	23%	23%	12%	2%	1%	0%
XELJANZ	22%	22%	36%	14%	3%	2%	2%
Grand Total	32%	23%	28%	11%	3%	1%	2%

Tables 7.1: % total dollars spent on coupons by pharmaceutical companies across copay band for MS and RA, 2012Q1 - 2014Q2

Percent of coupon amount	$0 - $25	$26 - $50	$51 - $100	$101 - $250	$251 - $500	$501 - $1000	$1001 AND UP	Dollars spent by firms on coupons ($)
AMPYRA	0%	1%	14%	18%	23%	21%	22%	1,644,498
AUBAGIO	0%	6%	13%	12%	6%	16%	47%	1,191,547
AVONEX	0%	4%	6%	15%	9%	15%	51%	337,086
BETASERON	1%	6%	8%	10%	4%	28%	44%	295,076
COPAXONE	1%	7%	10%	12%	6%	11%	54%	13,366,080
EXTAVIA	6%	47%	0%	47%	0%	0%	0%	425
GILENYA	1%	10%	19%	16%	3%	8%	43%	355,652
MITOXANTRONE	0%	0%	0%	0%	0%	0%	0%	767,684
REBIF	0%	0%	0%	11%	2%	6%	75%	3,717,462
TECFIDERA	1%	5%	11%	13%	6%	10%	54%	53,261
Grand Total	1%	6%	10%	12%	7%	12%	52%	21,728,771

Table 7.2

Percent of coupon amount	$0- $25	$26 - $50	$51 - $100	$101 - $250	$251 - $500	$501 - $1000	$1001 AND UP	Dollars spent by firms on coupons ($)
ACTEMRA	2%	8%	9%	18%	24%	7%	31%	61,027
CIMZIA	1%	8%	19%	20%	13%	14%	25%	1,638,926
CIMZIA KIT	0%	4%	12%	7%	4%	11%	62%	74,888
ENBREL	1%	6%	12%	16%	13%	15%	37%	35,450,527
HUMIRA	2%	9%	17%	20%	15%	11%	26%	48,353,121
KINERET	0%	0%	100%	0%	0%	0%	0%	60
METHOTREXATE	94%	6%	0%	0%	0%	0%	0%	1,055
METHO SODIUM	100%	0%	0%	0%	0%	0%	0%	84
ORENCIA	0%	6%	16%	19%	15%	15%	29%	3,335,794
OTREXUP	0%	100%	0%	0%	0%	0%	0%	30
SIMPONI	0%	5%	12%	14%	10%	13%	46%	5,537,847
XELJANZ	0%	9%	18%	23%	14%	13%	23%	1,248,928
Grand Total	1%	8%	15%	18%	14%	13%	31%	95,702, 287

Table 8.1 Cost burden born by insurer, consumer, and manufacturer for Multiple Sclerosis

Percent paid by…	**Insurance**	**Patient (out of pocket)**	**Coupon (Manufacturer)**	**Federation (Charity)**
$0 - $25	99%	0%	1%	0%
$26 - $50	100%	0%	0%	0%
$51 - $100	99%	0%	0%	0%
$101 - $250	98%	2%	1%	0%
$251 - $500	95%	3%	3%	0%
$501 - $1000	84%	8%	8%	0%
$1001 AND UP	60%	22%	18%	0%
Grand Total	99%	1%	1%	0%

Table 8.2 Cost burden born by insurer, consumer, and manufacturer for Rheumatoid Arthritis

Percent paid by…	**Insurance**	**Patient (out of pocket)**	**Coupon (Manufacturer)**	**Federation (Charity)**
$0 - $25	100%	0%	0%	0%
$26 - $50	99%	1%	0%	0%
$51 - $100	98%	2%	1%	0%
$101 - $250	96%	4%	1%	0%
$251 - $500	90%	10%	1%	0%
$501 - $1000	76%	24%	1%	0%
$1001 AND UP	50%	50%	2%	0%
Grand Total	97%	3%	6%	0%

Table 9.1 Multiple Sclerosis drugs brands: coupon use, sales, and relative market size ranking

2013 annual national figures			
Brand name	**Percent of transactions with coupon**	**Sales ($B)**	**Market share ranking**
COPAXONE	37.5	4.3	1
AVONEX	0.9	3	2
GILENYA	3.4	1.9	3
TYSABRI	0.9	1.7	4
BETASERON	2.7	1.1	5
TECFIDERA	34.6	0.88	6
REBIF	2.2	0.62	7
AMPYRA	18.6	0.3	8
AUBAGIO	35.1	0.23	9
EXTAVIA	0.5	0.12	10

Notes: Sales and market share figures come from Genetic Engineering & Biotechnology News.

Table 9.2 Rheumatoid Arthritis drugs brands: coupon use, sales, and relative market size ranking

2013 annual national figures			
Brand name	**Percent of transactions with coupon**	**Sales ($B)**	**Market share ranking**
HUMIRA	51.4	5	1
ENBREL	40.7	4.6	2
ORENCIA	33.1	0.9	3
CIMZIA	51.9	0.49	4
SIMPONI	40.4	0.38	5
KINERET	0.0	0.35	6

Notes: Sales and market share figures come from FiercePharma industry report.

Table 10 Percent of transactions with coupon in Massachusetts for Multiple Sclerosis and Rheumatoid Arthritis drugs

	% of transactions with coupon, MS									
	2012Q1	**2012Q2**	**2012Q3**	**2012Q4**	**2013Q1**	**2013Q2**	**2013Q3**	**2013Q4**	**2014Q1**	**2014Q2**
AMPYRA	0.46	0	0	0.49	7.66	11.29	10.57	12.65	10.92	12.35
AUBAGIO	-	-	-	23.53	22.73	29.41	43.21	34.55	31.63	30.97
COPAXONE	0.26	0.25	1.12	3.02	4.52	4.98	6.68	6.87	4.22	17.09
TECFIDERA	-	-	-	-	-	14.65	24.24	21.84	8.01	25.83
AVONEX	0	0	0.23	0.26	0	0.54	0.3	0	0	0
BETASERON	0	0	0	0	0	0	0	0	0	1
EXTAVIA	0	0	0	0	0	0	0	0	0	0
GILENYA	0.87	1.61	1.63	1.39	0.61	0.61	0	0.51	0	0
REBIF	0	0	0	1.16	0.78	0.43	0.5	1	1.09	1.07
TYSABRI	0	0	0	0	0	0	0	2.08	0	0
Total	0.2	0.2	0.58	1.65	3.13	5.15	8.24	8.19	5.03	12.76

	% of transactions with coupon, RA									
	2012Q1	**2012Q2**	**2012Q3**	**2012Q4**	**2013Q1**	**2013Q2**	**2013Q3**	**2013Q4**	**2014Q1**	**2014Q2**
CIMZIA	2.44	2.33	2.22	5.77	5.26	18	19.61	19	34	36.21
ENBREL	0.2	0.23	2.96	10.27	9.07	14.81	16.68	16.76	15	20
HUMIRA	0.79	0.86	3.12	9.16	12.96	15	17	17.08	19.82	20.71
ORENCIA	0	0	0	0.78	5.76	8.06	9.88	7.65	10	11.17
SIMPONI	0	0	2	8.4	8.87	10.74	14.91	15	21.13	22.01
XELJANZ	NA	NA	NA	0	28.57	38.1	37.93	28.57	25	27
ACTEMRA	0	0	0	0	0	0	0	0	0	6.67
KINERET	0	0	0	0	0	0	0	0	0	0
METHOTREXATE	0	0	0	0	0	0	0	0	0	0
Total	0.46	0.51	2.88	9.18	10.54	14.25	16.24	16.24	17.07	19.77

Note: CIMZIA KIT, METHO SODIUM, OTREXUP, and SIMPONI ARIA are excluded because they have less than 5 observations.

Figure 4.1 Rate of coupon use by treatment for Multiple Sclerosis drugs in MA

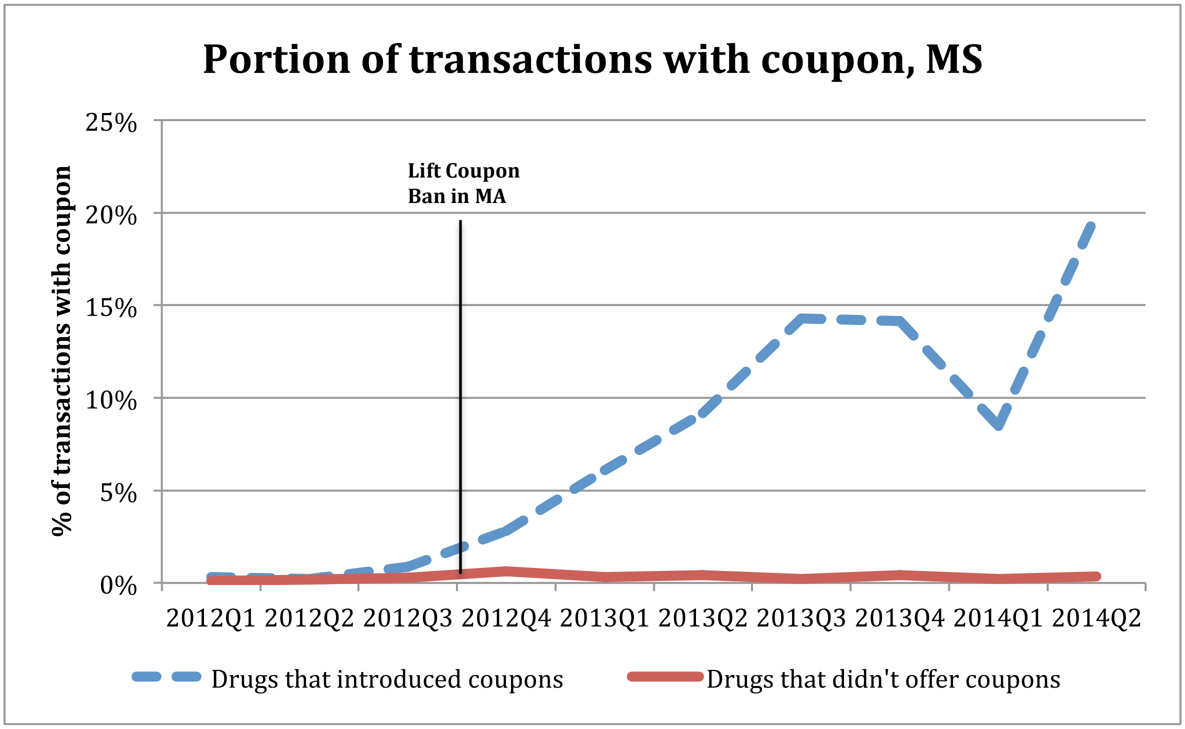
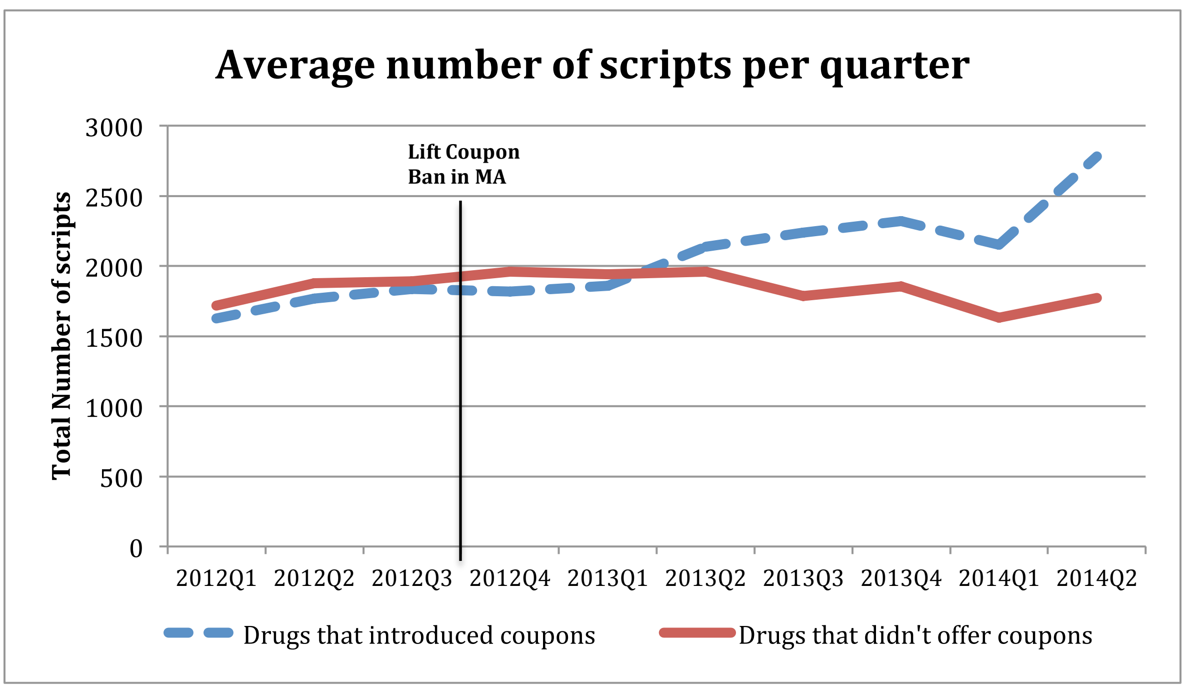
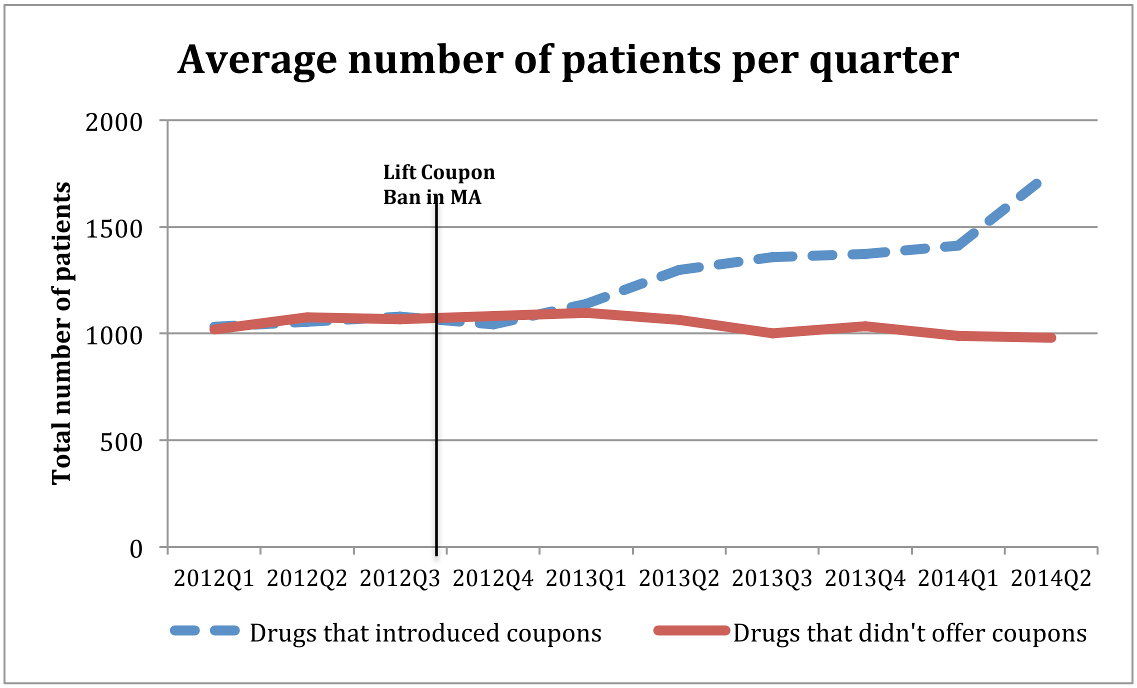


Chart 4.2 Comparing total scripts for treatment and control group, MS



Note: y-axis measures the average number of scripts for each brand per quarter.

Chart 4.3 Comparing total patients for treatment and control group, MS



Note: y-axis measures the average number of patients for each brand per quarter.

Table 11 Diff-in-diff regression results for coupon effect on total scripts and patients per quarter

	Total scripts per quarter	**Total patients per quarter**
Interaction term	1339.6**	866.3**
	(587.8)	(389.3)
Post ban lift	93.8	16.9
	(415.6)	(275.3)
Offered coupon after ban lift	6584***	4329***
	(525.7)	(348.2)
_cons	1881.5	1112.0
	(371.8)	(246.2)
Fixed Effects	Yes	Yes
R-sq	0.003	0.009
F	67	200
N	63445	63445

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Note: Dependent variables are total number of scripts and patients for each drug per quarter. Sample consists of all transactions that took place in Massachusetts for insured individuals from 2012Q1-2014Q2. Specifications include controls for the specialty of the prescribing physician. The regressions also include drug brand fixed effects to pick up characteristics of brands that are constant over the period and year fixed effects to allow for brand-wide changes. The dummy post ban lift equals one if the transaction took place after 2012Q3 and the dummy offered coupon after ban lift equals one if the brand name offered coupons after the ban was lifted. The interaction term equals one if the transaction took place after the ban lift and included a brand name that offered coupons; it is the variable of interest.

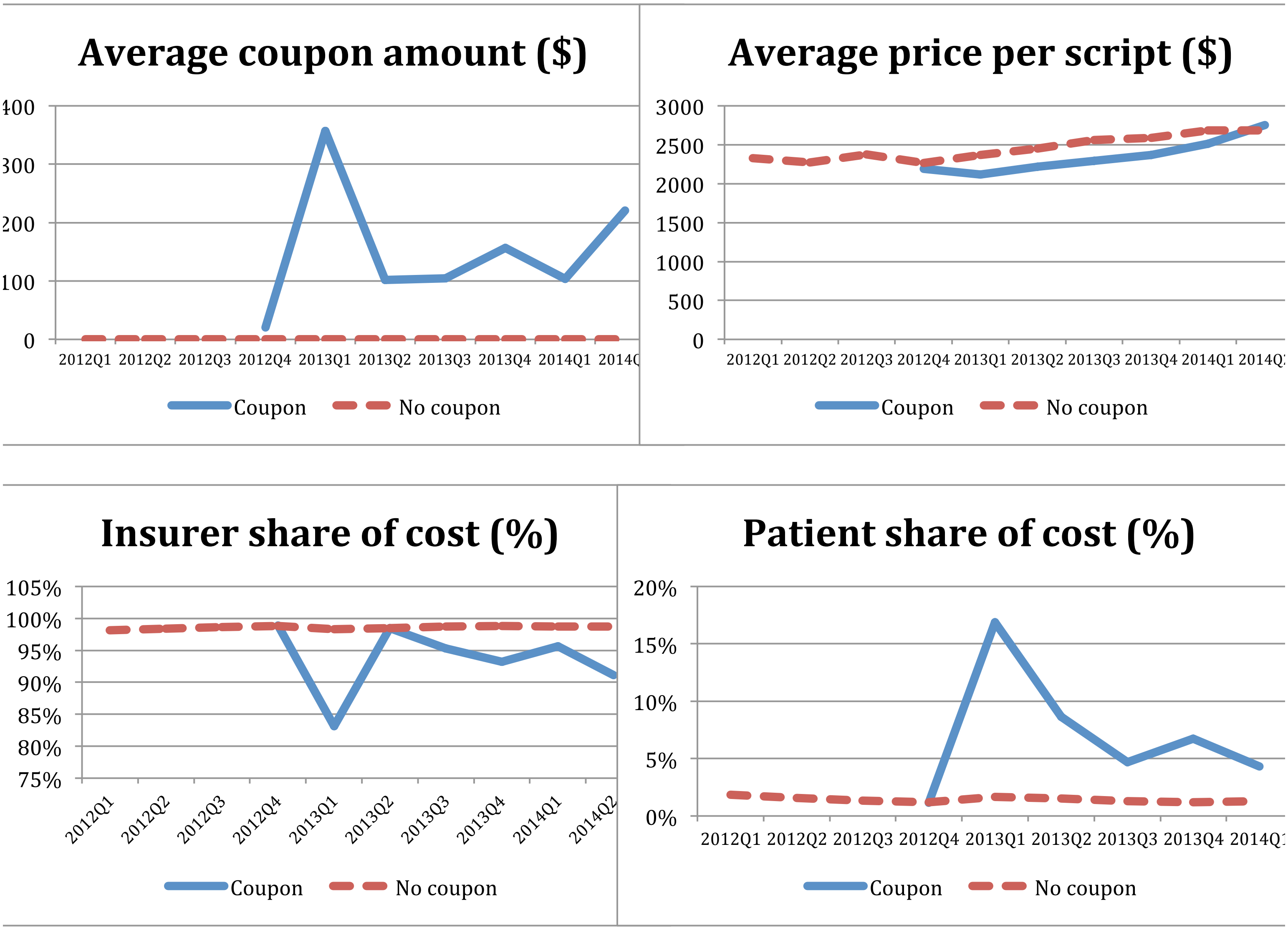
Table 12 Multinomial logistic regression on the determinants of copay amount

Copay Band		**CopayBand**			
\$0-\$25	(base outcome)				
\$26-\$50	coupon	1.3**	**\$251-\$500**	coupon	3.3***
		(0.4)			(0.6)
	MS	-0.2***		MS	-0.3
		(0.04)			(0.2)
	refill	-0.1*		refill	0.08
		(0.04)			(0.2)
	_cons	1.6***		_cons	-4.09***
		(0.04)			(0.2)
\$51-\$100	coupon	1.6***	**\$501-\$1000**	coupon	1.7
		(0.5)			(1.1)
	MS	-0.08		MS	-0.8***
		(0.06)			(0.2)
	refill	-0.6***		refill	-0.1
		(0.06)			(0.2)
	_cons	-1.09***		_cons	-3.6***
		(0.05)			(0.2)
\$101-\$250	coupon	2.7***	**\$1000+ UP**	coupon	-9.5
		(0.5)			(436.7)
	MS	0.4***		MS	1.2***
		(0.1)			(0.3)
	refill	-0.5***		refill	-0.2
		(0.1)			(0.3)
	_cons	-2.7***		_cons	-5.0***
		(0.09)			(0.2)
Pseudo R-sq	0.0082				
N	12238				
Fixed Effects	Yes				

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Note: Copay Band is a discrete dependent variable that takes on 7 possible values of increasing copay bands (see Table 5). Sample consists of all transactions that took place in Massachusetts for insured individuals after the ban lift. Specifications include controls for the drug's indication (MS is a dummy that equals 1 if it is for Multiple Sclerosis and 0 if it is for Rheumatoid Arthritis) and a dummy that equals 1 if the transaction was refill and 0 if new. Coupon dummy equals 1 if transaction has coupon amount that is great than zero and 0 otherwise; it is the variable of interest.

Figure 5 Allocation of cost burden across insurer and patient for Rheumatoid Arthritis drug Orencia



Note: Sample consists of all transactions that took place in Massachusetts for insured individuals after the ban lift. Coupon group includes transactions with a coupon amount greater than zero. All transactions are for the same drug Orencia.

Table 13 Regression on cost sharing outcomes

	Total spend per script ($)	Amount covered by insurance ($)	Share of cost covered by insurance (%)	Share of cost covered by copay (%)	Amount covered by copay ($)	Patient's OOP including coupon ($)
Coupon	-77.6	-134.9	-0.021***	0.022***	57.4**	-0.012***
	(287.2)	(284.9)	(0.0008)	(0.0008)	(24.9)	(0.0006)
Refill	-642***	-33.3***	-0.001	0.0012**	-8.8**	-0.002***
	(37.6)	(37.1)	(0.001)	(0.0005)	(3.3)	(0.0004)
Fixed Effects	drug brand	drug brand	drug brand	drug brand	drug brand	drug brand
	physician specialty	physician specialty	physician specialty	physician specialty	physician specialty	physician specialty
R-sq	0.233	0.218	0.218	0.218	0.218	0.207
F	228.9	212.5	212.5	212.5	212.5	199.6
N	63400	63383	63383	63383	63383	63383

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Note: Dependent variables include the total cost of the drug ($) the amount the insurance company pays for the drug ($), the share of the cost covered by insurance (%), share covered by the patient (%), the copay associated with the transaction ($ amount insurance company expects the patient to pay), and the actual amount the patient ends up paying (copay – coupon amount in dollars). Sample consists of all transactions that took place in Massachusetts for insured individuals after the ban lift. Specifications include controls for the drug's indication (none of the coefficients on the MS dummy were statistically significant at the 90% level) and a dummy that equals 1 if the transaction was refill and 0 if new. The regressions include drug brand fixed effects to pick up characteristics of brands that are constant over the period and fixed effects to capture the specialty of the prescribing physician. Coupon dummy equals 1 if the transaction has coupon amount that is greater than zero and 0 otherwise; it is the variable of interest.

Table 14 Effect of coupon on copay's share of total cost by subgroup

Subgroup	Coefficient of copay share on coupon dummy
MS drugs with above average price	0.01432***
MS drugs with below average price	0.03156***
RA drugs with above average price	0.02171***
RA drugs with below average price	0.02320***

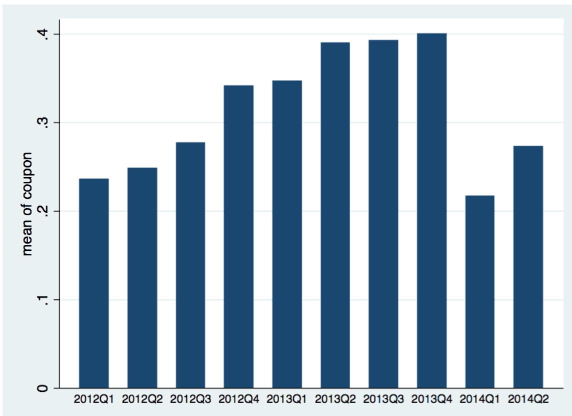
Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Note: The coefficients in this table are obtained by running the regression specified in table 13 when the dependent variable is the share of cost covered by copay. The regression splits the sample to those drugs with prices above or below the average. The reported coefficients are those attached to the coupon dummy. As a point of comparison, the coefficient reported in table 13 was 0.022***.

9 Appendix

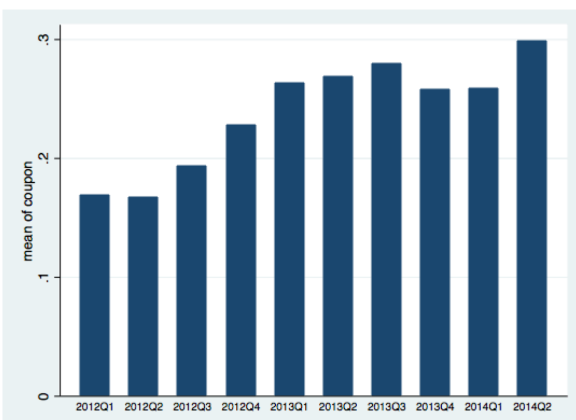
9.1 Comparing the coupon rate in Massachusetts to other states to show that the hike seen in MA is the result of the ban lift.

Rhode Island – no spike in coupon use

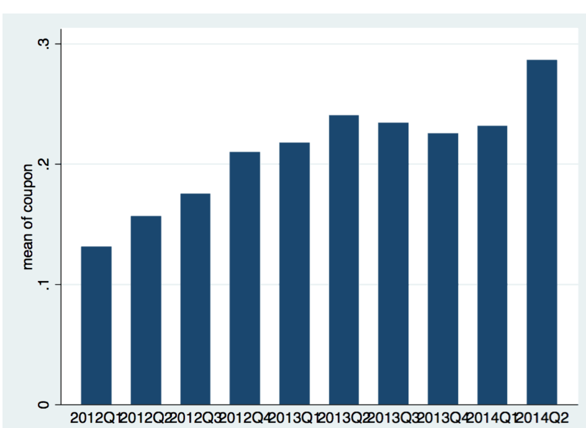


Note: y-axis is the percent of transactions with coupon.

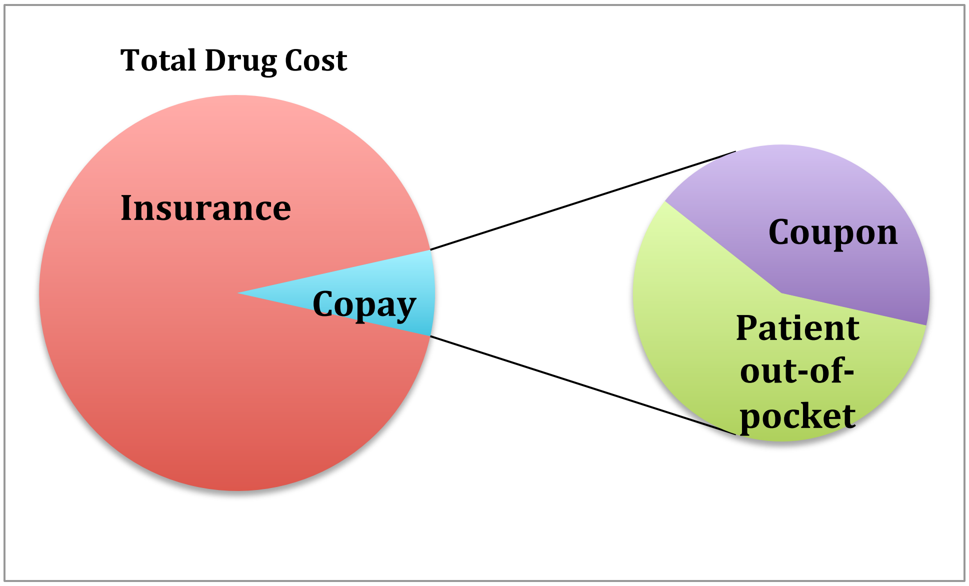
Connecticut– no spike in coupon use



New Hampshire – no spike in coupon use



9.2 Breakdown of total drug cost by coverage



Variables to quantify the cost burden on each player (in %):

Insur_share = insurance coverage / total cost of drug
Copay_share = copay / total cost of drug
Coupon_share = coupon / total cost of drug