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WHEN DISCOUNTS RAISE COSTS:
THE EFFECT OF COPAY COUPONS ON GENERIC UTILIZATION

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ABSTRACT

Branded pharmaceutical manufacturers frequently offer "copay coupons" that insulate consumers from cost-sharing, thereby undermining insurers' ability to influence drug utilization. We study the impact of copay coupons on branded drugs first facing generic entry between 2007 and 2010. To overcome endogeneity concerns, we exploit cross-state and cross-consumer variation in coupon legality. We find that coupons increase branded sales by 60+ percent, entirely by reducing the sales of bioequivalent generics. During the five years following generic entry, we estimate that coupons increase total spending by \$30 to \$120 million per drug, or \$700 million to \$2.7 billion for our sample alone.

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1 Introduction

Health insurance plans are increasingly relying on high-powered incentives to diminish moral hazard on the part of enrollees and to reduce the total cost of care. Enrollment in high-deductible employer-sponsored health plans tripled between 2009 and 2014, and 18% of employers report offering a high-deductible plan as employees’ only insurance option.¹ Several recent studies find reductions in spending when high-deductible or other, related “value-based” plan designs are adopted, e.g. Chernew et al. (2010), Brot-Goldberg et al. (2015), and Gruber and McKnight (2016). Consumer responses to high-powered incentives are likely to give rise to strategic responses by providers. Existing studies have short post-periods, and may be overstating savings as a result. The U.S. pharmaceutical industry offers a glimpse into how providers may respond to the new plan designs. Consumer cost-sharing and formulary tiering are bulwarks of pharmaceutical benefit design, and pharmaceutical manufacturers have developed programs to counter some of these mechanisms. One in particular – the “copay coupon” – has become particularly prevalent in the past decade. In this study, we explore the impact of copay coupons on drug utilization and spending. Understanding both the mechanisms through which coupons impact healthcare spending and the magnitude of the effect may provide important lessons for policymakers and insurers interested in designing more effective, value-based plans.

As branded and generic versions of the same molecule are very close substitutes – but branded drugs are considerably more expensive – it is no coincidence that pharmacy benefits have been at the vanguard of active plan design. The FDA reports that branded drugs are more than five times as costly as their bioequivalent generics.² In 2014, total U.S. spending for brands (including those without bioequivalent generics) accounted for 72 percent of \$300+ billion in pharmaceutical spending, but only 12 percent of total dispensed prescriptions.³ Given the large price differences between branded and generic drugs, insurers and pharmacy benefit managers (henceforth, “insurers”) utilize a variety of tools to steer enrollees toward lower-priced generic drugs in order to control costs. The most prominent of these tools is the copay. Most insurers require higher member copays for branded drugs, thereby discouraging their use, especially when a bioequivalent generic is available. The ability of insurers to steer patients with copays toward specific branded drugs also plays a meaningful role in insurer–

¹PricewaterhouseCoopers, *Health and Well-Being Touchstone Survey*, 2014.

²Source: FDA Facts about Generic Drugs. Available at www.fda.gov/drugs/resourcesforyou/consumers/buyingusingmedicinesafely/understandinggenericdrugs/ucm167991.htm, accessed 6/28/2016.

³IMS Institute for Healthcare Informatics, *Medicines Use and Spending Shifts: A Review of the Use of Medicines in the U.S. in 2014*, April 2015.

manufacturer negotiations. Insurers can offer to set a low copay for a given drug within a therapeutic category, thereby steering volume to that drug, in exchange for an attractive price from the drug manufacturer. In recent years, insurers have used increasingly complex copay tiering⁴ to steer consumers and to increase their leverage with drug manufacturers. For example, among consumers with prescription drug coverage from an employer, the share of consumers with three or more copay tiers increased from 27 percent in 2000 to 80 percent in 2014.⁵

These efforts to encourage the utilization of generic drugs have coincided with a surge of generic entry, spurred by the 1984 Hatch Waxman Act. Since the passage of the act, which smoothed the regulatory pathway for generic drug approvals by the FDA, the generic share of total prescriptions has risen from 19 percent in 1984 to 75 percent in 2009 and 88 percent in 2014.⁶ Part of the recent increase reflects the impact of the so-called “patent cliff” in which several blockbuster drugs such as Pfizer’s Lipitor lost patent protection, shifting large volumes to generics. However, even among drugs for which a bioequivalent generic is available, there have been steady increases in the percentage of prescriptions filled using those generics (henceforth “generic efficiency”). According to IMS Health, generic efficiency increased from 90 percent in 2006 to 95 percent in 2012, halving branded drug utilization in cases where a bioequivalent generic is available.⁷

One recent response by drug manufacturers to tougher negotiations with insurers, tighter drug formularies, and price-elastic patient demand is to offer “copay coupons.”⁸ A copay coupon is an offer by a branded drug manufacturer to pay some or all of a consumer’s copay for the manufacturer’s drug.⁹ By offering a copay coupon, a manufacturer can reduce the

⁴Under a tiered copay system, drugs are grouped into tiers with different copay amounts. Insurers typically place costly branded drugs in higher (more expensive) tiers, while cheaper generic drugs are placed in lower (less expensive) tiers. For example, one 2015 UnitedHealthcare three-tier system has (most) generic drugs in Tier 1 (\$10 copay), preferred branded drugs in Tier 2 (\$25 copay), and non-preferred branded and specialty drugs in Tier 3 (\$50 copay).

⁵The Kaiser Family Foundation and Health Research & Educational Trust: *Employer Health Benefits 2014 Annual Survey*, Exhibit 9.1.

⁶The numbers for 1984 and 2009 are from Berndt and Aitken (2011), while the number for 2014 is from IMS Institute for Healthcare Informatics, *Medicines Use and Spending Shifts: A Review of the Use of Medicines in the U.S. in 2014*, April 2015.

⁷The number for 2006 is from IMS Institute for Healthcare Informatics, *The Use of Medicines in the United States: Review of 2010*, April 2011. The number for 2012 is from IMS Institute for Healthcare Informatics, *Avoidable Costs in U.S. Healthcare*, June 2013.

⁸Other names for copay coupons include “copay cards” and “copay assistance programs.” We exclude means-based copay assistance programs from our sample.

⁹Coupons are also occasionally available for “branded generic” drugs. A branded generic drug is a drug that is (a) bioequivalent to the original branded drug but not made by the innovator firm and (b) marketed under a brand name (unlike generics).

out-of-pocket price difference for consumers between the manufacturer’s drug and competing drugs, thereby encouraging consumers to buy the manufacturer’s drug. By encouraging the use of high-priced branded drugs over low-priced generics, coupons can decrease generic efficiency and cause insurer costs to skyrocket. If these costs are passed through to consumers in the form of higher premiums, then consumers may lose in the long run as well.

The prevalence of copay coupons has increased steadily since their introduction in the mid-2000s. Figure 1 plots the share of total branded retail spending in the U.S. accounted for by drugs with coupons, from June 2007 to December 2010.¹⁰ During this period, the share of branded retail spending accounted for by drugs with coupons more than doubled from 26 percent to 54 percent. While the figure does not capture coupon usage — not all brand buyers use or are even eligible to use copay coupons — it suggests that coupons are an increasingly common phenomenon, highlighting the need for research on their effects.

To investigate the impact of copay coupons, we begin by compiling a dataset on coupons available from June 2007 to December 2010. We then match this information to two datasets from which we can calculate generic efficiency rates, one using “drug level” prescription counts and one using individual pharmacy claims data. Using several different empirical strategies, including difference-in-differences models that utilize cross-state variation in the availability of coupons (due to a coupon ban in Massachusetts) and triple-difference models that also exploit cross-consumer variation (due to a national coupon ban for Medicare-insured patients), we find that copay coupons meaningfully reduce generic efficiency rates. Our main difference-in-differences estimate indicates that coupons cause a 3.4 percentage point reduction in generic efficiency, on average. Given average generic efficiency rates of 95+ percent in the years following generic entry, a 3+ percentage point reduction in generic efficiency translates into a 60+ percent increase in the utilization of branded drugs.

Our analysis is limited to drugs for which a bioequivalent generic is available. It is generally accepted that there is no clinical differentiation between branded drugs and bioequivalent generics (see, e.g., Kesselheim et al. (2008)). In the absence of clinical differentiation, total spending (holding total quantity fixed) is a reasonable proxy for (static) consumer and insurer welfare.¹¹ Estimating the impact of coupons on total prescription drug outlays requires additional assumptions about the path of drug prices and the total quantity sold. To

¹⁰See section 3 for more information about the sources used to create Figure 1.

¹¹One may reasonably wonder why a consumer would ever buy branded drugs if branded and generic drugs were truly undifferentiated. One possibility is that there is a difference between “decision utility” at the time of the purchase choice and “experienced utility” at the time of consumption. Baicker et al. (2015) explore the implications of this idea for optimal copay design, and Handel and Kolstad (2015) pursue a similar idea in modeling the demand for health insurance.

inform these assumptions, we estimate models relating price and quantity to coupon introduction. Because these models assume that coupon status is exogenous, the results are best interpreted as suggestive.

We find that coupons are associated with faster branded price growth. Drugs without coupons experience real price growth of 7–8 percent per year, while drugs with coupons experience price growth of 12–13 percent per year. We do not find an association between coupons and quantity levels or growth rates. Incorporating these estimates into back-of-the-envelope calculations of the impact of coupons on total retail spending for a given drug, we estimate that the introduction of a copay coupon increases retail spending in the five-year period following generic entry by between 1.2 and 4.6 percent. For the average drug in our sample, this corresponds to an increase in spending of around \$30 to \$120 million in 2010 dollars (\$6 to \$24 million per year).

Our findings vis-a-vis generic efficiency paths, branded price growth following generic entry, and no appreciable increases in the quantity of a drug sold after generic entry, are consistent with a large prior literature on these topics (e.g., Caves et al. (1991); Frank and Salkever (1997); Berndt and Aitken (2011); Huckfeldt and Knittel (2011)). In addition to estimating the direct costs of copay coupons for branded drugs with an available bioequivalent generic, our analysis also builds on the literature documenting extensive agency problems in healthcare markets. The distortions to the provision of healthcare that can result when physicians have financial conflicts of interest are well-documented (e.g., Gruber and Owings (1996); Yip (1998); Baker (2010)), and indeed the role of physicians in determining generic utilization has been studied in several prior articles (e.g., Hellerstein (1998); Lundin (2000); Iizuka (2012)). Numerous regulations to prohibit self-referrals and kickbacks are currently in place (e.g., the “Stark laws”), however the rise in high-deductible health plans and coinsurance rates is likely to spark more creative attempts to circumvent these restrictions. The lessons learned from copay coupons are likely to be valuable to regulators, policymakers, and payers developing strategies to address the various actions that healthcare providers may take to weaken consumer cost-sharing incentives. Besides coupons, for instance, physicians may agree to waive patient copays and/or coinsurance to encourage out-of-network visits.¹² Several diagnostic laboratory firms have recently been sued for routinely waiving patient copays (and paying physicians processing fees for referrals).¹³ Absent interventions,¹⁴ these actions

¹²Freudenheim, M. (2003, December 27). Some Doctors Letting Patients Skip Co-Payments. *New York Times*.

¹³Department of Justice Press Release (2015, April 9). Two Cardiovascular Disease Testing Laboratories to Pay \$48.5 Million to Settle Claims of Paying Kickbacks and Conducting Unnecessary Testing.

¹⁴Generic substitution laws are one notable example of an intervention intended to encourage generic

may considerably limit the ability of cost-sharing incentives to help control healthcare spending. Finally, coupons are but one of the strategies pursued by pharmaceutical manufacturers facing loss of exclusivity, such as product reformulations (e.g., Huskamp et al. (2008)), that have attracted substantial legal and policy interest.

The remainder of the paper proceeds as follows. Section 2 explains how health insurance creates a novel mechanism that makes it attractive for drug manufacturers to offer copay coupons, and develops predictions regarding the effects of copay coupons on behavior. Section 3 describes our data on coupons and pharmaceutical sales. Section 4 presents the empirical analyses of the effects of copay coupons on generic efficiency, drug pricing, total quantity, and spending. Section 5 presents robustness checks. Section 6 concludes.

2 Conceptual Framework

There are several theories for why firms offer coupons, e.g. to facilitate price discrimination or encourage trial use (see Nevo and Wolfram (2002) for a review of such theories). These factors may be present in the pharmaceutical industry as well, but here we highlight a mechanism unique to healthcare: undermining insurer copayment systems.

One of the primary goals of health insurance is risk protection, which means subjecting consumers to less than full cost-sharing. To fix ideas, suppose that insurers do not bargain directly with drug manufacturers; instead, they just set a coinsurance rate and then let manufacturers set prices. For a drug manufacturer, this means that price changes will in general be passed through to consumers imperfectly — i.e., a one dollar price reduction will decrease consumer out-of-pocket costs by less than a dollar. By contrast, if a manufacturer offers a copay coupon, then the full value of the coupon is passed through to the consumer. This asymmetry makes offering a copay coupon more profitable than offering a lower price directly to the insurer: a coupon is a less costly way to reduce consumers' out-of-pocket costs. (In the appendix, we develop this idea in a formal model that shows how coupons can undermine copayment systems.)

This basic logic suggests several predictions regarding the effect of coupons on behavior. Most immediately, since coupons reduce the out-of-pocket cost of branded drugs relative to generics, branded utilization for drugs with coupons is predicted to increase (equivalently, generic efficiency is predicted to decrease). We explore the impact of coupons on generic efficiency in section 4.1. In addition, since coupons allow manufacturers to offset the effects of utilization (see e.g., Masson and Steiner (1985); Andersson et al. (2007); Shrank et al. (2010)).

price increases on cost-sharing, coupons will increase manufacturers’ incentives to raise prices to insurers. As one biotech analyst put it, “It seems the best strategy for a pharmaceutical company is to price their drug as high as they possibly can and offer that co-pay assistance broadly.”¹⁵ We examine whether coupons are associated with higher branded drug prices in section 4.2. While in principle coupons could expand the market, for the drugs in our sample — drugs with bioequivalent generics — higher branded utilization is likely to come largely at the expense of generic utilization rather than through market expansion. We study whether coupons are associated with higher total quantity (brand and generic combined) in section 4.3, which would be indicative of market expansion. Finally, by shifting consumers away from generics to high-priced brands, coupons are predicted to increase drug spending. In section 4.4, we perform back-of-the-envelope calculations to estimate the magnitude of the effect of coupons on overall spending.

Given these predictions, a fair question is: why have insurers not banned redemption of copay coupons? Private insurers claim they are unable to prevent the use of coupons (although public insurance programs, some of which are administered by private insurers, do ban coupons, as discussed below). When an insurer receives a pharmacy claim, the claim does not reveal whether a consumer or a drug company paid the copay. According to F. Everett Neville, Chief Trade Relations Officer at the largest pharmacy benefits manager (PBM) Express Scripts, “The payer doesn’t know, and the PBM doesn’t know.... We have no ability to stop it and no ability to prohibit it.”¹⁶ In addition, insurer efforts to curtail coupon usage have faced strong consumer backlash.¹⁷ It may be that insurers are eventually able to find a way to restrict the usage of coupons and/or to appropriately adjust tiering to undo their effects, but there appear to be insufficient incentives and/or substantial frictions impeding this reaction at present.

3 Data

Our analysis relies on three datasets, which we discuss in turn below. (More detailed information is available in the appendix.) We collect data on copay coupons from archived copies of the website www.internetdrugcoupons.com. We use two data sources to estimate

¹⁵Pollack, A. (2011, January 1), “Coupons for Patients, but Higher Bills for Insurers,” *New York Times*.

¹⁶Ibid.

¹⁷For example, in April 2014, UnitedHealthcare backed down from a proposed policy to discontinue the use of copay coupons: “We have decided at this time to not implement the new initiative to have retail pharmacies discontinue the facilitation of copay coupons” (UnitedHealthcare, Pharmacy Retail Coupon Update, April 11 2014).

the effect of coupons on generic efficiency: the IMS National Prescription Audit (NPA) and the New Hampshire Comprehensive Health Care Information System (NHCHIS). We also use the IMS data to investigate the relationship between coupons, drug prices, and total quantity sold.

A. Coupon Data

Our source for information on copay coupons, www.internetdrugcoupons.com, was founded in 2007 and claims to be the most heavily utilized drug-coupon website. The website compiles comprehensive information about coupons for both prescription and over-the-counter drugs. Ross and Kesselheim (2013) use a single cross section of the data to study the prevalence of copay coupons. We build a longitudinal dataset of copay coupons using historical versions of the website, which are available at www.archive.org. By scraping the main website and the links it contains, we construct a dataset with one row per drug-month, capturing (a) whether a coupon was available for that drug in that month and (b) if so, the value of the coupon.¹⁸ To check the accuracy of the website, we verified coupon availability for 500 of the top-selling non-injectable drugs in the U.S. using the current version of the website, and we found only one error.

B. Retail Prescription Sales Data

We merge the coupon data with two datasets, the first of which is the IMS National Prescription AuditTM (NPA). The subsample of the NPA data that we use draws from approximately 57,000 retail pharmacies located throughout the United States.¹⁹ The data include revenues and prescription counts for each unique combination of national drug code (NDC) and month. Each NDC code corresponds to a molecule(s), manufacturer, dosage strength, dosage form, and package size. We collapse these data to the level of molecule-dosage form-month, aggregating over dosage strength and package size.^{20,21} Henceforth, we refer to a unique combination of molecule-dosage form as a “drug.”

¹⁸The website also tracks free-trial offers. We do not code free-trial offers as coupons.

¹⁹The full NPA dataset also contains information from mail-order pharmacies, but we exclude mail-order prescriptions because revenue data are missing for these prescriptions. In addition, mail-order pharmacies often do not accept copay coupons.

²⁰Dosage form refers to the physical characteristics of the product. Examples include tablets, capsules, solutions, and extended-release formulations (e.g., an extended-release capsule).

²¹We retain the distinction between dosage forms due to the recent rise of product reformulations such as extended-release products. For a given molecule, generic entry may occur at different times for different forms.

We begin by restricting the data to the 125 branded drugs that experienced generic entry during the overlapping period between our NPA and coupon datasets (June 2007 to December 2010). Spending on these drugs is roughly one-third of all spending on drugs with brand/generic competition at any point during the period. We do not consider drugs experiencing generic entry prior to June 2007, because we observe only a portion of the generic efficiency path for these drugs, and we do not know the coupon status of these drugs prior to June 2007.²²

We make three additional sample restrictions. First, we eliminate 22 drugs with either multiple branded manufacturers or at least one branded generic.²³ For these drugs, it is unclear how to define coupon status (e.g., if one brand offers a coupon and another does not) and/or generic efficiency (e.g., how should branded generic sales be counted?). Second, we drop 15 drugs with patent disputes or other circumstances that create difficulties in properly defining the timing of generic entry. Patent disputes can result in generics moving in and out of the data.²⁴ Other circumstances that make the timing of generic entry difficult to ascertain include partial entry (e.g., a generic enters but only in an atypical dosage strength) or apparent mistakes in generic classifications (e.g., a generic appears in the data prior to the earliest recorded approval of a generic in the FDA's Orange Book). Third, we exclude 3 drugs (none with coupons) that are Schedule II controlled substances. Prescriptions for such drugs are tightly controlled by state and federal laws, leading to different generic efficiency patterns from the rest of the sample.

Table 1 summarizes the effects of the sample restrictions. Our final sample of 85 drugs accounts for nearly 75 percent of all revenue (between 6/2007 and 12/2010) for drugs experiencing generic entry during the period and about 25 percent of total revenue for drugs with direct brand and generic competition at any point during the period. Of the 85 drugs in our final sample, 29 have a coupon for at least one month while facing generic competition. Figure 2 plots a histogram of the percentage of months (through December 2010) that a

²²A coupon is available during at least one month of our study period for only 8 percent of these drugs, as compared to 34 percent of drugs in our final sample.

²³Drugs with multiple branded manufacturers are identified by searching the data for different drug names within the same molecule-form combination. For example, Fortical (produced by Upsher-Smith) and Miacalcin (produced by Novartis) are both Calcitonin sprays.

²⁴For example, generic firm Teva launched a generic version of AstraZeneca's Pulmicort (budesonide) in November 2008, prior to the expiration of AstraZeneca's patents. As part of a settlement agreement between Teva and AstraZeneca reached shortly after Teva's launch, Teva agreed to pull its generic from the market until a year later, in December 2009. The generic efficiency pattern for budesonide solutions reflects these events (generic efficiency reaches almost 50 percent at the end of 2008 before falling back down to less than 10 percent prior to Teva's re-entry, at which point generic efficiency again increases).

coupon is available for drugs while they face generic competition. The figure demonstrates that, in general, a coupon is either never or always available for a given drug. For the few drugs that do experience changes in coupon status, the coupon is either discontinued shortly after generic entry or persists for nearly all months. With these facts in mind, we treat drugs as either (a) having a coupon or (b) not having coupon, rather than attempting to exploit the limited within-drug variation in coupon status. For us to classify a drug as having a coupon, a coupon must be available for that drug in at least 40 percent of the months during which generics are present.²⁵ For the 23 drugs classified as having a coupon according to this definition, the timing of coupon launches is strongly linked to the timing of generic entry. Nearly half of coupons are launched within 3 months of generic entry, and nearly 70 percent are launched within a year of generic entry.

We construct two dependent variables from the IMS data. The first, generic efficiency, is the share of prescriptions filled using generics.²⁶ Second, we measure price as average revenue per prescription. An unfortunate limitation of the IMS data is that revenues do not include off-invoice rebates from drug manufacturers to insurers. Therefore, our price measure is an upper bound for the true prices paid by insurers.

We also construct several control variables using the IMS data. First, we create a variable, refill percentage, which is the percentage of prescriptions for each drug that are refills in the three months prior to generic entry. Drugs for chronic conditions will have a higher refill percentage than drugs for acute illnesses. Next, we create a (time-varying) count of the number of generic firms competing with the branded drug in each month. We only count generic firms with a 1 percent or higher share of generic prescriptions, so that extremely small manufacturers do not affect the measure.

Table 2 provides descriptive statistics comparing drugs with coupons (23 drugs) to drugs without (62 drugs). The full list of drugs with coupons is given in Table 3. From Table 2, we see that both sets of drugs experience generic entry at similar times, although drugs with coupons tend to have higher sales volume and prices. The differences in revenue and the number of generic firms 12 months after generic entry are significant at the 10% level,

²⁵In section 5, we report that the results are robust to different classifications of the three drugs whose classification is sensitive to this threshold.

²⁶The IMS data have a field that marks whether a national drug code (NDC) pertains to a brand, generic, or branded generic medicine. To ensure the accuracy of the branded generic category, we utilize drug-approval information from the FDA — if available — to reclassify these NDCs as branded or generic. NDCs associated with a New Drug Application (NDA) and a brand name (i.e., with a product name other than the molecule) are reclassified as brands, while NDCs associated with an Abbreviated New Drug Application (ANDA) or without a brand name (thought to be Authorized Generics) are reclassified as generics. Branded generic NDCs without matching FDA approval information are left as branded generic.

suggesting that drugs with coupons have larger markets and attract more generic entry.

In addition to observing whether a drug is covered by a coupon, we also observe the value of the coupon. Coupons differ in their generosity; some coupons offer less than \$20 off a consumer’s copay, while others offer up to \$150 off. Whether a coupon is capable of affecting generic efficiency may depend on the degree to which it offsets consumer copays. As a measure of coupon intensity, we divide the value of each coupon by an estimate of an average consumer’s copay for the covered drug, which we obtain using Medical Expenditure Panel Survey (MEPS) data from 2007-2010.²⁷ The median of this measure across all drugs with coupons is 0.91; we use this cutoff to define coupons as “high-intensity” or “low-intensity.”²⁸ In the empirical analysis, we explore the effects of coupon intensity in addition to presence.

C. Insurance Claims Data

Massachusetts is the only state in the U.S. to pass a law banning certain copay coupons.²⁹ In neighboring New Hampshire, a state with a rich “all-payer claims database” that includes claims from residents of Massachusetts, there is no similar statewide ban. In section 4.1, we use the variation in coupon availability across these two states to estimate the effects of coupons using difference-in-differences models. To perform that analysis, we obtain pharmacy claims for 2007–2013 from the New Hampshire Comprehensive Health Care Information System (NHCHIS).³⁰ The analysis using the NHCHIS data is complementary to

²⁷The Medical Expenditure Panel Survey is a compilation of large-scale surveys about individuals’ and families’ healthcare utilization, costs, and insurance coverage. For prescription drugs, survey participants are asked about their prescription drug use and asked for permission to collect further information from their pharmacies (e.g., insurer payments).

To estimate consumer copays, we estimate a parametric model of the relationship between retail prices and consumer out-of-pocket cost using MEPS data and then apply the estimated relationship to prices in the IMS data. Specifically, we assume that $oop = \alpha p^\sigma$ and then estimate α and σ with nonlinear least squares using data from privately insured patients in the MEPS, 2007–2010 ($\hat{\alpha} = 2.36$ and $\hat{\sigma} = 0.50$).

²⁸Other potential definitions of intensity, such as the raw offer size or the offer divided by price (without converting price to out-of-pocket cost) yield essentially the same high-intensity and low-intensity split, with only two drugs changing classification.

²⁹In 2012, Massachusetts eliminated its ban on copay coupons for drugs without a bioequivalent generic. For drugs with a bioequivalent generic — the entirety of our sample — coupons are still banned. “Pharmaceutical manufacturing companies shall be prohibited from offering any discount, rebate, product voucher or other reduction in an individuals out-of-pocket expenses, including co-payments and deductibles, for any prescription drug that has an AB rated generic equivalent as determined by the United States Food and Drug Administration.” (Massachusetts House of Representatives, No. 4200, lines 1448–1451.)

³⁰Recall that the analysis using IMS data covers 2007–2010. We use the full 2007–2013 period to benefit from additional data, and we verify that drugs for which coupons are available in the 2007–2010 period typically also have coupons during later years. Specifically, we found that 19 of 23 coupon drugs still have coupons available as of December 2013 or later. Our results are both quantitatively and qualitatively similar when we restrict the NHCHIS analysis to 2007–2010. See section 5 for further details.

the analysis using the IMS data. The higher frequency (monthly rather than yearly), larger sample size (national coverage), and richer characteristics (e.g., the number of generic firms) in the IMS data make it ideal for defining the sample and for examining more detailed generic efficiency patterns. The NHCHIS data allow us to relax the assumption that coupon status is exogenous.

NHCHIS contains insurance claims from private insurers. Most of the sample derives from individuals with comprehensive private insurance. However, the dataset also includes claims from Medicare beneficiaries who receive supplemental Medicare coverage through their (possibly former) employers. The data do not contain traditional Medicare or Medicaid claims, or claims for Medicare Part D plans. We use data from individual pharmacy claims, including the year the prescription was filled, information about the drug (e.g., name and brand status), and information about the consumer (e.g., insurance type, age, and state of residence).

Importantly, all insurers and plan administrators must submit claims for (a) all New Hampshire residents and (b) all lives covered through policies issued in New Hampshire, including residents living outside of New Hampshire. For instance, if a national business has its headquarters in New Hampshire and health benefits for all of its employees are handled by headquarters, the insurer must submit claims for *all* of that business's employees. The data therefore include a nontrivial number of claims from residents of states that surround New Hampshire, particularly Massachusetts. As we examine the impact of Massachusetts' ban on copay coupons, our estimation sample focuses on just New Hampshire and Massachusetts, which generate 90.4 and 2.3 percent of pharmacy claims, respectively. In section 5, we also incorporate the data from other states to conduct falsification tests.

Table 4 contains descriptive statistics about the number of pharmacy claims filled for drugs in our final sample. While there are far more claims in the data for New Hampshire than Massachusetts, there are more than 80,000 claims for Massachusetts residents in our final sample. There is substantial variation across drugs in the number of observed claims. Four drugs, none of which have coupons, lack any claims in Massachusetts. Overall, however, the sample sizes are quite large: for the median drug, we see hundreds of claims for Massachusetts residents and more than 10,000 for New Hampshire residents. As we discuss in section 4.1, we use the claim-level data to calculate generic efficiency rates within unique combinations (cells) of drug, year since generic entry, insurance type, and state of residence. We then estimate regression models using the cell-level data.

One potential concern with the NHCHIS data is that some Massachusetts residents may

fill their prescriptions in New Hampshire (or other surrounding states). There is some ambiguity about whether it is legal for Massachusetts residents to redeem coupons even if they fill their prescriptions in other states, and in addition some drug manufacturers offering coupons appear to exclude Massachusetts residents from eligibility. Regardless, to the extent that Massachusetts residents travel out-of-state to use coupons, our estimates of the coupon effect will likely be biased downward (i.e., biased against finding an effect). That said, only 10 percent of Massachusetts residents’ prescriptions are filled in New Hampshire, and empirically we find no evidence of a bias: our results are essentially unaffected when excluding these claims, suggesting that Massachusetts residents are likely not traveling in large numbers to other states to circumvent Massachusetts’ coupon ban.

4 Analysis

4.1 Do coupons affect generic efficiency?

We pursue two approaches to investigate whether coupons have an effect on generic efficiency. In both, we estimate regression models to determine whether coupons are associated with decreased generic drug usage. The first analysis, which utilizes IMS data at the drug–month level, treats coupon status as exogenous — i.e., uncorrelated with unobserved determinants of generic efficiency. The second analysis, which utilizes claims data aggregated to the drug–year–consumer group level, addresses the possibility that coupon status is endogenous by estimating difference-in-differences models that compare differences in generic efficiency between New Hampshire (where coupons can be used) and Massachusetts (where coupons of the type we study are prohibited) for drugs with and without coupons.

A. Retail Prescription Sales Data (IMS)

Figure 3 plots average generic efficiency by coupon status and months since generic entry, weighting each drug by the average revenue of the branded version in the three months prior to generic entry. On average, drugs with a coupon experience slower increases in generic efficiency than drugs without. After two years of generic competition, the generic efficiency rate is 98.4 percent for drugs without a coupon but only 88.3 percent for drugs with a coupon. These differences are highly statistically significant.

We next estimate a more parametric model that incorporates control variables. Specifically, we estimate a “confined exponential” equation, as is commonly utilized in the literature

on growth and diffusion (see, e.g., Banks (1994)):

$$\text{geneff}_{dt} = 1 - \theta \cdot \exp(-\lambda_{dt} \cdot t) + \varepsilon_{dt}. \quad (1)$$

Generic efficiency in the month of generic entry ($t = 0$) is given by $1 - \theta$, and λ_{dt} controls the speed at which generic efficiency approaches 1. We model λ_{dt} as a linear function of coupon status and other covariates X_{dt} :

$$\lambda_{dt} = \beta_0 + \beta_1 \cdot \text{coupon}_d + X_{dt}\beta_X. \quad (2)$$

In X_{dt} , we follow the literature (e.g., Caves et al. (1991) and Frank and Salkever (1997)) and control for generic competition using the number of generic firms. The number of generic firms is associated with lower generic prices and hence should be a positive predictor of generic efficiency. We also control for refill percentage, the proportion of total prescriptions accounted for by refills (in the three months prior to generic entry). The anticipated sign on refill percentage is ambiguous. On one hand, refills will automatically have the same branded/generic status as the initial fill, suggesting that a higher refill percentage should lead to lower generic substitution. On the other hand, chronic drug expenses may be more salient and consumers may be better informed about the availability and quality of generic substitutes for chronic drugs, suggesting that a high refill percentage might lead to higher generic substitution. We do not control for brand or generic prices because coupons may affect generic efficiency at least partially through pricing; we explore this mechanism in section 4.2.

Estimates of equation (1) (estimated via iterated GMM) are presented in Table 5. In column (1), we estimate the model without any controls. We control for the number of generic firms in column (2) and add refill percentage in column (3). In columns (4) to (6), we explore the effect of coupon intensity. Column (4) estimates separate effects for low-intensity and high-intensity coupons, while columns (5) and (6) directly interact the coupon indicator with our intensity measure (linear and quadratic). To facilitate interpretation of the estimates, the bottom panel of the table shows the implied average generic efficiency over the first three years following generic entry ($t = 0$ to $t = 36$).

Across all six specifications, coupons are linked to lower generic efficiency. The coefficients on the coupon indicators are negative, statistically significant, and economically meaningful. Averaging over the first three years of generic entry, generic efficiency for drugs with coupons is estimated to be around 10 percentage points lower than for drugs without coupons. On balance, the evidence also supports the hypothesis that higher coupon intensity is connected

with lower generic efficiency. While the effect sizes in column (4) for low-intensity and high-intensity coupons cannot be statistically distinguished from one another, the specifications in columns (5) and (6) indicate statistically significant differences. In column (6), the estimated effect of intensity follows an intuitive pattern — starting around zero, decreasing, and then flattening out as intensity grows.

In unreported analyses, we also experimented with other control variables and alternative functional forms, such as using indicators for different numbers of generic firms (e.g., as in Reiffen and Ward (2005)). None of these modifications substantially improved model fit, and in all specifications examined, the estimated coefficient on the coupon indicator remained negative, significant, and of similar magnitude.

B. Insurance Claims Data (NHCHIS)

Difference-in-differences (DD)

The primary concern with the preceding analysis is that there may be unobserved factors that influence generic efficiency and are correlated with coupon status (i.e., coupons may be endogenous). Any such unobserved factors will bias our initial estimates, which use cross-drug variation in coupon status to estimate its effect. For instance, suppose that manufacturers launch coupons when generic efficiency is expected to increase particularly quickly following generic entry. In this case, our estimates will tend to understate the effect of coupons. On the other hand, if drugs with coupons were likely to have slow generic penetration even absent the coupon, our estimates will be biased toward finding that coupons have an effect.

In this section, we address this concern by exploiting Massachusetts’ copay coupon ban. For drugs with coupons, we can compare generic efficiency rates in Massachusetts (where coupons are banned) with those in New Hampshire (where coupons are permitted). However, in addition to the effect of coupons, this first difference also contains any other differences between the two states that may affect generic efficiency, such as physicians’ prescribing practices. To isolate the effect of coupons, we estimate a difference-in-differences model that compares the state differences in generic efficiency for drugs with and without coupons. The difference between states for drugs without coupons captures the impact of state-specific factors unrelated to coupons and potentially correlated with generic efficiency. Specifically, we estimate:

$$\text{geneff}_{dtk_s} = \alpha_d + \gamma_t + \delta_k + \beta_0 \cdot NH_s + \beta_1 \cdot NH_s \cdot \text{coupon}_d + \varepsilon_{dtk_s}, \quad (3)$$

where d is drug, t is years since generic entry,³¹ k is insurance type (HMO, PPO, POS, and other), and s is state (New Hampshire or Massachusetts). NH_s is an indicator variable equal to 1 for New Hampshire. The estimating equation includes fixed effects for drugs (α_d , which subsumes the coupon indicator $coupon_d$), years since generic entry (γ_t), and insurance type (δ_k). Observations more than four years after generic entry ($t > 4$) are pooled with observations four years after generic entry ($t = 4$). All models are estimated by weighted least squares, with observations weighted by the number of claims used to construct the relevant generic efficiency rate. Standard errors are clustered by drug. As we explain in the next subsection, since coupons are banned for consumers with Medicare-sponsored insurance, we estimate the difference-in-differences model using only claims from consumers under the age of 65.

The coefficient of interest is β_1 , which is the difference-in-differences estimate of the effect of coupons on generic efficiency. Table 6 presents the results. Column (1) gives the estimates of equation (3). Columns (2) to (4) explore the effects of coupon intensity. For drugs without coupons, we cannot reject the null of no difference in generic efficiency between the two states. For drugs with coupons, on the other hand, generic efficiency is more than 3 percentage points lower in New Hampshire, indicating that coupons significantly reduce generic utilization. In column (2), only the coefficient on high-intensity coupons is statistically significant, and a test for equality of the two coupon coefficients is rejected at the 1% level. While we fail to detect statistically significant effects when using the continuous intensity measure in columns (3) and (4), the pattern of the point estimates is very similar to what we found in the IMS data (though with a smaller overall magnitude).

Triple-difference (DDD)

The key identifying assumption in the difference-in-differences analysis above is that the observed difference across states in generic efficiency for drugs without coupons accurately captures the effect of state-specific factors other than coupons that are correlated with generic efficiency. This assumption may be violated if, for instance, differences in out-of-pocket costs between states vary by coupon status. Our analysis of the claims data does not support this particular hypothesis,³² but the potential for bias along unobserved dimensions remains. For

³¹Unlike the IMS data, in which data are available monthly, the claims data only capture the year in which a prescription was filled.

³²Estimating models like equation (3) but with the average out-of-pocket price difference between brands and generics as the dependent variable yields statistically insignificant copay differences between states, with or without coupons.

example, the estimated coupon effect may also reflect unobserved marketing efforts that coincide with the coupon and occur only in New Hampshire. Arguably, any marketing that co-occurs with a coupon strategy is part and parcel of a coupon effect, however to err on the conservative side we pursue a triple-difference model. This model compares the impact of coupons (in Massachusetts versus New Hampshire) in the under 65 versus 65 and over population. The Centers for Medicare & Medicaid Services bans coupon redemption for all individuals in Medicare-sponsored plans (whether traditional, Medicare Advantage, Part D, or subsidized employer supplemental plans). If, for example, the estimated effect in the difference-in-differences analysis is actually due to heavy television advertising in New Hampshire for drugs with coupons, we should observe this effect in the 65 and over population as well. To implement the model, we subdivide our unit of observation by less than/at least the age of 65 and add interactions with an indicator variable marking individuals under the age of 65 (*under65*) to the estimating equation. The resulting model is:

$$\begin{aligned} \text{geneff}_{dtksm} = & \alpha_d + \gamma_t + \delta_k + \beta_0 \cdot NH_s + \beta_1 \cdot \text{under65}_m + \beta_2 \cdot NH_s \cdot \text{under65}_m \\ & + \beta_3 \cdot NH_s \cdot \text{coupon}_d + \beta_4 \cdot \text{under65}_m \cdot \text{coupon}_d \\ & + \beta_5 \cdot NH_s \cdot \text{under65}_m \cdot \text{coupon}_d + \varepsilon_{dtksm}, \end{aligned} \quad (4)$$

where m denotes the consumer group with respect to the standard age for Medicare eligibility (65). The primary coefficient of interest is β_5 , which gives the triple-difference estimate of the effect of coupons on generic efficiency.

The DDD estimate of the coupon effect is likely to be conservative for several reasons. First, there is no automated system that monitors or restricts Medicare beneficiaries from using coupons. Indeed, a survey of Medicare beneficiaries by the National Coalition on Health Care found that 6 percent of respondents admitted to using copay coupons while on Medicare.³³ Second, it is possible that some of the consumers in our data aged 65 or older have prescription drug coverage that is not subsidized by Medicare at all, in which case they are legally able to use copay coupons. Unfortunately, our data do not permit us to identify which seniors are eligible to use coupons and which are not. Both of these factors will tend to cause the DDD estimate of the coupon effect to be understated (e.g., if all New Hampshire seniors in the data use coupons, then the age distinction ceases to be meaningful). Third, sample sizes in the data are relatively small for consumers aged 65 or older in Massachusetts,

³³National Coalition on Health Care (NCHC), "Seniors' Awareness and Use of Prescription Co-pay Coupons in Medicare," Survey. March 26-30, 2012.

which decreases the precision of the DDD estimate.

Table 7 displays the results. Rather than the individual β coefficients, which are difficult to interpret in isolation, we present the implied difference-in-differences estimates for the under 65 and 65 and over groups, as well as the DDD estimate β_5 . In the table, “NH-MA difference, with coupon” and “NH-MA difference, without coupon” refer to the estimated values (respectively) of:³⁴

$$\begin{aligned} & \mathbb{E}\left[\text{geneff}_{dtksm} \mid NH_s = 1, coupon_d = 1\right] - \mathbb{E}\left[\text{geneff}_{dtksm} \mid NH_s = 0, coupon_d = 1\right] \\ & \text{and} \\ & \mathbb{E}\left[\text{geneff}_{dtksm} \mid NH_s = 1, coupon_d = 0\right] - \mathbb{E}\left[\text{geneff}_{dtksm} \mid NH_s = 0, coupon_d = 0\right]. \end{aligned}$$

Based on the difference-in-differences estimate shown in panel A, for consumers under the age of 65 and eligible to use coupons, coupons are estimated to decrease generic efficiency by 3.4 percentage points. Panel B performs the same exercise for consumers aged 65 or older. For this group, coupons are estimated to *increase* generic efficiency, although the estimate is not statistically significant. This estimate provides evidence against the hypothesis of statewide marketing efforts for drugs with coupons in New Hampshire; if such marketing were present, we would expect generic efficiency in the 65 and over population for drugs with coupons to be lower in New Hampshire than in Massachusetts. Given the positive estimated effect of coupons on generic efficiency in the 65 and over population, the resulting DDD estimate is larger than the DD estimate, suggesting that coupons decrease generic efficiency by 6.3 percentage points. Separate DDD estimates for high-intensity and low-intensity coupons indicate negative effects of coupons on generic efficiency for both, although only the high-intensity coupon estimate is statistically significant.³⁵ When calculating the spending implications of permitting copay coupons for branded drugs with generic bioequivalents (section 4.4), we use the more conservative DD point estimate of 3.4 percentage points.

4.2 Do coupons affect drug pricing?

As noted in section 2, manufacturers utilizing copay coupons may also have incentives to increase prices, as coupons can be used to offset any copay increases resulting from price hikes. Contracts between insurers and drug manufacturers/retail pharmacies often do not

³⁴To be clear, the expectation is only over the error term ε_{dtksm} . Drug, years since generic entry, insurance type, and under/over age 65 are fixed, but the notation is suppressed for brevity.

³⁵Full results from these specifications are available upon request.

vary across states, so we are unable to exploit the Massachusetts coupon ban to study prices. Therefore, we explore the link between the use of coupons and pricing using only the IMS data. To begin, we estimate

$$\ln(p_{dt}) = \alpha + \beta_0 \cdot t + \beta_1 \cdot coupon_d + \beta_2 \cdot t \cdot coupon_d + X_{dt}\beta_X + \varepsilon_{dt}, \quad (5)$$

where p_{dt} is average revenue per prescription (for drug d , t months since generic entry). All prices are measured in CPI-adjusted 2010 dollars. The set of controls represented by X_{dt} contains the controls in the generic efficiency analysis (the number of generic firms and refill percentage), and also includes the log of the average brand price in the three months prior to generic entry. Since we control for brand price prior to generic entry, β_1 represents a time-invariant percentage change in the price level (i.e., a shift in the price intercept) associated with coupons, while β_2 reflects any change in the growth rate of prices (i.e., a shift in the slope).

We also estimate a fixed effects regression that relates within-drug price growth to the presence of coupons. This model eliminates unobserved, time-invariant factors that might explain differences in price levels for drugs with and without coupons, and which could bias our estimates of the effects of coupons on prices. Specifically, we estimate

$$\ln(p_{dt}) = \alpha_d + \beta_0 \cdot t + \beta_1 \cdot t \cdot coupon_d + X_{dt}\beta_X + \varepsilon_{dt}, \quad (6)$$

where α_d are drug fixed effects. The coupon indicator, pre-generic-entry brand price, and refill percentage variables are all subsumed by the drug fixed effects. In (6), X_{dt} therefore includes only a count of the number of generic firms. The coefficient β_1 measures whether prices for drugs with coupons change at different rates than prices for drugs without coupons.

We estimate (5) and (6) separately for the branded price and the average generic price (combining all generic firms). As with the IMS generic efficiency analysis, standard errors are clustered by drug and observations are weighted by the average revenue of the branded drug in the three months prior to generic entry. The estimates are presented in Table 8. Columns (1) to (3) contain the results for branded prices, while columns (4) to (6) contain the results for generic prices. Columns (1) and (4) give the estimates of equation (5), and columns (2) and (5) give the estimates of equation (6). In columns (3) and (6), we eliminate the $t \cdot coupon_d$ term in equation (6); this model captures average price growth across coupon statuses and is an input into our calculations of spending under different scenarios in section 4.4. We do not estimate models with the intensity measures on the right-hand side because

intensity is a function of price.³⁶

In columns (1) and (4), we see that (a) coupons are not associated with a statistically significant difference in initial branded or generic price levels, and (b) coupons are associated with faster branded price growth (12.2 percent yearly with coupons and 7.1 percent without) and slower generic price declines (-2.3 percent yearly with coupons and -8.8 percent without). The difference is statistically significant at the 5% level for brand prices and at the 10% level for generic prices. Slower generic price declines are consistent with a relaxation of the constraint on these prices imposed by the branded price. In columns (2) and (5), which include drug fixed effects, coupons continue to be associated with faster branded price growth (and with a similar magnitude as in column (1)), but the association between coupons and generic prices approaches zero and is statistically insignificant. This result may be due to limited within-drug price variation, however it is also consistent with perfectly competitive generic markets (which, if present, imply no impact of coupons on generic prices).

The remaining results are consistent with other published work. Branded prices rise after generic entry, and generic prices fall over time (see, e.g., Grabowski and Vernon (1992) and Frank and Salkever (1997)). Additional generic firms are associated with higher branded prices but substantially lower generic prices.

To summarize, we find evidence that copay coupons are associated with faster branded price growth and perhaps slower generic price declines, though the evidence for generic prices is weaker. The finding for branded prices in particular is consistent with the observation that copay coupons provide incentives for manufacturers to raise prices. However, because our analysis treats coupon status as exogenous, effectively comparing price trends for drugs with and without coupons, we view the pricing results as suggestive rather than conclusive. In light of the limitations of the analysis, in the spending calculations in section 4.4, we assume that coupons have no effect on generic prices and we perform the calculations with and without an effect of coupons on branded price growth.

4.3 Do coupons affect total quantity?

One of the main arguments advanced by proponents of copay coupons is that reduced copays improve patient medication adherence.³⁷ If so, then any increased spending resulting from decreased generic efficiency may have the offsetting benefit of improving patients' health. As

³⁶Price enters in the denominator of intensity via the estimated copay (see footnote 27).

³⁷For example, see Tenaglia, M. (January 2012), "Letting the Facts Get in the Way: An Empirical Defense of Coupons and Copay Offset Programs," *Pharmaceutical Executive*. For a review of the academic literature on the topic, see Eaddy et al. (2012).

the claims data lack an individual patient identifier, we cannot examine this question directly, but we can check whether the change in total quantity sold after generic entry is meaningfully different for drugs with and without coupons. To do so, we estimate specifications similar to those we estimate for prices but with the log of total retail prescriptions as the dependent variable. Table 9 presents the results. In columns (1)-(3), we include a control for the quantity sold in the three months prior to generic entry. Column (4) includes drug fixed effects, subsuming this quantity measure (and capturing any other time-invariant factors impacting post-generic entry quantity). In column (2), we add controls for the number of generic firms and refill percentage. In column (3), we allow for coupons to be associated with a change in the growth rate of prescriptions in addition to the level. As previously noted, column (4) includes drug fixed effects, thereby limiting attention to within-drug volume growth and its relationship to coupon status and the entry/exit of generic firms.

Columns (1) and (2) reveal small, statistically insignificant associations between coupons and the volume of retail prescriptions. In column (3), the estimates indicate that coupons are associated with higher initial quantity (relative to quantity prior to generic entry), but a slower growth rate (both estimates are significant at the 10% level). This pattern is consistent with highly publicized examples (e.g., Zocor) in which insurers have attempted to steer enrollees toward large drugs going off patent. The observed higher quantity for drugs with coupons following generic entry is consistent with the descriptive statistics, which show that coupons are introduced for higher volume drugs, on average. That said, the initial quantity bump is brief; around a year after generic entry, estimated total quantities are similar for drugs with and without coupons. When we add drug fixed effects in column (4), the estimated effect of coupons on total quantity growth remains negative but is no longer statistically significant.

On balance, then, we do not find any statistically or economically significant association between the presence of a coupon and quantity levels and/or growth rates. However, as with pricing, our analysis is limited to comparisons across drugs, and therefore should not be viewed as strong evidence of a causal relationship — or lack thereof. Lacking arguably exogenous variation in coupon status, we cannot rule out the possibility that coupons expand the market via improved medication adherence and/or by taking sales from therapeutic substitutes (i.e., different drugs). That said, given we do not find any clear correlation between coupons and quantity levels and/or growth rates, we assume that coupons have no effect on total quantity in the spending calculations below.

4.4 How much do coupons affect pharmaceutical spending?

We now use our estimates of the effects of coupons on generic efficiency and drug pricing to estimate the effect of coupons on retail drug spending. Because coupons may reduce generic utilization in non-retail channels as well (e.g., hospital pharmacies), channels which account for around 30 percent of all prescription activity in the U.S.,³⁸ we view these estimates as a lower bound for the total effect of coupons on spending.

We estimate the net present value of spending over the five-year period following generic entry for the average drug in our sample, with and without a coupon. To derive the estimates, we use inputs from the preceding analysis as well as several additional assumptions about unmeasured parameters that enter the calculation (e.g., the discount rate). The results of the spending calculations are shown in Table 10. We assume that generic efficiency behaves according to the confined exponential equation (1), as presented in section 4.1. In columns (1) and (2) (labeled “IMS”), we assume that coupons affect generic efficiency according to the estimates from the IMS data as presented in column (2) of Table 5. In columns (3) and (4) (labeled “NHCHIS”), we assume that coupons reduce generic efficiency by a fixed amount that is set using the estimates from the NHCHIS data as presented in column (1) of Table 6. We assume that brand and generic prices follow equation (6), as presented in section 4.2, using the estimates presented in Table 8. We perform the calculations assuming that coupons do not affect branded price growth (columns (1) and (3)) and that they do (columns (2) and (4)). In all columns, we assume that generic prices are unaffected by coupons; if coupons do slow generic price declines, then the effect of coupons on spending will be substantially larger than what we report here. We assume that market size is independent of coupon status.

A crucial piece of information that we lack is the fraction of consumers buying the branded drug who redeem a coupon; this fraction is significant because coupon redemption reduces (out-of-pocket) spending. We therefore consider several possible values, book-ended with the logical extremes. The upper bound is of course 1. We obtain a lower bound by assuming that manufacturers can perfectly target coupons, such that the only users of coupons are those who would have bought the generic in the absence of the coupon. If manufacturers can perfectly target coupons, then the fraction of brand buyers using the coupon is equal to the effect of coupons on generic efficiency divided by the total proportion of consumers who buy the branded formulation. Given a base of 5 percent branded utilization and a 3 percentage point coupon effect, this lower bound is given by $3/8=0.375$. We report the estimates for a

³⁸“The NPA represents and captures over 70 percent of all prescription activity in the United States.” IMS Institute for Healthcare Informatics, HSRN Data Brief: National Prescription Audit.

grid of values: 0.4, 0.6, 0.8, and 1. Additional details about the calculations are given in the notes under the table and in the appendix.

In the table, we report both the percentage change in spending due to coupons as well as the absolute change. The results indicate an increase in per-drug spending due to coupons of between 0.3 and 6.1 percent (\$6.5 to \$158.6 million). Spending effects are larger when (a) fewer brand buyers use the coupon, (b) coupons lead to faster branded price growth, and (c) we use the IMS generic efficiency estimates, which imply a larger effect of coupons over a five-year horizon. To evaluate the plausibility of our estimates, we also report the return on investment (ROI) of coupons to branded drug manufacturers as the additional revenues from the coupon divided by manufacturer spending on copays (implicitly assuming that both production costs and the fixed and operating costs of coupon programs are negligible). A value of 1 represents a breakeven result for the manufacturer — every additional dollar of revenue is offset by a dollar of coupon redemptions. Several industry sources indicate that drug manufacturers earn a 4:1 to 6:1 return on copay coupon programs, numbers which are in line with our results.³⁹ Given the reported ROIs from industry sources, we prefer the estimates with ROIs of at least 4:1 and no higher than 7:1 (particularly as our ROI calculations do not include any production or fixed costs). These estimates indicate an increase in retail spending over the five-year period following generic entry of between 1.2 and 4.6 percent, or \$30.9 to \$119.3 million.

It may be surprising that manufacturers can earn such high returns from copay coupons when total spending increases by only a few percent. The reason is that generic entry swiftly destroys brand profits, so even modest reductions in generic penetration can yield substantial gains to brand profits in percentage terms. The effects are also sizable in absolute terms; for our preferred estimates, the lowest estimated spending difference is \$30.9 million (about \$6 million per year on average). Our sample of drugs with coupons includes 23 drugs, so in total the estimates imply that coupons increased retail spending for our sample — drugs facing generic entry during the June 2007 to December 2010 period — by at least \$700 million over the five year period following generic entry, and as much as \$2.74 billion.

³⁹The 4:1 to 6:1 statistic is cited by both proponents and opponents of copay coupons. A proponent: “returns are as high as 4:1 (and up to 6:1)” (Tenaglia, M. (January 2012), “Letting the Facts Get in the Way: An Empirical Defense of Coupons and Copay Offset Programs,” *Pharmaceutical Executive*.) An opponent: “Manufacturers reportedly earn a 4:1 to 6:1 return on investment” (Visante. (November 2011), “How Copay Coupons Could Raise Prescription Drug Costs by \$32 Billion over the Next Decade.”)

5 Robustness Checks

A. Falsification tests

If the difference-in-differences estimates we obtain reflect Massachusetts' coupon ban rather than other factors that differ between New Hampshire and Massachusetts and that vary by coupon status, then the estimated effect should disappear when substituting Massachusetts with a state that does not have a coupon ban. To implement this falsification test, we re-estimated the difference-in-differences model (equation (3)) using data from Vermont — the most natural comparison state for New Hampshire — in place of Massachusetts. As coupons may be used in both states, we would not expect the difference in generic efficiency between New Hampshire and Vermont to depend on coupon status. The results are given in column (2) of Table 11; column (1) replicates the original difference-in-differences analysis using Massachusetts data. The estimated effect for Vermont is much smaller in magnitude than the estimated effect for Massachusetts and not statistically significant. However, a test for the equality of the Vermont effect and the Massachusetts effect fails to reject the null hypothesis that the effects are equal (narrowly; the p-value is just above 0.10). Since the number of underlying claims in Vermont is somewhat small (about 40% fewer claims than in Massachusetts), we add all other non-Massachusetts states in column (3) to increase the precision of the estimate.⁴⁰ The point estimate remains similar to the estimate using only Vermont, but due to the reduction in the standard error, we are able to reject equality of the coupon effect for Massachusetts and the coupon effect for other states. Overall, we take these results as evidence that our main results are likely attributable to Massachusetts' coupon ban rather than spuriously reflecting the effect of other factors.

B. Sensitivity to included fixed effects

In our difference-in-differences specifications, we include drug, year since generic entry, and insurance type fixed effects. To see if the result hinges on the inclusion of any of these fixed effects, we re-estimated the model varying the fixed effects included in the estimation. Table 12 presents the results, with column (5) replicating the main analysis for purposes of comparison. Specifications without drug fixed effects (columns (1) and (3)) instead include a coupon indicator. Across all specifications, the difference-in-differences estimate remains negative, statistically significant, and of a similar magnitude as the main result. The results

⁴⁰Besides Vermont, the three other states with the most claims in the data are Maine, Florida, and New York.

also indicate that the high R-squared value (0.746) for the main results is primarily driven by the inclusion of the drug and year since generic entry fixed effects, which increase R-squared from 0.020 (column (1)) to 0.745 (column (4)).

C. Other robustness checks

We conducted numerous other robustness checks to further examine the sensitivity of our results. We discuss the outcomes of several of these other checks here; tables are available upon request.

In Figure 2, we showed that a coupon is essentially either never or always available for a drug while facing generic entry, with the exception of three drugs for which coupons are present in 40 to 60 percent of the months after generic entry. In the results reported above, we coded these drugs as having copay coupons. We also estimated each model (a) treating these drugs as not having coupons and (b) dropping them. The results are extremely similar to the main results in both cases, with minimal changes in magnitudes and statistical significance.

Given our relatively small sample size (23 drugs with coupons and 62 without), a related concern is that the results may be driven by the generic efficiency and pricing patterns of only one or two drugs. We reran each analysis 23 separate times, each time leaving out one drug with a coupon. The results always remain similar to what is reported above: the coefficient on coupon status in the IMS generic efficiency regressions is always negative, statistically significant, and of a similar magnitude; the difference-in-differences and triple-difference results continue to indicate a negative and statistically significant effect of coupons on generic efficiency of a similar magnitude; and coupons continue to be associated with faster branded price growth.

We also estimated the branded price regressions using long differences, measuring prices for each drug several months prior to generic entry and then again several months after generic entry. We regressed the long differences on coupon status, the number of generic firms in the post month, and refill percentage, weighting observations by the average revenue of the branded drug in the three months prior to generic entry (as with the results reported in the text). We estimated specifications using prices 3 and 6 months prior to generic entry and 6, 12, and 18 months after generic entry. The results imply yearly branded price growth between 6 and 11 percent for drugs without coupons, and an additional boost of 3 to 7 percentage points for drugs with coupons. These results are similar to those reported in Table 8.

Finally, we repeated the NHCHIS analysis but restricting the data to the years 2007–2010

to match the sample period for the IMS data. The results remain similar. In the difference-in-differences analysis, the estimated coupon effect remains statistically significant and is similar in magnitude. In the triple-difference analysis, the DDD estimate remains similar in magnitude but is no longer statistically significant. The loss of significance is due to larger standard errors in the 65 and older (i.e., control) group, in which the number of underlying claims is substantially smaller.

6 Conclusion

Copay coupons have become increasingly common for branded prescription drugs in the United States. Over the period from June 2007 to December 2010, the share of branded retail spending accounted for by drugs with coupons more than doubled, increasing from 26 percent to 54 percent. These coupons cover at least a portion of consumers' out-of-pocket expenses, thereby reducing the out-of-pocket price difference between branded and generic medicines for those drugs where both are available. We examine the effect of copay coupons on generic utilization for a sample of branded drugs that first face generic entry during our time period.

We find that copay coupons lead to an economically and statistically significant reduction in generic efficiency of 3 or more percentage points. Since brand shares typically shrink to 5 percent or less in the years following generic entry, this corresponds to a 60+ percent increase in branded utilization. Assuming coupons reduce out-of-pocket costs to nearly zero, the implied demand elasticity with respect to out-of-pocket cost is at least -0.6. Estimates from the literature utilizing differences, changes, and/or kinks in benefit design find elasticities ranging from around -0.1 to as high as -0.7 (see Simonsen et al. (2015) for recent estimates along with a discussion of prior work). The demand response induced by coupons is at the upper end of prior estimates, which is consistent with coupons representing a particularly salient decrease in out-of-pocket cost compared with less prominent adjustments to benefit design. In addition, the outside option to purchasing a branded drug in our study includes purchasing a bioequivalent generic; in other studies the outside option may not include bioequivalent generics (and instead only include different drugs and/or nonadherence).

We find economically and statistically significant effects across several analyses. Our first analysis uses IMS retail prescription data to estimate the effect of copay coupons under the assumption that coupon status is exogenous. We then perform two analyses using claims data from residents of New Hampshire and Massachusetts: (1) a difference-in-differences analysis that exploits a ban on copay coupons in Massachusetts, and (2) a triple-difference

analysis that further exploits a ban on copay coupons for government-subsidized patients. These analyses mitigate concerns regarding confounding factors that could be correlated with coupon issuance as well as generic efficiency. We also find that copay coupons are correlated with faster branded price growth. Prices of branded drugs with coupons grow over 12 percent per year, while prices of branded drugs without coupons grow 7–8 percent per year. These results are suggestive, however, as coupon decisions may be endogenous.

The sizable implied demand elasticity for branded prescription drugs, paired with the relatively small share of drug spending represented by consumer copays, yields sizable estimates of the impact of coupons on the combined drug spending of consumers and insurers. For the average drug in our sample, introducing a copay coupon is estimated to increase retail spending (brand and generic combined) by 1.2 to 4.6 percent over the five-year period following generic entry, or roughly \$30 to \$120 million in 2010 dollars (\$6 to \$24 million per year). Our analysis utilizes only drugs for which bioequivalent generics are available. We find no compelling evidence of increases in utilization of drugs with coupons, as would result from improvements in patient compliance with recommended therapies. We are not aware of any studies documenting health benefits from brand utilization for our sample of drugs. According to 2010 IMS data, about 80% of all prescriptions are for drugs with an available bioequivalent generic, and these prescriptions account for roughly 50% of the more than \$300 billion in prescription drug spending. If copay coupons were offered for the entirety of this sample, even a 1% increase in spending would correspond to about \$1.5 billion in higher drug spending annually.

This study addresses only one type of copay coupon: coupons for branded drugs with generic bioequivalents. Copay coupons are also often available for branded drugs that do not face (direct) generic competition. In such cases, the static welfare implications of copay coupons are less clear. For instance, for branded drugs without an available bioequivalent generic, there may be a more nuanced trade-off between efficacy and price. In addition, business-stealing in that context does not necessarily raise spending. That said, while substitution between branded drugs may not raise spending, substitution between branded drugs and generics for different molecules likely still will.⁴¹ Moreover, without a competitive generic industry to temper pricing, copay coupons may be a more effective tool for softening price competition between brands that are therapeutic substitutes. This is an important area for future research, particularly given policy questions about whether and where copay

⁴¹For example, a copay coupon for the branded statin Lipitor (which faced loss of exclusivity in 2011) may have resulted in a loss of share for generic statins like simvastatin (Zocor; generic available in 2006).

coupons should be allowed. In 2012, Massachusetts overturned its copay coupon ban for drugs without a bioequivalent generic, while maintaining the ban for drugs with a bioequivalent generic. Our research provides evidence that the continued ban on copay coupons for drugs with a bioequivalent generic will help to control healthcare costs, but does not speak to the consequences of the removal of the coupon ban for drugs without a bioequivalent generic.

This study also highlights a more general problem for health insurance product design; if healthcare providers can make side payments to consumers, they can undermine insurers' attempts to steer consumer decisions via cost sharing. Side payments can also meaningfully impact the actions available to each party during insurer and provider negotiations. These issues are particularly pertinent given the renewed interest in selective contracting (and narrow network products in particular) and value-based insurance design. One important reason for tiered prescription drug formularies is that patients have heterogeneous responses to treatments and heterogeneous preferences over drugs. While more expensive to insurers and consumers, high-cost options such as specialty tier drugs may be a good value for some patients. Through tiering, insurers create incentives for consumers to reveal their valuations of products, thereby allowing insurers to provide the most costly care only to those patients who value it the most. Copayment forgiveness programs promote the over-diffusion of high-cost technology to low-benefit patients, which is one of the main drivers of innovation-related increases in healthcare spending (Chandra and Skinner (2012)). If providers can make side payments to consumers, insurers may have to default to the cruder tool of excluding providers who undermine the cost-sharing system, which threatens the insurance value that consumers get by knowing they can access the most costly care if it is necessary.

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7 Figures and Tables

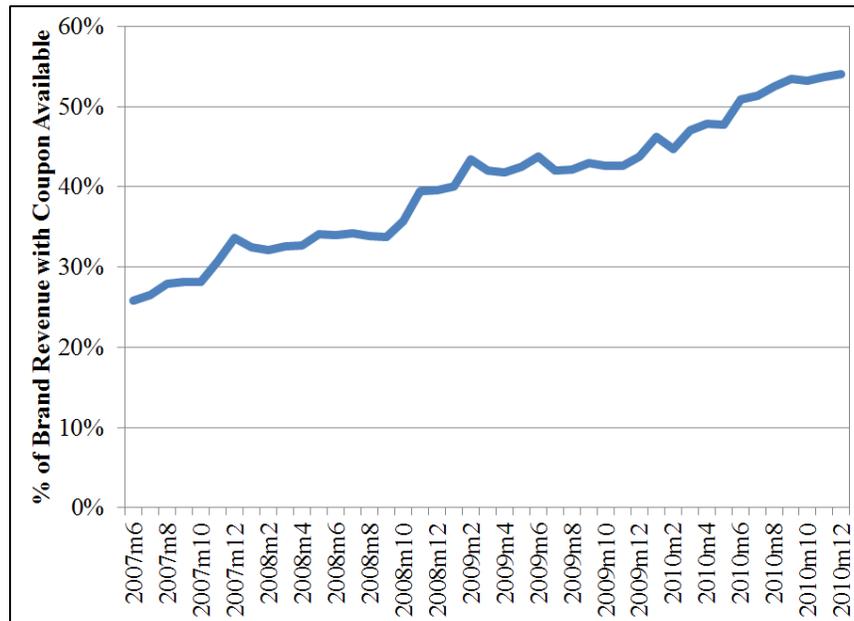


Figure 1: Share of Brand Spending with a Coupon Available, 6/2007–12/2010

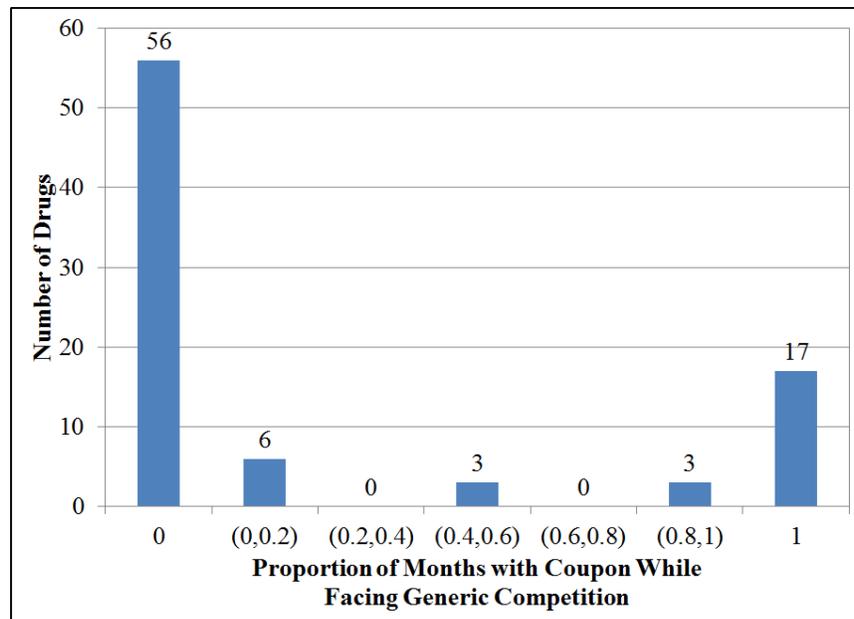


Figure 2: Coupon Frequency for Drugs in the Final Sample

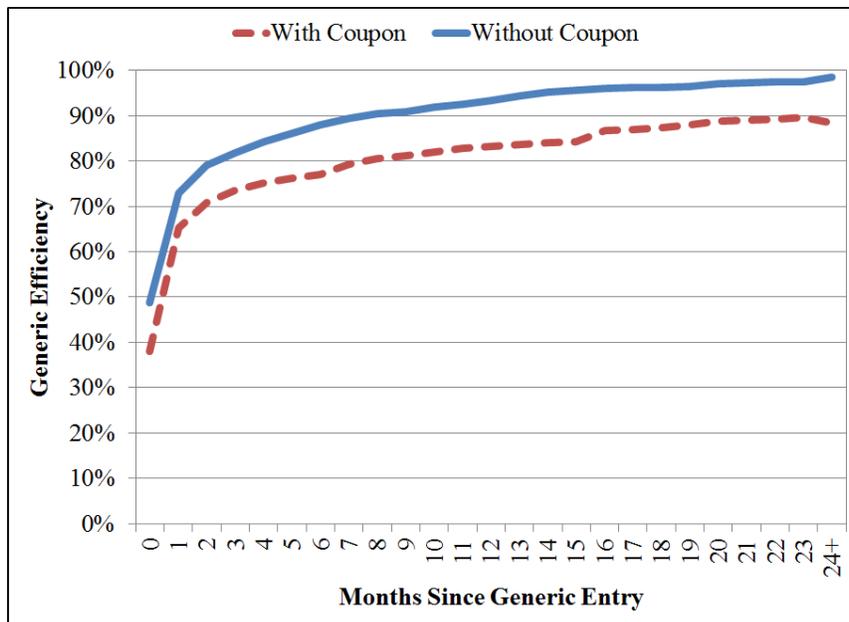


Figure 3: Generic Efficiency by Time Since Generic Entry and Coupon Status

Table 1: IMS Sample Restrictions

Restriction	Drugs (molecule-forms)	Revenue (\$ million)
Full data (6/2007 to 12/2010)	3,553	\$887,810
Any brand/generic competition	814	\$465,723
1 Branded drugs facing new generic entry	125	\$151,499
2 Only one brand, no branded generic	103	\$125,500
3 Timing of generic entry clear	88	\$118,933
4 Non-schedule II substances (final sample)	85	\$112,346

Notes: Restrictions are made successively, so, e.g., restriction 2 also makes restriction 1. Revenues are in CPI-adjusted 2010 dollars and are for all manufacturers, regardless of brand status.

Table 2: Drug Descriptive Statistics, by Coupon Status

Statistic (mean)	With Coupon	Without Coupon
Drugs	23	62
Coupon Value (\$ off)	\$47.29	–
Month of Generic Entry	4/2009	4/2009
<u>In the 3 months before generic entry:</u>		
Prescriptions (million)	0.256	0.169
Revenue (\$ million)	\$54.3	\$30.1
Revenue per Prescription	\$260.71	\$217.73
Refill Percentage	51.2%	56.2%
<u>Generic firms:</u>		
$t = 0$ (month of generic entry)	2.04	2.10
$t = 6$ (6 months after entry)	3.21	2.98
$t = 12$ (12 months after entry)	4.47	3.30

Notes: All monetary quantities are in CPI-adjusted 2010 dollars. The differences in means for revenue and the number of generic firms at $t = 12$ are statistically significant at the 10% level.

Table 3: List of Drugs with Coupons

Brand Name	Manufacturer	Molecule(s)	Dosage Form	Drug Category	Generic Entry	Brand Revenue ⁺
Protonix	Wyeth	Pantoprazole	ER Tablet	Gastrointestinal	Jan-08	
Lamictal	GlaxoSmithKline	Lamotrigine	Tablet	Neurological Disorders	Jul-08	≥\$100
Effexor XR	Wyeth	Venlafaxine	ER Capsule	Psychotherapeutics	Jul-10	
Keppra	UCB	Levetiracetam	Tablet	Neurological Disorders	Nov-08	
Depakote ER	Abbott Laboratories	Divalproex	ER Tablet	Neurological Disorders	Feb-09	
Depakote	Abbott Laboratories	Divalproex	Tablet	Neurological Disorders	Aug-08	\$50-\$100
Ambien CR	Sanofi	Zolpidem	ER Tablet	Sedatives & Hypnotics	Nov-10	
Trileptal	Novartis	Oxcarbazepine	Tablet	Neurological Disorders	Oct-07	
Prograf	Astellas Pharma	Tacrolimus	Capsule	Immunologic Agents	Sep-09	
Cellcept	Roche	Mycophenolate Mofetil	Tablet	Immunologic Agents	May-09	
Mirapex	Boehringer Ingelheim	Pramipexole	Tablet	Neurological Disorders	Jan-10	
Skelaxin	Pfizer	Metaxalone	Tablet	Musculoskeletal	Apr-10	
Cellcept	Roche	Mycophenolate Mofetil	Capsule	Immunologic Agents	May-09	
Famvir	Novartis	Famciclovir	Tablet	Antiviral	Sep-07	
Differin	Galderma	Adapalene	Gel	Dermatologicals	Jun-10	
Zegerid	Santarus	Omeprazole/Sodium	Capsule	Gastrointestinal	Jul-10	<\$50
Depakote	Abbott Laboratories	Divalproex	Capsule	Neurological Disorders	Feb-09	
Keppra	UCB	Levetiracetam	Solution	Neurological Disorders	Jan-09	
Differin	Galderma	Adapalene	Cream	Dermatologicals	Jul-10	
Evoclin	Stiefel Laboratories	Clindamycin	Aerosol	Dermatologicals	Apr-10	
Ovide	Taro	Malathion	Lotion	Dermatologicals	Jun-09	
Zyrtec	Pfizer	Cetirizine	Solution	Allergy/Cold Preps	Jun-08	
Loprox	Medicis	Ciclopirox	Gel	Anti-Fungal Agents	Dec-07	

Notes: ⁺average revenue in the 3 months prior to generic entry (\$ million, 2010 dollars). Sorted descending on brand revenue. “ER” refers to all extended release formulations.

Table 4: NHCHIS Claim Counts in Final Sample, 2007–2013

Statistic	State	With Coupon	Without Coupon
Total	NH	1,477,523	2,427,783
Claims	MA	33,024	48,011
Median Over	NH	29,839	14,594
Drugs	MA	588	202
Min Over	NH	2,067	11
Drugs	MA	23	0

Table 5: Effect of Coupons on Generic Efficiency (IMS)

	(1)	(2)	(3)	(4)	(5)	(6)
geneff _{t=0}	0.663*** (0.031)	0.673*** (0.027)	0.675*** (0.025)	0.674*** (0.025)	0.676*** (0.025)	0.687*** (0.026)
Coupon	-0.088*** (0.018)	-0.081*** (0.019)	-0.082*** (0.020)		-0.061*** (0.023)	0.006 (0.057)
Low-Intensity Coupon				-0.067** (0.029)		
High-Intensity Coupon				-0.084*** (0.020)		
Coupon*Intensity					-0.014* (0.008)	-0.092* (0.052)
Coupon*Intensity ²						0.018* (0.010)
Generic Firms		0.013*** (0.003)	0.013*** (0.003)	0.013*** (0.003)	0.015*** (0.003)	0.016*** (0.003)
Refill Percentage			-0.069 (0.089)	-0.053 (0.090)	-0.074 (0.089)	-0.046 (0.084)
Constant	0.134*** (0.021)	0.068*** (0.023)	0.108* (0.058)	0.099* (0.059)	0.104* (0.058)	0.076 (0.060)
Observations	1,740	1,740	1,740	1,740	1,740	1,740
<u>Generic Efficiency⁺</u>						
Without coupon	92.8%	91.9%	92.1%	92.0%	92.0%	91.7%
With coupon	83.3%	80.6%	81.2%			
Low-intensity				84.5%	83.5%	86.5%
High-intensity				80.4%	80.6%	74.8%

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. The unit of observation is the drug-month. Observations are weighted by the average revenue of the branded drug in the 3 months prior to generic entry, and standard errors are clustered by drug. ⁺The bottom panel gives the average predicted generic efficiency from $t = 0$ to $t = 36$, evaluated at the mean level of the covariates (generic firms and refill percentage: 3.43 and 0.55 respectively). The first row gives estimates for drugs without coupons and the second row gives estimates for drugs with coupons. For columns (4) to (6), separate estimates are given for low-intensity and high-intensity coupons. For column (4), low-intensity combines all coupons below the median intensity (0.91) and high-intensity combines all coupons above the median. For columns (5) and (6) — which require a specific intensity to evaluate — low-intensity is evaluated using the 25th percentile of the measure (0.69) and high-intensity is evaluated using the 75th percentile (1.52).

Table 6: Effect of Coupons on Generic Efficiency (DD)

	(1)	(2)	(3)	(4)
NH	-0.003 (0.007)	-0.003 (0.007)	-0.003 (0.007)	-0.003 (0.007)
NH*Coupon	-0.034*** (0.011)		-0.007 (0.019)	0.029 (0.046)
NH*Low-Intensity		-0.000 (0.011)		
NH*High-Intensity		-0.041*** (0.011)		
NH*Intensity			-0.022 (0.014)	-0.086 (0.080)
NH*Intensity ²				0.026 (0.030)
Observations	2,106	2,106	2,106	2,106
R-squared	0.746	0.746	0.746	0.746

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. The unit of observation is the drug-year since generic entry-insurance type-state. Observations are weighted by the number of insurance claims over which generic efficiency is calculated and standard errors are clustered by drug. All specifications include drug, year since generic entry, and insurance-type fixed effects.

Table 7: Effect of Coupons on Generic Efficiency (DDD)

Description	Expression	Estimate
A: Treated consumers (age<65)		
NH-MA difference, with coupon	$\beta_0 + \beta_2 + \beta_3 + \beta_5$	-0.037*** (0.008)
NH-MA difference, without coupon	$\beta_0 + \beta_2$	-0.003 (0.006)
Difference-in-differences	$\beta_3 + \beta_5$	-0.034*** (0.011)
B: Control consumers (age≥65)		
NH-MA difference, with coupon	$\beta_0 + \beta_3$	0.034 (0.024)
NH-MA difference, without coupon	β_0	0.004 (0.015)
Difference-in-differences	β_3	0.029 (0.031)
DDD	β_5	-0.063** (0.027)
Observations		3,630
R-squared		0.739

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. The table presents linear combinations of the estimated coefficients of equation (4). The unit of observation is the drug-year since generic entry-insurance type-state-consumer group. Observations are weighted by the number of insurance claims over which generic efficiency is calculated and standard errors are clustered by drug. The specification includes drug, year since generic entry, and insurance-type fixed effects.

Table 8: Effect of Coupons on Prices

	ln(Brand Price)			ln(Generic Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
t	0.006*** (0.001)	0.006*** (0.001)	0.008*** (0.001)	-0.008*** (0.001)	-0.007*** (0.001)	-0.007*** (0.002)
Coupon	0.015 (0.032)			0.030 (0.041)		
t*Coupon	0.004** (0.002)	0.003*** (0.001)		0.006* (0.003)	0.001 (0.004)	
Generic Firms	0.012** (0.006)	0.009** (0.004)	0.010* (0.005)	-0.094*** (0.008)	-0.070*** (0.010)	-0.070*** (0.010)
Refill Percentage	-0.109 (0.193)			-0.133 (0.222)		
ln(pre brand price) ⁺	0.982*** (0.033)			0.985*** (0.035)		
Drug Fixed Effects?	No	Yes	Yes	No	Yes	Yes
Observations	1,740	1,740	1,740	1,740	1,740	1,740
R-squared	0.961	0.993	0.992	0.932	0.979	0.978
<u>Yearly Price Change</u>						
Without Coupon	7.1%	8.0%	9.7%	-8.8%	-8.2%	-7.7%
With Coupon	12.2%	12.6%		-2.3%	-6.9%	

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. t is months since generic entry ($t = 0$ is the month of generic entry). Observations are weighted by the average revenue of the branded drug in the 3 months prior to generic entry, and standard errors are clustered by drug. ⁺“pre brand price” refers to the average brand price in the 3 months prior to generic entry. All prices are measured in CPI-adjusted 2010 dollars.

Table 9: Effect of Coupons on Total Quantity

	ln(Total Quantity)			
	(1)	(2)	(3)	(4)
t	0.003 (0.003)	0.001 (0.002)	0.003 (0.003)	0.004 (0.003)
Coupon	-0.006 (0.053)	0.009 (0.043)	0.097* (0.056)	
t*Coupon			-0.006* (0.004)	-0.004 (0.003)
Generic Firms		0.020*** (0.007)	0.019*** (0.006)	0.004 (0.007)
Refill Percentage		-0.001 (0.183)	-0.013 (0.182)	
ln(pre quantity) ⁺	1.008*** (0.018)	1.007*** (0.013)	1.009*** (0.012)	
Drug Fixed Effects?	No	No	No	Yes
Observations	1,740	1,740	1,740	1,740
R-squared	0.983	0.984	0.985	0.995

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. Observations are weighted by the average revenue of the branded drug in the 3 months prior to generic entry, and standard errors are clustered by drug. ⁺“pre quantity” refers to the average quantity in the 3 months prior to generic entry.

Table 10: Effect of Coupons on Spending

		(1)	(2)	(3)	(4)
		<u>Effect on Generic Efficiency</u>			
		<u>IMS</u>		<u>NHCHIS</u>	
		<u>Effect on Brand Prices?</u>			
Measure	Fraction Brand Buyers Using Coupon	No	Yes	No	Yes
Percent	0.4	5.0%	6.1%	1.7%	2.3%
	0.6	4.2%	5.4%	1.2%	1.8%
	0.8	3.4%	4.6%	0.7%	1.4%
	1	2.7%	3.8%	0.3%	0.9%
Absolute	0.4	\$128.8	\$158.6	\$43.0	\$59.5
	0.6	\$109.2	\$139.0	\$30.9	\$47.3
	0.8	\$89.6	\$119.3	\$18.7	\$35.2
	1	\$69.9	\$99.7	\$6.5	\$23.0
ROI	0.4	10.25	11.01	6.29	6.97
	0.6	6.84	7.34	4.20	4.65
	0.8	5.13	5.51	3.15	3.49
	1	4.10	4.40	2.52	2.79

Notes: All numbers are calculated over a fixed time horizon of 5 years. The (monthly) discount factor is set to $0.90^{1/12}$. ROI is defined as the ratio of additional brand revenues from the coupon and manufacturer spending on copays. Absolute spending differences are in millions of 2010 dollars. For generic efficiency: columns (1) and (2) use the estimates from the IMS data reported in column (2) of Table 5, and columns (3) and (4) use the difference-in-differences estimate from the NHCHIS data reported in column (1) of Table 6. For brand prices: columns (1) and (3) use the estimates from column (3) of Table 8, and columns (2) and (4) use the estimates from column (2) of Table 8. For generic prices: all columns use the estimates from column (6) of Table 8. Initial brand and generic prices, the number of generic firms, the value of the coupon, and market size are set to their average values in the data for drugs with coupons.

Table 11: Effect of Coupons on Generic Efficiency (DD): Falsification Tests

	(1)	(2)	(3)
	MA	VT	All non-MA
NH	-0.003 (0.007)	0.003 (0.010)	0.001 (0.004)
NH*Coupon	-0.034*** (0.011)	-0.009 (0.017)	-0.008 (0.012)
Observations	2,106	2,024	12,614
R-squared	0.746	0.748	0.733
p-value H_0^+	–	0.100	0.031**

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. The unit of observation is the drug-year since generic entry-insurance type-state. Observations are weighted by the number of insurance claims over which generic efficiency is calculated and standard errors are clustered by drug. All specifications include drug, year since generic entry, and insurance-type fixed effects. ⁺p-value of a test of the null hypothesis that the coupon effect is the same as the effect in MA (from a regression estimating both effects simultaneously).

Table 12: Effect of Coupons on Generic Efficiency (DD): Specification Checks

	(1)	(2)	(3)	(4)	(5)
NH	0.011 (0.010)	0.010 (0.008)	-0.008 (0.008)	-0.009 (0.006)	-0.003 (0.007)
Coupon	-0.025 (0.047)		-0.014 (0.055)		
NH*Coupon	-0.039*** (0.011)	-0.026** (0.012)	-0.041*** (0.012)	-0.033*** (0.011)	-0.034*** (0.011)
<u>Fixed Effects:</u>					
Drug	No	Yes	No	Yes	Yes
Years Since Generic Entry	No	No	Yes	Yes	Yes
Insurance Type	No	No	No	No	Yes
Observations	2,106	2,106	2,106	2,106	2,106
R-squared	0.020	0.277	0.486	0.745	0.746

Notes: *** $p < .01$, ** $p < .05$, * $p < .10$. The unit of observation is the drug-year since generic entry-insurance type-state. Observations are weighted by the number of insurance claims over which generic efficiency is calculated and standard errors are clustered by drug.

8 Appendix

8.1 Formal coupon analysis

In this section, we present a stylized formal model to illustrate the effect of coupons on behavior, emphasizing the incentives generated by insurance. Throughout, we assume that a bioequivalent generic for the branded drug is available and is produced by several generic firms. We further assume that the generic firms produce undifferentiated products and price at marginal cost. This assumption, which is consistent with evidence on generic pricing,⁴² allows us to abstract away from any strategic interactions between brand and generic pricing.

Pricing without coupons

Consider a brand-name pharmaceutical manufacturer (without the ability to offer copay coupons) setting the price p of its drug to an insurer. While the manufacturer receives p for every prescription filled, the price that determines demand is not p itself. Rather, insured consumers pay only $m(p)$ for a prescription, where $m(\cdot)$ is a function chosen by the insurer. The price facing consumers — $m(p)$ — is what determines demand rather than p directly. In practice, $m(\cdot)$ typically consists of several tiers of copayments, but for the purposes of the analysis here, we will assume that $m(\cdot)$ is a smooth, differentiable function of p .

To get a sense of what $m(p)$ looks like in the data, Figure 4 plots consumer out-of-pocket cost and total (insurer plus consumer) payments for privately insured consumers in the Medical Expenditure Panel Survey (MEPS) from 2005 to 2012. Based on the pattern in Figure 4, we make the following three assumptions about $m(\cdot)$ in the subsequent analysis:

1. $m(0) = 0$ and $m(p) < p$ for all $p > 0$ (insurance)
2. $m'(p) > 0$ for all p (increasing absolute cost sharing)
3. $m''(p) < 0$ for all p (decreasing proportional cost sharing)

Suppose there is a mass of consumers (normalized to 1) with unit demand who choose between the branded drug and a bioequivalent generic.⁴³ The proportion of consumers choosing the branded drug is given by demand curve $Q(\cdot)$, while the remaining $1 - Q(\cdot)$ consumers

⁴²For example, Berndt et al. (2011) note that generic prices eventually fall close to typical estimates of marginal cost, a result that is consistent with perfectly competitive markets.

⁴³The analysis here assumes away quantity effects; in principle coupons could also generate sales through cross-drug substitution or by reducing non-adherence.

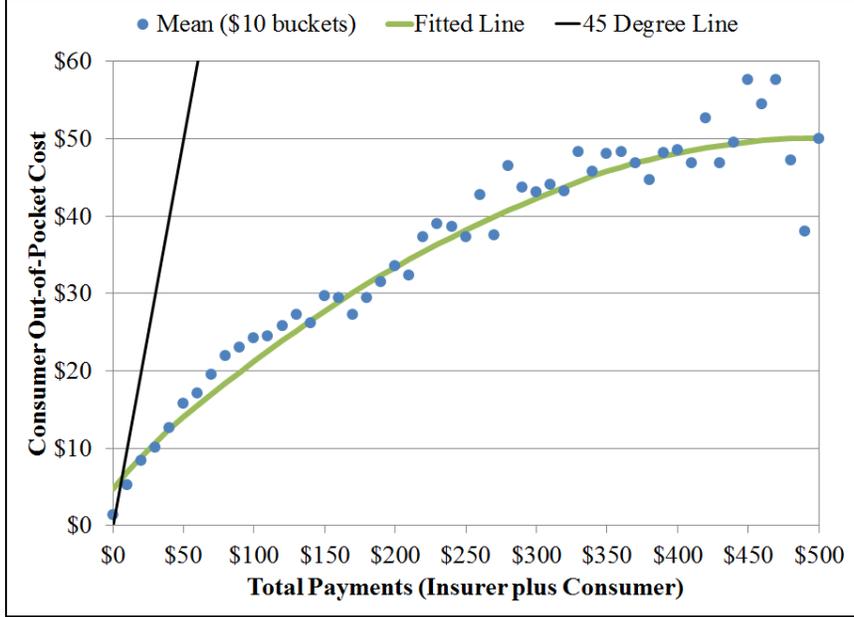


Figure 4: MEPS Expected Out-of-Pocket Costs, 2005–2012 All numbers are measured in CPI-adjusted 2010 dollars. Total payments are censored from above at \$500 — 97 percent of prescriptions in the data have total payments of less than \$500. The points are averages within \$10 buckets, and the fitted line is a locally weighted scatterplot smoothing (lowess) line through the points.

buy generic (generic efficiency). Given (constant) marginal cost c , the manufacturer chooses price to maximize profits:

$$\max_p (p - c) \cdot Q(m(p)). \quad (7)$$

The difference between (7) and the standard profit-maximization problem is that, due to the presence of insurance, the price received by the manufacturer is not the same price that determines demand. (If there is no insurance, $m(p) = p$ and (7) reduces to the standard profit-maximization problem.) Further assume that $Q' < 0$ and $Q'' \leq 0$, which are sufficient conditions to guarantee that the manufacturer’s profit function is concave.

Given the assumptions made on $m(\cdot)$ and $Q(\cdot)$, it can be shown that the manufacturer’s optimal price when facing insured consumers is higher than the optimal price without insurance. Intuitively, the cost to the manufacturer of increasing price — lower quantity — is dampened by the presence of insurance, which passes through price increases to consumers at less than a 1:1 rate. The manufacturer optimally responds by increasing price beyond the optimal price in the absence of insurance (a similar result is shown in Berndt et al. (2011)).

Adding coupons

Suppose now that the manufacturer is able to offer consumers a coupon which reduces their out-of-pocket cost by $z \in [0, m(p)]$. Further assume that all consumers who buy the branded drug use the coupon. This simplifying assumption — though unlikely to be true in practice — enables us to focus on the interaction between coupons and the insurer copayment mechanism rather than other rationales for coupons such as price discrimination. With coupons, the manufacturer’s problem becomes

$$\max_{(p,z)} (p - z - c) \cdot Q(m(p) - z). \quad (8)$$

Unlike p , which is dampened by $m(\cdot)$, the coupon z reaches consumers directly. We derive three specific propositions with regard to the effects of coupons on behavior. Here we present the intuition and interpretation of the predictions; the proofs follow in the next section.

Proposition 1. *Suppose that the manufacturer is constrained to price no higher than \bar{P} (i.e., $p \in [0, \bar{P}]$).⁴⁴ When coupons are allowed, the manufacturer’s optimal price is $p^* = \bar{P}$.*

Proposition 1 states that, holding $m(\cdot)$ fixed, coupons undermine the efficacy of copays in limiting prices. No matter how high \bar{P} is, the manufacturer optimally prices at the maximum. In essence, the addition of coupons creates a money tree for the manufacturer. By increasing both p and z by the same amount, for instance, the manufacturer can hold its margin constant while simultaneously reducing consumers’ out-of-pocket cost, thereby increasing quantity sold.⁴⁵ Of course, insurers are unlikely to leave $m(\cdot)$ unchanged as they see their costs skyrocket. Proposition 1 is therefore best interpreted as explaining why copay coupons undermine standard copayment systems. The existing copayment rule $m(\cdot)$ is no longer suitable when manufacturers are able to offer coupons.

Proposition 2. *Denote the manufacturer’s optimal price without coupons ($z = 0$) by \hat{p} , and let $\bar{P} \geq \hat{p}$. When coupons are allowed, the manufacturer (a) offers a coupon ($z^* > 0$), (b) consumers’ out-of-pocket cost is lower (i.e., $m(p^*) - z^* < m(\hat{p})$), and (c) generic efficiency is lower.*

By Proposition 1, we know that the manufacturer’s optimal price is $p^* = \bar{P}$. Given a coupon that leaves out-of-pocket cost unchanged from the situation without coupons,

⁴⁴The price cap \bar{P} can be interpreted as a choke price beyond which the insurer drops the drug from the formulary.

⁴⁵This intuition is not complete because of boundary cases, but the basic idea is correct.

$z = m(\bar{P}) - m(\hat{p})$, it can be shown that the manufacturer still has an incentive to increase the value of the coupon. Intuitively, at out-of-pocket cost $m(\hat{p})$, demand is relatively elastic but price reductions are not profitable because the pass-through from price to out-of-pocket cost is imperfect. Since coupons reach consumers directly, however, the manufacturer can induce the same increase in quantity as any price cut but with a smaller effect on the margin. Part (c) of the proposition follows directly from part (b): since coupons decrease consumers' out-of-pocket cost for the branded drug, they lead to an increase in the quantity consumed of the branded drug.

Proposition 3. *Again denote the manufacturer's optimal price without coupons by \hat{p} , and let $\bar{P} \geq \hat{p}$. Further assume that generic marginal cost c_g is weakly less than brand marginal cost, i.e., $c_g \leq c$. When coupons are allowed, total spending (insurer plus consumer) is higher.*

Proposition 3 contains the final prediction about the effects of coupons that we study in the empirical analysis in the text — total spending increases as a result of coupons. Whether coupons increase total spending depends crucially on the price of available substitutes (in this case, a bioequivalent generic). A sufficient — albeit not necessary — condition for total spending to increase is weakly lower generic marginal costs, together with a competitive generic market where generics price at marginal cost. More generally, as long as the gap between the brand's price net of the coupon ($p^* - z^*$) and the generic price is large, which is true in practice, total spending will tend to increase with the addition of coupons.

8.2 Proofs

Proposition (unnumbered): The manufacturer's optimal price when facing insured consumers is higher than the optimal price without insurance.

Proof: Denote the manufacturer's optimal price when consumers are uninsured by \tilde{p} . Writing out the derivative of manufacturer profit when consumers are insured ($\partial\pi/\partial p$) with respect to price, evaluated at \tilde{p} :

$$\begin{aligned} \frac{\partial\pi}{\partial p}(\tilde{p}) &= Q(m(\tilde{p})) + (\tilde{p} - c) \cdot Q'(m(\tilde{p})) \cdot m'(\tilde{p}) \\ &> Q(\tilde{p}) + (\tilde{p} - c) \cdot Q'(\tilde{p}) \\ &= 0 \end{aligned}$$

The equality at the end follows by the definition of \tilde{p} as the optimal price facing uninsured consumers. The inequality follows because:

- $Q(m(\tilde{p})) > Q(\tilde{p})$ (since Q is decreasing and $\tilde{p} > m(\tilde{p})$)
- $Q'(m(\tilde{p})) \cdot m'(\tilde{p}) > Q'(\tilde{p})$ (since $Q' < 0$, $m'(\tilde{p}) < 1$, and $Q'(m(\tilde{p})) > Q'(\tilde{p})$ because Q' is decreasing)⁴⁶

Therefore, the manufacturer facing insured consumers benefits from increasing price beyond the optimal price when facing uninsured consumers. \square

Proposition 1: Suppose that the manufacturer is constrained to price no higher than \bar{P} (i.e. $p \in [0, \bar{P}]$). When coupons are allowed, the manufacturer's optimal price is $p^* = \bar{P}$.

Proof: Suppose the optimal price/coupon pair is given by (p, z) , with $p < \bar{P}$. Now consider the alternative pair $(p', z') = (\bar{P}, \min(z + \bar{P} - p, m(\bar{P})))$. We will show that (p', z') yields higher profits and thus (p, z) cannot be optimal.

Suppose that $z + \bar{P} - p \leq m(\bar{P})$. Profits from (p', z') are given by:

$$\begin{aligned}\pi(p', z') &= (\bar{P} - z - \bar{P} + p - c) \cdot Q(m(\bar{P}) - z - \bar{P} + p) \\ &= (p - z - c) \cdot Q(m(\bar{P}) - z - \bar{P} + p)\end{aligned}$$

The margin above is the same as for (p, z) . Therefore profits are higher under (p', z') if quantity is higher, or equivalently if consumer out-of-pocket cost is lower. Consumer out-of-pocket cost is lower if $m(\bar{P}) - z - \bar{P} + p < m(p) - z$. Rearranging, this holds if $\bar{P} - m(\bar{P}) > p - m(p)$, which is true because m is concave.

Now suppose instead that $m(\bar{P}) < z + \bar{P} - p$. Profits from (p', z') are given by:

$$\pi(p', z') = (\bar{P} - m(\bar{P}) - c) \cdot Q(0)$$

Quantity can be no higher than $Q(0)$ under (p, z) , so profits will be higher under (p', z') if the margin is higher. The margin is higher if $\bar{P} - m(\bar{P}) - c > p - z - c$. Rearranging, this holds if $m(\bar{P}) < z + \bar{P} - p$, which is exactly what we started with. \square

Proposition 2: Denote the manufacturer's optimal price without coupons ($z = 0$) by \hat{p} , and let $\bar{P} \geq \hat{p}$. When coupons are allowed, the manufacturer (a) offers a coupon ($z^* > 0$),

⁴⁶To see that $m'(\tilde{p}) < 1$, note that $m'(0) = \lim_{\Delta \rightarrow 0} \frac{m(\Delta) - m(0)}{\Delta} = \lim_{\Delta \rightarrow 0} \frac{m(\Delta)}{\Delta} < \lim_{\Delta \rightarrow 0} \frac{\Delta}{\Delta} = 1$. $m'(p) < 1$ for all $p > 0$ then follows because m' is decreasing.

(b) consumers' out-of-pocket cost is lower (i.e. $m(p^*) - z^* < m(\hat{p})$), and (c) generic efficiency is lower.

Proof: By Proposition 1, we know that the manufacturer's optimal price is $p^* = \bar{P}$. Now take a coupon that leaves consumer out-of-pocket cost unchanged from the situation without coupons, $z = m(\bar{P}) - m(\hat{p}) \geq 0$. We will show that $\frac{\partial \pi}{\partial z}(\bar{P}, m(\bar{P}) - m(\hat{p})) > 0$, so the manufacturer would like to further increase the value of the coupon.

$$\begin{aligned}
\frac{\partial \pi}{\partial z}(\bar{P}, m(\bar{P}) - m(\hat{p})) &= -Q(m(\hat{p})) - (\bar{P} - m(\bar{P}) + m(\hat{p}) - c) \cdot Q'(m(\hat{p})) \\
&\geq -Q(m(\hat{p})) - (\hat{p} - c) \cdot Q'(m(\hat{p})) \\
&> -Q(m(\hat{p})) - (\hat{p} - c) \cdot Q'(m(\hat{p})) \cdot m'(\hat{p}) \\
&= -1 \cdot \left[Q(m(\hat{p})) + (\hat{p} - c) \cdot Q'(m(\hat{p})) \cdot m'(\hat{p}) \right] \\
&= 0
\end{aligned}$$

The first inequality follows because $\bar{P} - m(\bar{P}) \geq \hat{p} - m(\hat{p})$ (since m is concave and $\bar{P} \geq \hat{p}$). The second inequality follows because $m'(\hat{p}) < 1$. The last equality holds because the expression inside the brackets on the line before is the derivative of profits with respect to price when coupons are not allowed, and since \hat{p} is optimal when coupons are not allowed, this expression is equal to zero. Therefore, the optimal coupon value z^* is greater than $m(\bar{P}) - m(\hat{p}) \geq 0$, which implies that consumer out-of-pocket spending is lower than without coupons because $m(\bar{P}) - z^* < m(\bar{P}) - m(\bar{P}) + m(\hat{p}) = m(\hat{p})$. Part (c) follows immediately from part (b) and the fact that Q is decreasing in out-of-pocket cost. \square

Proposition 3: Again denote the manufacturer's optimal price without coupons by \hat{p} , and let $\bar{P} \geq \hat{p}$. Further assume that generic marginal cost c_g is weakly less than brand marginal cost, i.e. $c_g \leq c$. When coupons are allowed, total spending (insurer plus consumer) is higher.

Proof: Denote the optimal price/coupon pair with coupons by (p^*, z^*) and the optimal pair without coupons by $(\hat{p}, 0)$. The difference between total spending with coupons and without coupons is given by:

$$\left(\underbrace{(p^* - z^*) \cdot Q(m(p^*) - z^*) + c_g \cdot [1 - Q(m(p^*) - z^*)]}_{\text{spending with coupons}} \right) - \left(\underbrace{\hat{p} \cdot Q(m(\hat{p})) + c_g \cdot [1 - Q(m(\hat{p}))]}_{\text{spending without coupons}} \right)$$

Rearranging:

$$\begin{aligned}
& (p^* - z^*) \cdot Q(m(p^*) - z^*) - \hat{p} \cdot Q(m(\hat{p})) - c_g \cdot [Q(m(p^*) - z^*) - Q(m(\hat{p}))] \\
& \geq (p^* - z^*) \cdot Q(m(p^*) - z^*) - \hat{p} \cdot Q(m(\hat{p})) - c \cdot [Q(m(p^*) - z^*) - Q(m(\hat{p}))] \\
& = (p^* - z^* - c) \cdot Q(m(p^*) - z^*) - (\hat{p} - c) \cdot Q(m(\hat{p})) \\
& \geq 0
\end{aligned}$$

The first inequality follows because $Q(m(p^*) - z^*) > Q(m(\hat{p}))$ (by Proposition 2) and $c_g \leq c$. The expression following the equal sign is the difference between manufacturer profits with coupons and manufacturer profits without coupons. This difference is at least weakly positive because $(\hat{p}, 0)$ is a feasible choice for the manufacturer in the problem with coupons. \square

8.3 Spending calculation details

Suppose that generic efficiency, brand prices (gross of any coupon discounts), and generic prices are given by a set of functions that depend on the time since generic entry t and a variable marking coupon status ($c \in \{0, 1\}$). Denote these functions by $g(t, c)$, $p_b(t, c)$, and $p_g(t, c)$ (respectively). Several additional objects affect total spending: total market size (in prescriptions), the value of the coupon, and the fraction of brand buyers utilizing a coupon. Denote these objects by M , z , and ψ , respectively, all of which we assume to be time invariant. As we do not find compelling evidence of an association between volume and coupons, we assume that market size is independent of coupon status. Given monthly discount factor δ and a fixed time horizon T , the net present value of spending (in $t = 0$ dollars) as a function of coupon status, $S(c)$, can be written as:

$$S(0) = \sum_{t=0}^{T-1} \delta^t \cdot M \cdot \left[\underbrace{p_b(t, 0) \cdot (1 - g(t, 0))}_{\text{brand buyers}} + \underbrace{p_g(t, 0) \cdot g(t, 0)}_{\text{generic buyers}} \right] \quad (9)$$

$$\begin{aligned}
S(1) = \sum_{t=0}^{T-1} \delta^t \cdot M \cdot \left[\underbrace{(p_b(t, 1) - z) \cdot \psi \cdot (1 - g(t, 1))}_{\text{brand buyers using coupon}} \right. \\
\left. + \underbrace{p_b(t, 1) \cdot (1 - \psi) \cdot (1 - g(t, 1))}_{\text{brand buyers not using coupon}} + \underbrace{p_g(t, 1) \cdot g(t, 1)}_{\text{generic buyers}} \right]. \quad (10)
\end{aligned}$$

To summarize the effect of copay coupons, we calculate the percentage change in spending from adding a coupon ($S(1)/S(0) - 1$) as well as the absolute change ($S(1) - S(0)$). For generic

efficiency, we assume that $g(t, c)$ behaves according to the confined exponential equation (1), presented in section 4.1. We use estimates from both the IMS and NHCHIS analyses to calculate (9) and (10). For IMS, we use the parameter estimates reported in column (2) of Table 5. For NHCHIS, generic efficiency for drugs without coupons is still assumed to behave according to equation (1), while generic efficiency for drugs with coupons is assumed to be a fixed amount lower. We use the estimate reported in column (1) of Table 6 which indicates that coupons result in a 3.4 percentage point reduction in generic efficiency.

For prices, we assume that $p_b(t, c)$ and $p_g(t, c)$ behave according to equation (6), in which coupons affect only price growth rates. For brand pricing, we perform the calculation both with and without coupon effects. When coupons are allowed to affect brand price growth, we use the estimates from column (2) of Table 8. When not, we use the estimates from column (3). In all scenarios, we assume no effect of coupons on generic prices (using the estimates from column (6) of Table 8). For initial prices, we use the average prices in the month of generic entry for drugs with coupons (about \$264 per prescription for the brand price and \$218 per prescription for the generic price). The number of generic firms is set to the average number in the data for drugs with coupons (3.68). For the coupon value z , we use the average over drugs with coupons (about \$47 per prescription). We set market size M to be the average number of prescriptions sold per month for drugs with coupons (about 295,000). We set the (monthly) discount rate to $0.90^{1/12}$, and measure spending over a fixed time horizon of five years ($T = 60$).

8.4 Data construction details

This section provides additional information about the steps we take to go from the raw data to the dataset used to perform the analyses discussed in the main text. For further information beyond what we describe here, please feel free to contact any of us with questions.

Coupon Data (www.internetdrugcoupons.com)

Figure 5 displays an example of the content available on the internetdrugcoupons website: the main page on the left and a drug-specific page on the right. We begin by scraping the text data of historical versions of the website from www.archive.org. We scrape and then clean the data (e.g., converting text that says “save up to \$600 per year” to “\$50 off” to reflect savings on a single prescription) both from the main page and the drug-specific pages linked therein. Of the 43 months from June 2007 and December 2010, we have data

<p><i>Blood Pressure</i></p> <p>Bystolic Coupon Save Up To \$20 Caduet Coupon Save \$20 Cardura XL Coupon Save \$20 Coreg CR Coupon Save \$120 Cozaar Coupon 30 Days Free Diovan Coupon Save Up To \$240/Year Diovan HCT Save Up To \$240/Year Exforge Coupon Save Up To \$75 Tekturna Coupon Save Up to \$75</p> <p><i>Cancer</i></p> <p>Aromasin Coupon: Free Trial Offer Femara Coupon 30 Days FREE Tarceva Save Up To \$4,000 /Year</p> <p><i>Cholesterol</i></p> <p>Caduet Coupon Save \$20 Crestor Coupon 15 Days Free Lipitor 1 Month Free + \$180 Off Lipofen Coupon Save \$30 Trilipix® Coupon: Save \$15</p>	<p>Altanax Coupon Save \$15 Benzacilin Coupon \$15 Rebate Brevoxyl Coupon Save \$25 Clenia Coupon \$15 Rebate Clindagel Coupon \$15 Rebate Clinda reach Coupon \$30 Rebate Clobex Coupon \$45 Rebate Cultivate Coupon Save \$20 Desonate Coupon Save Up To \$125 Differin Coupon \$ 35 Rebate Dorvx Coupon \$ 50 Rebate Duac Coupon Save \$25 Epiduo Coupon: Co-Pay Reduction Offer Epiquin Coupon \$35 Rebate Ertaczo Coupon \$50 Rebate Eucerin \$1 Coupon Evoclin Coupon Save \$25 Evotence Coupon: \$150 Rebate Extina Coupon \$35 Rebate Fiancea® Coupon Save \$10 Locoid Lipocream Coupon \$35 Rebate Loprox Coupon \$25 Rebate</p>	<div style="border: 1px dashed orange; padding: 10px;"> <p>Coupon For Taclonex®; Manufacturer Offer; \$50Rebate</p> <p>CLICK HERE</p> </div> <p><i>Name of Offer:</i> Taclonex \$50 rebate <i>Description:</i> Manufacturer Printable Rebate</p> <p>There are no forms to fill out or submit, no eligibility requirements and the coupon never expires. It is accepted at all the major chains and most private pharmacies. Click HERE to instantly print out your coupon</p>
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Figure 5: Content on www.internetdrugcoupons.com, June 2009

from 30 months. To fill out coupon data for the missing months, we interpolate data. For example, if the same coupon is known to be present in May and August of some year while the data for June and July is missing, then we code that coupon as also being present in June and July. To take another example, suppose the coupon is not present in May but is available in August, and again the data for June and July is missing. In that case, we use the midpoint, coding the coupon as first being available in July. We also make several manual corrections based on internet searches, e.g. to fill out coupon information in cases where the text scraping program does not pull down sufficient information to identify discount types (e.g. free samples, which we do not code as coupons) or amounts.

Retail Prescription Sales Data (IMS National Prescription Audit)

One row in our raw NPA data is essentially a unique combination of national drug code (NDC) and month. To perform the analyses presented in the text, we collapse this data to the molecule-dosage form-month level. Before doing so, we execute several steps to clean the data.

First, we drop repackager firms who buy drugs from manufacturers and then repack them into different package forms (e.g., blister packs), as it is possible that including repackagers will double-count sales. The list of firms considered to be repackagers is contained in Table I-5 of FTC (2011). Second, we drop injectable drugs because they appear in our data starting in 2009, well after the beginning of our study period. Injectable drugs are identified using the three-letter product code (TLC) variable in the IMS data: the code for injectable preparations typically begin with the letter “F” or “G”. Third, we drop products for which over-the-counter use, which is identified by a prescription status variable in the data, accounts for 10 percent or more of total retail prescriptions in the data over all years. Fourth, we

convert the three-letter product code variable into a less granular measure of dosage form. For example, the TLC distinguishes between coated and uncoated tablets, and we combine both under the same umbrella. We do retain more significant distinctions that are often associated with new drug applications and/or patents, such as extended release, chewable, and orally disintegrating formulations. Fifth, we reclassify products identified as branded generic in the IMS data using drug approval information from the FDA, when available. As explained in footnote 26, products associated with a New Drug Application (NDA) and a brand name are reclassified as brands. Products associated with an Abbreviated New Drug Application (ANDA) and/or without a brand name are reclassified as generics. Branded generic products without matching FDA approval information maintain their classification as branded generics.

After aggregating the data to the molecule-dosage form level, we convert all monetary quantities to January 2010 dollars using the Bureau of Labor Statistics' Consumer Price Index for All Urban Consumers. We identify the first month during which a drug faces generic competition as the first month in which at least 5 percent of total prescriptions are accounted for by generics. We then perform the four sample restrictions reported in the text:

1. Restrict the sample to drugs facing (new) generic entry between June 2007 and December 2010, the overlapping period of the coupon and IMS datasets.
2. Restrict the sample to drugs with only a single brand and no branded generics.
3. Restrict the sample to drugs for which the timing of generic entry is clear to define (e.g., no patent disputes that result in generics moving in and out of the data).⁴⁷
4. Restrict the sample to non-Schedule II controlled substances⁴⁸

In the coupon data, coupons are linked to brand names. For instance, internetdrug-coupons shows that there is a copay coupon for Differin, not for branded Adapalene (the active ingredient in Differin). The IMS data contains fields listing product brand name in addition to the corresponding molecule(s) and dosage forms. Therefore, we can merge the two datasets using brand names. We carefully scrub the brand names in both datasets to ensure a clean match; for instance, a brand name may originally appear as "Allegra D" in

⁴⁷The 15 drugs dropped according to this restriction are (brand names): Buphenyl, Ceftin, Fibracor, Flovent, Focalin, Ionamin, Kytril, Phoslo, Ponstel, Pulmicort, Seromycin, Solodyn, Sular, Vesanoïd, and Zerit.

⁴⁸The 3 drugs dropped according to this restriction are (brand names): Adderall XR, Combunox, and Opana.

one dataset and “Allegra-D” in another. Since our final sample is restricted to molecule-dosage form combinations with only a single branded drug, we do not need to worry about aggregating coupon information for multiple branded drugs into a single measure for the corresponding molecule-dosage form.

Insurance Claims Data (NHCHIS)

We begin by restricting the data to claims from residents of New Hampshire and Massachusetts. To identify the same sample of drugs used in the IMS analysis, we merge the list of drugs in the IMS sample into the NHCHIS data using fields in the NHCHIS data that list a drug’s name and brand status, again carefully scrubbing the names to ensure a clean match. In some cases, the drug name in the NHCHIS data also identifies the form. For example, “Depakote ER” and its generic “Divalproex Sodium ER” are distinguished from regular “Depakote” and its generic “Divalproex Sodium”.

In other cases, however, it is not possible to distinguish between forms in the NHCHIS data. For example, while “Aricept” and “Aricept ODT” are distinct names in the data, all generics appear under the name “Donepezil HCl”, not indicating if the tablet is orally disintegrating. In these cases, we combine the different dosage forms, e.g. looking at Aricept and its generics as a whole rather than separating out the orally disintegrating formulation. One problem with this approach is that different dosage forms do not necessarily share the same generic entry dates, or coupons. When same molecule drugs with different dosage forms cannot be separated due to a lack of information in the NHCHIS drug name field, and there is a substantial conflict in the generic entry date and/or coupon information, we drop the drug. As a result, we lose Cleocin (Clindamycin; powder dosage form), Evoclin (Clindamycin; aerosol dosage form), Prevacid (Lansoprazole; extended release capsule, orally disintegrating tablet, and powder dosage forms) and Trileptal (Oxcarbazepine; tablet and suspension dosage forms) from the sample. Jointly, these drugs account for around 10 percent of total revenue for in-sample drugs (measuring revenue for each drug over the three months prior to generic entry).