Evaluating Rationality in Responses to Health Insurance Cost-Sharing: Comparing Deductibles and Copayments

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This version: November 11, 2016; For the latest version click
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Abstract

Many studies find that consumers reduce spending in response to higher health insurance cost-sharing, but there is mixed evidence as to whether these spending reductions reflect a rational trade-off between health benefits and costs. This paper provides new evidence on the rationality of consumer responses to cost-sharing using novel variation in two common types of cost-sharing incentives: deductibles and copayments. Economic theory predicts that a fully informed, rational consumer would respond equivalently to a marginal dollar in out-of-pocket (OOP) costs from all types of cost-sharing incentives. In contrast, I find that consumers are substantially more responsive to copayment than to deductible OOP costs. Further, both types of cost-sharing have negative cross-price effects onto non-targeted services. These results are consistent with barriers to consumers' understanding how different types of cost-sharing translate into OOP costs. Finally, I show that both deductibles and copayments reduce adherence to highly valuable chronic medications. Together, my findings indicate that copayment-based plans may be more effective in protecting consumers from high OOP costs while achieving significant spending reductions, and that more complex plans may not result in the outcomes intended.

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1 Introduction

There is increasing interest in the effect of health insurance cost-sharing on consumer behavior and welfare. In part, this interest is driven by a desire to evaluate the implications of higher cost-sharing within both employer-sponsored plans and Affordable Care Act (ACA) marketplace plans. The share of workers enrolled in an employer plan with an individual deductible of $1,000 or more increased from 10% to 51% between 2006 and 2016 (Kaiser Family Foundation, 2016). Within the federally facilitated ACA marketplaces, the average deductible among the most commonly sold silver plans was $3,064 in 2016 (Rae et al., 2015). Even within an overall level of plan generosity, the types of cost-sharing incentives in use can vary a great deal. For example, ACA marketplace plans in the same metal tier have the same average level of generosity, but can have widely different cost-sharing structures.[1] In the 2016 Texas marketplace, one silver plan had a $5,900 deductible, while another actuarially equivalent silver plan option had a $0 deductible with different types of first-dollar cost-sharing for particular services, including a $30 copayment for physician office visits and 40% coinsurance for inpatient care (Rae et al., 2015). Evidence is lacking on which type of cost-sharing incentive structure is preferable.

While a large literature of both experimental (Newhouse and the Insurance Experiment Group, 1993; Finkelstein et al., 2012) and quasi-experimental (Schwartz, 2010) evidence finds that cost-sharing reduces spending in a variety of contexts, there is not yet a consensus as to what extent demand responses to cost-sharing reflect a rational trade-off between health benefits and out-of-pocket (OOP) costs. A compelling test of whether consumer responses to cost-sharing are rational is whether higher cost-sharing causes adverse health effects. The RAND Health Insurance Experiment found that increases in cost-sharing were not accompanied by changes in a variety of health outcomes on average, suggesting that cost-sharing causes rational reductions in spending of little health benefit relative to cost (Newhouse and the Insurance Experiment Group, 1993). However, the experiment did find that cost-sharing led to worse outcomes among lower-income patients with hypertension, indicating that at least some forgone spending was suboptimal. Other more recent studies also find that cost-sharing causes negative health effects for some vulnerable populations with chronic conditions (Chandra et al., 2010; Choudhry et al., 2011), but there is still no strong evidence of adverse health effects for the average individual. More evidence is needed on the rationality of consumer responses to cost-sharing, particularly for the average consumer.

[1] Generosity is measured by the plan's actuarial value, defined as the average percent of total costs paid for by the plan. The Department of Health and Human Services does allow for minimal variation of plus or minus 2 percentage points around each metal tier. For example silver plans, which target a 70 percent actuarial value, may in practice range in actuarial value from 68-72 percent.

This paper tests the rationality of consumer responses to cost-sharing along a new dimension using novel variation in two common types of cost-sharing incentives: deductibles and copayments. Economic theory predicts that consumers should respond to all dollars of marginal OOP costs equally, regardless of whether they are due to deductibles or copayments. I test this prediction by estimating whether consumers are differentially price sensitive to OOP costs due to these two incentives.

I utilize data on employer-sponsored plans in Massachusetts from 2009-2013 using the Massachusetts All Payer Claims Database. The dataset contains independent variation in deductibles and copayments for office visits and prescription drugs, making it possible to directly compare deductible and copay price elasticities in the same setting.[2] I estimate the impact of cost-sharing by comparing changes in spending among individuals whose employers changed plan cost-sharing to those whose employers did not change cost-sharing. To compare equivalent responses to deductibles and copayments, I translate each into their implied OOP costs for patients. I compute implied OOP costs by simulating the average OOP costs a fixed sample of other people would pay if they were enrolled in each individual's plan.

I find that patients are substantially more responsive to OOP costs from copayments relative to deductibles. Both deductibles and copayments reduce spending, with average annual effects in line with other estimates in the literature. However, copayments drive significantly larger reductions in spending per dollar in OOP costs relative to deductibles. A $10 increase in monthly deductible OOP costs reduces total spending by 1.1%, while a $10 increase in monthly copayment OOP costs reduces total spending by 14.7%, an order of magnitude larger. This discrepancy is not driven by a difference in the types of services subject to deductibles and copayments. A $10 increase in monthly deductible OOP costs attributable to office visits and prescription drugs reduces spending on visits and drugs by 1.4%, while a $10 increase in monthly copayment OOP costs for the same services reduces spending on those services by 8.6%.

I examine consumer responses to cost-sharing along several other dimensions and find further evidence of suboptimal behavior. I estimate that both deductibles and copayments have negative cross-price effects on non-targeted services. That is, copayments affect the use of services subject only to the deductible, and vice versa. Further, I show that deductible responses do not reflect forward looking behavior. Consumers respond to the current deductible amount, even if they are likely to exceed the deductible by the end of the year. Finally, I show that both deductibles and

[2] The existing empirical literature generally studies variation in a single dimension of cost-sharing, such as copayments (Goldman et al., 2004; Chandra et al., 2010) or deductibles (Haviland et al., 2016; Brot-Goldberg et al., 2015), in isolation and is thus unable to compare responses to different types of incentives in the same environment.

copayments reduce adherence to highly valuable chronic medications, with copayments again driving larger reductions per dollar in OOP costs.

These findings are consistent with a misunderstanding of plan cost-sharing details. The most notable difference between deductibles and copayments is their complexity. Not only are deductibles non-linear incentives, but they also require numerous pieces of information to arrive at the OOP cost of a given treatment. To compute deductible OOP costs, a patient must know her spending history, the specific services a provider will use in treatment, the price of those services, and her expected future spending. The higher information barriers for deductibles suggest the wedge between deductible and copayment spending responses could be driven by differences in understanding of the OOP costs associated with deductibles relative to copayments. The estimated negative cross-price effects for both deductibles and copayments may similarly indicate that consumers do not understand which services are subject to copayments or deductibles.

A natural question is whether these inconsistencies remain for those with lower information barriers. In contrast, I find that these effects persist among subgroups likely to have better information: higher income individuals and those with more experience with the healthcare system. This could indicate that even groups with somewhat better information are still unable to overcome the information requirements and complexity to fully understand OOP costs. The decrease in valuable chronic medications in response to both deductibles and copayments suggests that imperfect information on health benefits or irrational behavior are also important in interpreting responses to cost-sharing.

Optimal cost-sharing depends on the model of consumer behavior used to interpret demand response estimates. Studies assuming a fully informed and rational model of consumer behavior estimate that raising cost-sharing would be welfare improving (Feldstein, 1973; Feldman and Dowd, 1991). However, more recent work formalizes how departures from this model can result in welfare losses from cost-sharing if consumers respond by reducing high value services where benefits exceed costs (Baicker et al., 2015; Pauly and Blavin, 2008). Under this framework, optimal cost-sharing may be lower than current levels and may even be negative for selected services and patients. Ultimately, the optimal cost-sharing structure hinges on to what extent demand responses reflect a rational trade-off between true health benefits and costs.

This paper contributes to a growing literature documenting suboptimal responses to cost-sharing. Previous studies show that higher cost-sharing results in lower adherence to highly effective chronic medications (Goldman et al., 2004), more hospitalizations among elderly patients with a chronic illness (Chandra et al., 2010), and higher rates of major vascular events among patients with a prior heart attack (Choudhry et al., 2011). Although high deductibles provide an incentive for consumers to substitute toward lower priced providers, Sood et al. (2013) and Brot-Goldberg et al. (2015) find that high deductible plans don't cause consumers to price shop. In another set of papers studying responses to deductibles, Aron-Dine et al. (2015); Einav et al. (2015); and Brot-Goldberg et al. (2015) find that consumers are not perfectly forward looking in response to deductibles as rational behavior would predict. This paper complements these studies by providing evidence of suboptimal behavior along a new dimension.

The rest of the paper proceeds as follows. Section 2 presents the framework for comparing responses to copayments and deductibles in terms of testing against a fully informed, rational consumer. Section 3 describes the data and specific cost-sharing changes I study. In Section 4, I present my empirical strategy for identifying the impact of cost-sharing and constructing measures of OOP costs. Section 5 contains my main estimates comparing price sensitivity to deductibles and copayments for different types of spending, which reject the fully informed, rational benchmark. Having rejected the null hypothesis of fully informed, rational behavior, I then provide evidence on the mechanisms of deductible and copayment price responses in Section 6. In Section 7, I conclude with a discussion of policy implications and directions for future work.

2 Framework

I begin with a benchmark model of a fully informed and rational health care consumer who 1) fully understands the OOP costs of treatment, 2) fully understands the health benefits of treatment, and 3) given full information on costs and benefits, makes rational decisions. With perfect information on the marginal benefit and marginal OOP costs of treatment, a perfectly rational consumer maximizes utility by consuming health care up to the point where marginal benefit equals marginal OOP cost. When higher cost-sharing causes OOP costs to increase, consumers will reduce spending until marginal OOP costs and benefits are again equalized. Under these assumptions, all spending reductions in response to higher cost-sharing represent care that consumers value at less than cost and are therefore efficient. Testing against this model is of interest because deviations indicate suboptimal welfare outcomes that represent opportunities to improve consumer welfare by adjusting health insurance benefit design.

In this model, two clear predictions emerge. First, a marginal dollar in OOP costs should have the same effect on demand whether that additional dollar is due to copayments or deductibles. A fully informed, rational consumer demands health care as a function of OOP costs and is able to perfectly translate all forms of cost-sharing into their implied OOP cost. Conditional on OOP costs, the type cost-sharing does not enter the consumer's problem. Since demand responds to OOP costs, and not copayments and deductibles per se, consumers should respond equivalently to a marginal dollar in OOP costs whether a copayment or deductible causes the change in OOP costs. Under a deductible, where spending in the current period affects the probability of exceeding the deductible later in the plan year, the relevant marginal OOP price for a forward looking consumer is the expected end-of-year (EOY) OOP amount (Keeler et al., 1977; Ellis, 1986). If consumers are not forward looking, but otherwise fully informed and rational, the relevant marginal OOP price is the "spot" OOP amount in the current period. Since copayments are static incentives, the only relevant marginal OOP price is the OOP amount in the current period.[3]

Second, if the health benefit of a treatment is greater than the total cost, then that treatment should always be consumed and cost-sharing (of any type) should have no impact. Treatments that meet this criteria of positive net social benefit are often referred to as high value care.

While the fully informed, rational model is a useful benchmark for optimal consumer behavior, the literature points to many potential violations to this model. Consumers may make sub-optimal choices as a result of misunderstanding the OOP costs of treatment, misunderstanding the benefits of treatment, or making irrational decisions.

First, consumers may have difficulty computing the OOP costs associated with using care for each type of cost-sharing in their plan. In my setting, computing OOP costs first requires that consumers understand the concepts of deductibles and copayments. Loewenstein et al. (2013) find that 78% of individuals could correctly define a deductible and 72% could correctly define a copayment in multiple choice questions, indicating some gaps in conceptual knowledge of cost-sharing incentives. For deductibles, additional information and calculations are necessary to arrive at OOP costs. An individual must know her own, and possibly her family's, year-to-date spending history in order to compute the amount remaining to hit the deductible. In addition, she must form an expectation for what services her physician will recommend should she seek treatment. Further, she must determine the prices her chosen provider will charge for each of these services. Finally, she must compare the expected total cost of the encounter (the sum of services times prices) to the amount remaining in the deductible to arrive at the expected deductible OOP costs. Consumers are unlikely to always have the service and price information necessary for this calculation, and acquiring the necessary information can require a great deal of effort. In particular, patients may have little basis for predicting the recommended services for treating a new set of symptoms, and even with knowledge

[3]This is not 100% accurate, as the plan out-of-pocket maximum creates an upper bound on total OOP costs. However, the vast majority of consumers have a very low probability of exceeding the OOP maximum.

of particular services health care prices are notoriously difficult to obtain.[4]

Even with knowledge of specific services and prices, putting all the information together to arrive at OOP costs may prove difficult for some consumers. Loewenstein et al. (2013) find that even though 78% of people understand the concept of a health insurance deductible, a much lower percent of people are actually able to estimate their OOP cost for using a particular service at a given price in a series of multiple choice questions. For example, only 41% of people answering the survey correctly computed their OOP cost for an in-network MRI before meeting the deductible, and 57% of people computed the correct OOP cost after meeting the deductible.

Consumers are also unlikely to possess full information on the health benefits of treatment, as demonstrated by evidence of underuse of high value care and overuse of low value care. McGlynn et al. (2003) estimate that Americans only receive about half of recommended care, including preventive, acute, and chronic care. Choudhry et al. (2011) study the impact of eliminating cost-sharing for highly valuable medications among patients who had previously experienced a heart attack . Although adherence increased following the elimination of cost-sharing, even under zero cost-sharing less than half of patients achieved full adherence to these recommended medications. These patients were notified by both mail and phone of the change, and so were well informed that they faced zero cost-sharing, indicating that lack of adherence was due to an underestimate of health benefits or a decision making bias such as myopia. Other evidence indicates that patients may overestimate the health benefits of some services. Patients consume care that the medical literature indicates is of zero benefit or, in some cases, harmful (Schwartz et al., 2014).[5]

Finally, the literature also identifies violations to frictionless, fully rational decision making in health care. Recent papers find evidence against fully forward looking behavior in responses to deductibles. Aron-Dine et al. (2015) and Einav et al. (2015) find evidence of partial (although imperfect) forward looking behavior, while Brot-Goldberg et al. (2015) find that consumers are completely myopic. Liquidity constraints are one potential friction for consumers. If patients are

[4]For example, an audit study conducted in the Denver market found that only 7 out of 19 hospitals contacted provided any price information when asked for a price quote for a total knee replacement, and most of those hospitals that did provide information provided a price range or average, rather than an exact quote (United States Government Accountability Office, 2011). The same study requested price information for a diabetes screening from physician offices and found that, although 14 out of 20 offices provided some type of price estimate, none provided the relevant negotiated rate for the patient's insurer. Acquiring price information in Massachusetts was thought to be difficult enough that in 2012 the state legislature passed a law requiring providers and insurers to make price information available to consumers beginning in 2014 (after my sample period). The law requires providers to disclose prices for specific services to patients upon request within two business days and requires insurers to make price information available to their enrollees via an online cost estimator tool. Even after the price transparency law took effect, a recent survey found that many specialists do not comply with the law's requirement to provide prices for requested services within two business days (Anthony, 2015). Altogether, many consumers do not have access to accurate price information when making treatment decisions.

[5]For a summary of the evidence on underuse of high value care and overuse of high value care, see Baicker et al. (2015), in particular Online Appendix Table 1.

liquidity constrained, they may be forced to delay or forgo care they would otherwise choose to consume. There is little direct evidence of how liquidity affects cost-sharing responses, but a recent survey suggests that liquidity constraints are unlikely to play a major role in explaining responses to the types of plans I study. Claxton et al. (2015) find that households with private health insurance have an average of $9,751 in liquid assets, ranging from $1,454 among those between 100-250% of the federal poverty level (FPL) to $20,379 among those with over 400% FPL, meaning even the typical low income consumer has enough liquidity to cover a typical copayment or moderate deductible expenditure. In addition, the impact of liquidity constraints is likely to be mitigated if cost-sharing is not due at the point of service or if consumers can use credit cards to pay costs due at the point of service. Other decision making biases identified in the behavioral economics literature, including salience and difficulty making decisions under uncertainty, are also likely to affect demand responses to cost-sharing.

3 Data

I study non-elderly individuals enrolled in employer-sponsored plans in Massachusetts from 2009-2013. I use the Massachusetts All Payer Claims Database (APCD), which contains health insurance claims and enrollment data for all privately insured individuals in the state over the years 2009-2013. The underlying data in the APCD are submitted by insurers to the Massachusetts Center for Health Information and Analysis, which consolidates the submitted data into files available to researchers through an open application process.[6] I observe each individual's plan and plan characteristics, the ID of the employer sponsoring the plan, prescription drug and medical claims, and some limited demographic information (including age, gender, and zip code). I focus on the four largest private insurers in the state, which cover 79% of commercial lives.

3.1 Plan characteristics

The APCD contains limited information on individual plan enrollment and plan characteristics. For each individual-plan observation, I observe the start and end dates of enrollment in the plan, the plan ID, the employer ID, the insurer ID, the insurance type (e.g. HMO, PPO), whether the product is fully or self-insured, and the plan deductible. I also infer a number of additional plan characteristics from the data.

[6] For more information on the APCD, see http://www.chiamass.gov/ma-apcd/

Plan year The plan year is a 12 month period over which a plan's cost-sharing rules apply. In the enrollment file, I observe the start and end dates each individual is enrolled in a product (e..g. January 2009 to June 2011), but not the start and end of each plan year. Identifying the plan year is particularly important for plans with a deductible because out-of-pocket spending accumulates towards the deductible within each plan year. In the employer-sponsored market, each firm generally has a common plan year that applies to all enrollees, regardless of the month of enrollment. Most employees enroll in their plan at the start of the plan year and are unable to change plans until the start of the next plan year. However, some individuals may not start or end enrollment in line with the plan year due to entering/exiting the firm or experiencing a life changing event (e.g. an employee's new spouse or child joins a plan mid-year). Because most individuals will enroll at the start of a plan year, I assign each employer a plan year start month if at least 70% of individual-plan observations associated with the employer enroll in that month. For example, if at least 70% of observations enroll in January, I define that employer's plan years to run from January 2009 to December 2009, January 2010 to December 2010, and so forth. The most common plan years begin in January (36%), July (12%), and April (8%).

Office visit and prescription drug benefits The main variables of interest for this project are the plan cost-sharing characteristics. However, only the deductible and the insurance type (e.g. HMO, PPO) are directly observed on the APCD enrollment file. Fortunately, for each claim line I observe the copayment amount, the total amount the consumer paid in copayments for the service, and the deductible amount, the total amount the consumer paid towards her deductible for the service. I use this information to infer each plan's office visit and prescription drug cost-sharing using the claims files as follows. I infer benefits separately for primary care office visits, specialist office visits, generic drugs, and branded drugs.[7]

For plans with a positive deductible, I first determine whether each type of service is subject to the deductible or carved out with copayments. I assign the service as subject to the deductible if I observe at least 5 claims with a positive deductible amount in the plan year.[8] Otherwise, I determine that the service is carved out of the deductible.

Next, for zero deductible plans and positive deductible plans with carve-outs, I infer service-specific copayments from the claims. For both types of office visits and generic drugs, I assign a

[7]Office visits are defined as the following CPT codes: 99201-99205, 99211-99215. Office visits are defined as primary care visits if the physician specialty is one of Primary Care, Family Practice, Family Medicine, General Practice, General Medicine, Internal Medicine, Pediatrics, Preventive Medicine. All other office visits are classified as specialist visits. Prescription drugs are defined as generic or branded using a flag on the pharmacy claims file.

[8]I allow for a small buffer in assigning a service as subject to the deductible because some plans will have a separate out-of-network deductible.

copay to a plan if at least 70% of service claims have the same copay amount in the plan year and at least 5 claims for that service exist in the plan year. I take a different approach for branded drug copayments, because it is common for a plan to have two or more tiers of copayments for branded drugs. For branded drugs, I take all the copayment amounts where that amount was paid for at least 10% of branded drug copayments and order those copayments to arrive at the branded drug tiers. For example, if I observe a \$20 copayment for 40% of branded prescriptions, \$40 for 35% of prescriptions, and \$75 for 15% of branded prescriptions, I would define the plan to have three tiers of brand copayments with tiers \$20, \$40, and \$75.

Final benefit structure Given each plan's visit and prescription drug carve out status and use of copayments, I categorize plans into the following benefit types:

1. Zero deductible, with positive copayments for office visits and prescription drugs (51%)
2. Positive deductible, with office visits and prescription drugs carved out and subject to copayments (34%)
3. Positive deductible, with prescription drugs carved out and subject to copayments and office visits subject to deductible (12%)
4. Positive deductible, with both prescription drugs and office visits subject to deductible (3%)

Other combinations of benefits (e.g. positive deductible with drugs carved out but not visits; zero deductible and zero copayments), had too few observations to be analyzed separately.

3.2 Sample restrictions

I impose a number of sample restrictions to the original APCD to arrive at the final analysis sample. My identification strategy relies on employer-level changes in plan offerings to identify responses to cost-sharing. Beginning with all individuals enrolled in employer-sponsored plans, the first set of restrictions are made due to incomplete data on elements necessary for the analysis. I exclude plans for which I am unable to link both their medical and pharmacy claims to the enrollment file, individuals who are missing the employer ID, and employer IDs for which I am unable to infer the plan year. Second, to facilitate use of individual fixed effects, I restrict the sample to individuals who I observe enrolled for at least two full years in the same employer. Next, I exclude plans for which I am unable to infer office visit and prescription drug benefits. Finally, I impose an employer-level restriction based on the nature of the choice set of plans offered by the employer.

Table 1: Impact of Sample Restrictions on Demographic Composition of the Sample

	All	+ 2 yrs	+ Benefits	+ Choice Set
N Years in Sample	2.04	2.83	2.94	2.99
Age				
0 - 20	0.31	0.32	0.32	0.32
21 - 34	0.21	0.18	0.18	0.18
35 - 44	0.17	0.17	0.18	0.18
45 - 64	0.32	0.33	0.33	0.32
Choice Set				
N Options	2.30	2.35	1.43	1.40
One Option	0.40	0.39	0.62	0.64
One Ins Type Option	0.67	0.67	1.00	1.00
Insurance Type				
HMO	0.71	0.71	0.75	0.77
PPO	0.23	0.23	0.19	0.17
POS	0.04	0.03	0.04	0.03
EPO	0.02	0.02	0.02	0.02
Annual Med+Rx Spending	\$4,278	\$4,118	\$4,054	\$3,969
Observations	2,322,098	1,316,897	799,353	699,219

Table reports the average demographic characteristics of individuals in their first year in the sample after making key sample restrictions. Data is at the individual level. Column (1) includes all individuals enrolled in employer-sponsored plans for whom complete data on medical and pharmacy claims, employer ID, and plan year are available. Column (2) further restricts the sample to individuals I observe enrolled for at least two full years with the same employer. Column (3) additionally restricts the sample to those enrolled in plans for which I am able to infer office visit and prescription drug benefits. Column (4) is the final analysis sample and imposes the last restriction requiring individuals to be enrolled through employers that offer only one plan option per insurance type (e.g. one HMO and one PPO).

Table 2: Average Copayments and Deductibles for Analysis Sample, by Benefit Structure

	Zero Deductible	Deductible Visits+Rx Carved Out	Deductible Rx Carved Out	Deductible Visits+Rx Included
Individual Deductible	$0.00	$1,038.20	$1,474.19	$1,922.30
Primary Care Visit Copay	$18.98	$21.12	$0.00	$0.00
Specialist Visit Copay	$20.67	$27.12	$0.00	$0.00
Generic Rx Copay	$10.99	$13.94	$11.61	$0.00
Brand Rx Tier 1 Copay	$19.88	$23.17	$25.83	$0.00
Brand Rx Tier 2 Copay	$35.43	$40.21	$41.65	$0.00
Brand Rx Tier 3 Copay	$44.23	$48.69	$47.82	$0.00
Observations	844,963	540,092	160,887	36,400

Table reports average copayments and deductibles for the final analysis sample, within each of the four benefit structures. Data is at the individual-year level. The first column includes plans with a zero deductible and copayments for office visits and prescription drugs. The second column includes positive deductible plans, with office visits and prescription drugs carved out and subject to copayments. The third column includes positive deductible plans, with prescription drugs carved out and subject to copayments and office visits subject to deductible. The fourth column includes positive deductible plans, with both prescription drugs and office visits subject to deductible.

I restrict the sample to employers that offer a simplified choice set, only one plan option for each insurance type (e.g. one HMO and one PPO), which allows me to identify the effects of interest using within employer-insurance type variation in cost-sharing. The motivation for this restriction will be explained more in the following section. After these restrictions, 30% of individuals remain. Table 1 describes the impact of these restrictions on the sample composition and sample size. The final sample is representative in terms of the age distribution, but has somewhat lower average spending. The final sample contains 699,219 individuals and 28,295 employers. Table 2 describes the average deductible and copayments for the final sample at the individual-year level, within each of the four benefit structures.

4 Empirical Strategy

4.1 Annual identification

The usual concern with identifying the effect of cost-sharing on spending is adverse selection: when given a choice, sicker individuals generally select into plans with lower cost-sharing. My approach isolates variation in plan cost-sharing that is uncorrelated with health status using changes in plan generosity within individuals across years. Since individual plan changes may be correlated with unobserved health shocks, I isolate changes due to employer-level changes in plan offerings using an instrumental variables strategy. The strategy exploits the fact that employees are very inertial in plan choice. In my sample, over 90% of people remain in the same type of plan (e.g. HMO, PPO) in every year. To take advantage of this, I restrict the sample to employers that offer a simplified choice set of only one option per insurance type to their employees. The most common example is an employer offering one HMO and one PPO plan. I then instrument for each individual's plan cost-sharing using the cost-sharing of her predicted plan, where her predicted plan is the plan of the same insurance type she was enrolled in the base year. For example, if an individual is enrolled in the PPO option in the base year, for all future years I predict he remains in the PPO option and instrument for his cost-sharing with the PPO plan's cost-sharing in that year. This approach effectively uses within employer-plan type cost-sharing changes to identify the effects of interest. For employers offering only one plan option, the instrument perfectly predicts the plan.[9]

The identification assumption is that individuals whose employers did not change cost-sharing serve as an appropriate counterfactual for individuals whose employers did change cost-sharing. Most of the changes I observe occur early in a relatively short panel, leaving limited ability to test the common trends assumption directly by comparing pre-trends. For the subsample of individuals for whom I do observe at least three years of data, I test this assumption by regressing changes in cost-sharing on lagged changes in spending in Appendix Table A.1. I find that lagged spending changes do not predict cost-sharing changes for this subsample, providing support for the identification assumption.

The primary empirical objective of this paper is to compare price sensitivity to deductibles and copayments by estimating spending elasticities with respect to OOP costs. Before estimating elasticities with respect to OOP costs, which requires constructing new OOP price variables, I first present simple treatment effects of deductibles and copayments on annual spending. Because plan features vary at the annual level, this presents the cleanest way to understand the pure average treatment effects of these contract dimensions before interpreting these effects in terms of OOP costs. For individual i, in firm f, and plan year y, I regress log annual spending on plan deductibles and copayments in specifications of the form

$$log(y_{ify} + 1) = \alpha_d deduct_{ify} + \alpha_c copay_{ify} + X'_{ify}\beta + \delta_y + \eta_i + \epsilon_{ify}$$

[9] An alternative would be to use employer by plan type fixed effects, rather than individual fixed effects, since this is the level of treatment. I choose to use individual FE because of concerns with changes in the composition of individuals within employers when cost-sharing changes. For example, a married couple who originally obtains coverage through spouse A's employer may switch to obtaining coverage through spouse B's employer if spouse A's employer raises cost-sharing.

where y_{ify} is health care spending (including both the insurer and patient components), X_{ift} are time-varying characteristics of the individual and firm (age, industry, self-insured status, 3 digit zip code fixed effects, employer size, single/family plan status, plan type - HMO/PPO/POS/EPO, family size), η_i are individual fixed effects, and δ_y are plan year fixed effects (including separate time trends by insurer and self-insured status). I include $deduct_{ify}$ and $copay_{ify}$ as dummy variables for different categories of deductibles and copayments and instrument for each cost-sharing element using the cost-sharing of the individual's predicted plan. Due to highly inertial plan choice and the prevalence of employers offering only one plan option in my sample, the instruments are extremely strong, with first stage partial F statistics greater than 1,000 in all specifications. I cluster standard errors at the employer level.

Table 3 presents results from annual regressions of log spending on the cost-sharing features of interest. I present the own price effects of each type of cost-sharing separately. As shown in panel (a), I estimate that on average moving from a \$0 to a \$1,000 individual deductible decreases annual spending on deductible-eligible services by about 13.6%. Since the services that are subject to the deductible vary depending on whether office visits and prescription drugs are carved out, I define this spending category as services that are never carved out of the deductible. That is, as all spending excluding preventive care, office visits, and prescription drugs. This annual effect is consistent with other recent studies of deductibles in employer-sponsored plans. For example, Brot-Goldberg et al. (2015) find that an individual deductible of \$1,500 that applied to all non-preventive services reduced total spending by 12-14% in one large firm. In a sample of large firms, Haviland et al. (2016) find that consumer directed health plans with individual deductibles of \$1,000 or more that apply to all non-preventive services decrease total spending by 22% in the first year. However, this is a local average treatment effect (LATE) identified off of employees with much lower take-up compared to my sample. If employees who take-up high cost-sharing plans are more price sensitive, this LATE would overstate the average effect over all employees. Among high take-up firms, a closer comparison to my research design, they find a spending decrease of 15%. I do not find an additional marginal effect of moving from a \$1,000 to a \$2,000 deductible, which could be idiosyncratic to my sample.

Panels (c) and (d) present the effects of office visit copayments for primary care and specialist visits on office visit spending. I control directly for whether the plan has visits or prescription drugs subject to the deductible, so the copay effects are identified off of changes in copay levels among plans with copayments. Moving from a primary care office visit copayment of \$10 (the omitted category) to \$20 reduces primary care visit spending by 8.0%, and moving from a specialist copay of \$10 to \$30 or more reduces specialist office visit spending by 10.5%. In comparison, Chandra et

Table 3: Annual Own-Price Treatment Effects of Deductibles and Copayments

	Deductible
Deductible	
\$1-499	-0.219
	(0.133)
\$500-999	-0.092***
	(0.023)
\$1000-1999	-0.136***
	(0.020)
\$2000-2999	-0.131***
	(0.027)
\$3000+	-0.025
	(0.070)
N	1,904,579
R^2	0.646

(a) Deductible

	Rx
Rx Copayments	
Generic (\$10s)	-0.121***
	(0.036)
Brand Tier 1 (\$10s)	-0.018*
	(0.010)
Brand Tier 2 (\$10s)	0.015**
	(0.007)
Brand Tier 3 (\$10s)	-0.015**
	(0.007)
Deductible Includes Rx	-0.306***
	(0.069)
N	1,904,579
R^2	0.803

(b) Rx

	Primary Care Visits
Primary Care Visit Copayments	
\$15	-0.030
	(0.022)
\$20	-0.080***
	(0.022)
$\geq$ \$25	-0.082***
	(0.023)
Deductible Includes Visits	-0.134***
	(0.026)
N	1,904,579
R^2	0.643

(c) Primary Care

	Specialist Visits
Specialist Visit Copayments	
\$15	-0.056*
	(0.029)
\$20	-0.072**
	(0.028)
\$25	-0.068**
	(0.031)
$\geq$ \$30	-0.105***
	(0.039)
Deductible Includes Visits	-0.126***
	(0.033)
N	1,904,579
R^2	0.643

(d) Specialist

* p<0.10, ** p<0.05, *** p<0.01. Standard errors are in parentheses and clustered at the employer level.
Table reports coefficients from IV regressions of log annual spending on plan cost-sharing levels. Panel (a) reports coefficients from IV regressions of log deductible-eligile spending on indicator variables for individual deductible categories. The omitted category is zero deductible. Panel (b) reports coefficients from IV regressions of log primary care visit spending on indicator variables for levels of the primary care visit copayment. The omitted category is a \$10 copayment. Panel (c) reports the equivalent specifications for specialist visit spending and copayments. Panel (d) reports coefficients from IV regressions of log prescription drug spending on prescription drug copayment levels in \$10s. For panels (b)-(d), a dummy variable indicating that the plan uses deductible incentives for drugs or visits is included so that the copayment coefficients can be interpretted as the effect of higher copayment levels among plans using copayments for these services. In all panels, each cost-sharing feature is instrumented using the corresponding cost-sharing feature of the individual's predicted plan (see text for details). All specifications include individual and time fixed effects.

al. (2010) find that increasing office visit copayments by $10 reduced visits by 17% in an elderly population.

Panel (b) presents the effect of prescription drug copayments on prescription drug spending. This specification controls for whether the plan has prescription drugs subject to the deductible, so that the copay effects are identified off of changes in copay levels among plans with copayments, and includes the generic and tiers of branded copayments linearly in $10s. Increasing the generic drug copay by $10 decreases prescription drug spending by 12.1% and increasing the lowest tier branded copay by $10 decreases prescription drug spending by 1.8%. The coefficients on the branded drug copayments are difficult to interpret in these specifications, since the particular drugs included in each tier are likely to vary across plans. The main specifications will take this into account by assigning each branded drug to a fixed tier for simulating OOP costs. Joyce et al. (2002) find that doubling copayments for all types of drugs from $5 to $10 reduced prescription drug spending by 22%. For another type of plan, they find that jointly doubling copayments for generic drugs from $5 to $10 and for branded drugs from $10 to $20 reduced prescription drug spending by 33%. They also find that adding an additional $30 non-preferred brand drug tier reduced spending by 1.8%. My drug copayment effects are somewhat smaller, however the plans I study have somewhat higher copayments, particularly for branded drugs, at baseline compared to this study.

These estimates illustrate the average annual impact of deductibles and copayments. However, deductibles and copayments are fundamentally different types of prices measured in different units. Raising the deductible by $1 has different implications for OOP costs compared to raising a copayment by $1. From these estimates alone it is impossible to say whether consumers are more or less price sensitive to deductibles relative to copayments.

4.2 Constructing OOP costs

To compare price sensitivity to copayments and deductibles, I transform both into their implied OOP costs. Doing so scales deductibles and copayments into comparable units, allowing me to compare how individuals respond to an additional dollar in OOP costs due to copayments or deductibles. I construct monthly-level measures that capture the marginal OOP amount an individual is predicted to face over the course of a month for using deductible or copay services. Ideally, I would construct these prices with knowledge of all the OOP costs each patient faced over the month, including costs for services that the individual considered but were not chosen. Since claims data only record services that are actually consumed, which reflects the demand response to cost-sharing, I instead estimate the OOP costs each individual is predicted to face over the course of the month.

I estimate the OOP costs faced by each patient in a given month using the consumption of a fixed sample of other individuals of a similar risk type. In the spirit of a simulated instrument, I simulate individual i's OOP costs as the average OOP costs other individuals of the same risk type would pay if they were enrolled in individual i's plan. Constructing OOP costs within risk type reflects the fact that individuals of different spending risk are likely to face different OOP costs due to differences in health status.

Risk classification To define an individual's risk type, I first categorize individuals by their ex-ante spending risk using the John's Hopkins ACG algorithm predictive risk score.[10] I run the ACG algorithm on each individual's claims from their first year in the sample and divide individuals into deciles of their base year ACG risk score. I then interact these deciles with 3 different age categories (0-19, 20-39, 40-65), leaving me with 30 risk categories. After collapsing a few small cells to ensure that each cell contains at least 5,000 individuals, I am left with 28 categories. Since risk groups are defined based on characteristics in the base year, they do not change over the sample period.

Copay price The monthly copay price, P^c_{igt} is the predicted dollar OOP amount individual i of risk type g faces over month t for using services subject to copayments. For individual i, in risk group g, at time t, enrolled in a plan with $copay_{ist}$ for service s

$$\begin{aligned} P^c_{igt} =& \frac{1}{|J_g|} \sum_{j \in J_g} \sum_{s \in S_i} q_{jst} \times copay_{ist} \\ =& \sum_{s \in S_i} \bar{q}_{gst} \times copay_{ist} \end{aligned}$$

where $\bar{q}_{gst}$ is the average number of service s used by other people of the same risk type, g, in a month and S_i is the set of all services subject to copayments in individual i's plan. In other words, this measure scales the copay amounts of individual i's plan by her probability of using services subject to copayments. This OOP price reflect the joint effect of copayment generosity for all services summed.[11]

The set of services subject to copayments depends on the plan benefit type defined earlier and can include primary care visits, specialist visits, generic drug prescriptions, and branded drug prescriptions. Depending on the plan, there may be up to three tiers of branded drug copayments,

[10] The John's Hopkins ACG algorithm is proprietary software that uses the diagnoses observed on an individual's claims, together with age and gender, to generate an index of the individual's predicted spending in the future.

[11] This approach is similar to how Chandra et al. (2014) aggregate multiple copayment changes into a single measure of copay OOP costs, with the difference that their utilization weights do not vary by risk type.

with different plans placing drugs in different tiers. To scale the branded copayments using average utilization, I categorize each branded drug into a consistent tier. To do so, I pool all the pharmacy branded claims and, for each drug, compute the most common tier across plans. I then use those simulated tiers to compute the $\bar{q}_{gst}$'s used to scale the branded copayments.

Deductible price I construct two types of deductible prices, beginning with the deductible spot price. A completely myopic consumer considers his marginal price to be the current spot OOP price when deciding how much to consume at time t. I define the monthly deductible spot price, P^s_{igt}, as the predicted dollar OOP amount individual i, in risk group g, faces over month t for using services subject to the deductible. This price is computed as

$$P^s_{igt}\left(R_{it}\right) = \frac{1}{|J_g|} \sum_{j \in J_g} \min\left\{R_{it}, DeductSpend^i_{jt}\right\}$$

where $R_{it} = \min\left\{Deductible_i - M_{ift}, 0\right\}$ is the amount remaining for individual i to hit the deductible at the beginning of month t given family cumulative year to date spending $M_{ift} = \sum_{m=1}^{t-1} \sum_f DeductSpend_{ifm}$ at the beginning of month t on services subject to the deductible, J_g is the set of other people in risk cell g, and $DeductSpend^i_{jt}$ is spending on services that are subject to the deductible in individual i's plan by individual j in month t.[12] In other words, I compute each person j's spot price as if each was in individual i's plan and had i's spending history and then average. Once individuals hit the deductible, $R_{it} = 0$ and P^s_{igt} is zero for the rest of the plan year.[13] This measure reflects the deductible of individual i's plan, her progress toward meeting the deductible at the beginning of month t, and her underlying propensity for using services subject to the deductible.

A fully rational, forward looking consumer realizes that her spending today affects the probability of exceeding the deductible, and thus her OOP price, in the future. Thus she considers her true marginal price to be the expected spot price she will face in the last month of the plan year, referred to as the expected end-of-year (EOY) price, and makes consumption decisions at time t based on the expected EOY price rather than the spot price. I define the monthly deductible expected EOY price at the beginning of month t, P^e_{igt}, as the OOP amount the individual expects to face in the last month T of the plan year, where the expectation is taking conditional on her risk group g, her family's history of spending in the plan year up to month t, M_{ift}, and family size F_{it}.[14] I compute P^e_{igt} as a rational expectation by taking the average spot price in month T others in same

[12] For individuals in single plans, M_{ift} only includes the individual's own spending.
[13] This ignores any coinsurance individuals pay after hitting the deductible, which I do not observe.
[14] Family size is included because for family plans, a larger number of people increases the probability of hitting the deductible.

(M_{gt}, G, F_i) cell would have if they were enrolled in individual i's plan

$$P^e_{igt} = E_t \left[P^s_{igT} \left(R_{iT} \right) \mid M_{gt}, G, F_i \right]$$

where M_{gt} is decile of cumulative family spending within risk-cell, G is risk cell, F_i is family size cell (1,2,3+).[15] The cells were chosen to ensure at least 100 observations per cell. This approach to computing expected EOY prices is adapted from Brot-Goldberg et al. (2015).

4.2.1 OOP price instruments

The OOP prices defined above are functions of each individual's demographics, plan cost-sharing, and within-year spending history (for P^s and P^e). Of these, plan cost-sharing and spending history are potentially correlated with unobservables affecting demand due to adverse selection (cost-sharing) or within-year health shocks (spending history). As described earlier, the concern with plan cost-sharing is that individuals with high expected spending will adversely select into low cost-sharing plans. The concern with spending history is that, since health shocks and health spending are serially correlated, individuals with an adverse health event and associated spending in the beginning of the plan year will have lower P^s and P^e (due to spending toward the deductible) and higher expected spending (due to subsequent care related to the initial adverse event) later in the plan year.[16] To address these endogeneity concerns, I construct instruments for P^c, P^s, and P^e that are functions of demographics, *predicted* plan cost-sharing and the within-year spending history of *other* people. As in the annual specifications, predicted plan cost-sharing is based on the plan of the same insurance type the individual was enrolled in the base year, so that all cost-sharing variation is a result of employer-chosen plan changes.

For individual i, in risk group g, at time t, enrolled in a plan with $copay_{ist}$ for service s, the copay instrument is defined as

$$\tilde{P}^c_{igt} = \sum_{s \in \hat{S}_i} \bar{q}_{gst} \times cop\hat{a}y_{ist}$$

where $cop\hat{a}y_{ist}$ is the copay of individual i's predicted plan and $\hat{S}_i$ is the set of services subject to copayments in the predicted plan. The only difference here is the substitution of the predicted copayment for the actual copayment and predicted set of services for the actual set of services.

[15] Computed as leave-one-out means so the individual's own behavior does not affect the expectations.

[16] Different papers have used different approaches to dealing with this mechanical correlation of deductible spot and expected prices and within-year spending. For example, Aron-Dine et al. (2015) estimate off of individuals with exogenously different spot and expected prices based on the month of the year they join their plan. Brot-Goldberg et al. (2015) construct hypothetical spot and expected prices for individuals in the same spending quantile under a different deductible.

I instrument for P^s and P^e using price instruments, $\tilde{P}^s$ and $\tilde{P}^e$, that are constructed using the spending history of other people of the same risk type and family size. I construct these instruments in two steps. First, I predict each person j's spot and expected prices as if each was enrolled in individual i's predicted plan. The predicted spot price is

$$\hat{P}^s_{ijgt}\left(\hat{R_{ijt}}\right) = \frac{1}{|J_g|}\sum_{j \in J_g} \min\left\{\hat{R_{ijt}}, DeductSpend^i_{jt}\right\}$$

where $\hat{R_{ijt}} = \min\left\{Ded\hat{uctible}_i - M_{jft}, 0\right\}$ is the amount remaining based on individual j's spending under individual i's predicted deductible, $Ded\hat{uctible}_i$. The corresponding expected EOY price is

$$\hat{P}^e_{ijgt} = E_t\left[\hat{P}^s_{ijgT}\left(\hat{R_{ijT}}\right) \mid M_{gt}, G, F_{jt}\right]$$

The key difference between these prices and the original prices defined above is that these are based on j's spending history, rather than i's. Second, for each individual i I compute instruments by averaging the predicted spot and expected price of other people in individual i's risk cell. For $k = s, e$ the price instrument for individual i in month t is

$$\tilde{P}^k_{igft} = \frac{1}{|J_{gf}|}\sum_{j \in J_{gf}} \hat{P}^k_{ijgt}$$

where J_{gf} is the set of all people in the same (G, F_t) cell. Because the individual's own spending is not used to construct the instrumented prices, the mechanical correlation of the prices and within-year spending is removed, leaving only variation coming from the exogenous (predicted) deductible change. Note that since individual fixed effects are included in all specifications, the effects of being in a given risk group are already averaged out. Family size is controlled for directly as a covariate. These instruments are highly predictive, yielding first stage partial F statistics greater than 1000 in all specifications. See Appendix Table A.2 for the first stage estimates.

Table 4 describes the variation in P^c, P^s, and P^e for patients of below and above median risk score. Since spot and expected prices evolve over the course of the plan year, I show variation in both the first and last month of the year. Deductibles result in more monthly OOP costs than copayments. About 16% of low risk individuals and 82% of high risk individuals can expect to face \$72.78 or more in deductible OOP costs in the first month, whereas nearly all low risk consumers and 50% of high risk consumers are predicted to face \$19.07 or less in copayment OOP costs in any given month. Prices are on average higher for higher risk individuals, reflecting a greater propensity

Table 4: Variation in Constructed OOP Price Variables, by Spending Risk

	Low Risk Month 1	Low Risk Month 12	High Risk Month 1	High Risk Month 12
Zero Deductible	0.51	0.51	0.50	0.50
Positive Deductible: \$ Spot OOP				
0 - 41.50	0.49	0.81	0.02	0.68
41.51 - 72.77	0.35	0.14	0.17	0.09
72.78 - 130.81	0.14	0.05	0.35	0.13
130.82 +	0.02	0.00	0.47	0.09
Positive Deductible: \$ Expected EOY OOP				
0 - 11.35	0.34	0.53	0.17	0.64
11.36 - 21.36	0.31	0.10	0.19	0.01
21.37 - 38.73	0.26	0.16	0.24	0.02
38.74 +	0.09	0.21	0.40	0.33
Copay OOP				
0.77 - 6.01	0.50	0.50	0.00	0.00
6.02 - 11.01	0.39	0.39	0.11	0.11
11.02 - 19.07	0.11	0.11	0.39	0.39
19.08 +	0.00	0.00	0.49	0.49
Observations	941,096	940,585	966,113	965,746

Table reports the distribution of the constructed OOP price variables, broken out by plan month and low vs high risk type. Data is at the individual-month level. I compute the OOP price variables by simulating the average OOP costs a fixed sample of other people of the same risk type would pay as a result of copayments or deductibles if they were enrolled in each individual's plan (see Section 4.2 for details). Columns (1) and (2) report the distributions for individuals of below median spending risk in the first and last month of the plan year, respectively. Columns (3) and (4) report the same distributions for individuals of above median spending risk. The first row reports the share of these groups enrolled in zero deductible plans, for reference. The distributions of the deductible spot and expected OOP price variables are only reported for individuals enrolled in positive deductible plans (they are zero otherwise). The distribution of the copayment OOP price variable is reported for individuals in all plans.

for using health care. Although the high risk group is more likely to hit the deductible, which pushes them to have lower spot prices as the plan year progresses, they face more OOP costs in a given month given their overall higher propensity for using health care services.

4.3 Main specifications

I estimate responses to OOP costs at the monthly level, where for individual i in firm f in risk group g, plan year y, and plan month t

$$log(y_{ifgyt} + 1) = \alpha_{ds} P^{s}_{ifgyt} + \alpha_{de} P^{e}_{ifgyt} + \alpha_c P^{c}_{gyt} + \lambda_{rx} + \lambda_{off} + X'_{ify}\beta + \delta_y + \delta_t + \eta_i + \epsilon_{ifgyt}$$

where δ_t are plan month fixed effects. I include indicators, λ_{rx} and λ_{off}, for whether the plan has a deductible with prescription drugs or office visits subject to the deductible. As described above, I instrument for P^c_{gyt}, P^e_{ifgyt}, and P^s_{ifgyt} in all specifications. I also instrument for λ_{rx} and λ_{off} with indicators for whether the *predicted* plan has a deductible with prescription drugs or office visits subject to the deductible. Standard errors are clustered at the employer level for all specifications.

The choice to model spending as a linear specification with a $log(y + 1)$ transformation was made based on its common use in the literature (Aron-Dine et al., 2015; Brot-Goldberg et al., 2015; Finkelstein et al., forthcoming) and ease of estimation with a large number of fixed effects. The next draft of the paper will explore sensitivity to alternative approaches to modeling spending, including alternative transformations, quantile regression, and generalized linear models.

5 Results

Table 5 presents my main estimates of the own price effects of deductibles and copayments on monthly spending for total spending, services always subject to the deductible, office visits, and prescription drugs. Services always subject to the deductible include all types of spending with the exception of office visits, prescription drugs, and preventive care. The specifications include the copayment and deductible spot OOP price measures defined in the previous section (in $10's), along with indicators for whether visits and prescription drugs are subject to the deductible. I omit the expected EOY OOP price in this first set of specifications to focus on the contrast between copayment and deductible effects. Later, I will show that the deductible effects are driven by responses to the spot price rather than the expected EOY price. Recall that if visits and prescription drugs are subject to the deductible, they will be included in the deductible OOP price, otherwise they will be included in the copay OOP price.

I estimate that for all types of spending, copayments elicit greater spending reductions for each additional dollar in OOP costs. The last row of the table displays the p-values from Wald tests that the deductible and copay coefficients are equal. I can reject that the deductible and copay coefficients are equal at the 1% level for all spending types. I show that the own price effects of deductibles are much smaller relative to the own price effects of copayments, rejecting the first prediction of the fully informed, rational model. A \$10 increase in the deductible spot price reduces spending on deductible services by 0.9%, while a \$10 increase in the copay OOP price reduces spending on office visits and prescription drugs by 8.4%.

I also find that both deductibles and copayments affect spending on types of care they do not directly incentivize. In fact, I find even larger copay elasticities for total and deductible spending relative to the own price elasticities. There are two ways to interpret these cross-price effects. First, that they represent a misunderstanding of benefit design. Given the complexity of health insurance, perhaps consumers are confused or forget which services are subject to deductibles vs copayments. Indeed, one survey found very low consumer understanding of whether office visits, emergency department visits, and medical tests were subject to the deductible (Reed et al., 2009). Second, if services subject to deductibles and copayments are complements, then a price increase in one type of spending will cause a decrease in both types of spending. This seems particularly plausible for office visits. Some tests and procedures may only be performed when a patient goes in for an office visit. Other types of care require a physician's diagnosis or referral before the patient can receive treatment.

There are also large direct effects of including visits and prescription drugs in the deductible. Even controlling for OOP costs, subjecting visits to the deductible reduces total spending by 9.5% and subjecting prescription drugs reduces total spending by 14.4%.

The strongest comparison of deductible and copayment price responsiveness compares OOP costs for the same set of services observed under both types of cost-sharing. To make this comparison, I decompose the deductible spot price into two components: OOP costs for office visits and prescription drugs and OOP costs for all other types of spending.[17] The visit and drug component of the spot price is identified off of plans that have visits and drugs subject to the deductible, while the component that includes other types of spending is identified off of all types of plans. Comparing the visit and drug component of the spot price to the copay price, which only includes visits and prescription drugs, in Table 6 indicates that the copayment response is still significantly larger than the deductible response. Column (3) shows that a \$10 increase in monthly deductible OOP costs attributable to visits and prescription drugs reduces spending on visits and drugs by 1.4%, while a \$10 increase in monthly copayment OOP costs for visits and prescription drugs reduces spending on visits and drugs by 8.6%. The last row of the table displays the p-values from Wald tests that the coefficients on the visit and drug component of the spot price and the copay price are equal. I can

[17] I decomposed the spot price by re-simulating OOP costs separately for both types of spending using the method outlined in Section 4.2.

Table 5: Impact of Copayments and Deductibles for Targeted Spending Categories

	(1) Total	(2) Deductible	(3) Visits+Rx	(4) Visits	(5) Rx
Spot Price ($10s) [a]	-0.011***	-0.009***	-0.008***	-0.005***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Copay Price ($10s) [b]	-0.147***	-0.113***	-0.084***	-0.052***	-0.059***
	(0.014)	(0.009)	(0.011)	(0.006)	(0.010)
Deductible Includes Visits [c]	-0.095***	-0.068***	-0.050***	-0.038***	-0.026***
	(0.010)	(0.007)	(0.008)	(0.004)	(0.007)
Deductibles Includes Rx [d]	-0.144***	-0.054**	-0.112***	-0.057***	-0.097***
	(0.042)	(0.025)	(0.030)	(0.016)	(0.025)
N	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538
R^2	0.377	0.235	0.430	0.173	0.538
N Clusters	28,295	28,295	28,295	28,295	28,295
N FE	699,214	699,214	699,214	699,214	699,214
Test P-value [e]	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses and clustered at the employer level

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from IV regressions of log monthly spending on OOP deductible spot and OOP copay prices. Each column reports a different type of spending as the dependent variable. The spot and copay coefficients are interpretted as the percentage impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively. For example, in Column (1) a $10 increase in copayment OOP costs reduces total monthly spending by 14.7%. Each variable reported is instrumented using the predicted version of the variable (see text for details). The partial F-statistics for all four variables are greater than 1,000. All specifications include individual and time fixed effects.

[a] The spot price is the predicted dollar OOP amount the individual faces over the month for using services subject to deductibles. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to deductibles under each individual's plan.

[b] The copay price is the predicted dollar OOP amount the individual faces over the month for using services subject to copayments. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to copayments under each individual's plan. Services subject to copayments include office visits and prescription drugs, depending on the plan.

[c] An indicator that office visits are subject to the deductible.

[d] An indicator that prescription drugs are subject to the deductible.

[e] P-value is from a Wald test that the spot and copay coefficients are equal.

reject that the effects are equal at the 1% level for all spending types.

Table 7 shows the price effects on more detailed categories of spending: preventive care, professional services, inpatient facility, outpatient facility, and emergency department.[18] Consistent with prior work, inpatient care is the least sensitive to cost-sharing. Column (1) shows that both deductibles and copayments reduce preventive care, which by law is exempt from all cost-sharing following the 2010 passage of the ACA. Previous studies also find that moving to a high deductible plan reduces preventive care (Buntin et al., 2011; Brot-Goldberg et al., 2015) and prescription drugs (Huckfeldt et al., 2015) even when they are exempt from the deductible.[19] As discussed in the previous paragraph, this could be due to misunderstanding of benefits or a complementarity of preventive care with services subject to cost-sharing. One survey of enrollees in a high deductible health plan with preventive care exempt found that only 18% understood preventive visits were exempt and only 10% understood that preventive tests were exempt (Reed et al., 2012).

In Table 8, I benchmark these estimates to spending elasticities from prior work. I present spending effects in both arc elasticities, commonly reported due to the RAND Health Insurance Experiment (HIE), and monthly dollar semi-elasticities, the measure I use in my main specifications. For details on how I translate the reported spending effects from other studies into arc elasticities and monthly semi-elasticities, see Appendix B. Compared to the coinsurance elasticities estimated from the 1970s RAND HIE (Manning et al., 1987; Newhouse and the Insurance Experiment Group, 1993), my copay elasticities are somewhat higher and deductible elasticities quite a bit lower. A more recent study by Chandra et al. (2014) estimates the joint effect of increasing copayments for hospital admissions, emergency room visits, outpatient surgery, office visits, and prescription drugs on total spending and finds an arc elasticity in line with the RAND HIE. My estimates of copayments on total spending are very similar to comparable estimates in Chandra et al. (2014), however my own-price effects of copayments from Table 5 (which do not have an analogue in Chandra et al. (2014) due to the nature of their price changes) are smaller. I also find somewhat smaller deductible spending responses compared to a recent study of a large employer's transition to a high deductible health plan (Brot-Goldberg et al., 2015).

Robustness The main result that copayment responses are significantly larger than deductible responses is robust to a number of alternative specifications. One concern is that I must compare consumer price sensitivity to deductibles and copayments using measures of OOP costs that are estimated from the data. As a result, my price measures of interest contain measurement error.

[18] I define preventive care using the requirements in the ACA. See http://www.cdc.gov/prevention/billingcodes.html

[19] Other studies find that preventive care does not respond to deductibles (Rowe et al., 2008).

Table 6: Decomposing the Deductible Effect into OOP Costs for Visits+Rx and Other Services

	(1) Total	(2) Deductible	(3) Visits+Rx	(4) Visits	(5) Rx
Spot Price, Visit+Rx	-0.024***	-0.021***	-0.014***	-0.007***	-0.010***
Component (10s) [a]	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Spot Price, Other	-0.009***	-0.008***	-0.007***	-0.005***	-0.006***
Component (10s) [a]	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Copay Price (10s) [b]	-0.155***	-0.122***	-0.086***	-0.054***	-0.060***
	(0.013)	(0.009)	(0.010)	(0.006)	(0.009)
Deductible Includes	-0.064***	-0.047***	-0.034***	-0.034***	-0.015**
Visits [c]	(0.011)	(0.007)	(0.008)	(0.005)	(0.007)
Deductibles Includes Rx [d]	-0.139***	-0.038	-0.120***	-0.061***	-0.103***
	(0.047)	(0.026)	(0.033)	(0.017)	(0.027)
N	19,932,808	19,932,808	19,932,808	19,932,808	19,932,808
R^2	0.380	0.238	0.433	0.175	0.541
N Clusters	28,077	28,077	28,077	28,077	28,077
N FE	636,095	636,095	636,095	636,095	636,095
Test P-value [e]	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses and clustered at the employer level.

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from IV regressions of log monthly spending on OOP deductible spot and OOP copay prices. Each column reports a different type of spending as the dependent variable. The spot and copay coefficients are interpretted as the percentage impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively. For example, in Column (1) a $10 increase in copayment OOP costs reduces total monthly spending by 15.5%. Each variable reported is instrumented using the predicted version of the variable (see text for details). The partial F-statistics for all four variables are greater than 1,000. All specifications include individual and time fixed effects.

[a] The spot price is the predicted dollar OOP amount the individual faces over the month for using services subject to deductibles. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to deductibles under each individual's plan. In this specification, the spot price is decomposed into a component attributable to office visits and prescription drugs and a component of all other services. The two components sum to the total spot price used in Table 5.

[b] The copay price is the predicted dollar OOP amount the individual faces over the month for using services subject to copayments. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to copayments under each individual's plan. Services subject to copayments include office visits and prescription drugs, depending on the plan.

[c] An indicator that office visits are subject to the deductible.

[d] An indicator that prescription drugs are subject to the deductible.

[e] P-value is from a Wald test that the spot visit+rx component and copay coefficients are equal.

Table 7: Impact of Copayments and Deductibles for Other Spending Categories

	(1) Preventive	(2) Professional	(3) Inpatient	(4) Outpatient	(5) ED
Spot Price (10s)	-0.003***	-0.009***	-0.000**	-0.006***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Copay Price (10s)	-0.046***	-0.130***	-0.008***	-0.073***	-0.018***
	(0.004)	(0.011)	(0.002)	(0.007)	(0.002)
Deductible Includes Visits	-0.028***	-0.089***	-0.004***	-0.041***	-0.009***
	(0.003)	(0.008)	(0.001)	(0.005)	(0.001)
Deductibles Includes Rx	-0.038***	-0.095***	-0.011***	-0.068***	-0.014***
	(0.010)	(0.034)	(0.003)	(0.017)	(0.004)
N	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538
R^2	0.099	0.252	0.065	0.204	0.061
N Clusters	28,295	28,295	28,295	28,295	28,295
N FE	699,214	699,214	699,214	699,214	699,214
Test P-value	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from IV regressions of log monthly spending on OOP deductible spot and OOP copay prices. Each column reports a different type of spending as the dependent variable. The spot and copay coefficients are interpretted as the percentage impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively. For example, in Column (1) a $10 increase in copayment OOP costs reduces monthly spending on preventive care by 4.6%. Each variable reported is instrumented using the predicted version of the variable (see text for details). The partial F-statistics for all four variables are greater than 1,000. All specifications include individual and time fixed effects.

[a] The spot price is the predicted dollar OOP amount the individual faces over the month for using services subject to deductibles. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to deductibles under each individual's plan.

[b] The copay price is the predicted dollar OOP amount the individual faces over the month for using services subject to copayments. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to copayments under each individual's plan. Services subject to copayments include office visits and prescription drugs, depending on the plan.

[c] An indicator that office visits are subject to the deductible.

[d] An indicator that prescription drugs are subject to the deductible.

[e] P-value is from a Wald test that the spot and copay coefficients are equal.

Table 8: Comparison to Price Elasticity Estimates from the Literature

Study	Type of Price Change	Setting	Arc elasticity	Monthly semi-elasticity ($10s)
RAND HIE	coinsurance	Experiment, 1974-1981	-.20	-.103
BCHK	deductible	Large firm case study, 2009-2014	-.07	-.020
CGM	copay	MA low income exchange, 2007-2009	-.20	-.158
Stockley	deductible	MA employer-sponsored plans, 2009-2013	-.04	-.011
Stockley	copay	MA employer-sponsored plans, 2009-2013	-.32	-.147
Stockley	joint	MA employer-sponsored plans, 2009-2013	-.10	-.011

Note: In all cases, the elasticities reported are for total spending with respect to each of the cost-sharing measures. The estimated monthly dollar semi-elasticities from my paper can be found in Table 5, column 1. RAND HIE is the RAND Health Insurance Experiment (Manning et al., 1987); BCHK is Brot-Goldberg, Chandra, Handel, and Kolstad (2015); CGM is Chandra, Gruber, and McKnight (2014). See Appendix B for details.

Classical measurement error would bias both the copay and deductible effects toward zero. The concern for comparing deductible and copayment effects is if there is differential measurement error in the copayment and deductible OOP price measures. To test for this, I present alternative specifications where I instrument for the constructed deductible and copayment OOP prices using the deductible and copayment levels of the individual's predicted plan. Since OOP prices are functions of the deductible and copayment levels and the utilization of other people, the levels are correlated with the OOP price but not the measurement error. A comparison of these new estimates with the original estimates can be found in Appendix Tables A.4 and A.5. The magnitudes of the deductible and copay coefficients are actually somewhat smaller, but the result that the copayment effects are an order of magnitude larger than the deductible effects is robust to this alternative specification. I also show that the results are robust to different ways of conditioning on the plan benefit structure in Appendix Table A.3.

6 Mechanisms

Having found that consumers are more responsive to OOP costs due to copayments relative to deductibles, I now aim to explain this result and how it relates to other previously studied deviations from fully informed, rational behavior.

First, since survey evidence indicates that many consumers misunderstand cost-sharing, I test to what extent the wedge in OOP cost responsiveness is mitigated among groups with better information. Next, I revisit two of the most studied deviations from fully informed, rational behavior in the prior literature: reductions in highly valuable medications and lack of forward looking behavior in response to deductibles. Prior studies find robust evidence that higher cost-sharing causes lower adherence to highly valuable chronic medications. If the use of copayments exacerbates this effect, this is a cause of concern for copayment-based plans. A number of papers also find that consumers are myopic in responding deductibles. I test for forward looking behavior in my setting and ask whether forward looking behavior can explain the difference in copayment and deductible price responsiveness.

6.1 Information

One potential explanation for the much larger behavioral response to copayments is that consumers have better information on copayment OOP costs and are thus more price responsive to costs they can observe. As discussed in Section 2, computing OOP costs associated with a treatment encounter involves acquiring and applying multiple pieces of information and is likely to be particularly difficult for deductibles. Although I expect information barriers to exist to some extent for all consumers, they may be lower for certain groups. I test whether better information reduces the wedge between copay and deductible price responsiveness by comparing behavioral responses among groups likely to have better information.

The best proxies for information in my data are zip code level income and individual health risk. Higher income consumers are likely to have higher financial literacy and may be better informed about the health care system as a result of higher education levels and peer groups. Since I do not observe income directly, I instead categorize individuals according to the per capita income within their five digit zip code.[20] Higher risk consumers may also have better information as a result of having more experience with the health care system and thus more opportunity to learn about the health care system and insurance over time. A recent survey by Loewenstein et al. (2013) finds that higher income and education predicts conceptual understanding of cost-sharing, but neither education, income, nor experience with the healthcare system predicts ability to compute OOP costs. Although these findings are not encouraging that these groups are substantially better at understanding OOP costs, I nonetheless test for differences in price responsiveness using these proxies for information suggested by Loewenstein et al. (2013).

[20] Income by zip code was obtained from the American Community Survey.

In Table 9, I estimate separate regressions by risk score quartile for four categories of spending. I show that higher risk consumers are somewhat less price sensitive overall, which is to be expected if sicker consumers have a higher expected benefit of treatment. However, I find no evidence that the wedge between copay and deductible OOP price responsiveness is reduced for higher risk consumers. Similarly, I do not find evidence that higher income consumers close the gap in copay and deductible price responsiveness when I estimate separate regressions by income quartile in Table 10.[21] For all groups and spending outcomes in Tables 9 and 10, I can reject the null hypothesis that the deductible and copay effects are the same at the 1% level.

Although I do not find strong evidence from these tests that groups predicted to have better information respond more consistently to copayments and deductibles, this is not necessarily an indication that misunderstanding of costs plays no role in explaining these results. As shown in the Loewenstein et al. (2013) survey results, it's likely that even the groups with somewhat better information are still poorly informed.

6.2 High value care

Next, I test whether both deductibles and copayments reduce highly valuable care and whether the wedge between deductible and copayment price sensitivity persists for high value care. I focus on highly valuable chronic condition medications, for which the medical literature documents large health benefits among their targeted patient populations. Previous studies find reductions in high value chronic medications in response to both deductibles (Fronstin et al., 2013; Huckfeldt et al., 2015) and copayments (Goldman et al., 2004; Chandra et al., 2010) separately, but none have compared the relative effects of deductibles and copayments on high value medications in the same setting.[22] Following Huckfeldt et al. (2015), I focus on medication adherence among patients for the following three chronic conditions: 1) high cholesterol, 2) hypertension, and 3) diabetes.[23] These are all generally considered to be medications that should have very low or zero copayments in plans following Value Based Insurance Design principals (Chernew et al., 2010). The medical literature shows these patients to have such large benefits from medication that their expected benefit far exceeds the cost, even when consumers are responsible for the full OOP cost. As a result, any reductions in these medications can be interpreted as consumer mistakes in the sense that a perfectly informed and rational consumer would never reduce utilization as a result of greater cost-sharing.

[21] In my sample the 25th, 50th, and 75th percentiles of zip code level per capita income are $30,999; $36,598; and $45,929 respectively.

[22] Goldman et al. (2007) review the evidence on prescription drug responses to cost-sharing up to 2006.

[23] Unlike Huckfeldt et al. (2015), I include both type I and type II diabetes patients in my sample.

Table 9: Impact of Copayments and Deductibles, By Risk Score Quartile

	(1) Risk Q1	(2) Risk Q2	(3) Risk Q3	(4) Risk Q4
Total				
Spot Price (10s)	-0.016***	-0.018***	-0.012***	-0.007***
	(0.003)	(0.002)	(0.001)	(0.000)
Copay Price (10s)	-0.130*	-0.180***	-0.113***	-0.069***
	(0.071)	(0.041)	(0.023)	(0.011)
Deductible				
Spot Price (10s)	-0.009***	-0.012***	-0.009***	-0.007***
	(0.002)	(0.001)	(0.001)	(0.000)
Copay Price (10s)	-0.048	-0.088***	-0.059***	-0.073***
	(0.036)	(0.023)	(0.015)	(0.009)
Visits				
Spot Price (10s)	-0.006***	-0.006***	-0.004***	-0.003***
	(0.002)	(0.001)	(0.001)	(0.000)
Copay Price (10s)	-0.057*	-0.051***	-0.040***	-0.032***
	(0.034)	(0.018)	(0.011)	(0.006)
Rx				
Spot Price (10s)	-0.006***	-0.009***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.000)
Copay Price (10s)	-0.002	-0.112***	-0.083***	-0.036***
	(0.035)	(0.027)	(0.018)	(0.010)
N	5,285,739	5,992,886	5,853,465	5,725,448
N Clust	17,337	19,630	21,499	22,717
N FE	160,931	183,047	178,749	176,487

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from IV regressions of log monthly spending on OOP deductible spot and OOP copay prices. Each column reports estimates from separate regression estimated on individuals in each risk score quartile. The spot and copay coefficients are interpretted as the percentage impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively. The specifications also condition on indicators for whether office visits and prescription drugs are subject to the deductible, as in Table 5, but the coefficients are suppressed for space. Each panel represents a different spending outcome.

Table 10: Impact of Copayments and Deductibles, By Income Quartile

	(1) Inc Q1	(2) Inc Q2	(3) Inc Q3	(4) Inc Q4
Total				
Spot Price (10s)	-0.009***	-0.010***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Copay Price (10s)	-0.167***	-0.131***	-0.154***	-0.132***
	(0.018)	(0.017)	(0.022)	(0.016)
Deductible				
Spot Price (10s)	-0.008***	-0.009***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Copay Price (10s)	-0.138***	-0.115***	-0.103***	-0.097***
	(0.015)	(0.014)	(0.014)	(0.013)
Visits				
Spot Price (10s)	-0.004***	-0.005***	-0.005***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Copay Price (10s)	-0.065***	-0.059***	-0.048***	-0.039***
	(0.009)	(0.009)	(0.010)	(0.008)
Rx				
Spot Price (10s)	-0.006***	-0.006***	-0.006***	-0.008***
	(0.001)	(0.000)	(0.000)	(0.000)
Copay Price (10s)	-0.065***	-0.044***	-0.069***	-0.058***
	(0.013)	(0.014)	(0.015)	(0.013)
N	5,685,778	5,703,159	5,717,224	5,734,999
R^2	0.394	0.383	0.371	0.356
N Clust	13,186	14,744	15,731	15,597
N FE	176,307	175,957	174,659	171,821

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from IV regressions of log monthly spending on OOP deductible spot and OOP copay prices. Each column reports estimates from separate regression estimated on individuals in each income quartile. The spot and copay coefficients are interpretted as the percentage impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively. The specifications also condition on indicators for whether office visits and prescription drugs are subject to the deductible, as in Table 5, but the coefficients are suppressed for space. Each panel represents a different spending outcome.

For high cholesterol, I focus on a cohort of patients taking statins. Clinical studies find that statins both reduce low-density lipoprotein cholesterol (LDL-C) and significantly lower the risk of developing cardiovascular disease, adverse events (e.g. heart attack, stroke), and mortality (Stone et al., 2014). National clinical guidelines recommend statins as the first-line treatment for patients diagnosed with high cholesterol.

As in Huckfeldt et al. (2015), for hypertension I focus on patients using the antihypertensives angiotensin-converting-enzyme (ACE) inhibitors and angiotensin II receptor antagonists (ARBs). Hypertension, or high blood pressure, increases the risk of cardiovascular disease, chronic kidney disease, stroke, and mortality. Clinical trials show that the use of antihypertensive medications reduces blood pressure and decreases the risk of these conditions. During the sample period, national guidelines recommended ACE inhibitors or ARBs as the second line treatment for hypertension (Chobanian and et al., 2003). [24]

I construct a cohort of diabetic patients taking insulin, oral hypoglycemics/antihyperglycemics, or metformin to manage blood glucose. Because metformin can also be used to treat other conditions, I include patients taking metformin in the diabetes cohort only if they also have at least two diagnoses of diabetes in the medical claims.[25] For diabetics, controlling blood glucose reduces the risk of developing eye, nerve, and kidney complications (Centers for Disease Control and Prevention, 2014). Nearly all patients with type 1 diabetes require insulin to manage blood glucose. For patients with type 2 diabetes, metformin is the primary first line treatment for managing blood glucose. If metformin alone is ineffective, guidelines recommend a combination therapy of metformin and hypoglycemics/antihyperglycemics or insulin (American Diabetes Association, 2016).

I assign patients to these chronic medication cohorts if they purchased at least 9 months (270 days) supply of one of the identified medications in the base year. This results in cohorts of 30,280 individuals with hypertension, 33,060 with high cholesterol, and 11,134 with diabetes. There is some overlap between these cohorts. For example, 5,216 individuals are both in the hypertension and diabetes cohorts. Since all patients used medication in the base year, these results should be interpreted as the impact of cost-sharing on adherence to high value medications.

As shown in Table 11, I find that both deductibles and copayments lead to reductions in the days

[24]The most recent guidelines also recommend ACE inhibitors and ARBs as first line treatments, although thiazide diuretics and calcium channel blockers are still preferred for black patients (James et al., 2014).

[25]This is following the Healthcare Effectiveness Data and Information Set (HEDIS) guidelines to identify patients with diabetes. The HEDIS guidelines identify a patient as diabetic if the patient 1) uses insulin or oral hypoglycemics/antihyperglycemics, or 2) has at least two diagnoses of diabetes in the medical claims. My criteria mirror the HEDIS guidelines by defining cohorts of diabetic medication users as those either 1) using insulin or oral hypoglycemics/antihyperglycemics, or 2) using metformin and with at least two diagnoses of diabetes in the medical claims.

Table 11: Impact of Copayments and Deductibles on Days Supply of Chronic Medications

	(1) Hypertension	(2) Statins	(3) Diabeties
Spot Price (10s) [a]	-0.061***	-0.046***	-0.121***
	(0.008)	(0.008)	(0.017)
Copay Price (10s) [b]	-0.393***	-0.428**	-0.815**
	(0.147)	(0.183)	(0.356)
Deductible Includes	-0.234	-0.391*	0.053
Visits [c]	(0.203)	(0.218)	(0.603)
Deductibles Includes Rx [d]	-2.835***	-2.199***	-5.910**
	(0.843)	(0.727)	(2.983)
N	982,308	1,091,022	361,275
R^2	0.062	0.061	0.178
N Clusters	9,221	9,819	4,750
N FE	30,280	33,060	11,134
Outcome Mean	25.970	24.795	40.111
Test P-value [e]	0.023	0.037	0.051

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

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

Table reports coefficients from IV regressions of monthly days supply of prescription drugs on OOP deductible spot and OOP copay prices. Each column reports estimates from a different type of prescription drug and cohort of individuals observed to be consuming that type of drug in the base year. The spot and copay coefficients are interpretted as the impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively, on the monthly days supply of that drug. For example, in Column (1) a $10 increase in copayment OOP costs reduces monthly days supply of hypertension medication among individuals taking hypertension medication by 0.393 days. Each variable reported is instrumented using the predicted version of the variable (see text for details). The partial F-statistics for all four variables are greater than 1,000. All specifications include individual and time fixed effects.

[a] The spot price is the predicted dollar OOP amount the individual faces over the month for using services subject to deductibles. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to deductibles under each individual's plan.

[b] The copay price is the predicted dollar OOP amount the individual faces over the month for using services subject to copayments. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to copayments under each individual's plan. Services subject to copayments include office visits and prescription drugs, depending on the plan.

[c] An indicator that office visits are subject to the deductible.

[d] An indicator that prescription drugs are subject to the deductible.

[e] P-value is from a Wald test that the spot and copay coefficients are equal.

supply of highly valuable medication among these disease cohorts. Again, the deductible OOP price effect is smaller than the copayment effect. Among patients with diabetes, a \$10 increase in the deductible spot OOP price reduces diabetes medication by 0.12 days per month, and a \$10 increase in the copay spot OOP price reduces diabetes medication by 0.82 days per month. There is also an additional effect of having prescription drugs subject to the deductible. Including prescription drugs in the deductible reduces diabetes medication by 5.9 days per month. These patterns are similar for the hypertension and statin cohorts, although the effects are somewhat smaller.

Although not entirely surprising given previous evidence of chronic medication reductions, these results are concerning. The average spot price among these chronic medication cohorts for a plan with a \$1,000 individual deductible is \$87.57. These estimates imply that moving from a \$0 to a \$1,000 deductible with drugs carved out of the deductible results in an average decrease in monthly days supply of 0.53 days for antihypertensives, 0.40 days for statins, and 1.06 days for diabetes and 3.37 days. If drugs are subject to the deductible, the estimates imply a decrease of 3.37 for antihypertensives, 2.60 for statins, and 6.97 for diabetes.[26] In terms of the number of prescriptions filled per year, for plans with drugs subject to the deductible these estimates equate to 1.35 fewer prescriptions for antihypertensives, 1.04 fewer prescriptions for statins, and 2.79 fewer prescriptions for diabetes. Huckfeldt et al. (2015) find that switching to a plan with an individual deductible of \$1,000 with drugs subject to the deductible caused an average monthly decrease of 3.07 days for antihypertensives, 3.23 days for statins, and 3.10 for diabetes, while moving to a high deductible plan with drugs carved out of the deductible caused an average monthly decrease of 0.82 days for antihypertensives, 0.93 days for statins, and 1.53 for diabetes.

The average copay OOP price change from moving from a \$10 to \$15 generic drug copayment among these chronic medication cohorts is \$6.15. The estimates in Table 11 imply that a typical \$5 increase in the generic drug copayment results in an average decrease in monthly days supply of 0.24 days for antihypertensives, 0.26 days for statins, and 0.50 days for diabetes.

6.3 Forward looking behavior

To test for forward looking behavior, I estimate whether the demand response to deductibles is driven by the spot price or the expected EOY price. A fully informed, rational consumer would only respond to the expected EOY price, whereas a completely myopic consumer would only respond to

[26]The first set of estimates are the result of multiplying the spot price coefficients by 8.757 (the average spot price of a \$1,000 deductible in \$10s). For example, $8.757 \times .061 = 0.534$. The second set of estimates also adds the coefficient capturing the average effect of the deductible including prescription drugs. For example, the estimate for antihypertensives is computed as $8.757 \times .061 + 2.835 = 3.369$.

the spot price. Recent papers studying consumer responses to non-linear health insurance contracts have used the spot and expected EOY price to test for and estimate the degree of forward looking behavior in consumer responses to deductibles. Aron-Dine et al. (2015) and Einav et al. (2015) find evidence of partial, imperfect forward looking behavior, whereas Brot-Goldberg et al. (2015) find that consumers only respond to spot prices. The strongest test of forward looking behavior in my sample tests for responsiveness to the expected EOY price when there is the most variation between spot and expected prices. I focus on spending responses in the first month, when spot prices are at their highest, but expected EOY prices can be much lower as a function of the size of their deductible and expected future spending.

I first show in columns (1) and (2) of Table 12 that when I estimate the spending response to the spot and expected price separately both are significant, and the magnitude of the spot price coefficient in column (1) is larger. The spot and expected price are highly correlated, as both are functions of the deductible level. Column (3) shows that when both the spot and expected EOY prices are included, spending reductions are entirely driven by the spot price. The estimated coefficient on the expected EOY price is actually positive, a result explained by the high degree of correlation between spot and expected prices. There is the most variation between spot and expected EOY price in the first month for the highest risk consumers, since they have high spot prices but a high probability of hitting the deductible later in the year. Columns (3)-(6) present the estimates for the highest ACG risk score quartile. I continue to find no evidence of forward looking behavior even among this predictably high risk group of consumers.

7 Conclusion

This paper rejects the prediction of fully informed, rational behavior that consumers treat a marginal dollar in OOP costs equivalently. I show that copayments drive much larger reductions in spending per dollar of OOP costs relative to deductibles. I also find that both deductibles and copayments have negative cross-price effects on other services, and that deductible responses are driven by the spot price, rather than the true marginal expected end-of-year price. Together, these findings call into question the extent to which patients fully understand the structure of their cost-sharing incentives and what they imply for OOP costs. Indeed, even groups expected to have better information do not respond to deductibles and copayments as expected.

My results have two main implications for improving plan cost-sharing in the face of imperfect consumer behavior. First, shifting to copayment-based plans could improve welfare by reducing

Table 12: Test of Whether Deductible Effect is Driven by the Spot or Expected End-of-Year Price

	(1) All	(2) All	(3) All	(4) Risk Q4	(5) Risk Q4	(6) Risk Q4
Spot Price (10s) [a]	-0.020***		-0.025***	-0.011***		-0.016***
	(0.001)		(0.001)	(0.001)		(0.002)
Expected EOY Price (10s) [b]		-0.013***	0.028***		-0.007	0.027***
		(0.004)	(0.005)		(0.005)	(0.006)
Copay Price (10s) [c]	-0.175***	-0.146***	-0.186***	-0.114***	-0.116***	-0.113***
	(0.020)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Deductible Includes	-0.032*	-0.138***	-0.017	-0.061	-0.192***	0.003
Visits [d]	(0.019)	(0.019)	(0.018)	(0.038)	(0.035)	(0.039)
Deductibles Includes Rx [e]	-0.120*	-0.202***	-0.132**	-0.231*	-0.413***	-0.175
	(0.065)	(0.065)	(0.065)	(0.118)	(0.115)	(0.119)
N	1,902,932	1,902,932	1,902,932	476,592	476,592	476,592
R^2	0.592	0.591	0.592	0.552	0.551	0.552
N Clusters	28,257	28,257	28,257	22,687	22,687	22,687
N FE	697,278	697,278	697,278	175,944	175,944	175,944

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from IV regressions of log monthly spending on OOP deductible spot and OOP copay prices. Each column reports a different type of spending as the dependent variable. The spot and copay coefficients are interpretted as the percentage impact of a $10 increase in monthly OOP costs due to deductibles or copayments, respectively. For example, in Column (1) a $10 increase in copayment OOP costs reduces total monthly spending by 17.5%. Each variable reported is instrumented using the predicted version of the variable (see text for details). The partial F-statistics for all four variables are greater than 1,000. All specifications include individual and time fixed effects.

[a] The spot price is the predicted dollar OOP amount the individual faces over the month for using services subject to deductibles. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to deductibles under each individual's plan.

[b] The expected end-of-year (EOY) price is the predicted dollar OOP amount the individual expects to face in the last month of the plan year for using services subject to deductibles. It is computed by simulating the OOP amount other people of the same risk type would expect to pay in the last month for services subject to deductibles under each individual's plan.

[c] The copay price is the predicted dollar OOP amount the individual faces over the month for using services subject to copayments. It is computed by simulating the OOP amount other people of the same risk type would pay for services subject to copayments under each individual's plan. Services subject to copayments include office visits and prescription drugs, depending on the plan.

[d] An indicator that office visits are subject to the deductible.

[e] An indicator that prescription drugs are subject to the deductible.

consumer risk exposure while maintaining lower spending. Cost-sharing has a benefit of reducing inefficient spending, but a cost of exposing consumers to risk and reducing efficient spending. The optimal cost-sharing structure balances the dual goals of risk protection and promoting efficiency in healthcare spending. This paper shows that it takes a much larger exposure to OOP deductible costs to achieve a given spending reduction compared to copayments, arguing for a greater use of copayments in plan design. The risk exposure cost of cost-sharing is a concern particularly for lower-income households. Collins et al. (2015) estimate that 23% of insured adults in 2014 were underinsured, defined as having high OOP costs or deductibles relative to household income. Copayment-based plans are likely to be particularly attractive for these lower-income households.

Second, evidence of consumer misunderstanding of cost-sharing implies a trade-off between value-based cost-sharing and plan complexity. Value-based cost-sharing attempts to correct for imperfect responses to cost-sharing by charging low or zero cost-sharing for highly beneficial care and higher cost-sharing for less valuable care (Chernew et al., 2007; Baicker et al., 2015). A fully value-based plan would specify different levels of cost-sharing for different services and different patients according to health benefit, requiring many different prices and contingencies of when and for whom those prices would apply. Such a plan would be highly complex. If consumers have difficulty responding to complex plan designs, as this paper indicates, value-based cost-sharing may not be able to target the particular types of spending plan designers intend. To understand the optimal complexity of value-based cost-sharing, future work should study consumer responses to plan cost-sharing at different point along the complexity spectrum.

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Table A.1: OLS Regressions of Changes in Cost-Sharing on Lagged Changes in Spending

	(1) Deductible Change	(2) Visit Copay Change	(3) Rx Copay Change
Lagged change in log spending	-0.001 (0.000)	-0.000 (0.000)	0.000 (0.000)
N	509,495	509,495	509,495
R^2	0.051	0.090	0.359
N Clusters	17,476	17,476	17,476

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

* p<0.10, ** p<0.05, *** p<0.01

Table reports coefficients from regressing an indicator for whether the individual's predicted plan changed the deductible, primary care office visit copayment, and generic drug copayment on the individual's lagged change in log annual spending. Specifications also include time fixed effects and all demographic controls included in the main specifications.

A Additional Tables

Table A.2: First Stages for Full Sample

	(1) Deductible Visits	(2) Rx Visits	(3) Spot Price (10s)	(4) Copay Price (10s)
Predicted Deductible Includes Visits	0.984***	-0.002***	0.117***	0.007***
	(0.002)	(0.001)	(0.033)	(0.001)
Predicted Deductibles Includes Rx	-0.032***	0.988***	0.026	0.025***
	(0.010)	(0.004)	(0.136)	(0.009)
Predicted Spot Price (10s)	-0.000***	-0.000**	0.983***	0.000***
	(0.000)	(0.000)	(0.002)	(0.000)
Predicted Copay Price (10s)	0.000	0.000	-0.055	0.995***
	(0.001)	(0.000)	(0.036)	(0.001)
N	22,857,538	22,857,538	22,857,538	22,857,538
R^2	0.993	0.993	0.779	0.999
N Clusters	28,295	28,295	28,295	28,295
N FE	699,214	699,214	699,214	699,214
SW F statistic	608246.5	416410.3	262626.2	1954285.0

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

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

Table reports first stage estimates for the main specifications reported in Table 5. SW F statistic is the Sanderson-Windmeijer first-stage partial F test statistic for weak identification of each engogenous regressor.

Table A.3: Alternative Specifications

	(1) Total	(2) Total	(3) Total	(4) Total
Spot Price (10s)	-0.011***	-0.008***	-0.007***	-0.012***
	(0.000)	(0.001)	(0.001)	(0.000)
Copay Price (10s)	-0.147***	-0.156***	-0.123***	-0.097***
	(0.014)	(0.014)	(0.011)	(0.010)
Spot Price (10s) × Deductible Includes Visits		-0.005***	-0.007***	
		(0.001)	(0.001)	
Spot Price (10s) × Deductible Includes Rx		0.001	0.000	
		(0.001)	(0.001)	
Deductible Includes Visits	-0.095***	-0.069***		
	(0.010)	(0.010)		
Deductibles Includes Rx	-0.144***	-0.156***		
	(0.042)	(0.043)		
N	22,857,538	22,857,538	22,857,538	22,857,538
R^2	0.377	0.377	0.377	0.377
N Clust	28,295	28,295	28,295	28,295
N FE	699,214	699,214	699,214	699,214

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

* p<0.10, ** p<0.05, *** p<0.01

Table reports alternative specifications of log monthly spending on OOP copayment and deductible prices.

Table A.4: Robustness to Alternative Instruments

	(1) Total Version 1	(2) Total Version 2	(3) Total Version 1	(4) Total Version 2	(5) Deductible Version 1	(6) Deductible Version 2	(7) Deductible Version 1	(8) Deductible Version 2
Spot Price (10s)	-0.011***	-0.004**	-0.011***	-0.004**	-0.009***	-0.005***	-0.009***	-0.006***
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Copay Price (10s)	-0.147***	-0.131***			-0.113***	-0.074***		
	(0.014)	(0.023)			(0.009)	(0.012)		
Visit Copay Price (10s)			-0.108***	-0.133**			-0.092***	-0.117***
			(0.026)	(0.063)			(0.019)	(0.030)
Rx Copay Price (10s)			-0.167***	-0.122***			-0.124***	-0.051***
			(0.016)	(0.024)			(0.011)	(0.012)
Deductible Includes Visits	-0.095***	-0.103***	-0.073***	-0.103***	-0.068***	-0.057***	-0.057***	-0.080***
	(0.010)	(0.016)	(0.015)	(0.036)	(0.007)	(0.009)	(0.010)	(0.018)
Deductibles Includes Rx	-0.144***	-0.147***	-0.166***	-0.136***	-0.054**	-0.025	-0.067***	0.002
	(0.042)	(0.046)	(0.043)	(0.047)	(0.025)	(0.026)	(0.026)	(0.027)
N	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538
R^2	0.377	0.376	0.377	0.376	0.235	0.235	0.235	0.235
N Clust	28,295	28,295	28,295	28,295	28,295	28,295	28,295	28,295
N FE	699,214	699,214	699,214	699,214	699,214	699,214	699,214	699,214

Standard errors in parentheses

Standard Errors Clustered at the Employer Level. Version 1 uses simulated instruments. Version 2 uses deductible and copay levels as instruments.

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

Table compares specifications using the original set of instruments (version 1) with specifications using an alternative set of instruments (version 2). Version 2 instruments for copayment and deductible OOP price variables using the predicted deductible and copayment levels. The partial first stage F statistics for the deductible and copayment OOP price variables in Version 2 are 1,691.4 and 3,654.7, respectively. The complete set of first stage estimates for Version 1 can be found in Appendix Table A.2. Outcome variables are log monthly total spending (columns (1)-(4)) and log monthly deductible-eligible spending (columns (5)-(8)).

Table A.5: Robustness to Alternative Instruments

	(1) Visits Version 1	(2) Visits Version 2	(3) Visits Version 1	(4) Visits Version 2	(5) Rx Version 1	(6) Rx Version 2	(7) Rx Version 1	(8) Rx Version 2
Spot Price (10s)	-0.005***	-0.003***	-0.005***	-0.003***	-0.007***	0.000	-0.007***	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Copay Price (10s)	-0.052***	-0.049***			-0.059***	-0.079***		
	(0.006)	(0.009)			(0.010)	(0.017)		
Visit Copay Price (10s)			-0.031***	-0.057**			-0.059***	-0.040
			(0.012)	(0.023)			(0.017)	(0.040)
Rx Copay Price (10s)			-0.063***	-0.043***			-0.059***	-0.087***
			(0.007)	(0.009)			(0.013)	(0.020)
Deductible Includes Visits	-0.038***	-0.043***	-0.027***	-0.048***	-0.026***	-0.053***	-0.026**	-0.032
	(0.004)	(0.007)	(0.007)	(0.013)	(0.007)	(0.011)	(0.010)	(0.024)
Deductibles Includes Rx	-0.057***	-0.061***	-0.069***	-0.055***	-0.097***	-0.139***	-0.097***	-0.149***
	(0.016)	(0.018)	(0.016)	(0.018)	(0.025)	(0.030)	(0.027)	(0.032)
N	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538	22,857,538
R^2	0.173	0.173	0.173	0.173	0.538	0.538	0.538	0.538
N Clust	28,295	28,295	28,295	28,295	28,295	28,295	28,295	28,295
N FE	699,214	699,214	699,214	699,214	699,214	699,214	699,214	699,214

Standard errors in parentheses

Standard Errors Clustered at the Employer Level.

* p<0.10, ** p<0.05, *** p<0.01

Table compares specifications using the original set of instruments (version 1) with specifications using an alternative set of instruments (version 2). Version 2 instruments for copayment and deductible OOP price variables using the predicted deductible and copayment levels. The partial first stage F statistics for the deductible and copayment OOP price variables in Version 2 are 1,691.4 and 3,654.7, respectively. The complete set of first stage estimates for Version 1 can be found in Appendix Table A.2. Outcome variables are log monthly office visit spending (columns (1)-(4)) and log monthly prescription drug spending (columns (5)-(8)).

B Benchmarking spending elasticities

[DETAILS TO BE ADDED]