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ABSTRACT

How Do Low-Income Enrollees in the Affordable Care Act Marketplaces Respond to Cost-Sharing?*

The ACA requires insurers to provide cost-sharing reductions (CSRs) to low-income consumers on the marketplaces. We link 2013-2015 All-Payer Claims Data to 2004-2013 administrative hospital discharge data from Utah and exploit policy-driven differences in the value of CSRs that are solely determined by income. We find that enrollees with lower cost sharing have higher levels of health care spending, controlling for past health care use. We estimate the demand elasticity of total health care spending to be -0.10, but find larger elasticities for emergency room care, lifestyle drugs, and low-value care. We also find positive cross-price elasticities between outpatient and inpatient care.

JEL Classification: H24, H41, H43, H51, I11, I18, J32, J33, J68

Keywords: demand elasticities, health insurance, moral hazard, ACA, marketplaces, AV-variants, low-value care, lifestyle drugs, value-based CSRs, Utah

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1 Introduction

The 2010 Affordable Care Act (ACA) provides two forms of insurance subsidies to low-income consumers who purchase private health insurance on the ACA Marketplaces—tax credits towards the payments of premiums and cost-sharing reductions (CSRs). CSRs reduce the amount of cost-sharing (e.g., deductibles) required by enrollees. They are motivated by a concern that high-levels of cost-sharing might lead low-income consumers to forgo needed health care. However, little is known about how low-income consumers respond to cost-sharing in private insurance markets. In this study, we examine the extent to which the CSR program achieved its goal of increasing the use of health care, especially needed health care, among low-income enrollees in ACA Marketplace plans.

The most influential study on how consumers respond to cost sharing is the RAND Health Insurance Experiment (RAND HIE; Manning et al., 1987; Manning et al., 1986; O'Grady et al. 1985), which concluded that the price elasticity of demand for medical care is around -0.2. Both the RAND HIE and, more recently, Brot-Goldberg et al. (2017) examine whether cost-sharing differentially affects different types of care and find that increases in cost-sharing leads to across-the-board reductions in utilization, including of both low-value and high-value medical care.

To date, however, the literature has primarily examined how higher income populations respond to cost-sharing. Most studies that do focus on lower-income populations, such as Finkelstein et al. (2012), examine the impact of gaining Medicaid coverage without any cost-sharing whatsoever. One exception is Chandra, Gruber, & McKnight (2014), who study the effect of policy-driven changes in cost-sharing rates among the low-income enrollees in the Massachusetts Commonwealth Care program.

We provide the first estimates of how low-income enrollees in the ACA Marketplaces respond to lower levels of cost-sharing induced by CSRs. We estimate elasticities of demand for different types of care by exploiting policy-driven differences in the amount of cost-sharing subsidies across enrollees. We also investigate whether enrollees differentially respond to cost-sharing in their demand for high-value versus low-value health care and also estimate demand elasticities for different types of prescription drugs. We finally estimate cross-price elasticities between different types of care. Using these estimates, we present a counterfactual simulation of the effects of eliminating CSRs on the health care spending of low-income consumers.

We use All-Payer Claims Data (APCD) from Utah between 2013 and 2015. These data contain insurance coverage and claims records for nearly every commercially-insured Utah resident. Using commercially-available software, the 2013 APCD data allow us to calculate each enrollee's health risk score prior to selecting ACA plans in 2014. We also link the APCD records for each individual to administrative hospital inpatient and ER discharge records from 2004 to 2013. This linkage allows us to condition on a full decade of hospital-based health care utilization prior to ACA Marketplace enrollment.

Because we do not observe exact reported income in the APCD, we provide evidence that income manipulation to obtain higher CSRs is unlikely to be a major threat to our estimates. However, even though we focus on a relatively narrow income range and comprehensively control for health, we recognize that income may have a separate effect on health care spending that does not operate through health. Hence, we provide a thorough discussion of the issue and several back-of-the-envelope calculations. In particular, we assess the sensitivity of our findings with respect to different income elasticity values. We conservatively interpret our estimates as lower bounds.

Our main estimates imply an overall demand elasticity for health care of -0.1 among low-income ACA enrollees. This estimate is close to the commonly-cited RAND HIE estimate of -0.2. Also in line with the RAND HIE, our elasticity estimates for inpatient care are close to zero, whereas those for outpatient care are -0.13. Elasticity estimates for emergency room (ER) care are larger at -0.2. These ER elasticities are consistent with the findings of Taubman et al. (2014), based on the Oregon Medicaid lottery. Corroborating the first stage variation in cost-sharing levels, we find that lower-cost sharing substantially reduces out-of-pocket (OOP) spending. We also find that sicker enrollees (those with higher pre-ACA risk scores) are less price responsive to cost-sharing. Moreover, we find highly significant and economically meaningful cross-price elasticities between outpatient and ER spending as well as between outpatient and inpatient spending.

Consistent with evidence from Brot-Goldberg et al. (2017) and the RAND HIE, we find similar demand responsiveness for both high-value (-0.26) and low-value (-0.23) medical care. We also use the categorization of prescription drugs developed by Chandra, Gruber, and McKnight (2010) to estimate relatively large elasticities for lifestyle drugs (-0.27) and relatively small elasticities for drugs to treat chronic illnesses (-0.08) and for brand name drugs (0.05). The overall elasticity for prescription drugs is -0.12, which is similar to the -0.2 estimate for elderly enrollees in Medicare Part D from Einav, Finkelstein, & Polyakova (2018).

Our findings suggest that demand-side price mechanisms in health insurance design work similarly for low-income enrollees as they do for broader groups of higher-income enrollees. Our estimates imply that the CSR program led the low-income enrollees of the ACA Marketplaces to increase their health care spending by 24% while simultaneously reducing their OOP spending. Thus, the evidence we present suggests that, overall, the CSR program is working as intended.

2 Background

Consumers shopping for health insurance on the ACA Marketplaces are offered a standardized menu of regulated plans. Plans are differentiated by metallic tiers corresponding to the actuarial value (AV) of the plan: "Bronze" plans are those with an AV of 60%, "Silver" plans have an AV of 70%, "Gold" plans have an AV of 80% and "Platinum" plans have an AV of 90%. An AV of 70% implies that a "representative enrollee" would expect to pay 30% of health care costs out-of-pocket. Plans with higher AVs must have lower cost sharing, though plans can achieve a certain AV in a number of ways (for example, by lowering deductibles versus lowering out-of-pocket maximums).

Low-income consumers who purchase insurance on the ACA Marketplaces can receive income-dependent premium tax credits and cost-sharing reductions (CSRs). The ACA requires insurers to offer three CSR-variant plans along with each Silver plan offered on the Marketplaces. CSR-variant plans are Silver plans that, instead of an AV of 70%, have AVs of 94%, 87%, or 73%. Importantly, the CSR-variant plans must be identical to their corresponding Silver plan in all aspects other than cost-sharing—for example, they must be sold at the same premium and have the same network.

Consumers who report projected incomes on their application between 100 and 400% of the federal poverty line (FPL) are eligible for advanced premium tax credits.[5] The actual value of a consumer's premium tax credit, however, is determined by that consumer's realized income as reported on their federal tax return in the subsequent year. Differences between the actual value and the amount received in advance are reconciled on the tax return.

Consumers who report projected incomes between 100% and 250% of FPL are offered CSR-variant Silver plans instead of unsubsidized Silver plans with a 70% AV. In particular, consumers

[5] In 2014, 100% of FPL was $11,490 per year for a single household and $23,550 for a four-person household. By 2019, these values had increased to $12,490 and $25,750 (U.S. Department of Health and Human Services, 2019).

with incomes between 100% and 150% of FPL are offered CSR plans with a 94% AV; consumers with reported incomes between 150% and 200% of FPL are offered CSR plans with a 87% AV; and consumers with reported incomes between 200% and 250% of FPL are offered CSR plans with a 73% AV. Unlike the case with advanced premium tax credits, eligibility for CSR-variant plans does not change if realized income differs from projected income.[6]

The ACA does not specify how CSRs alter deductibles, copayments and coinsurance rates in order to achieve the targeted AV. This means that each carrier designs their own CSR plans. However, a common way to achieve a higher AV is to lower or eliminate deductibles. For example, the average deductible of Marketplace plans in 2015 was $2,556 among 70% AV Silver plans, $2,077 among 73% AV Silver plans, $737 among 84% AV Silver plans, and $229 among 94% AV Silver plans (Kaiser Family Foundation, 2015). Many carriers eliminate the deductible entirely in 94% AV Silver plans(Center for Budget and Policy Priorities, 2018). Gabel et al. (2016) report that, in 2015, 65% of all 94% AV Silver plans had a $0 deductible, compared with only 2% of 73% AV Silver plans. Carriers also reduce co-payments and coinsurance to achieve a higher AV in their CSR-variant plans (Kaiser Family Foundation, 2015).

When a consumer's income falls below 250% of FPL, from that consumer's point of view, the deductible and other cost-sharing rules are automatically adjusted to increase the AV of every Silver plan offered from 70% to 73%. Similarly, when income falls below 200% and 150% of FPL, plan designs automatically increase Silver plan AVs from 73% to 87% and 94%, respectively. In fiscal year 2017, a total of $7.3 billion in taxpayer funds was spent on CSRs (Fernandez, 2018).

We study the effects of this policy-driven variation in cost-sharing rules in Utah, a state that chose not to expand Medicaid coverage under the ACA. In April 2014, at the end of the first open-enrollment period on the ACA Marketplace, about 85 thousand residents of Utah had enrolled in individual non-group plans on Utah's Marketplace (Kaiser Family Foundation, 2014). During the second open-enrollment period, in January 2015, enrollment increased to 116 thousand (U.S. Department of Health and Human Services, 2015). Although Utah did not expand Medicaid eligibility under the ACA, there is evidence that the Utah Marketplace helped 50 thousand residents enroll in Medicaid (Norris, 2018). Gallup survey data suggest that the uninsurance rate in Utah decreased from 15.6% to 13.3% between 2013 and 2014, or by about 65 thousand

[6] Projected income on the application is subject to a verification process in which it is compared with previous years' incomes from tax returns. In cases where projected income is substantially lower than the previous year's income, additional documentation supporting the projected income level may be required.

individuals relative to the pre-ACA level of 407 thousand (Kaiser Family Foundation, 2014; Witters, 2015). At its inception in 2014, six different carriers offered 1,712 plans at the plan-rating area level on the Utah Marketplace. The majority of plans were Silver plans (39%) followed by Bronze plans (29%).

3 Prior Research

This paper contributes to the large and growing literature on the responsiveness of consumers to cost sharing in health care and to the more recent literature on the ACA Marketplaces. The RAND HIE provided experimental evidence on the price elasticity of demand for health care and produced a set of estimates that are still considered the gold standard. For coinsurance rates below 25%, the RAND HIE reported arc elasticities of around -0.2 with larger point estimates for “well-care” and mental health care. The experiment showed that even modest amounts of cost sharing could substantially reduce health care utilization with minimal effects on health or quality of care.

Studies outside the U.S. have also found elasticities close to -0.2 for most medical services, though these studies typically rely on variation in small copayment amounts in public systems (Chiappori, Durand, & Geoffard, 1998; Cockx & Brasseur, 2003; Gerfin & Schellhorn, 2006; Shigeoka, 2014; Ziebarth, 2010). One exception is Duarte (2012) who exploits variation in cost-sharing in Chile, one of the few primarily private health insurance markets outside of the U.S.

Many studies have examined the responsiveness of different types of medical care. The RAND HIE showed that consumers are less responsive in their demand for preventive care (Zweifel & Manning, 2000) and are equally responsive in their demand for “well” visits as for general outpatient visits (Keeler & Rolph, 1983). It also showed that cost-sharing reduced health care demand “across the board” with reductions in both “appropriate” and “inappropriate” care (Manning et al., 1987, 1986; O’Grady et al., 1985). More recently, Ellis, Martins, & Zhu (2017) report a wide range of elasticity estimates for 26 different types of care; they calculate an overall elasticity of -0.44 and elasticities for preventive care and ER visits that are close to zero.

There is also a large literature addressing the policy-relevant question is whether there are “offsets” or substitution effects between different types of care (Chandra et al., 2010; DeLeire et al., 2013; Gaynor, Li, & Vogt, 2007; McKnight, 2006; Ziebarth, 2014; Zweifel & Manning, 2000) and whether a decrease in medical care utilization today would increase the demand for medical care tomorrow (Fang & Gavazza, 2011).

This paper also contributes to the growing economic literature on the ACA Marketplaces (Cox et al., 2015; DeLeire et al., 2017; Hinde, 2017; Kowalski, 2014; Richardson & Yilmazer, 2013). Studies focusing on premium determinants use Marketplace health plan data to show that more competition on an exchange reduces premiums (Dafny, Gruber, & Ody, 2015), that the Medicaid expansion improved risk pools and lowered premiums (Sen & DeLeire, 2018), and that premiums are lower in larger "coverage regions" (Dickstein et al. 2015). Sacks et al. (2017) show theoretically that the ACA Risk Corridor program incentivized insurers to lower premiums. They also provide empirical evidence that the defunding of the program (effective 2016) contributed to higher premium growth. The relevance of age-based pricing regulations has also been studied (Orsini & Tebaldi, 2017) and this work finds that age-based pricing restrictions have reduced participation on the exchanges. Tebaldi (2017) shows that age-based subsidies would lead to equilibria where all buyers would be better off.

Three papers study the impact of premium and cost-sharing subsidies on *take-up* in the ACA Marketplaces. Frean, Gruber, & Sommers (2017) use American Community Survey (ACS) data linked to ACA area premiums and find very modest take-up effects of premium subsidies and no crowd-out of private coverage as a result of the Medicaid expansions. DeLeire et al. (2017) use administrative data to estimate the impact of cost-sharing subsidies on take-up and find health plan elasticities with respect to the actuarial value of around one. Saltzman (2019) combines ACS data with consumer data from the Washington and California exchange to estimate nested logit models with insurer-market fixed effects. He finds that exchange enrollment decreases by slightly more than one percent when the base premiums of all exchange plans increase by one percent.

4 Empirical Approach

This section discusses the methods we use to estimate the effect of cost-sharing on health care spending among low-income enrollees in ACA Marketplace health insurance plans. We first present two different econometric models for estimating the relationship between cost-sharing and health care spending. After specifying our model, we discuss the underlying assumptions we make for identification in our empirical setting. As our identification strategy mainly exploits variation in AVs across types of plans, this discussion relates to the institutional details in Section 2. Finally, we discuss how we interpret our estimates as own and cross-price elasticities of demand for health care.

4.1 Empirical Model

Much has been written on methods for modeling health care spending; Jones (2009), Manning (2012), and Mihaylova et al. (2011) provide comprehensive overviews of alternative approaches. A widely-used approach is the generalized linear model (GLM) with a log-link function (Deb, Norton, & Manning, 2017; Manning, Basu, & Mullahy, 2005; Manning & Mullahy, 2001; Mullahy, 1998). This modeling approach can capture two important stylized facts about health spending distributions—they tend to be highly skewed, with a long right tail, and they tend to have a large mass point at zero spending—and is more efficient than the transformed log model (Buntin & Zaslavsky, 2004).[7]

We follow this approach, using GLM with a log link function and gamma variance. In our context, an advantage of this specification is that it facilitates predictions of health care spending on a linear scale, with transformation (Deb, Norton, & Manning, 2017; Manning, 2012).[8]

Our main empirical specification is:

$$\boldsymbol{y_{it} = exp\Big(\alpha + \beta_{87}AV^{87}_{p(it)} + \beta_{94}AV^{94}_{p(it)} + \gamma_1 Risk_{i,2013} + \gamma_2 RiskMissing_{i,2013} + \phi Inpatient_{i,2004-2013} + \tau ER_{i,2004-2013} + Z_{it}\theta + \delta_t + \rho_{c(it)}\Big)} \quad (1)$$

where y_{it} measures either total health care spending (in dollars) of individual i in month t or categories of spending—ER, outpatient, inpatient, pharmacy, and out-of-pocket spending. Our primary variable of interest is $AV_{p(it)}$ which is the Actuarial Value (AV) of plan p chosen by individual i in month t.

[7] GLMs are based on "link functions" (which model the relationship between covariates and the conditional mean of the spending distribution) and "variance functions" (which model the relationship between the mean and the variance of the spending distribution). The link function determines the shape of the conditional mean and how untransformed mean spending relates to the covariates. For example, the link function *g(.)* is the natural logarithm if the conditional mean of y_{it} is an exponential function of the covariates $\mathbf{X_{it}}$: $\mathbf{E}(y_{it}|\mathbf{X_{it}})=\exp(\mathbf{X_{it}}\xi)=g^{-1}(\mathbf{X_{it}}\xi)$. In other words, the inverse of the link function *g(.)* maps the covariate index into the conditional expected spending mean. The relationship between the mean and the variance of the (skewed) spending distribution is modeled by a power function of the linear exponential family; for example, the gamma variance, which is proportional to the square of the mean. Of all models tested, the log-link and a gamma variance provide the best fit in our setting, but a log-link negative binomial variance model yields very similar results. As Deb, Norton, & Manning (2017) point out, one only needs to correctly specify the link function and the covariates $\mathbf{X_{it}}$ for consistent estimates. The choice of the distribution, i.e., the gamma variance, only affects the efficiency of the estimates. We estimate the model by quasi-maximum likelihood in Stata.

[8] Deb, Norton, & Manning (2017) provide an updated discussion with further details about the GLM, including Stata codes and examples. Other approaches include (i) transforming the spending distribution by taking its logarithm—plus one, to avoid excluding zeros (Aron-Dine et al., 2013; Manning & Mullahy, 2001), (ii) the two-part model, which employs a binary outcome model along with a conditional model for positive spending (Manning et al., 1987; Mullahy, 1998), and (iii) the use of count data models or latent class models that differentiate between frequent and infrequent users of health care; for example, when modeling the number of outpatient doctor visits (Deb & Trivedi, 1997, 2002; Pohlmeier & Ulrich, 1995). While our main estimates use the GLM approach, our findings are quite similar using log-transformed spending, as we show in the Appendix.

The measure of AV that we use corresponds to the CSR-variant plan. For Silver plans with cost-sharing subsidies that we focus on in this paper, $AV_{p(it)}$ has three values: 73%, 87%, and 94%. CMS determines that each CSR-variant plan falls within a +/-1% of the expected plan AV using an AV calculator and a fixed enrollee population; hence, actual plan selection does not confound the AV measure. In robustness and alternative specifications, we also use alternative measures of the AV—actual, *ex-post*, realized AVs at the plan-year-spending category level, and end-of-year spot prices at the enrollee-year level.

$Risk_{i,2013}$ represents the risk score of individual i in 2013, prior to choosing an ACA Marketplace plan. We calculate the risk scores using APCD and the Johns Hopkins ACG© System software. Individuals who were uninsured in 2013 do not have data from which we can calculate a 2013 risk score. These individuals receive a risk score of 1 (the average) and we include a binary flag that equals 1 if the 2013 risk score is missing.

$Inpatient_{i,2004\text{-}2013}$ and $ER_{i,2004\text{-}2013}$ count the number of cumulative individual inpatient days and ER visits between 2004 and 2013. Controlling for a ten-year panel of hospital utilization relaxes conditional exogeneity assumptions related to the independence of health status and plan selection. To our knowledge, this is the longest longitudinal panel of health claims data ever used to control for health of enrollees when estimating demand elasticities in the United States.

Z_{it} are socio-demographic controls including gender, age, and age squared. δ_t and $\rho_{c(it)}$ are month-year and county fixed effects, respectively. They adjust for average differences in health care spending over time and across the 29 counties in Utah, for example, due to differences in average price levels. (We also control for issuer fixed effects in a set of specifications that we report in the Appendix.) Errors are clustered at the household level to allow for serial correlation and for correlation that may be caused by shared deductibles and other nonlinear plan features at the household level (Cameron & Miller, 2015).

A related specification, from which we can derive demand elasticity estimates, includes $ln(1-AV_{p(it)})$ as an independent variable:

$$\boldsymbol{y_{it} = exp\big(\alpha + \beta ln\big(1 - AV_{p(it)}\big) + \gamma_1 Risk_{i,2013} + \gamma_2 RiskMissing_{i,2013} + \phi Inpatient_{i,2004-2013} + \tau ER_{i,2004-2013} + Z_{it}\theta + \delta_t + \rho_{c(it)}\big)} \quad (2)$$

In this specification, β has a direct interpretation as an estimate of the own-price elasticity of demand for medical care.

Finally, a specification from which we can estimate both own-price and cross-price elasticities of demand includes spending-category specific coinsurance rates (outpatient, inpatient, ER, pharmaceutical) as independent variables:

$$\boldsymbol{y_{it}} = \boldsymbol{exp\big(\alpha + \beta^{I} ln\big(1 - AV^{I}_{p(it)}\big) + \beta^{O} ln\big(1 - AV^{O}_{p(it)}\big) + \beta^{ER} ln\big(1 - AV^{ER}_{p(it)}\big) + \beta^{Rx} ln\big(1 - AV^{Rx}_{p(it)}\big) + \gamma_1 Risk_{i,2013} + \gamma_2 RiskMissing_{i,2013} + \phi Inpatient_{i,2004-2013} + \tau ER_{i,2004-2013} + Z_{it}\theta + \delta_t + \rho_{c(it)}\big)} \quad (3)$$

where y_{it} is spending on a particular category of care (ER, outpatient, inpatient, pharmacy) and the category-specific AVs are the actual, *ex-post*, realized AVs at the plan-year-spending category level. *O* represents outpatient care, *ER* represents ER care, *I* represents inpatient care, and, *Rx* represents pharmaceuticals. The coefficients on the category-specific coinsurance rates can be interpreted as own-price and cross-price elasticities of demand. For example, when the dependent variable is inpatient spending, β^{I} is the own-price demand elasticity for inpatient spending while β^{O}, β^{ER}, and β^{Rx} are the cross-price elasticities.

4.2 Interpretation

We identify the effect of cost-sharing on health care spending by between-enrollee variation in AVs. This variation is driven by the assignment of enrollees to plans with different AV based on enrollees' household incomes. This income-based assignment, within a relatively narrow band of the income distribution from 100-250% of FPL, leaves less scope for the type of endogenous plan choice driven by unobserved health status that is typically a concern in the estimation of demand elasticities. Despite this, it would be inappropriate to interpret our estimates as casual effects of CSR subsidies on utilization without considering several important factors that could influence interpretation.

First, assignment to plans with a different AV is caused by differences in household income. Unfortunately, the Utah APCD does not have information on exact household income, and thus we cannot estimate regression discontinuity models as in DeLeire et al. (2017). The APCD data do include categorical information on the CSR group (73%, 87%, or 94%) in which an individual is enrolled, allowing us to know precisely whether an enrollee's family income falls into the income categories 100-150%, 150-200% or 200-250% of FPL. To keep this range of income levels relatively narrow, our analyses focuses on Silver plans with cost-sharing subsidies, excluding the standard 70% Silver plan. We do not use any AV variation between Platinum, Bronze, Silver and Gold plans for identification.

Because CSRs increase as income declines, any potential increase in utilization caused by larger subsidies may be partially offset by the effect of lower income on spending. Consequently, our baseline estimates may represent lower bound price elasticity estimates of demand for medical care. To assess the relevance of these potential income effects on our estimates, we apply income elasticities from the literature.

Second, lower-income individuals who are enrolled in plans with less cost sharing may have worse health. Our approach to addressing this concern is to include an extensive set of controls for past health and health care use. Specifically, we condition on individual-level risk scores for 2013 (the year before enrollment into an ACA Marketplace plan) and control for a decade of pre-enrollment data on inpatient and ER visits that are linked at the individual-level to each Marketplace enrollee. Although researchers may be rightfully skeptical about the general strategy of controlling for prior health status to eliminate bias caused by adverse selection, there is arguably cause for more optimism in our specific setting. Because enrollees must choose a Silver plan to obtain CSRs, there is little incentive for a CSR-eligible individual to not choose a Silver plan. As a result, private knowledge about health has far less impact on plan choice than would occur in most individual or small group markets. That is, the standard concern about Akerlof-style adverse selection is greatly attenuated by the design of CSR subsidies. Moreover, we control for a richer set of health status and utilization measures, over a much longer time horizon, than has been possible in previous studies (in addition to age, gender, county, and month-year effects). Given the limited scope for potential selection based on health status, it is not surprising that we find little evidence of selection on observables, including measures of past health. Following the intuition from Altonji, Elder, & Taber (2005), we interpret the absence of selection-on-observables as evidence that there is little room for additional selection into plans based on unobservables. The overall combination of all these factors—CSR plan design, rich health information, no evidence of selection on observables—alleviates our concerns about potentially endogenous plan assignment based on private health information.

Third, enrollees may strategically manipulate their estimated incomes to maximize subsidies. Below we provide evidence that does not support the view that enrollees manipulated their anticipated household incomes to become eligible for more cost-sharing subsidies. This lack of strategic manipulation may be a function of the institutional features: if an individual reports estimated income that is substantially lower (> 10%) than what is implied by administrative payroll records, the application is likely to be flagged, and additional documentation is required to justify the reduction in estimated income before CSR subsidies can be obtained (Centers for Medicare Medicaid Services, 2013; Jacobs et al., 2013).

Finally, we experimented with including individual fixed effects in the model as a potential solution to some of the selection issues described above. Unfortunately, because fewer than 5% of enrollees switched CSR categories between 2014 and 2015 this approach was not feasible. While this stability in incomes limits our ability to exploit within-enrollee variation in AV levels, it is also reassuring because it reinforces our argument that endogenous income manipulation is unlikely to be a major threat to our estimates.

4.3 Estimating Demand Elasticities

Subject to these caveats, $\hat{\beta}$ from equation (2) can be interpreted as the own-price elasticity of demand for medical care. As the independent variable in this specification is $ln(1\text{-}AV_{p(it)})$, or the log of the average coinsurance rate, the assumption implicit in this interpretation is that consumers respond to average prices.

As discussed in Aron-Dine et al. (2013), a similar assumption is also made in the original estimates from the RAND HIE. A potential concern with this assumption is that marginal health care prices change dynamically over the course of a year, given the non-linear pricing schedule of most private health insurance contracts in the U.S. Overall, cost-sharing is typically a function of an annual deductible, several coinsurance rates (which differ by types of care) and an annual out-of-pocket (OOP) spending limit, in addition to copayments by types of drugs and episodes of care. Because deductibles and OOP spending limits are reset at the end of each calendar year, the spot price of medical care can differ from expected prices, realized end-of-year prices, and average prices over a year. Researchers have therefore imposed a variety of assumptions to calculate price changes, ranging from extreme myopia (spot prices) to perfectly forward-looking rational agents. Empirical evidence supports the existence of both behavioral biases and forward-looking behavior (Abaluck & Gruber, 2011; Brot-Goldberg et al., 2017; Ketcham, Lucarelli, & Powers, 2015), suggesting that average prices may reasonably approximate typical behavior.

Aron-Dine et al. (2013) call for "more attention to how the nonlinearities in the health insurance contracts may affect the spending response" (p.219). We conduct several tests for whether nonlinearities matter (Section 6.5). First, we test whether the estimated elasticities for plans with high deductibles (above the median) differ from those with low deductibles (below the median), conditional on plan AV and find economically and statistically insignificant differences for ER, outpatient, and inpatient spending. Prescription drug spending was modestly more responsive to cost-sharing in higher deductible plans (-0.127 versus -0.087). In addition, we estimate elasticities using an alternative measure of AV—the enrollee-specific end-of-year AV—and find very robust results. We take these findings as evidence that not explicitly accounting for nonlinearities in pricing is a reasonable and justifiable approach when the main objective is to estimate average price elasticities of demand.

5 Data

In this section, we describe the datasets we use, our outcomes, and our key health-related controls.

5.1 Datasets

We use three main datasets: Utah's All-Payer Claims Data (APCD) from 2013 to 2015, Inpatient Hospital Discharge Data from 2004 to 2013, and Emergency Department Data from 2004 to 2013. We describe each in turn below.

APCD 2013-2015. Our main dataset is the Utah All-Payer Claims Data (APCD) from 2013 to 2015. This database was created in accordance with state law, the Utah Health Data Authority Act, which requires every commercial insurance carrier in Utah to submit, each quarter, every health care claim to the Office of Health Care Statistics.[9] Relative to the overall state population of 2.9 million in 2013 (State of Utah, 2014) the APCD contains 2.1 million unique enrollees between 2013 and 2015. For each enrollee (with a primary residence in Utah), insurers must provide all medical claims for the individual and dependents, regardless of the state in which services were provided (Utah Department of Health, 2018a).

[9] The law exempts extremely small insurers with fewer than 2500 total enrollees across all plans. It also does not cover self-insured employers. These exemptions do not apply to any of the ACA Marketplace plans analyzed in this paper.

Each insurer submits the data to the state in a standardized way, consisting of four components of which we use three in this study. The first component is the person-month eligibility file containing every individual enrolled in each plan, in each month, even if the enrollee never has a medical claim. The eligibility file contains information about individuals, relationships between individuals enrolled in the same plan, and details about the source of coverage. The key components for our analysis include: an individual identifier, gender, month and year of birth, location of residence, plan identifiers that are linkable to publicly-available CMS data on Marketplace plan characteristics (including deductibles and other cost-sharing rules), metallic AV codes, and CSR subsidy categories.

The second and third components are the medical and prescription drug claim files. These databases contain charged amounts, negotiated amounts, amounts payed by insurers, member liabilities, copayment amounts, deductible amounts, and provider identifiers. The medical claim files also contain service codes, dates, and diagnoses. The drug claim files include NDC codes, purchase dates, quantities, refills, days supplied, dispensing fees, and pharmacy identifiers.

Inpatient and ER data 2004-2013. To comprehensively control for enrollees' pre-ACA health status and health care utilization, we link the APCD with two additional administrative datasets at the individual level (Utah Department of Health, 2018b). The first auxiliary dataset is the Inpatient Hospital Discharge Data from 2004 to 2013. The second auxiliary dataset is the Emergency Department Data from 2004 to 2013. These data come from hospital discharge records for all hospitals in the state. The data include hospital identifiers, admission and discharge dates, diagnosis codes, procedure codes, and charged amounts. We also observe individual demographics including age, location, and sources of insurance coverage.

5.2 Sample Restrictions

The population we study is Utah residents who were enrolled in CSR-variant plans purchased on the Utah Marketplace in 2014 or 2015.[10] We restrict the sample to adults between the ages of 18 and 64 who were enrolled for at least 9 months in either 2014 or 2015.[11] To reduce the influence

[10] We omit all claims from SelectHealth for August, September and November 2015 because of missing data. A robustness check consisting of omitting all data after July 2015 does not change the results.

[11] Our specific sample selection criteria are that enrollee-year pairs are included if the enrollee was between 18 and 64 years old on January 1, 2014 and was enrolled for any 9 calendar months during the corresponding calendar year in any CSR-variant plan.

of extreme outliers in the heavily skewed health care spending distributions, we omit enrollees in the top 0.5% of the overall spending distribution.

We collapse the claims-level data to the enrollee-month level and obtain an unbalanced panel of 495,986 person-months and 51,784 unique individuals.[12] Over half of the observations are for person-months enrolled in CSR-variant plans with a 94% AV, roughly one-third are for person-months in CSR-variant plans with an 87% AV, and the remainder are in CSR-variant plans with a 73% AV. Figure A1 in the Appendix shows enrollment over time by CSR category. As seen, enrollment in all plans increased smoothly over the course of 2014. At the beginning of 2015, we observe a significant increase in enrollment for all CSR-variant plans and then again an increase over the course of the year.[13]

5.3 Health Care Spending

Our main outcome of interest is total health care spending, which we calculate for each individual in each month by summing over all recorded "allowed amount" claims (actual payments based on negotiated prices). Panel A of Table 1 presents summary statistics on total spending by CSR category and category of medical care, including ER spending, inpatient spending, outpatient spending, pharmaceutical spending, and OOP spending. All values are in nominal dollars.

[Insert Table 1 about here]

As seen in the rightmost column of Table 1, among all enrollees in CSR-variant plans purchased on the Utah Marketplace in 2014 and 2015, average monthly total medical spending was $384. This level of health care spending is similar to that of the commercially insured population of Utah.[14] However, it is worth noting that it is low relative to that of a national sample, as Utah has among the lowest levels of health care spending in the country. Most spending was on care received in an outpatient setting ($211 per month), followed by pharmaceutical spending ($69 per month), inpatient spending ($60 per month), and ER spending ($44 per month). Average OOP spending on medical care was $33 per month, of which $16 was on deductibles.

[12] Although the data allow us to identify family plans, in the main approach, we cluster standard errors at the family level but conduct the analysis at the individual level. The main reason is that the health plan pricing structure does not offer discounts when purchasing a plan as a couple or a family. Two adults who are insured in a family plan as a couple have plan premiums and deductibles equal to twice that of an individual plan.

[13] The observed decrease after July 2015 is due to missing SelectHealth data described above.

[14] This statement is based on authors' calculations from the 2014 and 2015 Utah APCD.

The descriptive statistics presented in Table 1 suggest, but are not sufficient for us to conclude, that lower prices due to less cost-sharing leads people to spend more on health care. Individuals who are enrolled in plans with the highest levels of cost-sharing (73% AV) have lower levels of total monthly medical spending ($330) than individuals enrolled in plans with an 87% AV ($379) or a 94% AV ($399). This pattern of lower spending among those with more cost-sharing holds across all categories of care, with the exception of inpatient spending. In addition, OOP spending is substantially lower among individuals with less cost-sharing; it is $22 per month among individuals in plans with a 94% AV versus $63 per month among individuals with a 73% AV.

Spending on both low-value and high-value care increases along with plan AV, but there is stronger correlation between AV and low-value care.[15] Specifically, the amount of high-value care consumed increases by one third (from $3.6 to $4.8 per month) comparing plans with 73% AV to plans with 94% AV. However, the amount of low-value care consumed increases by two thirds (from $2.2 to $3.7 per month) comparing plans with 73% AV to plans with 94% AV. This descriptive finding provides first suggestive evidence that cost-sharing reduces the consumption of both types of care, but in particular, low-value care.

Figure 1 displays the cumulative density function for total spending for enrollees in the three types of CSR plans. The figure shows that the higher spending among enrollees in 94% AV and 87% AV plans, relative to that by enrollees in 73% AV plans, occurs across the spending distribution. For ER spending (Figure 2a), only 7% of enrollees in plans with an AV of 73% had any ER spending, compared with 9% of enrollees in plans with an AV of 87% and 12% of enrollees in plans with an AV of 94%. Among those with positive ER spending, the distributions of ER spending are shifted right among those with less cost sharing. Among enrollees in CSR plans with a 73% AV, the top 3% of ER consumers consume ER care worth more than $2,000 per year, while the top 3% of CSR 94 enrollees spend more than $4,000 per year. We observe similar patterns for outpatient spending (Figure 2c), though the differences across different plan AV are smaller. Roughly two-thirds of all enrollees in our sample have any OOP spending, but among those with positive OOP spending, lower AV plans have obviously higher OOP (Figure 2b). By contrast, we

[15] We follow Schwartz et al. (2014) and Brot-Goldberg et al. (2017) and categorize health care spending into low-value and high-value care. Low-value care is an "evidence-based list of services that provide minimal clinical benefit," which includes specific types of low-value cancer screening, diagnostic and preventive testing, preoperative testing, imaging, cardiovascular testing and procedures, and other low-value surgical procedures. High-value care includes certain forms of preventive care, mental health care, physical therapy, and drugs used to manage diabetes, high cholesterol, depression, and hypertension. As seen, most health care spending is not categorized as either low-value care ($3.2 per month) or high-value care ($4.5 per month); in fact, both types of care just make up 2% of overall spending for all CSR enrollees (percentages not shown in Table 1).

see few differences in the distribution of inpatient spending across individuals in plans with different AVs (Figure 2d).

[Insert Figure 1 and 2 about here]

5.4 Controls for Health

We comprehensively control for prior health in our empirical models using three measures of each individual's past health care use. First, we use the rich diagnoses and claims information for each individual in the Utah APCD to calculate their risk scores for 2013 using the John Hopkins ACG System© software. Several previous studies similarly have used risk scores as a comprehensive measure of individual health risks (Einav et al., 2013; Handel, 2013). Risk scores are normalized to have a mean of 1 in the full population of commercially insured non-elderly adults in the Utah APCD. In our population of individuals purchasing CSR-variant plans on the Utah Marketplace, the mean risk score is quite similar to that in the overall population (see Panel B of Table 1).[16] Fifty percent of individuals do not have data from which we can calculate a risk score for 2013, however. These individuals receive a risk score of 1 and, in the empirical models, we include a binary flag that equals 1 if the 2013 risk score is missing.

Second, we condition on health care utilization histories for an entire decade, from 2004 to 2013. We derive these histories from administrative data on hospital discharge records at the individual level, and from these histories we construct measures of the total number of inpatient days and the total number of ER visits for each individual over this 10-year period. For our population, the mean number of inpatient days between 2004 and 2013 was 2.08 and the mean number of ER visits over this period was 1.66.

Note that the 2013 risk scores and the mean numbers of inpatient visits vary only slightly across CSR categories, while ER visits and the number of months uninsured in 2013 are higher for individuals in plans in plans with higher AVs. Thus, in order to address selection concerns regarding systematic between-enrollee variation in health status that may be correlated with plan selection, it is important to control both for individual-level risk scores and prior utilization in years before 2014, the first year of ACA Marketplace enrollment in Utah.

[16] The distribution of risk scores (not shown) is heavily skewed to the right. This pattern is consistent with the highly-skewed health spending distributions in other populations (French & Kelly, 2016).

5.5 Other Controls

Panel B of Table 1 also reports descriptive statistics on gender and age, which we also control for in our empirical models. Slightly more than half of our observations are for women. Roughly a third of observations are from enrollees between 18 to 30 years old, slightly more than a third are from enrollees between 31 to 50 years old, and slightly less than a third are from enrollees between 51 to 64 years old. Eighty-one percent of enrollees live in an urban county, and 75 percent of enrollees are in an HMO.

6 Results

In this section, we present our empirical findings. In Section 6.1, we estimate the impact of varying levels of coinsurance on total health care spending and on categories of health care spending. We also report the implied own-price elasticity estimates. In Section 6.2, we report our estimates of demand elasticities for low-value and high-value care and for different types of pharmaceuticals. In Section 6.3, we investigate potential selection concerns and present a series of robustness checks. In Section 6.4, we present evidence on heterogeneity in responses to cost-sharing. In Section 6.5, we investigate the relevance of non-linearities in insurance contracts. In Section 6.6, we present estimates of cross-price elasticities between categories of care. Finally, in Section 6.7, we discuss the relevance of a possible income-health channel that could lead to downward bias in our elasticity estimates.

6.1 Demand Responses to Cost-Sharing by Types of Care

Tables 2 and 3 show our main results, which are from our GLM estimates of equations (1) and (2). Each column of Tables 2 and 3 reports estimates from separate regressions where the dependent variable is total monthly spending or monthly spending on different categories of care. The estimates reported in Table 2 are from the empirical specification that includes binary indicators for individuals enrolled in a CSR-variant plan with an AV of 87% and for individuals enrolled in a CSR-variant plan with an AV of 94%. Individuals enrolled in a CSR-variant plan with an AV of 73% are the baseline category.

[Insert Table 2 about here]

Compared with individuals in plans with an AV of 73%, individuals in plans with an AV of 94% have total spending that is 19% higher, after adjusting for prior health status as captured by the 2013 ACG© risk score, the number of inpatient days and ER visits from 2004-2013, age, gender, county fixed effects, and calendar month fixed effects. Those in a plan with an AV of 87% have total spending that is 13% higher than those in a plan with an AV of 73%. These differences are statistically meaningful.

Looking at categories of spending—ER, outpatient, and inpatient—individuals enrolled in plans with the highest AVs spend more than individuals in plans with the lowest AVs in all three categories of spending. ER spending is 32% higher and outpatient spending is 23% higher among enrollees in plans with a 94% AV compared with enrollees in a 73% AV, but the difference in spending on inpatient care is small and not statistically meaningful. Enrollees in plans with an AV of 87% also have higher spending than those in plans with a 73% AV in all three categories of health care spending, but only the difference in spending for outpatient care is statistically significant.

Out-of-pocket (OOP) spending is substantially lower among individuals in plans with an AV of 94% (66% lower) and for individuals in plans with an AV of 87% (41% lower) compared with individuals in plans with an AV of 73%. Reassuringly, Table 2 also shows that all three measures of pre-2014 health status are positively and significantly correlated with total health care spending in 2014 and 2015 as well as with all categories of health care spending.

[Insert Table 3 about here]

Table 3 reports the results of our estimation of equation (2), which transforms AV into a continuous variable, the log coinsurance rate or $ln(1\text{-}AV_{p(it)})$. Since the GLM specification has a log-link function, and the independent variable is the log coinsurance rate, the reported coefficients in this table can be directly interpreted as estimates of own-price elasticities of demand.

We estimate an elasticity of demand for total medical care spending of -0.10 (first column). This estimate is statistically different from zero and close to the conventional estimates in the literature (Manning et al., 1987). In contrast, but also in line with current research (Finkelstein et al., 2012), the elasticity of demand for ER care (-0.20) is twice as large as the overall elasticity, while outpatient spending (-0.13) has an elasticity similar to the overall average. The elasticity for inpatient spending is not statistically different from zero. In line with Table 2, the final column of

Table 3 shows that a higher coinsurance rate is significantly related to higher out-of-pocket spending.[17]

6.2 Does Cost-Sharing Discourage the Use of Low-Value Care?

In this subsection, we report results on the price responsiveness for low-value and high-value medical care. Recall that spending on low-value care represents only 0.8% of total spending, and spending on high-value care represents only 1.2% of total spending; thus, there is a substantial residual category of spending that cannot be categorized as high-value or low-value care.

[Insert Table 4 about here]

As Table 4 shows, low-income enrollees of Marketplace plans are more than twice as responsive to prices in their demand for low-value medical care, with an implied elasticity of -0.23 (column 3), as they are overall for care, with an elasticity of -0.10 (column 1). Interestingly, and in line with Brot-Goldberg et al. (2017), low-income enrollees of Marketplace plans also have a substantial price responsiveness in their demand for high-value care, with an average elasticity of -0.26. Both elasticity estimates are more than twice as large as the estimated elasticity (-0.10) for the remaining "uncategorized" health care services.

We also examine differences in price-responsiveness across classes of prescription drugs and report these results in Table 5. We group drugs based on their potential to prevent subsequent hospitalizations, following the approach in (Chandra et al., 2010), which assigns drug classes to three groups. Acute drugs are those that, if not taken, are likely to lead to hospitalization within one to two months. Chronic drugs are those that, if not taken, are likely to lead to hospitalization within one year. Lifestyle drugs include those that are unlikely to result in hospitalization if not taken. We also, separately, examine differences in demand elasticities for branded and generic drugs.

[Insert Table 5 about here]

[17] Appendix Table A1 reports estimates from an OLS log-log specification of equation (2), conditional on enrollees with any positive medical spending. We condition on positive spending because this intensive margin variation corresponds to the identifying variation in the GLM estimates. The implied elasticity estimates for total spending (-0.13) and outpatient spending (-0.14) are similar to the GLM estimates. However, ER (-0.04) and inpatient (-0.01) spending estimates are substantially smaller, but still statistically different from zero, driven in part by the smaller fraction of individuals who use these categories of care (see Figure 2). These patterns suggest that some estimates, especially those with substantial extensive-margin variation, may be sensitive to the restrictions imposed in the OLS specification, which is one reason why we prefer the GLM specification.

Low-income enrollees of Marketplace plans have an overall demand elasticity for prescription drugs of -0.12. These consumers have a slightly larger price responsiveness in their demand for acute care drugs (-0.19), but are less responsive in their demand for drugs to treat chronic disease (-0.08, with a standard error of 0.09) as well as branded drugs (-0.05, with a standard error of 0.07). Low-income consumers are much more responsive in their demand for lifestyle (-0.27) and generic (-0.17) drugs. These two elasticity estimates are statistically different from zero.

6.3 Selection Concerns

As we discuss above, there are two potential channels through which non-random assignment of consumers to plans with different AVs could confound the interpretation of our estimates. First, prior health status could affect present demand for insurance generosity and could also affect present income. Second, CSR beneficiaries could strategically manipulate the incomes that they report on healthcare.gov to affect assignment to CSR tiers (and this manipulation may be correlated with health).

We address the first concern by conditioning on a rich set of controls for health status and health care utilization prior to enrollment, including 2013 ACG© risk score and ten years of inpatient and ER utilization measures. However, to the extent that—despite our rich health measures—unobserved health status is still leading to selection into plans, our estimates may still be biased. In order to shed some light on whether unobserved health factors may be an issue in this setting, we re-estimate equation (2) adding in our controls for prior health in a step-wise manner. This test is similar in spirit to the "using selection on observables to measure selection on unobservables" approach of (Altonji et al., 2005). We first estimate models with only age, gender, county, and calendar month fixed effects. We then add the control for 2013 ACG© risk score. Then, we omit the risk score but add controls for inpatient days and ER visits from 2004 through 2013, and finally, we control for all available health measures jointly. The results are reported in Table 6. To the extent that our estimates change little as we add controls, there is little evidence of unobserved health factors (that are correlated with our prior health measures) being important.

[Insert Table 6 about here]

As seen, Table 6 shows that our estimates of the overall elasticity of demand, as well as our estimates of the elasticities of demand for categories of care or for out-of-pocket spending, change little as we add controls stepwise. Specifically, controlling for the 2013 risk score almost does not alter any of the five point estimates, whereas adding the decade of inpatient and ER measures let four of five point estimates decrease in size. However, none of the five point estimates decrease in a statistically significant manner when we add very rich and comprehensive administrative health controls stepwise to the models. In our view, this lends support to the plausible exogeneity of the coinsurance rate in our models.[18]

The second concern is that enrollees may strategically manipulate their reported income to obtain higher cost-sharing subsidies. However, there appears to be no evidence, based on CMS data on Marketplace enrollment, that this was the case. DeLeire et al. (2017) examined the density of Marketplace enrollment by income in all states (including Utah) with Federally-Facilitated Marketplaces from 2014 to 2017 using individual-level enrollment data from CMS's Multidimensional Insurance Data Analytics System and found no evidence of income manipulation (see Figure 3). A similar analysis using data only from Utah in 2014 and 2015 also shows no evidence of income manipulation (not shown).

[Insert Figure 3 here]

6.4 Effect Heterogeneity

In this subsection, we investigate whether there is heterogeneity in our estimates of the elasticity of demand for medical care across individuals by demographic characteristics and by health. To do this, we re-estimate equation (2) including interactions between the log coinsurance rate and the covariates of interest.

[Insert Table 7 about here]

We find little evidence of differences in demand elasticities by age. Panel A of Table 7 reports elasticities stratified by the three age groups: 18 to 30, 31 to 50, and 51 to 64 years. With the exception of inpatient spending, there is no economically or statistically meaningful difference in the elasticity estimates across age category.

Men are significantly more responsive to cost-sharing than are women; the estimated elasticity of demand for total spending is -0.21 for men versus -0.02 for women (see Panel B). This pattern

[18] Estimated elasticities are also robust to including insurer fixed effects, as reported in Appendix Table A3.

holds across all categories of care except for ER spending, where the difference in responsiveness between men and women is not statistically significant.

There is little evidence of geographic heterogeneity in responses to cost-sharing, except for OOP spending (see Panel C). Enrollees in urban areas have smaller increases in OOP spending as cost-sharing rises, compared with enrollees in rural areas. It is worth noting that a very large share of Utah residents lives in the Salt Lake City metro area, so rural enrollees represent only 11% of the sample.

In Panel D, we provide suggestive evidence that enrollees in family plans are significantly more responsive to cost-sharing than individual enrollees. Note that because of our sample selection criteria, these estimates are only based on adults' claims, not children's. An interesting topic for further research is which aspects of family insurance plans, or selection into families, can explain these differences in price responsiveness. One potential candidate is the use of combined deductibles, which generally double when increasing the plan size from one adult to two adults. Families may also have different budget constraints or preferences.

[Insert Table 8 about here]

Finally, there is some evidence that sicker people are less responsive to cost-sharing than healthier people; while the estimated differences are large, they are not statistically meaningful. Table 8 reports estimates where we stratify by the 2013 ACG© risk score. There is a clear pattern in all categories of care: individuals with higher risk scores are less responsive to cost-sharing. For ease of interpretation, the bottom of the table reports the implied marginal elasticities at the 10^{th}, 50^{th}, and 90^{th} percentiles of the distribution of Utah risk scores. For example, for overall care, the 10^{th} percentile elasticity is -0.14, the 50^{th} percentile elasticity is -0.11, and the 90^{th} percentile elasticity is -0.07. All of these elasticities are statistically different from zero, though few of them are statistically different from one another. Inpatient spending is particularly sensitive to pre-period risk scores, while outpatient and ER spending are not highly sensitive.

6.5 Nonlinearities in Plan Design

As we discuss above, it is conceivable that nonlinearities in the ACA health insurance plan designs may have an effect on health care spending. In this subsection, we report the results of two tests for whether nonlinearities matter. First, we test whether the estimated elasticities for plans with high deductibles differ from those with low deductibles, conditional on plan AV. By conditioning on plan AV, this model tests for whether differences in nonlinearities result in different elasticities, when holding plan generosity constant. Second, we estimate price responsiveness to a measure of enrollee-specific end-of-year cost-sharing; that is, the last observed spot price in every year for every enrollee. Based on these robustness checks, we conclude that nonlinearities in plan designs do not appear be very relevant in this setting, as they do not substantially affect our average elasticity estimates.

Table 9 stratifies the estimates by the size of the deductible. In particular, we interact the coinsurance rate with a dummy variable indicating whether the plan has a deductible above the mean deductible within the CSR category. The deductible we use for this analysis is the combined deductible for medical and prescription drug spending.[19] Since the model conditions on the average coinsurance rate, the only variation that identifies the coefficient on the interaction term is variation in the nonlinearity of plan designs within a CSR category. This provides a straightforward test of the empirical relevance of nonlinearities in our demand elasticity estimates. As seen, elasticities for higher and lower deductible plans are very similar and not statistically different from one another for all categories except pharmaceutical spending. For drug spending, in line with priors, the elasticities for plans with lower deductibles are slightly smaller (-0.09 vs. -0.13), but the difference is also not statistically significant.

[Insert Table 9 about here]

Tables 10 reports estimated demand elasticities when using an enrollee-specific end-of-year measure of cost-sharing. Recall that, in our main specifications, to calculate average coinsurance rates, we have used the AV corresponding to the of the CSR category of the plan (73%, 87%, and 94%). The person-specific end-of-year coinsurance rate would be the correct coinsurance rate if enrollees were both forward looking and able to correctly anticipate their health care spending over the course of the year. As seen, the estimated demand elasticities based on this measure of coinsurance are very similar to our main estimates.

[Insert Table 10 about here]

[19] The average combined deductible among FFM plans in 2014 and 2015 was $2,077 for 73% AV CSR variants, $737 for 87% AV CSR variants, and $229 for 94% AV CSR variants (Kaiser Family Foundation, 2015).

6.6 Cross-Price Elasticities

In this section, we estimate cross-price elasticities of demand. The cross-price elasticities we are particularly interested in are how inpatient spending and ER spending respond to coinsurance rates for outpatient care and for pharmaceuticals, as these have been subject of much prior research interest (Chandra et al., 2010; Fang & Gavazza, 2011; Gaynor, Li, & Vogt, 2007; Manning et al., 1987; McKnight, 2006).

In Table 11, we report demand elasticities based on equation (3), which is similar to our main specifications, but includes all category-specific coinsurance rates simultaneously. We calculate coinsurance rates as the average *ex post* coinsurance rate by CSR category, spending category (outpatient, inpatient, ER, and drug spending), and year. To calculate these coinsurance rates, we sum out-of-pocket spending for all claims within a CSR category, spending category, and year and then divide by the total amount of all claims in that CSR category, spending category, and year. These *ex post* AVs are close to, but not exactly identical to, the AVs one would expect based on the CSR category. For example, while the *ex post* AV for pharmaceutical spending among 73% AV CSR variant plans in 2015 was exactly 73%, it was 74% for ER spending and 75% for outpatient spending. The overall *ex post* AV among 87% CSR variant plans was 89% and was 95% among 94% AV CSR variant plan.[20]

[Insert Table 11 here]

Using this specification does not substantively change the estimate of the own-price elasticities of demand for ER and inpatient spending; all remain negative and significant but do increase in size when we simultaneously control for the prices of other types of care. The cross-price elasticity between ER spending outpatient is negative and significant, providing evidence that ER and outpatient spending are substitutes. Similarly, the negative cross-price elasticity between inpatient spending and outpatient spending also indicates that these two types of care are substitutes. Finally, we also find outpatient spending (but not inpatient and ER spending) to be a substitute for pharmaceutical spending.

[20] We show in Appendix Table A2 that, if we use this ex post and category specific measure of the AV to calculate coinsurance rates and re-estimate equation (2), we obtain estimates that are quite similar to those reported in Table 3.

6.7 The Income-Health Gradient as a Possible Channel

As we discuss above, AVs are negatively related to income by policy design. Thus, any increase in health care utilization caused by CRSs may be partially offset by income effects, since we cannot control for income. Hence, we view our demand elasticity estimates as potentially lower bounds. In this subsection, we use income elasticity estimates from the literature to assess how large these potential offsets might be.

Several health economic studies assess the elasticity of health care spending with respect to income. A motivation of this literature is the strong income-health gradient, which we observe within and between countries. It is a stylized fact that health care spending as a share of the GDP increases more than proportionally when countries develop and become richer. One approach is to use macro data, along with panel and time series econometrics, to assess the empirical link between GDP, income and health care spending. All these studies find very large elasticities, often larger than 1, and conclude that health care is be a "luxury good" (Baltagi et al., 2017; Farag et al., 2012).

By contrast, recent studies based on micro data with well-identified designs are scarce. Getzen (2000) provides an overview of older studies, most of which conclude that the micro-level income elasticity for health care spending is close to zero. In one of the very few recent and well-identified papers, Cesarini, et al. (2016) use lottery winnings as exogenous variation and find no significant impact of wealth on hospitalizations, health or drug consumption (with the exception of a very small effect on mental health drugs).

Other papers, like our paper, that focus on low-income populations in the U.S., such as Chandra Gruber & McKnight (2014), implicitly assume an income elasticity of zero when using income-based cost-sharing variation to calculate price elasticities. We follow this convention. However, to provide some plausibility checks, let us consider the gross incomes of CSR beneficiaries. The mid-point of the income category for a single beneficiary in 2014 was $1,215 (125% of FPL) compared with $1,702 (175% of FPL) in the 87% AV CSR category, which is 40% higher (U.S. Department of Health and Human Services, 2019). An income elasticity of 0.5 would imply that an enrollee with a 87% AV CSR-variant plan would spend 20% more on health care (or $66 per month) than enrollees with a 73% AV CSR variant plan because of income effects *independent* of health status, age or preferences. Given the extreme poverty in which low-income populations live in, we believe that such an effect is unrealistic.[21] A more realistic income-health elasticity of 0.1 would imply that we are underestimating spending differences by only 4% when comparing enrollees with 87% AV plans and enrollees with 73% AV plans (a $364 difference instead of a $379 difference).

In any case, because a possible income effect on health care spending operates in the opposite direction than the main price effect, any income elasticity larger than zero would simply imply that we produce lower bound price elasticity estimates. As it is very likely that income elasticities for low-income populations are very small, the implied downward bias in our demand elasticity estimates is small as well.

7 Discussion

Our findings suggest that basic demand-side price mechanisms in health insurance design work similarly for low-income enrollees as they do for the broader groups of higher-income enrollees which have been studied by the previous literature. We find that low-income enrollees (who were uninsured for an average of two months in the year before the Utah Exchange was created) have roughly similar price-inelastic demand as the U.S. population more generally. However, they may be more responsive than the general population to cost-sharing for ER services. As a comparison, using recent U.S. data from 73 employers and 171 million person-month observations, Ellis et al. (2017) find overall elasticities of -0.4 and very small elasticities of -0.04 for ER visits.

We find that responses to cost-sharing among low-income ACA enrollees imply an overall demand elasticity for health care of -0.1. This estimate is close to the commonly-cited RAND HIE estimate of -0.2, especially when considering that it may be a lower bound if the income-health elasticity in this low-income population is significantly larger than zero. Our estimated elasticities for inpatient care are not statistically different from zero, and those for outpatient care are -0.13. However, for Emergency Room (ER) care, the demand elasticity is substantially larger (-0.2). These ER elasticities are consistent with results from the Oregon Medicaid lottery, which found a significant increase in ER utilization when individuals gained Medicaid coverage (Taubman et al., 2014). Corroborating the first stage variation in cost-sharing levels, we find an elasticity of out-of-

[21] For example, Rozema & Ziebarth (2017) use increases in cigarette taxes as an exogenous shifter of the disposable income of households below 175% FPL in the U.S. They find that a reduction in monthly disposable household income of just $35 per month induces eligible but not enrolled households to sign up for food stamps. In our opinion, the size of these numbers illustrates that $35 per month represents a substantial amount of money for low-income households in extreme poverty—enough to overcome the stigma and transaction costs of enrolling in SNAP. While the households in this case study are obviously strongly addicted to cigarettes, we believe it is unlikely that similar households would "voluntarily" spend $35 more on healthcare *independent* of health and insurance status, solely as a result of marginally higher household incomes.

pocket (OOP) spending with respect to average coinsurance rates of +0.71. We also find that sicker enrollees—those with higher pre-ACA risk scores—are less price responsive to cost-sharing. Consistent with evidence from the recent literature, we find meaningful responsiveness to both high-value (-0.26) and low-value (-0.23) medical care. This finding suggests that reducing cost-sharing is a blunt instrument for increasing the use of high-value health care among the low-income enrollees in ACA Marketplace insurance plans.

The findings on consumers' price responsiveness to drugs suggest that enrollees are more price sensitive for drugs that limit immediate risks of hospitalization than for drugs that treat chronic illness, suggesting the potential for inefficient spillover effects between less generous drug coverage and increased hospitalizations within this population. This may occur if blunt cost-sharing rules like deductibles attenuate insurers' ability to design drug-level incentives that encourage enrollees to purchase drugs with acute spillover risks. We do find, however, that lifestyle drugs have the largest elasticity, suggesting that there is some channel through which consumers respond to a lack of hospitalization spillover effects.

8 Counterfactual Policy Estimates

In late 2017, the Department of Justice determined that it was unlawful for the federal government to make CSR payments to insurers unless Congress had appropriated funds, which it had not. As a result, insurers are currently legally obligated to provide subsidies to consumers, but the federal government has ceased reimbursement to insurers for the cost of these subsidies. This, in turn, has led to explicit distortions of plan premiums on the exchanges (Branham & DeLeire, 2019; Kamal et al., 2017). To recoup these unfunded subsidies, insurers explicitly added surcharges of 7% to 38% to plan premiums (Kamal et al., 2017). One conceivable policy consequence of the lack of congressional appropriations to fund CSR payments in the future may be the termination of CSRs. Using our estimates of the elasticities of demand for categories of medical care, we estimate the counterfactual effect of eliminating all CSR subsidies on health care utilization and OOP spending, and discuss the potential implications of such a policy.

To predict the counterfactual health care spending of CSR recipients, if they had enrolled in standard 70% AV Silver plans instead of in CSR plans, we extrapolate from our elasticity estimates reported above. Note that this counterfactual exercise describes a partial equilibrium in which CSR recipients still enroll in Silver plans; we do not consider the impact of eliminating CSR subsidies on premiums or plan selections.

The first row of Table 12 reports the counterfactual estimates for all CSR recipients. As seen, eliminating CSRs would substantially reduce overall medical spending among CSR recipients by 24%, or $92 per month, from $384 to $292 (columns 1 to 3). At the same time, eliminating CSRs would increase OOP spending by $30 per month (column 6). Given the estimated decrease in spending by $92, this implies that the monthly taxpayer-funded amount in CSRs received would decrease by $62 per month (column 5).

These are values for the average CSR beneficiary in Utah. In 2018, nationwide, 6 million recipients (Centers for Medicare and Medicaid Services, 2019) were enrolled in CSR plans. Given total CSR spending of roughly $8 billion (Congressional Budget Office, 2017) these numbers suggest that the per-recipient spending on CSRs was over $1,300 per year, or $113 per month (assuming 12 months of enrollment).

[Insert Table 12 and 13 about here]

The next three rows of Table 12 show heterogeneity in the effects of removing CSR subsidies by income level. Compared to higher-income consumers, consumers with incomes between 100 and 150% of FPL (who receive greater CSRs to increase their Silver plan AVs to 94%) would reduce their medical spending by a greater percentage and dollar amount (-27% or -$108 per month). Analogously, their OOP spending would increase by a greater amount (+$41 per month).

We also estimate the impacts by age and by 2013 ACG© risk scores. Not surprisingly, older and sicker enrollees would experience the largest monetary cost from eliminating CSR subsidies. Specifically, we estimate that enrollees between ages 51 and 64 would have $107 lower medical spending per month (or -18%) and $37 higher OOP spending. Enrollees with risk scores above 1 (above the Utah population mean) would have $164 lower medical spending per month (or -24%) and $48 higher OOP spending.

Our counterfactual exercise illustrates that eliminating CSRs would also have differential effects on different types of medical spending (Table 13). In percentage terms, because of the larger elasticities for ER care (as reported in Table 3), the reductions are largest for (potentially inefficient) ER care (38%) and outpatient care (25%). However, we also predict disproportionately large reductions in certain types of preventive care, for example, in drugs that prevent hospitalizations; we estimate that eliminating CSRs would reduce low-income enrollees' spending on drugs that prevent hospitalizations by 28% (or $11 per month).

A possible implication of this result is that targeted information about the effectiveness and value of specific medical care and prescription drugs has not been effectively communicated by insurers, providers, and policymakers. On the other hand, our findings clearly suggest that consumers—even low-income consumers with little previous coverage experience—do respond to prices in the health care sector. Hence, differentiating CSRs by their value and effectiveness, as "value-based CSRs," could be an alternative policy.

A final policy implication of our results is that CSR payments to insurers (even prior to 2017), likely did not fully cover the costs of providing these subsidies. The reason is that in its formula for calculating advance CSR payments to issuers, CMS assumed that CSR Silver plans with a 94% AV or an 87% AV would induce 12% higher total medical spending relative to 70% AV silver plans (Federal Register, 2013). However, our results suggest that this adjustment is substantially too small. In addition, the standard methodology that insurers were to use to calculate their CSR costs for purposes of reconciliation assumed that the elasticity of medical care (with respect to the plan AV) was zero. This assumption would also lead to CSR payments that did not fully compensate issuers for the increased spending of CSR recipients (even prior to the decision to cease these payments in 2017).

9 Conclusion

This is the first paper to use APCD data to assess how low-income enrollees of the ACA Marketplaces respond to cost-sharing on the ACA Exchanges. We estimate the elasticity of demand separately by major category of medical care. We also test for heterogeneity in responsiveness for high-value and low-value care and for different classes of drugs that may offset the risk of hospitalization.

One important unresolved question is whether low-income enrollees on the ACA exchanges respond to cost-sharing in a similar fashion as higher-income enrollees that have been studied in the literature. This question is of increasing importance as many states have recently applied for and received Section 1155 Waivers from CMS to introduce cost-sharing in the Medicaid program. Our estimates suggest that taxpayer-funded price subsidies increase demand for high-value care, but also for inefficient low-value care. As a result, counterfactual estimates of the effects of eliminating CSR subsidies suggest across-the-board reductions in medical care utilization for high and low-value care.

Overall, our findings suggest that price mechanisms work in the health care sector, even for low-income enrollees with potentially little experience navigating complex private health plans and non-linear pricing schedules. Our findings suggest that demand-side price mechanisms in health insurance design work similarly for low-income enrollees as they do for broader groups of higher-income enrollees. Since the goal of the CSR program was to simultaneously reduce the out-of-pocket spending on medical care of low-income enrollees, while also increasing their use of needed medical care, our results suggests that, overall, the CSR program is working as intended.

REFERENCES

Abaluck, J., & Gruber, J. (2011). Choice inconsistencies among the elderly: evidence from plan choice in the Medicare Part D program. *American Economic Review*, *101*(4), 1180–1210.

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy*, *113*(1), 151–184. https://doi.org/10.1086/426036

Aron-Dine, A., Einav, L., & Finkelstein, A. (2013). The RAND health insurance experiment, three decades later. *Journal of Economic Perspectives*, *27*(1), 197–222.

Baltagi, B. H., Lagravinese, R., Moscone, F., & Tosetti, E. (2017). Health care expenditure and income: A global perspective. *Health Economics*, *26*(7), 863–874.

Branham, D. K., & DeLeire, T. (2019). Zero-Premium Health Insurance Plans Became More Prevalent In Federal Marketplaces In 2018. *Health Affairs*, *38*(5), 820–825.

Brot-Goldberg, Z. C., Chandra, A., Handel, B. R., & Kolstad, J. T. (2017). What does a deductible do? The impact of cost-sharing on health care prices, quantities, and spending dynamics. *The Quarterly Journal of Economics*, *132*(3), 1261–1318.

Buntin, M. B., & Zaslavsky, A. M. (2004). Too much ado about two-part models and transformation?: Comparing methods of modeling Medicare expenditures. *Journal of Health Economics*, *23*(3), 525–542.

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, *50*(2), 317–372.

Center for Budget and Policy Priorities. (2018). Key Facts: Cost-Sharing Reductions. Retrieved September 8, 2019, from https://www.healthreformbeyondthebasics.org/cost-sharing-charges-in-marketplace-health-insurance-plans-part-2/

Centers for Medicare and Medicaid Services. (2019). 2018 Marketplace Open Enrollment Period Public Use Files. Retrieved September 23, 2019, from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Marketplace-Products/2018_Open_Enrollment.html

Centers for Medicare Medicaid Services (CMS), H. (2013). Medicaid and Children's Health Insurance Programs: essential health benefits in alternative benefit plans, eligibility notices, fair hearing and appeal processes, and premiums and cost sharing; exchanges: eligibility and enrollment. Final rule. *Federal Register*, *78*(135), 42159–42322. Retrieved from https://www.federalregister.gov/documents/2013/07/15/2013-16271/medicaid-and-childrens-health-insurance-programs-essential-health-benefits-in-alternative-benefit

Cesarini, D., Lindqvist, E., Östling, R., & Wallace, B. (2016). Wealth, health, and child development: Evidence from administrative data on Swedish lottery players. *The Quarterly Journal of Economics*, *131*(2), 687–738.

Chandra, A., Gruber, J., & McKnight, R. (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review*, *100*(1), 193–213.

Chandra, A., Gruber, J., & McKnight, R. (2014). The impact of patient cost-sharing on low-income populations: evidence from Massachusetts. *Journal of Health Economics*, *33*, 57–66.

Chiappori, P.-A., Durand, F., & Geoffard, P.-Y. (1998). Moral hazard and the demand for physician services: First lessons from a French natural experiment. *European Economic Review*, *42*(3–5), 499–511.

Cockx, B., & Brasseur, C. (2003). The demand for physician services: evidence from a natural experiment. *Journal of Health Economics*, *22*(6), 881–913.

Congressional Budget Office. (2017). *The Effects of Terminating Payments for Cost-Sharing Reductions*. Retrieved from https://www.cbo.gov/system/files/115th-congress-2017-2018/reports/53009-costsharingreductions.pdf

Cox, N., Handel, B., Kolstad, J., & Mahoney, N. (2015). Messaging and the mandate: The impact of consumer experience on health insurance enrollment through exchanges. *American Economic Review*, *105*(5), 105–109.

Dafny, L., Gruber, J., & Ody, C. (2015). More insurers lower premiums: Evidence from initial pricing in the health insurance marketplaces. *American Journal of Health Economics*, *1*(1), 53–81.

Deb, P., Norton, E. C., & Manning, W. G. (2017). *Health econometrics using Stata*. Stata Press College Station, TX.

Deb, P., & Trivedi, P. K. (1997). Demand for medical care by the elderly: a finite mixture approach. *Journal of Applied Econometrics*, *12*(3), 313–336.

Deb, P., & Trivedi, P. K. (2002). The structure of demand for health care: latent class versus two-part models. *Journal of Health Economics*, *21*(4), 601–625.

DeLeire, T., Chappel, A., Finegold, K., & Gee, E. (2017). Do individuals respond to cost-sharing subsidies in their selections of marketplace health insurance plans? *Journal of Health*

Economics, *56*. https://doi.org/10.1016/j.jhealeco.2017.09.008

DeLeire, Thomas, Dague, L., Leininger, L., Voskuil, K., & Friedsam, D. (2013). Wisconsin experience indicates that expanding public insurance to low-income childless adults has health care impacts. *Health Affairs*, *32*(6), 1037–1045.

Dickstein, M. J., Duggan, M., Orsini, J., & Tebaldi, P. (2015). The impact of market size and composition on health insurance premiums: Evidence from the first year of the affordable care act. *American Economic Review*, *105*(5), 120–125.

Duarte, F. (2012). Price elasticity of expenditure across health care services. *Journal of Health Economics*, *31*(6), 824–841.

Einav, L., Finkelstein, A., & Polyakova, M. (2018). Private provision of social insurance: drug-specific price elasticities and cost sharing in Medicare Part D. *American Economic Journal: Economic Policy*, *10*(3), 122–153.

Einav, L., Finkelstein, A., Ryan, S. P., Schrimpf, P., & Cullen, M. R. (2013). Selection on moral hazard in health insurance. *American Economic Review*, *103*(1), 178–219.

Ellis, R. P., Martins, B., & Zhu, W. (2017). Health care demand elasticities by type of service. *Journal of Health Economics*, *55*, 232–243. https://doi.org/10.1016/j.jhealeco.2017.07.007

Fang, H., & Gavazza, A. (2011). Dynamic inefficiencies in an employment-based health insurance system: Theory and evidence. *American Economic Review*, *101*(7), 3047–3077.

Farag, M., NandaKumar, A. K., Wallack, S., Hodgkin, D., Gaumer, G., & Erbil, C. (2012). The income elasticity of health care spending in developing and developed countries. *International Journal of Health Care Finance and Economics*, *12*(2), 145–162.

Federal Register. (2013). *Federal Register Vol. 78, No. 47*.

Fernandez, B. (2018). Health Insurance Premium Tax Credits and Cost-Sharing Subsidies. *Congressional Research Service Report*, *April 24*.

Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., … Group, O. H. S. (2012). The Oregon health insurance experiment: evidence from the first year. *The Quarterly Journal of Economics*, *127*(3), 1057–1106.

Frean, M., Gruber, J., & Sommers, B. D. (2017). Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act. *Journal of Health Economics*, *53*, 72–86.

French, E., & Kelly, E. (2016). Medical spending around the developed world. *Fiscal Studies*, *37*(3–4), 327–344.

Gabel, J., Whitmore, H., Green, M., Call, A., Stromberg, S., & Oran, R. (2016). The ACA's Cost-Sharing Reduction Plans: A Key to Affordable Health Coverage for Millions of US Workers. *Issue Brief (Commonwealth Fund)*, *35*, 1–12.

Gaynor, M., Li, J., & Vogt, W. B. (2007). Substitution, spending offsets, and prescription drug benefit design. *Forum for Health Economics & Policy*, *10*(2). De Gruyter.

Gerfin, M., & Schellhorn, M. (2006). Nonparametric bounds on the effect of deductibles in health care insurance on doctor visits–Swiss evidence. *Health Economics*, *15*(9), 1011–1020.

Getzen, T. E. (2000). Health care is an individual necessity and a national luxury: applying multilevel decision models to the analysis of health care expenditures. *Journal of Health Economics*, *19*(2), 259–270.

Handel, B. R. (2013). Adverse selection and inertia in health insurance markets: When nudging hurts. *American Economic Review*, *103*(7), 2643–2682.

Hinde, J. M. (2017). Incentive (less)? the effectiveness of tax credits and cost-sharing subsidies in the Affordable Care Act. *American Journal of Health Economics*, *3*(3), 346–369.

Jacobs, K., Graham-Squire, D., Gould, E., & Roby, D. (2013). Large repayments of premium subsidies may be owed to the IRS if family income changes are not promptly reported. *Health Affairs*, *32*(9), 1538–1545.

Jones, A. M. (2009). *Models for health care*. University of York., Centre for Health Economics.

Kaiser Family Foundation. (2014). The Utah Health Care Landscape. Retrieved February 2, 2016, from https://www.kff.org/health-reform/fact-sheet/the-utah-health-care-landscape/

Kaiser Family Foundation. (2015). Cost-sharing Subsidies in Federal Marketplace Plans. Retrieved April 30, 2018, from https://www.kff.org/health-costs/issue-brief/cost-sharing-subsidies-in-federal-marketplace-plans/

Kamal, Rabah; Semanskee, Ashley; Long, Michelle; Claxton, Gary; Levitt, L. (2017a). *How the Loss of Cost-Sharing Subsidy Payments is Affecting 2018 Premiums*. Retrieved from https://www.kff.org/health-reform/issue-brief/how-the-loss-of-cost-sharing-subsidy-payments-is-affecting-2018-premiums/

Kamal, Rabah; Semanskee, Ashley; Long, Michelle; Claxton, Gary; Levitt, L. (2017b). *How the Loss of Cost-Sharing Subsidy Payments is Affecting 2018 Premiums*.

Keeler, E. B., & Rolph, J. E. (1983). How Cost Sharing Reduced Medical Spending of Participants in the Health Insurance Experiment. *JAMA: The Journal of the American Medical Association*. https://doi.org/10.1001/jama.1983.03330400066026

Ketcham, J. D., Lucarelli, C., & Powers, C. A. (2015). Paying attention or paying too much in Medicare Part D. *American Economic Review*, *105*(1), 204–233.

Kowalski, A. E. (2014). The Early Impact of the Affordable Care Act, State by State. *Brookings Papers on Economic Activity*, 320.

Manning, W. (2012). Dealing with skewed data on costs and expenditures. In *The Elgar Companion to Health Economics, Second Edition* (pp. 473–480). https://doi.org/10.4337/9780857938138.00061

Manning, W. G., Basu, A., & Mullahy, J. (2005). Generalized modeling approaches to risk adjustment of skewed outcomes data. *Journal of Health Economics*, *24*(3), 465–488.

Manning, W. G., & Mullahy, J. (2001). Estimating log models: to transform or not to transform? *Journal of Health Economics*, *20*(4), 461–494.

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., & Leibowitz, A. (1987). Health insurance and the demand for medical care: evidence from a randomized experiment. *The American Economic Review*, 251–277.

Manning, W. G., Wells, K. B., Duan, N., Newhouse, J. P., & Ware, J. E. (1986). How Cost Sharing Affects the Use of Ambulatory Mental Health Services. *JAMA: The Journal of the American Medical Association*, *256*(14), 1930–1934. https://doi.org/10.1001/jama.1986.03380140100030

McKnight, R. (2006). Home care reimbursement, long-term care utilization, and health outcomes. *Journal of Public Economics*, *90*(1–2), 293–323.

Mihaylova, B., Briggs, A., O'Hagan, A., & Thompson, S. G. (2011). Review of statistical methods for analysing healthcare resources and costs. *Health Economics*, *20*(8), 897–916.

Mullahy, J. (1998). Much ado about two: reconsidering retransformation and the two-part model in health econometrics. *Journal of Health Economics*, *17*(3), 247–281.

Norris, L. (2018). Utah Health Insurance Exchange Marketplace. Retrieved April 2, 2018, from https://www.healthinsurance.org/utah-state-health-insurance-exchange/

O'Grady, K. F., Manning, W. G., Newhouse, J. P., & Brook, R. H. (1985). The impact of cost sharing on emergency department use. *New England Journal of Medicine*, *313*(8), 484–490.

Orsini, J., & Tebaldi, P. (2017). Regulated age-based pricing in subsidized health insurance:

Evidence from the Affordable Care Act. *Becker Friedman Institute for Research in Economics Working Paper*, (2017–02).

Pohlmeier, W., & Ulrich, V. (1995). An econometric model of the two-part decisionmaking process in the demand for health care. *Journal of Human Resources*, 339–361.

Richardson, L. E., & Yilmazer, T. (2013). Understanding the impact of health reform on the states: Expansion of coverage through Medicaid and exchanges. *Journal of Consumer Affairs*, *47*(2), 191–218.

Rozema, K., & Ziebarth, N. R. (2017). Taxing consumption and the take-up of public assistance: The case of cigarette taxes and food stamps. *The Journal of Law and Economics*, *60*(1), 1–27.

Sacks, D. W., Vu, K., Huang, T.-Y., & Karaca-Mandic, P. (2019). How do insurance firms respond to financial risk sharing regulations? Evidence from the Affordable Care Act. *National Bureau of Economic Research Working Paper No. 21429*, *July*. https://doi.org/10.2139/ssrn.3201686

Saltzman, E. (2019). Demand for health insurance: Evidence from the California and Washington ACA exchanges. *Journal of Health Economics*, *63*, 197–222.

Schwartz, A. L., Landon, B. E., Elshaug, A. G., Chernew, M. E., & McWilliams, J. M. (2014). Measuring low-value care in Medicare. *JAMA Internal Medicine*, *174*(7), 1067–1076.

Sen, A. P., & DeLeire, T. (2018). How does expansion of public health insurance affect risk pools and premiums in the market for private health insurance? Evidence from Medicaid and the Affordable Care Act Marketplaces. *Health Economics*, *27*(12), 1877–1903.

Shigeoka, H. (2014). The effect of patient cost sharing on utilization, health, and risk protection. *American Economic Review*, *104*(7), 2152–2184.

State of Utah. (2014). Utah Census Data 2013 All Counties. Retrieved May 18, 2018, from https://opendata.utah.gov/Government-and-Taxes/Utah-Census-Data-2013-All-Counties-Utah/rcc6-4r27

Taubman, S. L., Allen, H. L., Wright, B. J., Baicker, K., & Finkelstein, A. N. (2014). Medicaid increases emergency-department use: evidence from Oregon's Health Insurance Experiment. *Science*, *343*(6168), 263–268.

Tebaldi, P. (2017). Estimating equilibrium in health insurance exchanges: Price competition and subsidy design under the aca. *Becker Friedman Institute for Research in Economics Working*

Paper, (2017–05).

U.S. Department of Health and Human Services. (2015). Health Insurance Marketplace 2015 Open Enrollment Period: January Enrollment Report. Retrieved September 7, 2017, from https://aspe.hhs.gov/report/health-insurance-marketplace-2015-open-enrollment-period-january-enrollment-report

U.S. Department of Health and Human Services. (2019). Annual Update of the HHS Poverty Guidelines. Retrieved August 23, 2019, from https://www.federalregister.gov/documents/2019/02/01/2019-00621/annual-update-of-the-hhs-poverty-guidelines

Utah Department of Health. (2018a). About the All Payer Claims Data. Retrieved May 18, 2018, from http://stats.health.utah.gov/about-the-data/apcd/

Utah Department of Health. (2018b). About the Healthcare Facility Database. Retrieved May 18, 2018, from http://stats.health.utah.gov/about-the-data/healthcare-facility-data/

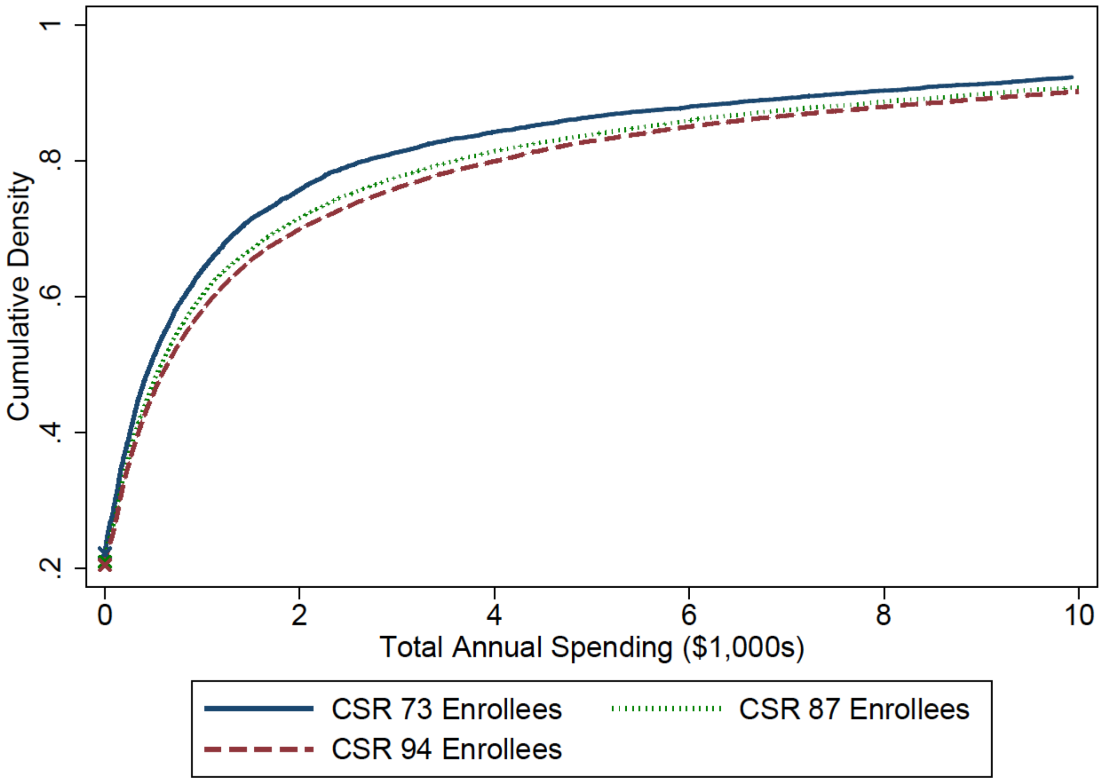
Witters, D. (2015). Arkansas, Kentucky see most improvement in uninsured rates. *Gallup, February*, *24*.

Ziebarth, N. R. (2010). Estimating price elasticities of convalescent care programmes. *The Economic Journal*, *120*(545), 816–844.

Ziebarth, N. R. (2014). Assessing the effectiveness of health care cost containment measures: evidence from the market for rehabilitation care. *International Journal of Health Care Finance and Economics*, *14*(1), 41–67.

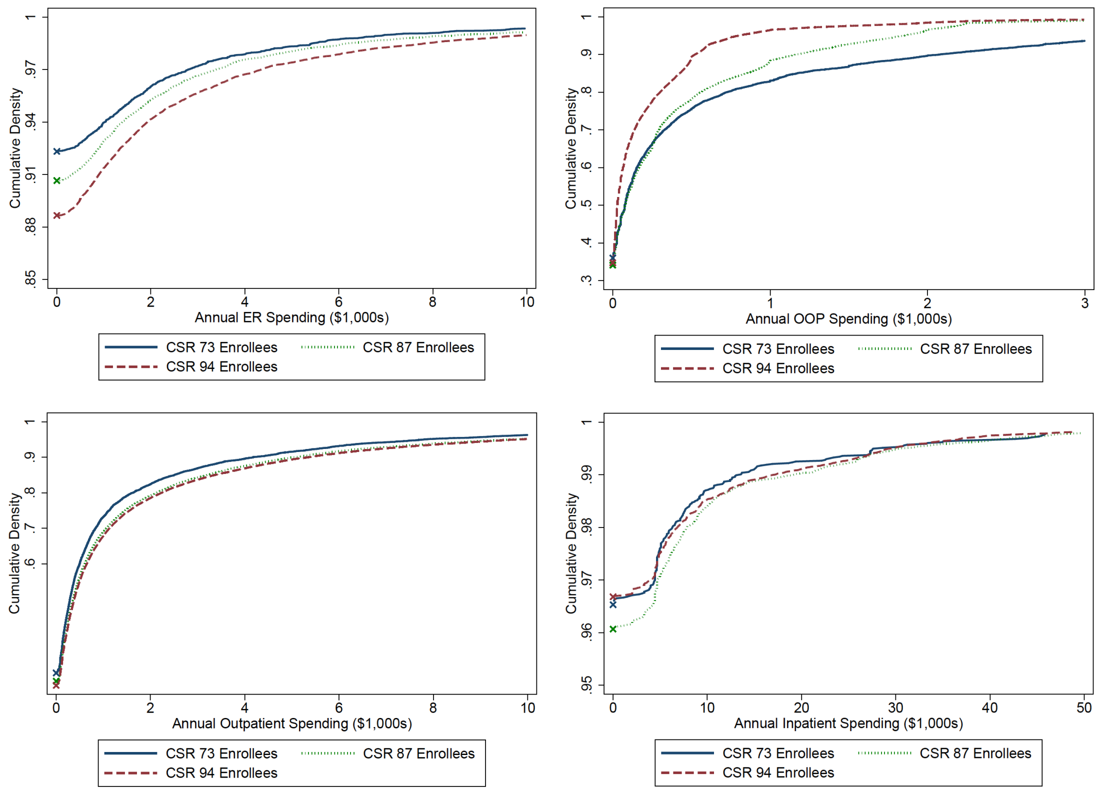
Zweifel, P., & Manning, W. G. (2000). Moral hazard and consumer incentives in health care. In *Handbook of health economics* (Vol. 1, pp. 409–459). Elsevier.

Figure 1. Cumulative Density Functions of Total Spending by CSR Category



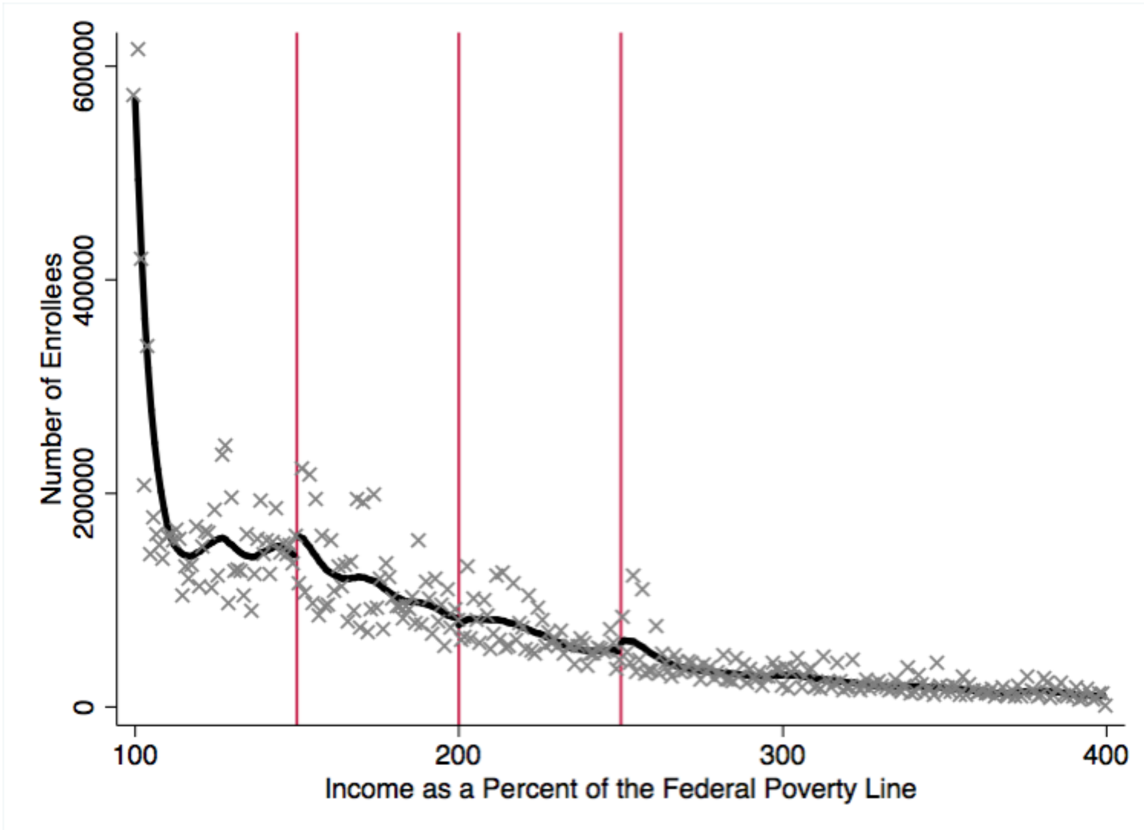
Source: 2013-2015 Utah APCD

Figure 2. Cumulative Density Functions by Spending by Spending and CSR Category



Source: 2013-2015 Utah APCD

Figure 3. Density of Marketplace Enrollment, by FPL



Source: Individual-level administrative data on marketplace enrollment in all states using Healthcare.gov platform from 2014-2017.

Notes: Enrollment in Marketplace plans in a one-percentage point FPL cell is reported. The fitted lines are four separate local linear regressions estimated on individual enrollment between 100 and 149% of FPL, 150 and 199% of FPL, 200 and 249% of FPL, and 250 and of 400% FPL with a bandwidth of 10 percentage points. Originally published in DeLeire, Chappel, Finegold, & Gee (2017).

Figure A1. Enrollment of Adults across CSR Categories over Time

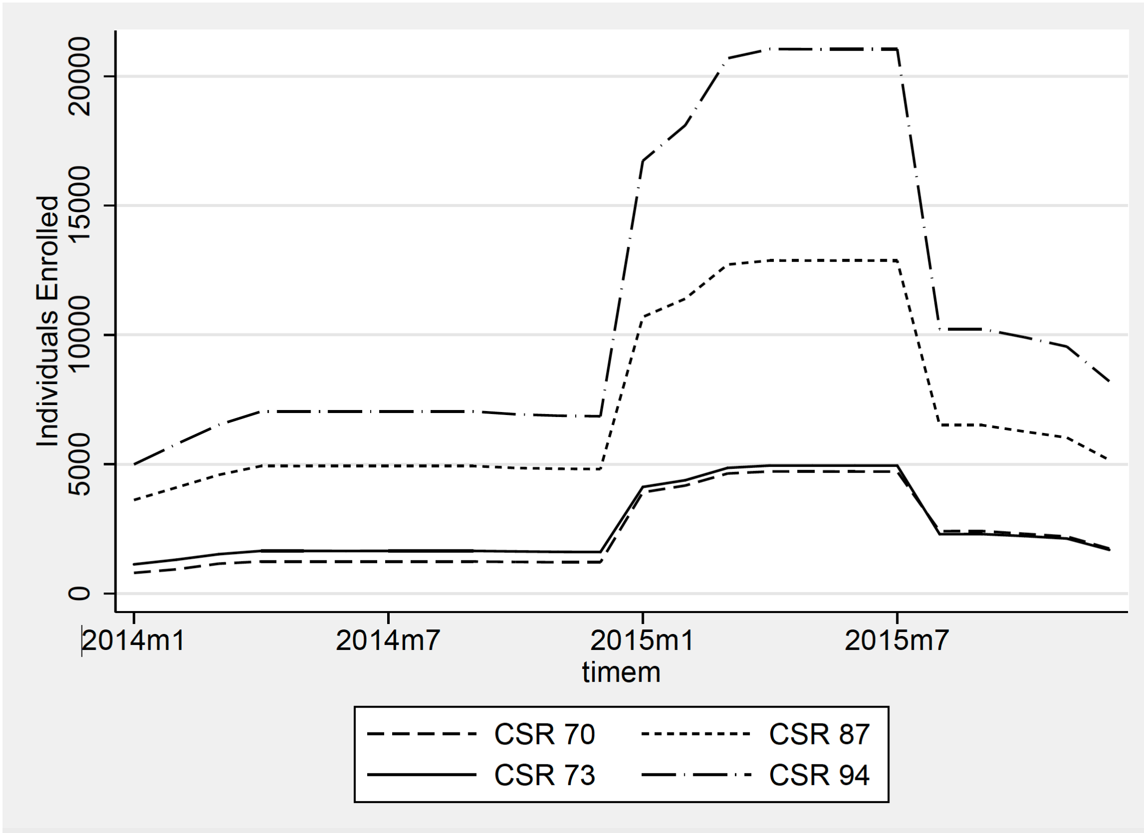


Table 1
Variable Means by CSR Category

	CSR 73 Enrollees	CSR 87 Enrollees	CSR 94 Enrollees	All CSR Enrollees
Panel A: Monthly Health Care Spending				
Log Coinsurance Rate	$ 330	$ 379	$ 399	$ 384
ER Spending	$ 33	$ 40	$ 50	$ 44
Inpatient Spending	$ 61	$ 62	$ 58	$ 60
Outpatient Spending	$ 178	$ 209	$ 219	$ 211
Pharmaceutical Spending	$ 59	$ 68	$ 72	$ 69
of which:				
Acute	$ 18	$ 20	$ 22	$ 21
Chronic	$ 20	$ 21	$ 19	$ 20
Lifestyle	$ 10	$ 11	$ 13	$ 12
Other Drugs	$ 11	$ 15	$ 18	$ 16
Out-of-Pocket Spending	$ 63	$ 39	$ 22	$ 33
of which:				
Deductible Spending	$ 44	$ 18	$ 8	$ 16
High Value Care	$ 4	$ 4	$ 5	$ 5
Low Value Care	$ 2	$ 3	$ 4	$ 3
Panel B: Controls and Other Variables				
Utah-Scaled 2013 Risk Score	0.86	0.89	0.91	0.90
Missing 2013 Risk Score	0.43	0.50	0.53	0.50
Inpatient Days 2004-2013	2.00	1.98	2.17	2.08
ER Visits 2004-2023	1.28	1.45	1.87	1.66
Female	0.53	0.53	0.56	0.55
Age	41.14	40.28	38.66	39.52
Age 18 to 30	0.26	0.31	0.35	0.32
Age 31 to 50	0.44	0.4	0.41	0.41
Age 51 to 64	0.3	0.29	0.25	0.27
Urban County	0.81	0.81	0.82	0.81
Family Plan	0.71	0.61	0.49	0.55
HMO Plan	0.77	0.74	0.75	0.75
Enrollee-Month	61,782	170,543	263,661	495,986
Unique Enrollees	6,538	17,564	27,682	51,784
Months Enrolled in 2014	11.3	11.4	11.4	11.4
Months Enrolled in 2015	11.5	11.5	11.4	11.4

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a CSR Silver plan in 2014 or 2015 and who were not in the top 0.5% of the total spending distribution. Urban county indicates counties with at least 80% of the population residing in an urban area (as defined by the 2010 Census). Months FFM Enrolled indicates enrolled in a CSR Silver plan. Risk scores are estimated using the Johns Hopkins ACG(c) System software. Utah-scaled risk scores are normalized to have a mean of 1 in the population of non-elderly insured individuals in the Utah APCD.

Table 2
GLM Estimates of Health Care Spending by CSR Category

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
CSR 94% AV Plan	0.17***	0.28***	0.21***	0.05	-1.07***
	(0.05)	(0.09)	(0.04)	(0.15)	(0.03)
	19%	*32%*	*23%*	*5%*	*-66%*
CSR 87% AV Plan	0.12**	0.10	0.14***	0.07	-0.52***
	(0.05)	(0.09)	(0.04)	(0.15)	(0.03)
	13%	*11%*	*15%*	*7%*	*-41%*
2013 Risk Score	1.80***	1.37***	1.48***	1.74***	1.19***
	(0.09)	(0.22)	(0.08)	(0.22)	(0.07)
Inpatient Days 2004-2013	0.02***	0.00	0.01***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.07***	0.03***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.
Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. Percentage differences between the CSR categories and the omitted category are reported in italics.

Table 3
GLM Estimates of the Price Elasticity of Health Care Spending

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	-0.10***	-0.20***	-0.13***	-0.02	0.71***
	(0.03)	(0.05)	(0.02)	(0.08)	(0.02)
2013 Risk Score	1.80***	1.36***	1.48***	1.73***	1.19***
	(0.09)	(0.22)	(0.08)	(0.22)	(0.07)
Inpatient Days 2004-2013	0.02***	--0.00	0.01***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.07***	0.03***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects.

Table 4
GLM Estimates of the Price Elasticity of Health Care Spending, by High-Value and Low-Value Care

	Total Spending	High-Value Spending	Low-Value Spending	Uncategorized Spending
Log Coinsurance Rate	-0.10***	-0.26***	-0.23***	-0.10***
	(0.03)	(0.05)	(0.08)	(0.03)
2013 Risk Score	1.80***	1.51***	3.62***	1.80***
	(0.09)	(0.17)	(0.24)	(0.09)
Inpatient Days 2004-2013	0.02***	0.00	--0.01**	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.03***	0.12***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.
Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects.

Table 5
GLM Estimates of the Price Elasticity of Prescription Drug Spending, by Type of Drug

	All	Acute	Chronic	Lifestyle	Branded	Generic
Log Coinsurance Rate	-0.12**	-0.19**	0.08	-0.27***	-0.05	-0.17***
	(0.05)	(0.08)	(0.09)	(0.06)	(0.07)	(0.03)
2013 Risk Score	3.09***	2.92***	3.37***	3.62***	3.27***	2.89***
	(0.12)	(0.20)	(0.21)	(0.12)	(0.19)	(0.12)
Inpatient Days 2004-2013	0.02***	0.03***	0.00	0.00	0.02**	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
ER Visits 2004-2023	0.09***	0.05***	0.10***	0.11***	0.11***	0.10***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Acute refers to drugs designated by Chandra et al. (2010} as those that "if not taken, will increase the probability of an adverse health event within a month or two." Chronic refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." Lifestyle refers to drugs that result primarily in lifestyle improvements. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects.

Table 6
GLM Demand Elasticity Estimates: Stepwise Inclusion of Health Controls

Total Spending	-0.16***	-0.15***	-0.10***	-0.10***
	(0.03)	(0.03)	(0.03)	(0.03)
ER Spending	-0.32***	-0.30***	-0.21***	-0.20***
	(0.05)	(0.05)	(0.05)	(0.05)
Outpatient Spending	-0.19***	-0.18***	-0.13***	-0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Inpatient Spending	-0.08	-0.07	-0.01	-0.02
	(0.08)	(0.08)	(0.08)	(0.08)
Out-of-Pocket Spending	-0.68***	-0.68***	-0.71***	-0.71***
	(0.02)	(0.02)	(0.02)	(0.02)
County Fixed Effects	X	X	X	X
Year by Month Fixed Effe	X	X	X	X
Age, gender	X	X	X	X
2013 Risk score		X		X
Inpatient Days 2004-2013			X	X
ER Visits 2004-2013			X	X

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.
Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. All models have 51,784 unique enrollee and 495,986 enrollee-months observations.

Table 7
Heterogeneity by Demographic Characteristics in Estimates of the Price Elasticity of Health Care Spending

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Panel A: Age					
Log Coinsurance Rate	-0.11***	-0.19***	-0.13***	-0.12	0.70***
	(0.04)	(0.06)	(0.03)	(0.14)	(0.03)
* Age 31-50	0.02	-0.01	0.00	0.19**	0.02
	(0.03)	(0.04)	(0.02)	(0.10)	(0.02)
* Age 51-64	0.00	-0.03	0.00	0.15	0.00
	(0.04)	(0.07)	(0.03)	(0.13)	(0.03)
Panel B: Gender					
Log Coinsurance Rate	-0.02	-0.17**	-0.06**	0.18*	0.79***
	(0.03)	(0.07)	(0.03)	(0.10)	(0.03)
* Male	-0.19***	-0.07	-0.15***	-0.45***	-0.17***
	(0.05)	(0.10)	(0.05)	(0.17)	(0.04)
Panel C: Urban County					
Log Coinsurance Rate	-0.06	-0.36***	-0.10*	0.16	0.79***
	(0.06)	(0.11)	(0.05)	(0.15)	(0.04)
* Urban	-0.05	0.2	-0.03	-0.22	-0.10**
	(0.06)	(0.12)	(0.06)	(0.18)	(0.05)
Panel D: Family Plan					
Log Coinsurance Rate	-0.02	-0.15*	-0.06*	0.02	0.64***
	(0.04)	(0.08)	(0.04)	(0.12)	(0.03)
* Family Plan	-0.10*	-0.06	-0.07	-0.06	0.15***
	(0.05)	(0.11)	(0.05)	(0.16)	(0.04)

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.
Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. All models have 51,784 unique enrollee and 495,986 enrollee-months observations.

Table 8
Heterogeneity by Risk Score in Estimates of the Price Elasticity of Health Care Spending

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	-0.14***	-0.21***	-0.14***	-0.17*	0.67***
	(0.04)	(0.08)	(0.03)	(0.10)	(0.03)
* 2013 Risk Score	0.27	0.03	0.09	1.10**	0.28**
	(0.16)	(0.38)	(0.16)	(0.44)	(0.14)
2013 Risk Score	2.44***	1.43	1.69***	4.37***	1.87***
	(0.42)	(1.04)	(0.39)	(1.12)	(0.33)
Inpatient Days 2004-2013	0.02***	0.00	0.01***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.07***	0.03***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Predicted Elasticities:					
10th Percentile Risk Score	-0.14	-0.21	-0.14	-0.17	0.67
p-value	0.00	0.01	0.00	0.09	0.00
50th Percentile Risk Score	-0.11	-0.20	-0.13	-0.04	0.70
p-value	0.00	0.00	0.00	0.63	0.00
90th Percentile Risk Score	-0.07	-0.20	-0.12	0.11	0.74
p-value	0.03	0.00	0.00	0.28	0.00

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. All models have 51,784 unique enrollee and 495,986 enrollee-months observations.

Table 9
Estimates of the Price Elasticity of Health Care Spending by Above Average

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Rx Spending
Log Coinsurance Rate	-0.168***	-0.021***	-0.145***	0.003	-0.127***
* High Deductible	(0.018)	(0.003)	(0.013)	(0.002)	(0.015)
Log Coinsurance Rate	-0.128***	-0.022***	-0.141***	0.000	-0.087***
* Low Deductible	(0.018)	(0.003)	(0.014)	(0.002)	(0.016)
2013 Risk Score	2.643***	0.166***	1.950***	0.056***	2.067***
	(0.170)	(0.038)	(0.124)	(0.016)	(0.135)
2013 Risk Score Unknown	-3.354***	0.040	-1.782***	-0.035**	-2.762***
	(0.142)	(0.024)	(0.107)	(0.015)	(0.121)
Inpatient Days 2004-2013	0.012***	0.000	0.009***	0.002***	0.009***
	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)
ER Visits 2004-2023	0.072***	0.026***	0.058***	0.002***	0.057***
	(0.008)	(0.002)	(0.005)	(0.000)	(0.006)

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. "High Deductible" is an above average deductible; "Low Deductible" is a below average deductible. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. All models have 51,784 unique enrollee and 495,986 enrollee-months observations.

Table 10
GLM Price Elasticity Estimates Using Enrollee-Specific End-of-Year Coinsurance Rate

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Rx Spending
Enrollee-Specific End-of-	-0.10***	-0.19***	-0.16***	-0.04	-0.42***
Year Coinsurance Rate	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)
2013 Risk Score	1.83***	1.41***	1.53***	1.76***	3.29***
	(0.09)	(0.36)	(0.08)	(0.42)	(0.14)
Inpatient Days 2004-2013	0.02***	0.00	0.01***	0.06***	0.02***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.07***	0.03***	0.09***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects.

Table 11
GLM Estimates of the Own-Price and Cross-Price Elasticities of Health Care Spending

	ER Spending	Inpatient Spending
Log Coinsurance Rate for ER Care	-0.49***	-0.14
	(0.09)	(0.14)
Log Coinsurance Rate for Outpatient Care	0.26*	0.49***
	(0.15)	(0.22)
Log Coinsurance Rate for Inpatient Care	0.06	-0.27***
	(0.04)	(0.09)
Log Coinsurance Rate for Pharmaceuticals	0.05	-0.29*
	(0.11)	(0.16)
Enrollee-Months	495,986	495,986
Unique Enrollees	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.
Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects.

Table 12
Counterfactual Effect of Eliminating CSRs by Recipient Characteristic

	Monthly Spending	Counter-factual Spending (70% AV)	Difference ($)		Difference (%)	Change in Subsidy	Change in OOP
All Enrollees	$383.66	$291.54	$92.12	***	24%	-$61.96	$30.16
Enrollees in:							
94% AV Plans	$399.07	$290.76	$108.31	***	27%	-$67.27	$41.04
87% AV Plans	$379.21	$291.76	$87.45	***	23%	-$63.26	$24.19
73% AV Plans	$330.19	$294.28	$35.91	***	11%	-$35.67	$0.24
Age 18-30	$255.27	$194.81	$60.47	***	24%	-$36.48	$23.99
Age 31-50	$348.45	$277.82	$70.63	***	20%	-$40.12	$30.51
Age 51-64	$581.97	$474.63	$107.34	***	18%	-$70.34	$37.01
Risk Score > 1	$685.38	$521.61	$163.78	***	24%	-$116.26	$47.52
Risk Score < 1	$341.92	$291.83	$50.08	***	15%	-$17.41	$32.67

Notes: Counterfactual simulations represent partial equilibrium effects and are based on the elasticity estimates reported in previous tables.

Table 13
Counterfactual Effect of Eliminating CSRs by Type of Medical Spending

	Monthly Spending	Counter-factual Spending (70% AV)	Difference ($)		Difference (%)
Log Coinsurance Rate	$ 383.66	$ 291.54	$ 92.12	***	24%
Spending on:					
ER	$ 44.12	$ 27.23	$ 16.88	***	38%
Outpatient	$ 243.24	$ 181.83	$ 61.41	***	25%
Acute/Chronic Drugs	$ 41.02	$ 29.72	$ 11.30	***	28%

Notes: Counterfactual simulations represent partial equilibrium effects and are based on the elasticity estimates reported in previous tables.

Table A1
OLS Estimates of the Price Elasticity of Health Care Spending, Conditional on Positive Total Spending

	Log Total Spending	Log ER Spending	Log Outpatient Spending	Log Inpatient Spending	Log OOP Spending
Log Coinsurance Rate	-0.13***	-0.04***	-0.14***	0.01**	0.38***
	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)
2013 Risk Score	0.75***	0.15***	0.75***	0.02	0.25***
	(0.07)	(0.05)	(0.07)	(0.02)	(0.06)
Inpatient Days 2004-2013	0.01***	0.00	0.01***	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.03***	0.03***	0.03***	0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Enrollee-Months	175,286	175,286	175,286	175,286	175,286
Unique Enrollees	24,386	24,386	24,386	24,386	24,386

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample is defined in the notes to Table 1. Dependent variables are conditioned on positive total spending in the calendar month. Models are estimated by OLS and talso control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects.

Table A2
GLM Estimates of the Price Elasticity of Health Care Spending Using Calculated Coinsurance Rate by CSR and Spending Categories

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Rx Spending
Log Coinsurance Rate	-0.13***	-0.23***	-0.16***	-0.04	-0.22***
	(0.03)	(0.06)	(0.03)	(0.12)	(0.08)
2013 Risk Score	1.80***	1.36***	1.48***	1.74***	3.10***
	(0.09)	(0.22)	(0.08)	(0.22)	(0.12)
Inpatient Days 2004-2013	0.02***	0.00	0.01***	0.06***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.07***	0.03***	0.09***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. The Log Coinsurance Rate is calculated as 1 less the ratio of the sum of acutal OOP spending by CSR category, spending category, and year to the sum of spending by CSR category, spending category, and year.

Table A3
GLM Estimates of the Price Elasticity of Health Care Spending with Insurer Fixed Effects

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	OOP Spending
Log Coinsurance Rate	-0.09***	-0.20***	-0.12***	-0.04	0.74***
	(0.03)	(0.05)	(0.02)	(0.09)	(0.02)
2013 Risk Score	1.64***	1.28***	1.37***	1.66***	1.15***
	(0.09)	(0.22)	(0.08)	(0.23)	(0.07)
Inpatient Days 2004-2013	0.02***	0.00	0.01***	0.05***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.07***	0.03***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Enrollee-Months	495,986	495,986	495,986	495,986	495,986
Unique Enrollees	51,784	51,784	51,784	51,784	51,784

Source: 2013-2015 Utah APCD linked with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data.

Notes: Standard errors are clustered at the family level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Sample is defined in the notes to Table 1. Models are estimated by GLM using a log-link and gamma variance and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, year by month fixed effects, and insurer fixed effects.