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DISCUSSION PAPER

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

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

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Abstract

The Affordable Care Act requires insurers to offer 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 actuarial value of CSR plans that are solely determined by income. This allows us to examine the effect of cost sharing on medical spending among low-income individuals. We find that enrollees facing lower levels of cost sharing have higher levels of health care spending, controlling for past health care use. We estimate demand elasticities of total health care spending among this low-income population of approximately -0.12, suggesting that demand-side price mechanisms in health insurance design work similarly for low-income and higher-income individuals. We also find that cost sharing subsidies substantially lower out-of-pocket medical care spending, showing that the CSR program is a key mechanism for making health care affordable to low-income individuals.

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

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

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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) that reduce the amount of cost sharing (e.g., deductibles) required by enrollees. CSRs were included in the ACA out of a concern that high-levels of cost sharing might make medical care unaffordable to low-income consumers and, moreover, might lead some to forgo needed health care. Little is known about how low-income consumers respond to cost sharing in private insurance markets. To our knowledge, this is the first study to examine whether CSRs increased the use of health care and reduced out-of-pocket spending among low-income enrollees in the ACA Marketplaces.

The most influential study on how consumers respond to cost sharing is the RAND Health Insurance Experiment (RAND HIE; Keeler & Rolph, 1983; Manning et al., 1987; Manning et al., 1986; O'Grady et al. 1985), which estimated the arc price elasticity of demand for medical care to be about -0.2. Both the RAND HIE and, more recently, Brot-Goldberg et al. (2017) examine whether cost sharing differentially affects different types of care. Both find that increases in cost sharing leads to reductions in utilization 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. Economic theory is unclear whether low-income individuals' demand for health care should be more or less price responsive than that of more affluent individuals.

Due to a lack of data and price variation, very few studies have estimated demand elasticities for this policy-relevant population in a real-world setting. One such study is Chandra, Gruber, and McKnight (2014), which examines the effect of policy-driven changes in cost sharing rates among low-income enrollees in the Massachusetts Commonwealth Care program. Another is Finkelstein et al. (2019) who also use administrative data from the exchange in Massachusetts. Similar to this paper but focusing on take-up decisions, they exploit discontinuities in the subsidy schedule to estimate willingness to pay among low-income adults. Their main finding shows that, among this low-income population, enrollees' willingness to pay lies below half of their expected costs. With these two studies being exceptions, most studies of the demand for medical care among lower-income populations examine the impact of gaining Medicaid coverage, a program with either zero or minimal cost sharing (e.g., Finkelstein et al. 2012).

In this paper, we estimate elasticities of demand for medical care by exploiting policy-driven differences in the amount of cost sharing subsidies across enrollees. We also investigate how out-of-pocket spending responds to different amounts of cost sharing and whether enrollees differentially respond to cost sharing in their demand for different types of services, for high-value versus low-value health care, and for different types of prescription drugs. Using these estimates, we present a counterfactual simulation of the effects of eliminating CSRs on the health care spending of low-income consumers. Understanding the impacts of CSRs is highly policy relevant, especially in light of the 2017 decision of the federal government to stop reimbursing insurers for their cost of providing CSR plans.

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. We also link the APCD records to administrative hospital inpatient and ER discharge records from 2004 to 2013, allowing us to condition on a full decade of hospital-based health care utilization prior to ACA Marketplace enrollment. We use these data to estimate both cross-sectional models controlling for past use of medical care and for health status as well as person-level fixed effects models that control for all time-invariant omitted variables.

We find that individuals with greater CSRs and correspondingly lower levels of cost sharing spend more on health care and have lower out-of-pocket spending. Our main estimates imply a demand elasticity for health care of -0.12 among this low-income population. While this estimate is statistically significant, it is less than both the commonly-cited RAND HIE arc elasticity estimate of -0.2 and the updated calculation by Aron-Dine et al., (2013) of about -0.5. We also find evidence of heterogeneity in these elasticity estimates with sicker enrollees and men being less price responsive to cost sharing. Consistent with previous studies (e.g., Brot-Goldberg et al. (2017) and the RAND HIE), we find similar demand elasticities for high-value (-0.31) and low-value (-0.25) medical care.

Our findings suggest that demand-side price mechanisms in health insurance design work similarly for low-income enrollees as they do for higher-income enrollees. Our estimates imply that the CSR program led low-income enrollees of the ACA Marketplaces to increase their health care spending by 25% while simultaneously reducing their OOP spending and that the CSR program is a key mechanism for making health care affordable to low-income individuals.

2 Background

Consumers shopping for health insurance on the ACA Marketplaces are offered a standardized menu of regulated plans, which 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 target 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 (PTCs) 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 provider network.

Consumers who report projected incomes on their application between 100 and 400% of the federal poverty line (FPL) are eligible for advanced PTCs, the value of which depend upon family income, income as a percent of FPL, and the premium of the second-lowest cost Silver plan available.[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 and any differences between the actual value and the amount received in advance are reconciled on the tax return.

Consumers who report projected incomes on their application between 100% and 250% of FPL are offered CSR-variant Silver plans instead of unsubsidized Silver plans with a 70% AV. In particular, consumers 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 an 87% AV; and consumers with reported incomes between 200% and 250%

[5] In 2014, 100% of FPL was $11,490 for a single-person household and was $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).

of FPL are offered CSR plans with a 73% AV. Unlike the case with advanced PTC, 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. Thus, 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, the consumer is offered a different set of Silver plans with different deductibles and other cost sharing rules so that the AVs of the offered Silver plans have AVs of 73% instead of 70%. Similarly, when income falls below 200% and 150% of FPL, the offered Silver plans will have different deductibles and cost sharing so that AVs increase 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).

In late 2017, as Congress had not appropriated funds, the Department of Justice determined that it was unlawful for the federal government to make CSR payments to insurers. As a result, insurers were, and continue to be as of 2022, legally obligated to provide subsidies to consumers, whereas the federal government has ceased reimbursement to insurers for these subsidies. This lack of reimbursement led carriers to increase the plan premiums on the exchanges, particularly the premiums of Silver plans. Since, premium tax credits depend, in part, on the premiums of Silver plans, this led to the widespread availability of plans with $0 premiums, net of the premium subsidy (see Branham & DeLeire, 2019; Drake & Anderson, 2020; and Branham et al., 2021).

We study the effects of the 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 non-group plans on Utah's Marketplace (Kaiser Family Foundation, 2014). During

[6] Projected income on the application is subject to a verification process in which it is compared with prior year income from tax return data. In cases where projected income is substantially lower than prior year income, the consumer may be required to provide additional documentation supporting the projected income level.

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) and that the percent of individuals without health insurance in Utah decreased from 15.6% to 13.3% between 2013 and 2014, or by about 65 thousand 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 most common 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.[7] The RAND HIE also 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). Moreover, 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. This paper contributes to this rich health economics literature by estimating price elasticities of demand for low-income ACA Exchanges enrollees in the United States.

Naturally, this paper also contributes to the economic literature on the ACA Marketplaces (Cox et al., 2015; Kowalski, 2014; Richardson & Yilmazer, 2013; Tebaldi, 2017).[8] Several

[7] 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..

[8] Several papers study impact factors of exchange plan premiums: Dafny, Gruber, & Ody (2015) use Marketplace health plan data to show that more competition on an exchange reduces premiums, whereas Sen & DeLeire (2018) find that the Medicaid expansion improved risk pools and lowered premiums. Dickstein et al.

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. According to Saltzman (2019), exchange enrollment decreases by about one percent when the base premiums of all exchange plans increase by one percent. DeLeire et al. (2017) use administrative data to estimate the impact of CSRs on take-up and report health plan take-up elasticities with respect to the actuarial value of around one. As a result of the termination of CSR payments to insurers, insurers increased the premiums of Silver plans, which in turn led to the widespread availability of zero-premium plans (Branham & DeLeire, 2019; Branham et al., 2021). Drake & Anderson (2020) simulate that, without the availability of zero-premium plans, enrollment in FFM plans would have been 200,000 lower in 2019. Finally, using CPS data, Hinde (2017) estimates the effects of the CSRs and PTCs on take-up and finds take-up elasticities that are statistically different from zero.

4 Data

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

4.1 Datasets

We use three main datasets in our analysis: Utah's All-Payer Claims Data (APCD) from 2013 to 2015, Utah Inpatient Hospital Discharge Data from 2004 to 2013, and Utah 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),

(2015) find that premiums are lower in larger "coverage regions", whereas Sacks et al. (2017) show theoretically that the ACA Risk Corridor program incentivized insurers to lower premiums. The relevance of age-based pricing regulations has also been studied (Orsini & Tebaldi, 2017).

[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.

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).

Each insurer submits data to the state in a standardized way; we use three components of these data 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 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.

4.2 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

[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 noticeably 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.

reduce the influence of extreme outliers in the heavily skewed health care spending distributions, we omit enrollees in the top 0.5% of the overall spending distribution.[12]

We collapse the claims-level data from 2014 and 2015 to the enrollee-month level and, after trimming the top 0.5% of the sample based on total monthly spending, obtain an unbalanced panel of 557,203 person-months and 49,471 unique individuals that we use in the cross-sectional models. In the panel-data models, we also include enrollee-months from 2013 and exclude adults with no spending in 2013, yielding an unbalanced panel of 731,305 person-months and 49,029 unique individuals. 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. For some analyses, we also restrict the sample to those adult Utah residents who were enrolled in health insurance plans in 2013. Of our main sample, 25,189 individuals also have 2013 data.

4.3 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 $376, a level of health care spending is similar to that of the commercially insured population of Utah but is low relative to that of a national sample.[13] Most spending was on care received in an outpatient setting ($207 per month), followed by pharmaceutical spending ($67 per month), inpatient spending ($58 per month), and ER spending ($44 per month). Average out-of-pocket (OOP) spending on medical care was $32 per month, of which $16 was on deductibles.

[12] In Appendix Table 1, we also report results that include these outliers.

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

The descriptive statistics presented in Table 1 are consistent with less cost sharing leading people to spend more on health care and to have less OOP spending. Individuals who are enrolled in plans with the highest levels of cost sharing (73% AV) spend less per month ($322) than individuals enrolled in plans with an 87% AV ($371) or a 94% AV ($400) and these differences are statistically significant. 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 $38 per month among individuals with an 87% AV and $61 per month among individuals with a 73% AV. These differences are also statistically significant.

There are also differences across the spending distribution. Figure 1 displays the cumulative density functions for total annual spending in 2014 and 2015 for enrollees in the three types of CSR plans. The figure shows higher spending across the spending distribution for enrollees in 94% AV and 87% AV plans relative to enrollees in 73% AV plans. Figure 2 displays the cumulative density functions for total annual spending in 2013 for enrollees in the three types of CSR plans who were also enrolled in insurance in 2013. In contrast to the 2014/2015 distributions, there are no visual differences between the 2013 distributions.

[Figures 1 and 2]

Figures 3 and 4 show the spending distributions by CSR category and spending category (ER, outpatient, inpatient) in 2014/15 and 2013 respectively. For ER spending in 2014/15 (Figure 3), 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, 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. By contrast, we see few differences in the distribution of inpatient spending across individuals in plans with different AVs. In 2013, by contrast, we do not see differences in the distribution of spending by CSR category, with the exception of ER spending.

[Figures 3 and 4]

4.4 Controls for Health

We include a broad set of controls for past health care use in order to help control for prior health status. First, we use 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 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).[14] Almost fifty percent of our sample does not have data for 2013, however, because they were not enrolled in an insurance plan in Utah in 2013. We assign these individuals a risk score of 1 and, in the empirical models, we include a binary flag for whether the 2013 risk score is missing.

Second, we use 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. 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 sample, the mean number of inpatient days between 2004 and 2013 was 2.06 and the mean number of ER visits over this period was 1.64.[15]

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. Summary statistics on these controls are reported in Panel B of Table 1.

[14] 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).

[15] Utah residents in 2014 and 2015 who did not reside in Utah in the 2004 - 2013 period will not have complete data on hospitalizations and ER visits. While we cannot observe residential mobility, we were able to link 92.3% of the observations in our analysis sample with individuals that have an administrative record in the state of Utah at some point in the 20 years prior to 2014. Thus, we estimate that, at most, 7.7% of observations could have incomplete hospitalization and ER histories. To assess whether using more recent hospital stay information provides more relevant information, we estimate two additional specifications and report the results in Appendix Table 1. In the first, we separately control for inpatient days and ER visits in the 2010-2013, 2007-2009, and 2004-2006 periods. In the second, we only control for inpatient stays and ER visits from 2010-2013. The estimated elasticates from these specifications are similar to those from our main specification.

4.5 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-three percent of enrollees live in an urban county.

5 Empirical Approach

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 the fact that health spending distributions tend to be highly skewed with a long right tail and to have a large mass point at zero spending, and it is more efficient than the transformed log model (Buntin & Zaslavsky, 2004).[16]

We follow this approach, using GLM with a log link function and gamma distribution. 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).[17]

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[16] GLMs are based on "link functions" (which model the relationship between covariates and the conditional mean of the spending distribution) and "distribution 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 distribution, which is proportional to the square of the mean. Of all models tested, the log-link and a gamma distribution provide the best fit in our setting, but a log-link negative binomial 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 distribution, only affects the efficiency of the estimates. We estimate the model by quasi-maximum likelihood in Stata.

[17] 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).

Our main empirical specification is:

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

where y_{it} measures total health care spending in dollars of individual i in month t or a category 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.

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.

$Risk_{i,2013}$ represents the risk score of individual i in 2013, prior to choosing an ACA Marketplace plan and $RiskMissing_{i,2013}$ is an indicator for whether the 2013 risk score being missing. We run models with the full sample and also the sample without missings on their 2013 risk score.

$Inpatient_{i,2004\text{-}2013}$ 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.

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. Errors are clustered at the policy level to allow for serial correlation and for correlation that may be caused by shared deductibles and other nonlinear plan features among family members enrolled in the same plan (Cameron & Miller, 2015). We derive an estimate of the elasticity of demand for health care from this specification as: $\beta_{94}/(\ln(0.06)-\ln(0.27))$.

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

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

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

A limitation to these specifications is that they may not fully control for unobserved determinants of heath spending that are correlated with income and thus AV, despite the controls for 2013 risk scores and past health care use.

As an alternative to controlling for 2013 risk scores and past health care use, we also estimate linear person-level fixed effects models in which we transform the dependent variable using the inverse-hyperbolic sine:

$$\boldsymbol{ihs}(\boldsymbol{y_{it}}) = \boldsymbol{\alpha} + \boldsymbol{\beta_{87}} \boldsymbol{AV}^{\boldsymbol{87}}_{\boldsymbol{p(it)}} + \boldsymbol{\beta_{94}} \boldsymbol{AV}^{\boldsymbol{94}}_{\boldsymbol{p(it)}} + \boldsymbol{\delta_t} + \boldsymbol{\rho_{c(it)}} \tag{3}$$

and

$$\boldsymbol{ihs}(\boldsymbol{y_{it}}) = \boldsymbol{\alpha} + \boldsymbol{\beta ln}\left(\boldsymbol{1 - AV_{p(it)}}\right) + \boldsymbol{\delta_t} + \boldsymbol{\rho_{c(it)}} \tag{4}$$

Since these models are best estimated using a linear specification with a transformed dependent variable, for comparison we also estimate equations (1) and (2) using that same model (without person-level fixed effects) and report the results in Appendix Table 1.

A limitation to the person-level fixed effects model is that 2013 health care spending is based on the selected sample of individuals who purchased insurance in the pre-ACA insurance market. Below, we run our main models with the full sample but also models using the restricted sample just with those whom we observe in all three calendar years 2013-2015 (Appendix Table 1, column (4)). Although the difference is not statistically significant, the full sample yields smaller demand elasticity estimates; Appendix Table 4 shows that those uninsured in 2013 had lower spending in 2014-2015, implying adverse selection on the extensive margin in the pre-ACA year 2013. Apparently, those who were uninsured in 2013 were less price responsive to Marketplace AVs, which is why we would expect the person-level fixed effects model to be slightly upward biased. Section 7 summarizes and discusses the limitations to our empirical approaches.

6 Results

In this section, we present our empirical findings on the impact of varying levels of coinsurance on total health care spending (Section 6.1). We also report estimates of demand elasticities by categories of health care spending, for low-value and high-value care, and for different types of pharmaceuticals (Section 6.2). In Section 6.3, we present evidence on heterogeneity in responses to cost sharing. \

6.1 Demand Responses to Cost Sharing

Our main estimates of the effect of cost sharing on total monthly medical care spending, based on the specifications described in equations (1) through (4), are reported in Table 2.

Compared with individuals in plans with an AV of 73%, individuals in plans with an AV of 94% have total spending that is roughly 19% higher, based on the GLM model that controls for the 2013 risk score, the number of inpatient days and ER visits from 2004-2013 (Column 1). 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 significant. The implied elasticity of demand (using the difference between those in 94% and 73% plans) is -0.128.

All three measures of pre-2014 health status – 2013 Risk Score, the number of inpatient days, and the number of ER visits – are positively and statistically significantly correlated with total health care spending in 2014 and 2015.

Columns (2) reports the results of our specification that 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 -0.115.[18]

Estimating equations (3) and (4), which control for person-level fixed effects and are estimated on a panel that includes person-months from 2013, yields similarly sized effects (Columns 3 and 4). Individuals in plans with an AV of 94% are estimated to have total spending that is roughly 19% higher and those in a plan with an AV of 87% are estimated to have total spending that is 10% higher than those in a plan with an AV of 73%. These differences are also statistically significant and imply a demand elasticity of -0.125. Using the continuous measure of AV yields an elasticity estimate of -0.122.

[Insert Table 2 about here]

Overall and across a range of specifications, we find that low-income consumers enrolled in ACA Marketplace plans respond to cost sharing, with implied elasticity estimates of roughly -0.12. While all of these estimates are statistically significant, they are smaller than (and generally statistically different from) the often-cited RAND HIE estimate of -0.2.

[18] Because of outliers, we trim the top 0.5% of the sample based on total monthly spending. In Appendix Table 1, we report the results of a model based on equation (2) in which we do not trim the sample get an estimate of the elasticity of -0.146. The confidence intervals of the two point estimates overlap. One interpretation could be that some of the top 0.5% of spenders are systematically lower income within the silver category and have a higher AV on their plan than the rest, which is why the full sample yields a slightly larger point estimate.

6.2 Variation in Health Care Spending Elasticities by Type of Care

In this subsection, we report results on the price responsiveness of health care spending by type of care, by low-value vs. high-value care, and by type of prescription drugs.

Table 3 reports estimates from separate models, based on equation (2), where the dependent variable is total monthly spending on different types of care. In the top panel we examine spending by category – ER, outpatient, inpatient – and total monthly out-of-pocket (OOP) spending. The results show that low-income consumers are especially sensitive to cost-sharing in their ER spending with an estimated elasticities of demand for ER spending of -0.24. Consumers also respond to cost sharing in their outpatient spending, with an estimated elasticity of is -0.14. Both of these estimates are statistically significant. Moreover, the estimated elasticity for ER spending is twice as large as (but is not statistically different from) the overall elasticity of -0.12 reported in Table 2. In contrast to ER and outpatient spending, consumers do not change their inpatient spending in response to cost sharing. The estimated elasticity of demand for inpatient care is -0.024 and is not statistically significant.

CSRs also substantially reduce OOP spending, suggesting that CSRs are an important factor in making health care affordable to low-income enrollees. Out-of-pocket (OOP) spending is strongly related to coinsurance rates, and the estimated elasticity is 0.694 is statistically significant from zero.

[Insert Table 3 about here]

We also report results on the price responsiveness for low-value vs. high-value medical care. As reported in Table 1, 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. That is, there is a substantial amount of medical care spending that cannot be categorized as high-value or low-value.[19]

Panel B of Table 3 shows that consumers respond to higher levels of cost-sharing by reducing their spending on both high-value and low-value care. Moreover, their respective elasticities are roughly equal (-0.314 and -0.248 respectively) and are not statistically different

[19] 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).

from one another. Low-income enrollees of Marketplace plans are more than twice as responsive to prices in their demand for both high-value and low-value medical care they are for care that is not categorized as either high-value or low-value, but these differences are not statistically significant. The finding that low-income enrollees in Marketplace plans have a substantial price responsiveness in their demand for high-value care is in line with the findings of Brot-Goldberg et al. (2017) and with the RAND HIE, which found that cost-sharing led to across the board reductions in the use of care.

We also examine the price-responsiveness of prescription drug spending and for categories of prescription drug spending. 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.

Panel C of Table 3 shows that low-income enrollees of Marketplace plans have an overall demand elasticity for prescription drugs of -0.146. The demand elasticity for acute drugs is larger than (-0.203), but not statistically different from, the overall elasticity for drugs. Consumers are less price responsive in their demand for chronic drugs, which have an elasticity of 0.005, which is not statistically significant. The elasticity of demand for lifestyle drugs is larger (-0.267) than that for drugs overall, but this difference is also not statistically significant. The elasticity estimate for branded drugs (-0.088) is less than half the magnitude of that generic drugs (-0.176), but again this difference is not statistically significant.

Note that these estimates differ from those reported in Einav et al. (2018), which reports unweighted averages of drug-specific elasticities by broad classes, including acute, chronic, branded and generic. Our estimates, by contrast, are drug category-level elasticities – that is, the responsiveness of aggregate spending on all drugs in the category. Thus, our estimated elasticities are not comparable to those reported in Einav et al., (2018).[20] Overall, their reported average drug-specific elasticity reported is -0.23 compared with our estimate of an elasticity on overall drug spending of -0.15. In addition, the ACA Marketplace population that underlie our study is both lower-income and younger than the population of Medicare Part D enrollees used in Einav et al., (2018).

[20] This lack of comparability is similar to the way that firm-level elasticities are not comparable to industry-level elasticities.

6.3 Heterogeneity in Elasticity Estimates

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 4 about here]

We find little evidence of differences in demand elasticities by age. Panel A of Table 6 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 significant difference in the elasticity estimates across age category. There are few estimates in the literature of differences in demand elasticities by age category. One exception is Leibowitz et al., (1985), which finds similarly sized demand elasticities for outpatient care for children as for adults.

Men are more responsive to cost sharing than are women and this difference is statistically significant. The estimated elasticity of demand for total spending is -0.22 for men versus -0.03 for women (see Panel B). The estimates in the literature of differences in demand elasticities between men and women similarly suggest that men are more price sensitive than women (e.g., Wallen et al. (1986); Gilleskie (2010); and Zheng et al. (2021)).

There is no statistically significant difference in the responses to cost sharing between urban and rural enrollees (see Panel C). However, 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 17% of the sample.

There is evidence that sicker people are less responsive to cost sharing than healthier people; the estimated differences are both large and are statistically significant (Panel E). This result is consistent with the literature on the demand for health insurance which has found lower demand elasticities for individuals in worse health or with chronic illnesses (e.g., Auerbach & Ohri (2006); Schmitz & Ziebarth (2017)).

In Panel F, we find no evidence that adult enrollees in family plans are significantly more responsive to cost sharing than individual enrollees. Note that because of our sample selection criteria, our estimates are only based on adults' claims so this lack of a difference should be interpreted with some caution.

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 a simple test for whether nonlinearities matter: we test whether the estimated elasticities for plans with high deductibles differ from those with low deductibles.

Table 6, Panel D reports our estimates of price elasticities for those enrolled in high and low deductible plans. To ease the interpretation, we interact the coinsurance rate twice 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.[21] This simple test provides a straightforward test of the empirical relevance of nonlinearities in our demand elasticity estimates. Elasticities for higher and lower deductible plans are very similar and not statistically different from one another. Thus, 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.

7 Discussion and Limitations

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. Kowalski, (2016), using an instrumental variable strategy, finds very large elasticities in the range of -0.76 to -1.49.

We find that responses to cost sharing among low-income ACA enrollees imply an overall demand elasticity for health care of roughly -0.12. These estimates are less than the commonly-cited RAND HIE estimate of -0.2, which was estimated on a sample with average income. One reason for why demand elasticities could be lower among a lower-income population is health insurance literacy. For example, studies provide evidence that many Americans have difficulties understanding the basic functioning of cost sharing tools such as deductibles

[21] 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).

(Loewenstein et al. 2013); there is also evidence that consumers pick the wrong health plans, leave money on the table and that health insurance literacy differs by income group (Bhargava, Loewenstein, & Sydnor 2017; Villagra et al. 2019).

Our estimated elasticities for inpatient care are not statistically different from zero, and those for outpatient care are -0.14. However, for Emergency Room (ER) care, the demand elasticity is larger than but not statistically different from than our overall estimate. This large and positive ER elasticity is 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-pocket (OOP) spending with respect to average coinsurance rates of +0.70. Consistent with evidence from the recent literature, we find statistically significant responsiveness to both high-value (-0.31) and low-value (-0.25) 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.

Our study and methods are subject to a number of limitations. First, lower-income individuals are both enrolled in plans with less cost sharing and may have worse health, which could lead to bias. Our approach to addressing this concern is to include an extensive set of administrative controls for past health and health care use in our cross-sectional models, to include person-level fixed effects in out panel models, and to restrict our sample to a relatively narrow band of the income distribution from 100-250% of FPL. Although researchers may be rightfully skeptical about the general strategy of controlling for prior health status or including fixed effects 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, and because we restrict our sample to those who are in the CSR-eligible income range, there is little incentive for a CSR-eligible individual to not choose a Silver plan. As a result, we believe that 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 (1970)-style adverse selection is greatly attenuated by the design of CSR subsidies.

Despite this, there is still potential for selection into plans based on unobserved health status. 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, including first age, gender, county, and calendar month fixed effects, second, adding 2013 ACG risk score, third, omitting risk score and adding controls for inpatient days and ER visits, and finally including all health controls. This test is similar in spirit to the "using selection on observables to measure selection on unobservables" approach of Altonji et al., (2005). We find that the estimated elasticities change little as we add controls, providing little evidence of unobserved health factors (that are correlated with our prior health measures) affecting the elasticity estimates. We report these results in Appendix Table 2.

Second, 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. 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). Since the income elasticity of medical spending is probably positive in the United States (Cesarini et al. 2016; Finkelstein et al. 2019), our baseline estimates may represent lower bound price elasticity estimates of demand for medical care.

A third concern is that enrollees strategically manipulate their estimated incomes to maximize subsidies. However, evidence from the literature suggests that Marketplace enrollees do not manipulate their income to become eligible for subsidies (Hinde, 2017 and DeLeire et al., 2017).

Fourth, our models implicitly assume that the price elasticity of demand does not vary over the income brackets examined. We believe that this is a reasonable assumption, given that we examine a very homogenous group of households in Utah who all purchased coverage on the ACA Exchange, many of whom were recently uninsured, and who all have incomes below 250% of FPL.

Fifth, an assumption implicit in our interpretation of the coefficients from our models as own-price elasticities of demand for medical care is that 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. Previous research has

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 (Aron-Dine et al. 2012; Abaluck & Gruber, 2011; Brot-Goldberg et al., 2017; Keeler and Rolph, 1998; Ketcham, Lucarelli, & Powers, 2015). For example, Keeler et al. (1988) re-analyze data from the RAND HIE grouping claims data into episodes of treatment. They find evidence for myopic behavior and consumers responding to spot prices. However, their average elasticity estimate is also at -0.2, very similar to the main models that abstain from non-linear pricing (Manning et al., 1987). Aron-Dine et al., (2013), by contrast, do find that consumers respond to end-of-year prices and find a statistically significant elasticity with respect to the future price. Given the evidence in the literature, 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 a test for whether nonlinearities matter (see Section 6.3). In particular, 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 that they do not. We take this finding as support that not explicitly accounting for nonlinearities in pricing is a reasonable and justifiable approach in our setting.

Sixth, as enrollees choose policy from a menu of options, so the specific co-insurance structure of their chosen plan may be endogenous to their expected use of service-specific health care services. However, on the Utah exchange 85% of plans (enrollment-weighted) have deductibles that are equal to the out-of-pocket maximum for medical care (that is, the typical plan design is 0% coverage, then 100% coverage once the OOP max is hit). Thus, we believe that endogenous selection based on service-specific copayments is not a practical concern in Utah. To ensure that this is indeed the case, we estimated our main models on the restricted sample of enrollees in plans where the deductible is equal to the out-of-pocket maximum and report the results in Appendix Table 3. The estimated overall and service-specific elasticities are nearly identical to those estimated on our full sample.

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 8 reports the counterfactual estimates for all CSR recipients. As seen, eliminating CSRs would substantially reduce overall medical spending among CSR recipients by 25%, or $96 per month, from $376 to $281. At the same time, eliminating CSRs would increase OOP spending by $28 per month. Given the estimated decrease in spending by $96, this implies that the monthly taxpayer-funded amount in CSRs received would decrease by $67 per month.

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 5 and 6 about here]

The next three rows of Table 8 decompose 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 (-29% or -$113 per month). Analogously, their OOP spending would increase by a greater amount (+$39 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 $113 lower medical spending per month (or -20%) and $35 higher OOP spending. Enrollees with risk scores above 1 would have $163 lower medical spending per month (or -25%) and $45 higher OOP spending.

Our counterfactual exercise illustrates that eliminating CSRs would also have differential effects on different types of medical spending (Table 9). In percentage terms, because of the larger elasticities for ER care (see Table 3), the reduction is largest for (potentially inefficient) ER care (-41%) as well as outpatient care (-26%). However, we also predict disproportionately large reductions in preventive care, for example drugs that prevent hospitalizations; we estimate that eliminating CSRs would reduce low-income enrollees' spending on drugs that prevent hospitalizations by 31% (or $12 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 spending (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, 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 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 low-income consumers – even low-income consumers with potentially little experience navigating complex private health plans – respond to price mechanisms in the health care sector. The twin goals of the ACA were to improve both access to and affordability of quality health care. Cost-sharing reduced plans were designed to play a crucial role in achieving both the goal of affordability (by reducing out-of-pocket spending) and the goal of access (by softening some of the effects of cost-sharing for the lowest-income enrollees, for whom cost-sharing might deter needed care). The fact that ACA plans do have cost-sharing elements (which is sometimes substantial, particularly in Bronze and non-CSR Silver plans) is evidence that insurers and policymakers are concerned about moral hazard. However, the fact that the ACA statute required the provision of CSR plans to low-income consumers is evidence that policymakers wanted low-income consumers to face fewer consequences of cost-sharing as would higher income consumers. As our paper provides evidence that CSRs both reduced OOP spending and increased total spending for low-income consumers, these results suggest that the CSR program has helped the Marketplaces achieve the goals of the ACA and is working as intended.

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Table 1
Variable Means by CSR Category

	CSR 73 Enrollees	CSR 87 Enrollees	CSR 94 Enrollees	All CSR Enrollees	Test of Equality
Panel A: Monthly Health Care Spending					
Total Spending	$ 322	$ 371	$ 400	$ 376	***
ER Spending	$ 32	$ 39	$ 50	$ 44	***
Inpatient Spending	$ 58	$ 61	$ 56	$ 58	***
Outpatient Spending	$ 176	$ 205	$ 216	$ 207	***
Pharmaceutical Spending	$ 56	$ 65	$ 71	$ 67	***
of which:					
Acute	$ 17	$ 20	$ 22	$ 21	***
Chronic	$ 18	$ 19	$ 19	$ 19	
Lifestyle	$ 9	$ 11	$ 13	$ 12	***
Other Drugs	$ 11	$ 14	$ 18	$ 16	***
Out-of-Pocket Spending	$ 61	$ 38	$ 22	$ 32	***
of which:					
Deductible Spending	$ 43	$ 18	$ 8	$ 16	***
High Value Care	$ 3	$ 4	$ 5	$ 4	***
Low Value Care	$ 2	$ 3	$ 4	$ 3	***
Panel B: Controls and Other Variables					
Utah-Scaled 2013 Risk Score	0.86	0.88	0.91	0.89	***
Missing 2013 Risk Score	0.42	0.48	0.51	0.49	***
Inpatient Days 2004-2013	1.94	1.96	2.14	2.06	***
ER Visits 2004-2023	1.25	1.44	1.86	1.64	***
Female	0.53	0.53	0.56	0.55	***
Age	41.04	40.23		39.50	***
Age 18 to 30	0.26	0.3	0.35	0.32	***
Age 31 to 50	0.44	0.41	0.41	0.41	***
Age 51 to 64	0.30	0.29	0.25	0.27	***
Urban County	0.82	0.82	0.83	0.83	*
Enrollee-Months	70,295	190,938	295,970	557,203	
Unique Enrollees	7,330	19,459	30,721	49,471	
Months Enrolled in 2014	11.35	11.44	11.40	11.40	
Months Enrolled in 2015	11.55	11.54	11.50	11.52	

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
Estimates of the Effect of Cost-Sharing on Total Monthly Health Care Spending

	(1)	(2)	(3)	(4)
Dependent Variable	Monthly Total Spending		IHS Transformed Monthly Total Spending	
Years of Data	2014 - 2015		2013 - 2015	
Estimation Method	GLM		Linear Fixed Effects	
Log Coinsurance Rate	--	-0.115***	--	-0.121***
		(0.026)		(0.025)
CSR 94% AV Plan	0.193***	--	0.187***	--
	(0.046)		(0.022)	
CSR 87% AV Plan	0.126***	--	0.100***	--
	(0.047)		(0.025)	
2013 Risk Score	1.706***	1.704***	--	--
	(0.084)	(0.084)		
2013 Risk Score Missing	-0.521**	-0.519**	--	--
	(0.196)	(0.195)		
Inpatient Days 2004-2013	0.018***	0.018***	--	--
	(0.001)	(0.001)		
ER Visits 2004-2023	0.072***	0.072***	--	--
	(0.001)	(0.001)		
Estimated Elasticity of Demand	-0.128	-0.115	-0.125	-0.121
Age, Age Squared, Gender Controls	Yes	Yes	No	No
Month by Year Fixed Effects	No	No	Yes	Yes
Month Effects	Yes	Yes	No	No
County Fixed Effects	Yes	Yes	No	No
Person Effects	No	No	Yes	Yes
Enrollee-Months	557,203	557,203	731,305	731,305
Unique Enrollees	49,471	49,471	49,027	49,027

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 includes adults aged 18 to 64 who were enrolled for at least 9 months in a CSR Silver plan in 2014 or 2015. The models reported in columns 3 and 4 include person-months from 2013 and are also restricted to enrollees with person-months in 2013. Models reported in columns 1 and 2 are estimated by GLM using a log-link and gamma distribution and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. The model reports in column 3 and 4 are estimated by linear regression and the dependent variable in those specification is transformed using the inverse-hyperbolic sine.

Table 3
Estimates of the Price Elasticity of Health Care Spending by Spending Categories

Panel A	*By Type of Care*					
	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending		
Log Coinsurance Rate	-0.240***	-0.135***	-0.024	0.694***		
	(0.054)	(0.023)	(0.080)	(0.020)		
Panel B	*By High-Value and Low-Value Care*					
	High-Value Spending	Low-Value Spending	Uncategorized Spending			
Log Coinsurance Rate	-0.314***	-0.248***	-0.112***			
	(0.051)	(0.074)	(0.026)			
Panel C	*By Type of Prescription Drug*					
	All Drugs	Acute	Chronic	Lifestyle	Branded	Generic
Log Coinsurance Rate	-0.146***	-0.203**	0.005	-0.251***	-0.088	-0.176***
	(0.045)	(0.073)	(0.091)	(0.057)	(0.072)	(0.027)
Enrollee-Months	557,203					
Unique Enrollees	49,471					

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 distribution and also include controls for 2013 Risk Score, missing 2013 Risk Score, number of inpatient days from 2004-2013, number of ER visits from 2004-2013, age, age squared, gender, county fixed effects, and month by year fixed effects. All models have 49,471 unique enrollee and 557, 203 enrollee-months observations.

Table 4

Heterogeneity in the Elasticity of Health Care Spending

	Total Spending		Total Spending
Panel A: Age		**Panel D: Deductible**	
Age 18-30 (reference)	-0.126	High Deductible (reference)	-0.167
Age 31-50	-0.106	Low Deductible	-0.133
Age 51-64	-0.115		
Panel B: Gender		**Panel E: Risk**	
Female (reference)	-0.032	Low Risk Score (reference)	-0.170
Male	-0.220***	High Risk Score	0.226**
Panel C: Rural-Urban		**Panel F: Family Plan**	
Rural (reference)	-0.058	Individual Plan (reference)	-0.051
Urban	-0.130	Family Plan	-0.110

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 that the difference between the group and the reference group is significant 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 distribution 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. Each panel represents one model where a stratifying variable as indicated in the cells of each panel is interacted with the main regressor “log coinsurance rate.” 'High Risk Score' equals 1 if the ACG risk score exceeds 1, where 1 is scaled to be the nationally representative mean risk score.

Table 5
Counterfactual Effect of Eliminating CSRs by Recipient Characteristic

	Monthly Spending	Counter-factual Spending (70% AV)	Difference ($)		Difference (%)	Change in Subsidy	OOP Spending
All Enrollees	$376.38	$280.77	-$95.61	***	-25%	-$67.21	$28.40
Enrollees in:							
94% AV Plans	$393.16	$280.56	-$112.60	***	-29%	-$73.53	$39.07
87% AV Plans	$370.58	$280.76	-$89.83	***	-24%	-$67.29	$22.53
73% AV Plans	$321.53	$281.71	-$39.82	***	-12%	-$40.43	-$0.61
Age 18-30	$250.00	$183.31	-$66.69	***	-27%	-$44.76	$21.94
Age 31-50	$343.58	$265.53	-$78.05	***	-23%	-$50.21	$27.84
Age 51-64	$570.68	$457.24	-$113.44	***	-20%	-$78.50	$34.94
Risk Score > 1	$656.73	$494.17	-$162.56	***	-25%	-$117.61	$44.95
Risk Score < 1	$337.45	$278.25	-$59.20	***	-18%	-$28.58	$30.62

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

Table 6
Counterfactual Effect of Eliminating CSRs by Type of Medical Spending

	Monthly Spending	Counter-factual Spending (70% AV)	Difference ($)	Difference (%)
Log Coinsurance Rate	$376.38	$280.77	-$95.61 ***	-25%
Spending on:				
ER	$ 43.70	$ 25.71	-$18.00 ***	-41%
Outpatient	$ 238.98	$ 176.72	-$62.26 ***	-26%
Acute/Chronic Drugs	$ 39.99	$ 27.64	-$12.34 ***	-31%

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

Appendix Table A1
Estimates of the Effect of Cost-Sharing on Total Monthly Health Care Spending

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Monthly Total Spending				IHS Transformed Monthly Total Spending	
Years of Data	2014 - 2015				2014 - 2015	
Estimation Method	GLM			GLM	Linear Fixed Effects	
Sample	Trimmed	Trimmed	Full	Trimmed, Must Have 2013 Observations	Trimmed	Trimmed
CSR 94% AV Plan	--	--			0.267***	--
					(0.030)	
CSR 87% AV Plan	--	--			0.138***	--
					(0.031)	
Log Coinsurance Rate	-0.111***	-0.112***	-0.146***	-0.190***	--	-0.175***
	(0.026)	(0.026)	(0.029)	(0.031)		(0.019)
2013 Risk Score	1.636***	1.658***	1.801***	1.786***	2.932***	2.932***
	(0.083)	(0.081)	(0.094)	(0.085)	(0.176)	(0.176)
2013 Risk Score Missing	-0.493**	-0.541**	-0.390	--	-3.743***	-3.742***
	(0.196)	(0.195)	(0.230)		(0.150)	(0.150)
Inpatient Days 2004-2013	--	--	0.023***	0.015***	0.014***	0.014***
			(0.002)	(0.001)	(0.002)	(0.002)
ER Visits 2004-2023	--	--	0.068***	0.063***	0.082***	0.082***
			(0.002)	(0.002)	(0.008)	(0.008)
Inpatient Days 2010-2013	0.022***	0.023***	--	--	--	--
	(0.002)	(0.002)				
ER Visits 2010-2013	0.104***	0.138***	--	--	--	--
	(0.003)	(0.003)				
Inpatient Days 2007-2009	0.0145**	--	--	--	--	--
	(0.003)					
ER Visits 2007-2009	0.062***	--		--	--	--
	(0.006)					
Inpatient Days 2004-2006	0.011***	--	--	--	--	--
	(0.003)					
ER Visits 2004-2006	0.036***	--	--	--	--	--
	(0.007)					
Estimated Elasticity of Demand	-0.111	-0.112	-0.146	-0.190	-0.178	-0.175
Age, Age Squared, Gender C	Yes	Yes	Yes	Yes	Yes	Yes
Month by Year Fixed Effects	No	No	No	No	No	No
Month Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Person Effects	No	No	No	No	No	No
Enrollee-Months	557,203	557,203	559,175	278,594	557,203	557,203
Unique Enrollees	49,471	49,471	49,663	25,189	49,471	49,471

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 includes adults aged 18 to 64 who were enrolled for at least 9 months in a CSR Silver plan in 2014 or 2015. The models reported in column 4 includes person-months from 2013 and are also restricted to enrollees with person-months in 2013. Models reported in columns 1 and 2 are estimated by GLM using a log-link and gamma distribution and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and year by month fixed effects. The model reports in column 5 and 6 are estimated by linear regression and the dependent variable in those specification is transformed using the inverse-hyperbolic sine.

Appendix Table 2

GLM Demand Elasticity Estimates: Stepwise Inclusion of Health Controls

Total Spending	-0.17***	-0.16***	-0.11***	-0.12***
	(0.03)	(0.03)	(0.03)	(0.03)
ER Spending	-0.35***	-0.33***	-0.24***	-0.24***
	(0.05)	(0.05)	(0.05)	(0.05)
Outpatient Spending	-0.20***	-0.18***	-0.14***	-0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Inpatient Spending	-0.08	-0.07	-0.02	-0.02
	(0.08)	(0.08)	(0.08)	(0.08)
Out-of-Pocket Spending	0.66***	0.66***	0.70***	0.69***
	(0.02)	(0.02)	(0.02)	(0.02)
County Fixed Effects	X	X	X	X
Year by Month Fixed Effects	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 family 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 49,471 unique enrollee and 557,203 enrollee-months observations.

Appendix Table 3
Estimates of the Price Elasticity of Health Care Spending Restricting to Plans where OOP Max is Equal to the Deductible

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	-0.11***	-0.24***	-0.13***	0.01	0.78***
	(0.03)	(0.06)	(0.02)	(0.08)	(0.02)
Risk Score	Yes	Yes	Yes	Yes	Yes
Inpatient Days and ER Visits	Yes	Yes	Yes	Yes	Yes
Age, Age Squared, Gender Controls	Yes	Yes	Yes	Yes	Yes
Month Effects	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes

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 and also restricted to enrollees in plans in which the maximum out-of-pocket is equal to the deductible. Models are estimated by GLM using a log-link and gamma distribution and also control for age, age squared, gender, a missing 2013 Risk Score indicator, county fixed effects, and month by year fixed effects. All models have 46,651 unique enrollee and 483,753 enrollee-months observations.

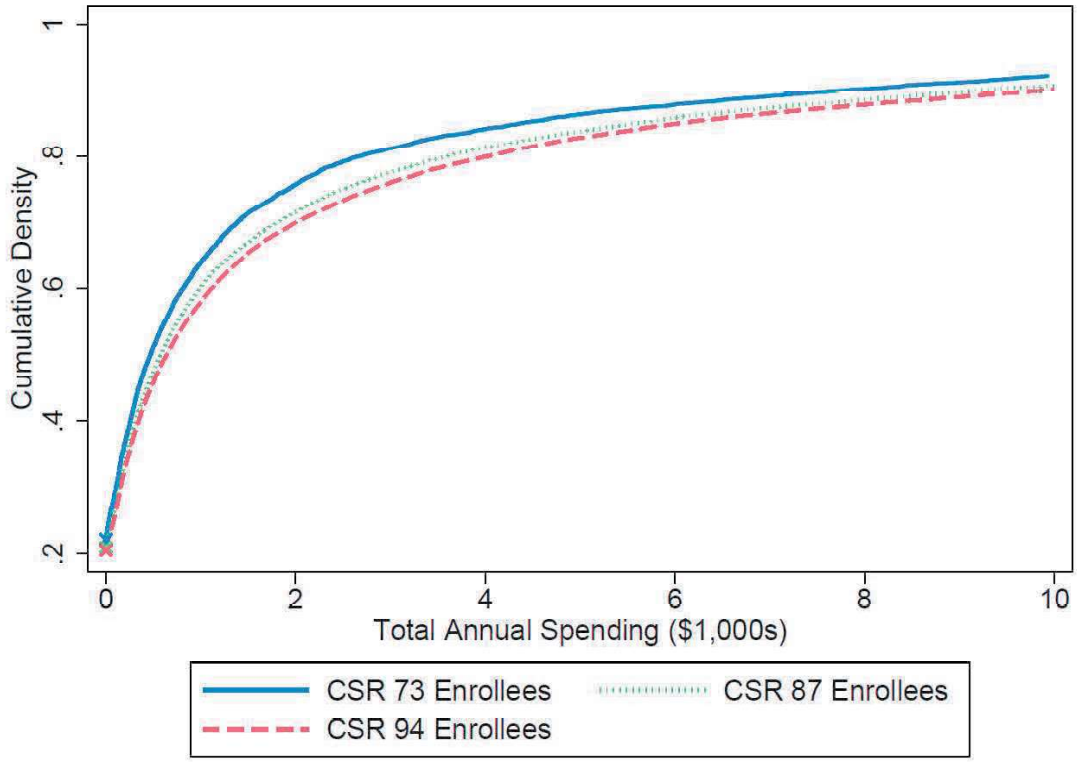
Appendix Table 4
Variable Means by CSR Category

	CSR Enrollees With 2013 Insurance	CSR Enrollees Without 2013 Insurance	Test of Equality
Panel A: Monthly Health Care Spending			
Total Spending	404	349	***
ER Spending	45	43	***
Inpatient Spending	62	54	***
Outpatient Spending	220	194	***
Pharmaceutical Spending	78	57	***
Panel B: Controls and Other Variables			
Inpatient Days 2004-2013	2.72	1.37	***
ER Visits 2004-2023	1.90	1.39	***
Female	0.56	0.53	***
Age	38.39	39.85	***
Age 18 to 30	0.35	0.31	***
Age 31 to 50	0.41	0.41	
Age 51 to 64	0.24	0.28	***
Urban County	0.84	0.84	
Family Plan	0.61	0.51	***
Enrollee-Months	278,594	278,609	
Unique Enrollees	25,189	24,286	

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

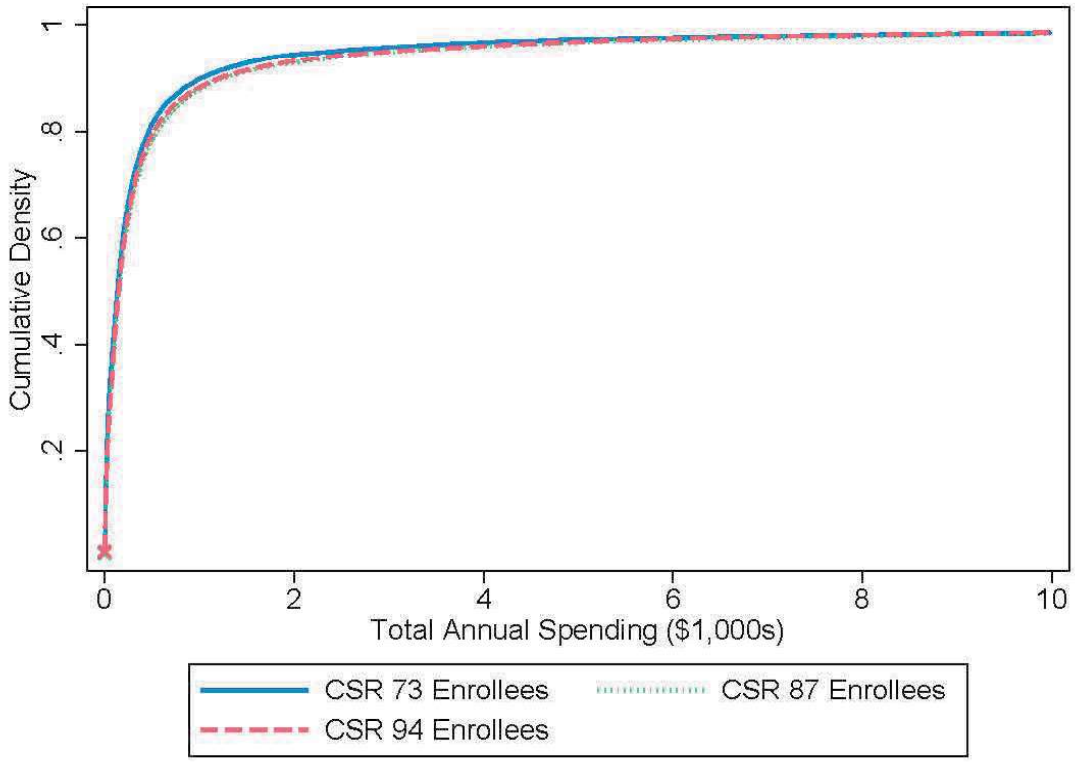
Silver plan in 2014 or 2015 . Urban county indicates counties with at least 80% of the population residing in an urban area (as defined by the 2010 Census). *** indicates significance at the 1% level.

Figure 1. Cumulative Density Functions of Total Spending by CSR Category, 2014-2015



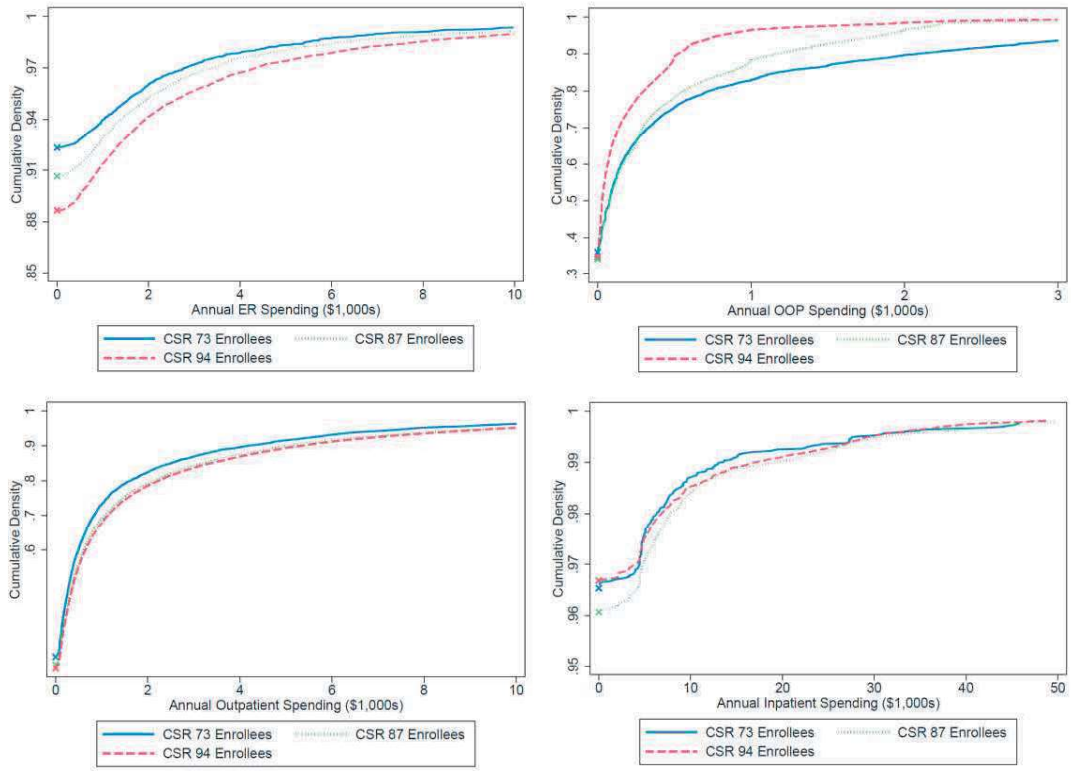
Source: 2014-2015 Utah APCD

Figure 2. Cumulative Density Functions of Total Spending by CSR Category, 2013



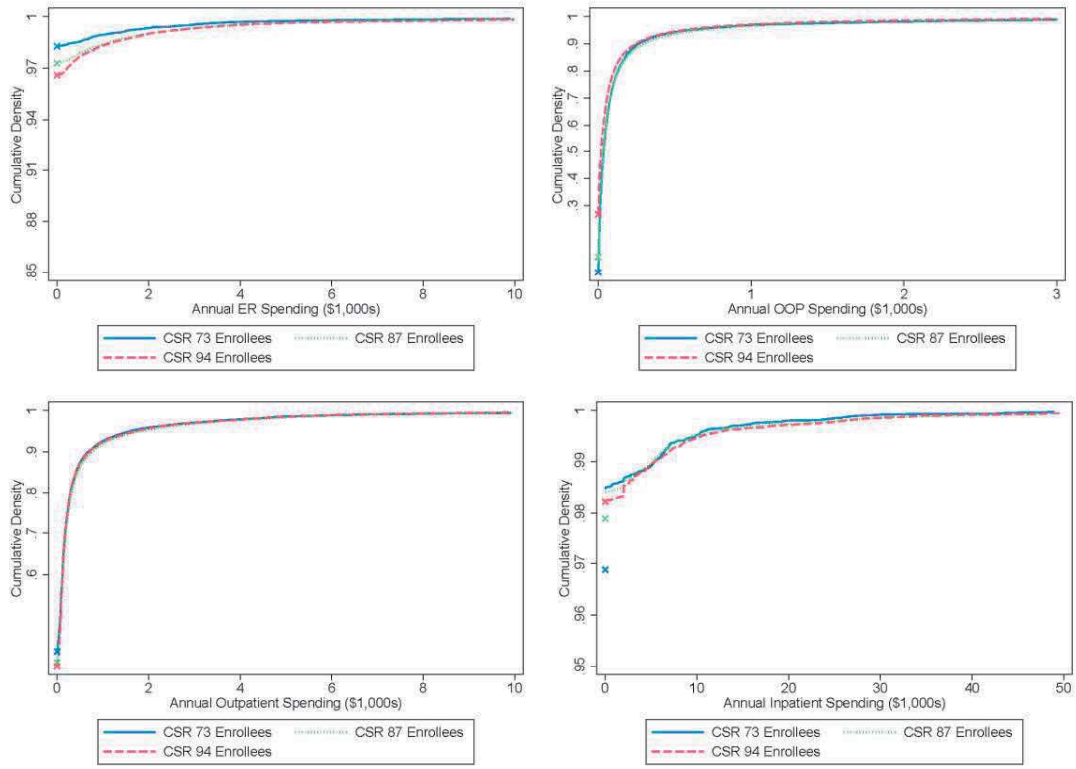
Source: 2013 Utah APCD

Figure 3. Cumulative Density Functions by Spending by Spending and CSR Category, 2014-2015



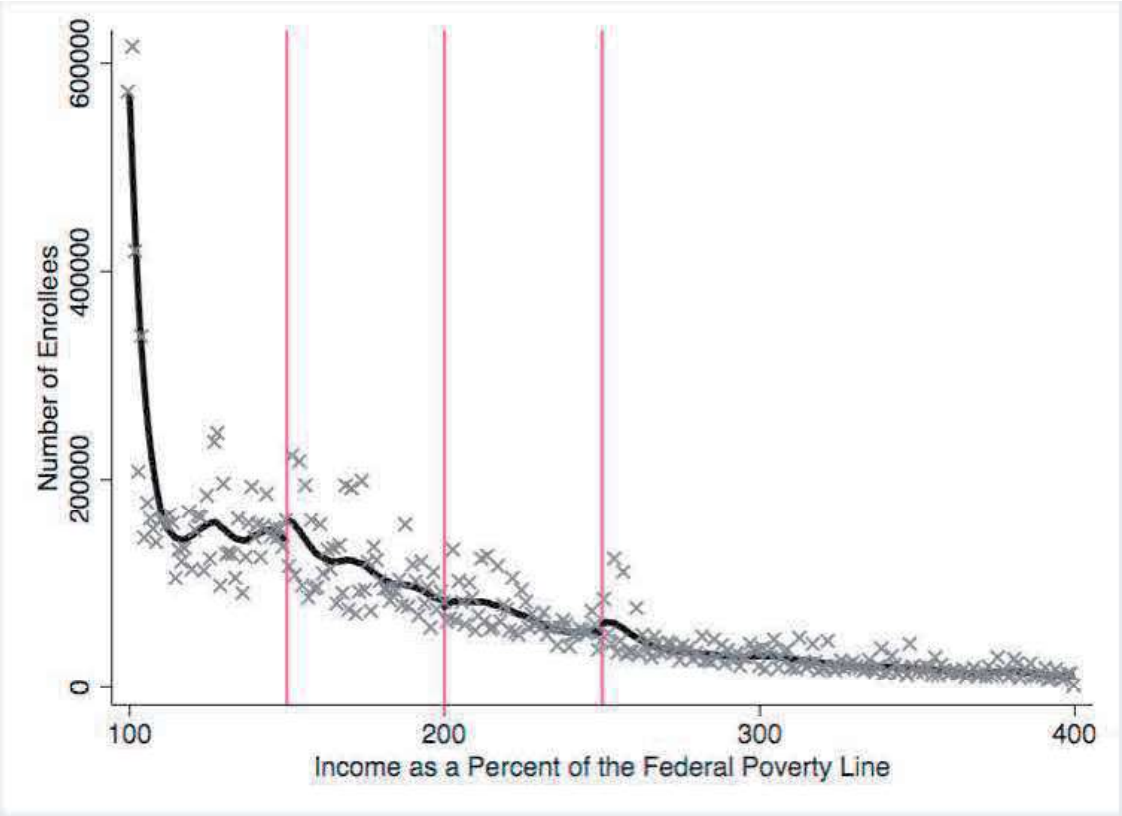
Source: 2014-2015 Utah APCD

Figure 4. Cumulative Density Functions by Spending by Spending and CSR Category, 2013



Source: 2013 Utah APCD

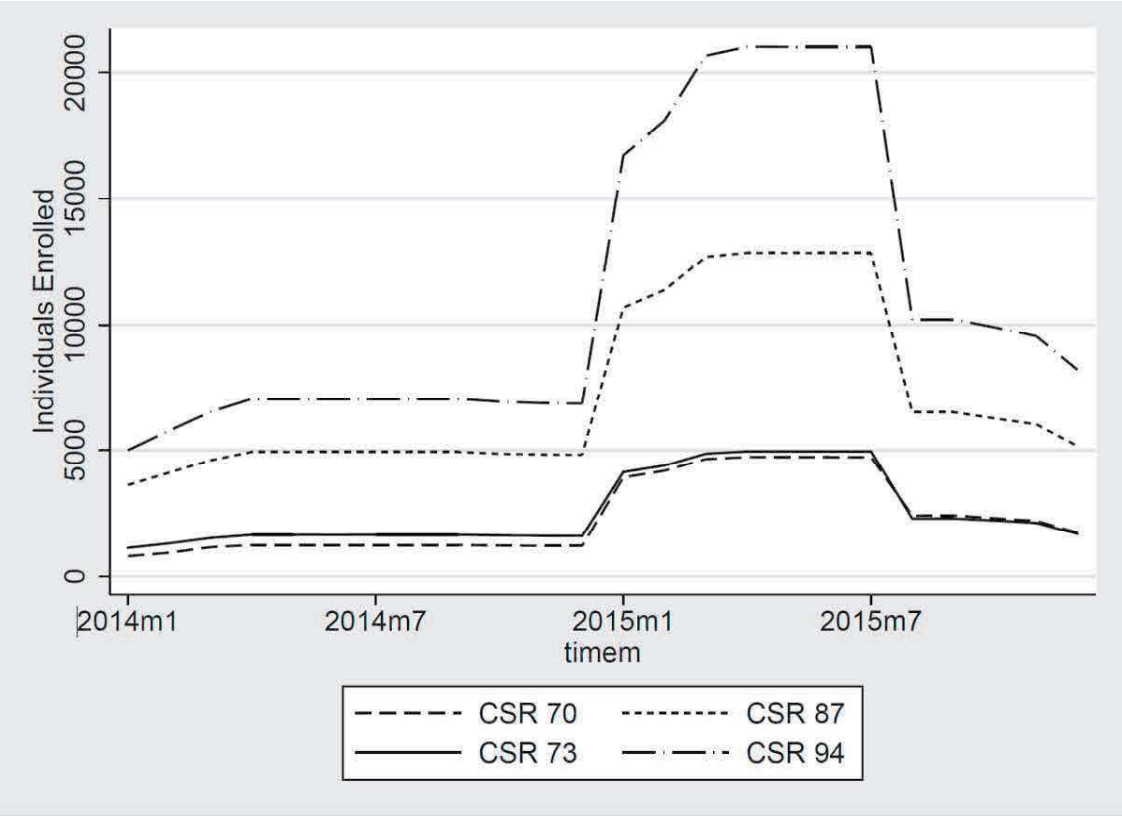
Appendix Figure 1. Density of Marketplace Enrollment, by FPL



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



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