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

Kurt Lavetti
Ohio State University*

Thomas DeLeire
Georgetown University†

Nicolas R. Ziebarth
Cornell University‡

April 1, 2019

Abstract

In addition to providing tax credits to lower insurance premiums, the Affordable Care Act (ACA) requires insurers to provide cost-sharing reductions (CSRs) to low-income consumers who purchase private health insurance plans on the ACA Marketplaces. CSRs reduce the amount of cost-sharing (e.g., deductibles) required by enrollees. They are mandated out of concern that high levels of cost-sharing could deter needed healthcare among low-income individuals. We use 2013-2015 All-Payer Claims Data from Utah, linked to 2004-2013 administrative hospital discharge data, to determine whether CSRs increase the healthcare utilization of low-income consumers. Exploiting policy-driven differences in the value of CSRs that are solely determined by income, we find that enrollees enrolled in health insurance plans with lower amounts of cost-sharing have higher healthcare spending, controlling for past healthcare use. Based on these responses, we estimate the demand elasticity of total health care spending to be -0.13. We find a larger responsiveness for emergency room care, lifestyle drugs, and low-value care. The results suggest that low-income consumers in the ACA Marketplaces, many of whom were previously uninsured, exhibit a price responsiveness that is similar in magnitude to that of higher-income populations examined in the previous literature. Our results imply that eliminating CSRs would lead to a substantial reduction in healthcare utilization by low-income consumers across all categories of care.

Keywords: demand elasticities, health insurance, uninsured, ACA, marketplaces, exchanges, low-value care, lifestyle drugs, Utah

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

*Ohio State University, Department of Economics, Arps Hall 433, Columbus, OH 43210, and IZA Bonn e-mail: lavetti.1@osu.edu

†Georgetown University, McCourt School of Public Policy, 37th and O Streets, NW, Washington, DC 20057, NBER, and IZA Bonn e-mail: thomas.deleire@georgetown.edu

‡Cornell University, Department of Policy Analysis and Management (PAM), 106 Martha Van Rensselaer Hall, Ithaca, NY 14850, DIW Berlin, and IZA Bonn e-mail: nrz2@cornell.edu

‡We are grateful to the Utah Office of Health Care Statistics, especially Norman Thurston, Charles Hawley, Mike Martin, and Sterling Petersen, for their assistance in making this research possible; to seminar participants at the 29^th Annual Health Economics Conference at Texas A&M University and at Georgetown University; to the helpful comments of Michael Richards; to Apoorva Rama for excellent research assistance; and to the Robert Wood Johnson Foundation's "Policy-Relevant Insurance Studies" grant program (I.D. 72674) for funding. Support for this project was also provided by the Ohio State University Institute for Population Research through a grant from the Eunice Kennedy Shriver National Institute for Child Health and Human Development of the National Institutes of Health, P2CHD058484. The content is solely the responsibility of the authors and does not necessarily represent the official views of the Eunice Kennedy Shriver National Institute for Child Health and Human Development or the National Institutes of Health. This research is not the result

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 and are motivated from 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. To date, previous literature has primarily examined how higher income populations or individuals covered by Medicaid respond to cost-sharing. 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). In the 1970s, the RAND HIE randomized families into health plans with different levels of cost-sharing. Following participants for up to three years, the study concluded that the price elasticity of demand for episodes of treatment is around -0.2.[1] More recently, Brot-Goldberg et al. (2017) exploit an exogenous change in cost-sharing in employer-sponsored insurance plans at a large technology company. The study concludes that increases in cost-sharing resulted in across-the-board reductions in utilization, including both low-value and high-value medical care. Neither of these studies, however, focused on low-income consumers similar to those target by the ACA's CSR program.

Two relevant empirical settings in which low-income populations have been studied include the Oregon Medicaid lottery and the Massachusetts health insurance reform in 2006. Finkelstein et al. (2012) study the effects of a lottery that determined the *right to apply* for Medicaid in Oregon in 2008. They find that obtaining Medicaid coverage without *any* cost-sharing increased the probability of inpatient stays and outpatient visits in the first year of coverage by 30% each. This experiment yields important insights into the health care utilization effects of expanding Medicaid coverage for previously uninsured (i.e., on the *extensive* margin), but provides less guidance about the effects of changing levels of cost-sharing among those who have private health insurance (i.e., on the *intensive* margin). Similar to this paper, Chandra et al. (2014) focus on the intensive margin to estimate

of a for-pay consulting relationship, nor do the authors have a financial interests that might constitute a conflict of interest.

[1]Despite pointing out limitations related to external validity and attrition, Aron-Dine et al. (2013) confirm these main findings when re-analyzing the original data.

demand elasticities of low-income populations in the Massachusetts Commonwealth Care program. Exploiting discontinuous changes in cost-sharing rates at 100 and 200% of the federal poverty line (FPL), they estimate demand elasticities of between -0.1 and -0.3 for different categories of care.

This paper provides the first estimates of how low-income enrollees in the ACA Marketplaces respond to lower levels of cost-sharing induced by the CSR program. We begin by estimating elasticities of demand for different types of care by exploiting differences in CSRs across tiers of plans for low-income enrollees. We then investigate whether enrollees differentially respond to cost-sharing in their demand for high-value versus low-value health care, a hypothesis for which both the RAND HIE and Brot-Goldberg et al. (2017) find little evidence. Next, we decompose drug elasticity estimates by type of prescription drug, based on a classification developed by Chandra et al. (2010). Finally, we simulate a counterfactual CSR policy to assess the effects of eliminating CSR subsidies for low-income consumers.

To this end, we use All-Payer Claims Data (APCD) from Utah between 2013 and 2015. They contain insurance coverage and claims records for nearly every commercially-insured Utah resident, including monthly plan enrollment records, the CSR subsidy category of each low-income enrollee, all medical care utilization, prescription drug purchases, diagnoses, negotiated prices, payments, and spending. The 2013 APCD data allow us to calculate each enrollees' health risk scores prior to selecting ACA plans in 2014 using Johns Hopkins ACG© System software. A unique feature of our data is that we are also able to 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 information of hospital-based health care utilization prior to exchange enrollment. Although we do not observe exact reported income in the claims records, we determine that income manipulation to obtain higher CSRs is not a threat to our estimates. However, because income can have a separate effect on health care spending that does not operate through health, we interpret our estimates as lower bounds and provide a series of robustness checks. In particular, we assess the sensitivity of our findings with respect to different income elasticity values reported by the literature.

We find that responses to cost-sharing among low-income ACA enrollees imply an overall demand elasticity for health care of -0.13. This estimate is surprisingly close to the commonly-cited RAND HIE estimate of -0.2. Our estimated elasticities for inpatient and outpatient care are -0.15. However, for Emergency Room (ER) care, they are substantially larger (-0.28). These ER elasticities are consistent with the Oregon Medicaid lottery, which found a significant increase in ER utilization when gaining 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 +0.55.

We also find that sicker enrollees, with higher pre-ACA risk scores, are less price responsive to cost-sharing. For example, elasticity of demand falls from -0.21 to -0.05 when 2013 risk scores increase from the 10^{th} percentile to the 90^{th} percentile of the sample distribution. Consistent with evidence from Brot-Goldberg et al. (2017), we find meaningful responsiveness to both high and low-value medical care, with a slightly larger price elasticity of -0.29 for low-value care. We also use the categorization of prescription drugs developed by Chandra et al. (2010) to estimate the largest elasticities for lifestyle drugs (-0.25) and the smallest elasticities for chronic illnesses drugs (-0.09). The overall elasticity for prescription drugs is -0.15, which is similar to the -0.2 estimate for elderly enrollees in Medicare Part D from Einav et al. (2018). Overall, 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.

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 are currently legally obligated to provide subsidies to consumers, whereas the federal government has ceased reimbursement to insurers for these subsidies. This, in turn, led to explicit distortions of plan premiums on the exchanges. Motivated by this policy uncertainty surrounding the future of CSR payments in the ACA, we apply our elasticity estimates to simulate what would happen to low-income enrollees if CSR subsidies were eliminated. We find that eliminating subsidies would lead to a 29% reduction in health care spending. This estimate reflects a 34% reduction in subsidy payments, but only a 7% increase in OOP spending ($23 per enrollee, per month). In relative terms, reductions in spending disproportionately affect young enrollees, those who were sicker prior to enrolling, and the lowest of low-income households with incomes close to the federal poverty line. While potentially inefficient ER spending would decrease by almost 50%, spending on high-value prescription drugs that may prevent hospitalizations would also decrease by 34%. The latter findings illustrate the double-edged sword of cutting cost-sharing subsidies. It may imply that "value-based" CSRs could be welfare-enhancing.

2 Background

Consumers shopping for heath insurance on the ACA Marketplaces are offered a standardized menu of regulated plans. Plans offered on the exchanges 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 Marketplace can receive income-dependent premium tax credits and plans with reduced cost-sharing or CSRs. The ACA requires insurers selling plans on the exchanges to offer three CSR-variant plans for each Silver plan offered. 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 in all aspects other than cost-sharing as their corresponding Silver plan—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.[2] The actual value of premium tax credits is determined by a consumer's realized income as reported on their federal tax return; differences between the actual value and the amount received in advance are reconciled on the tax return.

Consumers with reported incomes between 100% and 250% of FPL are offered CSR-variant plans instead of 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 a 87% AV; 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 reported income.[3]

The ACA does not specify how exactly 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, among all Federally Facilitated Marketplace (FFM) plans in 2015 with combined medical and prescription

[2]In 2014, 100% of FPL was $11,490 per year for a single household and $23,550 for a four person household (Internal Revenue Service, 2015). In 2017, these values had increased to $12,060 and $24,400 (Department of Health and Human Services, 2017).

[3]Reported income is subject to a verification process in which it is compared with previous years' incomes from tax returns. In cases where reported income is substantially lower that previous years' incomes, additional documentation supporting the reported income level may be required.

drug coverage, the average deductible was $2556 in 70% AV Silver plans, $2077 in 73% AV Silver plans, $737 in 84% AV Silver plans, and $229 in 94% AV Silver plans (Kaiser Family Foundation, 2015).

When consumers report income that crosses below 250% of the FPL, the deductible and other cost-sharing rules are automatically and discontinuously adjusted to increase the generosity of every Silver plan shown from 70% AV to 73% AV. Similarly, when income crosses below 200% and below 150% of FPL, plan designs change and discontinuously adjust cost-sharing so to increase AVs from 73% to 87% and then to 94%, respectively. In fiscal year 2017, a total of $7.3 billion in taxpayer funds was spent on CSRs (Congressional Research Service, 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 the Utah FFM exchange (Kaiser Family Foundation, 2014). During the second open-enrollment period, in January 2015, overall enrollment had further increased to 116 thousand (Department of Health and Human Services, 2015). Although Utah did not expand Medicaid eligibility under the ACA, there is evidence that the Utah FFM exchange 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 about 65 thousand individuals relative to the pre-ACA level of 407 thousand (Kaiser Family Foundation, 2014; Gallup, 2015). At its inception in 2014, six different carriers offered 1,712 Qualified Health Plans (QHP) at the plan-rating area level on the Utah FFM exchange. The majority of them were Silver plans (39%) followed by Bronze plans (29%).

3 Prior Research

The RAND HIE produced a set of elasticity point estimates which are still considered the gold standard for health care demand elasticity studies. 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. However, the cost-sharing reduced health care demand "across the board" with reductions in both "appropriate" and "inappropriate" care (O'Grady et al., 1985; Manning et al., 1986, 1987).

As a result of largely public health care systems, studies outside the U.S. typically rely on moderate variation in small copayment amounts to estimate demand elasticities of care. The few reported findings are consistent with a point estimate of -0.2 for most medical services (Chiappori et al., 1998; Cockx and Brasseur, 2003; Gerfin and Schellhorn, 2006; 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. He reports elastic demand for home visits and psychologists as well as inelastic demand (close to zero) for acute services. Using data from 73 U.S. employers and the years 2008 to 2014, Ellis et al. (2017) report a wide range of elasticity estimates for the 26 investigated types of care. Assuming backward myopic consumers, Ellis et al. (2017) calculate an overall elasticity of -0.44 and surprisingly small elasticities for prevention (-0.02) and ER visits (-0.04).

Moreover, two recent areas of the literature investigate (a) whether health care consumers are rational decision-makers, and (b) to what extent the non-linear budget sets in private insurance contracts induce intertemporal demand substitution as a result of dynamic price changes (which forward-looking consumers exploit). There is clear evidence that (some) consumers do not understand insurance products (Loewenstein et al., 2013), leave money on the table when choosing health plans (Abaluck and Gruber, 2011, 2016; Bhargava et al., 2017), and react to price framing (Schmitz and Ziebarth, 2017). However, there is also evidence that consumers learn over time (Ketcham et al., 2012, 2015, 2016), that some are forward-looking, and that intertemporal substitution exists (Dalton, 2014; Einav et al., 2015; Kowalski, 2015; Cabral, 2017; Lin and Sacks, 2016; Brot-Goldberg et al., 2017). For example, DeLeire et al. (2017) find that very few consumers have enrolled in financially dominated health plans in the exchanges.

This paper also contributes to the growing economic literature on the ACA Marketplaces (Richardson and Yilmazer, 2013; Kowalski, 2014; Cox et al., 2015; Hinde, 2017). Studies focusing on premium determinants use FFM health plan data to show that more competition on an exchange reduces premiums (Dafny et al., 2015), that Medicaid expansion improved risk pools and lowered premiums (Sen and DeLeire, 2018), and that premiums are lower in larger "coverage regions" (Dickstein et al., 2015). Sacks et al. (2017) show theoretically that the Exchange 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 have also been studied. Orsini and Tebaldi (2017) find that age-based pricing restrictions have reduced participation on the exchanges and Tebaldi (2017) shows that age-based subsidies would lead to equilibria where all buyers would be better off.

Finally, three papers study the impact of premium and cost-sharing subsidies on take-up. Frean et al. (2017) use American Community Survey (ACS) data linked to ACA area prices to identify 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. They find health plan elasticities with respect to the actuarial value of around one. And Saltzman (2019) combine 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 expenditures among the population of 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 need to make for causal 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 the underlying assumptions we make for interpreting our estimates as own price elasticities of demand for healthcare.

4.1 Empirical Model

Among health econometricians, one of the core topics of inquiry is the question of how to appropriately model health care spending in microeconometric models. Manning (2006); Jones (2011), and Mihaylova et al. (2011) provide comprehensive overviews of these models.

The empirical fact that health care spending distributions are highly skewed with a long right tail and a mass point at zero drives much of the discussion regarding the econometric modeling of health care spending. We follow two general approaches: estimating linear models on log transformed data and estimating generalized linear models (GLM).

Our approach is to estimate a nonlinear specification using a Generalized Linear Model (GLM) with a log link and a gamma variance, as developed by Mullahy (1998); Manning and Mullahy (2001), and Manning et al. (2005). Buntin and Zaslavsky (2004) compare several healthcare spending models and find that the GLM substantially reduces mean squared error relative to the transformed log model.[4] One main advantage of the GLM model is its ability to make predictions based on the original health care spending scale—a re-transformation of the dependent variable is not necessary, see Manning (2006) and Deb et al. (2017) for details. Deb et al. (2017) provide an updated discussion with further details about the GLM, including Stata codes and examples.[5] Thus, our basic empirical model can be written as:

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

where y_{it} measures health care spending (in dollars) of individual i in month t. Our main variable of interest is $AV_{p(i,t)}$ which is the Actuarial Value (AV) of plan p chosen by individual i in month t. We focus on Silver plans with cost-sharing subsidies, such that $AV_{p(i,t)}$ takes three values: 73%, 87%, and 94%.

In our favored specification, and one from which we can derive the demand elasiticity, our independent variable of interest is $(1 - AV_{p(i,t)})$, which is the average coinsurance rate. As we discuss below, β from equation 2 provides our estimate of the demand elasticity.

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

[4]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 $\boldsymbol{X_{i,t}}$: $\mathbb{E}(y_{it}|\boldsymbol{X_{i,t}}) = \exp(\boldsymbol{X_{i,t}\xi}) = g^{-1}(\boldsymbol{X_{i,t}\xi})$. 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 et al. (2017) point out, one only needs to correctly specify the link function and the covariates $\boldsymbol{X_{i,t}}$ 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.

[5]Other approaches include transforming the spending distribution by taking its logarithm—plus one, to avoid excluding zeros (Manning and Mullahy, 2001; Aron-Dine et al., 2013), 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 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 (Pohlmeier and Ulrich, 1995; Deb and Trivedi, 1997, 2002). While our main estimates use the GLM approach, our findings are quite similar using log transformed spending, as we show in the Appendix (cf. Buntin and Zaslavsky, 2004).

$Risk_{i,2013}$ represents the risk score of individual i in 2013, prior to choosing an ACA Marketplace plan. We calculate the risk scores using All-Payer-Claims-Data (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.

$Inpatient_{i,2004-2013}$ and $ER_{i,2004-2013}$ count the number of cumulative individual inpatient days and Emergency Room (ER) visits between 2004 and 2013. Controlling for pre-period risk scores and hospital utilization allows plan selection to be correlated with health.

$Z_{i,t}$ are socio-demographic controls including gender, age, and age squared. δ_t and $\rho_{c(i,t)}$ 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. ϵ_{it}, the error term, is 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 and Miller, 2015).

4.2 Threats to Identification

Our estimates of the effect of cost-sharing on health care spending are identified by between-enrollee variation in AVs. We believe this variation is sufficient to identify this effect because AVs are effectively ”assigned” to enrollees based on income categories. This income-based assignment leaves little room for plan choice to lead to biased estimates.

Despite this, there are four threats to the identification of the effect of cost-sharing on health care spending using variation in AVs stemming from the CSR program. We discuss each potential threat in turn.

The first threat to identification is the role of income on the demand for health care. We do not have information on the exact household income and thus cannot estimate Regression Discontinuity models as in DeLeire et al. (2017). What our data include is the information of whether the individuals enrolled in a CSR-variant plan with an AV of 73%, 87%, or 94%. Thus, while we do not know exact income, we do know precisely whether an enrollee's family income falls into the income categories 100-150%, 150-200% or 200-250% of FPL. To minimize income-related selection concerns, our empirical approach focuses on Silver plans with cost-sharing subsidies (or CSR-variant plans). That is, it focuses on Silver plans with AVs between 73% and 94%, excluding the standard 70% Silver plan; thereby we are not using variation between Platinum, Bronze, Silver and Gold plans. This implies that the identifying AV variation is solely determined by the applicants' indicated income category during the open enrollment period. Each income category triggers different CSR levels and results in different plan AVs (see Section 2). [6]

To the extent that income has a *direct* impact on healthcare spending (above and beyond its impact through health for which we control comprehensively), our estimates represent lower bounds as we cannot directly control for income (as income categories are collinear with AV categories).

A second concern for a causal interpretation of our coefficients of interest is that lower-income individuals who are enrolled in plans with less cost sharing will have worse health. We believe we address this concern by including an extensive set of controls for past health and health care use. We have access to all commercially insured medical claims for every resident of Utah, allowing us to calculate individual-level risk scores for 2013 (the year before enrollment into an ACA Marketplace plan) and control for $Risk_{i,2013}$ in our models. Controlling for the risk score prior to actual enrollment should substantially mitigate concerns about selection based on unobserved health risks. Fourth, we exploit a decade of pre-enrollment data on inpatient and ER visits and link them at the individual-level to each Marketplace enrollees. Hence, our model controls for extensive medical histories in addition to $Risk_{i,2013}$. Fifth, we also control for age, gender, county, and month-year fixed effects. Given that we find little to no selection on observables, including measures of past health, we believe that it is reasonable to assume that there is little room for additional selection into plans based on health (Altonji et al. (2005)).

Finally, our robustness checks do not yield evidence that enrollees manipulated their anticipated household incomes to become eligible for more cost-sharing subsidies. This may be a function of the institutional features: if an individual reports estimated income that is substantially lower (more than approximately 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 (Department of Health and Human Services, 2013).[7]

We experimented with including individual fixed effects in the model, very few enrollees switch plans across CSR categories (3,113 individuals, or 7% of all silver plan enrollees) between 2014 and

[6]Note that $AV_{p(i,t)}$ does *not* measure the realized AV of the health plan. Instead, it is the expected *ex ante* plan AV, estimated by a CMS calculator. Moreover, the CMS calculator uses a fixed enrollee population such that plan selection does not confound the AV estimates.

[7] To be specific, according to Jacobs et al. (2013), "HHS contracted with Equifax to use its database of 54 million payroll records [...] for instant verification." Moreover, while some tax lawyers appear to promote their business by listing (limited) legal possibilities to reduce their clients' taxable income below 250% FPL, many websites warn about deliberately understating the true income. In addition to requiring additional documentation, the PTC will always be reconciled after the tax declaration in the next year, and applicants "may be guilty of fraud, a punishable crime" (Davis, 2016). Because regulators obviously anticipated that systematic income manipulation is very unlikely to happen, there is no reconciliation with CSR amounts.

2015, see Appendix, Table A9. While this 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 (see footnote 7 below and the regulatory tools to avoid income manipulation).

4.3 Estimating Demand Elasticities

We interpret the coefficient β from equation (2) as the own price elasticity of demand for health care. Since the independent variable in this specification is $ln(1 - AV_{p(i,t)})$, or the log of the average coinsurance rate, we are assuming that consumers respond to average prices.

The most widely cited estimates of the own price elasticity of demand for health care come from the RAND HIE, which produced a point estimate of -0.2. However, several assumptions are required to produce such an estimate. Aron-Dine et al. (2013) provide an excellent discussion of these assumptions.

The main difficulty in calculating price elasticities of demand is that health care prices change dynamically over the course of a year, given the non-linear pricing schedule of 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 the expected and realized end-of-year prices or the average price 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 and Gruber, 2011; Ketcham et al., 2015; Brot-Goldberg et al., 2017), 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). However, in combination with skewed health spending data that may be sensitive to the modeling approach (Section 4.1), allowing for different behavioral assumptions introduces even more statistical uncertainty. As we describe below and report in the Results Section 6.5, we conduct a simple test for whether nonlinearities matter: we test whether the estimated elasticities among individuals enrolled in plans with high deductibles (above the median) differ from those with low deductibles (below the median), *conditional on plan AV*. The variation in deductibles conditional on plan AV will lead to different nonlinearities in pricing across plans with the same AV. As we report below, we find economically and statistically insignificant differences in the estimated elasticities across individuals with high and low deductibles. We take this as evidence that not explicitly accounting for non-linearities 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, out outcomes, and several of our key health-related controls.

5.1 Datasets

We use three main datasets in our empirical analysis: Utah All-Payer Claims Dataset (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 Dataset (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[8] to submit, each quarter, every health care claim to the Office of Health Care Statistics. Relative to the overall state population of 2.9 million in 2013 (State of Utah, 2013), 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).

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. 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 CMS data on FFM plan characteristics (including deductibles and other cost-sharing rules), metallic value codes, and CSR subsidy categories.

[8]The law exempts extremely small insurers with fewer than 2500 total enrollees across all plans.

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 FFM Marketplace in 2014 or 2015.[9] 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.[10] We collapse the data to the enrollee-month level and obtain an unbalanced panel of 381,161 person-months and 43,247 unique individuals.[11] 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 enrolled in CSR-variant plans with an 87% AV, and the remainder are in CSR-variant plans with a 73% AV.

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

[9]We omit all claims from *SelectHealth* for August, September and November 2015 because of missing data. In the Appendix, we provide robustness checks omitting all *SelectHealth* enrollees in 2015 (Table A7).

[10]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.

[11]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. Hence, 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. (Recall that our approach links variation in plans AVs—not individual point-in-time cost-sharing amounts—to individual health care spending.) In robustness checks, we also provide estimates for family plans.

negotiated prices). We also calculate spending by category of care, including ER spending, inpatient spending, outpatient spending, pharmaceutical spending, other spending, and OOP spending (see Panel A of Table 1). All values are in nominal dollar terms. Table 1 presents summary statistics on total spending by CSR category and by type of medical care for all CSR enrollees, and for enrollees stratified by AV.

[Insert Table 1 about here]

Among all enrollees in CSR-variant plans on the Utah Marketplace in 2014 and 2015, average monthly total medical spending was $4319 per year. This level of average spending is similar to that of the commercially insured population of Utah. However, it is worth noting that this level of health care spending 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 ($987 per month), followed by pharmaceutical spending ($782 per month), inpatient spending ($765 per month), and ER spending ($447 per month). Average spending out-of-pocket on medical care was $345 per month, of which $183 was on deductibles. The summary statistics on health care spending reported in table 1 suggest that individuals who are enrolled in plans with the highest levels of cost sharing (with 73% AVs), have lower levels of total monthly medical spending ($3898) than individuals enrolled in plans with an 87% AV ($4275) or a 94% AV ($4451). This pattern of lower spending among those with less cost sharing and higher spending among those with more cost sharing holds for all categories of care, with the exception of inpatient spending. Moreover, out-of-pocket medical care spending is substantially lower among individuals with less cost sharing, for example $253 per month among individuals in plans with a 94% AV versus $592 per month among individuals in plans with a 73% AV.

We follow Schwartz et al. (2014) and Brot-Goldberg et al. (2017) to categorize health care spending into low-value care and high-value care. ow-value care as "evidence-based lists 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. We follow the identical categorization criteria used by Brot-Goldberg et al. (2017). Not all health care spending is categorized as either low- or high-value care.

[Insert Figure 1 about here]

Because of the skewness in health care spending, the difference in health care spending between individuals enrolled in plans with lower levels of cost sharing and higher levels of cost sharing tend to be driven by individuals at the top of the spending distribution. Figure 1 displays the cumulative density functions for four categories of health care spending for enrollees in the three types of CSR plans. For ER spending, 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. The top 3% of ER consumers among CSR 73 enrollees consume ER care worth at least $2000 per year, while the top 3% of CSR 94 enrollees spend over $4000.

Similar patterns are shown for outpatient spending, though the differences across enrollees with different AVs are smaller. Roughly two-thirds of all enrollees in our sample have any out-of-pocket health care spending, but among those with positive out-of-pocket costs, these costs are higher among those in lower AV plans. We see few differences in distribution of inpatient spending across individuals enrolled in plans with different AVs.

These descriptive statistics 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.

5.4 Controls for Health

We construct three measures of each individual's past health spending in order to comprehensively control for prior health in our empirical models. 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 have used risk scores similarly as a comprehensive measure of individual health risks (cf. 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 (reported in Panel B of Table 1), the mean risk score is quite similar to that in the overall population. The distribution of risk scores is heavily skewed to the right with a substantial shares of enrollees having values between 1 and 2, between 2 and 3, and above 3. This pattern is consistent with the highly skewed health spending distributions in other populations (French and Kelly, 2016).

In addition to controlling for the individual-level risk score for 2013, we condition on health care utilization histories for an entire decade, from 2004 to 2013, which we derive from administrative data on hospital discharge records on the individual level. In particular, we measure the total number of inpatient days and the total number of ER visits for each individual over this 10-year period. For our population and as reported in Panel B of Table 1, the mean number of inpatient days between 2004 and 2013 was 2.16 and the mean number of ER visits over this period was 1.61. As we discuss above, individuals who were uninsured in 2013 do not have data from which we can calculate a risk score for 2013. 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.

Note that the 2013 risk scores and the mean numbers of inpatient and ER visits vary only slightly across CSR categories; low-income individuals who were enrolled in plans with less cost-sharing have higher risk scores and more visits. 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 our data and the first year of ACA Marketplace enrollment in Utah.

5.5 Other Variables

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.

5.6 Characteristics of CSR-Variant Plans Offered on the Utah Marketplace

While the details differ by the specific plans selected, the deductible in a CSR 94 plan could be as low as $0, whereas CSR 73 plans typically have substantial deductibles (Center on Budget and Policy Priorities, 2015). Gabel et al. (2016) report that, in 2015, only 65% of all CSR 94 plans had a deductible but 98% of CSR 73 plans did. Moreover, according to Kaiser Family Foundation (2015), about three quarters of all FFM plans either charged copayments or coinsurance rates specifically for ER use, both in CSR 73 and 94 plans. In CSR 73 plans, however, the average copayment was $270 and the average coinsurance rate 27%. By contrast, in CSR 94 plans, the average copayment was $168 and the average coinsurance rate 19%. Three-quarters of the plans selected by enrollees in our sample are HMOs, and there is no difference in the fraction of selected plans that are HMOs across CSR categories.

6 Results

In this section, we present our empirical findings. First, in Section 6.1, we report the results of our GLM estimation of 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.

Second, in Section 6.2, we estimate demand elasticities for low and high-value care. We follow the categorization of Brot-Goldberg et al. (2017) to indicate treatment episodes containing low or high-value care. In addition, we estimate elasticities for different types of drugs, including prescription drugs used to treat acute and chronic diseases, following the categorization of Chandra et al. (2010), as well as brand name versus generic drugs.

Next, in Section 6.3 we investigate potential selection concerns. We provide a series of robustness checks suggesting that, conditional on enrolling in CSR plan, enrollees do not appear to have strategically manipulated their reported incomes to obtain higher cost-sharing reductions.

In Section 6.4, we present evidence on heterogeneity in responses to cost-sharing, stratifying estimates by age, gender, family plan, and health status.

Finally, we discuss the impact of non-linearities in insurance contracts in Section 6.5 and present evidence that the presence of non-linearities in this setting does not seem to impact our findings.

6.1 Estimating Demand Responses to Cost-Sharing by Types of Care

Tables 2 and 3 show the main parametric estimates from our GLM estimates of equations (1) and (2). Each column of Tables 2 and 3 represents estimates from separate regressions where the dependent variable measures total spending or spending on different categories of care in $1,000s.

[Insert Table 2 about here]

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 87% AV and for individuals enrolled in a CSR-variant plan with a 94% A. Individuals enrolled in a CSR-variant plan with a 73% AV are the baseline category. Recall that the availability of these different plans with different AVs is determined solely by income categories; individuals who have a plan with an 94% AV do not have the option of selecting a variant with a 87% or 73% AV.

The results show that, compared with individuals in plans with an AV of 73%, individuals in plans with an AV of 94% have total spending that is 18% 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, and time fixed effects effects. Those in a plan with an AV of 87% have total spending that is 7% higher than those in a plan with an AV of 73%, though this difference is not statistically meaningful.

Looking at categories of spending—ER, outpatient, and inpatient–individuals enrolled in plans with highest AVs spend more than individuals in plans with the lowest AVs in all three categories. ER spending is 37% higher, outpatient spending is 23% higher, and inpatient spending is 25% higher among enrollees in plans with a 94% AV compared with enrollees in a 73% AV. Enrollees in plans with an 97% AV also have higher spending than those in plans with a 73% AV in all three categories of health care spending, but only in the category of outpatient spending is the 12% difference statistically meaningful.

Out-of pocket spending is substantially lower among individuals in plans with a 94% AV and for individuals in plans with an 87% AV—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 three 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 $LogCoinsurance_{p(i,t)} = Log(1 - AV_{p(i,t)})$. Since the GLM specification has a log-link function, and the independent variable is the log coinsurance rate, the reported estimates in this table can be directly interpreted as own price elasticities of demand.

We estimate an overall elasticity of demand for medical care of -0.13, an estimate that is also statistically different from zero. We also estimate expenditure elasticities ER, outpatient, and impatient spending. The elasticity of demand for ER care (-0.28) is more than twice as large as the overall elasticity, while inpatient and outpatient spending (-0.15) have elasticities similar to the overall average. A higher coinsurance rate is also related to higher out-of-pocket spending.

Appendix Table A3 reports estimates from an OLS log-log specification, conditional on enrollees with any positive medical spending (this intensive margin variation corresponds to the identifying variation in the GLM estimates.) The implied elasticity estimates for total spending (-0.12) and outpatient spending (-0.14) are similar to the GLM estimates. However, ER and inpatient spending estimates are substantially smaller, driven in part by the small sample of individuals who use these categories of care (see above and Figure 1). These patterns suggest that some estimates, especially those with substantial extensive-margin variation, may be sensitive to the restrictions imposed in the OLS specification.

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

In this section, we decompose estimates of price responsiveness for low- and high-value medical care. As we discuss above, we follow the categorization used by Brot-Goldberg et al. (2017) in defining low- and high-value care. In Table 4, we report expenditure elasticity estimates from equation (2) where the dependent variable is (again) total health care spending as well as spending on high-value care, and spending on low-value care.

[Insert Table 4 about here]

As a benchmark, column (1) reports again the overall elasticity of -0.13. As seen in column (3), the low-income enrollees of Marketplace plans are more than twice as responsive to prices in their demand for low-value medical care as they are overall for care, with an implied elasticity of -0.29. Interestingly, and in line with Brot-Goldberg et al. (2017), our findings also reveal that low-income consumers have a substantial price responsiveness in their demand for high-value care, with an average elasticity -0.24 (column 2).

We also examine differences in price-responsiveness across classes of prescription drugs, and we report these results in 5. As we discuss above, we group drugs based on their potential to prevent subsequent hospitalizations. We do so following the approach developed by 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 1-2 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 if hospitalization if not taken. We also, separately, examine differences in demand elasticities for branded and generic drugs.

[Insert Table 5 about here]

Table 5 shows that low-income consumers have an overall demand elasticity for drugs of -0.15. We estimate that consumers have a similar price responsiveness in their demand for acute care drugs (-0.17) as for drugs overall, but are less responsive in their demand for chronic drugs (-0.09, with a standard error of 0.11), and more responsive in their demand for lifestyle drugs (-0.25).

6.3 Plan Selection

There are three 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 affect present income. Second, the duration of enrollment spells could be endogenously determined by CSR subsidies, altering the distribution of person-month health care utilization across CSR groups. Third, CSR beneficiaries could strategically manipulate the incomes 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 rich set of controls for health status and health care utilization prior to enrollment, including 2013 ACG risk scores, and ten years of inpatient and ER utilization measures. However, to the extent that 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, we re-estimate equation (2) adding in out controls for prior health in a step-wise manner. We first estimate models with only age, gender, county, and month fixed effects. We then add the control for the 2013 risk score. Finally, we add controls for inpatient days and ER visits from 2004 through 2013. 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.[12]

[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 as add controls stepwise. In our view, this lends support to the plausible exogeneity of the coinsurance rate in our models.

To address the second concern, we restrict our analysis sample to those with at least 9 months of enrollment in the same CSR category in the calendar year. This prevents the composition of the sample from being overly affected by attrition rates. As shown in Table 1, after imposing this restriction the length of average enrollment spells differs by only about one week across CSR categories.

The third concern is that enrollees may strategically manipulate their reported income to obtain higher cost-sharing subsidies. However, there appears to be no evidence, neither in the APCD data

[12]This test is similar in spirit to the "using selection on observables to measure selection on unobservables" approach of Altonji et al. (2005).

nor the CMS data that this was the case. DeLeire et al. (2017) examined the density of enrollment by income in all FFMs in 2014 -2017 using individual-level enrollment data from CMS's Multidimensional Insurance Data Analytics System and found no evidence of income manipulation.

6.4 Estimating Effect Heterogeneity

To investigate heterogeneity in elasticities, we re-estimate equation (2) including interactions between $LogCoinsurance_{p(i,t)}$ and other covariates of interest.

[Insert Table 7 about here]

Panel A of Table 7 stratifies the estimates by the three age groups 18 to 30, 31 to 50, and 51 to 64 years. We find very small differences in overall elasticities by age, though younger enrollees had significantly more elastic demand for inpatient care (-0.27 versus -0.07 to -0.09 for older age groups). We also find that men (-0.21) are systematically more responsive to cost-sharing than women (-0.06), and that this pattern holds across all categories of care.

Notably, the increased use of ER care in lower income groups is driven largely by men, who have an elasticity of -0.41 for ER care (Panel B).

Panel C shows that we find little evidence of geographic heterogeneity in responses to cost-sharing, although it is worth noting that a very large share of Utah residents live in the Salt Lake City metro area, so rural enrollees represent only 11% of the sample.

Panel D also provides evidence of interesting heterogeneity, suggesting 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]

Table 8 stratifies estimates by 2013 ACG© risk score. 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. There is a clear pattern in all categories of care: sicker people are less responsive to cost-sharing. For example, for overall care, the 10^{th} percentile elasticity is -0.21, which is statistically different from zero, as is the 50^{th} percentile elasticity at -0.14. However, the 90^{th} percentile elasticity is -0.05 and not statistically different from zero. Inpatient spending is particularly sensitive to pre-period risk scores.

6.5 Considering Nonlinearities

Finally, we stratify estimates by the size of the deductible. To do this, 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 is always the combined deductible for medical and prescription drug spending.[13] Since the model conditions on the average coinsurance rate, the only variation that can identify 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 in Table 9, the interaction term has a small and insignificant coefficient across all types of care. Accordingly, we conclude that, while the role of nonlinearities is generally a topic worth exploring explicitly in many settings, nonlinearities in plan designs do not appear to substantially affect our average elasticity estimates.

[Insert Table 9 about here]

7 Discussion

We find that responses to cost-sharing among low-income ACA enrollees imply an overall demand elasticity for health care of -0.13. This estimate is surprisingly close to the commonly-cited RAND HIE estimate of -0.2. Our estimated elasticities for inpatient and outpatient care are -0.15. However, for Emergency Room (ER) care, they are substantially larger (-0.28). These ER elasticities are consistent with the Oregon Medicaid lottery, which found a significant increase in ER utilization when gaining 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 +0.55.

We also find that sicker enrollees, with higher pre-ACA risk scores, are less price responsive to cost-sharing. For example, elasticity of demand falls from -0.21 to -0.05 when 2013 risk scores increase from the 10^{th} percentile to the 90^{th} percentile of the sample distribution.

[13] Kaiser Family Foundation (2015) report that the average combined deductible on all 37 FFMs was \$2,077 for CSR 73, \$737 for CSR 87 and \$229 for CSR 94.

Consistent with evidence from Brot-Goldberg et al. (2017), we find meaningful responsiveness to both high and low-value medical care, with a slightly larger price elasticity of -0.29 for low-value care. We also use the categorization of prescription drugs developed by Chandra et al. (2010) to estimate the largest elasticities for lifestyle drugs (-0.25) and the smallest elasticities for chronic illnesses drugs (-0.09). The overall elasticity for prescription drugs is -0.15 which is similar to the -0.2 estimate for elderly enrollees in Medicare Part D from Einav et al. (2018).

These findings on consumers price responsiveness to different types of pharmaceutical drugs suggest, surprisingly, that enrollees appear to more price sensitive for drugs that limit immediate risks of hospitalization that 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, -0.25, suggesting that there is some channel through which consumers respond to a lack of hospitalization spillover effects. We find no difference in the responsiveness to cost sharing for generic versus branded drugs.

Overall, 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 has been studied by the previous literature. We find that low-income enrollees (who were uninsured for an average of 2 months in the year before the Utah FFM was created) have roughly similar price-inelastic demand as the U.S. population more generally, but may be more responsive than the general population to cost-sharing for ER services. As a comparison, using recent US 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.

8 Counterfactual Policy Estimates

Although the federal government stopped making CSR subsidy payments to insurers in 2017, insurers are still required by law to provide CSR subsidies to consumers. To recoup these unfunded subsidies, insurers then explicitly added surcharges of 7% to 38% to plan premiums (Kaiser Family Foundation, 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 the findings above, we estimate the 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 instead enrolled in standard AV 70% silver plans, we extrapolate the GLM elasticity estimates with respect to coinsurance rates from Tables 3, 5, 7, 8. Our estimates therefore describe a partial equilibrium, in which CSR recipients still enroll in Silver plans; we do not consider the impact of eliminating CSR subsidies on relative premiums or plan selection.

The first row of Table 10 reports the counterfactual estimates for all CSR recipients. As seen, eliminating CSRs would substantially reduce overall medical spending among CSR recipients by 29%, or $142 per month, from $490 to $349 (Columns (1) to (3)). At the same time, eliminating CSRs would increase OOP spending by $23 per month (Column (4)). Given the estimated decrease in spending by $142, this implies that the monthly taxpayer-funded amount in CSRs received would decrease by $164 per month (Column (5)).

These are values for the average CSR beneficiary in Utah. In February 2017, nationwide, close to six million recipients (5,895,662, see Centers for Medicare and Medicaid Services (2017)) were enrolled in CSR eligible plans. Given total CSR spending in 2017 ($7.317 billion, see Congressional Research Service (2018)), these national numbers equal $1,241 per year and recipient, or $103 per month (assuming 12 months of enrollment).

[Insert Table 10 about here]

The next three rows in Table 10 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 (-32% or -$164 per month). Analogously, their OOP spending would increase by a greater amount (+$34 per month).

We also estimate the impacts by age and by 2013 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 $161 lower medical spending per month (or -22%) and $31 higher OOP spending. Enrollees with risk scores above 1 (above the Utah population mean) would have $271 lower medical spending per month (or -31%) and $36 higher OOP spending.

[Insert Table 11 about here]

Table 11 illustrates that eliminating CSRs would also have differential effects on different types of medical spending. In percentage terms, because of the larger elasticities (see Table 3), the reduction is largest for (potentially inefficient) ER care (-47%) as well as outpatient care (-31%). However, we also predict disproportionately large reductions in preventive care. For the latter exercise, we follow (Chandra et al., 2010) and identify drugs that prevent hospitalizations, i.e., “high-value drugs.” We estimate that eliminating CSRs would reduce low-income enrollees’ spending on drugs that prevent hospitalizations by 34% (or $19 per month).

The finding that health care consumers reduce utilization across the board and do not differentiate between high and low-value care confirms Brot-Goldberg et al. (2017) for a highly policy-relevant low-income population. Specifically, it implies that taxpayer-funded subsidies for low-income consumers do not only increase their utilization of necessary high-value care and drugs, but also their utilization for low-value and potentially inefficient care.

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 effective communicated (or not communicated at all) by insurers, providers, and policymakers alike. 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 another policy implication.

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, 2014). 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

To our knowledge, this is the first paper to use APCD data for an entire state over three years and to exploit variation in income category determined AVs to assess how low-income enrollees 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 and low-value care (following Brot-Goldberg et al., 2017) and for different classes of drugs that may offset the risk of hospitalization (following Chandra et al., 2010).

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.

A unique feature of our research design is the ability to link rich all-payer claims data on ACA exchange enrollees to pre-period claims, including ten years of administrative hospital discharge records (inpatient and ER care). This allows us to compare spending differences by differences in actuarial values across FFM Silver plans, while controlling for the short, medium, and long-term heterogeneity in health status that may be correlated with income.

Although we remain conservative as ours might be lower-bound estimates, they are surprisingly close to those from the RAND HIE, which is now four decades old and does not focus on low-income enrollees. We find an overall demand elasticity of -0.13, and larger price responsiveness for ER care (-0.28), low-value care (-0.29), and for lifestyle prescription drugs (-0.25). In contrast, the elasticity for drugs to treat chronic conditions is not statistically different from zero (-0.09).

These 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. However, in line with Brot-Goldberg et al. (2017) for ESI enrollees, the findings also suggest that health care consumers do not appear to systematically differentiate between high and low-value care. This might imply that the value of care is not effectively communicated by providers and insurers. One policy implication could be a call for "value-based CSRs."

References

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

Abaluck, J. and J. Gruber (2016). Evolving choice inconsistencies in choice of prescription drug insurance. *American Economic Review 106*(8), 2145–2184.

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

Aron-Dine, A., L. Einav, and A. Finkelstein (2013). The RAND Health Insurance Experiment, three decades later. *Journal of Economic Perspectives 27*(1), 192–222.

Bhargava, S., G. Loewenstein, and J. Sydnor (2017). Do individuals make sensible health insurance decisions? Evidence from a menu with dominated options. *The Quarterly Journal of Economics 32*(3), 1319–1372.

Brot-Goldberg, Z. C., A. Chandra, B. R. Handel, and J. T. Kolstad (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. and A. M. Zaslavsky (2004). Too much ado about two-part models and transformation? Comparing methods of modeling Medicare expenditures. *Journal of Health Economics 23*(3), 525 – 542.

Cabral, M. (2017). Claim timing and ex post adverse selection. *Review of Economic Studies 84*(1), 1–44.

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

Center on Budget and Policy Priorities (2015). *Key Facts: Cost-Sharing Reductions*. CBPP. http://www.healthreformbeyondthebasics.org/cost-sharing-charges-in-marketplace-health-insurance-plans-part-2/, last retrieved on September 8, 2017.

Centers for Medicare and Medicaid Services (2017). *2017 Effectuated Enrollment Snapshot*. CMS. https://downloads.cms.gov/files/effectuated-enrollment-snapshot-report-06-12-17.pdf, last retrieved on December 7, 2016.

Chandra, A., J. Gruber, and R. McKnight (2010). Patient cost-sharing, hospitalization offsets, and the design of optimal health insurance for the elderly. *American Economic Review 100*(1), 192–213.

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

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

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

Congressional Research Service (2018). *Health Insurance Premium Tax Credits and Cost-Sharing Subsidies*. https://fas.org/sgp/crs/misc/R44425.pdf, last retrieved on April 30, 2018.

Cox, N., B. Handel, J. Kolstad, and N. Mahoney (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., J. Gruber, and C. Ody (2015). More insurers lower premiums. *American Journal of Health Economics 1*(1), 53–81.

Dalton, C. (2014). Estimating demand elasticities using nonlinear pricing. *International Journal of Industrial Organization 37*(C), 178–191.

Davis, E. (2016). Lying on your health insurance subsidy application–it won't help in the long run. https://www.verywell.com/lying-on-insurance-subsidy-application-1738410, last retrieved Sept 6, 2017.

Deb, P., E. C. Norton, and W. G. Manning (2017). *Health Econometrics Using Stata* (first edition. ed.). Stata Press.

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

Deb, P. and P. K. Trivedi (2002). The structure of demand for health care: Latent class versus two-part models. *Journal of Health Economics 21*(4), 610–625.

DeLeire, T., A. Chappel, K. Finegold, and E. Gee (2017). Do individuals respond to cost-sharing subsidies in their selections of marketplace health insurance plans? *Journal of Health Economics 56*, 71 – 86.

Department of Health and Human Services (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*. HHS. https://www.federalregister.gov/documents/2013/07/15/2013-16271/medicaid-and-childrens-health-insurance-programs-essential-health-benefits-in-a last retrieved on April 30, 2018.

Department of Health and Human Services (2015). *Health Insurance Marketplace 2015 Enrollment Period: January Enrollment Report, 2015*. HHS. https://aspe.hhs.gov/system/files/pdf/33826/ib_2015jan_enrollment.pdf, last retrieved on Sept 7, 2017.

Department of Health and Human Services (2017). *Annual Update of the HHS Poverty Guidelines*. HHS. https://www.federalregister.gov/documents/2017/01/31/2017-02076/annual-update-of-the-hhs-poverty-guidelines, last retrieved on April 30, 2018.

Dickstein, M. J., M. Duggan, J. Orsini, and P. Tebaldi (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., A. Finkelstein, and M. Polyakova (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., A. Finkelstein, S. P. Ryan, P. Schrimpf, and M. R. Cullen (2013). Selection on moral hazard in health insurance. *American Economic Review 103*(1), 178–219.

Einav, L., A. Finkelstein, and S. P. Schrimpf (2015). The response of drug expenditure to nonlinear contract design: Evidence from Medicare Part D. *The Quarterly Journal of Economics 130*(2), 841–899.

Ellis, R. P., B. Martins, and W. Zhu (2017). Health care demand elasticities by type of service. *Journal of Health Economics 55*, 232–243.

Federal Register (2014). Patient Protection and Affordable Care Act; HHS Notice of Benefit and Payment Parameters for 2015 . https://www.federalregister.gov/documents/2014/03/11/2014-05052/patient-protection-and-affordable-care-act-hhs-notice-of-benefit-and-payment-pa last retrieved on June 18, 2018.

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, and K. Baicker (2012). The Oregon Health Insurance Experiment: Evidence from the first year. *The Quarterly Journal of Economics 127*(3), 1057–1106.

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

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

Gabel, J., H. Whitmore, S. Stromberg, M. Green, A. Call, and R. Oran (2016). The ACA's cost-sharing reduction plans: A key to affordable health coverage for millions of U.S. workers. The Commonwealth Fund Blog, http://www.commonwealthfund.org/publications/issue-briefs/2016/oct/aca-cost-sharing-reduction-plans, last retrieved September 8, 2017.

Gallup (2015). Arkansas, Kentucky see most improvement in uninsured rates. http://www.gallup.com/poll/181664/arkansas-kentucky-improvement-uninsured-rates.aspx?utm_source=tagrss&utm_medium=rss&utm_campaign=syndication, last retrieved Feb 2, 2018.

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

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.

Internal Revenue Service (2015). *Information regarding the 2014 instructions for Form 8962, Premium Tax Credit (PTC)*. IRS. https://www.irs.gov/pub/irs-prior/i8962--2014.pdf, last retrieved on Dec 7, 2016.

Jacobs, K., D. Graham-Squire, E. Gould, and D. Roby (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. (2011). Models for health care. In M. P. Clements and D. F. Hendry (Eds.), *The Oxford Handbook of Economic Forecasting*.

Kaiser Family Foundation (2014). *The Utah Health Care Landscape*. KFF. http://kff.org/health-reform/fact-sheet/the-utah-health-care-landscape/, last retrieved on Feb 2, 2016.

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

Kaiser Family Foundation (2017). *How the Loss of Cost-Sharing Subsidy Payments is Affecting 2018 Premiums*. KFF. https://www.kff.org/health-reform/issue-brief/how-the-loss-of-cost-sharing-subsidy-payments-is-affecting-2018-premiums/, last retrieved on June 2, 2018.

Ketcham, J. D., N. V. Kuminoff, and C. A. Powers (2016). Choice inconsistencies among the elderly: Evidence from plan choice in the Medicare Part D Program: Comment. *American Economic Review 106*(12), 3932–3961.

Ketcham, J. D., C. Lucarelli, E. J. Miravete, and M. C. Roebuck (2012). Sinking, swimming, or learning to swim in Medicare Part D. *American Economic Review 102*(6), 2639–2673.

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

Kowalski, A. (2014). The early impact of the Affordable Care Act, state by state. *Brookings Papers on Economic Activity 29*(2), 277–355.

Kowalski, A. E. (2015). Estimating the tradeoff between risk protection and moral hazard with a nonlinear budget set model of health insurance. *International Journal of Industrial Organization 43*, 122–135.

Lin, H. and D. W. Sacks (2016). Intertemporal substitution in health care demand: Evidence from the RAND Health Insurance Experiment. NBER Working Papers 22802.

Loewenstein, G., J. Y. Friedman, B. McGill, S. Ahmad, S. Linck, S. Sinkula, J. Beshears, J. J. Choi, J. Kolstad, D. Laibson, B. C. Madrian, J. A. List, and K. G. Volpp (2013). Consumers misunderstanding of health insurance. *Journal of Health Economics 32*(5), 850–862.

Manning, W. G. (2006). Dealing with skewed data on costs and expenditures. In A. M. Jones (Ed.), *The Elgar Companion to Health Economics*, pp. 439–447. Edward Elgar Publishing.

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

Manning, W. G., N. Duan, and W. Rogers (1987). Monte carlo evidence on the choice between sample selection and two-part models. *Journal of Econometrics 35*(1), 59–82.

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

Manning, W. G., J. P. Newhouse, N. Duan, E. B. Keeler, and A. Leibowitz (1987). Health insurance and the demand for medical care: Evidence from a randomized experiment. *The American Economic Review 77*(3), 251–277.

Manning, W. G., K. Wells, J. P. Newhouse, N. Duan, and J. Ware (1986). How cost sharing affects the use of ambulatory mental health services. *JAMA 256*(14), 1930–1934.

Mihaylova, B., A. Briggs, A. O'Hagan, and S. G. Thompson (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. https://www.healthinsurance.org/utah-state-health-insurance-exchange/, last retrieved April 2, 2018.

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

Orsini, J. and P. Tebaldi (2017). Regulated age-based pricing in subsidized health insurance: Evidence from the Affordable Care Act. http://www.pietrotebaldi.com/uploads/8/1/3/6/81364040/age-rating-subsidized-exchanges-jun24_submit.pdf, last retrieved July 18, 2017.

Pohlmeier, W. and V. Ulrich (1995). An econometric model of the two-part decision making process in the demand for health care. *The Journal of Human Resources 30*(2), 339–361.

Richardson, L. E. and T. Yilmazer (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.

Sacks, D. W., K. Vu, T.-Y. Huang, and P. Karaca-Mandic (2017). The effect of the risk corridors program on marketplace premiums and participation. Technical Report 24129, National Bureau of Economic Research.

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

Schmitz, H. and N. R. Ziebarth (2017). Does price framing affect the consumer price sensitivity of health plan choice? *Journal of Human Resources 52*(1), 89–128.

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

Sen, A. and T. DeLeire (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.

State of Utah (2013). Utah Census Data 2013 All Counties. https://opendata.utah.gov/dataset/Utah-Census-Data-2013-All-Counties/ww3j-23xv, retrieved May 18, 2018.

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

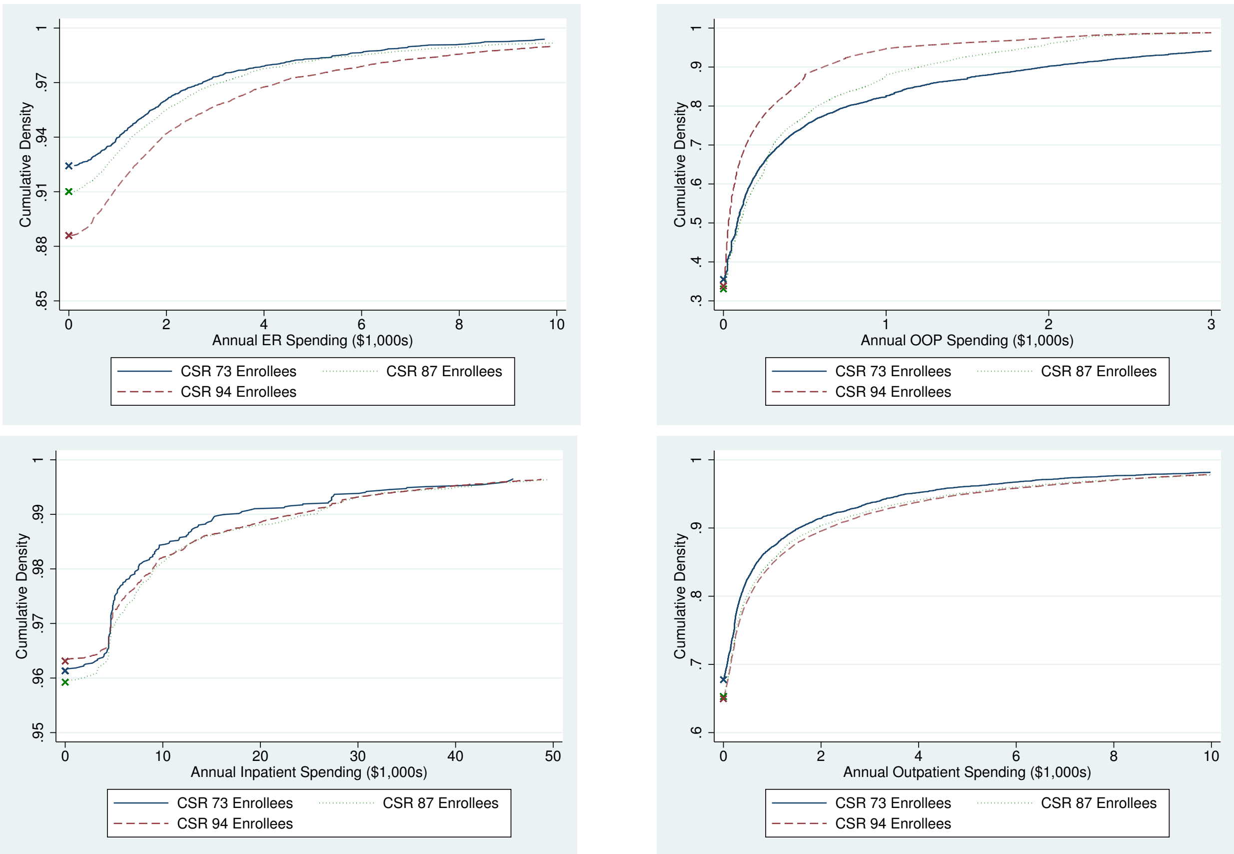
Tebaldi, P. (2017). Estimating equilibrium in Health Insurance Exchanges: Price competition and subsidy design under the ACA. http://www.pietrotebaldi.com/uploads/8/1/3/6/81364040/eqexchanges_jan25_17.pdf, last retrieved July 18, 2017.

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

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

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

Figure 1: Cumulative Density Functions by Spending and CSR Categories



Source: Utah APCD, own calculations, own illustration

Table 1: Variable Means by CSR Category

	CSR 73 Enrollees	CSR 87 Enrollees	CSR 94 Enrollees	All CSR Enrollees
Panel A				
Total Annual Medical Spending	3898	4275	4451	4319
ER Spending	324	403	505	447
Inpatient Spending	709	785	766	765
Outpatient Spending	865	984	1018	987
Pharmaceutical Spending	670	776	814	782
Out Of Pocket Spending	592	395	253	345
Deductible Spending	411	217	105	183
Panel B				
Female	0.52	0.54	0.56	0.55
Age 18 to 30	0.25	0.29	0.33	0.31
Age 31 to 50	0.44	0.40	0.41	0.41
Age 51 to 64	0.31	0.30	0.26	0.28
Members per Plan	2.88	2.30	1.88	2.15
Urban County	0.87	0.88	0.89	0.89
HMO Plan	0.76	0.75	0.75	0.75
Months FFM Enrolled in 2014	11.13	10.98	10.88	10.95
Months FFM Enrolled in 2015	11.40	11.37	11.28	11.32
Total Monthly Medical Spending	430.49	478.13	507.02	487.33
Utah-Scaled Risk Score in 2014	0.96	0.98	0.96	0.97
Utah-Scaled Risk Score in 2015	1.00	1.04	1.09	1.06
Uninsured Months in 2013	1.50	1.77	2.18	1.94
Inpatient Days 2004-2013	2.07	2.09	2.22	2.16
ER Visits 2004-2013	1.26	1.41	1.82	1.61
Person-Months	50,229	128,931	202,001	381,161
Persons	5689	14,403	23,155	43,247

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. In Panel A, all spending amounts are annual averages and the sum of allowed amounts by category. For example, *Total Medical Spending* is the sum of allowed amounts for all medical and drug spending in any insurance plan for individuals that satisfy the sample inclusion criteria. *Urban county* stands for counties with at least 80% of the population residing in an urban area (as defined by the 2010 Census). *Months FFM Enrolled* includes only months enrolled in a subsidy-eligible silver exchange plan, and is reported for only the subset of enrollees who met the 9-month selection criterion in 2014 or 2015, respectively. Risk scores are estimated using the Johns Hopkins ACG© 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 by CSR Category

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
CSR 94% AV Plan	0.18***	0.37***	0.23***	0.25*	–0.84***
	(0.05)	(0.10)	(0.05)	(0.13)	(0.04)
CSR 87% AV Plan	0.07	0.08	0.12**	0.16	–0.44***
	(0.05)	(0.11)	(0.06)	(0.14)	(0.03)
Risk Score 2013	1.84***	1.04***	2.07***	1.23***	1.21***
	(0.10)	(0.34)	(0.11)	(0.27)	(0.08)
Inpatient Days 2004-2013	0.03***	0.01**	0.02***	0.07***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2013	0.08***	0.15***	0.09***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table 3: GLM Coinsurance Estimates

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.13***	–0.28***	–0.15***	–0.15*	0.55***
	(0.03)	(0.07)	(0.03)	(0.08)	(0.02)
2013 Risk Score	1.84***	1.02***	2.07***	1.23***	1.21***
	(0.10)	(0.33)	(0.11)	(0.27)	(0.08)
Inpatient Days 2004-2013	0.03***	0.01*	0.02***	0.07***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.08***	0.15***	0.09***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category.

Table 4: Elasticity Estimates by Low and High-Value Care (Brot-Goldberg et al., 2017)

	Total Spending	High-Value Spending	Low-Value Spending
Log Coinsurance Rate	–0.13***	–0.24***	–0.29***
	(0.03)	(0.05)	(0.08)
2013 Risk Score	1.84***	1.63***	3.49***
	(0.10)	(0.20)	(0.24)
Inpatient Days 2004-2013	0.03***	0.00	–0.01***
	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.08***	0.04***	0.15***
	(0.00)	(0.00)	(0.00)
Person-Months	381,161	381,161	381,161
Persons	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. The categorization of high and low-value care follows Brot-Goldberg et al. (2017).

Table 5: Elasticity Estimates by Type of Prescription Drug (Chandra et al., 2010)

Dependent Variable	All Drugs	Acute	Chronic	Lifestyle	Branded Drugs	Generic Drugs
Log Coinsurance Rate	–0.15***	–0.17*	–0.09	–0.25***	–0.15*	–0.14***
	(0.05)	(0.09)	(0.11)	(0.07)	(0.09)	(0.03)
2013 Risk Score	2.89***	2.42***	2.90***	4.00***	3.20***	2.50***
	(0.14)	(0.18)	(0.27)	(0.23)	(0.23)	(0.10)
Inpatient Days 2004-2013	0.02***	0.03***	0.02	0.00	0.02**	0.01***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
ER Visits 2004-2023	0.09***	0.05***	0.08***	0.12***	0.10***	0.11***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Person-Months	381,161	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. *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. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table 6: GLM Coinsurance Estimates: Stepwise Inclusion of Controls

Total Spending			
Log Coinsurance Rate	–0.15***	–0.16***	–0.12***
	(0.04)	(0.03)	(0.03)
ER Spending			
Log Coinsurance Rate	–0.38***	–0.36***	–0.28***
	(0.07)	(0.07)	(0.07)
Outpatient Spending			
Log Coinsurance Rate	–0.21***	–0.21***	–0.15***
	(0.03)	(0.03)	(0.03)
Inpatient Spending			
Log Coinsurance Rate	–0.20***	–0.19***	–0.15***
	(0.09)	(0.08)	(0.08)
Out-of-Pocket Spending			
Log Coinsurance Rate	–0.51***	–0.52***	–0.55***
	(0.02)	(0.02)	(0.02)
County Fixed Effects	X	X	X
Calendar Month Fixed Effects	X	X	X
Age, gender	X	X	X
2013 Risk score		X	X
Inpatient Days 2004-2013			X
ER Visits 2004-2013			X

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category. All models have 28,271 unique person and 381,161 person-month observations.

Table 7: Heterogeneity in GLM Coinsurance Estimates

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Panel A: Age					
Log Coinsurance Rate	–0.14***	–0.26***	–0.15***	–0.27**	0.56***
	(0.04)	(0.08)	(0.04)	(0.11)	(0.03)
Log Coinsurance Rate*Age 31-50	0.01	–0.06	0.00	0.18**	–0.00
	(0.03)	(0.06)	(0.04)	(0.08)	(0.03)
Log Coinsurance Rate*Age 51-64	0.02	0.01	–0.01	0.20*	–0.02
	(0.04)	(0.11)	(0.05)	(0.12)	(0.04)
Panel B: Gender					
Log Coinsurance Rate	–0.06	–0.18**	–0.08*	–0.06	0.64***
	(0.04)	(0.08)	(0.04)	(0.08)	(0.03)
Log Coinsurance Rate*Male	–0.15**	–0.23*	–0.16**	–0.21	–0.19***
	(0.06)	(0.13)	(0.07)	(0.17)	(0.05)
Panel C: Urban					
Log Coinsurance Rate	–0.08	–0.40**	–0.08	–0.07	0.58***
	(0.09)	(0.19)	(0.08)	(0.23)	(0.06)
Log Coinsurance Rate*Urban	–0.05	0.13	–0.09	–0.09	–0.03
	(0.09)	(0.20)	(0.09)	(0.24)	(0.07)
Panel D: Family Plan					
Log Coinsurance Rate	–0.03	–0.11	–0.06	–0.17	0.45***
	(0.04)	(0.09)	(0.05)	(0.12)	(0.03)
Log Coinsurance Rate*Family Plan	–0.12*	–0.27**	–0.10	0.09	0.20***
	(0.06)	(0.13)	(0.07)	(0.16)	(0.05)
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table 8: Heterogeneity in GLM Coinsurance Estimates by 2013 ACG© Risk Score

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.21***	–0.38***	–0.20***	–0.38***	0.49***
	(0.04)	(0.12)	(0.05)	(0.10)	(0.03)
Log Coinsurance Rate*2013 Risk Score	0.63***	0.75	0.34	1.64***	0.40***
	(0.20)	(0.53)	(0.22)	(0.45)	(0.15)
2013 Risk Score	3.34***	2.81**	2.88***	5.03***	2.18***
	(0.50)	(1.33)	(0.55)	(1.20)	(0.35)
Inpatient Days 2004-2013	0.03***	0.01*	0.02***	0.07***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.08***	0.15***	0.09***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Predicted Elasticities:					
10th Percentile Risk Score	-0.21	-0.38	-0.20	-0.38	0.49
P-Value $\varepsilon_{10} = 0$	0.00	0.00	0.00	0.00	0.00
50th Percentile Risk Score	-0.14	-0.30	-0.16	-0.19	0.54
P-Value $\varepsilon_{50} = 0$	0.00	0.00	0.00	0.02	0.00
90th Percentile Risk Score	-0.05	-0.20	-0.11	0.03	0.60
P-Value $\varepsilon_{90} = 0$	0.14	0.01	0.00	0.75	0.00
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category.

Table 9: Elasticity Estimates by Above Average Deductible

	Total Spending		ER Spending		Outpatient Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Coinsurance Rate	–0.169***	–0.153***	–0.024***	–0.025***	–0.144***	–0.138***
	(0.027)	(0.032)	(0.005)	(0.006)	(0.024)	(0.029)
Log Coinsurance Rate ×	0.051	–0.031	0.005	0.000	0.038	–0.020
Above Mean Deductible	(0.032)	(0.039)	(0.006)	(0.007)	(0.029)	(0.035)
Above Mean Deductible	–0.003	–0.222**	0.011	–0.003	0.023	–0.137
	(0.074)	(0.095)	(0.012)	(0.016)	(0.067)	(0.085)
2013 Risk Score	2.911***	2.924***	0.198***	0.223***	2.571***	2.574***
	(0.166)	(0.180)	(0.040)	(0.046)	(0.149)	(0.161)
2013 Risk Score Unknown	–2.690***	–2.826***	0.068**	0.055*	–2.373***	–2.502***
	(0.150)	(0.157)	(0.027)	(0.029)	(0.137)	(0.143)
Inpatient Days 2004-2013	0.004	0.018***	0.000	0.000	0.003	0.015***
	(0.004)	(0.003)	(0.000)	(0.001)	(0.003)	(0.003)
ER Visits 2004-2023	0.088***	0.080***	0.031***	0.032***	0.084***	0.078***
	(0.011)	(0.011)	(0.003)	(0.003)	(0.010)	(0.010)
Person-Months	432,500	381,161	432,500	381,161	432,500	381,161
Sample Includes CSR70 Plans	Y	N	Y	N	Y	N

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Each column reports estimates from separate OLS specifications using a model as in equation (1). All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table 10: Counterfactual Impact of Eliminating CSRs by CSR Recipient Characteristics

	Monthly Medical	Counterfactual AV 70%	$$ Reduction	% Reduction	OOP Increase	Subsidy Decrease
All CSR	$490.09	$348.54	$141.55	29%	$23.44	$164.99
100-150% FPL	$510.18	$346.60	$163.59	32%	$33.54	$197.13
150-200% FPL	$477.54	$351.37	$126.17	26%	$18.36	$144.53
200-250% FPL	$441.53	$349.17	$92.36	21%	$(4.17)	$88.19
Age 18-30	$306.63	$211.47	$95.16	31%	$20.95	$116.11
Age 31-50	$439.18	$326.60	$112.58	26%	$24.93	$137.51
Age 51-64	$748.97	$587.49	$161.48	22%	$31.43	$192.91
Sick 2013 (Utah Risk Score>1)	$907.52	$629.45	$278.07	31%	$36.49	$314.56

Note: Counterfactual simulations represent partial equilibrium effects and are based on the estimates in the other tables.

Table 11: Counterfactual Impact of Eliminating CSRs by Type of Medical Spending

	Monthly Medical	Counterfactual AV 70%	$$ Reduction	% Reduction
Total Spending	$490.09	$348.54	$141.55	29%
ER Spending	$50.73	$27.04	$23.68	47%
Outpatient Spending	$235.38	$161.59	$73.80	31%
Spending on Drugs to Prevent Hospitalizations	$55.36	$36.73	$18.63	34%

Note: Counterfactual simulations represent partial equilibrium effects and are based on the estimates in the other tables.

Appendix

Table A1: CMS Data on Utah in 2014: Characteristics of Enrollees by FPL Category and Metal Level

	All	100-150% FPL			150-200% FPL			200-250% FPL		
	.	**Gold& Platinum**	**Silver**	**Bronze**	**Gold& Platinum**	**Silver**	**Bronze**	**Gold& Platinum**	**Silver**	**Bronze**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Age	32.7	35.0	34.4	34.3	32.4	33.1	35.1	27.1	29.7	29.1
White	93.6%	91.0%	91.6%	92.6%	94.4%	93.8%	95.2%	95.7%	94.5%	95.8%
Black	1.2%	1.3%	1.4%	2.0%	1.0%	1.3%	1.5%	0.8%	0.8%	0.5%
Asian	4.0%	6.0%	5.7%	3.4%	3.5%	3.6%	2.1%	2.3%	4.0%	2.5%
Hispanic	4.7%	5.4%	5.9%	5.2%	4.2%	5.6%	5.8%	3.6%	3.5%	2.7%
Tobacco Use	4.1%	4.4%	5.2%	7.2%	3.5%	4.4%	5.4%	2.4%	3.3%	3.2%
Enrollment	105,861	1450	26,001	1971	1995	20,451	2268	6628	9592	4183
Enrollment in %		4.9%	88.0%	3.6%	8.0%	82.5%	6.7%	32.22%	46.6%	20.3%

Source: Centers for Medicare & Medicaid Services, Multidimensional Insurance Data Analytics System (MIDAS), also see DeLeire et al. (2017). Table shows sociodemographics of Utah FFM enrollees by income and tier selection in FY 2014. Take-up rates do not sum to 100% because Catastrophic Plans are not displayed. Take-up rates for income category 250-400% of FPL are 41% (Platinum/Gold), 28.5% (Silver) and 28.6% (Bronze). Take-up rates for income category >400% of FPL are 38.8% (Platinum/Gold), 37.7% (Silver) and 20.5% (Bronze). Among all Utah FFM enrollees in 2014, 2.5% had incomes below 100% of FPL, 70.7% had incomes between 100 and 250% of FPL, 15.4% had incomes between 250 and 400% of FPL, and 11.4% had incomes above 400% of FPL.

Table A2: Variable Means by Coverage Tiers and CSR Categories

	Platinum	Gold	Silver 94	Silver 87	Silver 73	Silver 70	Bronze
Total Medical Spending	6849	4589	4449	4267	3897	4078	2164
ER Spending	490	333	504	402	324	367	232
Inpatient Spending	1447	962	766	782	708	807	387
Outpatient Spending	2668	925	1018	983	865	851	475
Pharma Spending	978	908	813	775	670	848	310
OOP Spending	571	563	252	393	591	653	545
Deductible Spending	294	270	105	217	410	430	483
Number Individuals	5107	70,182	23,148	14,399	5687	5799	45,658
Number Person-Months	42,063	751,659	433,553	310,555	145,437	132,690	456,314

Source: 2013-2015 Utah APCD. Sample includes adults aged 18 to 64 in 2014 and 2015 who were enrolled for at least 9 months per calendar year in the same plan metallic category. All spending amounts are annual averages of the sum of allowed amounts by category.

Table A3: Robustness: OLS Estimates, Conditional on Positive Total Spending

	Log Total	Log ER	Log Outpatient	Log Inpatient	Log OOP
Log Coinsurance Rate	–0.12***	–0.05***	–0.14***	0.01*	0.33***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
2013 Risk Score	0.92***	0.21***	1.18***	0.02	0.30***
	(0.09)	(0.07)	(0.11)	(0.03)	(0.07)
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 2004-2013	0.03***	0.04***	0.04***	0.00	0.01***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
N	175,286	175,286	175,286	175,286	175,286
N Clusters	24,386	24,386	24,386	24,386	24,386

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Each column reports estimates from separate OLS regressions using equation (1), and conditions on enrollees with positive total spending in the calendar month. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table A4: GLM Coinsurance Estimates Excluding CSR 73 Enrollees

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.14***	–0.38***	–0.14**	–0.11	0.53***
	(0.05)	(0.11)	(0.06)	(0.12)	(0.03)
2013 Risk Score	1.75***	1.14***	2.00***	1.05***	1.14***
	(0.11)	(0.36)	(0.11)	(0.29)	(0.09)
Inpatient Days 2004-2013	0.02***	0.01*	0.02***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2013	0.07***	0.15***	0.09***	0.05***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	330,932	330,932	330,932	330,932	330,932
Persons	25,308	25,308	25,08	25,308	25,308

Source: Utah APCD. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category.

Table A5: GLM Coinsurance Estimates Using Calculated Plan AV

	Total Spending	Outpatient Spending	Inpatient Spending	Pharmaceutical Spending
Log Coinsurance Rate	–0.28***	–0.30***	–0.33***	–0.24***
	(0.05)	(0.05)	(0.12)	(0.07)
2013 Risk Score	1.84***	2.06***	1.27***	2.89***
	(0.10)	(0.11)	(0.27)	(0.14)
Inpatient Days 2004-2013	0.03***	0.02***	0.07***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2013	0.08***	0.09***	0.06***	0.09***
	(0.00)	(0.00)	(0.01)	(0.00)
N Person-Months	381,161	381,161	381,161	381,161
N Individuals	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category. Actual coinsurance rate is calculated by using actual out-of-pocket spending divided by the sum of claims.

Table A6: GLM Coinsurance Estimates Using Exact Plan AV

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.11***	–0.23***	–0.14***	–0.16**	0.54***
	(0.03)	(0.07)	(0.03)	(0.08)	(0.02)
2013 Risk Score	2.03***	1.33***	2.32***	1.31***	1.21***
	(0.11)	(0.32)	(0.12)	(0.28)	(0.09)
Inpatient Days 2004-2013	0.02***	0.01**	0.02***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.08***	0.16***	0.09***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	328,712	328,712	328,712	328,712	328,712
Persons	25,196	25,196	25,196	25,196	25,196

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category.

Table A7: Main Estimates: Drop All Data After July 2015

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.11***	–0.27***	–0.13***	–0.12	0.57***
	(0.03)	(0.07)	(0.03)	(0.08)	(0.02)
2013 Risk Score	1.82***	0.90***	2.02***	1.36***	1.17***
	(0.10)	(0.35)	(0.11)	(0.27)	(0.09)
Inpatient Days 2004-2013	0.02***	0.01*	0.02***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.08***	0.15***	0.09***	0.05***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	330,306	330,306	330,306	330,306	330,306
Persons	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table A8: GLM Coinsurance Estimates With Insurer Fixed Effects

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.12***	–0.28***	–0.15***	–0.17**	0.58***
	(0.03)	(0.06)	(0.03)	(0.08)	(0.02)
2013 Risk Score	1.65***	1.16***	1.87***	1.11***	1.16***
	(0.10)	(0.31)	(0.11)	(0.27)	(0.08)
Inpatient Days 2004-2013	0.02***	0.01*	0.02***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2013	0.08***	0.15***	0.09***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. Equation (1) is estimated by GLM using a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects. *Coinsurance Rate* is the average coinsurance rate of the plan category. All models use insurer fixed effects.

Table A9: CSR Category Transition Matrix, 2014-2015

	0	CSR 70	CSR 73	CSR 87	CSR 94	Total
0	0	3253	3630	9155	15,547	31,585
CSR 70	1064	117	115	288	487	2071
CSR 73	969	48	102	164	192	1475
CSR 87	2518	149	169	541	499	3876
CSR 94	3658	232	242	528	1011	5671
Total	8209	3799	4258	10,676	17,736	44,678

Source: Utah APCD. Rows are 2014 enrollment counts (N unique individuals), columns are 2015 enrollment. 0 means the person was enrolled in one year but not the other.