

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

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December 7, 2018

## Abstract

The Affordable Care Act (ACA) provides premium subsidies and cost-sharing reductions (CSRs) to low-income consumers who purchase private health insurance plans on the ACA Marketplaces. We use 2013-2015 All-Payer Claims Data from Utah, linked to 2004-2013 administrative hospital discharge data, to assess how CSRs relate to healthcare utilization of low-income consumers. Exploiting policy-driven differences in the value of CSRs that are solely determined by income, 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 price responsiveness similar to that of higher-income populations examined in the previous literature. We estimate 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

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

# 1 Introduction

Evaluating the responsiveness of consumers to cost-sharing for health care services is instrumental to understanding the welfare effects of health insurance. The 2010 Affordable Care Act (ACA) provides premium subsidies and cost-sharing reductions (CSRs) to low-income consumers who purchase private health insurance on the ACA Marketplaces. CSRs are motivated in part by concern that cost-sharing might lead low-income consumers to forgo needed health care. However, little is known about how low-income consumers actually respond to cost-sharing in subsidized private insurance markets. To date, most of the literature has focused on higher income populations or individuals covered by Medicaid, a program that typically has minimal or no cost-sharing.

For example, the RAND Health Insurance Experiment (RAND HIE) in the 1970s 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  $-0.2$ .<sup>1</sup> [Brot-Goldberg et al. \(2017\)](#) exploit an exogenous change in cost-sharing in employer-sponsored insurance plans at a large technology company, and concluded that increases in cost-sharing resulted in across-the-board reductions in utilization, including both low-value and high-value medical care.

Two empirical settings in which low-income populations have been studied include the Oregon Medicaid lottery and the Massachusetts health insurance reforms 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 healthcare utilization effects of expanding Medicaid coverage for previously uninsured (i.e., on the *extensive* margin), but provides less guidance about the effects of changing coverage generosity for those who have health insurance (i.e., on the *intensive* margin). Similar to this paper, [Chandra et al. \(2014\)](#) focus on the intensive margin to estimate 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 the responsiveness to cost-sharing among low-income enrollees in the ACA Exchanges. 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

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<sup>1</sup>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.

investigate whether enrollees differentially respond to cost-sharing for high-value versus low-value care, a hypothesis for which the RAND HIE and [Brot-Goldberg et al. \(2017\)](#) find little evidence. We also decompose drug elasticity estimates based on the classification developed by [Chandra et al. \(2010\)](#). We find, reassuringly, that enrollees are less responsive to cost-sharing for drugs that are more likely to prevent hospitalizations. Finally, we simulate a counterfactual CSR policy to assess the effects of eliminating CSR subsidies for consumers.

Low-income consumers who shop for insurance on the ACA exchanges are offered a standardized menu of regulated health plans, along with income-dependent premium and cost-sharing subsidies. These plans are differentiated by metallic tiers corresponding to the actuarial value (AV) of the plan. For example, “Silver plans” have an AV of 70%, implying that a representative enrollee would expect to pay 30% of health care costs out-of-pocket. However, when consumers shopping for silver plans 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 increase AVs from 73% to 87% and then to 94%, respectively.<sup>2</sup> 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 choose not to expand Medicaid coverage under the ACA. Using All-Payer Claims Data (APCD) from Utah between 2013 and 2015, we observe 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<sup>®</sup> 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 healthcare utilization prior to Exchange enrollment, alleviating concerns about the conditional exogeneity of plans with different AVs based on health. Although we do not observe exact reported income in the claims records, we obtained summary statistics for Utah exchange enrollees from administrative data collected by the Centers for Medicare & Medicaid Services (CMS). These data contain enrollment choices and house-

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<sup>2</sup>CSRs are provided in addition to premium subsidies, which are available to consumers between 100% and 400% of FPL.

hold incomes reported by all Exchange enrollees in Utah on [healthcare.gov](https://healthcare.gov). The data show that there is very little heterogeneity in plan choices within CSR income categories. Moreover, they do not provide evidence that income manipulation to obtain higher CSRs is a serious threat to our estimates. However, because income can have a separate effect on healthcare 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<sup>th</sup> percentile to the 90<sup>th</sup> 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 has 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 healthcare 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 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 (OGrady 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 under-

stand 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 ACA Exchanges.

This paper also contributes to the growing economic literature on the ACA Exchanges (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, two papers study the impact of premium and cost-sharing subsidies on take-up. Frean et al. (2017) use American Community Survey 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. And 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.

### **3 Institutional Details on the Utah Marketplace**

In April 2014, at the end of the first open-enrollment period on the ACA Exchange, 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, six different carriers offered 1,712 Qualified Health Plans (QHP) at the plan-rating area level on the Utah Exchange. The majority of them were silver plans (39%) followed by bronze plans (29%). All plans have to cover Essential Health Benefits but differ in their degree of cost-sharing and thus their actuarial values (AVs). Silver plans cover on average 70% of all costs, while bronze plans cover 60% and gold plans cover 80%. Specifically, insurers cover the actuarial value, on average in expectation over the enrollee population. This implies that enrollees pay on average 30%, 40% and 20% of their health care costs, respectively, out-of-pocket (OOP). Insurers have the flexibility to set different combinations of cost-sharing amounts to achieve the target AVs in the tier; however, the maximum OOP stop loss is set by the regulator (in 2014, it was \$6,350 per individual and \$12,700 per family).

**AVs and CSRs.** For policyholders with annual gross household incomes below 250% of FPL<sup>3</sup>, the ACA provides taxpayer-funded cost sharing reductions (CSRs). Only enrollees in silver plans are eligible for CSR subsidies. Households with incomes between 100-150% of FPL who purchase silver plans automatically receive plans with 94% AV instead of the standard 70%. CSR subsidy payments from the federal government to insurers are supposed to cover the additional 24 AV points (also see Section 7). When household income exceeds 150% of FPL, CSRs drop discontinuously, reducing the AV of a silver plan from 94% to 87%. The subsidy again drops discontinuously at 200% of FPL, reducing the AV further to 73%. CSRs are eliminated when household income exceeds 250% of FPL.

Every insurer that offers a silver plan on the FFM must submit four plans, corresponding to AVs of 70%, 73%, 87%, and 94%. Conditional on purchasing a silver plan, assignment to one of these four plans is automatically determined based on reported income. 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 FFM plans in 2015 with combined medical and prescription drug coverage, the average deductible was \$2556 in 70% AV silver plans,

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<sup>3</sup>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).

\$2077 in 73% AV silver plans, \$737 in 84% AV silver plans, and \$229 in 94% AV silver plans ([Kaiser Family Foundation, 2015](#)).

## 4 Empirical Approach

This section discusses the methods used by health econometricians to model health expenditure data. After specifying our model, we discuss the underlying assumptions for causal identification. As our identification strategy mainly exploits variation in AVs across types of plans, this discussion relates to the institutional details in Section 3. The final subsection summarizes the underlying assumptions for calculating point elasticities of demand.

### 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 microeconomic models. [Manning \(2006\)](#); [Jones \(2011\)](#), and [Mihaylova et al. \(2011\)](#) provide comprehensive overviews.

The starting point is the stylized fact that health care spending distributions are highly skewed with a long right tail and a mass point at zero. In addition, the error terms typically exhibit a high degree of heteroscedasticity, and state dependence within individuals is large (cf. [Karlsson et al., 2016](#)). Moreover, the relationship between spending and observed covariates is often nonlinear.

One simplistic approach is to transform the spending distribution by taking its logarithm—plus one, to avoid excluding zeros ([Manning and Mullahy, 2001](#)).<sup>4</sup> Hence, the basic model can be written as:

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

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  $AV_{p(i,t)}$  varies stepwise between

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<sup>4</sup>While the log-transformation approach has seen a revival in recent years ([Aron-Dine et al., 2013](#)), a classic health econometric model is the Two-Part Model (2PM), which employs a binary outcome model along with a conditional model for positive spending ([Manning et al., 1987](#); [Mullahy, 1998](#)). Other classic models are count data 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](#)).

73% to 94%. However, in most specifications, our variable of interest is  $(1 - AV_{p(i,t)})$ , which is the coinsurance rate. Taking the logarithm allows us to approximate the demand elasticity with  $\beta$ .

$Risk_{i,2013}$  represents the risk score of individual  $i$  in 2013, prior to choosing an Exchange plan. We calculate the risk scores using All-Payer-Claims-Data (APCD) and the Johns Hopkins ACG<sup>©</sup> System software.

$Inpatient_{i,2004-2013}$  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.  $\delta_t$  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.  $\epsilon_{it}$ , 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).

An alternative to estimating equation (1) by OLS is to estimate a nonlinear specification using a Generalized Linear Model (GLM), 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. 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.

In summary, 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  $g(\cdot)$  is the natural logarithm if the conditional mean of  $y_{it}$  is an exponential function of the covariates  $\mathbf{X}_{i,t}$ :  $\mathbb{E}(y_{it}|\mathbf{X}_{i,t}) = \exp(\mathbf{X}_{i,t}\boldsymbol{\xi}) = g^{-1}(\mathbf{X}_{i,t}\boldsymbol{\xi})$ . In other words, the inverse of the link function  $g(\cdot)$  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.<sup>5</sup> While our main estimates use the GLM approach, our findings are quite similar across alternative classes of models (cf. [Buntin and Zaslavsky, 2004](#)). As we show in the Results section, estimating equation (1) by OLS instead of using a GLM approach yields similar results.

## 4.2 Identification

Although we experimented with including individual fixed effects in the model, very few enrollees switch plans across CSR categories (3113 individuals, or 7% of all silver plan enrollees) between 2014 and 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).

Instead, our primary empirical estimates are identified by between-enrollee variation in AVs. Proper interpretation of  $\beta$  in equation (1) therefore requires an evaluation of potential reverse causality, or violations of the conditional exogeneity assumption of  $AV_{p(i,t)}$ . Reverse causality is unlikely to be an issue because of timing restrictions; it would require higher *ex post* health care spending in year  $t$  to causally affect *ex ante* plan assignment, which must be chosen during the open-enrollment period. 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.

Another talking point for a causal interpretation of  $\beta$  is the role of income. Recall that we do not have information on the exact household income and thus cannot estimate Regression Discontinuity models as in [DeLeire et al. \(2017\)](#)—although we use CMS data to check for possible evidence of income manipulation. What our data include is the information of whether the enrollee receives CSR 73, 87 or 94 subsidies; that is, we know whether enrollees' income fall into the household income categories 100-150%, 150-200% or 200-250% of FPL. This information should be measure with very little error. However, 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

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<sup>5</sup> As [Deb et al. \(2017\)](#) point out, one only needs to correctly specify the link function and the covariates  $\mathbf{X}_{i,t}$  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.

AV categories). We apply two types of check to bound the extent of this underestimation. First, we conduct placebo checks.<sup>6</sup> In a first check, we run our standard model but pretend that subsidies were already provided in 2013 (instead of the treatment years 2014 and 2015). Second, we use the income-spending elasticities reported in the literature and manually reduce healthcare spending by income categories to correct for income-related underestimation of our reported elasticities.

A third talking point for a causal interpretation of  $\beta$  is selection into plans based on unobservables. In the Results Section 6.3 below, we carry out several checks to assess the potential for such selection. First, recall that our sample is homogeneous as it contains low-income residents of Utah without access to employer-sponsored insurance (ESI). We further restrict the sample to non-elderly adults who were enrolled in silver CSR plans for at least 9 months during each calendar year. Second, we provide standard covariate balance checks. Third, 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 FFM enrollment) 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 of the 28,271 enrollees. Hence, our model controls for a decade of medical histories in addition to  $Risk_{i,2013}$ . Fifth, we also control for age, gender, county, and month-year fixed effects.

To further minimize selection concerns, our empirical approach focuses on silver plans with cost-sharing subsidies. That is, it focuses on silver plans with AVs between 73% and 94%, excluding the standard 70% silver plan, thereby shutting down selection 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 category triggers different CSR levels and results in different plan AVs. 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](#)).<sup>7</sup>

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<sup>6</sup>We would like to thank a very constructive referee for these suggestions.

<sup>7</sup>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

### 4.3 Estimating Demand Elasticities

Although the RAND HIE has produced a widely cited point elasticity estimate of -0.2, 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 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.

Another unresolved question is whether consumers respond to entire episodes of care (in a forward-looking manner), the intensity of care, and/or follow-up treatments. The RAND HIE bundled all individual claims into episodes of care. Because [Keeler and Rolph \(1988\)](#) found no significant relationship between cost-sharing and average episode costs, they concluded that follow-up visits and intensity of care are not price responsive (and potentially driven by physicians). Absent sufficient evidence for forward-looking behavior, the RAND HIE focused on spot prices and individuals in distance to the OOP spending cap ([Keeler and Rolph, 1988](#)). Then the RAND HIE investigators related differences in the number of treatment episodes (“quantity”) to differences in coinsurance rates (“prices”) to calculate demand elasticities.

[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. In the Results Section 6.5, we

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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.

test whether the estimated elasticities differ among individuals enrolled in plans with deductibles above the median deductible *conditional on plan AV*. This variation in deductibles within a CSR-category should then be driven by differences in nonlinearities across plans with the same actuarial value. We find economically and statistically insignificant differences in the implied elasticities when altering the nonlinearities, conditional on AVs. Hence we conclude that differences in non-linearities are not a major driving force of our elasticity estimates.

## 5 Data

### 5.1 Datasets

**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<sup>8</sup> 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 specific 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.

The second and third components are the medical and prescription drug claim files. These databases contain charged amounts, negotiated amounts, amounts paid by insurers, member liabilities, copayment amounts, deductible amounts, and provider identifiers. The medical claims 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.

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<sup>8</sup>The law exempts extremely small insurers with fewer than 2500 total enrollees across all plans.

**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 Selection

We restrict the main working sample to Utah residents who were enrolled in silver FFM plans between January 2014 and December 2015.<sup>9</sup> Moreover, because we focus on ACA health plans and the impact of cost-sharing on utilization, we restrict the sample to adults between the ages of 18 and 64 who were enrolled for at least 9 months in a CSR silver plan in either 2014 or 2015.<sup>10</sup> We collapse the data to the enrollee-month level and obtain an unbalanced panel of 381,161 person-months and 43,247 unique individuals.

Figure 1 shows enrollment pattern by CSR category and coverage tier over time. While platinum plans have by far the lowest enrollment numbers, gold plans have the highest enrollment numbers, followed by CSR 94 silver plans (for enrollees with incomes between 100 and 150% of FPL), bronze plan and CSR 87 silver plan (for enrollees with incomes between 150 and 200% of FPL). Overall, silver plans are the most popular, which is not surprising given that only silver plans provide CSRs. Figure 1 also shows strong enrollment increases over time, with particularly large jumps during the 2015 open-enrollment period.

[Insert Figure 1 about here]

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

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<sup>9</sup>In the current version, we have to 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).

<sup>10</sup>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 plan.

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.

### 5.3 Health Care Spending Measures

Our main dependent variable is total health care spending, which we calculate by summing over all recorded “allowed amount” claims (actual payments based on negotiated prices). We also calculate spending by category of care, including ER spending, outpatient spending, inpatient 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.

**[Insert Table 1 about here]**

Average annual medical spending in the sample was \$4319 per year. This may appear relatively low, but there are two factors that contribute to this. First, most enrollees had less than 12 months of coverage. Average monthly spending conditional on being enrolled during the month was \$487, which implies an average 12-month spending rate of \$5844. Second, there was a substantial reduction in average spending in 2015, due to a combination of changes in the composition of enrollees and to the large number of enrollees who experienced spells of uninsurance in 2013. As a result, average monthly spending conditional on enrollment dropped from \$644 in 2014 to \$434 in 2015. The average risk score of enrollees was similar to that of the commercially insured population of Utah. However, it is worth noting that Utah has among the lowest levels of health care spending in the country. We also find that lower income enrollees, in 94% AV plans, were more likely to be uninsured in 2013, and had 44% more ER visits in the preceding decade than enrollees in 73% silver plans, suggesting that these control variables are important for the research design.

### 5.4 Risk Scores

We use the rich diagnoses and claims information for each individual in our database to calculate their risk scores for all three years 2013, 2014, and 2015 using the John Hopkins ACG System<sup>©</sup> software. Several previous studies have used risk scores similarly as a comprehensive measure of individual health risks (cf. Einav et al., 2013; Handel, 2013).

**[Insert Figure 2 about here]**

Figure 2 shows histograms of the risk scores of our working sample in 2014 and 2015. The risk scores are normalized to have a mean of 1 in the full population of commercially insured non-elderly individuals in the Utah APCD. As expected, the distribution is heavily skewed to the right with the mass point just below 1. However, a substantial share of enrollees have risk score values between 1 and 2 or even above 3 and 4. This pattern is consistent with health spending distributions around the world (French and Kelly, 2016).

By controlling for risk scores at the individual level as of 2013, the year prior to the Utah FFM plan enrollment, we address selection concerns to the extent that these continuous and precise health risk measures capture systematic between-enrollee variation in health status that may be correlated with plan selection.

### 5.5 Inpatient Days and ER Visits 2004-2013

In addition to controlling for the individual-level 2013 Risk Score, we condition on health care utilization histories for an entire decade, from 2004 to 2013. As described above, we link the Utah APCD data with hospital discharge records on the individual level.

Panel B of Table 1 shows that the average number of *Inpatient Days* was 2.16 and varied only very slightly across CSR categories. The average number of *ER Visits* was 1.61 between 2004 and 2013.

### 5.6 Other Variables

Panel B of Table 1 lists the descriptive statistics of the remaining socio-demographic variables. For example, slightly more than half of all enrollee-month observations are women. Roughly a third of all enrollees are between 18 to 30 years old, slightly more than a third are 31 to 50 years old, and slightly less than a third are 51 to 64 years old. 89% live in an urban county (as defined by the 2010 Census). On average, there are 2.15 individuals per plan, and the large majority of plans (75%) are HMO plans.

## 6 Results

We present our empirical findings in the following order. First, in Section 6.1, we estimate equation (1) by GLM using variation in average coinsurance rates,  $1 - AV_{p(i,t)}$ . Our elasticity estimates directly

draw on its logarithm  $\ln(1 - AV_{p(i,t)})$ . We present analogous estimates from OLS log-transformation models in the Appendix.

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. 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.

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

Our main empirical approach focuses on enrollees between 18 and 64 who selected FFM silver plans, had earnings below 250% FPL, and were enrolled for at least 9 months in 2014 or 2015. Table 1 shows average annual spending by types of care and for the three AV categories 73%, 87% and 94% (CSR 73, CSR 87 and CSR 94). As seen, total spending is lowest for the lowest AV category 73% (\$3898) and increases substantially for AV categories 87% (\$4275) and 94% (\$4451). The spending patterns by types of care show that Emergency Room (ER) spending strictly increases with the plans' AVs from \$324 to \$505 (i.e., by 56%).

[Insert Figure 3 about here]

The difference in ER spending between CSR 73 and CSR 94 enrollees is also graphically illustrated by Figure 3. Figure 3a shows that differences in ER spending are driven by the top 10% of spenders, whereas around 90% of all enrollees have zero annual ER spending. Put differently, 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.

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%.

Figure 3b shows that about 20% of all CSR 73 enrollees had OOP spending of at least \$1000 but only 10% of all CSR 94 enrollees had OOP spending of \$1000 or more. Consequently, as seen in Panel A of Table 1, OOP spending and spending below the deductible strictly decreases in AVs (from \$592 to \$253 for OOP spending and from \$411 to \$105 for spending below the deductible).

Table 1 also shows that spending on inpatient care (+8%), outpatient care (+18%) and pharmaceuticals (+21%) increases across AV categories (percent changes not shown in Table 1). However, these spending categories appear to be less responsive to cost-sharing than ER or OOP spending. This point is underscored by the cumulative density functions by AV categories in Figures 3c and d.

**[Insert Table 2 about here]**

Tables 2 and 3 show the main parametric estimates from our GLM approach that estimates a model like in equation (1). Each column of Tables 2 and 3 represents estimates from separate regressions where the dependent variable measures different categories of care.

Table 2 includes binary indicators for CSR 87 and CSR 94 plans, with CSR 73 plans as the baseline category. The dependent variable is spending by category in \$1000s. When comparing CSR 94 to CSR 73 plans—and after controlling for the 2013 ACG<sup>©</sup> Risk Score, the number of inpatient days and ER visits from 2004-2013, age, gender county and time fixed effects effects—spending in all five categories is significantly different in the CSR 94 plans. Total spending is \$180 (4%), ER spending is \$370 (83%), outpatient spending is \$230 (23%), and inpatient spending is \$250 (33%) higher. Enrollees in CSR 87 plans also have significantly higher outpatient spending than those in CSR 73 plans (\$120 or 12%), and significantly lower OOP spending. The model lacks the statistical power to reject the equality of the spending differences between CSR 87 and 73 enrollees in other categories of care.

Reassuringly, Table 2 also shows that all three measures of pre-ACA health status are positively and significantly correlated with contemporaneous health care spending. One additional ER visit in the prior decade is associated with 8 log points higher total spending in exchange plans, for example.

**[Insert Table 3 about here]**

Table 3 uses the continuous variation in cost-sharing across AV categories, measured as  $\text{LogCoinsurance}_{p(i,t)} = \text{Log}(1 - AV_{p(i,t)})$ . 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 elasticities.

We estimate an overall elasticity of demand for medical care of -0.13. However, there is substantial variation in responsiveness to cost-sharing across categories of care. 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. Corroborating the first-stage effect of assignment to more generous plans, the point estimate for OOP spending is highly correlated with the *Coinsurance Rate*. These findings suggest 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.

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 people who use these categories of care (see above and [Figure 3](#)). 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. Following [Schwartz et al. \(2014\)](#) and [Brot-Goldberg et al. \(2017\)](#), we categorize low-value care as including “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. \(2017\)](#).

[Insert Table 5 about here]

As shown in column (3) of Table 5, low-income enrollees are disproportionately responsive to out-of-pocket costs for low-value medical care, with an implied elasticity of -0.29, more than twice as large as the overall elasticity of demand. Interestingly, and in line with Brot-Goldberg et al. (2017), our findings also reveal substantial price responsiveness to high value care, with an average elasticity -0.24. This evidence suggests that: (1) price and market mechanisms appear to work for low-income enrollees, who may have less experience navigating private insurance plans, and (2) low income enrollees are price sensitive across all types of care (even high-value care) to a similar degree as higher income populations studied in the previous literature. These patterns are in line with Brot-Goldberg et al. (2017), who show that ESI enrollees respond to cost-sharing by curtailing utilization across all types of care.

**[Insert Table 6 about here]**

We also test for differences in price-responsiveness across classes of drugs, grouping drugs based on their potential to prevent subsequent hospitalizations. To do this, we use the categorization 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 in hospitalization if not taken.

We find that CSR enrollees have inelastic demand for chronic drugs (-0.09, SE 0.11), but are still somewhat responsive to the costs of acute care drugs (-0.17, SE 0.09). This suggests, surprisingly, that enrollees appear to be more price sensitive for drugs that limit immediate risks of hospitalization, 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.

### **6.3 Plan Selection**

There are two potential channels through which non-random assignment to plans across different CSR tiers could confound the interpretation of our estimates. First, past health status could affect

present earnings potential. Second, the duration of enrollment spells could be endogenously determined by CSR subsidies, altering the distribution of person-month healthcare 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 healthcare utilization prior to enrollment, including 2013 ACG risk scores, and ten years of inpatient and ER utilization measures. Although there are many enrollees in exchange plans with relatively short enrollment spells, 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 in 2014, and by half that amount in 2015.

Directly evaluating the potential threat of income manipulation is more challenging. We were able to obtain summary statistics for Utah FFM enrollees based on administrative data from the Multidimensional Insurance Data Analytics System (MIDAS) of the Centers for Medicare & Medicaid Services (CMS). The MIDAS data contain the responses that individuals provided when enrolling in plans on healthcare.gov, and include the full population of FFM enrollees in Utah who selected plans during the 2014 enrollment period (October 1, 2013 to March 31 2014). Appendix Table A1 shows the take-up rates by tiers and income levels. Overall, only 2.5% of all enrollees had incomes below 100% of FPL and 11% had incomes above 400% of FPL. The large majority of enrollees (71%) falls within the income range that we investigate, 100 to 250% of FPL.

Plan selection clearly takes place between different *metal tiers* outside the CSR eligibility range, as we discuss in Appendix Table A1. For example, among the poorest enrollees with incomes of less than 100% of FPL, 18% selected bronze, 20% gold and 41% silver plans (note that enrollees with incomes <100% of FPL are *not* eligible for CSRs). Among the richest enrollees with incomes of more than 400% of FPL, 20% selected bronze, 38% silver, but 39% selected gold plans. Without premium and cost-sharing subsidies, it is highly likely that sicker enrollees chose to enroll in more generous plans, like gold plans. Consequently, when interpreting spending differences across tiers as in Appendix Table A2, it is difficult to disentangle responses to cost-sharing from underlying enrollee characteristics that may be correlated with sorting (cf. Einav et al., 2013).

To avoid this selection issue, we limit the analysis sample to not only on silver plans, but to enrollees in silver plans that also have incomes between 100% and 250% of FPL. Sorting into different

AV tiers is much less concerning within the silver metal tier. The reasons are that (a) the subsidy design incentivizes enrollees to take-up silver plans in these income brackets, as only silver plans are eligible for CSRs, and (b) CSR categories, and thus AVs, are solely determined by household income. As shown in Appendix Table A1, reassuringly, *within* income brackets (100-150, 150-200, 200-250% of FPL), socio-demographics appear to be balanced across tiers. A large majority of enrollees within these income brackets selected silver plans: 88% of enrollees with incomes between 100 and 150% and 82.5% of enrollees with incomes between 150% and 200% FPL selected silver plans. *Within* those income brackets, there are only minor imbalances across metallic plan tiers with respect to socio-demographics. For example, among enrollees with incomes between 100 and 150% FPL, the average age of those who selected silver plans was 34.4 years, compared to 35.0 years for those who selected gold or platinum plans. Similarly, conditional on having income between 100 and 150% of the FPL, 1.4% of enrollees who selected silver plans were black, compared to 1.3% for gold/platinum plans, and 2.0% for bronze plans.

While socio-demographics within income brackets are balanced, Table A1 also indicates that—not surprisingly—socio-demographics generally differ across income categories: people in the analysis sample with incomes between 200% and 250% of FPL are younger, less likely to be black, and less likely to be smokers. However, note that unconditional socio-demographic differences between CSR categories are only problematic to the extent that these characteristics are systematically correlated with health care utilization, conditional on 2013 ACG<sup>©</sup> risk scores, 2004-2013 inpatient and ER utilization, age, gender, county and calendar month fixed effects.

To underscore the validity of this final last point, we also re-estimate our models but exclude the 200% to 250% FPL CSR, using only 94% and 87% AV silver plans. As Table A1 shows, the largest differences in demographics are between the lower two categories and the 200% to 250% category, so omitting this category substantially reduces observed demographic differences. The results, presented in Appendix A4 imply very similar, though slightly larger, elasticities estimates across all types of care. This suggests that, if anything, our main estimates may slightly understate the elasticity of demand.

**[Insert Figure 4 about here]**

Finally, one remaining 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 nor the CMS data that this was the case. Figure 4 plots take-up rates for silver plans along the distribution of incomes reported on healthcare.gov among FFM enrollees in Utah in 2014.

One may expect that, if CSR beneficiaries under-report their income to increase the CSR subsidy, this should cause an increase in average silver plan take-up rates to the left of the CSR subsidy thresholds. Although take-up levels clearly differ across income categories (see also Table A1), there is little evidence that income manipulation or selective take-up at the margins are an identification issue. DeLeire et al. (2017) provide further details and an array of robustness checks along these lines.

#### 6.4 Estimating Effect Heterogeneity

To investigate heterogeneity in elasticities, we re-estimate equation (1) including interactions between  $\text{LogCoinsurance}_{p(i,t)}$  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 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<sup>©</sup> Risk Score. For ease of interpretation, the bottom of the table reports the implied marginal elasticities at the 10<sup>th</sup>, 50<sup>th</sup> and 90<sup>th</sup> 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<sup>th</sup> percentile elasticity is -0.21, which is statistically different from zero, as is the 50<sup>th</sup> percentile elasticity at -0.14. However, the 90<sup>th</sup> 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.<sup>11</sup> 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 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 healthcare 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, 6, 7, 8. Our estimates therefore describe a partial equilibrium, in which CSR

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<sup>11</sup>[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.

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 effectively 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).

## 8 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, while controlling for the short, medium, and long-term heterogeneity in health status that may be correlated with income. While we do not have information on the exact income reported, we carry out a battery of robustness checks and test the sensitivity of our lower-bound estimates with respect to the various income-spending elasticities reported in the literature. Using administrative records of reported income, we also demonstrate that systematic income manipulation to obtain higher cost-sharing subsidies does not appear to have systematically occurred on the ACA Exchanges.

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.”

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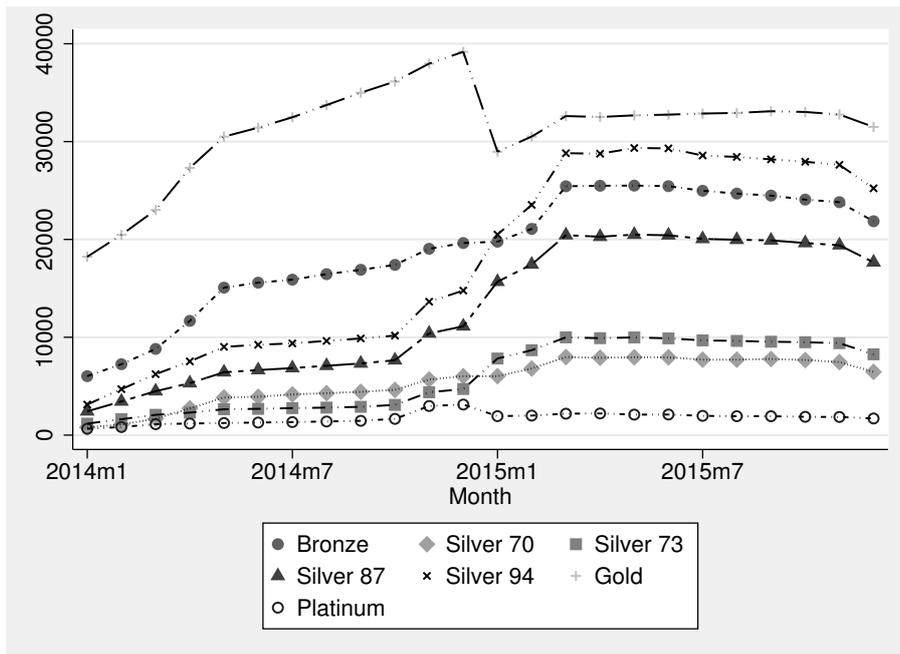
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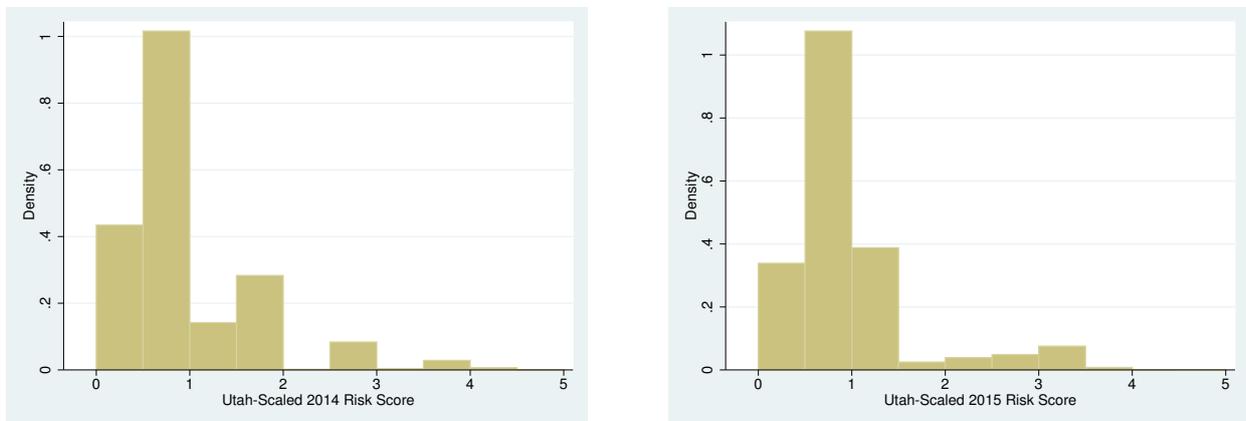
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**Figure 1: Enrollment on Utah FFM Exchange by Coverage Tier and CSR Categories**



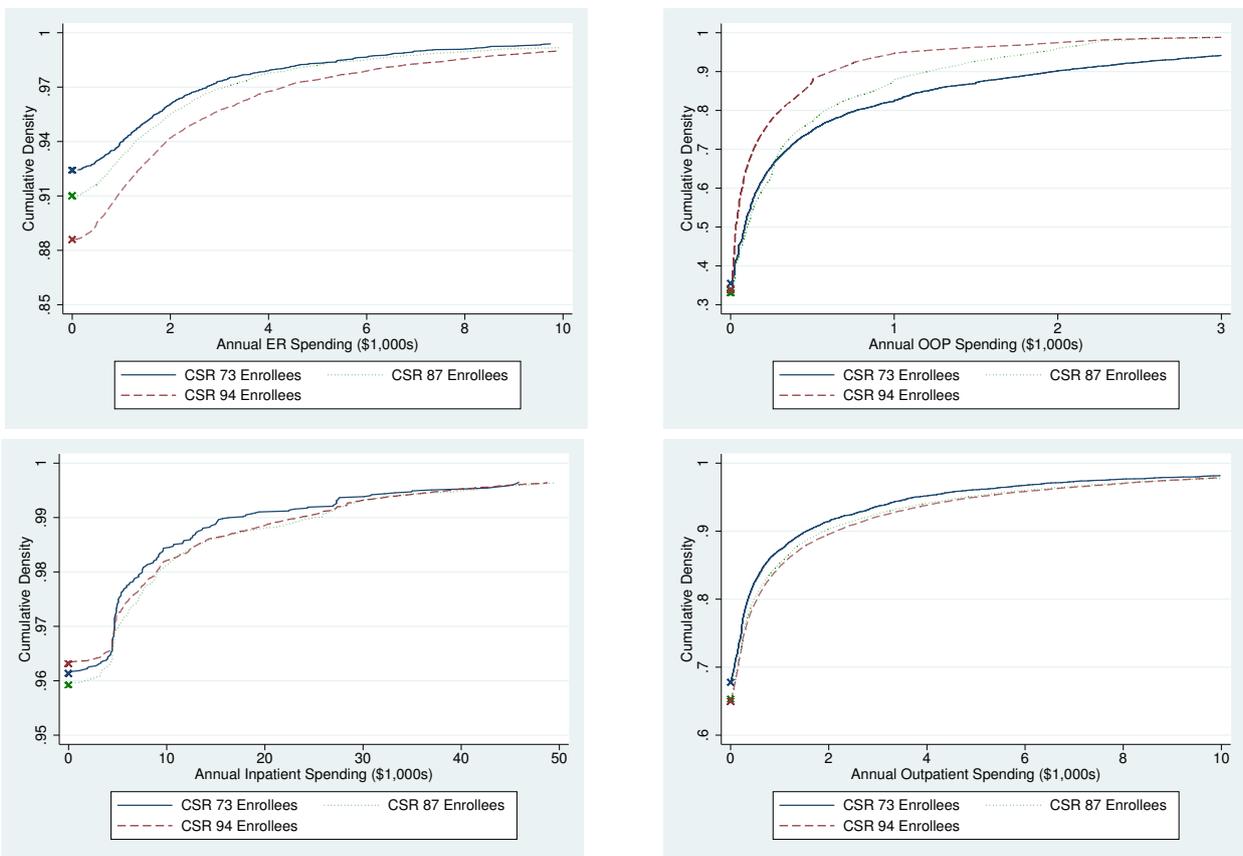
Source: Utah APCD, own calculations, own illustration.

**Figure 2: ACG<sup>©</sup> Risk Score Distributions for Working Sample**



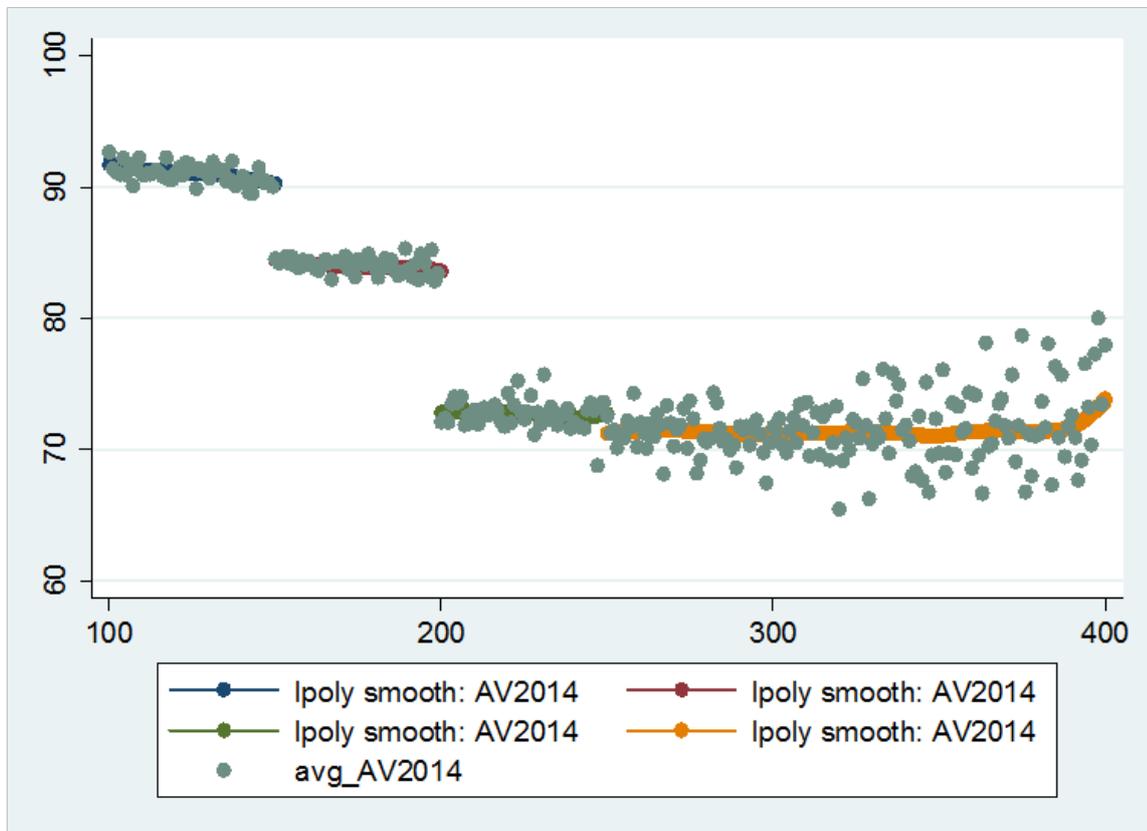
Source: Utah APCD, own calculations, own illustration.

**Figure 3: Cumulative Density Functions by Spending and CSR Categories**



Source: Utah APCD, own calculations, own illustration

Figure 4: Silver Plan Take-Up Rate by Household Income on Utah FFM Exchange in 2014



Source: Centers for Medicare & Medicaid Services, Multidimensional Insurance Data Analytics System (MIDAS), also see [DeLeire et al. \(2017\)](#).

**Table 1: Variable Means by CSR Category**

	CSR 73 Enrollees	CSR 87 Enrollees	CSR 94 Enrollees	All CSR Enrollees
<b>Panel A</b>				
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
<b>Panel B</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<sup>©</sup> 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*** (0.05)	0.37*** (0.10)	0.23*** (0.05)	0.25* (0.13)	-0.84*** (0.04)
CSR 87% AV Plan	0.07 (0.05)	0.08 (0.11)	0.12** (0.06)	0.16 (0.14)	-0.44*** (0.03)
Risk Score 2013	1.84*** (0.10)	1.04*** (0.34)	2.07*** (0.11)	1.23*** (0.27)	1.21*** (0.08)
Inpatient Days 2004-2013	0.03*** (0.00)	0.01** (0.00)	0.02*** (0.00)	0.07*** (0.00)	0.01*** (0.00)
ER Visits 2004-2013	0.08*** (0.00)	0.15*** (0.00)	0.09*** (0.00)	0.06*** (0.01)	0.06*** (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*** (0.03)	-0.28*** (0.07)	-0.15*** (0.03)	-0.15* (0.08)	0.55*** (0.02)
2013 Risk Score	1.84*** (0.10)	1.02*** (0.33)	2.07*** (0.11)	1.23*** (0.27)	1.21*** (0.08)
Inpatient Days 2004-2013	0.03*** (0.00)	0.01* (0.00)	0.02*** (0.00)	0.07*** (0.00)	0.01*** (0.00)
ER Visits 2004-2023	0.08*** (0.00)	0.15*** (0.00)	0.09*** (0.00)	0.06*** (0.01)	0.06*** (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: GLM Coinsurance Estimates: Stepwise Inclusion of Controls**

<b>Total Spending</b>			
Log Coinsurance Rate	-0.15*** (0.04)	-0.16*** (0.03)	-0.12*** (0.03)
<b>ER Spending</b>			
Log Coinsurance Rate	-0.38*** (0.07)	-0.36*** (0.07)	-0.28*** (0.07)
<b>Outpatient Spending</b>			
Log Coinsurance Rate	-0.21*** (0.03)	-0.21*** (0.03)	-0.15*** (0.03)
<b>Inpatient Spending</b>			
Log Coinsurance Rate	-0.20*** (0.09)	-0.19*** (0.08)	-0.15*** (0.08)
<b>Out-of-Pocket Spending</b>			
Log Coinsurance Rate	-0.51*** (0.02)	-0.52*** (0.02)	-0.55*** (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 5: 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*** (0.03)	-0.24*** (0.05)	-0.29*** (0.08)
2013 Risk Score	1.84*** (0.10)	1.63*** (0.20)	3.49*** (0.24)
Inpatient Days 2004-2013	0.03*** (0.00)	0.00 (0.00)	-0.01*** (0.00)
ER Visits 2004-2023	0.08*** (0.00)	0.04*** (0.00)	0.15*** (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 6: 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*** (0.05)	-0.17* (0.09)	-0.09 (0.11)	-0.25*** (0.07)	-0.15* (0.09)	-0.14*** (0.03)
2013 Risk Score	2.89*** (0.14)	2.42*** (0.18)	2.90*** (0.27)	4.00*** (0.23)	3.20*** (0.23)	2.50*** (0.10)
Inpatient Days 2004-2013	0.02*** (0.00)	0.03*** (0.01)	0.02 (0.01)	0.00 (0.01)	0.02** (0.01)	0.01*** (0.00)
ER Visits 2004-2023	0.09*** (0.00)	0.05*** (0.00)	0.08*** (0.01)	0.12*** (0.00)	0.10*** (0.00)	0.11*** (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 7: Heterogeneity in GLM Coinsurance Estimates**

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
<b>Panel A: Age</b>					
Log Coinsurance Rate	-0.14*** (0.04)	-0.26*** (0.08)	-0.15*** (0.04)	-0.27** (0.11)	0.56*** (0.03)
Log Coinsurance Rate*Age 31-50	0.01 (0.03)	-0.06 (0.06)	0.00 (0.04)	0.18** (0.08)	-0.00 (0.03)
Log Coinsurance Rate*Age 51-64	0.02 (0.04)	0.01 (0.11)	-0.01 (0.05)	0.20* (0.12)	-0.02 (0.04)
<b>Panel B: Gender</b>					
Log Coinsurance Rate	-0.06 (0.04)	-0.18** (0.08)	-0.08* (0.04)	-0.06 (0.08)	0.64*** (0.03)
Log Coinsurance Rate*Male	-0.15** (0.06)	-0.23* (0.13)	-0.16** (0.07)	-0.21 (0.17)	-0.19*** (0.05)
<b>Panel C: Urban</b>					
Log Coinsurance Rate	-0.08 (0.09)	-0.40** (0.19)	-0.08 (0.08)	-0.07 (0.23)	0.58*** (0.06)
Log Coinsurance Rate*Urban	-0.05 (0.09)	0.13 (0.20)	-0.09 (0.09)	-0.09 (0.24)	-0.03 (0.07)
<b>Panel D: Family Plan</b>					
Log Coinsurance Rate	-0.03 (0.04)	-0.11 (0.09)	-0.06 (0.05)	-0.17 (0.12)	0.45*** (0.03)
Log Coinsurance Rate*Family Plan	-0.12* (0.06)	-0.27** (0.13)	-0.10 (0.07)	0.09 (0.16)	0.20*** (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<sup>©</sup> Risk Score**

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	-0.21*** (0.04)	-0.38*** (0.12)	-0.20*** (0.05)	-0.38*** (0.10)	0.49*** (0.03)
Log Coinsurance Rate*2013 Risk Score	0.63*** (0.20)	0.75 (0.53)	0.34 (0.22)	1.64*** (0.45)	0.40*** (0.15)
2013 Risk Score	3.34*** (0.50)	2.81** (1.33)	2.88*** (0.55)	5.03*** (1.20)	2.18*** (0.35)
Inpatient Days 2004-2013	0.03*** (0.00)	0.01* (0.00)	0.02*** (0.00)	0.07*** (0.00)	0.01*** (0.00)
ER Visits 2004-2023	0.08*** (0.00)	0.15*** (0.00)	0.09*** (0.00)	0.06*** (0.00)	0.06*** (0.00)
<b>Predicted Elasticities:</b>					
10th Percentile Risk Score	-0.21	-0.38	-0.20	-0.38	0.49
P-Value $\epsilon_{10} = 0$	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 $\epsilon_{50} = 0$	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 $\epsilon_{90} = 0$	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*** (0.027)	-0.153*** (0.032)	-0.024*** (0.005)	-0.025*** (0.006)	-0.144*** (0.024)	-0.138*** (0.029)
Log Coinsurance Rate × Above Mean Deductible	0.051 (0.032)	-0.031 (0.039)	0.005 (0.006)	0.000 (0.007)	0.038 (0.029)	-0.020 (0.035)
Above Mean Deductible	-0.003 (0.074)	-0.222** (0.095)	0.011 (0.012)	-0.003 (0.016)	0.023 (0.067)	-0.137 (0.085)
2013 Risk Score	2.911*** (0.166)	2.924*** (0.180)	0.198*** (0.040)	0.223*** (0.046)	2.571*** (0.149)	2.574*** (0.161)
2013 Risk Score Unknown	-2.690*** (0.150)	-2.826*** (0.157)	0.068** (0.027)	0.055* (0.029)	-2.373*** (0.137)	-2.502*** (0.143)
Inpatient Days 2004-2013	0.004 (0.004)	0.018*** (0.003)	0.000 (0.000)	0.000 (0.001)	0.003 (0.003)	0.015*** (0.003)
ER Visits 2004-2023	0.088*** (0.011)	0.080*** (0.011)	0.031*** (0.003)	0.032*** (0.003)	0.084*** (0.010)	0.078*** (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 (1)	100-150% FPL			150-200% FPL			200-250% FPL		
		Gold& Platinum (2)	Silver (3)	Bronze (4)	Gold& Platinum (5)	Silver (6)	Bronze (7)	Gold& Platinum (8)	Silver (9)	Bronze (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*** (0.02)	-0.05*** (0.01)	-0.14*** (0.02)	0.01* (0.01)	0.33*** (0.02)
2013 Risk Score	0.92*** (0.09)	0.21*** (0.07)	1.18*** (0.11)	0.02 (0.03)	0.30*** (0.07)
Inpatient Days 2004-2013	0.01*** (0.00)	-0.00 (0.00)	0.01*** (0.00)	0.00*** (0.00)	0.00 (0.00)
ER Visits 2004-2013	0.03*** (0.00)	0.04*** (0.00)	0.04*** (0.01)	0.00 (0.00)	0.01*** (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*** (0.05)	-0.38*** (0.11)	-0.14** (0.06)	-0.11 (0.12)	0.53*** (0.03)
2013 Risk Score	1.75*** (0.11)	1.14*** (0.36)	2.00*** (0.11)	1.05*** (0.29)	1.14*** (0.09)
Inpatient Days 2004-2013	0.02*** (0.00)	0.01* (0.00)	0.02*** (0.00)	0.06*** (0.00)	0.01*** (0.00)
ER Visits 2004-2013	0.07*** (0.00)	0.15*** (0.00)	0.09*** (0.00)	0.05*** (0.01)	0.06*** (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*** (0.05)	-0.30*** (0.05)	-0.33*** (0.12)	-0.24*** (0.07)
2013 Risk Score	1.84*** (0.10)	2.06*** (0.11)	1.27*** (0.27)	2.89*** (0.14)
Inpatient Days 2004-2013	0.03*** (0.00)	0.02*** (0.00)	0.07*** (0.00)	0.02*** (0.00)
ER Visits 2004-2013	0.08*** (0.00)	0.09*** (0.00)	0.06*** (0.01)	0.09*** (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*** (0.03)	-0.23*** (0.07)	-0.14*** (0.03)	-0.16** (0.08)	0.54*** (0.02)
2013 Risk Score	2.03*** (0.11)	1.33*** (0.32)	2.32*** (0.12)	1.31*** (0.28)	1.21*** (0.09)
Inpatient Days 2004-2013	0.02*** (0.00)	0.01** (0.00)	0.02*** (0.00)	0.06*** (0.00)	0.01*** (0.00)
ER Visits 2004-2023	0.08*** (0.00)	0.16*** (0.00)	0.09*** (0.00)	0.06*** (0.01)	0.06*** (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*** (0.03)	-0.27*** (0.07)	-0.13*** (0.03)	-0.12 (0.08)	0.57*** (0.02)
2013 Risk Score	1.82*** (0.10)	0.90*** (0.35)	2.02*** (0.11)	1.36*** (0.27)	1.17*** (0.09)
Inpatient Days 2004-2013	0.02*** (0.00)	0.01* (0.00)	0.02*** (0.00)	0.06*** (0.00)	0.01*** (0.00)
ER Visits 2004-2023	0.08*** (0.00)	0.15*** (0.00)	0.09*** (0.00)	0.05*** (0.01)	0.06*** (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*** (0.03)	-0.28*** (0.06)	-0.15*** (0.03)	-0.17** (0.08)	0.58*** (0.02)
2013 Risk Score	1.65*** (0.10)	1.16*** (0.31)	1.87*** (0.11)	1.11*** (0.27)	1.16*** (0.08)
Inpatient Days 2004-2013	0.02*** (0.00)	0.01* (0.00)	0.02*** (0.00)	0.06*** (0.00)	0.01*** (0.00)
ER Visits 2004-2013	0.08*** (0.00)	0.15*** (0.00)	0.09*** (0.00)	0.06*** (0.01)	0.06*** (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.