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

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Abstract

The 2010 Affordable Care Act (ACA) provides subsidies for premiums 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. This paper uses All-Payer Claims Data from Utah for 2013-2015, linked to administrative hospital discharge records from 2004-2013, to estimate how the healthcare utilization decisions of low-income consumers respond to cost-sharing reductions. Exploiting policy-driven discontinuities in the value of CSRs across plans that are solely determined by income, we estimate the demand elasticity of total health care spending to be -0.13. We find larger responsiveness for emergency room care, lifestyle drugs, and low-value care. The results show 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 29% reduction in healthcare utiltization by low-income consumers, with substantial reductions 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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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 subsidies for premiums 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 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.[1] Brot-Goldberg et al. (2017) exploited 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. (cf. Finkelstein et al., 2012; Baicker et al., 2013; Taubman et al., 2014) 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 utilization effects of expanding Medicaid coverage on the *extensive* margin, but provides less information about smaller intensive-margin changes in coverage generosity. Chandra et al. (2014) estimate intensive-margin demand elasticities in the low-income population of enrollees 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 between -0.1 and -0.3 for different categories of care.

In this paper, we provide 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, and evaluating whether newly-insured enrollees were responsive to intensive-margin

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

price mechanisms. We then 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 estimates of the elasticity of demand for drugs based on the classification system developed by Chandra et al. (2010), and find, reassuringly, that enrollees are less responsive to cost-sharing for drugs that are more likely to causally prevent hospitalizations. Finally, we simulate a counterfactual CSR policy to estimate the distribution of effects of eliminating CSR subsidies for consumers.

The variation in cost-sharing that we use for estimation comes from sharp changes in income-based cost-sharing reduction (CSR) subsidies provided under the ACA. 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 an average 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 the threshold corresponding to 250% of the FPL, the deductible and other cost-sharing rules they are shown are automatically and discontinuously adjusted in a way that increases the generosity of every silver plan from 70% AV to 73% AV. Similarly, when income crosses below 200% and below 150% of FPL, plan designs change in a way that causes generosity to discontinuously increase from 73% to 87% and then to 94%, respectively.[2] 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 in Utah, a state that choose not to expand Medicaid coverage under the ACA. Using All-Payer Claims Data (APCD) from Utah between 2013-2015, 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 exchange enrollee, all medical care utilization, prescription drug purchases, diagnoses, negotiated prices, payments, and spending. The 2013 APCD data allow us to calculate each enrollees' health risk scores prior to selecting ACA plans in 2014 using Johns Hopkins ACG© System software. A unique feature of our data is that we are also able to link the APCD records for each individual to administrative hospital inpatient and ER discharge records from 2004-2013. This linkage allows us to condition on up to a full decade of information on hospital-based healthcare utilization prior to enrollment, alleviating concerns about the conditional exogeneity of assignment to plans with different

[2]These CSRs are provided in addition to premium subsidies, which are available to consumers between 100% and 400% of FPL.

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), which contain enrollment choices and household incomes reported by all exchange enrollees in Utah on `healthcare.gov`. These data allow us to show that there is very little heterogeneity in plan choices within CSR income categories, and that there no evidence of bunching in reported incomes around the CSR subsidy thresholds.

We find that responses to cost-sharing among low-income ACA enrollees imply an overall demand elasticity for health care of -0.13, surprisingly close to the commonly-cited RAND HIE estimate of -0.2. Estimated elasticities for inpatient and outpatient care are -0.15, but are substantially larger (-0.28) for Emergency Room (ER) care. These ER elasticities are consistent with the evidence from the Oregon HIE, which found a significant increase in ER utilization associated with gaining Medicaid coverage (Taubman et al., 2014). Corroborating the first stage variation in cost-sharing levels, we find an elasticity of out-of-pocket (OOP) spending with respect to average coinsurance rates of +0.55.

We also find that sicker enrollees, with higher pre-ACA risk scores, are less price responsive to cost-sharing. For example, elasticity of demand falls from -0.21 to -0.05 when 2013 risk scores increase from the 10^{th} percentile to the 90^{th} percentile of the sample distribution. Consistent with evidence from Brot-Goldberg et al. (2017), we find meaningful responsiveness to both high and low-value medical care, with a slightly larger price elasticity of -0.29 for low-value care. We also use the categorization of prescription drugs developed by Chandra et al. (2010), and find the largest elasticities for lifestyle drugs (-0.25) and the lowest responsiveness for drugs that treat chronic illnesses (-0.09).[3] These 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 enrollees studied in previous literature.

In late 2017, the Department of Justice determined that it was unlawful for the federal government to make CSR payments to insurers, since Congress had not appropriated funds, As a result, insurers are currently legally obligated to offer subsidies to consumers, but 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 these 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

[3] The total elasticity of demand for prescription drugs is -0.15 in this low-income population. This is roughly the same magnitude as the -0.2 estimate based on elderly enrollees in Medicare Part D from Einav et al. (2018).

only a 7% increase in OOP spending ($23 per enrollee, per month) to counteract the reduction in subsidized spending. 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 closest 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, and 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, it also showed that cost-sharing reduced demand for health care "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 and 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).

Since the RAND HIE, an unresolved question has been whether "offset" or substitution effects between different types of care exist (Zweifel and Manning, 2000; McKnight, 2006; Glied et al., 2007; Chandra et al., 2010; Ziebarth, 2014) and whether a decrease in medical care utilization today could increase the demand for medical care tomorrow (Fang and Gavazza, 2011).

Moreover, two recent areas of the literature investigate (a) whether health care consumers are rational decision-makers, and (b) to what extent the non-linear budget sets in private insurance contracts induce intertemporal demand substitution as a result of dynamic price changes (which forward-looking consumers exploit). There is clear evidence that (some) consumers do not understand insurance products (Loewenstein et al., 2013), leave money on the table when choosing health plans (Abaluck and Gruber, 2011, 2016; Bhargava et al., 2017), and react to price framing (Schmitz and Ziebarth, 2017). However, there is also evidence that consumers learn over time (Ketcham et al., 2012, 2015, 2016), that some are forward-looking, and that intertemporal substitution exists (Dalton, 2014; Einav et al., 2015; Kowalski, 2015; Cabral, 2017; Lin and Sacks, 2016; Brot-Goldberg et al., 2017). For example, DeLeire et al. (2017) finds 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). Existing studies 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 rural counties obtain more insurer choice when bundled with urban areas (Dickstein et al., 2015). 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. 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. Orsini and Tebaldi (2017) find that age-pricing restrictions have reduced participation on the Exchanges. And Tebaldi (2017) shows that age-dependent subsidies would lead to equilibria where all buyers would be better off.

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, 1,712 Qualified Health Plans (QHP) were offered by six different carriers on the Utah Exchange. The majority of them were silver plans (39%) followed by bronze plans (29%). All plans are required 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%. This implies that enrollees have to pay on average 30%, 40% and 20% of their health care costs, respectively, out-of-pocket (OOP) up to a maximum OOP cap. In 2014, the maximum OOP stop loss was $6,350 per individual ($12,700 per family).

AVs and CSRs. For policyholders with annual gross household incomes below 250% of FPL[4], 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% 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, $2077 in 73% AV silver plans, $737 in 84% AV silver plans, and $229 in 94% AV silver plans (Kaiser Family Foundation, 2015b).

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

[4]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).

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 Modeling Health Expenditure Distributions

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

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). While this 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).

An alternative approach is to estimate a nonlinear specification within a Generalized Linear Model (GLM), as in Mullahy (1998); Manning and Mullahy (2001); Manning et al. (2005). GLMs are based on "link functions" (which model the relationship between covariates and the conditional mean of the spending distribution) as well as "variance functions" (which model the relationship between the mean and the variance of the spending distribution). This approach allows for heteroscedasticity and relies on the original, non-transformed, spending data (Manning, 2006; Jones, 2011). Buntin and Zaslavsky (2004) compares the performance of a range of methods for modeling healthcare spending, and finds the GLM specification performs well, and substantially reduces mean squared error relative to the transformed log model.

4.2 Empirical Model

After evaluating diagnostic tests, our main estimates use the GLM approach. As we show in the Results section and the Appendix, our findings are quite similar across alternative classes of models (cf. Buntin and Zaslavsky, 2004). Using a log link function $g(\mu_{i,t})$, where $\mu_{i,t}$ is the conditional mean of health care spending, the model can be written as:

$$E[y_{it}|x_{i,t}] = exp(\alpha + \beta AV_{p(i,t)} + \gamma Risk_{i,2013} + \phi Inpatient_{i,2004-2013} + \tau ER_{i,2004-2013} \\ + X'_{i,t}\theta + \delta_t + \rho_{c(i,t)} + \epsilon_{i,t}) \tag{1}$$

where y_{it} measures health care spending (in dollars) of individual i in month t. Our main variable of interest is $AV_{p(i,t)}$ which is the Actuarial Value (AV) of plan p chosen by individual i in month t. We focus only on silver plans with cost-sharing subsidies, so $AV_{p(i,t)}$ varies in a stepwise manner between 73% to 94% according to income. $Risk_{i,2013}$ measures the risk score of individual i in 2013, prior to choosing an Exchange plan. The risk scores are calculated using All-Payer-Claims-Data (APCD) and the Johns Hopkins ACG© System software. $Inpatient_{i,2004-2013}$ and $ER_{i,2004-2013}$ are count variables of the number of cumulative individual inpatient days and Emergency Room (ER) visits between the years 2004 and 2013. Controlling for pre-period risk scores and hospital utilization allows for the possibility that plan selection may be correlated with unobserved health status (that is not explained by other covariates). $X_{i,t}$ is a vector of socio-demographic control variables including gender, age, and age squared. δ_t and $\rho_{c(i,t)}$ are month-year and county fixed effects, respectively. They adjust for average differences in health care spending over time and across the 29 counties in Utah, for example due to differences in average price levels. ϵ_{it}, the error term, is clustered at the household level to allow for serial correlation and for correlation that may be caused by shared deductibles and other nonlinear plan features at the household level (Cameron and Miller, 2015).

The link function determines the shape of the conditional mean and how untransformed mean spending relates to the covariates. One 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. The relationship between the mean and the variance of the (skewed) spending data 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 (Manning et al., 2005; Jones, 2011). Of the models tested, the log-link and gamma variance model provide the best fit in our setting, but a log-link negative binomial variance model yields very similar results.

4.3 Identification

Although we experimented with including fixed person 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 A7.). 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.

Instead, our primary empirical estimates are identified by between-enrollee variation in AVs. Proper interpretation of β in equation (1) therefore requires some evaluation of potential reverse causality, or violations of the conditional exogeneity of $AV_{p(i,t)}$. Reverse causality is unlikely to be an issue because of timing restrictions, since 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 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.

The main threat for a causal interpretation of β 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. This implies that the identifying AV variation is solely determined by the applicants' indicated household income during the open enrollment period. Specifically, the identifying AV variation stems from differences in the household income categories 100-150%, 150-200% and 200-250% of FPL. Each category triggers different CSR levels and results in different plan AVs. In our standard model, we focus on subsidized silver plans and thus shut down selection between platinum, bronze, silver and gold plans. Moreover, 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).[5]

4.4 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

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

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. When calculating point elasticities of demand, we relate variation in individual-level spending to variation in the average coinsurance rates across plans, i.e., we substitute $(1 - AV_{p(i,t)})$ for $AV_{p(i,t)}$ in equation (1).

In the Results Section 6.5, we 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 are 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[6] 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

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

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 payed 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.

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.[7] 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.[8] We collapse the data to the enrollee-month level and obtain and 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

[7] 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 A6).

[8] 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.

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 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© 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 the GLM model in equation (1) using variation in average cost-sharing rates, defined as $1 - AV_{p(i,t)}$, as well as elasticity estimates using the logarithm of the coinsurance rate, $log(1 - AV_{p(i,t)})$. 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 (2015b), 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 model, corresponding to 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© 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 $LogCoinsurance_{p(i,t)} = Log(1 - AV_{p(i,t)})$. Since the GLM specification has a log-link function, and the independent variable is the log coinsurance rate, the reported estimates in this table can be directly interpreted as 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 than 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 4 about here]

As shown in column (3) of Table 4, 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 5 about here]

We also test for differences in price-responsiveness across classes of drugs, grouping drugs based on their potentially 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 if 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 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© 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 concerns 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 of bunching near the threshold margins. This suggests that income manipulation or selective take-up at the margins do not appear to be 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 $LogCoinsurance_{p(i,t)}$ and other covariates of interest.

[Insert Table 6 about here]

Panel A of Table 6 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 7 about here]

Table 7 stratifies estimates by 2013 ACG© Risk Score. For ease of interpretation, the bottom of the table reports the implied marginal elasticities at the 10^{th}, 50^{th} and 90^{th} percentiles of the distribution of Utah risk scores. There is a clear pattern in all categories of care: sicker people are less responsive to cost-sharing. For example, for overall care, the 10^{th} percentile elasticity is -0.21, which is statistically different from zero, as is the 50^{th} percentile elasticity at -0.14. However, the 90^{th} percentile elasticity is -0.05 and not statistically different from zero. Inpatient spending is particularly sensitive to pre-period risk scores.

6.5 Considering Nonlinearities

Finally, we stratify estimates by the size of the deductible. To do this, we interact the coinsurance rate with a dummy variable indicating whether the plan has a deductible above the mean deductible *within* the CSR category. The deductible is always the combined deductible for medical and prescription drug spending.[9] 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 8, 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 8 about here]

[9] Kaiser Family Foundation (2015b) 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.

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, 5, 6, 7. Our estimates therefore describe a partial equilibrium, in which CSR recipients still enroll in silver plans; we do not consider the impact of eliminating CSR subsidies on relative premiums or plan selection.

The first row of Table 9 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 9 about here]

The next three rows in Table 9 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 10 about here]

Table 10 illustrates that eliminating CSRs would also have differential effects on different types of medical spending. In percentage terms, because of the larger elasticities (see Table 3), the reduction is largest for (potentially inefficient) ER care (-47%) as well as outpatient care (-31%). However, we also predict disproportionately large reductions in preventive care. For the latter exercise, we follow (Chandra et al., 2010) and identify drugs that prevent hospitalizations, i.e., "high-value drugs." We estimate that eliminating CSRs would reduce low-income enrollees' spending on drugs that prevent hospitalizations by 34% (or $19 per month).

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

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

A final policy implication of our results is that CSR payments to insurers (even prior to 2017), likely did not fully cover the costs of providing these subsidies. The reason is that in its formula for calculating advance CSR payments to issuers, CMS assumed that CSR silver plans with a 94% AV or an 87% AV would induce 12% higher total medical spending relative to 70% AV silver plans (Federal Register, 2014). However, our results suggest that this adjustment is substantially too small. In addition, the standard methodology that insurers were to use to calculate their CSR costs for purposes of reconciliation assumed that the elasticity of medical care (with respect to the plan AV) was zero. This assumption would also lead to CSR payments that did not fully compensate issuers for the increased spending of CSR recipients (even prior to the decision to cease these payments in 2017).

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, and 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 intensive-margin 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 makes it possible to identify the effects of differences in actuarial values across FFM silver plans driven solely by income, while controlling for the short, medium, and long-term heterogeneity in health status that may be correlated with income. We can also demonstrate using administrative records of reported income that systematic income manipulation to obtain higher AV plans does not appear to have occurred.

Our estimates in this setting are surprisingly close to those from the RAND HIE, which is now four decades old. 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 strongly suggest that price mechanisms work in the health care sector, even for the average low-income CSR recipient 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 differentiate between high and low-value care. This implies 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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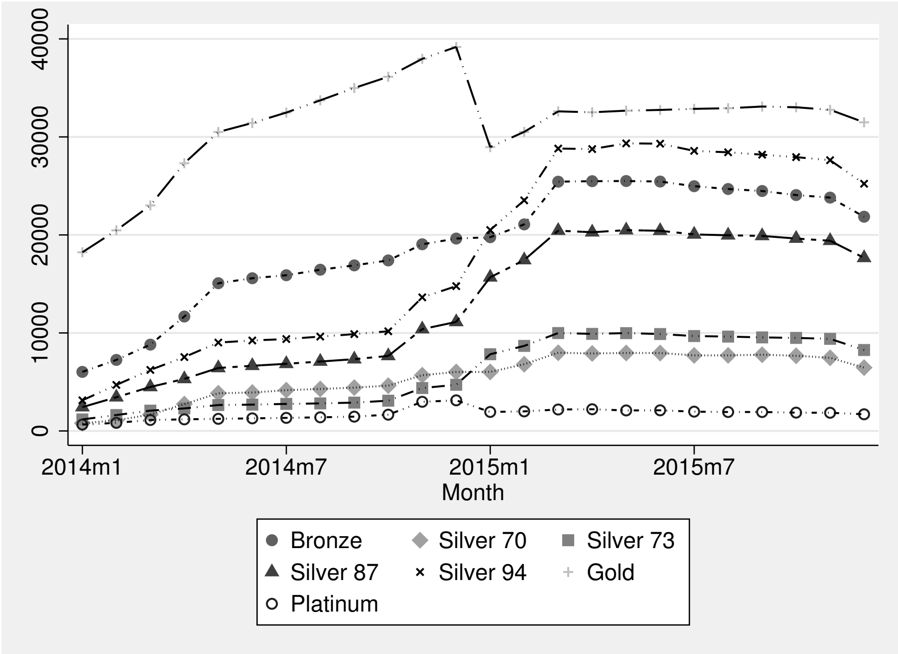
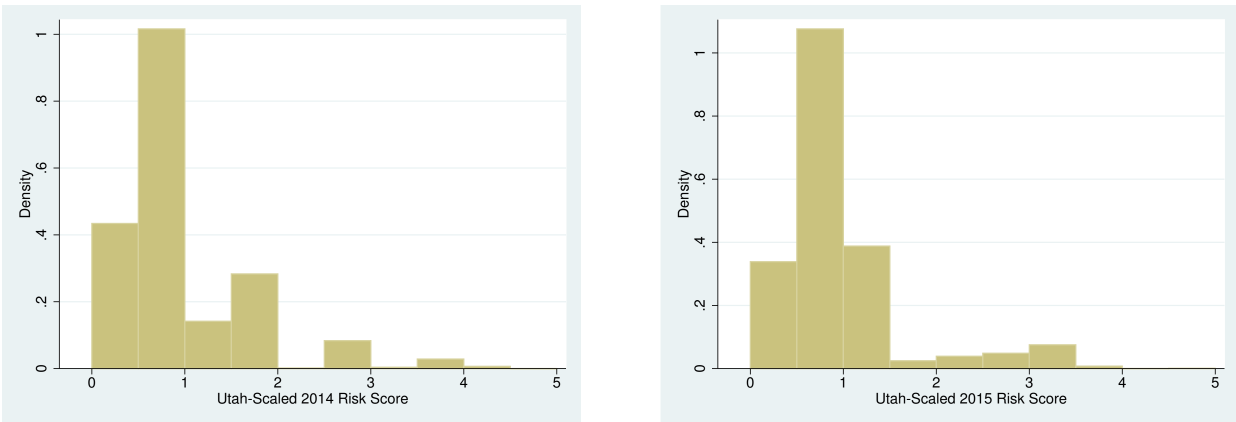
Figure 1: Enrollment on Utah FFM Exchange by Coverage Tier and CSR Categories



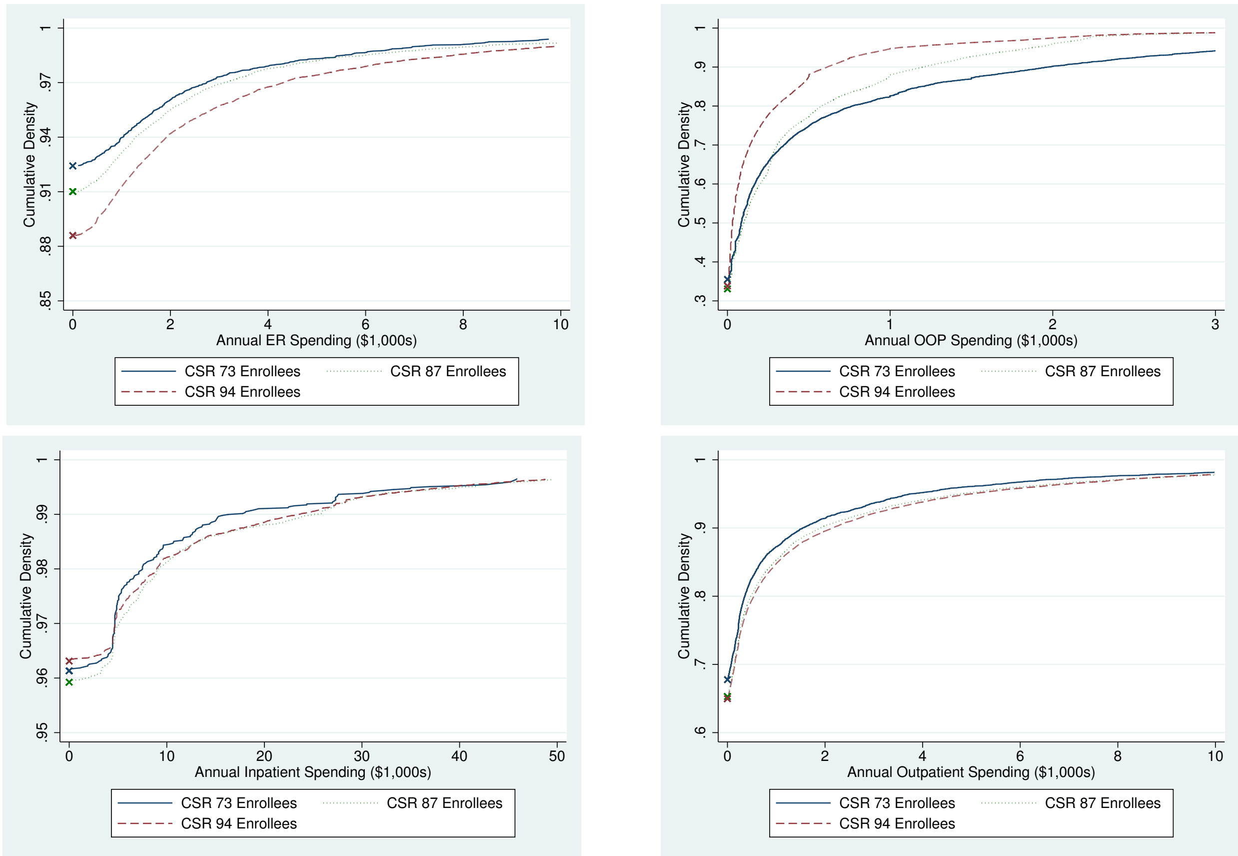
Source: Utah APCD, own calculations, own illustration.

Figure 2: ACG© Risk Score Distributions for Working Sample



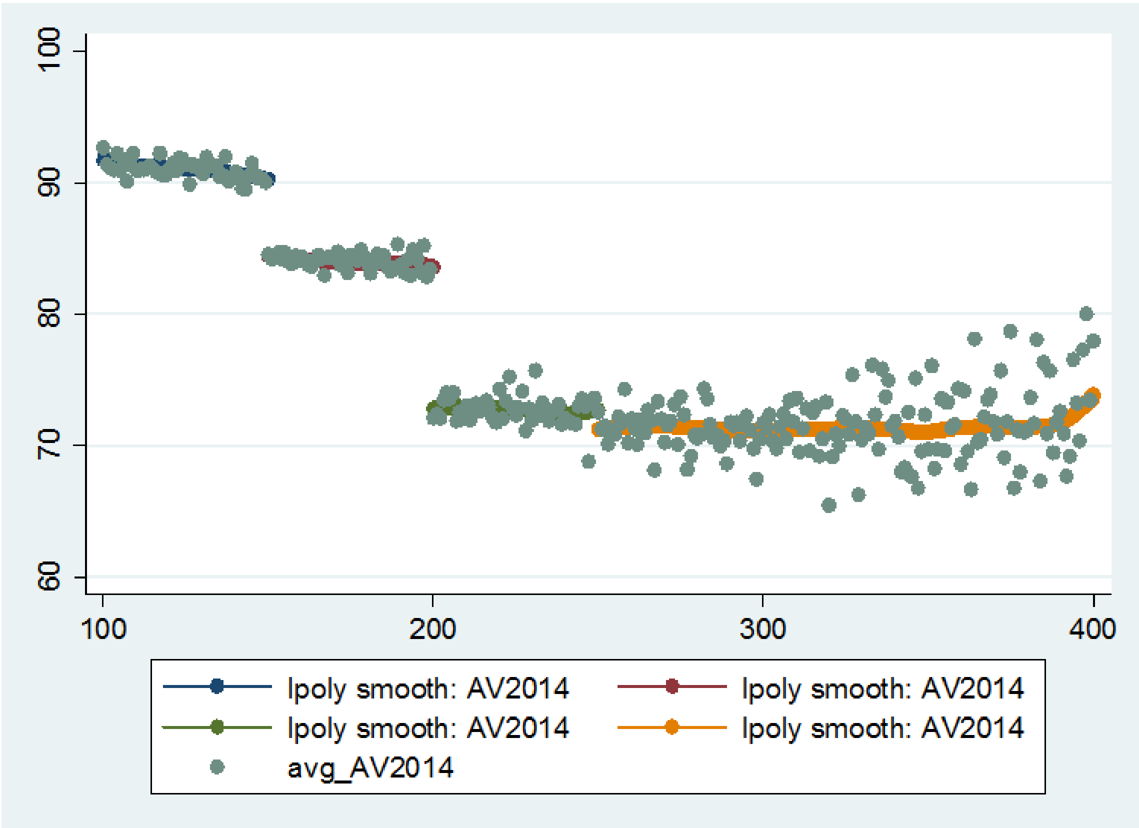
Source: Utah APCD, own calculations, own illustration.

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

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. In Panel A, all spending amounts are annual averages and the sum of allowed amounts by category. For example, *Total Medical Spending* is the sum of allowed amounts for all medical and drug spending in any insurance plan for individuals that satisfy the sample inclusion criteria. *Urban county* stands for counties with at least 80% of the population residing in an urban area (as defined by the 2010 Census). *Months FFM Enrolled* includes only months enrolled in a subsidy-eligible silver exchange plan, and is reported for only the subset of enrollees who met the 9-month selection criterion in 2014 or 2015, respectively. Risk scores are estimated using the Johns Hopkins ACG© System software. Utah-scaled risk scores are normalized to have a mean of 1 in the population of non-elderly insured individuals in the Utah APCD.

Table 2: GLM Estimates by CSR Category

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

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

Table 3: GLM Coinsurance Estimates

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

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

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

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

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

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

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

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. *Acute* refers to drugs designated by Chandra et al. (2010) as those that, "if not taken, will increase the probability of an adverse health event within a month or two." *Chronic* refers to drugs "designed to treat more persistent conditions that, if not treated, will result in a potentially adverse health event within the year." *Lifestyle* refers to drugs that result primarily in lifestyle improvements. The GLM specification as in equation (1) uses a log-link and gamma variance. All models control for age, age squared, gender, a missing 2013 Risk Score indicator, county effects, and calendar month effects.

Table 6: Heterogeneity in GLM Coinsurance Estimates

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

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. The GLM specification as in equation (1) uses 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 by 2013 ACG© Risk Score

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

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. The GLM specification as in equation (1) uses 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 8: Elasticity Estimates by Above Average Deductible

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

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

Table 9: 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 10: Counterfactual Impact of Eliminating CSRs by Type of Medical Spending

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

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

Appendix

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

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

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

Table A2: Variable Means by Coverage Tiers and CSR Categories

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

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

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

	Log Total	Log ER	Log Outpatient	Log Inpatient	Log OOP
Log Coinsurance Rate	–0.12***	–0.05***	–0.14***	0.01*	0.33***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
2013 Risk Score	0.92***	0.21***	1.18***	0.02	0.30***
	(0.09)	(0.07)	(0.11)	(0.03)	(0.07)
Inpatient Days 2004-2013	0.01***	–0.00	0.01***	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.03***	0.04***	0.04***	0.00	0.01***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
N	175,286	175,286	175,286	175,286	175,286
N Clusters	24,386	24,386	24,386	24,386	24,386

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

Table A4: GLM Coinsurance Estimates Excluding CSR 73 Enrollees

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.14***	–0.38***	–0.14**	–0.11	0.53***
	(0.05)	(0.11)	(0.06)	(0.12)	(0.03)
2013 Risk Score	1.75***	1.14***	2.00***	1.05***	1.14***
	(0.11)	(0.36)	(0.11)	(0.29)	(0.09)
Inpatient Days 2004-2013	0.02***	0.01*	0.02***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.07***	0.15***	0.09***	0.05***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Person-Months	330,932	330,932	330,932	330,932	330,932
Persons	25,308	25,308	25,08	25,308	25,308

Source: Utah APCD. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. The GLM specification as in equation (1) uses 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 Exact Plan AV

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

Source: 2013-2015 Utah APCD merged with 2004-2013 Utah Inpatient Hospital Discharge and Emergency Department data. Standard errors are clustered at the family level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Sample includes adults aged 18 to 64 who were enrolled for at least 9 months in a subsidy-eligible silver exchange plan in 2014 or 2015. The GLM specification as in equation (1) uses 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 A6: Main Estimates: Drop All Data After July 2015

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Log Coinsurance Rate	–0.11***	–0.27***	–0.13***	–0.12	0.57***
	(0.03)	(0.07)	(0.03)	(0.08)	(0.02)
2013 Risk Score	1.82***	0.90***	2.02***	1.36***	1.17***
	(0.10)	(0.35)	(0.11)	(0.27)	(0.09)
Inpatient Days 2004-2013	0.02***	0.01*	0.02***	0.06***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ER Visits 2004-2023	0.08***	0.15***	0.09***	0.05***	0.06***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
N	330,306	330,306	330,306	330,306	330,306
N Clusters	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. The GLM specification as in equation (1) uses 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 A7: 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.