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

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Abstract

This paper uses unique All-Payer Claims Data (APCD) from Utah between 2013 and 2015 to estimate demand elasticities for various types of health care services. We focus on low-income enrollees, without access to employer-sponsored coverage, who purchased private insurance on the ACA Exchanges and received cost-sharing reduction (CSR) subsidies. Exploiting policy-driven variation in actuarial values and CSR levels across plans, we find that consumers in this demographic group are quite responsive to out-of-pocket costs. We estimate the overall elasticity of demand for healthcare is -1.2, with a larger elasticity of -2.6 for Emergency Room care. We find that consumers are more responsive to costs for lifestyle drugs (-2.3) relative to drugs that treat chronic illnesses (-0.6), and for low-value care (-3.3). These findings suggest that price mechanisms have large impacts on both the level and composition of healthcare utilization.

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

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

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1 Introduction

Estimating the responsiveness of consumers to out-of-pocket costs for health care is one of the fundamental elements of understanding the social welfare effects of health insurance. The empirical findings of this literature are highly policy-relevant as they may deliver clues to addressing the difficult question of how to contain spending growth and implement efficient health care delivery models. For the U.S., with its large number of uninsured and underinsured individuals, understanding heterogeneity in demand elasticities across a wide range of demographic groups is key to developing targeted health insurance policies, and predicting the utilization and spending impacts of these policies.

To date, the 1970s RAND Health Insurance Experiment (RAND HIE), which randomized families in six U.S. regions into health insurance plans with different levels of cost-sharing, has been the gold standard in the literature. The RAND HIE showed that even modest amounts of cost sharing could substantially reduce health care utilization with minimal effects on health or quality of care. However, the experiment also showed that cost-sharing tended to reduce care "across the board" with reductions in both "appropriate" and "inappropriate" care. Despite pointing out limitations related to external validity and attrition, Aron-Dine et al. (2013) confirmed the main findings of the RAND HI when re-analyzing the original data. More recently, Brot-Goldberg et al. (2017) exploited an exogenous change in cost-sharing at a large technology company and found effects on health care spending similar to those in the RAND HIE—across the board reductions in health care utilization spanning both "low-value" and "high-value" categories of care.

Despite its age, the RAND HIE continues to be influential in today's policy discussions, and cost-sharing continues to be considered an important tool for reducing national health care spending. Moreover, the durability of the estimates from the RAND HIE illustrates the challenges of identifying exogenous price variation in natural settings, or of designing and implementing similar social experiments.

However, the findings of the RAND HIE are potentially limited in the current policy environment, simply because the study was designed to evaluate demand elasticities for an "average" population, whereas most recent policy developments have targeted low-income populations. These developments include (but are not limited to) the 2010 Affordable Care Act (ACA), which expanded public and publicly subsidized private health insurance to low-income populations. Partially as a result of these expansions, low-income populations with either private or public coverage face varying degrees of cost-sharing. For example, low-income individuals and families who purchase private health insurance policies through the ACA Exchanges are eligible for subsidies that reduce cost sharing. These "cost-sharing reductions" (or CSRs) kick in at 100% of the Federal Poverty Line (FPL) and decrease sharply at 150%, 200%, and 250% of FPL, after which they fall to zero. In fiscal year 2017, a total of $7.3 billion in taxpayer funds was spent on CSRs (Congressional Research Service 2018, 2018). However, in October 2017, the Trump Administration stopped payments to insurers because Congress had not provided appropriations. At the same time, many states have applied for and received 1155 Waivers to impose cost-sharing in the Medicaid program. To-date, the intensive-margin impact of changes in cost-sharing on the use of care among low-income populations remains unclear.

A recent study that did examine a low-income population is the Oregon Health Insurance Experiment (Oregon HIE) (cf. Finkelstein et al., 2012; Baicker et al., 2013; Taubman et al., 2014). The Oregon HIE is a "natural" experiment, based on a fortunate coincidence in which a lottery was used to assign the right to enroll in Medicaid, creating true randomization in a natural setting. The findings from this experiment show large increases in health care utilization across all types of care, and yield important insights into the utilization, spending and health effects of expanding extensive-margin Medicaid coverage to low-income adults. However, the insights are also limited to the provision of free taxpayer-funded coverage with (almost) no cost-sharing; the extremely high generosity of the coverage makes it difficult to estimate demand elasticities that can be extrapolated to private insurance with substantially greater cost-sharing.

The main objective of this paper is to empirically investigate how the low-income enrollees in the ACA Exchanges respond to cost-sharing. We are particularly interested in whether these enrollees respond—similarly to the higher income individuals in the RAND HIE and in the Brot-Goldberg et al. (2017) study—-by reducing health care utilization for both high value and low-value care. In addition, following the classification in Chandra et al. (2010), we investigate whether different types of prescription drugs carry differently sized elasticity estimates.

We focus on Utah, a state that did not expand Medicaid but, effective 2014, offered subsidized private health insurance coverage via a Federally Facilitated Marketplace (FFM). The Exchanges are marketplaces for private insurance and provide a standardized menu of regulated health plans along with income-dependent premium and cost-sharing subsidies. The default plan on the Exchanges, the Silver Plan, has an actuarial value (AV) of 70% implying that an "average" enrollee would pay 30% of their health care costs out of pocket. However, CSRs for enrollees with incomes between 100 and 250% FPL increase AVs stepwise to 94%.

Our empirical identification strategy exploits income-based discontinuities in AVs. Using a unique All-Payer Claims Data (APCD) spanning the years 2013 to 2015, we are able to observe every commercially-insured Utah resident, including monthly coverage choices, health care utilization, negotiated prices and spending, diagnoses, and payments. Our analyses focus on a fairly homogenous sample of low-income residents who bought FFM Silver Plans and whose AVs only differ due to differences in income (stemming from differences in CSRs which are only available for Silver Plans through the Exchanges). Importantly, since our data begin in 2013, we are able to control for enrollees' detailed health risk scores prior to selecting ACA plans using the Johns Hopkins ACG© System software. Although we do not observe individual income, we can see the CSR categories of each enrollee. In addition, we present robustness checks based on administrative data containing enrollment choices and incomes reported on `healthcare.gov` from the Centers for Medicare & Medicaid Services (CMS) to show that there is very little evidence of manipulation in reported incomes that could affect CSR eligibility.

In line with Abraham et al. (2017), we find demand elasticities that are substantially larger than the standard RAND HIE estimate of -0.2. Among people with incomes below 250% FPL, we estimate the overall demand elasticity to be -1.2. Estimates are substantially larger and at -2.6 for ER spending. These large ER elasticities are very consistent with the widely cited findings from the Oregon HIE, according to which ER utilization strongly increased (not decreased) when low-income populations obtained coverage through Medicaid with very little cost-sharing (Taubman et al., 2014). Corroborating the first stage variation in cost-sharing levels, we estimate the elasticity of out-of-pocket spending with respect to average coinsurance rates is +3.9.

We also find that price responsiveness increases with age and is higher for male enrollees, while sicker enrollees with higher pre-period risk scores are less price responsive. When we follow the approach of Brot-Goldberg et al. (2017) and categorize medical care into high and low-value care, compared to overall care, we find a significantly larger price elasticities of -3.3 for low-value care among our sample of low-income enrollees who sought private coverage on the Utah FFM Exchange. Moreover, when we follow the approach of Chandra et al. (2010) and categorize prescription drugs, we find the largest elasticities for lifestyle drugs (-2.3) and the lowest for chronic disease drugs (-0.6). The total elasticity of demand for drugs in this population is -1.3, substantially more elastic than the -0.24 estimate based on elderly enrollees in Medicare Part D from Einav et al. (2016). Overall, our findings clearly suggest that basic price mechanisms also appear to work among low-income enrollees with little previous insurance experience.

The next section summarizes previous research on the topic. Section 3 explains institutional details of the Utah Exchange and Section 4 our empirical model and identification. Section 5 discusses the Utah APCD and how we generated the main variables of interest. Section 6 shows the empirical findings and Section 7 concludes.

2 Prior Research

An old, but closely related, study is the RAND HIE. In addition to estimating the impact of cost-sharing on health care utilization by types of care, the RAND HIE produced a set of elasticity point estimates. These are still considered the benchmark for any health care demand elasticity study. 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 (OGrady et al., 1985; Manning et al., 1986, 1987). Another important finding is the rejection of the "offset" hypothesis according to which higher cost-sharing for health service A would reduce its demand but also lead to substitution effects and higher demand for health service B.

As a result of largely public health care systems, studies outside the U.S. typically rely on moderate variation in copayments to estimate demand elasticities of care. The few reported findings are very 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 cost-sharing variation in one of the few private markets outside the U.S.—in Chile. 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 elasticities 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 very recent substrands of the literature investigate the following two questions: (a) whether health care consumers are rational decision-makers, and (b) to what extend 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). First, 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, second, 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.[1]

In addition to estimating demand elasticities of medical care, related studies estimate price elasticities of health plan choice or insurance take-up (Cutler and Reber, 1998; Royalty and Solomon, 1999; Strombom et al., 2002; Buchmueller, 2006; Gaynor and Town, 2012; Guthmuller et al., 2014; Schmitz and Ziebarth, 2017). In the U.S. context, these studies typically exploit premium variation (in the employee share) and then estimate the likelihood that employees switch or choose (employer-provided) plans or that the uninsured take-up coverage. In the former case, reduced-form studies typically find inelastic "out-of-pocket premium elasticities"—plan enrollment decreases by less than one percent when the employee share of the premium in-

[1]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). However, to our knowledge, none of the existing papers exploits ACPD for an entire U.S. state. Existing studies use FFM health plan data to show that more competition on an Exchange reduces premiums (Dafny et al., 2015) 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 (Tebaldi) shows that age-dependent subsidies would lead to equilibria where all buyers would be better off.

creases by one percent. In the latter case, when estimating take-up elasticities, most estimates are close to zero (Chernew et al., 1997; Gruber and Washington, 2005; Moriya and Simon, 2016).

However, basically all these studies focus on individuals who have insurance (through their employer). One notable exception is Krueger and Kuziemko (2013) who elicit the willingness to pay for health insurance among the uninsured. They find significantly larger demand elasticities of around -1. Given the large fraction of uninsured in the U.S. (and the ongoing debate of how to cover them with market-based approaches), this is a crucial finding as it suggests that premium subsidies may induce more uninsured to take up coverage than previously thought. However, Krueger and Kuziemko (2013) use a hypothetical survey experiment with unknown external validity. Another exception is Abraham et al. (2017) who estimate the ACA take-up elasticity in the Exchanges to be -1.7 (using marketplace plan enrollment data and changes in plan premiums over time). Abraham et al. (2017) argue that this high elasticity would reflect "several unusual features of the market."

This paper is among the very first to use APCD data from an entire state and to focus on low-income people with substantial uninsurance experience. We use real-world data on actual treatments and claims of this low-income population and then calculate demand elasticities using variation in AVs (as compared to studies focusing on utilization effects of free public insurance).

3 Institutional Details on the Utah FFM Exchange

In April 2014, after the first open enrollment period, 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). Moreover, although Utah has not expanded Medicaid, there is evidence that the Utah FFM Exchange has helped 50 thousand residents to enroll in Medicaid (Norris, 2018). Moreover, Gallup survey data suggest that the uninsurance rate had decreased from 15.6% to 13.3% between 2013 and 2014, or by about 65 thousand from a 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 FFM. The majority of them were Silver plans (39%) followed by Bronze plans (29%). All plans (have to) cover Essential Health Benefits but differ in their degree of cost-sharing and thus their actuarial values (AVs). Silver plans cover on average 70% of all costs while bronze plans cover 60% and gold plans cover 80%. This implies that enrollees have to pay on average 30%, 40% and 20% of all 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[2], the ACA provides 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% AVs, instead of the standard 70%. The additional 24 points of actuarial value is paid for through CSR subsidies from the federal government to insurers. When household income crosses the 150% FPL threshold, CSR subsidies drop discontinuously, reducing the AV of a silver plan to 87%. The subsidy again decreases at 200% of FPL, reducing the AV to 73%, and CSR subsidies are eliminated when income exceeds 250% of FPL. The ACA does not specify how exactly CSRs alter deductibles, copayments or coinsurance rates meaning that each carrier implements their own CSR algorithm. Every insurer that offers a silver plan for sale on the FFM must submit four plans, corresponding to AVs of 70%, 73%, 87%, and 94%. These four plans are set in advance, and plan assignment, conditional on purchasing a silver plan, is automatically determined based on reported income. For example, among all FFM plans in 2015 with combined medical and prescription drug coverage, the average deductible was $2556 in CSR70 silver plans, $2077 in CSR73 plans, $737 in CSR84 plans, and $229 in CSR94 plans (Kaiser Family Foundation, 2015b).

4 Empirical Approach

In this section we discuss the methods used by health econometricians to model health expenditure data. After specifying our model, we then discuss the underlying causal identification assumptions. As our identification strategy mainly exploits variation in AV values across types of plans, this discussion is closely related to the institutional details in the previous section. The

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

final subsection summarize the main assumptions required for calculating point elasticities of demand.

4.1 Modeling Health Expenditure Distributions

One of the core topics of inquiry among health econometricians has been 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 distributions of health care spending 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 (e.g. 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 the logarithm of spending 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 which 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). In addition to other approaches (see Gilleskie and Mroz (2004) for a semiparametric proposal) a popular model incorporates a nonlinear model within a Generalized Linear Model (GLM), see Mullahy (1998); Manning and Mullahy (2001); Buntin and Zaslavsky (2004); 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).

After evaluating several diagnostic tests, we report results from two types of models: (a) the shifted log transformation used by Aron-Dine et al. (2013), and (b) the econometrically more sophisticated GLM approach. As we show in the Results Section and the Appendix, our findings are quite similar across these two classes of models (cf. Buntin and Zaslavsky (2004)).

4.2 Empirical Model

Our first model, based on the log-transformation of healthcare spending, is:

$$log(y_{it}) = \alpha + \beta AV_{p(i,t)} + \gamma Risk_{i,2013} + X_{i,t}'\theta + \delta_t + \rho_{c(i,t)} + \epsilon_{it} \tag{1}$$

where y_{it} measures health care spending (in dollars) of individual i in month t. When presenting our results, we differentiate by total spending and the spending category. 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. As discussed in Section 3, the AV is determined by two factors: the plan chosen and the household income relative to the FPL. The household income determines the cost-sharing subsidies which decrease the AV of silver plans stepwise from 94% to 70% for incomes between 100% and 250% of FPL.

$Risk_{i,2013}$ is a crucial control variable (Section 3 discusses details,) which measures the risk score of individual i in 2013, prior to choosing an Exchange plan. The risk scores are calculated using the APCD and Johns Hopkins ACG software, which is used by many commercial insurers to estimate individual spending and determine premiums. By including pre-period $Risk_{i,2013}$, the model allows for plan selection that is potentially correlated with unobserved health status that is not explained by $X_{i,t}$ or 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 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 correlation that may be caused, for example, by shared deductibles and other nonlinear plan features at the household level (Cameron and Miller, 2015).

Our second estimation approach is the GLM model. Specifying the "log link" as the link function $g(\mu_{i,t})$, where $\mu_{i,t}$ is the conditional mean of health care spending, the model can be written as:

$$E[y_{it}|x_{i,t}] = exp(\alpha + \beta AV_p + \gamma Risk_{i,2013} + X'_{i,t}\theta + \delta_t + \rho_c + \epsilon_{it}) \tag{2}$$

The link function determines the shape of the conditional mean and also 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). We found that the log-link and gamma variance model provided the best fit of the models tested, and a log-link negative binomial variance model yields very similar results.

4.3 Identification

Our empirical model exploits between-enrollee variation in AVs. We experimented with exploiting within-enrollee variation in AVs by adding enrollee fixed effects to our models but, not surprisingly, we lack the statistical power for this exercise: very few enrollees can and do switch plans within a year or between 2014 and 2015. Only 3113 individuals (7% of all silver plan enrollees) changed AV categories within the silver coverage tier between 2014 and 2015 (see Appendix, Table A5). 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.

For β in equation (1) to have a causal interpretation, $AV_{p(i,t)}$ must be conditionally exogenous. That is, first, reverse causality must not be driving a relationship between $y_{i,t}$ and $AV_{p(i,t)}$. Second, there must not be an omitted variable that is correlated with both $y_{i,t}$ and $AV_{p(i,t)}$.

Reverse causality is unlikely to be an issue. It would only be relevant if higher ex post health care spending in year t causally affected the actuarial values (AVs) of the plan, which must be chosen ex ante during an open-enrollment window. Note that $AV_{p(i,t)}$ does not measure the realized AV of the plan, but is instead the ex ante expectation of the AV that is estimated using a calculator provided by CMS, and is based on a fixed population of individuals so that plan selection does not confound AV estimates. In addition, to minimize selection concerns, we focus only on silver plans with cost-sharing subsidies (that is, with AVs between 73% and 94%, excluding standard 70% silver plans). This implies that the identifying variation is solely determined by the applicant's indicated household income during the open enrollment period.

The main threat for a causal interpretation of β is selection into plans based on unobservables. We carry out several checks to assess the potential for such selection. First, recall that our sample is very homogenous as it contains low- to middle-income residents of Utah without access to employer-sponsored insurance (ESI). Also note that 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, as seen in equation (1), we control for age, gender, county, and month-year fixed effects.

Finally, the identifying AV variation stems from differences in household income categories 100-150%, 150-200% and 200-250% 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. Rational forward-looking agents may be tempted to do so. However, 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).[3]

[3] 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.

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 co-insurance 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. The 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 the average price may approximate the average behavior reasonably well.

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

Aron-Dine et al. (2013) call for "more attention to how the nonlinearities in the health insurance contracts may affect the spending response" (p.219). However, in combination with skewed health spending data that may be sensitive to the modeling approach (Section 4.1), allowing for different behavioral assumptions introduces even more statistical uncertainty. 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). We also test whether the estimated elasticity differs among individuals enrolled in plans with dedctibles above the median deductible *conditional on plan AV*. This variation in deductibles within a CSR-category can only be achieved by differences in non-linearities across plans with the same actuarial value. We find economically and statistically insignificant differences in the implied elasticities associated with changing the nonlinearity of plan benefits conditional on AV. In addition, we stratify the estimates by socio-demographics and categorize the care received into low-value and high-value care (Brot-Goldberg et al., 2017).

5 Data

The main dataset we use is the Utah All-Payer Claims Dataset (APCD) from 2013 to 2015. This database contains the universe of commercially insured claims for Utah residents along with all claims and their health insurance information on a monthly basis over three years. To be precise, we observe anyone who utilized health care in the state of Utah or who was resident and insured between 2013 and 2015.

This database was created in accordance with state law, the Utah Health Data Authority Act, and requires virtually every commercial insurance carrier in the Utah to submit every healthcare claim to the Office of Health Care Statistics each quarter. Relative to the overall state population of 2.9 million in 2013, the APCD contains 2.1 million unique commercially-insured enrollees between 2013 and 2015. For each individual (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.

The data are submitted to the state in a standardized way, consisting of four specific components, of which we use three components in this study. First, insurers provide a person-month eligibility file containing every individual enrolled in each plan each month. This enrollment information is provided even if the enrollee never has a medical claim. The eligibility file contains information about individuals, relationships between individuals enrolled in the same plan, and details about the source of coverage. The key components for our analyses 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 claims files. These databases contain charged amounts, negotiated amounts, amounts payed by insurers, member liabilities, copayment amounts, deductible amounts, and provider identifiers. The medical claims also contain service codes, dates, and diagnoses. The drug claims include NDC codes, purchase dates, quantities, refills, days supplied, dispensing fees, and pharmacy identifiers.

5.1 Sample Selection

Although we use 2013 risk scores, we restrict the main working sample to Utah residents enrolled in silver FFM plans between January 2014 to December 2015.[4] 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 subsidy-eligible silver plan (that is, with household incomes between 100% and 250% of FPL, who purchased a silver plan) either in 2014 or 2015.[5] The focus on silver plans helps reduce concerns about selection into bronze, gold or platinum plans, which may be more likely to be based on health status.

We collapse the data at the enrollee-month level and obtain 43,247 unique individuals with incomes below 250% FPL who enrolled in ACA silver plans in 2014 and 2015. The total number of enrollee-month observations is 381,161, and the panel is unbalanced.

[Insert Figure 1 about here]

Figure 1 shows enrollment pattern by CSR category and coverage tier over time. While the platinum plan has by far the lowest enrollment numbers, the gold plan has the highest enrollment numbers, followed by CSR 94 (silver plan for enrollees with incomes between 100 and 150% FPL), the bronze plan and CSR 87. Overall, when adding up enrollment by tiers (gold, silver, bronze, platinum), the silver plan is the most popular plan, which is not surprising given that cost-sharing subsidies are only provided in the silver plan category. In terms of enrollment pattern over time, one finds a strong increase of enrollment over the course of the first exchange year 2014, and then again over the course of the year 2015. There also appears to be substitution out of gold plans into silver plans at the end of 2014.

[4] 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.

[5] Specifically, our sample selection criterion specifies that enrollees have to be between 18 and 64 on January 1, 2014. Moreover, they had to be enrolled for any 9 calendar months per calendar year in any CSR plan.

Although the data allow us to identify family plans, in the main approach, we only 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 the plans' average (not actual) AVs to individuals' health care spending. In robustness checks, we also provide estimates for family plans.

5.2 Health Care Spending Measures

Our main dependent variable is health care spending. Summing over all recorded claims (these are actual payments based on negotiated prices or "allowed amounts") we differentiate by the spending categories shown in the Descriptive Statistic in Panel A of Table 1. All values are in nominal dollar terms. In Table 1, we sum over all allowed amounts recorded in the Utah APCD over the course of the calendar year.

[Insert Table 1 about here]

As seen, total spending averages $4329 per year. This may appear as a relatively low value when compared to the average amount for employer-sponsored insurance (ESI) in Utah. In 2014, the total ESI premium was $5538 in Utah (Kaiser Family Foundation, 2015a). However, note that this is a sample of low-income residents without stable insurance. In 2013, the year before the exchange was established, individuals in our sample were uninsured for 1.9 months, on average.

Mean Total Monthly Spending in Panel B is $487, which would equal $12 \times \$487 = \$5844$ over 12 months. This number is very close to the average ESI premium in Utah. Looking at *Utah-Scaled 2015 Risk Score* in Panel B of Table 1 reinforces that notion. While our sample is in slightly worse health than the average resident of Utah, the state of Utah has one of the lowest average levels of health spending in the country, and the enrollees in our sample have lower risk scores than the average non-elderly adult nationally.

As seen in Panel A of Table 1, the other spending categories are annual spending for ER care ($447) as well as inpatient ($765), outpatient ($987), pharmaceutical ($782) and OOP spending ($345). Annual spending below the deductible amounts to $183 per year.

5.3 Risk Scores

We make use of 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. We use the John Hopkins ACG System© software to calculate risk scores. This is the state-of-the art approach in the literature to measure the health status of individuals; insurers use the same software and approach (e.g. Einav et al. (2013) or Handel (2013)).

[Insert Figure 3 about here]

Figure 3 shows a histogram of the risk scores from our analysis 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 remaining selection concerns to the extent that these continuous and very precise health risk measures capture all systematic between-enrollee variation in health status that is also correlated with plan selection.

5.4 Other Variables

Panel B of Table 1 also lists the descriptive statistics of the remaining socio-demographic variables that we use. For example, slightly more than half of all enrollee-month observations are women. Roughly a third of 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 (2) as our main model. Analogous and robust findings from the simpler log-OLS variant in equation (1) are in the Appendix. Both models link individual-level variation in health care spending to variation in AVs. We present findings using variation in AVs as well as elasticity estimates using the logarithm of the coinsurance rate.

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 flag treatment episodes as low or high-value care. In addition, we estimate elasticities for different types of drugs, such as prescription drugs for acute and chronic diseases as well as brand name drugs, generic drugs or lifestyle drugs. For this approach, we follow the categorization of Chandra et al. (2010).

Next, in Section 6.3, we investigate potential selection concerns. We provide a series of robustness checks and do not find much evidence that, conditional on having selected silver plans, enrollees strategically manipulated their incomes to obtain higher CSRs. In Section 6.4, we investigate effect heterogeneity. We stratify the findings by age, gender, family plan, and health status. Finally, we provide evidence on the role of non-linearities 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 category 87% ($4275) and 94% ($4451). The spending patterns by types of care show that ER spending strictly increases with the plans' AV from $324 to $505 (i.e., by 56%).

[Insert Figure 2 about here]

The difference in ER spending between CSR 73 and CSR 94 enrollees is also graphically illustrated by Figure 2. Figure 2a 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. The top 3% of ER consumers among CSR 94 enrollees consume ER care worth more than $4000.

While the details differ by the specific plans selected, the deductible in a CSR 94 plan could be as low as $0, whereas a CSR 73 plan typically would have a $1000 deductible (Center on Budget and Policy Priorities, 2015). Gabel et al. (2016) report that 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 2b 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. As a result, as seen in Panel A of Table 1, OOP spending and spending below the deductible strictly decreases in AVs (from $592 to $253 for *Out-of-Pocket Spending* and from $411 to $105 for *Deductible Spending*).

Table 1 also illustrates 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 is also illustrated by the cdfs by AV categories in Figures 2c and d.

[Insert Table 2 about here]

Tables 2 and 3 show the main parametric estimates from our GLM model, corresponding to equation (2). Each column of Tables 2 and 3 represents estimates from separate regressions where the outcome measures different categories of care.

Table 2 includes binary categorical controls for CSR 87 and CSR 94 plans, with CSR 73 as the baseline category. The dependent variable is spending by category in $1000. When comparing CSR 94 to CSR 73 plans—and after controlling for the 2013 risk score, age, gender county and time fixed effects effects—spending in all five categories is significantly different in the CSR 94 plans. Total spending is $230 (5%), ER spending is $510 (114%), and inpatient and outpatient spending are $300 (39% and 31% respectively) higher. OOP spending is a highly significant $790 (229%) lower.

When comparing CSR 87 to CSR 73 plans, the CSR 87 plans have significantly higher outpatient spending ($150 or 15%). And OOP spending is $420 (106%) lower. The model lacks the statistical power to precisely estimate the other spending differences which are, however, suggestive.

[Insert Table 3 about here]

Table 3 collapses the three AV categories into one *Coinsurance Rate*, which is measured as 1 minus the plan average AV. Recall that we estimate a GLM model with a log-link and a gamma variance. Consequently, under some assumptions (Section 4.3), the point estimates from this table can be interpreted as demand elasticities.

Compared to the inelastic estimates of -0.2 from the RAND HIE, our overall elasticity point estimate is substantially larger in magnitude, -1.2. It is also statistically different from -0.2. Moreover, ER spending (-2.6), inpatient and outpatient spending (-1.5) are all estimated to be quite elastic in this population. Corroborating the first-stage effect of assignment to more generous plans, the point estimate for OOP spending is a highly correlated with 1 minus the average plan AV.

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 much more price-elastic demand than the US population more generally. As a comparison, using recent US data from 73 employers and 171 million person-month observations, Ellis et al. (2017) find overall elasticities of -0.44 and very small elasticities of -0.04 for ER visits.

Table A3 in the Appendix runs the simple OLS models in equation (1) and conditions on enrollees with any positive medical spending (the intensive margin component of spending variation corresponds to the identifying variation in the reported GLM estimates). As seen, the findings for total spending and outpatient spending are relatively similar to the GLM estimates. However, the elasticity estimates for ER and inpatient spending are smaller, driven in part by the small sample of people who use these categories of care. For example, the inpatient spending elasticity is estimated to be 0.06 (compared to -1.5), the outpatient elasticity at -1.4 (compared to -1.5), and the ER elasticity is -0.6 (compared to -2.6). This pattern suggests that the ER and inpatient spending elasticities are mainly driven by the extensive rather than the intensive margin. This is consistent with Figure 2a, which shows that 90% of enrollees do not use any ER care.

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

In this section, we follow Brot-Goldberg et al. (2017) and categorize medical care into high and low-value care. We then re-estimate elasticities separately for these two categories. The results are in Table 4.

[Insert Table 4 about here]

We find that low-income enrollees are very price responsive with respect to low-value medical care, with an implied elasticity of -3.3, almost three times larger, and statistically significantly different than the overall elasticity of demand. However, less reassuringly, we also find substantial price responsiveness to unambiguously high value care, which has an average elasticity of -2.0. These findings suggest that: (1) price and market mechanisms appear to work for low-income enrollees with less experience navigating private insurance plans, and (2) low income enrollees are very price sensitive across all types of care, even with respect to high-value care. These findings are in line with Brot-Goldberg et al. (2017). Brot-Goldberg et al. (2017) do not calculate elasticities but show that ESI enrollees respond to cost-sharing by cutting back demand across all types of care. Our findings extend their results to FFM enrollees.

6.3 Investigating Selection into Health Plans

To minimize concerns related to sorting into health plans, we employ several strategies. First, we homogenize the sample as much as possible. Recall that Utah already has a relatively homogenous population. Further, we focus on adult FFM enrollees between the ages of 18 and 64 and who had a stable enrollment of at least 9 months in a given calendar year.

Second, in addition to APCD data, we use administrative data from the Multidimensional Insurance Data Analytics System (MIDAS) of the Centers for Medicare & Medicaid Services (CMS). These data are FFM enrollment data for Utah and include everybody who selected FFM plans during the official 2014 enrollment period (Oct 1, 2013 to March 31 2014). Table A1 (Appendix) shows the take-up rates by tiers and income levels. Overall, only 2.5% of all enrollees had incomes below 100% FPL and 11% had incomes above 400% FPL. The large majority of enrollees (71%) falls within the income range that we investigate, namely 100 to 250% FPL.

As seen in the notes to Table A1 (Appendix), selection clearly takes place between different *tiers* of plans outside the CSR eligibility range. For example, among the poorest enrollees with incomes of less than 100% FPL, 18% selected Bronze, 20% Gold and 41% Silver Plans (ironically, enrollees with incomes <100% FPL are *not* eligible for CSRs). Among the richest enrolles with incomes of more than 400% FPL, 20% selected Bronze, 38% Silver, but 39% Gold Plans. Without premium and cost-sharing subsidies, it is safe to conclude that sicker enrollees were more likely to enroll in Gold plans with more generous coverage. Consequently, when interpreting spending differences across tiers as in Table A2 (Appendix), it is very difficult to disentangle responses to cost-sharing from underlying enrollee characteristics based on which enrollees may have sorted into plans (e.g. Einav et al. (2013)).

To shut down such selection into tiers, we condition our working sample not only on silver plans but silver plans for enrollees with incomes between 100% and 250% of FPL. Sorting into different AV tiers is much less concerning within the silver tier. The reasons are that (a) the subsidy design nudges enrollees to take-up Silver Plans in these income brackets as only Silver Plans are eligible for CSR. And (b) CSR categories, and thus AVs, are solely determined by household income category. Next we show that socio-demographics are indeed very balanced across tiers *within* the CSR eligibility range. We also show that there is no evidence that enrollees strategically manipulated their incomes to obtain higher CSRs.

Related to (a), as shown in Table A1, reassuringly, *within* the CSR income brackets (100-150, 150-200, 200-250% FPL), the socio-demographics appear to be balanced across tiers; a 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 with respect to socio-demographics. For example, the average age of enrollees who selected Silver Plans and whose income was between 100 and 150% FPL was 34.4 years, whereas those who selected Gold/Platinum plans were 35 years old and those who selected Bronze plans were 34.3 years old. Similarly, 1.4% of enrollees who selected Silver Plans with incomes between 100 and 150% FPL were black; the shares for Gold/Platinum and Bronze plans were 1.3% and 2.0% respectively. These findings are in line with Table 1 which illustrates only minor socio-demographic differences across CSR categories.

While socio-demographics within income brackets are balanced, Table A1 also indicates that—not surprisingly—socio-demographics differ 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 socio-demographic differences across CSR categories only bias our estimates to the extent that unobservables exist that are systematically correlated with the CSR category and health care utilization. However, it is difficult to think of obvious unobservables that are related to both differences in cost-sharing and health status (which we control for using the 2013 risk score). In addition to controlling for precise health measures in the year prior to enrollment, our models also control for age, gender, county and calendar month fixed effects.

[Insert Figure 4 about here]

Finally, one of the few remaining concerns is that enrollees strategically manipulate their income to obtain higher cost-sharing levels. However, there appears to be no evidence, neither in the APCD data nor the CMS data that this was the case. Figure 4 plots the take-up rates for silver plans along the income distribution in Utah in 2014. Although the level of take-up clearly differs across income categories (see also Table A1), we do not observe any bunching at the income threshold margins. This finding strongly 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 Effect Heterogeneity

Next, we investigate heterogeneity in the elasticity estimates. Specifically we stratify our results by age, gender, urban counties, family plans, and enrollees' health status in 2013. Technically, we run our preferred model in equation (2) but interact the main regressor of interest, $Coinsurance_p = (1 - AV_{p(i,t)})$, with the covariate of interest and add this interaction term to the model (in addition to keeping the two variables in levels).

[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. Although not always precisely estimated, across all types of care, we find that price responsiveness increases with age. It is also systematically larger for males (Panel B). The same is true for people in urban areas (Panel C), with one exception: demand for ER care. This suggests that the medical care infrastructure in urban areas offers more alternatives to seek care and hence be more price responsive. For example, free charity care is certainly easier accessible and availability in urban regions. At the same time, the smaller (yet still elastic) demand elasticity estimate for ER care suggests that people who seek ER care in urban counties primarily represent medical emergencies.

Panel D investigates the elasticity for family plans. Enrollees in family plans are more price sensitive with respect to ER care and OOP spending in particular. Because family plans typically have embedded deductibles and other cost-sharing elements, the larger price responsiveness is not a function of larger cost-sharing amounts. Rather, it is likely that families' budget constraints or preferences differ. (Note that the spending amounts only refer to adults' claims, not children's, who fall under our sample selection criteria Section 5.1.)

In Panel E of Table 6, a clear pattern emerges: The higher the risk score, the less elastic the demand for health care. In other words: Sicker people are less price responsive.

6.5 Considering Nonlinearities and Other Checks

In this final subsection, we stratify the estimates by the size of the deductible. Specifically, 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. 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. Holding the *Coinsurance Rate* fixed, a higher deductible can only occur by changing the nonlinearity of a plan within a CSR category. We interpret this evidence as a check for the empirical relevance of nonlinearities in our demand elasticity estimates.

[Insert Table 7 about here]

As seen in Table 7, the interaction term *Log Coinsurance* $\times$ *Above Mean Deductible* is small in size and insignificant for 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.

7 Conclusion

This paper's findings are based on unique All-Payer Claims Data (APCD) from Utah over three years. Our empirical models exploit within-silver plan variation in actuarial values (AVs) as a result of differences in cost-sharing subsidies based on differences in income categories. Several checks let us conclude that strategic income manipulation to obtain higher AV plans are unlikely to be a major threat to our estimates. In addition, our elasticity estimates condition on pre-enrollment risk scores to control for possible differences in health across AV categories. Our models also control for age, gender, calendar-month and county fixed effects and are based on expected AVs over a calendar year (rather than actual endogenous spot prices).

To our knowledge, this is the first paper to use APCD data for an entire state over three years and to exploit within silver plan variation in AVs (which are solely determined by enrollees' income). Moreover, we distinguish our demand elasticity estimates not only by standard medical care categories but also by definitions of low and high-value care following Brot-Goldberg et al. (2017) and different types of drugs following Chandra et al. (2010).

Our findings are generally in line with existing demand elasticity estimates, particularly recent ones which are also based on ACA Exchange enrollees (Abraham et al., 2017). We consistently find substantially larger demand elasticities than typically reported for the general population. Our overall estimate is -1.2 (as compared to the RAND HIE estimate of -0.2)—estimates for ER (-2.6) and OOP spending (3.9) are even larger. Maybe most importantly, we find very large price responsiveness for low-value care (-3.3) and lifestyle prescription drugs (-2.3) as compared to drugs for chronic conditions (-0.6). These findings suggest that price mechanisms appear to work even (or especially) for a low-income population that potentially has less experience navigating private health insurance plans.

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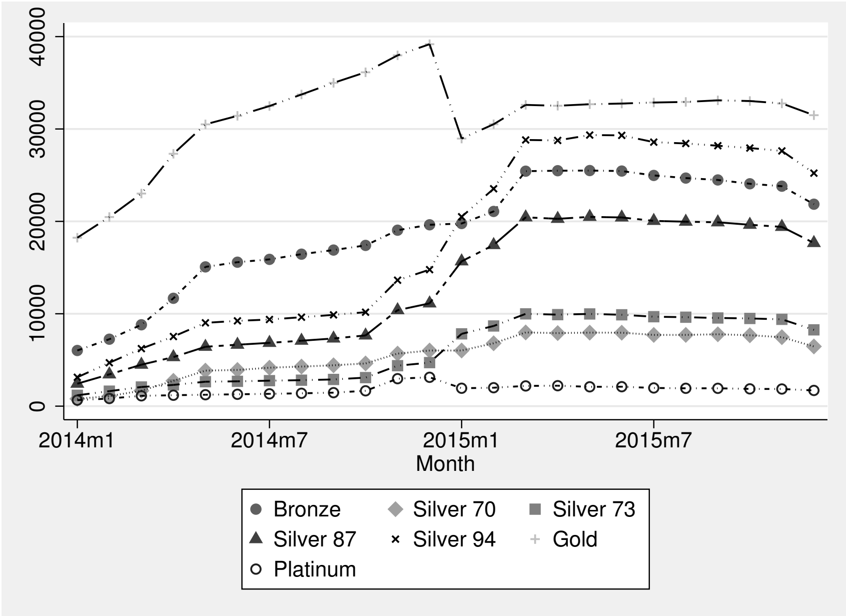
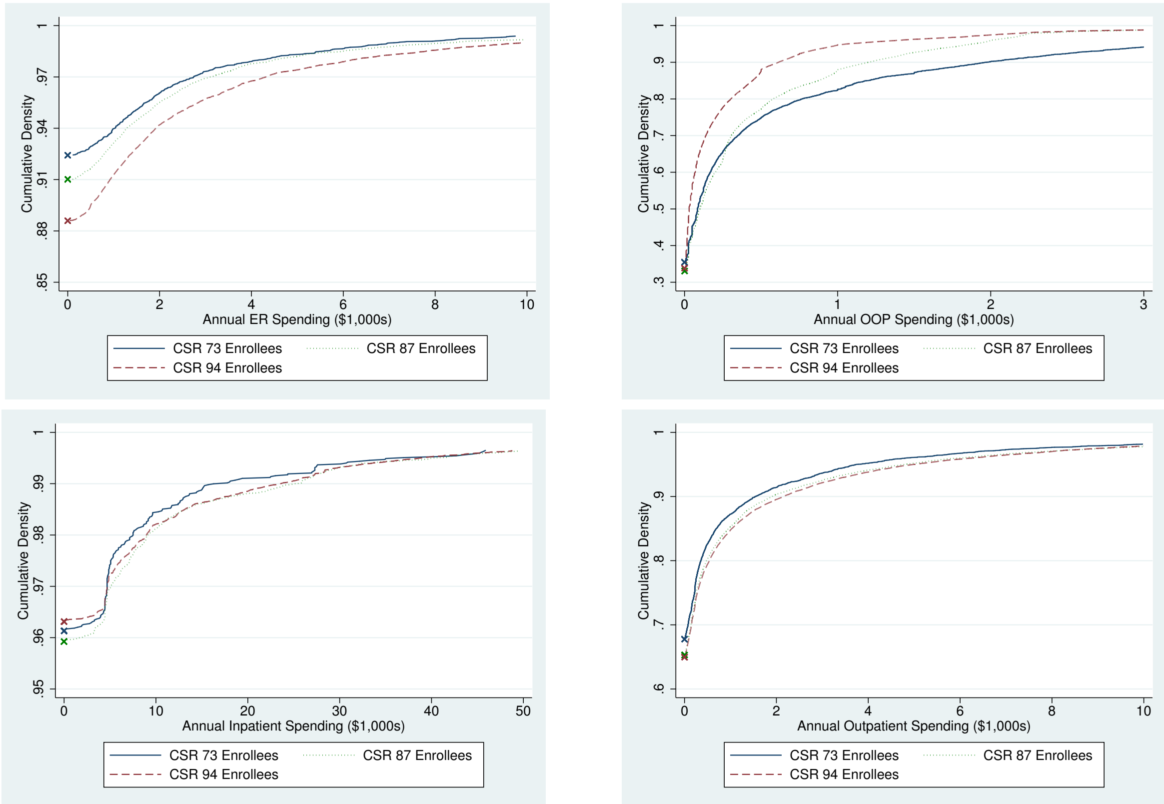
Figure 1: Enrollment on Utah FFM Exchange by Coverage Tier and CSR Categories



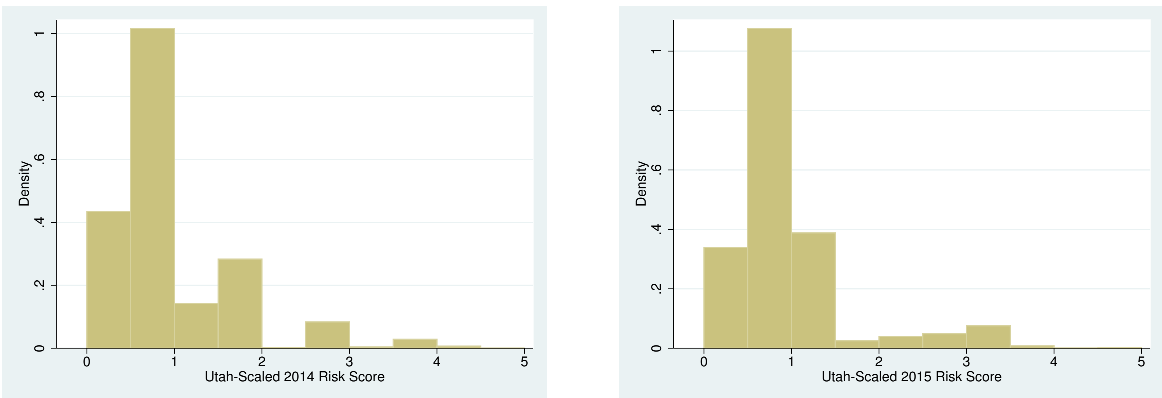
Source: Utah APCD.

Figure 2: Cumulative Density Functions by Spending and CSR Categories



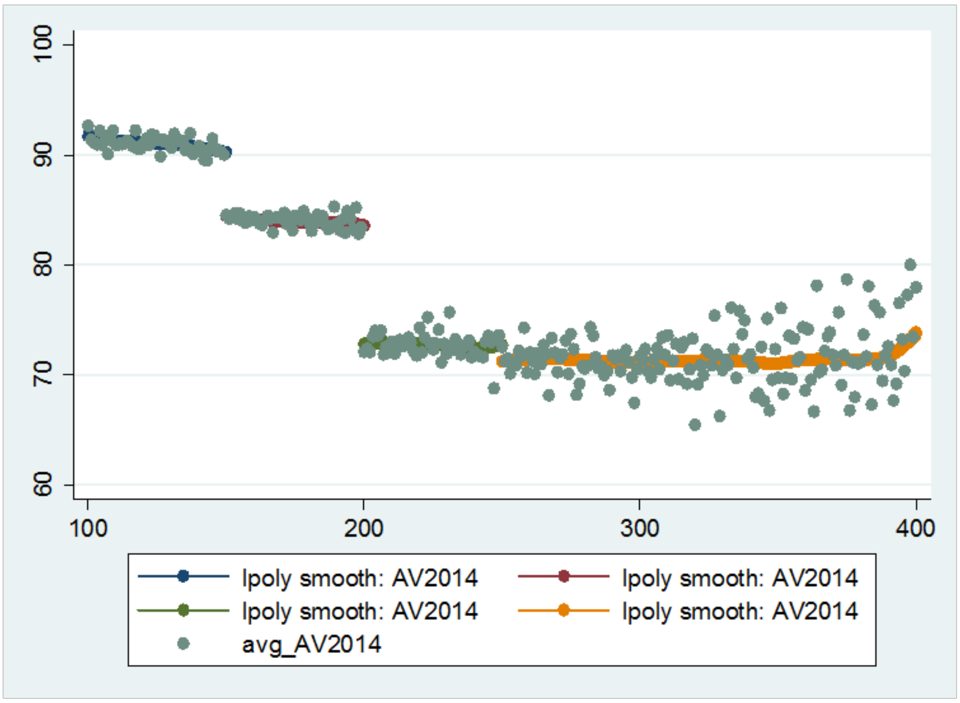
Source: Utah APCD, own calculations, own illustration

Figure 3: Risk Score Distributions for Working Sample



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
Mean Total Monthly Spending	430.49	478.13	507.02	487.33
Utah-Scaled 2014 Risk Score	0.96	0.98	0.96	0.97
Utah-Scaled 2015 Risk Score	1.00	1.04	1.09	1.06
Uninsured Months in 2013	1.50	1.77	2.18	1.94
Person-Months	50,229	128,931	202,001	381,161
Persons	5689	14,403	23,155	43,247

Source: Utah APCD. 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	0.23*	0.51*	0.31*	0.30*	–0.79*
	(0.05)	(0.11)	(0.05)	(0.13)	(0.04)
CSR 87% AV Plan	0.09	0.17	0.15*	0.17	–0.42*
	(0.06)	(0.12)	(0.06)	(0.14)	(0.03)
2013 Risk Score	2.81*	2.46*	2.89*	3.05*	1.67*
	(0.13)	(0.27)	(0.11)	(0.47)	(0.08)
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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
Coinsurance Rate	–1.17*	–2.60*	–1.55*	–1.48*	3.93*
	(0.26)	(0.56)	(0.25)	(0.63)	(0.16)
2013 Risk Score	2.82*	2.45*	2.89*	3.05*	1.66*
	(0.14)	(0.27)	(0.11)	(0.48)	(0.08)
Person-Months	381,161	381,161	381,161	381,161	381,161
Persons	28,271	28,271	28,271	28,271	28,271

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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
Coinsurance Rate	–1.17*	–1.97*	–3.28*
	(0.26)	(0.44)	(0.61)
2013 Risk Score	2.82*	1.86*	4.30*
	(0.14)	(0.19)	(0.22)
Person-Months	381,161	381,161	381,161
Persons	28,271	28,271	28,271

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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
Average Coinsurance Rate	–1.30*	–1.65*	–0.58	–2.28*	–1.04	–1.52*
	(0.40)	(0.66)	(0.79)	(0.50)	(0.67)	(0.21)
2013 Risk Score	3.67*	3.09*	3.67*	4.76*	3.90*	3.40*
	(0.14)	(0.18)	(0.31)	(0.20)	(0.21)	(0.10)
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: APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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					
Coinsurance Rate	–0.77	–2.11*	–1.57*	0.31	4.28*
	(0.47)	(0.85)	(0.46)	(0.95)	(0.29)
Coinsurance Rate*Age 31-50	–0.73	–0.91	–0.17	–2.69*	–0.40
	(0.48)	(0.90)	(0.50)	(1.09)	(0.31)
Coinsurance Rate*Age 51-64	–0.33	–0.47	0.31	–1.94	–0.60
	(0.59)	(1.20)	(0.58)	(1.23)	(0.37)
Panel B: Gender					
Average Coinsurance Rate	–0.87*	–2.52*	–1.20*	–0.43	4.52*
	(0.28)	(0.56)	(0.31)	(0.63)	(0.19)
Coinsurance Rate*Male	–0.64	–0.18	–0.76	–2.37	–1.30*
	(0.52)	(1.10)	(0.50)	(1.37)	(0.32)
Panel C: Urban					
Average Coinsurance Rate	–0.75	–3.86*	–0.96	0.03	4.23*
	(0.66)	(1.34)	(0.59)	(1.72)	(0.43)
Coinsurance Rate*Urban	–0.48	1.40	–0.67	–1.72	–0.35
	(0.72)	(1.46)	(0.65)	(1.85)	(0.46)
Panel D: Family Plan					
Average Coinsurance Rate	–0.28	–0.95	–0.83*	–1.41	3.37*
	(0.39)	(0.84)	(0.36)	(0.98)	(0.25)
Coinsurance Rate*Family Plan	–1.15*	–2.66*	–0.71	0.25	1.23*
	(0.51)	(1.08)	(0.50)	(1.30)	(0.33)
Panel E: Health					
Average Coinsurance Rate	–2.11*	–2.48*	–1.86*	–1.73*	3.54*
	(0.37)	(0.83)	(0.39)	(0.80)	(0.24)
Coinsurance Rate*2013 Risk Score	6.62*	–0.91	2.24	1.77	2.81*
	(2.25)	(3.72)	(1.96)	(5.01)	(1.10)
2013 Risk Score	2.10*	2.54*	2.65*	2.87*	1.37*
	(0.26)	(0.52)	(0.22)	(0.91)	(0.16)
N	381,161	381,161	381,161	381,161	381,161
N Clusters	28,271	28,271	28,271	28,271	28,271

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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: Elasticity Estimates by Above Average Deductible

	Total Spending	ER Spending	Outpatient Spending
	(1)	(2)	(3)
Log Coinsurance	–1.907*	–0.387*	–1.774*
	(0.331)	(0.057)	(0.299)
Log Coinsurance × Above Mean Deductible	–0.109	0.068	0.020
	(0.400)	(0.070)	(0.363)
Above Mean Deductible	–0.170*	–0.019	–0.117*
	(0.049)	(0.010)	(0.045)
2013 Risk Score	3.928*	0.457*	3.537*
	(0.202)	(0.068)	(0.185)
Person-Months	381,161	381,161	381,161
R^2	0.078	0.005	0.081

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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.

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% FPL are 41% (Platinum/Gold), 28.5% (Silver) and 28.6% (Bronze). Take-up rates for income category >400% 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% FPL, 70.7% had incomes between 100 and 250% FPL, 15.4% had incomes between 250 and 400% FPL, and 11.4% had incomes above 400% 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: 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	–1.21*	–0.57*	–1.43*	0.06	2.69*
	(0.14)	(0.07)	(0.17)	(0.04)	(0.15)
2013 Risk Score	1.20*	0.46*	1.57*	0.05*	0.41*
	(0.10)	(0.09)	(0.12)	(0.03)	(0.07)
N	175286	175286	175286	175286	175286
N Clusters	24386	24386	24386	24386	24386

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 one model as in equation (1) but 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: Main Estimates: Drop All Data After July 2015

	Total Spending	ER Spending	Outpatient Spending	Inpatient Spending	Out-of-Pocket Spending
Average Coinsurance Rat e	–1.29*	–2.19*	–1.39*	–1.21	4.21*
	(0.29)	(0.59)	(0.26)	(0.65)	(0.17)
2013 Risk Score	2.88*	2.46*	2.90*	3.21*	1.62*
	(0.15)	(0.29)	(0.11)	(0.49)	(0.08)
Person-Months	333,207	333,207	333,207	333,207	333,207
Persons	30,270	30,270	30,270	30,270	30,270

Source: Utah APCD. Standard errors are clustered at the family level. * indicates significance at 5%. 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 (2) 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 A5: 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.