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Los Angeles

Essays on the Economics of  
Health Insurance Markets

A dissertation submitted in partial satisfaction of the  
requirements for the degree Doctor of Philosophy  
in Economics

by

Richard Raymond Domurat

2018

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## ABSTRACT OF THE DISSERTATION

Essays on the Economics of  
Health Insurance Markets

by

Richard Raymond Domurat

Doctor of Philosophy in Economics

University of California, Los Angeles, 2018

Professor John William Asker, Co-Chair

Professor Adriana Lleras-Muney, Co-Chair

This dissertation includes three chapters on the health insurance markets established by the Affordable Care Act (ACA), known as exchanges. Chapter 1 estimates the demand for each plan in the exchange in California using a discrete choice model. The model incorporates heterogeneity in consumer preferences and in product characteristics, including hospital and primary care physician (PCP) networks. I address two complications in the estimation regarding prices: First, endogeneity of prices is addressed by using networking hospital costs as instruments, and second, prices for any given plan can vary across consumers within the market. I combine many data sources to account for differences in plan networks and in underlying costs. The estimates imply consumers are highly sensitive to prices, with market shares declining by 3%-5% for just a \$1 increase in the premium. Demand also responds to hospital and PCP networks, but to a relatively small degree. Consumers are relatively price-sensitive along the take-up margin: for a \$1 increase in premium subsidy, average take-up increases 1.4% (1.2% and 2.1% for subsidized and unsubsidized populations respectively).

Chapter 2 uses the demand model from Chapter 1 to examine how insurance market regulations affect prices and enrollment in the ACA exchange in California. I examine two supply-side policies from the ACA—community rating and risk adjustment. Particular attention is placed on quantifying how these policies impact adverse selection. Without risk adjustment, community rating in the ACA would lead to a significant reduction in enrollment in desirable plans and in take-up overall. Risk adjustment under the ACA roughly restores relative shares across plans to what they would be without community rating; however, the reduction in overall take-up from community rating is not restored with risk adjustment. An alternative risk adjustment method can increase enrollment by 3.0% and would have little impact on government spending. Other policies besides risk adjustment would be needed to further address low take-up among price-sensitive, low-cost consumers under community rating.

Chapter 3, written jointly with Isaac Menashe and Wesley Yin, examines the impact of information on insurance take-up in the ACA. We exploit experimental variation in the information mailed to 87,000 households in California’s ACA Health Benefits Exchange to study the role of frictions in insurance take-up. We find that a basic reminder of the enrollment deadline raised enrollment by 1.4 pp (or 16 percent) in this typically low-uptake population. Compared to the reminder alone, also reporting personalized subsidy benefits increases take-up among low-income individuals, but decreases take-up among higher-income individuals. This is despite reminder-only recipients eventually observing their subsidies before purchase, a pattern consistent with lack of awareness of subsidy benefits and either transaction costs of the purchase process or reference dependence. Finally, the letter interventions induced healthier individuals into the market, lowering aggregate spending risk by 5.9 percent. These findings suggest that procrastination/inattention and various search costs impact insurance take-up, and that basic reminders and greater salience can improve both enrollment and average market risk.

The dissertation of Richard Raymond Domurat is approved.

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University of California, Los Angeles

2018

*To my parents  
for encouraging me to be curious  
in life and to search for answers*

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# Chapter 1

## What is the Demand for Health Insurance Plans in ACA Markets? Evidence from California

### 1.1 Introduction

The U.S. government has been increasingly relying on market mechanisms to provide public health insurance benefits, such as in the longstanding Medicare and Medicaid programs. Recently, the government passed the Affordable Care Act (ACA), which established subsidized markets—or “exchanges”—where insurers compete for individuals that do not get health care coverage elsewhere. Understanding how these programs benefit consumers requires an understanding of what plan characteristics consumers value. This paper quantifies what plan attributes are valued by consumers in the ACA exchange in California—*Covered California*—by modeling plan demand based on enrollment decisions.

In this paper, I estimate a discrete choice model of insurance plans in Covered CA using individual-level enrollment data. The model is augmented from standard demand

models in the Industrial Organization literature<sup>1</sup> to fit this setting. Given the richness of the data, I model preference heterogeneity using observed household characteristics such as age and income. As is typical, prices are allowed to be correlated with unobservable plan characteristics—i.e. endogenous. To identify price sensitivity, I use costs from the hospitals in each plans networks. These are correlated with plan costs—and hence premiums—but uncorrelated with plan demand conditional on the explicit utility of the hospital network. Unlike in the traditional setting, prices for a given plan in Covered CA vary across consumers. To address this, I construct a method of moments estimator that allows for the usual endogeneity combined with this price heterogeneity across consumers. In addition to price, the demand model includes the plan utility generated from networks of hospitals and primary care physicians (PCPs), which I observe from plan provider directories. To my knowledge, this is the first paper to examine the effects of both provider types on plan demand in an ACA market. Finally, I use exogenous variation in choice sets to identify the demand for any insurance, and quantify how take-up responds to changes in subsidies.

I find that consumers in Covered CA are highly price-sensitive, more so than documented in other insurance markets. For a typical plan, a premium increase of \$1 causes a decrease in shares between 3% and 5%. While this is quite high relative to most health insurance products,<sup>2</sup> it is close to elasticities in similar markets (Shepard, 2016; Finkelstein et al., 2017a). While price seems to be a primary driver of plan choice for most enrollees, provider networks—both hospitals and PCPs—also matter and affect plan choice. For a typical enrollee, an academic hospital like UCLA is valued at \$2.41/month and doubling the number of PCPs within 5 miles is valued at \$2.76/month. Last, I use the model to calculate an

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<sup>1</sup>For example, Berry et al. (2004); Goolsbee and Petrin (2004); Nevo (2001)

<sup>2</sup>See footnote 56 in Ho (2006) for a good discussion of estimated elasticities in health insurance markets. My estimates are roughly between 3 and 6 times the elasticities in those markets with group insurance. The individual market in the ACA would be expected to have higher elasticities for a number of reasons (lower incomes, larger choice sets, transparency and plan standardization, etc.).

“extensive margin” price elasticity—i.e., how much overall take-up responds to a change in the subsidy level. I find that the probability of take-up decreases 1.17% for a \$1 decrease in the subsidy among the subsidized population, which represents the majority of exchange enrollees. This also is higher than previously documented in related work (Finkelstein et al., 2017a; Hackmann et al., 2015), and I address possible explanations in Section 1.6.

These results help understand the benefits of the ACA exchanges and have a number of implications. One major result is that consumers are highly responsive to premiums, which implies consumers put a high value on low-premium plans. Hence, low-cost plans such as Medicaid-style HMOs are likely to add a lot of value when entering an ACA market. Although consumers also value provider networks, the effects appear to be relatively small on average compared to the value of premium reductions. This suggests that “narrow networks” in ACA markets could provide significant welfare to consumers, if narrower networks lead to significant premium reductions without compromising quality. The high price sensitivity also has implications on the supply side of the market and means there is relatively low profitability for insurers. ACA markets have been characterized by few entrants,<sup>3</sup> and this is likely part of the explanation. All these results should be taken in the context of California’s exchange, which has been noted for its success.<sup>4</sup> The state employs many strategies that ensure increased competition (see Section 1.2), and could be a guide for other markets. Finally, the noted high price sensitivity along the extensive margin—which has been discussed elsewhere (Finkelstein et al., 2017a)—implies that subsidy design is important for determining the uninsured population going forward (Tebaldi, 2016).

These findings of this study contribute to a number of related areas of economics literature. First, it’s related to the recent work on the ACA exchanges (Ericson and Starc, 2015;

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<sup>3</sup>See <https://www.kff.org/health-reform/issue-brief/insurer-participation-on-aca-marketplaces/>

<sup>4</sup>See <http://www.modernhealthcare.com/article/20170613/NEWS/170619961>

Hackmann et al., 2015; Tebaldi, 2016; Panhans, 2017). It also relates more broadly to work on health insurance demand (Town and Liu, 2003; Ho, 2006; Shepard, 2016; Curto et al., 2014). To add to that previous literature, this is one of the first studies to use data from an actual ACA market (Tebaldi (2016) being the exception), but is the first to do so incorporating the effect of provider networks. Given the relatively low income of the ACA population, caution should be taken when extrapolating from the individual market pre-ACA, as is done in many papers studying the policy.<sup>5</sup> Moreover, since many plan characteristics are standardized, networks are the primary means by which plans are differentiated. By including the networks in demand, I can quantify how important networks actually are for plan choice. As a result, this paper presents accurate own-price and extensive margin elasticities that can be used for future policy analysis. The second contribution is to the methods of demand estimation more broadly (Berry et al., 2004; Nevo, 2001; Goolsbee and Petrin, 2004; Train, 2009). In most models, prices for a product are common to all consumers in a market. This paper provides a method to allow for prices that vary across consumers within the market.

## 1.2 Background: ACA Exchanges and Covered California

The US health insurance system is made up of separate markets, depending on enrollee age and income. Most older Americans and those with lower incomes are eligible for public insurance through Medicare and Medicaid respectively. For all other households, most get insurance through their employer. The remaining population is left with the option of being uninsured or getting coverage alone in the “individual market.” Prior to the introduction of the ACA, this market was notoriously riddled with problems (Claxton et al., 2016). Hence,

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<sup>5</sup>This can be seen by the differences in elasticities found in many of those papers relative to the current study.

a major part of the ACA was to address the market failures of the individual market and to make insurance affordable by providing government subsidies tied to income—the solution being the introduction of the exchanges.

While the exchanges are heavily regulated, the goal is for market mechanisms to provide a menu of options to consumers at competitive prices. The government established a number of regulations for the exchanges,<sup>6</sup> but generally any insurer that wants to participate can offer their plans in any market they would like. This implies larger markets can support more plans, all else equal. Plans are characterized by metal tiers which indicate the level of Actuarial Value (AV), ranging from Bronze (60% AV) to Platinum (90% AV). For households with incomes below 250% of the Federal Poverty Level (FPL), Silver plans get subsidies for additional cost sharing reductions. As in other health insurance markets, plans are also characterized by their provider networks. Generally speaking, this includes the doctors and hospitals that members can access when they are enrolled in a particular plan. In California, there are three broad types of networks: Preferred Provider Organizations (PPOs), Exclusive Provider Organizations (EPOs), and Health Maintenance Organizations (HMOs). These different levels of managed care, sorted from least to most, put constraints on what health services an enrollee can access.<sup>7</sup> In summary, insurers that want to compete in a given market enter with a given network type, a network of providers, and one or more of the aforementioned metal tiers. Aside from the premium, these are the primary characteristics of plan differentiation and therefore, the characteristics that determine plan choice.

The other main characteristic that determines plan choice is the premium. After the introduction of the ACA, premiums can only vary across enrollees by certain allowable

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<sup>6</sup>A good summary can be found here: <https://www.kff.org/health-reform/fact-sheet/summary-of-the-affordable-care-act/>

<sup>7</sup>PPOs have a preferred set of providers in-network where services are offered at a lower negotiated price. For EPOs, an enrollee is not allowed to see any providers outside of this network. Finally for HMOs, enrollees have additional restrictions on the types of providers (or services) an enrollee can access, even if they are in-network.

rating factors—only age in California; this notably excludes gender and preexisting health conditions. In Covered CA, plans set their premium for a 21 year-old and the premium for all other ages is determined by a regulated scaling factor that ranges from 0.65 for children to 3 for 64 year-olds. As a result, the premium for a 64 year-old will be exactly 3 times that of a 21 year-old for any plan in Covered CA.<sup>8</sup>

Most households that can potentially enroll in an exchange plan are eligible for subsidies and hence do not pay the full premium. The *net premium* the household pays is the gross premium less a government subsidy, called the Annual Premium Tax Credit (APTC). APTCs are available to households with incomes below 400% FPL.<sup>9</sup> The APTC is determined by the amount that guarantees the second lowest Silver (SLS) plan is a fixed share of income, ranging from 2% to 9.5%. Hence, regardless of age, the net premium for the SLS plan will be the same for all households with a given income. Moreover, the APTC is a fixed amount for all plans. Hence, the price of all plans relative to being uninsured varies with APTC, but the price *differences across plans* is unaffected.<sup>10</sup> Households with incomes above 400% FPL can buy a plan on the exchange or off the exchange but either way are ineligible for government subsidies. In the early years of the Exchanges, all households that were uninsured were also required to pay a penalty (i.e., the “mandate”), which was increasing in income. Unlike the APTCs, the penalty was realized when taxes were paid in the following year. For this reason, consumers may have been less responsive to the penalty than to the APTCs, despite them having the same theoretical incentives.

In addition to the regulations established by the federal government for the ACA, Cov-

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<sup>8</sup>A related regulation is the Guaranteed Issue requirement. Plans cannot exclude any enrollee that is willing to pay the aforementioned premium. Importantly, this prevents plans from excluding certain high risk individuals based on preexisting health conditions.

<sup>9</sup>In 2015, this income threshold was \$47,080 for singles and \$97,000 for a household of 4.

<sup>10</sup>The only exception is among the lowest income households when the APTC exceeds a plan’s gross premium. This occurs for about 40% of households in Covered CA, but only for about 8% of household-plans.



ered CA adds additional regulations to make the market more competitive. First, beyond the normal AV standardizations with metal tiers, cost sharing and benefits are also largely standardized.<sup>11</sup> Part of this standardization also includes a set of provider network requirements that ensures networks are adequate in size and quality for the number of plan enrollees. Additionally, insurers in California must offer a plan in each metal tier with a few exceptions to prevent segmenting the market.

## 1.3 Econometric Model of Plan Choice

In this section, I describe the model of demand for insurance in the ACA exchanges that I use for the empirical analysis. Plans are endowed with reputations and networks of physicians and hospitals. Before the start of the year, plans set premiums based on characteristics that are known by the consumers but unobservable to the econometrician. At the start of the year, all potential enrollees choose the plan that gives them the highest utility given expectations about medical needs.

### 1.3.1 Demand for Health Insurance

The insurance choice model is similar to other discrete choice models in the Industrial Organization and Health Care Economics literatures (Berry et al., 2004; Goolsbee and Petrin, 2004; Town and Liu, 2003; Ho, 2006). The key features of this model are that plan choice depends on *observable* characteristics of the plans and enrollees, while there is unobserved heterogeneity in the preference to remain uninsured—as in the “nested logit” model (Berry, 1994). I treat all plans as part of one “nest,” and the option to remain uninsured as its own separate nest. In the context of random coefficient models, this can analogously be thought of as a random coefficient on the outside option of remaining uninsured. The reason for

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<sup>11</sup>See: <http://hbex.coveredca.com/solicitations/QHP/library/QHPModelContract-Final.pdf>

using this structure is it allows for flexible substitution patterns along the extensive margin, and relaxes the *independence of irrelevant alternatives* (IIA) property of logit models.<sup>12</sup>

Potential enrollees are offered a menu of plan options and choose that which yields the highest idiosyncratic utility. The indirect utility of household  $i$  for plan  $j$  in market  $t$  is given as follows:

$$u_{ijt} = \underbrace{\alpha_i p_{ijt}}_{\text{Prem Disutility}} + \underbrace{EV_{ijt}^H + EV_{ijt}^P}_{\text{Network Utility}} + \underbrace{x'_{ijt} \beta_i}_{\text{Other Obs. Utility}} + \underbrace{\xi_{jt} + \zeta_{it}^{Ins} + (1 - \sigma)\varepsilon_{ijt}}_{\text{Unobservable Utility}} \quad (1.1)$$

where  $p_{ijt}$  is the net-of-subsidy premium and  $x_{ijt}$  is a vector of plan attributes (e.g. carrier and tier).  $EV_{ijt}^H$  and  $EV_{ijt}^P$  are the expected utilities derived from hospitals and PCPs respectively and are explained below in Section 1.3.2.<sup>13</sup>  $\xi_{jt}$  is an unobservable component of utility for plan  $j$  which is common to all households in market  $t$ , and can take on any distribution.  $\varepsilon_{ijt}$  is the idiosyncratic utility for each plan, and is i.i.d. Type I Extreme Value.  $\zeta_{it}^{Ins}$  is the household-specific utility of having insurance and is common across all plans. As in the nested logit model, the distribution of this variable is characterized by  $\sigma \in [0, 1]$ , and satisfies the property that  $\zeta_{it}^{Ins} + (1 - \sigma)\varepsilon_{ijt}$  is itself Generalized Extreme Value (Berry, 1994; Train, 2009).  $\sigma$  can be thought of as the degree of correlation in the unobserved utility of all plans relative to the outside option. If it is 0, then there is no correlation in the unobserved utilities and it becomes a standard logit model. In the context of random coefficients,  $\sigma$  can be thought

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<sup>12</sup>Intuitively, IIA means that within observable demographic groups, as prices increase, marginal consumers substitute to other options proportional to the group's market share. Adding in unobserved heterogeneity conversely allows for disproportionate substitution to certain options in the choice set. In the context of this model, it allows for consumers to disproportionately substitute to other insurance options rather than being uninsured. In Covered CA, roughly half of the market remains uninsured. Removing unobserved heterogeneity would imply roughly half of the marginal enrollees would choose to be uninsured rather than another insurance option when facing price increases, which is unlikely to be true.

<sup>13</sup>Note the functional form assumes separability of utility from hospitals and doctors. It is possible these interact in a non-additive way. For example, in 2014 Anthem Blue Cross contracted with Stanford Health Care hospital but *not* the physicians group. One could argue the hospital being in-network generated relatively little utility without the complimenting physicians that worked at the hospital. These cases are rare and are beyond the scope of this paper.

of as the relative variance of the random coefficient on the insurance indicator variable. As this variance approaches its maximum, there is no substitution along the extensive margin.

Preference parameters are indexed by  $i$  to indicate heterogeneity across households. I assume this heterogeneity is purely based on observable household characteristics so  $\beta_i = \mathbf{B}z_i$  where  $z_i$  is a vector of household demographics and  $\mathbf{B}$  is a matrix of parameters to be estimated. Since the ACA exchange population excludes the elderly, many chronically disabled, and those with the lowest incomes, this assumption is more plausible than in other government programs.

As discussed in Section 1.2, net premiums are a function of income and age and can be written succinctly as:

$$p_{ijt} = \theta_i^P p_{jt} - \tau(FPL_i, p_{(2)t}) \quad (1.2)$$

where  $p_{jt}$  is the premium set by plan  $j$  for a 21 year-old.  $\theta_i^P$  is the rating profile set by Covered CA ranging from 1 to 3 based on age. Since  $i$  is the household, this term is the sum of rating profiles for all members in the household.  $\tau(\cdot)$  is the premium subsidy (APTC), which is bounded above so that  $p_{ijt}$  is constrained to be at least \$1 per enrollee.

The outside option is the choice to not enroll in any of the available insurance plans and remain uninsured. The associated utility depends on individual characteristics  $z_i$  and is given by:

$$u_{i0t} = z_i' \omega + \varepsilon_{i0t} \quad (1.3)$$

where  $\varepsilon_{i0t}$  is also distributed i.i.d. Type I Extreme Value.  $z_i$  includes a constant and income so this is the reduced-form utility of remaining uninsured, which includes the penalty from the individual mandate. Note that this is a degenerate “nest” since it only contains a single option, so there’s no nest-level heterogeneous coefficient.

Given that this model follows a nested structure, it is helpful to think of the choice probabilities as two different levels (Train, 2009)—though to be clear, this doesn’t reflect the

timing of the decision process. The different levels can be thought of as an “upper model”–the choice of which nest–and a “lower model”–which choices within the nests. In the context of this study, the upper model is the decision whether or not to buy *any* plan. The lower model is *which* plan to purchase conditional on buying a plan. In the nested logit framework, “nest 0” should be thought of as remaining uninsured, and the other nest contains all plans in the market. Hereafter, I refer to the upper model as the “take-up” model and the lower model as the “plan choice” model.

Working backwards, first consider the plan choice model. Household  $i$  chooses plan  $j$  if it generates the highest utility–i.e. if  $u_{ijt} > u_{ikt} \forall k \neq j$ . Let  $s_{ijt|Ins}$  be the probability that household  $i$  chooses plan  $j$ , conditional on choosing to buy insurance. Given the distributional assumptions, the probability of making such a choice is:

$$s_{ijt|Ins} = \frac{\exp(v_{ijt})}{\sum_{k \in J_i} \exp(v_{ikt})} \quad (1.4)$$

where  $v_{ijt}$  is  $u_{ijt}$  less the idiosyncratic unobservable utility ( $\zeta_{it}^{Ins} + (1 - \sigma)\varepsilon_{ijt}$ ) and is normalized by  $(1 - \sigma)$ . Note that in Covered CA, different households within a market have different choice sets based on zip code, represented by  $J_i$ .

Next consider the take-up decision. Let  $s_{it}^{Ins}$  be the probability of choosing to buy any plan, i.e.  $s_{it}^{Ins} \equiv \Pr(\max_{j \neq 0} \{u_{ijt}\} > u_{i0t})$ . Then the assumptions of the model imply:

$$s_{it}^{Ins} = \frac{\exp((1 - \sigma)I_{it})}{\exp(z'_i \omega) + \exp((1 - \sigma)I_{it})} \quad (1.5)$$

Where  $I_{it} = \ln(\sum_{k \in J_i} \exp(v_{ikt}))$ .  $I_{it}$  is often referred to as the “inclusive value” since it represents the expected utility of the entire set of plans (Train, 2009). Combining the above formulas, the unconditional probability of choosing any particular plan is  $s_{ijt} = s_{it}^{Ins} s_{ijt|Ins}$ .

Market shares  $s_{jt}$  are defined by summing the individual probabilities over the population

in a market:

$$s_{jt} = \frac{1}{M_{jt}} \sum_i s_{ijt}$$

where  $M_{jt}$  is the number of households that are offered plan  $j$  in market  $t$ .<sup>14</sup>

## Price Elasticities

Given this framework, the effect on plan  $j$ 's market share of increasing its premium by \$1 is:

$$\begin{aligned} \partial s_{jt} / \partial p_{ijt} &= \frac{1}{M_{jt}} \sum_i \partial s_{ijt} / \partial p_{ijt} \\ &= \frac{1}{M_{jt}} \sum_i \alpha_i s_{ijt} \left( \frac{1 - s_{ijt|Ins}}{1 - \sigma} + s_{ijt|Ins} (1 - s_{it}^{Ins}) \right) \end{aligned}$$

and similarly, the cross-price effect of a price change for plan  $k$  on enrollment for plan  $j$  is:

$$\begin{aligned} \partial s_{jt} / \partial p_{ikt} &= \frac{1}{M_{jt}} \sum_i \partial s_{ijt} / \partial p_{ikt} \\ &= \frac{1}{M_{jt}} \sum_i -\alpha_i s_{ijt} s_{ikt|Ins} \left( \frac{1}{1 - \sigma} - (1 - s_{it}^{Ins}) \right) \end{aligned}$$

To get semi-elasticities, I normalize these derivatives by dividing by market shares  $s_{jt}$ .

Another object of interest in this study is the sensitivity along the extensive margin: how much does overall take-up change given a dollar decline in the premiums of all plans? In this setting, this is analogous to a change in take-up for a dollar increase in the premium subsidy (APTC). In this model, the change in take-up corresponding to an increase in the

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<sup>14</sup>Note that  $M_{jt}$  can differ within a market since some plans are not offered to all consumers. Hence, these "shares" will not necessarily add to 1.

APTC is :

$$\begin{aligned}\partial s_t^{Ins} / \partial \tau &= \frac{1}{M_{jt}} \sum_i \partial s_{it}^{Ins} / \partial \tau_{it} \\ &= \frac{1}{M_{jt}} \sum_i -\alpha_i s_{it}^{Ins} (1 - s_{it}^{Ins})\end{aligned}$$

Where again  $\tau$  is the premium subsidy that is applied to all plans.<sup>15</sup> Notice the second equality comes from  $v_{ijt}$  being normalized by  $(1 - \sigma)$ .<sup>16</sup>

### 1.3.2 Demand for Providers

An important part of plan choice is access to particular in-network providers (Ho, 2006). Provider network utilities, represented by  $EV^H$  and  $EV^P$  in (1.1), are derived from 2 features: 1) beliefs about the likelihood of needing certain medical providers, and 2) access available given by plan networks. In this section, I present the demand models for hospitals and PCPs that underly the values for  $EV^H$  and  $EV^P$ .

#### Hospital Demand

The hospital model is similar to those used in other papers on health plan competition (Ho, 2006; Gowrisankaran et al., 2014; Shepard, 2016). Enrollees have beliefs about their likelihood of needing different types of hospitalizations given their age and gender. Conditional on needing a hospitalization of a certain type, each plan's network generates a certain *expected* utility for each enrollee. The expectation is over idiosyncratic provider-patient utility which is unknown to even the enrollee until the hospitalization is needed. The deterministic

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<sup>15</sup>Since premiums are constrained to be positive, the APTC is capped for Bronze plans among the lowest income households. This formulation assumes this constraint away. It still has an economic meaning but is an overestimate of what an increase in the *max* APTC would do in practice in the ACA.

<sup>16</sup>This means the value of  $\alpha$  in the estimation also depends on the estimated value of  $(1 - \sigma)$ .

portion of network utility is based on the “quality” of the hospitals in the network, discounted by their distance from the enrollee. Similar to the plan choice model, the hospital quality is inferred from revealed preferences, based on which hospitals patients choose given the possible alternatives.

The utility of any particular hospital  $h$  for a hospitalization of type  $\kappa \in \{\text{Labor, Other inpatient, Outpatient}\} \times \{\text{Childrens', Adults'}\}$  is given by:

$$u_{ih\kappa}^H = \phi_h^\kappa - d_\kappa^H(\text{dist}_{ih}) + \varepsilon_{ih\kappa}$$

$\phi_h^\kappa$  is the common deterministic utility of hospital  $h$  for hospitalization  $\kappa$ , and  $d_\kappa^H(\text{dist}_{ih})$  is a function for the disutility of travel.  $\varepsilon_{ih\kappa}$  is unknown to the enrollee until needing the hospitalization and is also distributed i.i.d. Type 1 Extreme Value.

Then  $EV_{ij}^H$  is the expected utility of a network given the utilities of all networking hospitals, and weighted by the probability of needing each type of hospitalization:

$$EV_{ijt}^H = \sum_{\kappa} \lambda_i^\kappa \ln \left( \sum_{h \in \mathfrak{N}_j^H} \exp(\phi_h^\kappa - d_\kappa^H(\text{dist}_{ih})) \right) \quad (1.6)$$

where  $\lambda_i^\kappa$  is the probability of needing a  $\kappa$  hospitalization (which can sum to more or less than 1).  $\mathfrak{N}_j^H$  is plan  $j$ 's hospital network.<sup>17</sup>

## Physician Demand

The PCP model follows a similar structure, though I make a number of simplifying assumptions to handle the thousands of doctors that could be in plan networks.

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<sup>17</sup>Note this implicitly assumes the units of each hospitalization type utility function are the same. In the context of the logit model, this more fundamentally assumes the variance of the unobservable  $\varepsilon_{ih\kappa}$  is constant across types. This could be relaxed by separating  $EV_{ij}^H$  into each type  $\kappa$  in the plan indirect utility function, e.g.  $EV_{ij}^{H,\kappa}$ .

The utility of PCP  $p$  for household  $i$  is:

$$u_{ip}^P = \phi_p - d^P(\text{dist}_{ip}) + \varepsilon_{ip}$$

Where  $\phi_p$ ,  $d^P(\text{dist}_{ip})$ , and  $\varepsilon_{ip}$  are analogous to the terms defined above for hospitals.

The first simplifying assumption is that the mean utility of each physician  $\phi_p$  is constant. In this discrete choice framework, the level is unidentified and so without loss of generality I assume  $\phi_p = 0$ . I also discretize the distance disutility  $d^P(\text{dist}_{ip})$  to bins indexed by  $b$ . These assumptions reduce  $EV_{ij}^P$  to be a function of the *number* of plan  $j$  PCPs ( $N_{ij,b}^P$ ) within different distance bins ( $b$ ) from the enrollee:

$$EV_{ijt}^P = \lambda_i^P \ln \left( \sum_b N_{ij,b}^P \exp(-d^b) \right) \quad (1.7)$$

where  $\lambda_i^P$  is the probability of needing to visit a PCP.  $d^b$  is the disutility of traveling to distance  $b$  noted above.

In Section 1.4.4 on estimation, I describe further simplifications used in this study.

## 1.4 Fitting the Model to Data

### 1.4.1 Data Sources

#### Covered CA Data

The primary data sources for this study come from Covered CA and include information on enrollment and provider networks. The enrollment data include the unidentified set of all households enrolled in any plan in 2015. The associated variables are each household's plan choice, income, zip code, age, gender, and race. Because carriers might offer their plans to only a subset of a rating region, I use data on coverage areas at the region-county-zip level



to construct choice sets for each household. I apply a number of exclusions to simplify the analysis, which have a small impact on the overall sample. Specifically, I exclude households with any of the following characteristics: more than 4 members, an income less than 138% of the FPL, any members greater than 64 years old, chose a plan that wasn't offered in the household's zip code, or enrolled in a highly uncommon plan.<sup>18</sup> The size exclusion simplifies the demand estimation, while the income and age exclusions omit enrollees that are possibly eligible for other government insurance programs. Combined, all exclusions account for 8.3% of total enrollment, virtually all coming from the income and household size exclusions in equal parts. Other than plans which are explicitly omitted, these exclusions do not affect plan shares. While the data include the universe of enrollees, I only use a 20,000 household sample, weighted evenly across rating regions. This significantly speeds up the analysis but otherwise has little impact on the estimation.<sup>19</sup>

This study also uses provider directories that Covered CA collects to ensure plans meet network adequacy standards outlined in the ACA. The directories include listings of all hospitals and physicians considered to be in-network for each plan in quarter 1 of 2015. Provider networks are identified by a carrier and network type (HMO, PPO, EPO), and are assumed to be the same across tiers. For this study, I use hospitals and Primary Care Physicians (PCPs) for a given plan. From the hospital data, I use provider identifiers which are later merged with external data listed in the next section. From the PCP data, I use the office zip code.

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<sup>18</sup>Specifically, I exclude households that enrolled in any of the following rare plans: "catastrophic" plans, Kaiser in Regions 1 and 13, Anthem's HMO in 3, 11, 19, Health Net's PPO in 5, and Molina in 19.

<sup>19</sup>There are households that enroll in individual plans outside of Covered CA. The data in this study comes specifically from the Covered CA enrollment website. Hence, it includes all subsidized enrollment (i.e. less than 400 FPL *and* electing to receive APTCs), but it need not include enrollment among those that do not receive subsidies. In fact, among those with incomes above 400% FPL, the data generating process that makes a household enroll through Covered CA is unclear. Among this income group without group insurance, there is actually a significant share that buys individual coverage. See footnote 20 for how this impacts the analysis.

## Supplemental Data

While the data from Covered CA is very detailed, it does not include all the necessary information for this study. First, it doesn't include data on households that could have enrolled in a plan but chose not to (i.e. taking the "outside option"). Additionally, while the data indicates which providers are in different networks, it does not indicate the cost of those providers or their relative value to consumers. Hence, I bring in external data sources to fill these gaps.

For this study, I consider households choosing the outside option as those that were uninsured in 2015.<sup>20</sup> To measure uninsured households, I use the individual-level 2015 American Community Survey (ACS) from IPUMS (Ruggles et al., 2017). The key variables are health insurance status, location of residence (as a PUMA), income, and household composition (i.e. age, gender, race of each household member). More details on how the ACS data is supplemented with the Covered CA data are provided in Appendix A.1. I make the same exclusions in the ACS as described above for Covered CA enrollees when possible.

Another data source is needed for exogenous determinants of plan premiums (i.e. "cost shifters") to identify how enrollment responds to prices. For this, I use the costs of each plan's networking hospitals. Data on hospital costs can be found in the Healthcare Cost Report Information System (HCRIS) collected by the Centers for Medicare and Medicaid Services (CMS).<sup>21</sup> Combining these reports with IPSS data on average hospital severity, I create a measure of the risk-adjusted cost of a hospitalization at every hospital similar to

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<sup>20</sup>This could also include those in the "off-exchange" individual market (as in Tebaldi (2016)). However, since most of the Covered CA market is receiving premium subsidies, it's not unreasonable to think there is little substitution between on and off-exchange plans for the majority of Covered CA enrollees. Furthermore many of the plans available off the exchange are the same as those on the exchange, and have the same premiums. Omitting this group simplifies the problem of the outside option utility changing with price changes in the market.

<sup>21</sup>Source data is found here: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/>. I use the formatted data created by Jean Roth at the National Bureau of Economic Research (NBER): <http://www.nber.org/data/hcris.html>

that of Dafny (2009).<sup>22</sup>

To estimate the indirect utility function in the hospital model, I use external utilization data from the Office of Statewide Health Planning and Development (OSHPD). I use the 2014 Patient Origin and Market Share Reports<sup>23</sup> which give the number of discharges from a given patient zip code at each hospital by age category and type of hospitalization. Utility from networking PCPs is based only on network size so does not rely on external utilization data. However, in Appendix A.2, I describe how PCP utilization data can aid in the estimation.

Finally, I use the Medical Expenditure Panel Survey<sup>24</sup> (MEPS) Household Component to estimate the how expected spending and utilization vary by age and gender.

## 1.4.2 Descriptive Summaries

Table 1.1 gives a summary of the 19 markets, or “rating regions,” in California. For each region, the table displays the number of firms, share of enrollment in each network type, and the market Herfindahl-Hirschman Index (HHI). The southern regions (region 12 and above), tend to have more firms, be larger, and have a much higher HMO share. In Northern CA, non-Kaiser HMO enrollment makes up less than 10% in each region, with the exception of San Francisco. Kaiser is a key player throughout the state but its role varies regionally. In the Bay Area counties for example, Kaiser makes up around a half of all enrollment. In the southern counties, Kaiser’s enrollment ranges from 14% to 30%. The level of competitiveness ranges across the state with regions in Southern California generally being the most competitive. Unsurprisingly, the rural counties in the Central Valley, the Eastern Region, and the far

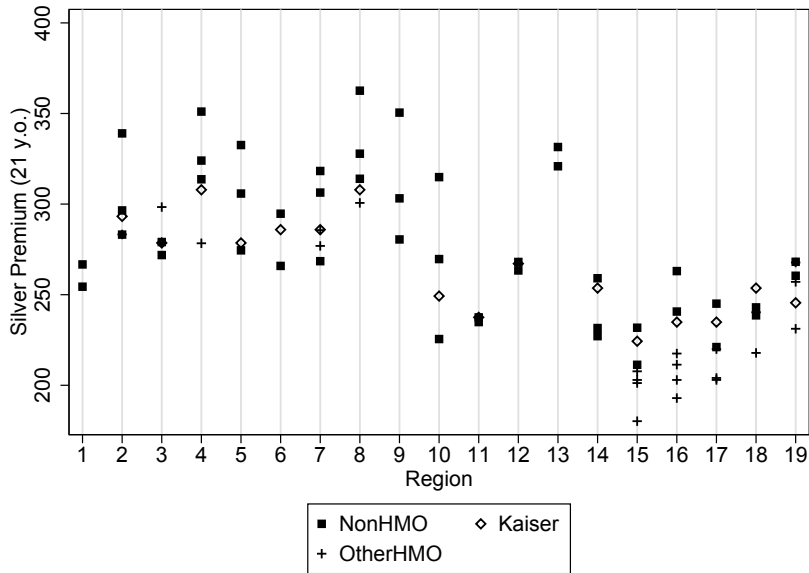
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<sup>22</sup>Source IPPS data also comes from NBER: <http://www.nber.org/data/cms-impact-file-hospital-inpatient-prospective-payment-system-ipps.html>. Since these are generated for Medicare reimbursement, hospitals that have little interaction with the Medicare system are excluded (e.g. Children’s and Kaiser).

<sup>23</sup>See: <https://www.oshpd.ca.gov/HID/POMS-Report.asp>

<sup>24</sup>See: <https://meps.ahrq.gov/mepsweb/>

Figure 1.1: Premiums for all Rating Regions and Network Types



Note: This figure gives Silver plan premiums in 2015 for each rating region. Premiums based on 21 year-olds. Markers differ by network type. Only among plans that meet exclusion criteria. Regions 1-11 are Northern California.

North (Regions 10, 13, and 1) are the least competitive with HHIs that exceed 5,000, well above what’s considered a concentrated market.<sup>25</sup>

The patterns in enrollment are not surprising given premiums across the state. Figure 1.1 plots 21 year-old Silver premiums across all regions, indexed by network type (Non-HMO, Kaiser, or Other HMO). The first pattern is that all premiums are significantly lower in Southern California (regions 12 and above). Moreover, the relative price of Kaiser plans is higher in Southern California than in the rest of the state which explains part of the Kaiser enrollment patterns. In Figure 1.2, I plot the enrollment in each plan against the relative premium. There is a clear negative correlation which suggests consumers are very price sensitive.

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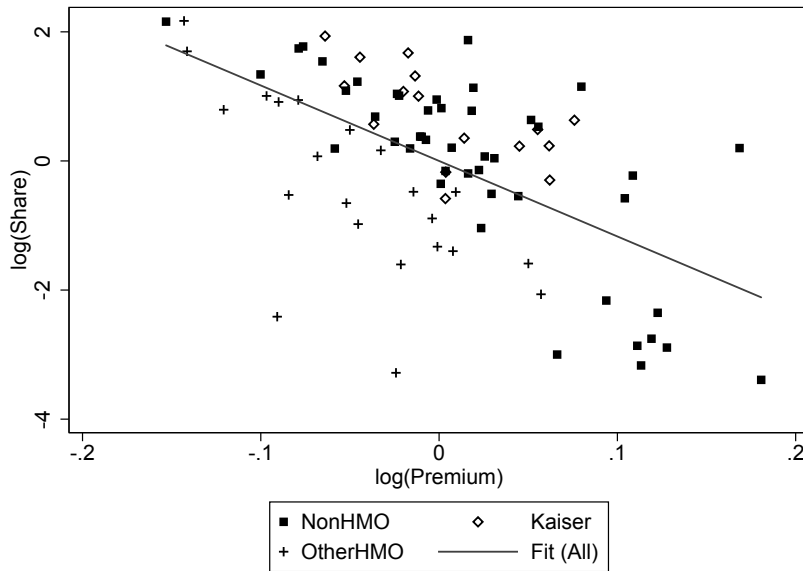
<sup>25</sup>Markets with HHIs greater than 2,500 are considered highly concentrated and those with HHIs between 1,500 and 2,500 are moderately concentrated. See U.S. Department of Justice & FTC, *Horizontal Merger Guidelines* §5.3 (2010).

Table 1.1: Market Summary for Covered CA

Rating Region	Total Firms	Offering HMOs	Num HHs (1,000s)	NonHMO Share	Kaiser Share	Other HMO Share	HHI
1. Northern Counties	2	0	39	1.00	-	-	8,508
2. N. Bay Counties	5	2	40	0.41	0.51	0.08	3,520
3. Sacramento	4	2	53	0.54	0.43	0.02	3,458
4. San Francisco	5	2	33	0.40	0.38	0.22	2,744
5. Contra Costa	4	1	29	0.42	0.58	-	4,683
6. Alameda	3	1	50	0.47	0.53	-	3,922
7. Santa Clara	5	3	47	0.62	0.32	0.06	3,819
8. San Mateo	5	2	20	0.38	0.54	0.08	3,672
9. Central Coast I	3	0	23	1.00	-	-	5,222
10. Central Valley I	4	1	43	0.79	0.21	-	5,427
11. Central Valley II	3	1	20	0.72	0.28	-	3,723
12. Central Coast II	3	1	45	0.88	0.12	-	4,121
13. Eastern Region	2	0	5	1.00	-	-	5,802
14. Central Valley III	4	1	12	0.85	0.15	-	4,061
15. LA-East	6	5	118	0.39	0.15	0.46	2,773
16. LA-West	6	5	161	0.34	0.18	0.48	2,174
17. Inland Empire	5	4	86	0.37	0.23	0.40	2,221
18. Orange County	4	3	94	0.58	0.14	0.28	2,866
19. San Diego	5	3	91	0.34	0.30	0.36	2,202

Note: This table gives summary statistics for each of the 19 rating regions in Covered CA in 2015. The first column is the number of firms operating in each region. The second is the number of HMOs offered in each region. The third column is the number of households enrolled in a Covered CA plan (in thousands). The following three columns are the shares of enrollment in Non-HMOs, Kaiser, and HMOs respectively. The last column is the Herfindahl-Hirschman index (HHI). All statistics are net of sample exclusions described above.

Figure 1.2: Enrollment Shares by Premium and Network Type

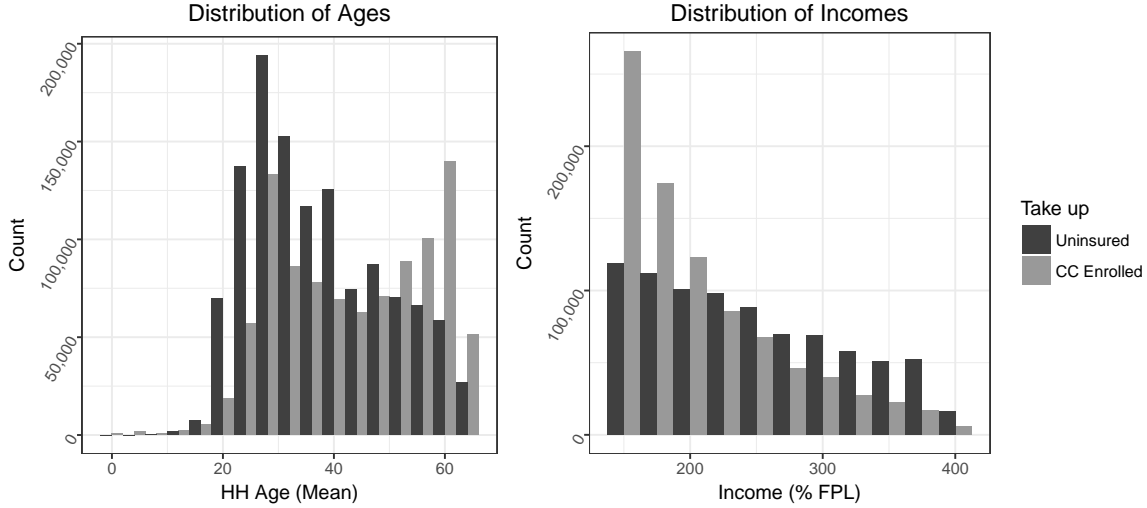


Note: This figure plots log of market shares by the log of the plan premium. Both measures are de-meanned at the region level. Only among Silver plans, which represent the majority of enrollment. Markers differ by network type. Fitted line based on all points in the figure. All data based on 2015.

Figure 1.3 plots the distributions of ages and incomes for the Covered CA and uninsured populations, those who could have enrolled but chose not to. Those taking up insurance are older and have lower incomes than their uninsured counterparts. Given that subsidies are decreasing in income, this latter result is not surprising, though the difference is relatively large.

Last, Table 1.2 presents statewide characteristics of the individuals enrolled in each plan type, by either network type or metal tier. Examining the first three rows, Non-HMO plans (known to be “preferred” but more expensive) have intermediate ages and incomes, but have disproportionately more female and white enrollees. Kaiser enrollees are disproportionately younger with higher incomes. The second set of rows presents the same for metal tier selection. Gold and Platinum enrollees are actually younger. This is likely because these plans are relatively lower priced for the young and there are many younger households with

Figure 1.3: Demographics by Insurance Coverage



Note: These figures plot the distributions of ages and incomes. The unit of analysis is household—hence, “age” is the mean of the ages of all members in the household. The distributions are stratified by whether or not the household chose to buy insurance from Covered CA, or remain uninsured. The income distribution is censored at 400% FPL.

relatively higher incomes. High generosity enrollees are also higher income and female, which is less surprising.<sup>26</sup>

### 1.4.3 Identification

In this subsection, I informally describe the moments in the data that identify each parameter. For most parameters, identification is relatively straightforward. Two parameters for which this is not the case are the mean price sensitivity (“ $\alpha_0$ ”) and the nesting parameter  $\sigma$ , which therefore receive disproportionate attention in this section.

Identification for all parameters in the plan choice model (1.1), come from Covered CA data combined with HCRIS cost reports. Parameters are identified from a combination of “micro” and “macro” moments. The micro moments identify how  $\alpha_i$  and  $\beta_i$  deviate from

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<sup>26</sup>Note that Silver plans are associated with large cost sharing reductions (CSRs) for over half of the population, so tiers are not necessarily increasing in coverage. However, we can compare Bronze to Gold/Platinum to get a sense of preference heterogeneity for plan generosity.

Table 1.2: Mean Demographics by Plan Type

	Members (1,000s)	Age	FPL	Female	Asian	Nonwhite
<b>Network Type</b>						
1. NonHMO	843	41.76	223	0.53	0.16	0.48
2. Kaiser	394	40.71	231	0.52	0.15	0.50
3. OtherHMO	394	42.73	202	0.51	0.20	0.60
<b>Tier</b>						
1. Minimum Coverage	12	24.22	326	0.45	0.18	0.44
2. Bronze	344	40.47	249	0.49	0.17	0.52
3. Bronze Hsa	72	41.04	260	0.49	0.14	0.46
4. Silver	1,038	42.97	200	0.54	0.18	0.53
5. Gold	89	38.39	276	0.52	0.12	0.47
6. Platinum	77	38.17	268	0.52	0.10	0.45

Note: This table presents characteristics of the enrollees choosing each plan type. The first column is the number of individuals enrolled in each plan type. The rest of the columns represent the mean of the individual characteristic among enrollees in the given plan type.

some baseline—i.e. heterogeneity across individuals—and are given by correlations between individual characteristics and the chosen plan’s characteristics (Train, 2009). Macro moments identify baseline values of these preference parameters based on how market shares correlate with plan characteristics (e.g. metal tier or insurer).

In the plan choice model, the only parameter for which identification is not straightforward is the baseline price sensitivity (the deviation based on individual characteristics is identified as above). First, as is always the case, premiums are endogenously set in response to anticipated demand, creating bias which underestimates the true magnitude of the parameter. The second problem is that in this environment, market prices vary across consumers so the standard “inversions” to separate out a market price are not valid (Berry et al., 2004; Goolsbee and Petrin, 2004).<sup>27</sup> The logic I use to address this problem of within-market heterogeneous pricing is fairly intuitive and involves a combination of the standard endogeneity

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<sup>27</sup>The usual logic is to isolate the mean plan utility, including the market price and unobservable  $\xi_{jt}$ , using a market-plan fixed effect. Then form moments given exogenous instruments and  $\xi_{jt}$  to identify the price coefficient. Either of the aforementioned references explain this in great detail.



methods, plus the micro moments outlined in the prior paragraph.

More formally, notice that (1.1) can loosely be re-written as follows:

$$\begin{aligned}
 u_{ijt} &= \alpha_i p_{ijt} + \overbrace{\nu_{ijt}}^{\text{All other utility}} + \xi_{jt} + \varepsilon_{ijt} \\
 &= (\tilde{\alpha}_i + \alpha_0)(\tilde{p}_{ijt} + p_{jt}) + \nu_{ijt} + \xi_{jt} + \varepsilon_{ijt} \\
 &= \underbrace{\alpha_0 p_{jt} + \bar{\nu}_{jt} + \xi_{jt}}_{\delta_{jt}} + \alpha_0 \tilde{p}_{ijt} + \tilde{\alpha}_i p_{ijt} + \tilde{\nu}_{ijt} + \varepsilon_{ijt}
 \end{aligned}$$

where  $p_{jt}$  is the premium for a 21 year-old as discussed above, and tilde (“-”) variables represent deviations from baseline values.  $\alpha_0$  is the parameter of interest. I isolate “ $\delta_{jt}$ ” to highlight the usual plan-market mean utility that is often used with instrumental variables to estimate  $\alpha_0$  in an unbiased way (Berry et al., 2004; Goolsbee and Petrin, 2004). Written this way, it’s clear that the usual method will not work because  $\alpha_0$  appears outside of the  $\delta_{jt}$  due to within-product variation in prices.

However, this formulation also suggests there are two potential moments that can identify  $\alpha_0$ . The first is the usual macro moment  $E(\xi_{jt}Z_{jt})$  where  $Z_{jt}$  is some instrumental variable that exogenously changes premiums. The instrument I use is costs of networking hospitals as cost shifters, as defined in Section 1.4. To be a valid instrument, this measure need only be correlated with the rates paid by Covered CA plans. Even though this cost index differs from the rates in Covered CA, I assume that the hospitals costs are correlated with the negotiated rates in Covered CA. To construct a plan-level cost, I take the average cost across the hospitals in each plan’s network, weighted by the number of annual discharges.<sup>28</sup> The identifying assumption is that plan utility doesn’t depend on hospital costs, *conditional on other observables*. Given that I have specified hospital network utility explicitly in the

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<sup>28</sup>Kaiser Permanente is a vertically integrated health system, so it has limited interaction with the Medicare and hence, poor cost measures based on how I have defined them. Therefore, I set hospital costs to 0 for all Kaiser plans. Since there are brand fixed effects in the model, identification is based only on costs of networks of non-Kaiser plans.

model ( $EV^H$ ), this assumption seems reasonable.<sup>29</sup> Using this as an instrument for *plan* prices,  $\alpha_0$  will be identified based on how market shares correlate with networking hospital costs.

The second moment to identify  $\alpha_0$  is more simple and is the same type of micro moment used for other heterogeneity parameters. Since there is variation in premiums *within plans*, it can be used to see how enrollment probabilities within a market-plan also vary in kind. More formally, this moment is  $E((e_{ijt} - s_{ijt|Ins})p_{ijt})$  where  $s_{ijt|Ins}$  is the model probability of enrollment into plan  $j$  and  $e_{ijt}$  is a dummy for whether the plan was chosen (Train, 2009; Berry et al., 2004). The validity of this moment relies on the fact that I condition on  $\xi_{jt}$ , which is correlated with premiums.

Since  $\alpha_0$  is over-identified, it is reasonable to consider using just one moment (particularly the micro moment) for simplicity. While in theory this is a valid strategy, in this environment it would likely be inadequate. Using only the micro moment would be using within-plan price variation which comes only from the regulated age rating profile in (1.2). Price differences between any two plans are larger for older consumers. This could create bias if  $\alpha_i$  varies with age as well, which is likely. One might want to “control for age” and rely on the functional form difference in the rating profile, but this is a strong assumption since this profile represents expected spending. Hence, adding the macro moment uses data variation that is plausibly exogenous and will yield an unbiased estimate. Not surprisingly, adding this moment substantially increases the estimated price sensitivity.<sup>30</sup> This strategy differs from other studies on the pre-ACA Massachusetts exchange where pricing discontinuities can be

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<sup>29</sup>A hospital’s costs are likely higher if they are a more demanded hospital (Ho, 2009), but this variation will not be used to identify  $\alpha_0$ . Instead, identification comes from hospital cost variation due to factors like underlying operational costs. Conditional on the explicit network utility, these should not directly affect plan utility.

<sup>30</sup>Alternatively, using only the macro moment would be relying on only  $JT$  sample observations. While the estimate would be unbiased, it would also be much less precise. Hence adding the micro moment with the large sample significantly reduces variance of the estimate.

used (Shepard, 2016; Ericson and Starc, 2015; Finkelstein et al., 2017a).

Next, consider the take-up model in (1.5). In most settings, the nesting parameter  $(1 - \sigma)$  can be identified from the correlation between take-up probabilities and variation in the value of all plans in the choice set  $I_{it}$  (which is “data” once the plan choice model has been estimated). Unfortunately, most of the variation in  $I_{it}$  in this setting comes from the APTC which is a function of income, among other things. Since income impacts  $I_{it}$  in a highly nonlinear way that interacts with other demographic variables (all of which enter the take-up decision), it is likely that  $E(\varepsilon_{i0t}I_{it}) \neq 0$ , which biases the estimates. Since lower-income consumers likely have a lower preference for insurance, large values of  $I_{it}$  from high APTCs will be among those with relatively lower values for insurance, and  $(1 - \sigma)$  will be biased down.<sup>31</sup>

Since estimating parametric models with non-linearities and interactions does not appear to fix this problem, I rely on an exogenous shifter of  $I_{it}$ . Recall that within rating regions, some plans are only offered to a subset of zip codes. Hence, I use variation in choice sets *within rating regions* to identify the nesting parameter  $(1 - \sigma)$ . Specifically, I use the number of plans available to the household. Hence, the identifying moment is how take-up is correlated with the number of plans being offered, conditional on age, income, race, and population density.<sup>32</sup> Importantly, this variation is correlated with  $I_{it}$  but not with the unobserved utility  $\varepsilon_{i0t}$  (conditioning on income and age).

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<sup>31</sup>In the model, this bias would imply very little substitution along the extensive margin—hence underestimating (in magnitudes) elasticities.

<sup>32</sup>In practice, I only use the variation in regions 1 and 9. Given the log functional form of  $I$ , the number of plans is only strongly correlated with  $I$  when the number of plans is small—i.e., that is when the first stage is strongest. In other regions, variation in  $I$  is more heavily driven by demographic factors, and hence is sensitive to data differences in the ACS.

## 1.4.4 Estimation

For tractability, the estimation is conducted sequentially and in the reverse order of the model timing.<sup>33</sup> The sequence of estimation is as follows: the provider models, the plan choice model, and last, the take-up model.<sup>34</sup>

### Provider Models

In this section, I present the estimation procedure for the hospital demand model. Recall, hospital utility is given by:

$$u_{ih\kappa}^H = \phi_h^\kappa - d_\kappa^H(\text{dist}_{ih}) + \varepsilon_{ih\kappa}$$

I estimate the model separately for each of the  $\kappa \in \{\text{Labor, Other inpatient, Outpatient}\} \times \{\text{Childrens}', \text{Adults}'\}$  hospitalizations—this creates 5 models since Children’s Labor is irrelevant. Hence, for each model, the utility comprises of hospital fixed effects and a distance disutility function. While the unit of observation in the data is the zip code  $\times$  hospital ( $zip, h$ ), these are just aggregations of individual decisions. For each  $\kappa$ , all individuals in zip code  $z$  are assumed to have the same choice set, which is all the hospitals that were visited by

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<sup>33</sup>This implies that inference in later steps of the sequence is not valid unless standard errors have been corrected for estimation error in earlier steps (see Ho (2006) for a discussion of this). The standard errors presented are not corrected for this sequence and hence are *underestimates* of the true standard errors. However, in the context of this paper, this isn’t too problematic. First, the sample sizes are sufficiently large so that most parameters are estimated with an extremely high degree of precision in all stages (e.g. the ratio of point estimates to standard errors is often far greater than 10). Second, as is often the case when relying on counterfactual policies for drawing conclusions, inference on the point estimates is less important than the robustness of the results to the model specification. To this end, I ensured that qualitative results did not change with changes in specifications of the demand model.

<sup>34</sup>The majority of the analysis is performed in R. The estimation routines and simulations were developed for this project, but rely heavily on the R development community which deserves a great deal of credit (R Core Team, 2017). I also use the following R packages: *nleqslv* (Hasselman, 2017) for solving non-linear systems of equations. *SQUAREM* (Varadhan, 2016) for increasing the speed of the contraction mapping (Reynaerts et al., 2012). *survey* (Lumley, 2017) for conducting a weighted logit for the take-up model. *ggplot2* (Wickham, 2009) for figures and *stargazer* (Hlavac, 2015) for outputting all results to L<sup>A</sup>T<sub>E</sub>X.

anyone from  $z$ .<sup>3536</sup>

Given the assumptions on the unobservable, this model can be estimated as a logit model with Maximum Likelihood (MLE). The probability of choosing a hospital  $h$  out of the choice set  $\mathcal{N}_i^H$  is:

$$p_{ih\kappa}^H = \frac{\phi_h^\kappa - d_\kappa^H(\text{dist}_{ih})}{\sum_{h' \in \mathcal{N}_i^H} \phi_{h'}^\kappa - d_\kappa^H(\text{dist}_{ih'})}$$

Hence, the individual contribution to the likelihood of  $i$  is given by:

$$l_{i\kappa}^H = \prod_{h' \in \mathcal{N}_i^H} p_{ih'\kappa}^H \mathbf{1}(i \text{ chooses } h')$$

And hence, the MLE objective is the sum of the log of these individual likelihood contributions—i.e. weighted by the number of patients in a zip code making a given decision  $N_{zip, h}$ :

$$\mathcal{L}_\kappa^H = \sum_{zip, h} N_{zip, h} \log(p_{ih\kappa}^H)$$

Additional attention is required to identify the fixed effects  $\phi_h^\kappa$ . Recall choice sets  $\mathcal{N}^H$  are defined as any hospital visited by any patient in the zip code. In order to identify  $\phi_h^\kappa$  for all hospitals, there must be a link of any two hospitals by a series of choice sets that contain

<sup>35</sup>This assumes patients in OSHPD data have unrestricted provider networks, different from the plans in this study. Since the majority of patients are covered by employer coverage which tends to have large networks, this assumption is less problematic in this context. Any violation in this assumption will lead to underestimated utilities for highly demanded hospitals. Capacity constraints are also ignored and would have a similar effect. This assumption is not expected to have a large impact on the conclusions in this paper since I also allow insurer utilities to vary by health status, which would absorb anything not measured by network variables.

<sup>36</sup>This choice set assumption combined with finite samples creates an upward bias in the utility of low-utility hospitals. Low-utility hospitals are censored since they aren't visited and assumed outside the choice set.

common hospitals. For example, to identify the relative utility of hospitals A and B, we do not require they be in the same choice set; however, having a hospital C that is in a choice set with both A and B would be sufficient. It would also be sufficient to have any degree of separation. In the data, there are disjoint sets of hospitals (particularly for rural areas) which implies the above condition is not satisfied. Hence, I identify all the disjoint sets of hospitals, and normalized one to be 0 utility. This assumption means that the mean level of latent utility in  $EV^H$  will be different for different parts of the state. It does not affect the plan demand since the effect of  $EV^H$  is identified by within-household differences across plans.<sup>37</sup>

The last component needed to estimate  $EV^H$  is the probability of each hospitalization type,  $\lambda_i^\kappa = \Pr(Hosp_\kappa | age_i, gender_i)$ . I estimate these with nonparametric local regression by age, separately for males and females.

Combining the above, I construct estimates  $EV^H$  in (1.6) as follows:

$$\widehat{EV}_{ijt}^H = \sum_{\kappa} \widehat{\lambda}_i^\kappa \ln \left( \sum_{h \in \mathfrak{N}_j^H} \exp(\widehat{\phi}_h^\kappa - \widehat{d}_\kappa^H(dist_{ih})) \right)$$

Finally, I estimate network utilities separately for Kaiser and Non-Kaiser plans, since Kaiser is generally a closed system.

For this study, I simplify the PCP model substantially since PCP utilization data is much less readily available (unlike OSHPD for hospitalizations). I simplify the functional form of (1.7) by assuming doctors within 5 miles have the same utility, and any beyond that distance provide no utility to enrollees. I further assume the probability of needing access to a PCP

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<sup>37</sup>In practice, I link hospitals that are connected by 4 degrees of separation or less. This helps with convergence when hospitals are more closely comparable.

is constant ( $\lambda_i^P = \lambda^P$ ) and so (1.7) reduces simply to:

$$\widetilde{EV}_{ij}^P = \ln \left( N_{ij,5}^P \right) \quad (1.8)$$

Note that  $\widehat{\lambda}_i^P$  is omitted and hence is absorbed into the coefficient on  $\widetilde{EV}_{ij}^P$  in the plan indirect utility. This simplified form is convenient since it can be calculated with only networking PCP data, and requires no additional utilization data. As a result, there is no need for a prior stage of estimation since  $\widetilde{EV}_{ijt}^P$  is directly observable in the data. The impact of this simplification is that I am capturing the local ( $\leq 5$  miles) regional differences in plan utilities caused by PCP networks, but not differences beyond that or that result from demographic differences. In Appendix A.2, I describe how basic PCP utilization data on PCP travel distances could be added to enhance the model.

## Plan Choice Model

The next step is to estimate the indirect utility function in (1.1) and (1.3). I estimate the model in two stages: The plan choice (“lower”) model includes all parameters in (1.1) less  $\sigma$ . The take-up (“upper”) model is the decision whether or not to be insured, and identifies  $\sigma$  and the parameters in the outside utility in (1.3). In this setting, sequential estimation is preferred for 2 reasons: 1) each stage is identified from two distinct data sets (Covered CA vs. ACS); and 2) separately estimating the take-up model allows for a concise way of using instrumental variables to identify  $\sigma$ .<sup>38</sup>

Working backwards through the nested model, I first estimate the plan choice model,

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<sup>38</sup>It’s possible to estimate these parameters simultaneously and is often preferred (Train, 2009; Hensher, 1986). By subsetting the data, I am throwing away information and increasing standard errors (or need to correct the standard errors in the take-up model which uses estimated data). Also, if there are any parameters in multiple nests, they cannot be estimated at all (Heiss, 2002). Additionally, because of the large enrollment sample and there being only 1 “nest,” the usual reasons not to use sequential estimation are not of particular importance.

conditional on take-up. This stage is estimated using only data within the market which is convenient since it comes from a different data source. Restating the main indirect utility function with a slight abuse of notation, let the plan utility conditional on buying insurance be:

$$\begin{aligned}
 u_{ijt} &= \alpha_i p_{ijt} + \gamma^H EV_{ijt}^H + \gamma^P EV_{ijt}^P + x'_{ijt} \beta_i + \xi_{jt} + \varepsilon_{ijt} \\
 &= \underbrace{x'_{jt} \beta + \xi_{jt}}_{\delta_{jt}} + \alpha_i p_{ijt} + \gamma^H EV_{ijt}^H + \gamma^P EV_{ijt}^P + \widetilde{x'_{ijt} \beta}_i + \varepsilon_{ijt}
 \end{aligned}$$

Notice that the  $\zeta_{it}^{Ins}$  has dropped out and the  $(1 - \sigma)$  coefficient has been removed, which means all other parameters have implicitly been rescaled by  $1/(1 - \sigma)$  (Heiss, 2002). Also, coefficients have been added to network  $EV$  terms to convert units from each provider utility model to the units in the demand model.<sup>39</sup>

The general idea of the estimation routine is very similar to “Micro BLP” (Berry et al., 2004). The two exceptions are that I use two moments to identify price sensitivity and I remove unobserved heterogeneity (i.e. there are no random coefficients).

An outline of the routine is as follows: I minimize a GMM objective function made up of micro and macro moments over the parameters related to variables that vary across consumers within a plan (including “ $\alpha_0$ ” described in Section 1.4.3)—call these  $\Theta_2$ . Baseline utility parameters ( $\Theta_1$ , or  $\beta$  above) can be determined analytically, given market shares and the current guess for  $\Theta_2$ .

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<sup>39</sup>In the case of  $EV^P$ , the coefficient also includes the probability of needing a physician,  $\lambda^P$ .



The sample analogs of the identifying moment conditions are:

$$\sum_{jt} \xi_{jt}(\Theta_2, \delta_{jt}) Z_{jt} = 0$$

$$\sum_{ijt} (e_{ijt} - s_{ijt|Ins}(\Theta_2, \delta_{jt})) z'_i x_{ijt} = 0$$

$e_{ijt}$  is an indicator for whether  $i$  enrolled in plan  $j$  conditional on getting insurance, such that  $e_{ijt} = \mathbf{1}(u_{ij} > u_{ij'}, \forall j' \notin \{0, j\})$ . The vectors  $z_i$  dictate heterogeneity in preferences and  $Z_{jt}$  are exogenous instruments including a cost shifter for  $p_{jt}$ .

$\xi_{jt}(\Theta_2, \delta_{jt})$  is determined by first matching model market shares with market shares in the data to get  $\delta_{jt}$ , given the guess of  $\Theta_2$ .<sup>40</sup> Given  $\delta_{jt}$ ,  $\xi_{jt}$  is the residual of two-stage least squares with instruments  $Z_{jt}$ . The vector  $Z_{jt}$  includes brand, tier, network type, region, and the premium instrument: networking hospital costs.<sup>41</sup>

The model is over-identified because of the two price moments so I construct a GMM weighting matrix as the inverse of the covariance matrix of instruments as in two-stage least squares. The gradient of this objective—which is also used for the calculation of standard errors with GMM—is described in the appendix of Nevo (2000).

I make a few other specifications to facilitate the estimation. First, I standardize all demographic variables ( $z_i$ ) to be mean 0 and variance 1. Second, household-level expected spending is based on the average of all household members. Next, I demean values of network utility:  $EV^H$  is demeaned at the market level and  $EV^P$  demeaned at the market-plan level.

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<sup>40</sup>I use a “contraction mapping” on  $\delta_{jt}$  with the SQUAREM (Varadhan, 2016) algorithm as recommended by Reynaerts et al. (2012).

<sup>41</sup>It’s important to note that one of the  $\delta_{jt}$ ’s in each market must be normalized to 0, so that the model is identified. In most models, this is the outside option (i.e. uninsurance in this case), so it’s reasonable to assume it has a common utility across markets. In this case, where the normalized option is a different plan in each market (since choice sets differ across markets), it is unreasonable to assume it has a constant utility relative to the other plans. Hence, it is important to include region fixed effects in  $X_{jt}$  to capture this difference across markets.

This implies the effect of PCP networks is identified by enrollment differences in different geographic areas for a given plan, while the effect of  $EV^H$  is identified from both differences across plans within a region as well as across consumers in different geographic areas.<sup>42</sup> The mean that is removed gets implicitly absorbed into  $\xi_{jt}$ . Last, I reduce the choice sets to be 10 random plans in the market (including the chosen plan) which significantly reduces computation time but doesn't bias the estimates given the logit functional form assumption (Train, 2009).

### Take-up Model

Once the parameters in the plan choice model are estimated, I estimate the take-up model of whether or not to buy insurance. Recall the probability of take-up in the model from (1.5):

$$\begin{aligned} s_{it}^{Ins} &= \Pr(\max_j u_{ijt} > u_{i0t}) \\ &= \frac{\exp((1 - \sigma)\hat{I}_{it})}{\exp(z_i'\omega) + \exp((1 - \sigma)\hat{I}_{it})} \end{aligned}$$

where  $\hat{I}_{it}$  is implied by estimates in the plan choice model:  $\hat{I}_{it} = \ln(\sum_{k \in J_i} \exp(\hat{v}_{ikt}))$ .<sup>43</sup>  $z_i$  is a vector of individual attributes including income, age, gender,<sup>44</sup> region, race, and population density. This formulation implicitly includes the mandate in a reduced-form way.

Recall the problem identifying  $(1 - \sigma)$  discussed in the above Section 1.4.3, and the

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<sup>42</sup>The reason for this difference is that the IV (networking hospital costs) is only valid conditional on  $EV^H$ , which varies across plans. Hence, it is invalid to subtract the plan-level differences.

<sup>43</sup>Since  $I_{it}$  is estimated rather than data, the standard errors are biased down and should be interpreted as such. Since I have a large sample, there is sufficient power to estimate these parameters with precision either way.

<sup>44</sup>Technically instead of age and gender, I use the measure of expected health care spending which is itself estimated nonparametrically based on age and gender.

proposal to use exogenous variation in the choice sets alone (i.e.  $J_i$ ). Since this is a nonlinear model, standard two-stage least squares cannot be applied. My preferred method is using a control function approach due to its relative simplicity. This method separates the error  $\varepsilon_{i0t}$  into two components, only one of which is allowed to be correlated with the endogenous  $I_{it}$ . This correlation is explicitly estimated using residuals from a first stage based on exogenous instruments (See Train (2009), Section 13.4.1). The method is as follows: first, I regress  $I_{it}$  on the instruments including the number of plans in regions 1 and 9 as my excluded instrument. I add the residuals from this first-stage regression as a “control variable” along with  $I_{it}$  in the take-up model. The control function is treated as an exogenous variable, and I estimate the model with MLE using the following probability of take-up:<sup>45</sup>

$$l_{it}^{Ins} = \frac{\exp((1 - \sigma)\hat{I}_{it} - z'_i\omega + \gamma CF_{it})}{1 + \exp((1 - \sigma)\hat{I}_{it} - z'_i\omega + \gamma CF_{it})}$$

Without controlling for the endogeneity of  $\hat{I}_{it}$ , standard MLE generates a value of  $(1 - \sigma)$  close to 0 and a value of insurance that is decreasing in income. This is expected given how subsidies decrease with income, but is inconsistent with theory. Using the control function approach outlined above, I get estimates that are theoretically plausible.

Finishing the estimation in the take-up model, I combine this with the plan choice model to fully characterize demand in the market.

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<sup>45</sup>This application is not precisely correct since I am assuming away the remaining variance in the unobservable component that is correlated with  $I$ . However, I estimated the correct specification and found this variance to be precisely near 0. Hence I proceed without it for simplicity.

## 1.5 Results

### 1.5.1 Hospital Demand

In this section, I present the estimates for the hospital demand model. I only present the non-Kaiser hospital models here but Kaiser models are qualitatively very similar. Note the effect PCPs on plan indirect utility enters directly as (1.8), so requires no prior stage estimation.

Recall for the hospital demand model, the underlying utility function to estimate is:

$$u_{ih\kappa}^H = \phi_h^\kappa - d_\kappa^H(\text{dist}_{ih}) + \varepsilon_{ih\kappa}$$

Hence, the two objects of interest are the hospital fixed effects  $\phi_h^\kappa$  and the distance disutility function  $d_\kappa^H(\cdot)$ . I use a nonlinear functional form on the distance disutility that is quadratic in distance and is allowed to vary by population density to allow for differential travel times in denser areas.<sup>46</sup> Specifically, I use the following function for the disutility of distance:

$$d_\kappa^H(\text{dist}_{ih}) = \beta_1^d \text{dist}_{ih} + \beta_2^d \text{dist}_{ih} * \text{Density}_{z(i)} + \beta_3^d \text{dist}_{ih}^2 + \beta_4^d \text{dist}_{ih}^2 * \text{Density}_{z(i)}$$

The estimated parameters in the above disutility function are presented for each hospitalization type in Table 1.3. In each type, utility is decreasing with distance, consistent with theory that further hospitals are less preferred. This effect is even larger in denser areas, as seen on the coefficients for  $\text{Dist} * \text{Density}$ . The third set of coefficients on the quadratic term indicate that the negative effect of distance is attenuated with distance—i.e. distance becomes less important the further the hospitals. This is consistent with the early

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<sup>46</sup>I use the standardized log of population density of the zip code of the patient, labeled  $z(i)$ .

Table 1.3: Estimated Utility for Distance to Hospitals

	(1)	(2)	(3)	(4)	(5)
	IP 0-17	OP 0-17	IP Labor 18-64	IP Other 18-64	OP 18-64
<i>Dist</i>	-0.120*** (0.000631)	-0.0708*** (0.00162)	-0.154*** (0.00103)	-0.0799*** (0.000617)	-0.133*** (0.000413)
<i>Dist * Dens</i>	-0.0905*** (0.000829)	-0.0405*** (0.00206)	-0.112*** (0.00124)	-0.0335*** (0.000755)	-0.0594*** (0.000557)
<i>Dist</i> <sup>2</sup>	0.00111*** (9.81e-06)	0.000479*** (2.21e-05)	0.00108*** (2.43e-05)	0.000641*** (8.98e-06)	0.00106*** (6.91e-06)
<i>Dist</i> <sup>2</sup> * <i>Dens</i>	0.00135*** (1.36e-05)	0.000574*** (3.03e-05)	0.00181*** (3.33e-05)	0.000547*** (1.16e-05)	0.000962*** (9.59e-06)
Observations	4,378,263	336,623	2,712,106	5,570,961	8,571,636

Standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Note: This table presents the estimated disutility for traveling to a hospital for each separate hospitalization type  $\kappa$ , from the hospital demand models. Density is logged and standardized and based on the zip code of the patient.

work by Capps et al. (2003). Comparing the magnitude of coefficients across hospitalizations types (i.e. columns), I find distance is most important for Labor hospitalizations, and least important among other adult inpatient hospitalizations and children's' outpatient hospitalizations. This reflects the urgency of getting to the hospital when giving birth, relative to other procedures.

Table 1.4 displays the top 5 hospitals in Los Angeles for each type, as indicated by the fixed effects in the model. Cedars Sinai consistently ranks among the top for all types, while for other hospitals, it depends on the type. For example, Ronald Reagan of UCLA is among the most demanded non-labor inpatient and outpatient hospitals, but not for labor.

## 1.5.2 Plan Demand

I now move to the plan demand given the aforementioned estimates from the hospital model. I begin with the plan choice model, conditional on choosing to buy a plan. The parameter

Table 1.4: Top Hospitals by Type in Los Angeles

Inpatient 0-17
<ol style="list-style-type: none"> <li>1. Cedars Sinai Medical Center</li> <li>2. Hollywood Presbyterian Medical Center</li> <li>3. Childrens Hospital Of Los Angeles</li> <li>4. White Memorial Medical Center</li> <li>5. Good Samaritan Hospital-Los Angeles</li> </ol>
Outpatient 0-17
<ol style="list-style-type: none"> <li>1. Childrens Hospital Of Los Angeles</li> <li>2. Ronald Reagan UCLA Medical Center</li> <li>3. Cedars Sinai Medical Center</li> <li>4. Keck Hospital Of USC</li> <li>5. White Memorial Medical Center</li> </ol>
IP Labor 18-64
<ol style="list-style-type: none"> <li>1. Cedars Sinai Medical Center</li> <li>2. Hollywood Presbyterian Medical Center</li> <li>3. White Memorial Medical Center</li> <li>4. California Hospital Medical Center - Los Angeles</li> <li>5. Good Samaritan Hospital-Los Angeles</li> </ol>
IP Other 18-64
<ol style="list-style-type: none"> <li>1. LAC+USC Medical Center</li> <li>2. Cedars Sinai Medical Center</li> <li>3. Keck Hospital Of USC</li> <li>4. Ronald Reagan UCLA Medical Center</li> <li>5. Los Angeles Community Hospital</li> </ol>
Outpatient 18-64
<ol style="list-style-type: none"> <li>1. Cedars Sinai Medical Center</li> <li>2. Ronald Reagan UCLA Medical Center</li> <li>3. Keck Hospital Of USC</li> <li>4. White Memorial Medical Center</li> <li>5. LAC+USC Medical Center</li> </ol>

Note: This table presents the top hospitals in Los Angeles for each separate hospitalization type  $\kappa$ , from the hospital demand models. Top hospitals are those with the highest estimated fixed effects in the model.

estimates for baseline utilities ( $\Theta_1$ ) and heterogeneity ( $\Theta_2$ ) are given in Tables 1.5 and 1.6 respectively. Given the results in Table 1.5, I find that there is a strong increasing utility in the level of coverage, with higher tiers yielding higher utilities. Also as expected, EPOs and PPOs generate higher utility than HMOs conditional on network quality and prices.

In Table 1.6, I find evidence of preference heterogeneity for different plan characteristics. I find a higher price sensitivity among those with lower expected health spending,<sup>47</sup> Asians and other nonwhites, as well as those living in denser areas. This latter result is consistent with two theories: 1) high costs of living in urban areas (Weinberg and Kallerman, 2017), and 2) possibly greater access to uncompensated care (Finkelstein et al., 2017a).<sup>48</sup> While non-HMOs yield higher utility in general, the difference is even larger among households with high incomes and those with higher expected health care spending. In the last set of rows, I also find that higher AV plans are more attractive for households with higher incomes and higher expected health expenditures.

The impact of providers on plan choice is also notable. Hospital networks matter, but not for Kaiser plans. This latter fact isn't surprising since hospital qualities do not vary in the Kaiser system as they do otherwise. For non-Kaiser plans, hospital networks affect plan choice but the magnitude in dollars is relatively small. Consider the UCLA hospital, which for a typical enrollee increases the *hospital network utility* by about 0.1. The hospital coefficient of 1.189 combined with the price coefficient of -4.935 imply an average valuation of

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<sup>47</sup>This is estimated from MEPS based on age and gender. It is described in more detail in Chapter 2, where it is referred to as  $\theta_i^c$ .

<sup>48</sup>Unlike in many other papers, I do not allow price sensitivity to vary with income. I consistently find that high income households are not less price-sensitive in this population. I attribute this to the APTC and the fact that high income households are facing higher prices overall. Hence my results are consistent with disutility in price that is convex rather than linear. Any conclusions should be interpreted within the context of the ACA rather than the broader individual insurance market. Also note that while income doesn't interact with price, it does interact with other product attributes which are associated with higher prices (e.g. metal tiers, network type, brand), as well as the preference for insurance in general.

Table 1.5: Select Demand Estimates: Baseline Utilities ( $\Theta_1$ )

	Coef	SE	p-val
Constant	-2.772	0.414	***
Bronze HSA	-2.192	0.200	***
Silver	4.104	0.216	***
Gold	5.969	0.221	***
Platinum	8.489	0.244	***
PPO	2.759	0.276	***
EPO	2.672	0.286	***

\*\*\*p<0.001; \*\*p<0.01; \*p<0.05; .p<0.1

Note: This table presents the baseline estimated coefficients from the plan choice model. “Baseline” represents the fact that this is common to all households in the market. Brand and region dummies omitted. Standard errors are not corrected for estimated provider models.

having UCLA in-network of only about \$2.41/month.<sup>49</sup> Regarding PCP networks, they also matter to consumers, and among both Kaiser and non-Kaiser plans. For non-Kaiser plans, given the PCP utility estimate of 0.136 combined with that of hospital networks (1.189), this implies a hospital like UCLA would generate the same utility as an 87% increase in the number of nearby PCPs.<sup>50</sup> Given the size of many medical groups, this implies large physicians groups have similar bargaining abilities with plans to many hospitals (Ho, 2009). Using the coefficient on price, roughly doubling the number of PCPs within 5 miles is worth \$2.76/month to a typical consumer in the market.

<sup>49</sup>This seems relatively low compared to other studies (Shepard, 2016; Ho, 2006). It could be due to actually low valuations in this market—especially given the high price elasticity—or bias for reasons described in Section 1.4.4. It could also be that prior studies have upward biased estimates as a result of omitting physicians, which are included in my model. Either way, any bias is not expected to change the results of this paper, since omitted heterogeneity is absorbed into carrier and network type preferences.

<sup>50</sup>This is based on an average over risk types (again assuming  $\lambda^P$  is constant) and averaging over population densities. In Los Angeles where it is much denser than the state average, the effect of local PCPs is likely much larger. Hence this 87% is an upper bound—i.e. the true percentage is smaller indicating PCPs are more valued.



Table 1.6: Select Demand Estimates: Heterogeneity Utilities ( $\Theta_2$ )

Plan Char	HH Char	Coef	SE	p-val
$p_{ijt}$		-4.935	0.186	***
$p_{ijt}$	$E(MedSpending) (\theta_i^c)$	1.048	0.041	***
$p_{ijt}$	$HHSize = 2$	2.076	0.086	***
$p_{ijt}$	$HHSize = 3$	3.225	0.131	***
$p_{ijt}$	$HHSize = 4$	3.991	0.154	***
$p_{ijt}$	Asian	-0.292	0.033	***
$p_{ijt}$	Nonwhite	-0.145	0.021	***
$p_{ijt}$	Density	-0.069	0.017	***
Silver AV94		2.389	0.087	***
Silver AV87		1.468	0.062	***
Silver AV73		0.456	0.059	***
HMO (non-Kaiser)	FPL	-0.193	0.035	***
HMO (non-Kaiser)	$E(MedSpending) (\theta_i^c)$	-0.125	0.044	**
$EV_{ijt}^{H,nonKais}$		1.189	0.343	***
$EV_{ijt}^{H,Kais}$		0.231	0.185	
$\log(PCPs \text{ in } 5 \text{ mi})^{nonKais}$		0.136	0.017	***
$\log(PCPs \text{ in } 5 \text{ mi})^{Kais}$		0.139	0.012	***
AV	FPL	0.118	0.009	***
AV	$E(MedSpending) (\theta_i^c)$	0.161	0.013	***
AV	$HHSize = 2$	0.389	0.032	***
AV	$HHSize = 3$	0.552	0.075	***
AV	$HHSize = 4$	0.444	0.099	***

\*\*\*p<0.001; \*\*p<0.01; \*p<0.05; .p<0.1

Note: This table presents heterogeneity coefficients from the plan choice model. These are the coefficients that dictate deviations from baseline utilities in the prior table. Preferences for plan characteristics are based only on the observable characteristics as indicated. Brand-demographic (income, spending, race) interactions omitted. Expected spending is the average  $\theta_i^c$  within the household. Density in Logs. FPL is censored at 400% FPL, and effect of additional income assumed negligible beyond that point. FPL, expected spending, and density are standardized. Prices in units of \$100.

Table 1.7 provides the estimates for the take-up model. Since this is a binary decision, I’ve moved all variables to the take-up side of the inequality, which implies these coefficients are the relative utilities of having insurance. The key parameter from this model is the coefficient on the “Inclusive Value,” estimated at 0.654. Recall that this value ( $1 - \sigma$ ) is the degree of *independence* between the unobservable utilities across insurance plans (hence in a logit model it is assumed to be 1). That it is significantly lower than 1 implies a correlation between the plan unobservable utilities. In other words, conditional on age, gender and race, consumers still disproportionately substitute between plans relative to choosing to be uninsured.

The coefficient on the control function is also important. It loosely represents the correlation between  $I_{it}$  and  $\varepsilon_{i0t}$ . That it is negative implies that the APTC (and hence  $I_{it}$ ) is highest among households with low willingnesses-to-pay for insurance in unobservable ways. Regarding other coefficients, we can see that the preference for insurance is increasing in income and lower for nonwhite and urban consumers.<sup>51</sup>

Figure 1.4 plots the distribution of elasticities by network type (non-HMO, Kaiser, Other HMO), tier, and geographic region (North vs. South). Price-sensitivity in the market is quite high, with market shares generally decreasing between 3% and 5% for a price increase of \$1. These are much higher than seen in the unsubsidized individual market (Cutler and Reber, 1998; Ho, 2006; Ericson and Starc, 2015), but close to those in other subsidized individual markets (Shepard, 2016; Finkelstein et al., 2017a). The fact that these are even slightly higher than those papers isn’t surprising. Relative to the pre-ACA Massachusetts exchange or the ACA markets in other states, Covered CA has a number of standardizing regulations

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<sup>51</sup>Notice that expected spending (as a function of age and gender) is associated with a negative coefficient in this model. Since the price sensitivity is lower among those with higher expectations of health spending, the value of insurance is already increasing in this variation through  $I_{jt}$ . Hence, this is a “reduced-form” effect, net of the already modeled preference for insurance. It is also possible that there are compositional differences between older and younger people that are eligible for the exchange and just have lower preferences for insurance—e.g., left employer because didn’t need insurance.

Table 1.7: Select Demand Estimates: Take-up Model ( $\Theta_3$ )

HH Char	Coef	SE	p-val
Constant	1.708	0.182	***
$I_{it}$	0.654	0.067	***
Control Function	-0.656	0.067	***
FPL	1.648	0.215	***
$E(\text{MedSpending})$	-0.258	0.082	**
Asian	0.120	0.043	**
Nonwhite	-0.410	0.029	***
Density	-0.163	0.019	***

\*\*\*p<0.001; \*\*p<0.01; \*p<0.05; .p<0.1

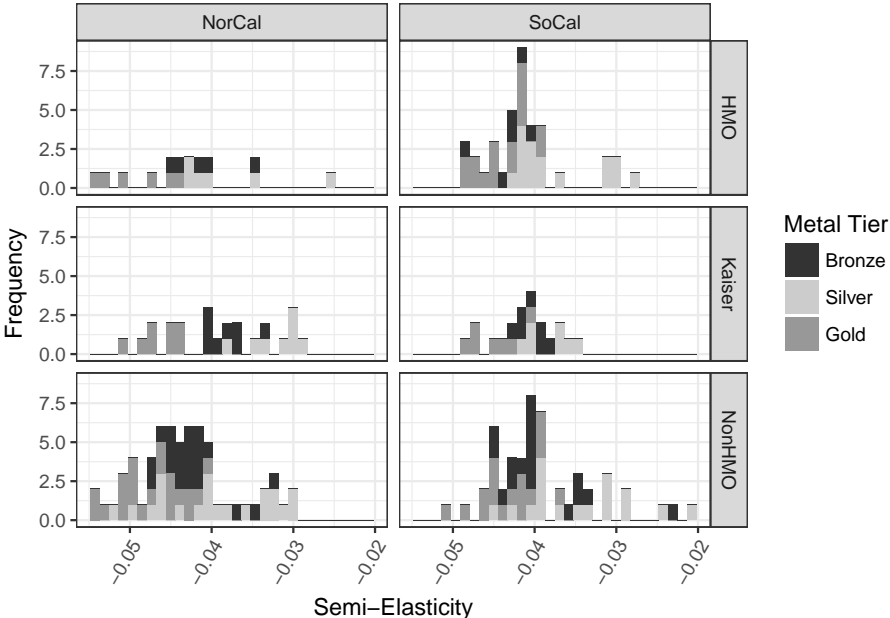
Note: This table presents coefficients from the take-up model. Utility is associated with taking up insurance. FPL is censored at 400% FPL, and effect of additional income assumed negligible beyond that point. FPL, expected spending, and density are standardized. Region dummies omitted.

that intensify price competition (see Section 1.2).

The elasticities vary somewhat by region, network type, and tier. Silver plans appear to be the least price elastic, which makes sense given the large cost sharing subsidies tied to Silver plans for a majority of enrollees. Generally, Gold plans are more elastic, especially for HMOs. Elasticities by network type depend on geography. Non-HMOs are generally less elastic in the South, while Kaiser plans are less elastic in the North. Interestingly, despite the relative concentration in Northern California (see Table 1.1), elasticities are not markedly lower.

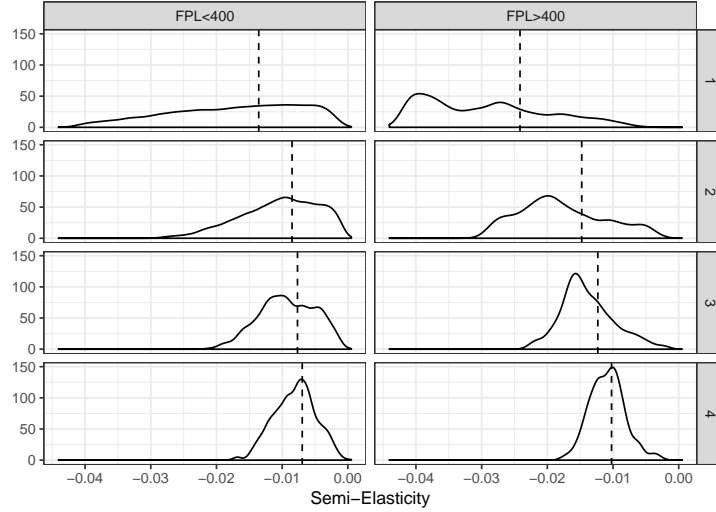
Figure 1.5 plots the distribution of household-level *extensive margin* semi-elasticities, by household size and whether the household is subsidy-eligible (i.e. income below 400% FPL). Notice that there is a wide distribution of elasticities, given the distribution of preferences in the market. It's also clear that the elasticity depends both on household size and whether or not the household is eligible for a subsidy. Larger households are less sensitive to a change in the APTC, as are subsidy eligible. The main reason that the subsidy ineligible

Figure 1.4: Semi-Elasticities by Geography and Network Type



Note: This figure plots the distribution of own-price semi-elasticities in the market. These give the percent change in plan enrollment associated with a \$1 increase in plan premium. Each “point” in the distribution is a single plan ( $jt$ ). Regions 1, 9, and 10 omitted.

Figure 1.5: Household Extensive Margin Semi-Elasticities by Household Size



Note: This figure plots the distribution of extensive margin semi-elasticities in the market, by household size and subsidy status. These give the percent change in take-up associated with a \$1 decrease in APTC (i.e., \$1 decrease in all plan premiums). Dashed lines are the group level elasticities defined as  $\frac{\sum_j \partial s_i^{Ins} / \partial \tau_{it}}{\sum s^{Ins}}$ .

are more responsive to APTC is because their baseline take-up rate is so low combined with the functional form of the logit model. It is important to note, however, that each group has other different underlying demographics—namely, the unsubsidized are more likely to be male and younger. This explains part of the difference.

Table 1.8: Extensive Margin Semi-Elasticities by Income and Household Size

HH Members	FPL Range			
	0-200	200-250	250-400	400+
1	-0.012	-0.014	-0.018	-0.024
2	-0.007	-0.009	-0.011	-0.015
3	-0.006	-0.008	-0.010	-0.012
4	-0.006	-0.007	-0.008	-0.010

Note: This table presents the group-level semi-elasticities by household size and FPL (income) range, defined as  $\frac{\sum_j \partial s_i^{Ins} / \partial \tau_{it}}{\sum s^{Ins}}$ .

Table 1.8 displays the group-level elasticities, further broken down by income group.

For a single-member household with an income below 200% FPL, the probability of take-up declines by 1.2% for a \$1 decrease in the APTC. For a similar income household of 2 members, the take-up rate declines by 0.7%. These semi-elasticities are roughly doubled for unsubsidized households with incomes above 400 FPL.

These imply an overall semi-elasticity in the market of 1.17% among the subsidized population and 2.17% in the unsubsidized population. These are relatively high compared to recent work by Finkelstein et al. (2017a) which finds a 25% decline in take-up for a \$40 decline in subsidies. I discuss possible explanations in Section 1.6.

## 1.6 Discussion

The first takeaway from the above results is that consumers in Covered CA are highly sensitive to plan premiums. As seen in Figure 1.4, a \$1 increase in premium is associated with a 3 - 5% decline in market share for most plans. This is perhaps unsurprising since this is a relatively low-income population for which there is little extra discretionary spending. Unlike in the Pre-ACA individual market where elasticities were documented to be much lower (Ericson and Starc, 2015), the findings in this study are similar in magnitude to similarly low-income markets (Shepard, 2016). The fact that these elasticities are even higher than previously documented in those subsidized markets is also not surprising given the additional regulations in California. In Covered CA, policymakers have taken additional steps to ensure a competitive environment. As noted in Section 1.2, regulators prevent plans from segmenting the market or “cream-skimming” by standardizing plan characteristics and enforcing network adequacy requirements. By ensuring plans are similar, it increases their substitutability making consumers more sensitive to price. Having transparent prices on the Shop & Compare tool on the Covered CA website makes this effect even stronger.

This high price sensitivity has a number of key implications. The first is that low-premium

plans—such as the Medicaid-style HMOs of southern California—are extremely valuable to consumers. In the broader ACA markets around the nation, there has been much attention on “narrow-network” and potentially low-quality plans after the introduction of the ACA (Polsky and Weiner, 2015). The results in this paper suggest that if these narrow networks lead to savings in costs, then they may generate significant welfare for consumers—a result that has been suggested elsewhere (Ho and Lee, 2017). The demand estimates imply that physician and hospital networks do affect plan choice, but not nearly to the degree of price—at least on average. Importantly, within Covered CA there are minimum network and benefit standards that ensure consumers are protected from truly low-quality plans. Hence, “lean” plans we see in the market which meet these standards could be an efficient outcome in the market since they are offered at low prices. More work is needed on the welfare implications of different plan network designs, especially in this relatively low income population. Regardless, caution should be used when considering policies that can increase plan costs (e.g. larger networks) given how important low premiums are for consumers.

The second implication of the high price sensitivity is that this market has low profitability and premiums will be set close to plan costs. In a simple model of profit-maximization, markups are equal to the inverse of the semi-elasticity (Nevo, 2001). With semi-elasticities in the order of 0.04 as we see here, a simple back-of-the-envelope calculation implies markups of about \$25, or 6.2% of a typical premium.<sup>52</sup> Since this is only variable profits over marginal costs, it implies total profits are even smaller when including the significant fixed costs of operating a plan. Interestingly, recall from Table 1.1 that most of these markets are fairly concentrated. Hence, even though there are relatively small number of plans, profitability is still relatively low. This is important because there has been much attention on the concentration of ACA markets around the country. The results from this study imply that even a

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<sup>52</sup>This is based on the average per-member gross premium in 2015 of \$402.

few plans is likely sufficient to get to fairly competitive prices.<sup>53</sup>

An important point on the above two implications is that these are for the aggregate population, and do not address important heterogeneity. There are individual consumers that place a high utility on networks (Shepard, 2016) and since my model doesn't capture heterogeneity from health conditions, I cannot accurately measure this.

The last main finding of this study is that consumers are also fairly responsive along the extensive margin of take-up. While results vary by income and household size, the probability of take-up declines by 1.4% for a \$1 decrease in the APTC on average. In the recent study by Finkelstein et al. (2017a), the authors find a 25% reduction in take-up for a \$40 reduction in APTC. The results from the current study imply a 43% reduction in take-up for a similar change in APTC—notably larger.<sup>54</sup>

There are a number of possible explanations for the difference, either due to measurement differences or to real structural differences in the two populations. Regarding measurement, the elasticities in this paper could be biased upwards in magnitude for two reasons: First, note that given functional form assumptions, semi-elasticities are declining in take-up rates. Hence, if I am under-measuring my take-up rates, I overestimate my semi-elasticities. This could happen if, for example, undocumented workers make up a large share of my uninsured population—who are not actually relevant in this market.<sup>55</sup> The second measurement reason is related to identification of the nesting term  $(1 - \sigma)$  in the take-up model. The estimated extensive margin semi-elasticities are increasing in  $(1 - \sigma)$ . If  $(1 - \sigma)$  is biased upwards, then the semi-elasticities will be as well. Recall  $(1 - \sigma)$  is identified by differences in take-up given

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<sup>53</sup>Having a small number of plans could be a concern insofar as it implies little variety for consumers. To the extent that preferences are heterogeneous in unobserved ways, the welfare of additional plans could dominate the effects of higher prices—at least for a fraction of consumers.

<sup>54</sup>Percent decline given by  $1 - (1 - 0.014)^{40}$

<sup>55</sup>This would also bias down my estimate of  $(1 - \sigma)$  and hence also  $\alpha_i$ , which would have the opposite effect. Hence, the true net effect is ambiguous.



different choice sets within a rating region—specifically the number of plans offered. This could be biased upward if the number of plans is correlated with the unobserved preference for insurance—conditional on observables like income, population density, and age. However, this is unlikely to be true since the offer sets are largely determined by Covered CA’s networks adequacy rules which is unlikely to be correlated with preferences, especially excluding observables. The last reason for the high extensive margin elasticity in this paper could be a true structural difference in this population relative to elsewhere—i.e., CA enrollees are more sensitive to APTC changes. This is quite possible since in CA, there is a higher share of minority enrollees which are indeed more price sensitive (See Table 1.6).

The implication of the high sensitivity along the extensive margin of take-up is that APTC design is important for determining the overall rate of uninsured. While the goal of the ACA was largely to get to complete coverage, the fact that there is a sharp decline in the APTC schedule with income implies there will be a nontrivial amount of uninsured as APTC fades. This has also been studied in more detail in other related work (Finkelstein et al., 2017a; Tebaldi, 2016). The high sensitivity along this margin also implies that the market as a whole is subject to adverse selection without proper remedies. By benchmarking APTCs in some way market prices as is done in the ACA (as opposed to exogenously determined outside the market), this can reduce market-wide adverse selection—at least among the subsidy eligible.<sup>56</sup>

## 1.7 Conclusion

This chapter contributes to the literature on demand for health insurance (Ho, 2006; Town and Liu, 2003; Shepard, 2016) and demand estimation methods more broadly (Berry et al., 2004; Goolsbee and Petrin, 2004) by estimating the demand for insurance in the ACA market in California. My estimation method augments the “BLP” type estimation procedure and

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<sup>56</sup>The same is true at the plan-level, highlighting the importance of risk adjustment.

can be used whenever there is individual-level price variation. I also provide exogenous sources of variation in prices and in the “inclusive value” to be able to identify the parameters of the demand model.

I find that among observable characteristics in the data, the plan premium is extremely important for plan choice. Despite the relative concentration in the market, semi-elasticities generally range between 3% and 5% for a \$1 increase in price. This is even higher than figures documented in similar markets in Massachusetts (Jaffe and Shepard, 2017; Shepard, 2016). Additionally, I find that plan demand not only responds to hospital networks as has been documented elsewhere, but also to PCP networks. I also find that the overall take-up rate is quite responsive to APTC. I estimate that a \$1 decline in APTC leads to a 1.2% decline in take-up among the subsidized population. Hence, APTC design plays an important role in who decides to purchase insurance. An important future step is examining welfare implications, especially by incorporating unobserved preference heterogeneity and distributional impacts. Moreover, these results point to the possibility of adverse selection in this market, a topic I explore in detail in the next chapter.

## Chapter 2

# How Do Supply-Side Regulations in the ACA Impact Market Outcomes? Evidence from California

### 2.1 Introduction

The Patient Protection and Affordable Care Act (ACA) was passed in 2010 with the goal of expanding health insurance coverage in the United States. One way of accomplishing that goal was establishing subsidized and regulated insurance marketplaces (“exchanges”) for consumers without other insurance options. The regulations in the exchanges aim to balance equity with efficiency, i.e. granting access to those most in need while maximizing consumer surplus. However, despite generous subsidies and guaranteeing access to those willing to pay for insurance, roughly 9% of the U.S. was still uninsured in 2016.<sup>1</sup> Along the same lines, nationwide enrollment was disproportionately lower in plans with either generous coverage or with wide provider networks (Polsky and Weiner, 2015). Some have

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<sup>1</sup>See: <http://www.kff.org/other/state-indicator/total-population/>

used these facts to suggest that the exchanges are experiencing adverse selection—that high-cost enrollees are driving other consumers out of quality plans or out of the market entirely. At the same time, low-cost plans that garner high enrollment also face financial difficulties (Holahan et al., 2016). This paper aims to reconcile these facts by examining the impact of two main supply-side regulations in the ACA: *community rating* and *risk adjustment*. How do these policies affect enrollment across plans in the market? And do they in fact lead to adverse selection, or is there another force that is driving these market outcomes? In this paper, I address these questions using a structural supply and demand model of ACA exchanges.<sup>2</sup>

I examine these two specific policies because they largely dictate how enrollment composition impacts prices and thus market outcomes in equilibrium. Yet they have received relatively little academic attention. First consider community rating, which limits what consumer characteristics plans can use to set premiums.<sup>3</sup> In the ACA, premiums are based only on age, and cannot exceed a ratio of 3:1 across ages. By eliminating the volatility in premiums due to preexisting health conditions, community rating increases welfare (Handel et al., 2015). However, as long as the preference for insurance is positively correlated with expected costs, community rating without other correcting policies can create adverse selection. This arises from two effects: 1) a *direct effect*: marginal enrollees face higher premiums as a result of being pooled with higher cost enrollees and opt out, and 2) an *equilibrium effect*: as low-cost enrollees opt out, the price perpetually increases, possibly even unraveling the entire market (Akerlof, 1970). These combined effects can reduce coverage along both the *extensive margin* of getting any insurance (Rabin and Abelson, 2013), and the *intensive*

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<sup>2</sup>The regulations in the ACA exchanges also apply to the unsubsidized or “off-exchange” individual insurance market. I do not study that market in this study, but the findings of this paper would generally apply there as well.

<sup>3</sup>Guaranteed Issue, which prohibits denials of coverage, is another major part of the ACA reforms. It can be thought of as a part of community rating since it prohibits setting “infinite” prices to certain consumers based on health conditions.

*margin* of the quality of the plan chosen (Cutler and Reber, 1998; Buchmueller and DiNardo, 2002).

One of the key mechanisms to limit adverse selection across different plan types in the ACA is risk adjustment, the other focus of this study. Risk adjustment prevents the unraveling effect described above by having plans with healthier enrollees make transfers to plans with sicker enrollees. By doing so, the effective marginal costs faced by plans do not depend on enrollee risk composition. Hence, prices do not spiral upward in equilibrium, and high quality plans that attract sick enrollees can remain in the market. In this way, risk adjustment is effectively a Pigovian-style tax that corrects for some of the welfare losses from adverse selection.

This paper quantifies the impact of community rating and risk adjustment in the ACA using data from Covered California, California’s ACA exchange. To do this, I estimate a structural model of demand and supply for health insurance, which includes specific details from the regulations. The demand side of the model is built from the common discrete choice framework with preference heterogeneity. Since plan heterogeneity is key to selection in this study, I include the utility generated from hospital and physician networks as a determinant of plan demand. The model also accounts for premium subsidies and the mandate to buy insurance. I estimate the demand model using individual-level plan choice data and provider directories from Covered CA in 2015. The supply side of the model allows for imperfect competition and assumes static profit maximization of all insurers—i.e. a static Nash-in-prices equilibrium. As in the regulations, I include community rating and risk adjustment in firm profit functions. Finally, I use the estimated model to simulate prices and enrollment under counterfactual scenarios where either a) risk adjustment is eliminated, or b) community rating is eliminated. I also simulate an alternative method of risk adjustment which has different properties from the method currently employed. This alternative somewhat resembles risk adjustment in Medicare Advantage, a similar market in the U.S. for the elderly.

There are a number of new findings from this study. First, consumers in this market are highly price-sensitive. For a typical plan, a premium increase of \$1 is associated with a decrease in shares between 3.5% and 4.5%. While these are quite high relative to most health insurance products, they are close to those found in similar markets (Shepard, 2016; Finkelstein et al., 2017a).<sup>4</sup> This implies profit margins on these plans are slim and range between 3% and 8% of total revenues, excluding any fixed costs. Second, using counterfactual simulations, I find that ACA *community rating* without risk adjustment would reduce the share of enrollment in generous plans and enrollment in the market overall, consistent with adverse selection. For example, the market share of non-HMO plans would decrease by 15%. Similarly, shares for plans with the most generous cost sharing would decrease by 86%. Community rating would also lead to a decline in the total number of insured households by 13.8%.<sup>5</sup> Adding *risk adjustment* as implemented in the ACA has little effect on total enrollment but does restore over half of the effect on shares from community rating. Under ACA risk adjustment, there is a small degree of persistent adverse selection. For a typical Gold or Platinum non-HMO plan, the marginal consumer has expected health expenditures \$2 less than the inframarginal average, net of risk adjustment. Finally, I simulate an alternative form of risk adjustment that can eliminate this persistent adverse selection. For each plan, this method flattens the perceived marginal cost curve and sets it equal to the plan's average cost in the population. In this case, I find that total enrollment would increase by 3.0%, with a disproportionate increase in plans that attract sicker enrollees. Net government spending would be roughly unchanged under this method. Premiums would decline and therefore so

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<sup>4</sup>See footnote 56 in Ho (2006) for a good discussion of estimated elasticities in health insurance markets. My estimates are roughly between 3 and 6 times the elasticities in those markets with group insurance. The individual market in the ACA would be expected to have higher elasticities for a number of reasons (lower incomes, larger choice sets, transparency and plan standardization, etc.).

<sup>5</sup>This decline in coverage should not be interpreted as welfare reducing. The main motive of community rating is to reduce reclassification risk from unpredictable health shocks. This study doesn't capture the true variation in underlying costs and so cannot capture the true benefit of eliminating this form of risk.

would premium subsidies, offsetting increases in government payments for risk adjustment.

The policy implications of these findings are threefold. First, the price elasticities in Covered CA suggest exchanges can be an effective mechanism to deliver care at competitive prices to consumers. Despite relatively high measures of market concentration, the high price-sensitivity in the market limits markups, and premiums are set close to costs. These low margins might partly explain why there are so few plans in other ACA markets around the country. Second, risk adjustment in the ACA plays an important role in mitigating adverse selection along the intensive margin. Without risk adjustment, generous plans and those with well-known providers would face significant cost pressure from high-risk enrollees that would drive down their enrollment. Risk adjustment does not, however, substantially reduce the decline in overall coverage caused by community rating. Any policies aimed at universal coverage will need to consider the high price-sensitivity of low-cost, low-demand consumers, as has been suggested in other work (Tebaldi, 2016; Panhans, 2017; Finkelstein et al., 2017a). Finally, the alternative risk adjustment method described above can increase the total rate of coverage with a negligible impact on government spending. However, the welfare consequences of this change, especially in the long run, are not clear.

On a broader level, this study can reconcile the nationwide observations described earlier: 1) a continuing high rate of uninsured, 2) the popularity of low generosity and narrow network plans, and 3) financial difficulties for low-cost plans despite popularity. Enrollment is high among low-cost plans not because of adverse selection but because consumers prefer low-price options. This high price-sensitivity puts downward pressure on prices and limits profit margins for all plans. And finally, despite the mandate and subsidies, community rating can decrease total enrollment in ways that cannot be corrected by risk adjustment. The use of community rating and risk adjustment extends well beyond the individual market established by the ACA. Medicare Advantage covers roughly 16 million elderly Americans in a similar market that uses both community rating and risk adjustment. Countries such

as Germany, Switzerland, and the Netherlands also use these policies. The U.S. and other countries are increasingly relying on private markets to deliver public health care benefits. This paper can help policymakers better understand how these common regulations shape insurance markets and ultimately benefit consumers.

## Contributions

This paper makes contributions to three bodies of academic literature. The first is related to existing work on ACA regulations. A number of studies have examined the demand-side regulations like the mandate and subsidies using similar approaches to this study (Hackmann et al., 2015; Tebaldi, 2016; Jaffe and Shepard, 2017). There has also been some work on the community rating and risk adjustment policies in the ACA, but it is either based on data from other markets (Handel et al., 2015; Layton, Forthcoming; Ericson and Starc, 2015) or discussed in a theoretical sense (Geruso and Layton, 2017; Layton et al., 2017). The paper by Handel et al. (2015) is particularly relevant to this study since they examine the welfare implications of community rating and different corrective policies. Importantly, they find community rating would cause some plans to unravel but the benefits dominate welfare losses since community rating eliminates *reclassification risk* (exposure to high premiums given health shocks). That paper also addresses risk adjustment, but in less detail. While these papers have all informed about how policies in the ACA impact welfare and other outcomes, they have not studied ACA risk adjustment in detail or they have used data from other markets. Hence, this paper adds insight to how these policies shape the market in practice.

Relatedly, this paper fits into a long history of work looking at risk adjustment in general (Newhouse et al., 1989; Glazer and McGuire, 2000; Brown et al., 2014; Einav et al., 2016). That literature has largely focused on the information that should be included when quantifying enrollee risk—i.e. risk scores. This paper, conversely, assumes risk scores are perfect



and observable, and instead focuses on *how* they are used in the risk adjustment process. As I show in this paper, this has implications on market outcomes that are generally ignored in this strand of literature.

The second contribution is to the extensive body of work on adverse selection (Akerlof, 1970; Rothschild and Stiglitz, 1976; Cutler and Reber, 1998; Buchmueller and DiNardo, 2002; Einav et al., 2010; Shepard, 2016). These papers have theoretically or empirically shown how community rating, or hidden information more generally, can lead to a reduction in coverage in high quality plans. Notably, Einav et al. (2010) identify sufficient conditions for adverse selection using the slope of the marginal cost curve. Their application is in a competitive environment with just two options in the choice set, and reduced form cost and demand functions. To add to that work, I introduce a metric of adverse selection in the presence of modified community rating and risk adjustment as in the ACA. My measure is derived from a structural model and hence allows for imperfect competition and many options in the choice set. I use this measure to explicitly quantify adverse selection in the market using the estimated model.<sup>6</sup> Additionally, this is the first paper to look at adverse selection at the plan level for ACA markets.

Finally, this paper contributes broadly to work examining health plan competition (Town and Liu, 2003; Ho, 2006; Curto et al., 2014). This paper is the first to measure the degree of competition in an ACA market that incorporates provider network differentiation. I include networking hospitals and physicians in the demand for insurance, and find both are important. Broader network plans attract higher cost enrollees, which is relevant for measuring selection. The estimates are used to quantify demand elasticities across all plans in the market, which I find to be quite high. Additionally, the estimation makes two methodological

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<sup>6</sup>The primary motivation of the adverse selection test in Einav et al. (2010) is to subsequently measure welfare losses. I make simplifying assumptions in my model that would underestimate welfare measures and hence I do not make welfare comparisons. Although, it could be added in the future with a refined choice model. Layton (Forthcoming) measures the welfare implications of risk adjustment when risk scores are imperfect.

contributions that can be applied for other demand models in ACA markets: 1) I specify a method of estimation that accounts for the *within-plan* price heterogeneity created by the ACA pricing policies, and 2) I exploit exogenous variation in insurance choice sets to identify the preference for getting coverage.

## 2.2 Background

This section discusses the theoretical motivation for regulation in insurance markets, and the details of those regulations in the ACA.

### 2.2.1 Theory of Community Rating and Risk Adjustment

Before discussing the details of the ACA, it is useful to think about how community rating creates adverse selection, and how risk adjustment can offset it. For this exposition, I use the graphical model presented by Einav et al. (2010). While it assumes perfect competition unlike in this paper, it still conveys the main economic forces.<sup>7</sup> I present the model with a single homogeneous insurance product relative to being uninsured, but it can also loosely be thought of as between plans of different desirabilities—though there are slight differences (Layton, Forthcoming).

Consider a market of consumers indexed by health status  $\theta$ . For each  $\theta$ , consumers have an expected health expenditure  $c(\theta)$  and willingness-to-pay for insurance  $v(\theta)$ , both of which are increasing in  $\theta$ . The implied demand and marginal cost curves are given in panel (a) of Figure 2.1. Note that the marginal cost curve is decreasing since  $v(\theta)$  and  $c(\theta)$  are positively correlated.

In a competitive market with full information (no community rating), prices would be

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<sup>7</sup>See Ericson and Starc (2015) for a discussion of how imperfect competition changes the results from community rating.

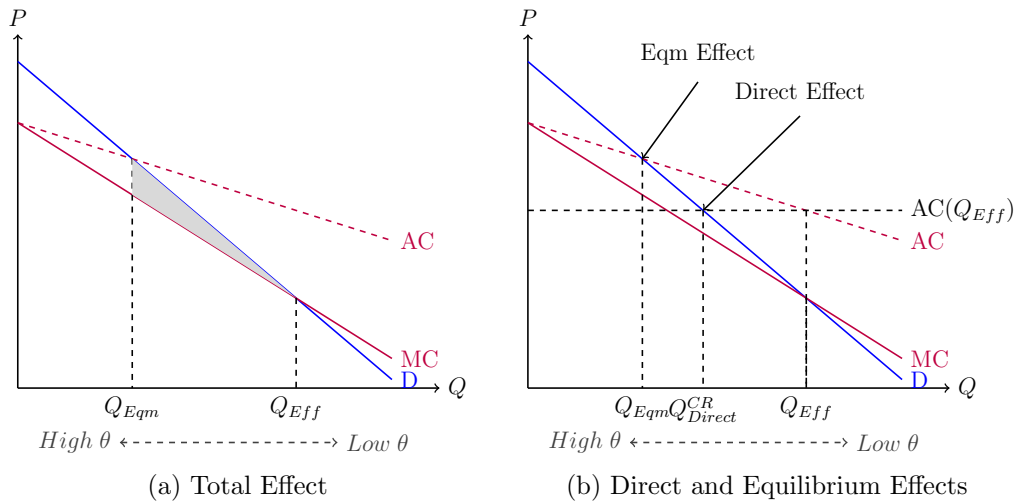


Figure 2.1: Adverse Selection from Community Rating

set for each  $\theta$  and equal to the cost of coverage  $c(\theta)$ . All consumers with valuations greater than the price would buy coverage. Since consumers purchase coverage if and only if their valuations exceed the cost, this is the efficient allocation. This is represented by  $Q_{Eff}$  in panel (a) of Figure 2.1, where the marginal cost curve intersects the demand curve.

Next consider the effect of community rating (or “hidden information” more generally). In this case, firms can only charge a single price for the entire population of  $\theta$ s. Since markets are assumed to be competitive, firms make no profits and prices are set equal to the average cost of the insured pool. The point at which the average cost curve equals the demand curve gives the equilibrium allocation under community rating. This is given by  $Q_{Eqm}$  in the same figure. The shaded region between these two quantity levels gives the welfare loss from community rating.

In panel (b) of Figure 2.1, I decompose the effect of community rating on quantities into the two effects described in the introduction: a direct effect and an equilibrium effect. The direct effect gives the reduction in quantities as a response to pooling enrolled consumers, holding the underlying composition constant. This is where the demand curve intersects the average cost of the efficient quantity  $Q_{Eff}$ . I label this point as  $Q_{Direct}^{CR}$ . The equilibrium

effect is that under this new allocation, the average cost has also increased and hence prices exceed the willingness-to-pay for marginal consumers at  $Q_{Direct}^{CR}$ . In equilibrium, quantities reduce until average costs equal demand at  $Q_{Eqm}$ . This decomposition is useful for two reasons: 1) it is related to how risk adjustment can correct for adverse selection, as will soon be clear, and 2) it is the second effect that can lead to the type of unraveling “death spirals” many policymakers are concerned about. For example, adding convexity to these curves could lead to a large unraveling effect.

In Figure 2.2, I present how risk adjustment impacts prices and quantities in this simple model. I use a simple “textbook” version of risk adjustment that has been used in other Economics literature (Mahoney and Weyl, 2017; Geruso and Layton, 2017). It need not be superior to alternatives, such as the method in the ACA (Layton et al., 2017), but it allows for an intuitive exposition.<sup>8</sup> Risk adjustment in this textbook form aims to match each firm’s perceived marginal cost to their average cost in the population. As noted in the introduction, it can be thought of as a Pigovian tax to roughly correct for the equilibrium effect created by community rating. For each enrollee that is higher than average risk, plans receive payments equal to the difference between the marginal cost and the average cost of that enrollee. For each enrollee that is lower than average risk, plans make payments equal to the difference. The marginal cost curve perceived by firms after risk adjustment is depicted in the figure as the horizontal line equal to  $AC(Pop)$ . Under perfect competition, the equilibrium quantity will be where  $AC(Pop)$  intersects demand, and is given by  $Q_{RA}$ .<sup>9</sup>

There are two observations in this figure worth highlighting. First, risk adjustment in this model reduces the welfare loss from community rating and increases the equilibrium

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<sup>8</sup>Mahoney and Weyl (2017) discuss the impact of risk adjustment under imperfect competition.

<sup>9</sup>Layton (Forthcoming) discusses how this differs when considering two plans instead of insured vs uninsured. The main difference comes from the fact that the “other” option is also getting risk adjustment. As a result, the perceived marginal cost curve is still flat but will be shifted down. This is because the average cost curve at the right-side intercept is really the average cost of the population in the high plan relative to the *healthiest enrollee* in the low cost plan (not average cost in the population for the low cost plan).

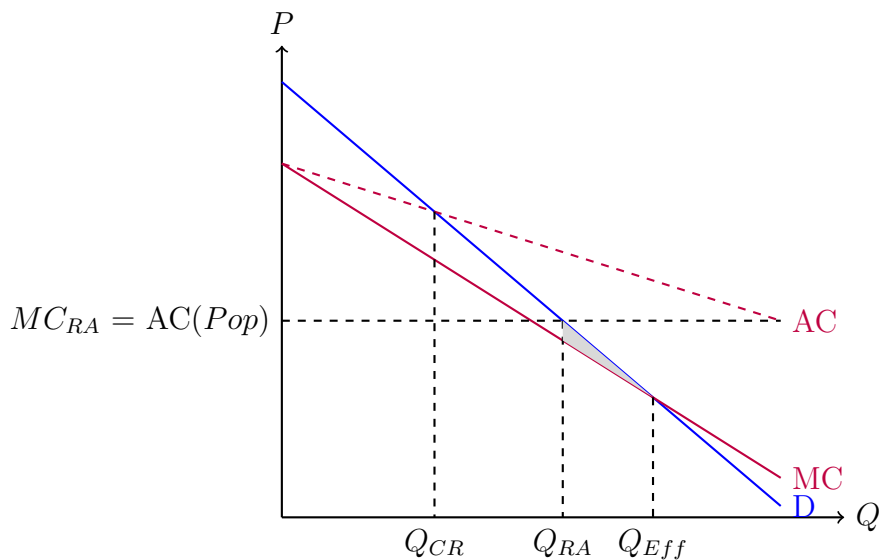


Figure 2.2: Adverse Selection with Risk Adjustment

quantity to be closer to  $Q_{Eff}$ . However, this need not always be the case. Second, this form of risk adjustment creates a constant marginal cost curve that inhibits the equilibrium effect—i.e. unraveling—described in the prior figures.

In reality, the market is much more complicated by having many multi-product firms, imperfect competition, complex heterogeneity in costs and preferences, and subsidized demand. Hence, to properly quantify the effects of these policies, I use a much richer model with all of these features. Motivated by this simple environment, I estimate the same objects (demand and marginal/average costs) in the market to quantify the degree of adverse selection.

### 2.2.2 ACA and Covered CA Regulations

This section gives an overview of the ACA policies most relevant to this study. A more detailed discussion can be found in Layton et al. (2017).

## **Exchange Motivation**

The individual health insurance market in the U.S. is for consumers who do not have coverage through other sources (e.g. employer or other public programs). Before 2014, the individual market was characterized by a lack of affordability, poor coverage, and even outright denials of coverage (Claxton et al., 2016). This was especially true for anyone with preexisting health conditions. Hence, a major goal of the ACA was to fix any potential market failures in the individual market through a regulated environment. The most commonly discussed of these regulations are: guaranteed issue, “modified” community rating, the mandate, and premium subsidies. The two former policies target reclassification risk and equity motives but create the type of adverse selection described above. The mandate and the subsidies, joint with risk adjustment, aim to mitigate that adverse selection.

Modified community rating in the ACA is a variant of the simple form described above. Premiums are allowed to vary across consumers but only based on age. Hence, community rating operates mainly across health conditions and genders. Additionally, premiums across ages cannot exceed a ratio of 3:1. To the extent that underlying costs across ages vary by more, this would imply there is community rating across ages as well. Guaranteed issue is a large part of the reform, but for the purposes of this paper, it can be considered part of community rating (where denials were effectively infinite prices). For reasons discussed in the prior section, these provisions on their own would lead to adverse selection along both extensive and intensive margins.

## **Extensive Margin Selection and Remedies**

To address adverse selection along the extensive margin, the ACA requires that all individuals have health insurance—i.e., the individual mandate. Anyone that does not have health insurance pays a penalty, which increases with income. For lower income households for which premiums would be too high, the policy provides subsidies through an Annual Pre-

mium Tax Credit (APTC, see Section 2.2.2). Despite these policy remedies, the extent of adverse selection along this margin is unclear. Nationwide, only 40% of those eligible chose to enroll in a plan in 2015.<sup>10</sup> It's theoretically possible that some of this was from high risk enrollees driving up prices, and is empirically true in some states (Panhans, 2017).

## **Intensive Margin Selection and Risk Adjustment**

Community rating creates adverse selection along the intensive margin in a similar manner. Plans that have more generous coverage and those with better known providers attract the sickest enrollees, and would experience disproportionate increases in premiums in response. To address this margin, the ACA uses risk adjustment.<sup>11</sup> The goal of risk adjustment in the ACA is for “plan premiums [to] reflect differences in scope of coverage and other plan factors, but not differences in health status” (Kautter et al., 2014). Hence, allowable differences would be due to cost sharing, provider payment rates, care management strategies, or administrative costs.

Risk adjustment in practice is generally calculated with two pieces of information: 1) some benchmark level of expected spending for a plan, and 2) some measure of the relative *expected* cost of a person that is invariant to the plan, called the “risk score.”<sup>12</sup> For each enrollee that is relatively sicker, plans receive a risk adjustment transfer in addition to the premium paid by the consumer, and vice versa for healthy enrollees. Risk adjustment

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<sup>10</sup>See: <http://www.kff.org/health-reform/state-indicator/marketplace-enrollment-as-a-share-of-the-potential-marketplace-population-2015>

<sup>11</sup>While risk adjustment can also partially address adverse selection along the extensive margin as in the prior section, this is not the motive under ACA risk adjustment.

<sup>12</sup>In practice, this is usually calculated by projecting expenditures on demographic and health information, and using that model for prediction. There is a long literature and constant debate on what should be included in that model, even in the ACA. Moreover, there have been studies that show health information is insufficient to eliminate adverse selection due to other unobservable factors (Glazer and McGuire, 2000; Einav et al., 2013; Shepard, 2016).

payments for person  $i$  in plan  $j$  usually take the form:

$$RiskAdj_{ij} = RiskScore_i * Benchmark_j$$

In the simplified “textbook” model in the prior section, the benchmark is the average cost among the population if all consumers were enrolled in plan  $j$ . The risk score in that model is the (plan invariant) expected cost of consumer  $i$  divided by the expected cost in the population.

In practice, the ACA uses slight variants of both of these objects. For a benchmark, the ACA uses the average premium in the state, standardized for the local region and generosity (i.e. metal tier). This has a number of advantages for policymakers. First, it ensures budget neutrality since it is the same across plans. Second, it incentivizes cost reductions in the long run. For plans that receive risk adjustment transfers, those with low costs will receive proportionately higher risk adjustment payments. Similarly, high cost plans do not receive the full wedge between the average and marginal cost, so face a degree of residual adverse selection. However, for plans that attract healthy enrollees and make transfer payments, the opposite is true. This mechanism requires larger payments from low-cost plans than the textbook model described above. In the short run, this puts upward price pressure on low-cost plans relative to the other model.<sup>13</sup>

The risk score also differs from the model described above. Instead of being costs relative to the whole population, the ACA uses costs relative to the insured population. First, there is a practical matter which is the uninsured have no medical claims data from which to measure their risk. Second, this is also partly because the intention of ACA risk adjustment is to correct intensive margin selection, leaving the other policies to address the extensive

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<sup>13</sup>This could also have long-run social benefits since it incentivizes efficient low-cost plans to attract sicker enrollees. These long-run incentives are important but beyond the scope of this study.



margin.<sup>14</sup>

Finally, risk adjustment in the ACA also discounts for revenue from age-based community rating. Since plans receive different premiums for different ages, this variation is subtracted from risk adjustment payments. The exact formula and other details are in Pope et al. (2014). In this paper, I simulate an alternative method similar to the one described in the prior section. These different methods have different implications on the market—especially in the long run—and the optimal choice ultimately depends on the objective function of regulators.

### **Other Standardizations in the ACA and Covered CA**

The ACA has additional regulations to enhance competition in the event that markets are dominated by a few firms or if there is any residual adverse selection. Plan generosities are standardized to 4 “metal tiers” which indicate the share of total expenditures that is covered by the plan, known as the actuarial value (AV). Standardizing plans in this way reduces differentiation and increases transparency, both of which should decrease markups. Covered CA adds other regulations to their exchange beyond the federal requirements, which further limit adverse selection and reduce price volatility. First, plan benefit designs are largely standardized, even beyond the AV requirements. For example, copays for a primary care visit are the same for all plans within the same tier. Similarly, Covered CA ensures that all plans meet high provider network adequacy standards. Finally, firms must offer their plans in all metal tiers to prevent segmenting the market.

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<sup>14</sup>Risk adjustment in the ACA combines enrollment from the on-exchange (i.e. subsidized) and off-exchange (unsubsidized) markets. In this paper, I only consider risk adjustment within the exchange, given data availability. Enrollment and premiums in these two groups likely differ due to income differences. However, evidence from MEPS shows the impact of income on utilization (i.e. cost) is small relative to the demographics used in this study.

## Plan Competition and Pricing in Covered CA

In Covered CA, premiums are set at the region level. There are 19 rating regions in the state made up of counties or aggregates of counties.<sup>15</sup> While prices within a rating region are all the same, whether or not the plan is actually offered is determined at the zip code level. While most plans are offered in the entire region, partial coverage areas occur when plans have geographic service constraints given networks.

In each rating region, an insurer can offer one or more of three networks types: a Preferred Provider Organization (PPO), an Exclusive Provider Organization (EPO), or a Health Maintenance Organization (HMO). These different levels of managed care, sorted from least to most, put constraints on what health services an enrollee can access.<sup>16</sup> All else equal, less constraints are associated with higher utility but also higher costs.

About halfway through the year, plans set their premiums for the following calendar year. In California, the premium variation by age is determined by an exogenous scaling profile set by regulators which preserves the 3:1 age requirement. This rating profile is presented in Figure 2.3. Plans submit their premiums for a 21 year-old enrollee only, and the rest of the rates are determined by the rating profile.

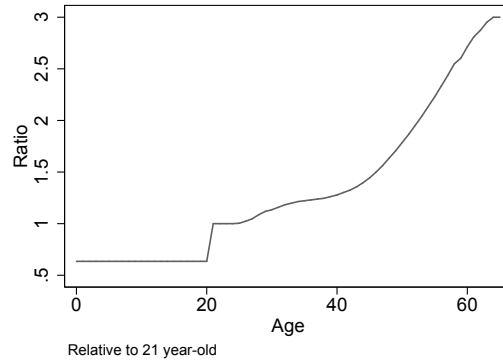
Premiums for the same plan also vary across households due to the aforementioned subsidies (APTC). Households with an income less than 400% of the federal poverty line (FPL) are eligible for a subsidy for enrolling in any plan. In 2015, this income threshold was \$47,080 for singles and \$97,000 for a household of 4. The subsidy is the amount of money that ensures the second lowest available silver (SLS) plan costs exactly a certain share of the household's

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<sup>15</sup>A map of the rating regions can be found on page 26 of the Covered CA Rate Book for 2017: <https://www.coveredca.com/news/PDFs/CoveredCA-2017-rate-booklet.pdf>

<sup>16</sup>PPOs have a preferred set of providers in-network where services are offered at a lower negotiated price. For EPOs, an enrollee is not allowed to see any providers outside of this network. Finally for HMOs, enrollees have additional restrictions on the types of providers (or services) an enrollee can access, even if they are in-network.

Figure 2.3: Pricing Profile in Covered CA



Note: This plot shows how premiums for a plan vary by age. Insurers set a price for a 21 year-old and the premiums for other ages are scaled by this function. The function represents the expected health care expenditures by age, but compressed to preserve the 3:1 ratio requirement in the ACA.

income. That share increases continuously with income from 2% to 9.5%. Note that this implies two subsidized individuals with the same income will face the same premium for the SLS, regardless of age. Since the APTC is household-specific, it does not affect the relative difference in prices between any two plans.<sup>17</sup> It does, however, affect the price of all plans relative to remaining uninsured, in effect increasing the effective penalty of the mandate.

In summary, the difference in prices between any two given plans is higher for older consumers. The relative prices of *all* plans compared to being uninsured varies with income, such that the high APTCs from lower incomes makes getting any plan more attractive. Since the APTC sets the SLS premium regardless of age, older households get larger APTCs as well.

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<sup>17</sup>The small exception is when APTC is maxed out and exceeds a plans premium, as with some low-cost Bronze plans. In this case the premium is \$1 per enrollee and the APTC is partially unused. This occurs for about 40% of households in Covered CA, but only about 8% of household-plans.

## 2.3 A Model of ACA Exchanges

In this section, I describe a full model of demand and supply for insurance in the ACA exchanges that I use for the empirical analysis. The timing of events in the model is as follows. Plans are endowed with demographic-specific reputations and networks of physicians and hospitals. Before the start of the year, plans simultaneously choose premiums in a static Nash-in-prices equilibrium. Finally, at the start of the year, all potential enrollees choose the plan that gives them the highest utility given expectations about medical needs.<sup>18</sup>

### 2.3.1 Demand for Health Insurance

The insurance choice model is similar to other discrete choice models in the Industrial Organization and Health Care Economics literatures (Berry et al., 2004; Goolsbee and Petrin, 2004; Town and Liu, 2003; Ho, 2006). The key features of this model are that plan choice depends on *observable* characteristics of the plans and enrollees, while there is unobserved heterogeneity in the preference to remain uninsured—as in the “nested logit” model (Berry, 1994). I treat all plans as part of one “nest,” and the option to remain uninsured as its own separate nest. In the context of random coefficient models, this can analogously be thought of as a random coefficient on the outside option of remaining uninsured. The reason for using this structure is it allows for flexible substitution patterns along the extensive margin, and relaxes the *independence of irrelevant alternatives* (IIA) property of logit models.<sup>19</sup>

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<sup>18</sup>Note that the demand model presented in this section is the same as described in Chapter 1, and largely identical to Section 1.3. I restate it here for convenience to make this chapter self contained.

<sup>19</sup>Intuitively, IIA means that within observable demographic groups, as prices increase, marginal consumers substitute to other options proportional to the group’s market share. Adding in unobserved heterogeneity conversely allows for disproportionate substitution to certain options in the choice set. In the context of this model, it allows for consumers to disproportionately substitute to other insurance options rather than being uninsured. In Covered CA, roughly half of the market remains uninsured. Removing unobserved heterogeneity would imply roughly half of the marginal enrollees would choose to be uninsured rather than another insurance option when facing price increases, which is unlikely to be true.

Potential enrollees are offered a menu of plan options and choose that which yields the highest idiosyncratic utility. The indirect utility of household  $i$  for plan  $j$  in market  $t$  is given as follows:

$$u_{ijt} = \underbrace{\alpha_i p_{ijt}}_{\text{Prem Disutility}} + \underbrace{EV_{ijt}^H + EV_{ijt}^P}_{\text{Network Utility}} + \underbrace{x'_{ijt} \beta_i}_{\text{Other Obs. Utility}} + \underbrace{\xi_{jt} + \zeta_{it}^{Ins} + (1 - \sigma)\varepsilon_{ijt}}_{\text{Unobservable Utility}} \quad (2.1)$$

where  $p_{ijt}$  is the net-of-subsidy premium and  $x_{ijt}$  is a vector of plan attributes (e.g. carrier and tier).  $EV_{ijt}^H$  and  $EV_{ijt}^P$  are the expected utilities derived from hospitals and PCPs respectively and are explained below in Section 2.3.2.<sup>20</sup>  $\xi_{jt}$  is an unobservable component of utility for plan  $j$  which is common to all households in market  $t$ , and can take on any distribution.  $\varepsilon_{ijt}$  is the idiosyncratic utility for each plan, and is i.i.d. Type I Extreme Value.  $\zeta_{it}^{Ins}$  is the household-specific utility of having insurance and is common across all plans. As in the nested logit model, the distribution of this variable is characterized by  $\sigma \in [0, 1]$ , and satisfies the property that  $\zeta_{it}^{Ins} + (1 - \sigma)\varepsilon_{ijt}$  is itself Generalized Extreme Value (Berry, 1994; Train, 2009).  $\sigma$  can be thought of as the degree of correlation in the unobserved utility of all plans relative to the outside option. If it is 0, then there is no correlation in the unobserved utilities and it becomes a standard logit model. In the context of random coefficients,  $\sigma$  can be thought of as the relative variance of the random coefficient on the insurance indicator variable. As this variance approaches its maximum, there is no substitution along the extensive margin.

Preference parameters are indexed by  $i$  to indicate heterogeneity across households. I assume this heterogeneity is purely based on observable household characteristics so  $\beta_i = \mathbf{B}z_i$  where  $z_i$  is a vector of household demographics and  $\mathbf{B}$  is a matrix of parameters to be estimated. Since the ACA exchange population excludes the elderly, many chronically

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<sup>20</sup>Note the functional form assumes separability of utility from hospitals and doctors. It is possible these interact in a non-additive way. For example, in 2014 Anthem Blue Cross contracted with Stanford Health Care hospital but *not* the physicians group. One could argue the hospital being in-network generated relatively little utility without the complimenting physicians that worked at the hospital. These cases are rare and are beyond the scope of this paper.

disabled, and those with the lowest incomes, this assumption is more plausible than in other government programs.

As discussed in Section 2.2.2, net premiums are a function of income and age and can be written succinctly as:

$$p_{ijt} = \theta_i^P p_{jt} - \tau(FPL_i, p_{(2)t}) \quad (2.2)$$

where  $p_{jt}$  is the premium set by plan  $j$  for a 21 year-old.  $\theta_i^P$  is the rating profile set by Covered CA ranging from 1 to 3 based on age. Since  $i$  is the household, this term is the sum of rating profiles for all members in the household.  $\tau(\cdot)$  is the premium subsidy (APTC), which is bounded above so that  $p_{ijt}$  is constrained to be at least \$1 per enrollee.

The outside option is the choice to not enroll in any of the available insurance plans and remain uninsured. The associated utility depends on individual characteristics  $z_i$  and is given by:

$$u_{i0t} = z_i' \omega + \varepsilon_{i0t} \quad (2.3)$$

where  $\varepsilon_{i0t}$  is also distributed i.i.d. Type I Extreme Value.  $z_i$  includes a constant and income so this is the reduced-form utility of remaining uninsured, which includes the penalty from the individual mandate. Note that this is a degenerate “nest” since it only contains a single option, so there’s no nest-level heterogeneous coefficient.

Given that this model follows a nested structure, it is helpful to think of the choice probabilities as two different levels (Train, 2009)—though to be clear, this doesn’t reflect the timing of the decision process. The different levels can be thought of as an “upper model”—the choice of which nest—and a “lower model”—which choices within the nests. In the context of this study, the upper model is the decision whether or not to buy *any* plan. The lower model is *which* plan to purchase conditional on buying a plan. In the nested logit framework, “nest 0” should be thought of as remaining uninsured, and the other nest contains all plans in the market. Hereafter, I refer to the upper model as the “take-up” model and the lower

model as the “plan choice” model.

Working backwards, first consider the plan choice model. Household  $i$  chooses plan  $j$  if it generates the highest utility—i.e. if  $u_{ijt} \geq u_{ikt} \forall k \neq j$ . Let  $s_{ijt|Ins}$  be the probability that household  $i$  chooses plan  $j$ , conditional on choosing to buy insurance. Given the distributional assumptions, the probability of making such a choice is:

$$s_{ijt|Ins} = \frac{\exp(v_{ijt})}{\sum_{k \in J_i} \exp(v_{ikt})} \quad (2.4)$$

where  $v_{ijt}$  is  $u_{ijt}$  less the idiosyncratic unobservable utility ( $\zeta_{it}^{Ins} + (1-\sigma)\varepsilon_{ijt}$ ) and is normalized by  $(1-\sigma)$ . Note from Section 2.2.2 that in Covered CA, different households within a market have different choice sets, represented by  $J_i$ .

Next consider the take-up decision. Let  $s_{it}^{Ins}$  be the probability of choosing to buy any plan, i.e.  $s_{it}^{Ins} \equiv \Pr(\max_{j \neq 0} \{u_{ijt}\} > u_{i0t})$ . Then the assumptions of the model imply:

$$s_{it}^{Ins} = \frac{\exp((1-\sigma)I_{it})}{\exp(z'_i \omega) + \exp((1-\sigma)I_{it})} \quad (2.5)$$

Where  $I_{it} = \ln(\sum_{k \in J_i} \exp(v_{ikt}))$ .  $I_{it}$  is often referred to as the “inclusive value” since it represents the expected utility of the entire set of plans (Train, 2009). Combining the above formulas, the unconditional probability of choosing any particular plan is  $s_{ijt} = s_{it}^{Ins} s_{ijt|Ins}$ .

Market shares  $s_{jt}$  are defined by summing the individual probabilities over the population in a market:

$$s_{jt} = \frac{1}{M_{jt}} \sum_i s_{ijt}$$

where  $M_{jt}$  is the number of households that are offered plan  $j$  in market  $t$ .

Given this framework, the effect on plan  $j$ 's market share of increasing the premium by

\$1 is given by:

$$\begin{aligned}\partial s_{jt}/\partial p_{ijt} &= \frac{1}{M_{jt}} \sum_i \partial s_{ijt}/\partial p_{ijt} \\ &= \frac{1}{M_{jt}} \sum_i \alpha_i s_{ijt} \left( \frac{1 - s_{ijt|Ins}}{1 - \sigma} + s_{ijt|Ins} (1 - s_{it}^{Ins}) \right)\end{aligned}$$

and similarly, the cross-price effect of a price change for plan  $k$  on enrollment for plan  $j$  is:

$$\begin{aligned}\partial s_{jt}/\partial p_{ikt} &= \frac{1}{M_{jt}} \sum_i \partial s_{ijt}/\partial p_{ikt} \\ &= \frac{1}{M_{jt}} \sum_i -\alpha_i s_{ijt} s_{ikt|Ins} \left( \frac{1}{1 - \sigma} - (1 - s_{it}^{Ins}) \right)\end{aligned}$$

To get semi-elasticities, I normalize these derivatives by dividing by market shares  $s_{jt}$ .

### 2.3.2 Demand for Providers

An important part of plan choice is access to providers, particularly for the purposes of studying adverse selection (Shepard, 2016). Provider network utilities, represented by  $EV^H$  and  $EV^P$  in (2.1), are derived from 2 features: 1) beliefs about likelihood of needing certain medical providers, and 2) access available given the plan networks. In this section, I present a general overview of the hospital and PCP models that underly the values for  $EV^H$  and  $EV^P$ . In Chapter 1, I provide a more detailed explanation of each.

The hospital model is similar to those used in other papers on health plan competition (Ho, 2006; Gowrisankaran et al., 2014; Shepard, 2016). Enrollees have beliefs about their likelihood of needing different types of hospitalizations given their age and gender. Conditional on needing a hospitalization of a certain type, each plan's network generates a certain *expected* utility for each enrollee. The expectation is over idiosyncratic provider-



patient utility which is unknown to even the enrollee until the hospitalization is needed. The deterministic portion of network utility is based on the “quality” of the hospitals in the network, discounted by their distance from the enrollee. Similar to the plan choice model, the hospital quality is inferred from revealed preferences, based on which hospitals patients choose given the possible alternatives.  $EV_{ijt}^H$  is the expected utility of a network given the utilities of networking hospitals, and weighted by the probability of needing each type of hospitalization:

$$EV_{ijt}^H = \sum_{\kappa} \lambda_i^{\kappa} \ln \left( \sum_{h \in \mathfrak{N}_j^H} \exp(\phi_h^{\kappa} - d_{\kappa}^H(\text{dist}_{ih})) \right) \quad (2.6)$$

where  $\kappa$  is the hospitalization type ( $\{\text{Labor, Other inpatient, Outpatient}\} \times \{\text{Childrens', Adults'}\}$ ), and  $\lambda_i^{\kappa}$  is the probability of needed a  $\kappa$  hospitalization (which can sum to more or less than 1).  $\mathfrak{N}_j^H$  is plan  $j$ 's hospital network.  $\phi_h^{\kappa}$  is the utility of hospital  $h$  for hospitalization  $\kappa$ . And  $d_{\kappa}^H(\text{dist}_{ih})$  is the disutility of travel.

The PCP model follows a similar structure, though I make a number of simplifying assumptions to handle the thousands of doctors that could be in plan networks. Most crucially, I assume the mean utility of each physician is the same. I also discretize the distance metric to bins. This reduces  $EV_{ijt}^P$  to be a function of the *number* of plan  $j$  PCPs ( $N_{ij,b}^P$ ) within different distance bins ( $b$ ) from the enrollee:

$$EV_{ijt}^P = \lambda_i^P \ln \left( \sum_b N_{ij,b}^P \exp(-d^b) \right) \quad (2.7)$$

where  $\lambda_i^P$  is the probability of needing to visit a PCP.  $d^b$  is the disutility of traveling to distance  $b$ .

A complete discussion of these models and the assumptions can be found in Chapter 1.

### 2.3.3 Insurance Market Supply

Firm entry, network types, and networks are exogenous in this model. Firms know their costs and those of competitors. They also know the distribution of preferences and demographics in the market. Importantly, firms also anticipate risk adjustment when setting premiums.<sup>21</sup> Given this information, firms set a price for each plan for a 21 year-old, and the premiums for other ages are scaled exogenously according to the regulated 3:1 age factor.

For firm  $f$  in market  $t$ , profits are given as follows:

$$\pi_{ft}(\mathbf{p}_{\mathbf{ft}}; \mathbf{p}_{-\mathbf{ft}}) = \sum_{j \in f} \sum_i s_{ijt}(\mathbf{p}_{\mathbf{ft}}; \mathbf{p}_{-\mathbf{ft}}) \left( \theta_i^p p_{jt} - \theta_i^c c_{jt} + T_{ijt} \right) \quad (2.8)$$

where  $p_{jt}$  is the premium for plan  $j$  for a 21 year old as in (2.2) and  $c_{jt}$  is the expected cost of a 21 year-old *male*.  $\mathbf{p}_{\mathbf{ft}}$  is the vector of the firm's premiums and  $\mathbf{p}_{-\mathbf{ft}}$  is the vector of all competitor premiums.  $\theta_i^p$  is the regulated 3:1 rating factor established by Covered CA.  $\theta_i^c$  is the actual expected cost factor relative to a 21 year old male—this can be thought of as the sum of the risk scores for household  $i$ .  $T_{ijt}$  is the risk adjustment and is the (possibly negative) payment firms receive from the program.

The precise formula I use for risk adjustment is based on that of the ACA (Pope et al., 2014) and is provided in Appendix A.3. The difference is that I use  $\theta_i^c$  as my measure of risk, since I do not observe risk scores. As described in Section 2.2.2, the conceptual idea of ACA risk adjustment can loosely be represented by the following form:

$$T_{ij}^{ACA} \approx \left( \frac{\theta_i^c}{\bar{\theta}_{CC}^c} - \frac{\theta_i^p}{\bar{\theta}_{CC}^p} \right) \bar{P}_{t,tier}$$

Where  $\bar{\theta}_{CC}$  represent averages among the Covered CA enrollees, and  $\bar{P}_{t,tier}$  is the average premium in the region for the tier. This is just a stylized representation, however, and does

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<sup>21</sup>Bindman et al. (2016) note that Covered CA's active purchasing role helped plans to anticipate how risk adjustment would impact costs, and were ultimately passed through to premiums.

not equal the formula in the ACA that I use in the model.

There are two crucial assumptions in this model regarding the structure imposed on cost variation across enrollees and plans. First, I assume multiplicative separability in the form of  $c_{ijt} = \theta_i^c c_{jt}$ , i.e. costs are risk scores times a baseline plan cost. This assumption rules out different plans having relative cost advantages covering different risk types. Variation in baseline plan costs ( $c_{jt}$ ) is driven by prices for providers, care management strategies, and administrative costs. Within an insurer,  $c_{jt}$  would vary across tiers due to higher actuarial value and the associated moral hazard. Second, I assume  $\theta_i^c$  is only a function of age and gender. Even though these two variables explain a small portion of total spending (Layton, Forthcoming), they explain a much higher share of the portion of expected spending that is correlated with preferences. Since the latter is the focus of this study, this formulation still can provide insight to the research question. It is, however, a strong assumption and I discuss the implications in greater detail in Section 2.8.

The degree of community rating in the model is given by the deviation between  $\theta_i^c$  and  $\theta_i^p$ . The source of adverse selection is the degree to which this deviation is correlated with plan preference parameters in (2.1).

Firms simultaneously set premiums in a static full information Nash equilibrium. While there is evidence of dynamic pricing in other insurance markets (Ericson, 2014a; Ho et al., 2015), the high rate of churn and the uncertainty of the ACA make dynamics less relevant in this market. Assuming full information is plausible as long as I exclude 2014, the first year of the market.

First order conditions of the above profit functions with respect to prices (and dropping  $t$  subscripts) can be written as:

$$\frac{\partial \pi_f}{\partial p_j} = \sum_i \left\{ \theta_i^p s_{ij} + \sum_{k \in f} \frac{\partial s_{ik}}{\partial p_j} \left( \theta_i^p p_k - \theta_i^c c_k + T_{ik} \right) \right\} = 0 \quad (2.9)$$

This is similar to the standard formulation with discrete choice demand and heterogeneous preferences (Berry et al., 1995). The two main differences come from the policies in this study, risk adjustment and community rating. The derivative  $\frac{\partial s_{ik}}{\partial p_j}$  is with respect to the 21 year-old price, given the modified community rating of the ACA.<sup>22</sup>

These first order conditions can be re-written in a more familiar form. Consider a single-product firm for convenience. Then (2.9) implies the profit-maximizing 21 year-old price for plan  $j$  is:

$$p_j = \underbrace{\frac{1}{\sum_i s'_{ij} \theta_i^p} \sum_i s'_{ij} (\theta_i^c c_j - T_{ij})}_{\text{“Standardized” Marginal Cost}} - \underbrace{\frac{\sum_i s_{ij} \theta_i^p}{\sum_i s'_{ij} \theta_i^p}}_{\text{Markup}} \quad (2.10)$$

where  $s'_{ij} = \frac{\partial s_{ij}}{\partial p_j}$ . Hence, as usual, the optimal price is equal to some measure of marginal cost plus a markup which is the inverse of the semi-elasticity. I label the first term as the “Standardized” Marginal Cost (*SMC*) to reflect that it is net of compensation from the premium scaling  $\theta_i^p$ . It effectively down-weights the true marginal cost to account for the fact that older enrollees are generating more revenue though a higher value of  $\theta_i^p$ . Note that the cost of the marginal consumer is a combination of both direct costs and the risk adjustment transfer ( $T_{ij}$ ) associated with that enrollee—receiving positive transfers reduces effective costs and hence lowers premiums.<sup>23</sup>

Note that I have ignored premium subsidies (APTC) in the context of firm optimization which is important because APTCs makes prices enter demand in a non-traditional way. Recall that the APTC ensures that the second lowest silver (SLS) premium exactly matches

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<sup>22</sup>There are two issues regarding risk adjustment that are being ignored in this setup. Premiums enter risk adjustment in two ways. First the benchmark is the average premium, so changing the premium changes the benchmark. Second, premiums affect the market composition which affects the “relative” risk in the risk score. I assume these effects are negligible when setting premiums.

<sup>23</sup>This formulation is the same idea as the model presented in Ericson and Starc (2015), except slightly more general and adding risk adjustment. They also describe the impact of multi-product firms on first order conditions, which affects both markups and “marginal costs.”

some income amount. Hence, if a plan is the SLS, for every dollar increase in the (scaled) premium, the APTC increases dollar-for-dollar in kind. This effectively shuts down competition with the outside option for the SLS. However, when the SLS premium increases by \$1, there is still a \$1 impact on the price difference between plans. Therefore, for the SLS only, APTC should theoretically enter the FOC ( $ds/dp$  specifically) by shutting down competition with the outside option only. In most ACA markets, this is likely a non-trivial force (Jaffe and Shepard, 2017). In Covered CA, however, this force will be much smaller.<sup>24</sup> For this reason and for simplification, I omit this endogeneity from the model.

### 2.3.4 Identifying Adverse Selection

The form in (2.10) is particularly useful because it ties pricing back to adverse selection. Recall from Section 2.2.1 that a sufficient condition to identify adverse selection is if the marginal cost curve is decreasing in quantity or increasing in price (Einav et al., 2010).

In this model with risk adjustment and community rating, the sufficient condition to identify adverse selection is:

$$\frac{\partial SMC_j(p_j)}{\partial p_j} > 0 \tag{2.11}$$

where  $SMC_j$  is the standardized marginal cost defined above. From (2.10), it is easy to see how this property could lead to upward spiraling prices.

In theory,  $\frac{\partial SMC_j(p_j)}{\partial p_j}$  could be calculated for each plan using the model. In this study, I use an alternative metric for adverse selection: the marginal cost relative to the average

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<sup>24</sup>Premiums within a carrier have the same ratio across tiers for all regions—for example, Kaiser’s premium ratio of Silver to Bronze in Los Angeles is the same as in San Francisco. Since carriers generally enter in many markets, being the SLS in any particular market cannot be fully exploited for this purpose. This brings up another issue which is that it is inconsistent with the model presented in (2.9) where I’ve assumed pricing across markets is independent. Since the purpose of this paper is not estimating the precise costs by tier or exact profits, this is less relevant. Moreover, for the purposes of measuring adverse selection, it should have little impact at all.

cost. Let the “Standardized” Average Cost be defined in a similar way:

$$SAC_j(p_j) = \frac{1}{\sum_i s_{ij}(p_j)\theta_i^p} \sum_i s_{ij}(p_j) (\theta_i^c c_j - T_{ij}) \quad (2.12)$$

where the average cost is discounted by revenue from age-based community rating ( $\theta_i^p$ ).

Under reasonable monotonicity assumptions on  $SMC$  (as are often assumed by parametric cost functions),  $SMC < SAC \iff \frac{\partial SMC_j(p_j)}{\partial p_j} > 0$ . Hence,  $SMC < SAC$  is also a sufficient condition for adverse selection, in addition to (2.11). I use this measure because it is straightforward to calculate, and has an intuitive interpretation: it implies the marginal consumer costs less than the inframarginal consumers who more highly demand the plan. In competitive markets,  $SAC$  would be the amount that dictates the price faced by the marginal consumer, who costs  $SMC$ . In the analysis, my measure of adverse selection is  $SMC - SAC$ .

Under what conditions can the policies in this model eliminate adverse selection (at least the equilibrium effect) by flattening the  $SMC$  curve? The first is if there is no community rating, and the pricing profile reflects the exact expected costs (i.e.  $\theta_i^p = \theta_i^c$ ). Then  $SMC_j = c_j$  (and  $p_j$  would reflect the premium for a 21 year old *male*). The other case is if risk adjustment ( $T_{ij}$ ) was designed in a way to make  $SMC$  constant. There are infinite possibilities for this since it could be set to any arbitrary level. However, motivated by the earlier discussion on “textbook” risk adjustment in Section 2.2.1, I consider how risk adjustment can set  $SMC$  equal to  $SAC$  in the population ( $SAC^{Pop}$ ).

Specifically, let  $SAC_j^{Pop} = \frac{\sum_i \theta_i^c c_j}{\sum_i \theta_i^p} = \frac{\bar{\theta}^c}{\bar{\theta}^p} c_j$ , where bars represent population averages. Setting  $SMC_j = SAC_j^{Pop}$  implies that risk adjustment is:

$$T_{ij}^{PlanPop} = \left( \frac{\theta_i^c}{\bar{\theta}^c} - \frac{\theta_i^p}{\bar{\theta}^p} \right) \bar{\theta}^c c_j \quad (2.13)$$

I call this “PlanPop” risk adjustment to denote that it has the properties of the textbook case defined in Section 2.2.1—it is benchmarked to *plan* costs ( $\bar{\theta}^c c_j$ ) and scales relative to risk in the total *population* ( $\theta_i^c/\bar{\theta}^c - \theta_i^p/\bar{\theta}^p$ ). One difference is that plans already receive revenue for age-based community rating, and so that compensation is subtracted.<sup>25</sup> Note that it need not generate greater welfare than the ACA method, and as seen earlier, it will not deliver the efficient allocations on its own. It is only “textbook” in the sense that it perfectly flattens the marginal cost curve and sets it exactly equal to the average cost in the population. I use this risk adjustment in the main analysis to see how it alters the market relative to the current method. It is similar in spirit to risk adjustment used in Medicare Advantage and hence has additional policy relevance. The main difference for Medicare is that it is benchmarked to premiums as opposed to costs.

## 2.4 Fitting the Model to Data

I estimate the parameters of the above model using the data and methods discussed in the following section. Each of the following three subsections describes the data, identification, and estimation respectively.<sup>26</sup>

### 2.4.1 Data Sources

#### Covered CA Data

The primary data sources for this study come from Covered CA and include information on enrollment and provider networks. The enrollment data include the unidentified set of all

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<sup>25</sup>Risk in this model is relative to 21 year-old males, but it could just as easily be relative to the average cost person in the population as is normally done for risk scores. In that case, risk adjustment would take the very familiar form:  $T_{ij} = (\theta_i^c - \theta_i^p/\bar{\theta}^p)\bar{c}_j$ .

<sup>26</sup>Note that the data and demand sections below are largely identical to those in Section 1.4 from the prior chapter. I present these sections again so this paper is self contained.

households enrolled in any plan in 2015. The associated variables are each household’s plan choice, income, zip code, age, gender, and race. Because carriers might offer their plans to only a subset of a rating region, I use data on coverage areas at the region-county-zip level to construct choice sets for each household. I apply a number of exclusions to simplify the analysis, which have a small impact on the overall sample. Specifically, I exclude households with any of the following characteristics: more than 4 members, an income less than 138% of the FPL, any members greater than 64 years old, chose a plan that wasn’t offered in the household’s zip code, or enrolled in a highly uncommon plan.<sup>27</sup> The size exclusion simplifies the demand estimation, while the income and age exclusions omit enrollees that are possibly eligible for other government insurance programs. Combined, all exclusions account for 8.3% of total enrollment, virtually all coming from the income and household size exclusions in equal parts. Other than plans which are explicitly omitted, these exclusions do not affect plan shares. While the data include the universe of enrollees, I only use a 20,000 household sample, weighted evenly across rating regions. This significantly speeds up the analysis but otherwise has little impact on the estimation.<sup>28</sup>

This study also uses provider directories that Covered CA collects to ensure plans meet network adequacy standards outlined in the ACA. The directories include listings of all hospitals and physicians considered to be in-network for each plan at quarter 1 of 2015. Provider networks are identified by a carrier and network type (HMO, PPO, EPO), and are assumed to be the same across tiers. For this study, I use hospitals and Primary Care

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<sup>27</sup>Specifically, I exclude households that enrolled in any of the following rare plans: “catastrophic” plans, Kaiser in Regions 1 and 13, Anthem’s HMO in 3, 11, 19, Health Net’s PPO in 5, and Molina in 19.

<sup>28</sup>There are households that enroll in individual plans outside of Covered CA. The data in this study comes specifically from the Covered CA enrollment website. Hence, it includes all subsidized enrollment (i.e. less than 400 FPL *and* electing to receive APTCs), but it need not include enrollment among those that do not receive subsidies. In fact, among those with incomes above 400% FPL, the data generating process that makes a household enroll through Covered CA is unclear. Among this income group without group insurance, there is actually a significant share that buys individual coverage. See footnote 29 for how this impacts the analysis.



Physicians (PCPs) for a given plan. From the hospital data, I use provider identifiers which are later merged with external data listed in the next section. From the PCP data, I use the office zip code.

## Supplemental Data

While the data from Covered CA is very detailed, it does not include all the necessary information for this study. First, it doesn't include data on households that could have enrolled in a plan but chose not to (i.e. taking the "outside option"). Additionally, while the data indicates which providers are in different networks, it does not indicate the cost of those providers or their relative value to consumers. Hence, I bring in external data sources to fill these gaps.

For this study, I consider households choosing the outside option as those that were uninsured in 2015.<sup>29</sup> To measure uninsured households, I use the individual-level 2015 American Community Survey (ACS) from IPUMS (Ruggles et al., 2017). The key variables are health insurance status, location of residence (as a PUMA), income, and household composition (i.e. age, gender, race of each household member). More details on how the ACS data is supplemented with the Covered CA data are provided in Appendix A.1. I make the same exclusions in the ACS as described above for enrollees when possible.

Another data source is needed for exogenous determinants of plan premiums (i.e. "cost shifters") to identify how enrollment responds to prices. For this, I use the costs of each plan's networking hospitals. Data on hospital costs can be found in the Healthcare Cost Report Information System (HCRIS) collected by the Centers for Medicare and Medicaid

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<sup>29</sup>This could also include those in the "off-exchange" individual market (as in Tebaldi (2016)). However, since most of the Covered CA market is receiving premium subsidies, it's not unreasonable to think there is little substitution between on and off-exchange plans for the majority of Covered CA enrollees. Furthermore many of the plans available off the exchange are the same as those on the exchange, and have the same premiums. Omitting this group simplifies the problem of the outside option utility changing with price changes in the market.

Services (CMS).<sup>30</sup> Combining these reports with IPPS data on average hospital severity, I create a measure of the risk-adjusted cost of a hospitalization at every hospital similar to that of Dafny (2009).<sup>31</sup>

To estimate the indirect utility function in the hospital model, I use external utilization data from the Office of Statewide Health Planning and Development (OSHPD). I use the 2014 Patient Origin and Market Share Reports<sup>32</sup> which give the number of discharges from a given patient zip code at each hospital by age category and type of hospitalization. Utility from networking PCPs is based only on network size so does not rely on external utilization data. However, in Appendix A.2, I describe how PCP utilization data can aid in the estimation.

Finally, I use the Medical Expenditure Panel Survey<sup>33</sup> (MEPS) Household Component to estimate the how expected spending and utilization vary by age and gender.

## Descriptive Summaries

Table 2.1 gives a summary of the 19 rating regions in California. For each region, the table displays the number of firms, share of enrollment in each network type, and the market Herfindahl-Hirschman Index (HHI). The southern regions (region 12 and above), tend to have more firms, be larger, and have a much higher HMO share. In Northern CA, non-Kaiser HMO enrollment makes up less than 10% in each region, with the exception of San Francisco. Kaiser is a key player throughout the state but its role varies regionally. In the Bay

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<sup>30</sup>Source data is found here: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/>. I use the formatted data created by Jean Roth at the National Bureau of Economic Research (NBER): <http://www.nber.org/data/hcris.html>

<sup>31</sup>Source IPPS data also comes from NBER: <http://www.nber.org/data/cms-impact-file-hospital-inpatient-prospective-payment-system-ipps.html>. Since these are generated for Medicare reimbursement, hospitals that have little interaction with the Medicare system are excluded (e.g. Children's and Kaiser).

<sup>32</sup>See: <https://www.oshpd.ca.gov/HID/POMS-Report.asp>

<sup>33</sup>See: <https://meps.ahrq.gov/mepsweb/>

Area counties for example, Kaiser makes up around a half of all enrollment. In the southern counties, Kaiser's enrollment ranges from 14% to 30%. The level of competitiveness ranges across the state with regions in Southern California generally being the most competitive. Unsurprisingly, the rural counties in the Central Valley, the Eastern Region, and the far North (Regions 10, 13, and 1) are the least competitive with HHIs that exceed 5,000, well above what's considered a concentrated market.<sup>34</sup>

The patterns in enrollment are not surprising given premiums across the state. Figure 2.4 plots 21 year-old Silver premiums across all regions, indexed by network type (Non-HMO, Kaiser, or Other HMO). The first pattern is that all premiums are significantly lower in Southern California (regions 12+). While insurance markets were identified to be more competitive in this region, the main results of this paper show this difference is more a function of the provider costs than plan markups. Moreover, the relative price of Kaiser plans is higher in Southern California than in the rest of the state which explains part of the Kaiser enrollment patterns. In Figure 2.5, I plot the enrollment in each plan against the relative premium. There is a clear negative correlation which suggests consumers are very price sensitive.

Figure 2.6 plots the distributions of ages and incomes for the Covered CA and uninsured populations, those who could have enrolled but chose not to. Those taking up insurance are older and have lower incomes than their uninsured counterparts. Given that subsidies are decreasing in income, this latter result is not surprising, though the difference is relatively large.

Last, Table 2.2 presents statewide characteristics of the individuals enrolled in each plan type, by either network type or metal tier. Examining the first three rows, Non-HMO plans (known to be "preferred" but more expensive) have intermediate ages and incomes, but have

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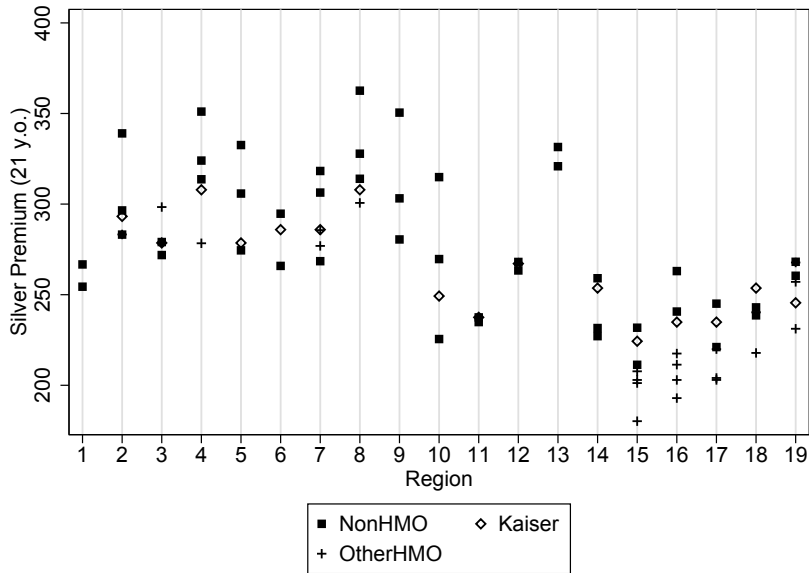
<sup>34</sup>Markets with HHIs greater than 2,500 are considered highly concentrated and those with HHIs between 1,500 and 2,500 are moderately concentrated. See U.S. Department of Justice & FTC, *Horizontal Merger Guidelines* §5.3 (2010).

Table 2.1: Market Summary for Covered CA

Rating Region	Total Firms	Offering HMOs	Num HHs (1,000s)	NonHMO Share	Kaiser Share	Other HMO Share	HHI
1. Northern Counties	2	0	39	1.00	-	-	8,508
2. N. Bay Counties	5	2	40	0.41	0.51	0.08	3,520
3. Sacramento	4	2	53	0.54	0.43	0.02	3,458
4. San Francisco	5	2	33	0.40	0.38	0.22	2,744
5. Contra Costa	4	1	29	0.42	0.58	-	4,683
6. Alameda	3	1	50	0.47	0.53	-	3,922
7. Santa Clara	5	3	47	0.62	0.32	0.06	3,819
8. San Mateo	5	2	20	0.38	0.54	0.08	3,672
9. Central Coast I	3	0	23	1.00	-	-	5,222
10. Central Valley I	4	1	43	0.79	0.21	-	5,427
11. Central Valley II	3	1	20	0.72	0.28	-	3,723
12. Central Coast II	3	1	45	0.88	0.12	-	4,121
13. Eastern Region	2	0	5	1.00	-	-	5,802
14. Central Valley III	4	1	12	0.85	0.15	-	4,061
15. LA-East	6	5	118	0.39	0.15	0.46	2,773
16. LA-West	6	5	161	0.34	0.18	0.48	2,174
17. Inland Empire	5	4	86	0.37	0.23	0.40	2,221
18. Orange County	4	3	94	0.58	0.14	0.28	2,866
19. San Diego	5	3	91	0.34	0.30	0.36	2,202

Note: This table gives summary statistics for each of the 19 rating regions in Covered CA in 2015. The first column is the number of firms operating in each region. The second is the number of HMOs offered in each region. The third column is the number of households enrolled in a Covered CA plan (in thousands). The following three columns are the shares of enrollment in Non-HMOs, Kaiser, and HMOs respectively. The last column is the Herfindahl-Hirschman index (HHI). All statistics are net of sample exclusions described above.

Figure 2.4: Premiums for all Rating Regions and Network Types



Note: This figure gives Silver plan premiums in 2015 for each rating region. Premiums based on 21 year-olds. Markers differ by network type. Only among plans that meet exclusion criteria. Regions 1-11 are Northern California.

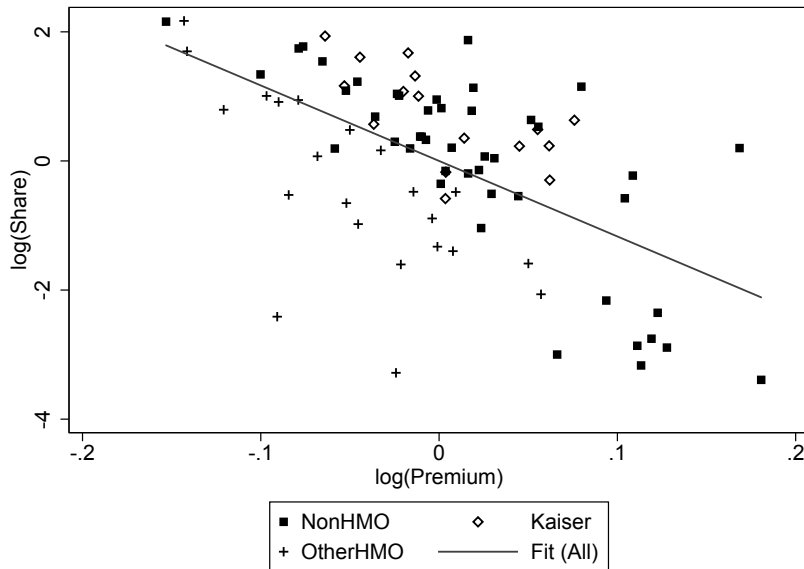
disproportionately more female and white enrollees. Kaiser enrollees are disproportionately younger with higher incomes. The second set of rows presents the same for metal tier selection. Gold and Platinum enrollees are actually younger. This is likely because these plans are relatively lower priced for the young and there are many younger households with relatively higher incomes. High generosity enrollees are also higher income and female, which is less surprising.<sup>35</sup>

These descriptive results are suggestive that preferences are positively correlated with costs, the key feature of selection markets. Enrollees with higher expected spending—older or females—have higher rates of coverage, and are generally getting better plans. Since these consumers are facing different prices and different choice sets, the more detailed model

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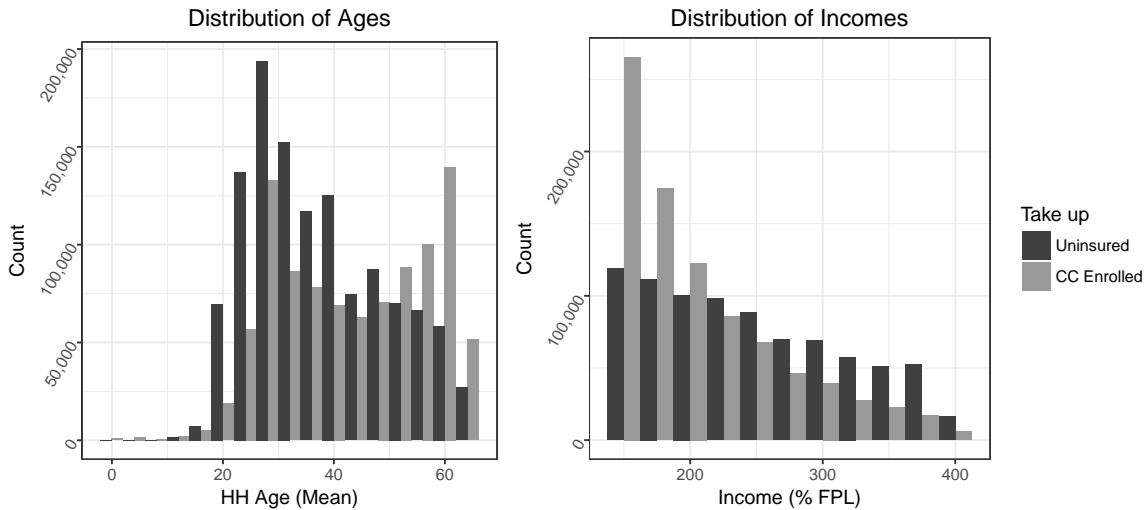
<sup>35</sup>Note that Silver plans are associated with large cost sharing reductions (CSRs) for over half of the population, so tiers are not necessarily increasing in coverage. However, we can compare Bronze to Gold/Platinum to get a sense for selection along the generosity margin.

Figure 2.5: Enrollment Shares by Premium and Network Type



Note: This figure plots log of market shares by the log of the plan premium. Both measures are de-meanned at the region level. Only among Silver plans, which represent the majority of enrollment. Markers differ by network type. Fitted line based on all points in the figure. All data based on 2015.

Figure 2.6: Demographics by Insurance Coverage



Note: These figures plot the distributions of ages and incomes. The unit of analysis is household—hence, “age” is the mean of the ages of all members in the household. The distributions are stratified by whether or not the household chose to buy insurance from Covered CA, or remain uninsured. The income distribution is censored at 400% FPL.

Table 2.2: Mean Demographics by Plan Type

	Members (1,000s)	Age	FPL	Female	Asian	Nonwhite
<b>Network Type</b>						
1. NonHMO	843	41.76	223	0.53	0.16	0.48
2. Kaiser	394	40.71	231	0.52	0.15	0.50
3. OtherHMO	394	42.73	202	0.51	0.20	0.60
<b>Tier</b>						
1. Minimum Coverage	12	24.22	326	0.45	0.18	0.44
2. Bronze	344	40.47	249	0.49	0.17	0.52
3. Bronze Hsa	72	41.04	260	0.49	0.14	0.46
4. Silver	1,038	42.97	200	0.54	0.18	0.53
5. Gold	89	38.39	276	0.52	0.12	0.47
6. Platinum	77	38.17	268	0.52	0.10	0.45

Note: This table presents characteristics of the enrollees choosing each plan type. The first column is the number of individuals enrolled in each plan type. The rest of the columns represent the mean of the individual characteristic among enrollees in the given plan type.

discussed above is needed to draw more robust conclusions.

## 2.4.2 Identification

In this subsection, I describe the moments in the data that identify each parameter. For most parameters, identification is relatively straightforward. Two parameters for which this is not the case are the mean price sensitivity (“ $\alpha_0$ ”) and the nesting parameter  $\sigma$ , which therefore receive disproportionate attention in this section.

Identification for all parameters in the plan choice model (2.1), come from Covered CA data combined with HCRIS cost reports. Parameters are identified from a combination of “micro” and “macro” moments. The micro moments identify how  $\alpha_i$  and  $\beta_i$  deviate from some baseline—i.e. heterogeneity across individuals—and are given by correlations between individual characteristics and the chosen plan’s characteristics (Train, 2009). Macro moments identify baseline values of these preference parameters based on how market shares correlate with plan characteristics (e.g. metal tier or insurer).

In the plan choice model, the only parameter for which identification is not straightfor-

ward is the baseline price sensitivity (the deviation based on individual characteristics is identified as above). First, as is always the case, premiums are endogenously set in response to anticipated demand, creating bias which underestimates the true magnitude of the parameter. The second problem is that in this environment, market prices vary across consumers so the standard “inversions” to separate out a market price are not valid (Berry et al., 2004; Goolsbee and Petrin, 2004).<sup>36</sup> The logic I use to address this problem of within-market heterogeneous pricing is fairly intuitive and involves a combination of the standard endogeneity methods, plus the micro moments outlined in the prior paragraph.

More formally, notice that (2.1) can loosely be re-written as follows:

$$\begin{aligned}
 u_{ijt} &= \alpha_i p_{ijt} + \overbrace{\nu_{ijt}}^{\text{All other utility}} + \xi_{jt} + \varepsilon_{ijt} \\
 &= (\tilde{\alpha}_i + \alpha_0)(\tilde{p}_{ijt} + p_{jt}) + \nu_{ijt} + \xi_{jt} + \varepsilon_{ijt} \\
 &= \underbrace{\alpha_0 p_{jt} + \bar{\nu}_{jt} + \xi_{jt}}_{\delta_{jt}} + \alpha_0 \tilde{p}_{ijt} + \tilde{\alpha}_i p_{ijt} + \tilde{\nu}_{ijt} + \varepsilon_{ijt}
 \end{aligned}$$

where  $p_{jt}$  is the premium for a 21 year-old as discussed above, and tilde (“-”) variables represent deviations from baseline values.  $\alpha_0$  is the parameter of interest. I isolate “ $\delta_{jt}$ ” to highlight the usual plan-market mean utility that is often used with instrumental variables to estimate  $\alpha_0$  in an unbiased way (Berry et al., 2004; Goolsbee and Petrin, 2004). Written this way, it’s clear that the usual method will not work because  $\alpha_0$  appears outside of the  $\delta_{jt}$  due to within-product variation in prices.

However, this formulation also suggests there are two potential moments that can identify  $\alpha_0$ . The first is the usual macro moment  $E(\xi_{jt} Z_{jt})$  where  $Z_{jt}$  is some instrumental variable that exogenously changes premiums. The instrument I use is the costs of networking hospitals

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<sup>36</sup>The usual logic is to isolate the mean plan utility, including the market price and unobservable  $\xi_{jt}$ , using a market-plan fixed effect. Then form moments given exogenous instruments and  $\xi_{jt}$  to identify the price coefficient. Either of the aforementioned references explain this in great detail.



as plan cost shifters, as defined in Section 2.4.1, and motivated by Dafny (2009). To be a valid instrument, this measure need only be correlated with the rates paid by Covered CA plans to hospitals. Even though this cost index differs from the actual rates in Covered CA, I assume they are correlated with the negotiated rates in Covered CA. To construct a plan-level cost, I take the average cost across the hospitals in each plan’s network, weighted by the number of annual discharges.<sup>37</sup> The identifying assumption is that plan utility doesn’t depend on hospital costs, *conditional on other observables*. Given that I have specified hospital network utility explicitly in the model ( $EV^H$ ), this assumption seems reasonable.<sup>38</sup> Using this as an instrument for *plan* prices,  $\alpha_0$  will be identified based on how market shares correlate with networking hospital costs.

The second moment to identify  $\alpha_0$  is more simple and is the same type of micro moment used for other heterogeneity parameters. Since there is variation in premiums *within plans*, it can be used to see how enrollment probabilities within a market-plan also vary in kind. More formally, this moment is  $E((e_{ijt} - s_{ijt|Ins})p_{ijt})$  where  $s_{ijt|Ins}$  is the model probability of enrollment into plan  $j$  and  $e_{ijt}$  is a dummy for whether the plan was chosen (Train, 2009; Berry et al., 2004). The validity of this moment relies on the fact that I condition on  $\xi_{jt}$ , which is correlated with premiums.

Since  $\alpha_0$  is over-identified, it is reasonable to consider using just one moment (particularly the micro moment) for simplicity. While in theory this is a valid strategy, in this environment it would likely be inadequate. Using only the micro moment would be using within-plan price variation which comes only from the regulated age rating profile in (2.2). Price differences between any two plans are larger for older consumers. This could create

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<sup>37</sup>Kaiser Permanente is a vertically integrated health system, so they have no hospital “prices” based on how I have defined them. Therefore, I set hospital prices to 0 for all Kaiser plans. Since there are brand fixed effects in the model, identification is based only on networks of non-Kaiser plans.

<sup>38</sup>A hospital’s prices will be higher if they are a more demanded hospital (Ho, 2009), but this variation will not be used to identify  $\alpha_0$ . Instead, identification comes from underlying operational costs. Conditional on the explicit network utility, these should not directly effect plan utility.

bias if  $\alpha_i$  varies with age as well, which is a reasonable assumption. One might want to “control for age” and rely on the functional form difference in the rating profile, but this is a strong assumption since this profile represents expected spending. Hence, adding the macro moment uses data variation that is plausibly exogenous and will yield an unbiased estimate. Not surprisingly, adding this moment substantially increases the estimated price sensitivity.<sup>39</sup> This strategy differs from other studies on the pre-ACA Massachusetts exchange where pricing discontinuities can be used (Shepard, 2016; Ericson and Starc, 2015; Finkelstein et al., 2017a).

Next, consider the take-up model in (2.5). In most settings, the nesting parameter  $(1 - \sigma)$  can be identified from the correlation between take-up probabilities and variation in the value of all plans in the choice set  $I_{it}$  (which is “data” once the plan choice model has been estimated). Unfortunately, most of the variation in  $I_{it}$  in this setting comes from the APTC which is a function of income, among other things. Since income impacts  $I_{it}$  in a highly nonlinear way that interacts with other demographic variables (all of which enter the take-up decision), it is likely that  $E(\varepsilon_{i0t}I_{it}) \neq 0$ , which biases the estimates. Since lower-income consumers likely have a lower preference for insurance, large values of  $I_{it}$  from high APTCs will be among those with relatively lower values for insurance, and  $(1 - \sigma)$  will be biased down.<sup>40</sup>

Since estimating parametric models with non-linearities and interactions does not appear to fix this problem, I rely on an exogenous shifter of  $I_{it}$ . Recall that within rating regions, some plans are only offered to a subset of zip codes. Hence, I use variation in choice sets *within rating regions* to identify the nesting parameter  $(1 - \sigma)$ . Specifically, I use the number of

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<sup>39</sup>Alternatively, using only the macro moment would be relying on only *JT* sample observations. While the estimate would be unbiased, it would also be much less precise. Hence adding the micro moment with the large sample significantly reduces variance of the estimate.

<sup>40</sup>In the model, this bias would imply very little substitution along the extensive margin—hence underestimating (in magnitudes) elasticities.

plans available to the household. Hence, the identifying moment is how take-up is correlated with the number of plans being offered, conditional on age, income, race, and population density.<sup>41</sup> Importantly, this variation is correlated with  $I_{it}$  but not with the unobserved utility  $\varepsilon_{i0t}$  (conditioning on income and age).

### 2.4.3 Estimation

For tractability, the estimation is conducted sequentially and in the reverse order of the model timing.<sup>42</sup> The sequence of estimation is as follows: the provider models, the plan choice model, the take-up model, then finally inferring costs given demand and market structure.<sup>43</sup>

#### Estimating Provider Models

The full details on the provider model estimation can be found in Chapter 1. In this section, I present a general overview.

I estimate network utilities separately for Kaiser and Non-Kaiser plans, since Kaiser is

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<sup>41</sup>In practice, I only use the variation in regions 1 and 9. Given the log functional form of  $I$ , the number of plans is only strongly correlated with  $I$  when the number of plans is small—i.e., that is when the first stage is strongest. In other regions, variation in  $I$  is more heavily driven by demographic factors, and hence is sensitive to data differences in the ACS.

<sup>42</sup>This implies that inference in later steps of the sequence is not valid unless standard errors have been corrected for estimation error in earlier steps (see Ho (2006) for a discussion of this). The standard errors presented are not corrected for this sequence and hence are *underestimates* of the true standard errors. However, in the context of this paper, this isn't too problematic. First, the sample sizes are sufficiently large so that most parameters are estimated with an extremely high degree of precision in all stages (e.g. the ratio of point estimates to standard errors is often far greater than 10). Second, as is often the case when relying on counterfactual policies for drawing conclusions, inference on the point estimates is less important than the robustness of the results to the model specification, which I examine in detail.

<sup>43</sup>The majority of the analysis is performed in R. The estimation routines and simulations were developed for this project, but rely heavily on the R development community which deserves a great deal of credit (R Core Team, 2017). I also use the following R packages: *nleqslv* (Hasselman, 2017) for solving non-linear systems of equations. *SQUAREM* (Varadhan, 2016) for increasing the speed of the contraction mapping (Reynaerts et al., 2012). *survey* (Lumley, 2017) for conducting a weighted logit for the take-up model. *ggplot2* (Wickham, 2009) for figures and *stargazer* (Hlavac, 2015) for outputting all results to L<sup>A</sup>T<sub>E</sub>X.

generally a closed system. I estimate the hospital demand model for each hospitalization type using maximum likelihood. Choice sets are all hospitals visited from a particular patient zip code in the OSHPD data.<sup>44</sup> I estimate the probability of needing each hospitalization type non-parametrically based on age and gender using MEPS. Hospital network utility can then be calculated for each plan using (2.6).

For PCP demand, I use the same simplifying assumptions described in Chapter 1. In short, I assume  $EV^P$  is simply the log of the number of networking PCPs within 5 miles of the enrollee. This is equivalent to assuming PCPs beyond 5 miles have no impact on plan choice and the probability of needing to see a PCP is the same for all enrollees. While these are strong assumptions, they alleviate a need to use external physician data as is done for hospitals.

## Estimating Plan Demand

The next step is to estimate the indirect utility function in (2.1). I estimate the model in two stages: The plan choice (“lower”) model includes all parameters in (2.1) less  $\sigma$ . The take-up (“upper”) model is the decision whether or not to be insured, and identifies  $\sigma$  and the parameters in the outside utility in (2.3).<sup>45</sup>

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<sup>44</sup>This assumes patients in OSHPD data have unrestricted provider networks, different from the plans in this study. Since the majority of patients are covered by employer coverage which tends to have large networks, this assumption is less problematic in this context. Any violation in this assumption will lead to underestimated utilities for highly demanded hospitals. Capacity constraints are also ignored and would have a similar effect. This assumption is not expected to have a large impact on the conclusions in this paper since I also allow insurer utilities to vary by health status, which would absorb anything not measured by network variables.

<sup>45</sup>It’s possible to estimate these parameters simultaneously and is often preferred (Train, 2009; Hensher, 1986). By subsetting the data, I am throwing away information and increasing standard errors (or need to correct the standard errors in the take-up model which uses estimated data). Also, if there are any parameters in multiple nests, they cannot be estimated at all (Heiss, 2002). In this setting, sequential estimation is preferred for 2 reasons: 1) each stage is identified from two distinct data sets (Covered CA vs. ACS); and 2) separately estimating the take-up model allows for a concise way of using instrumental variables to identify  $\sigma$ . Additionally, because of the large enrollment sample and there being only 1 “nest,” the usual reasons not to use sequential estimation are not of particular importance.

Working backwards through the nested model, I first estimate the plan choice model—conditional on take-up. Restating the main indirect utility function with a slight abuse of notation, let the plan utility conditional on buying insurance be:

$$\begin{aligned} u_{ijt} &= \alpha_i p_{ijt} + \gamma^H EV_{ijt}^H + \gamma^P EV_{ijt}^P + x'_{ijt} \beta_i + \xi_{jt} + \varepsilon_{ijt} \\ &= \underbrace{x'_{jt} \beta + \xi_{jt}}_{\delta_{jt}} + \alpha_i p_{ijt} + \gamma^H EV_{ijt}^H + \gamma^P EV_{ijt}^P + \widetilde{x'_{ijt} \beta_i} + \varepsilon_{ijt} \end{aligned}$$

Notice that the  $\zeta_{it}^{Ins}$  has dropped out and the  $(1 - \sigma)$  coefficient has been removed, which means all other parameters have implicitly been rescaled by  $1/(1 - \sigma)$  (Heiss, 2002). Also, coefficients have been added to network  $EV$  terms to convert units from each provider utility model to the units in the demand model.

A full description of the estimation routine is given in Chapter 1, but the idea is very similar to “Micro BLP” (Berry et al., 2004). The two exceptions are that I use two moments to identify price sensitivity and I remove unobserved heterogeneity. The routine is as follows: I minimize a GMM objective function made up of micro and macro moments over the parameters related to plan heterogeneity (including “ $\alpha_0$ ”)—call these  $\Theta_2$ . Baseline utility parameters ( $\Theta_1$ , or  $\beta$  above) can be determined analytically, given market shares and the current guess for  $\Theta_2$ . The macro moments are characterized by the vector  $\sum_{jt} \xi_{jt}(\Theta_2) Z_{jt}$ , where  $\xi_{jt}(\Theta_2)$  matches model shares with actual shares<sup>46</sup> and  $Z_{jt}$  is a vector of plan-market instruments: brand, tier, network type, and networking hospital prices. The micro moments are  $\sum_{ijt} (s_{ijt|Ins}(\Theta_2, \delta_{jt}) - e_{ijt}) z'_i x_{ijt}$ , where  $z_i$  are individual characteristics that dictate heterogeneity in  $\alpha_i$  and  $\beta_i$ , and  $e_{ijt}$  is an indicator for whether the plan was chosen. The model is over-identified because of the two price moments so I construct a GMM weighting matrix as the inverse of the covariance matrix of instruments as in two-stage least squares.

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<sup>46</sup>I use a “contraction mapping” on  $\delta_{jt}$  with the SQUAREM (Varadhan, 2016) algorithm as recommended by Reynaerts et al. (2012).

Once the parameters in the plan choice model are estimated, I estimate the take-up model of whether or not to buy insurance. Recall the probability of take-up in the model from (2.5):

$$s_{it}^{Ins} = \Pr(\max_j u_{ijt} > u_{i0t}) \\ = \frac{\exp((1 - \sigma)\hat{I}_{it})}{\exp(z_i'\omega) + \exp((1 - \sigma)\hat{I}_{it})}$$

where  $\hat{I}_{it}$  is implied by estimates in the plan choice model:  $\hat{I}_{it} = \ln(\sum_{k \in J_i} \exp(\hat{v}_{ikt}))$ .<sup>47</sup>  $z_i$  is a vector of individual attributes including income, age, gender, region, race, and population density. This formulation implicitly includes the mandate in a reduced-form way.

Recall the problem identifying  $(1 - \sigma)$  discussed in the above Section 2.4.2, and the proposal to use exogenous variation in the choice sets alone (i.e.  $J_i$ ). Since this is a nonlinear model, standard two-stage least squares cannot be applied. My preferred method is using a control function approach due to its relative simplicity. This method separates the error  $\varepsilon_{i0t}$  into two components, only one of which is allowed to be correlated with the endogenous  $I_{it}$ . This correlation is explicitly estimated using residuals from a first stage based on exogenous instruments (See Train (2009), Section 13.4.1). The method is as follows: I regress  $I_{it}$  on the instruments (including  $J_i$ ). I add the residuals from that first-stage regression as a “control variable” along with  $I_{it}$  in the take-up model. The control function is treated as an exogenous variable, and I estimate the model with MLE.<sup>48</sup>

Without controlling for the endogeneity of  $\hat{I}_{it}$ , standard MLE generates a value of  $(1 - \sigma)$

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<sup>47</sup>Since  $I_{it}$  is estimated rather than data, the standard errors are biased down and should be interpreted as such. Since I have a large sample, there is sufficient power to estimate these parameters with precision either way.

<sup>48</sup>This application is not precisely correct since I am assuming away the remaining variance in the unobservable component that is correlated with  $I$ . However, I estimated the correct specification and found this variance to be precisely near 0. Hence I proceed without it for simplicity.

close to 0 and a value of insurance that is decreasing in income. This is expected given how subsidies decrease with income, but is inconsistent with theory. Using the control function approach outlined above, I get estimates that are theoretically plausible.

Finishing the estimation in the take-up model, I now have all estimates to characterize demand across the state.

## Estimating Costs

I estimate plan costs using a standard procedure in the IO literature based on the first order conditions in (2.9) (Nevo, 2001; Berry et al., 1995). In these models, once demand is known, equilibrium assumptions provide a system of  $JT$  equations and  $JT$  unknown costs, which can therefore be inferred. In my model, there are two complications from the standard implementation. First, this is a “selection market” where the cost of a product depends on which consumer is buying the product (Einav et al., 2010). Second, profits rely on risk adjustments which have not yet been calculated in the model. Omitting risk adjustment in the first order condition would overestimate the amount of price variation that is attributed to enrollee health.<sup>49</sup>

With respect to selection, I impose the cost structure  $\theta_i^c c_{jt}$ . I estimate  $\theta_i^c$  non-parametrically from health care spending by age and gender in MEPS. This reduces each FOC to a single standardized plan cost  $c_{jt}$ . Since I assume expected cost variation comes only from age and gender, this underestimates the true variation. I discuss the implications and remedies in Section 2.8.

With respect to risk adjustment transfers, I use the estimated demand model combined with publicly available risk adjustment data to estimate transfer amounts for each potential

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<sup>49</sup>Including the risk adjustment transfers yields cost estimates which much more closely parallel premiums. By including risk adjustment, high generosity plans and those with generous networks (non-HMOs) have much higher estimated costs than if risk adjustment was ignored.

enrollee.<sup>50</sup> I calculate risk adjustment transfers using the same formula as given by the ACA, where  $\theta_i^c$  is my measure of risk scores. Since I do not observe enrollment off the exchange, I use “relative risk” ( $\theta_i^c/\bar{\theta}^c$ ) based on the on-exchange enrollment implied by the demand model.

Given  $\theta_i^c$  and risk adjustment transfers, costs can be computed using the standard method. Given demand estimated in the prior section and observed prices assumed to satisfy the  $JT$  first order conditions in (2.9), I solve for  $JT$  costs for each plan.

## 2.5 Estimated Model

This section discusses the estimated parameters from the model outlined above. Details on the estimates from the provider models can be found in Chapter 1. I proceed straight to the estimation of plan demand taking the provider models as given.<sup>51</sup>

### 2.5.1 Demand Estimates

I begin with the plan choice model, conditional on choosing to buy a plan. The parameter estimates for baseline utilities ( $\Theta_1$ ) and heterogeneity ( $\Theta_2$ ) are given in Tables 2.3 and 2.4 respectively. Given the results in Table 2.3, I find that there is a strong increasing utility in the level of coverage, with higher tiers yielding higher utilities. Also as expected, EPOs and PPOs generate higher utility than HMOs conditional on network quality and prices.

In Table 2.4, I find evidence of preference heterogeneity for different plan characteristics. I find a higher price sensitivity among those with lower expected health spending ( $\theta_i^c$ ), Asians and other nonwhites, as well as those living in denser areas. This latter result is consistent

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<sup>50</sup>Specifically, from the public data, I use geographic cost factors and the state average premium. See: <https://www.cms.gov/CCIIO/Programs-and-Initiatives/Premium-Stabilization-Programs/>

<sup>51</sup>Section 2.5.1 below is a review of the same estimates of Chapter 1, and largely identical to Section 1.5. I restate it here for convenience to make this chapter self contained.



with two theories: 1) high costs of living in urban areas (Weinberg and Kallerman, 2017), and 2) possibly greater access to uncompensated care (Finkelstein et al., 2017a).<sup>52</sup> While non-HMOs yield higher utility in general, the difference is even larger among households with high incomes and those with higher expected health care spending. In the last set of rows, I also find that higher AV plans are more attractive for households with higher incomes and higher expected health expenditures.

Table 2.3: Select Demand Estimates: Baseline Utilities ( $\Theta_1$ )

	Coef	SE	p-val
Constant	-2.772	0.414	***
Bronze HSA	-2.192	0.200	***
Silver	4.104	0.216	***
Gold	5.969	0.221	***
Platinum	8.489	0.244	***
PPO	2.759	0.276	***
EPO	2.672	0.286	***

\*\*\*p<0.001; \*\*p<0.01; \*p<0.05; .p<0.1

Note: This table presents the baseline estimated coefficients from the plan choice model. “Baseline” represents the fact that this is common to all households in the market. Brand and region dummies omitted. Standard errors are not corrected for estimated provider models.

The impact of providers on plan choice is also notable. Hospital networks matter, but not for Kaiser plans. This latter fact isn’t surprising since hospital qualities do not vary in the Kaiser system as they do otherwise. For non-Kaiser plans, hospital networks affect plan choice but the magnitude in dollars is relatively small. Consider the UCLA hospital,

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<sup>52</sup>Unlike in many other papers, I do not allow price sensitivity to vary with income. I consistently find that high income households are not less price-sensitive in this population. I attribute this to the APTC and the fact that high income households are facing higher prices overall. Hence my results are consistent with disutility in price that is convex rather than linear. Any conclusions should be interpreted within the context of the ACA rather than the broader individual insurance market. Also note that while income doesn’t interact with price, it does interact with other product attributes which are associated with higher prices (e.g. metal tiers, network type, brand), as well as the preference for insurance in general.

Table 2.4: Select Demand Estimates: Heterogeneity Utilities ( $\Theta_2$ )

Plan Char	HH Char	Coef	SE	p-val
$p_{ijt}$		-4.935	0.186	***
$p_{ijt}$	$E(MedSpending) (\theta_i^c)$	1.048	0.041	***
$p_{ijt}$	$HHSize = 2$	2.076	0.086	***
$p_{ijt}$	$HHSize = 3$	3.225	0.131	***
$p_{ijt}$	$HHSize = 4$	3.991	0.154	***
$p_{ijt}$	Asian	-0.292	0.033	***
$p_{ijt}$	Nonwhite	-0.145	0.021	***
$p_{ijt}$	Density	-0.069	0.017	***
Silver AV94		2.389	0.087	***
Silver AV87		1.468	0.062	***
Silver AV73		0.456	0.059	***
HMO (non-Kaiser)	FPL	-0.193	0.035	***
HMO (non-Kaiser)	$E(MedSpending) (\theta_i^c)$	-0.125	0.044	**
$EV_{ijt}^{H,nonKais}$		1.189	0.343	***
$EV_{ijt}^{H,Kais}$		0.231	0.185	
$\log(PCPs \text{ in } 5 \text{ mi})^{nonKais}$		0.136	0.017	***
$\log(PCPs \text{ in } 5 \text{ mi})^{Kais}$		0.139	0.012	***
AV	FPL	0.118	0.009	***
AV	$E(MedSpending) (\theta_i^c)$	0.161	0.013	***
AV	$HHSize = 2$	0.389	0.032	***
AV	$HHSize = 3$	0.552	0.075	***
AV	$HHSize = 4$	0.444	0.099	***

\*\*\*p<0.001; \*\*p<0.01; \*p<0.05; .p<0.1

Note: This table presents heterogeneity coefficients from the plan choice model. These are the coefficients that dictate deviations from baseline utilities in the prior table. Preferences for plan characteristics are based only on the observable characteristics as indicated. Brand-demographic (income, spending, race) interactions omitted. Expected spending is the average  $\theta_i^c$  within the household. Density in Logs. FPL is censored at 400% FPL, and effect of additional income assumed negligible beyond that point. FPL, expected spending, and density are standardized. Prices in units of \$100.

which for a typical enrollee increases the *hospital network utility* by about 0.1. The hospital coefficient of 1.189 combined with the price coefficient of -4.935 imply an average valuation of having UCLA in-network of only about \$2.41/month.<sup>53</sup> Regarding PCP networks, they also matter to consumers, and among both Kaiser and non-Kaiser plans. For non-Kaiser plans, given the PCP utility estimate of 0.136 combined with that of hospital networks (1.189), this implies a hospital like UCLA would generate the same utility as an 87% increase in the number of nearby PCPs.<sup>54</sup> Given the size of many medical groups, this implies large physicians groups have similar bargaining abilities with plans to many hospitals (Ho, 2009). Using the coefficient on price, roughly doubling the number of PCPs within 5 miles is worth \$2.76/month to a typical consumer in the market.

Note that these results imply the potential for adverse selection is large in this market—higher cost patients have stronger preferences for all of the following plan characteristics which are likely to have higher costs: better networks,<sup>55</sup> a non-HMO network type, and more generous cost sharing.

Table 2.5 provides the estimates for the take-up model. Since this is a binary decision, I’ve moved all variables to the take-up side of the inequality, which implies these coefficients are the relative utilities of having insurance. The key parameter from this model is the coefficient on the “Inclusive Value,” estimated at 0.654. Recall that this value ( $1 - \sigma$ ) is the degree of *independence* between the unobservable utilities across insurance plans (hence in a

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<sup>53</sup>This seems relatively low compared to other studies (Shepard, 2016; Ho, 2006). It could be due to actually low valuations in this market—especially given the high price elasticity—or bias for reasons described in Section 1.4.4. It could also be that prior studies have upward biased estimates as a result of omitting physicians, which are included in my model. Either way, any bias is not expected to change the results of this paper, since omitted heterogeneity is absorbed into carrier and network type preferences.

<sup>54</sup>This is based on an average over risk types (again assuming  $\lambda^P$  is constant) and averaging over population densities. In Los Angeles where it is much denser than the state average, the effect of local PCPs is likely much larger. Hence this 87% is an upper bound—i.e. the true percentage is smaller indicating PCPs are more valued.

<sup>55</sup>Recall that age and gender (both of which determine costs) enter the measures of *EV* directly through higher expectations of utilization.

logit model it is assumed to be 1). That it is significantly lower than 1 implies a correlation between the plan unobservable utilities. In other words, conditional on age, gender and race, consumers still disproportionately substitute between plans relative to choosing to be uninsured.

The coefficient on the control function is also important. It loosely represents the correlation between  $I_{it}$  and  $\varepsilon_{i0t}$ . That it is negative implies that the APTC (and hence  $I_{it}$ ) is highest among households with low willingnesses-to-pay for insurance in unobservable ways. Regarding other coefficients, we can see that the preference for insurance is increasing in income and lower for minorities and urban consumers.<sup>56</sup>

Table 2.5: Select Demand Estimates: Take-up Model ( $\Theta_3$ )

HH Char	Coef	SE	p-val
Constant	1.708	0.182	***
$I_{it}$	0.654	0.067	***
Control Function	-0.656	0.067	***
FPL	1.648	0.215	***
$E(MedSpending)$	-0.258	0.082	**
Asian	0.120	0.043	**
Nonwhite	-0.410	0.029	***
Density	-0.163	0.019	***

\*\*\*p<0.001; \*\*p<0.01; \*p<0.05; .p<0.1

Note: This table presents coefficients from the take-up model. Utility is associated with taking up insurance. FPL is censored at 400% FPL, and effect of additional income assumed negligible beyond that point. FPL, expected spending, and density are standardized. Region dummies omitted.

Figure 2.7 plots the distribution of elasticities by network type (non-HMO, Kaiser, Other HMO), tier, and geographic region (North vs. South). Price-sensitivity in the market is quite

<sup>56</sup>Notice that expected spending (as a function of age and gender) is associated with a negative coefficient in this model. Since the price sensitivity is lower among those with higher expectations of health spending, the value of insurance is already increasing in this variation through  $I_{jt}$ . Hence, this is a “reduced-form” effect, net of the already modeled preference for insurance.

high, with market shares generally decreasing between 3% and 5% for a price increase of \$1. These are much higher than seen in the unsubsidized individual market (Cutler and Reber, 1998; Ho, 2006; Ericson and Starc, 2015), but close to those in other subsidized individual markets (Shepard, 2016; Finkelstein et al., 2017a). The fact that these are even slightly higher than those papers isn't surprising. Relative to the pre-ACA Massachusetts exchange or the ACA markets in other states, Covered CA has a number of standardizing regulations that intensify price competition (see Section 2.2.2).

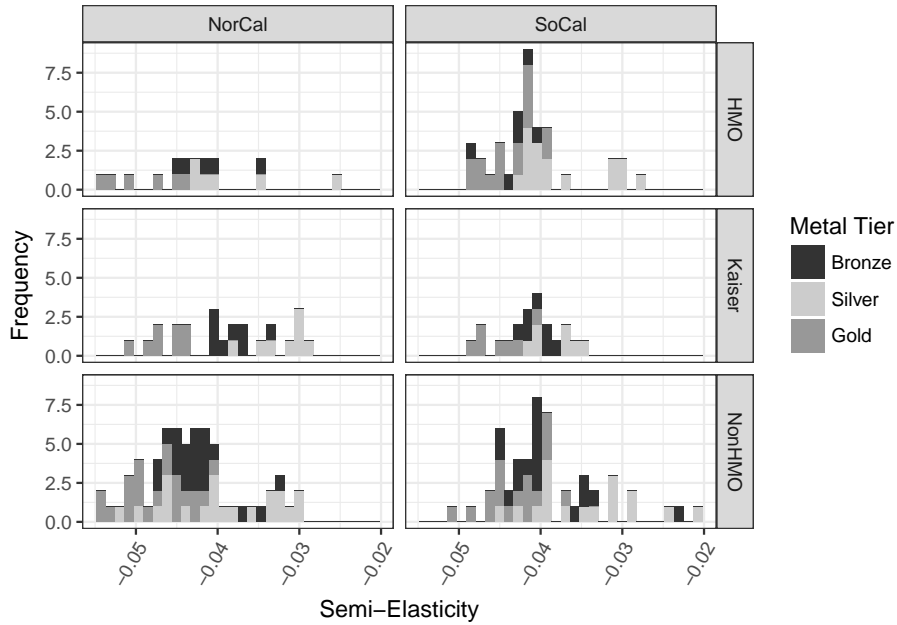
The elasticities vary somewhat by region, network type, and tier. Silver plans appear to be the least price elastic, which makes sense given the large cost sharing subsidies tied to silver plans for a majority of enrollees. Generally, Gold plans are more elastic, especially for HMOs. Elasticities by network type depend on geography. Non-HMOs are generally less elastic in the South, while Kaiser plans are less elastic in the North. Interestingly, despite the relative concentration in Northern California (see Table 2.1), elasticities are not markedly lower.

## 2.5.2 Supply Estimates

Figure 2.8 plots the expected spending by age and gender relative to that of a 21 year-old male. The figure indicates that women generally have higher expected spending than men before the age of 45, at which time they roughly converge. For men, the ratio of costs between 65 year olds and 21 year-olds is approximately 4:1, as opposed to the 3:1 ratio allowed in the regulations. The figure also plots the regulated rating profile by age as specified by Covered CA. Hence the two dashed curves and the solid curve represent  $\theta_i^c$  and  $\theta_i^p$  respectively.

Using estimates for  $\theta_i^c$  and first order conditions, I get implied plan costs and markups. I plot implied plan profit margins in Figure 2.9. The results are consistent with the high price elasticities described above. Namely, price markups on each plan are very low with variable profits making up only about 3%-8% of revenues (the main exception being Kaiser in the

Figure 2.7: Semi-Elasticities by Geography and Network Type



Note: This figure plots the distribution of own-price semi-elasticities in the market. These give the percent change in plan enrollment associated with a \$1 increase in plan premium. Each “point” in the distribution is a single plan ( $jt$ ). Regions 1, 9, and 10 omitted.

North). Interestingly, profit margins in the North for Non-HMO plans are especially low.

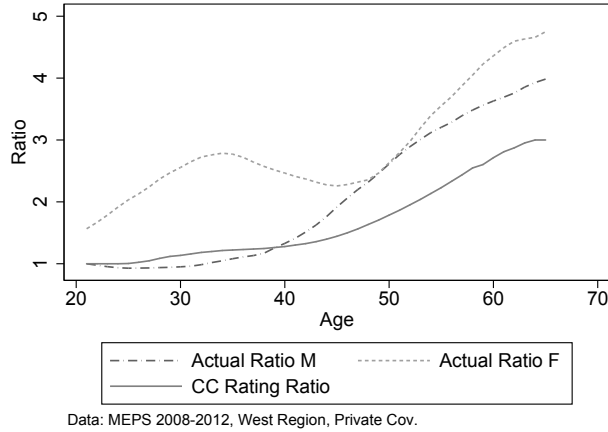
The evidence presented so far in this section—preferences correlated with costs and slim markups for generous plans—could be suggestive evidence of adverse selection. I now turn to the counterfactual simulations to test this more formally, and find this is not the case.

## 2.6 Counterfactual Simulations

### 2.6.1 Specifications

Using the above estimated model, I address the questions proposed in this paper. The objectives of this paper are to determine the effect of community rating and risk adjustment in the ACA on market outcomes, and quantify the associated adverse selection. To that end, there are four policy simulations of interest:

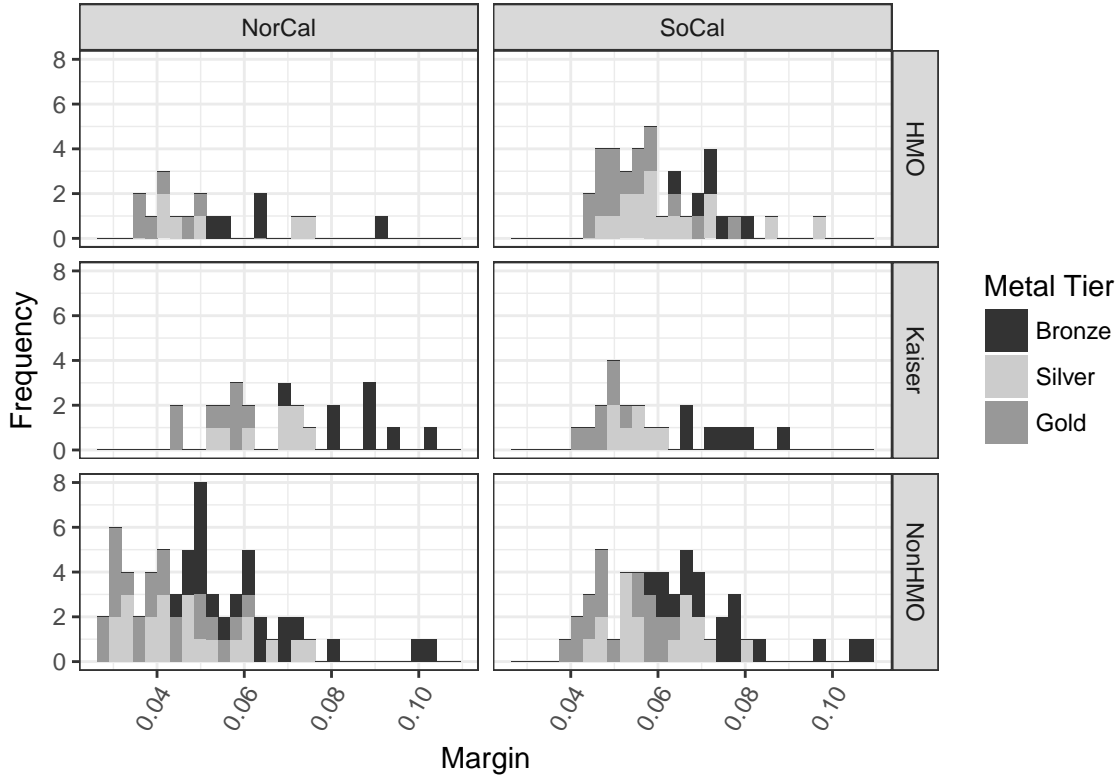
Figure 2.8: Estimated Health Utilization Spending by Age and Gender



Note: This figure plots the non-parametrically estimated spending levels by age and gender used in the model,  $\theta_i^c$ . All levels are relative to a 21 year-old male. The solid line gives the pricing profile set by Covered CA.

1. **No community rating:** This environment assumes prices are set proportional to expected costs such that there is no pooling across genders and premium ratios can exceed 3:1. Since prices reflect costs, there would be no adverse selection and hence no risk adjustment is needed. This simulation is purely to serve as a benchmark to compare market outcomes for the other policies. In the model, this scenario implies the administrative pricing factor is adjusted to match the variation in expected costs:  $\theta_i^p = \theta_i^c$ .
2. **Community rating without risk adjustment:** This environment preserves the rating regulations from the ACA (3:1 ratio and age-based pooling) but does not allow for any risk adjustment. In the model, this implies  $T_{ij} = 0$  and everything else preserved.
3. **Community rating with ACA risk adjustment (“Baseline”):** This is the current regulatory environment with potential adverse selection from the age rating rules, but offset with the current method of risk adjustment transfers. No policy changes are made to the baseline model.

Figure 2.9: Implied Plan Profit Margins at Baseline



Note: This figure plots the distribution of profit margins for all plans under current ACA regulations as implied by the assumptions in the model. Each “point” in the distribution is a single plan ( $jt$ ). Plans in regions 1, 9, and 10 omitted.

4. **Community Rating with alternative risk adjustment:** This is the “textbook” method derived in Section 2.3.4. It benchmarks to individual plan costs and scales relative to risk in the entire population. As derived earlier, this sets  $T_{ij}^{PlanPop} = (\theta_i^c / \bar{\theta}^c - \theta_i^p / \bar{\theta}^p) \bar{\theta}^c c_j$ .

Simulations are conducted by making changes to the regulatory environment (e.g. changing  $T_{ij}$  or  $\theta_i^p$ ), and solving for new equilibrium prices given by the first-order conditions in (2.9). Market shares and government spending are implied by demand under new equilibrium prices in each counterfactual scenario. Each of these are examined in the next section to evaluate the effect of the policies on market outcomes. In all scenarios, I use the APTC



*methodology* as in the current policy. This means that subsidized net premiums for the second lowest silver (SLS) will not be impacted, regardless of how premiums respond to counterfactuals. Most notably, this shields subsidized high-cost consumers from high premiums in the simulation without community rating.<sup>57</sup>

Under each policy, I also provide explicit measures of adverse selection. Recall the earlier discussion in Section 2.3.4 stating that adverse selection can be determined in this environment by the difference between standardized marginal costs (*SMC*) and standardized average costs (*SAC*). Therefore, I calculate adverse selection for any plan  $j$  as follows:

$$\begin{cases} SMC_j - SAC_j < 0 & \implies \text{Adverse Selection} \\ SMC_j - SAC_j > 0 & \implies \text{Advantageous Selection} \end{cases}$$

where again I define these objects as:

$$SMC_j(p_j) = \frac{\sum_i s'_{ij}(p_j) (\theta_i^c c_j - T_{ij})}{\sum_i s'_{ij}(p_j) \theta_i^p}$$

$$SAC_j(p_j) = \frac{\sum_i s_{ij}(p_j) (\theta_i^c c_j - T_{ij})}{\sum_i s_{ij}(p_j) \theta_i^p}$$

The degree to which  $SMC_j - SAC_j$  is negative is the degree of adverse selection for that plan. The benefit of this structural framework is that I can compare the degree of adverse selection under current vs. alternative risk adjustment policies, which allows me to identify the causal effect of risk adjustment on adverse selection.

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<sup>57</sup>For robustness, I also conducted the simulations holding the APTC *level* fixed. All the qualitative results were unchanged. The main difference is it changes the redistributive effects.

## 2.6.2 Simulation Results

This section reviews the results from the counterfactual simulations outlined above.<sup>58</sup> For each of the 4 different policy environments, I discuss premiums, enrollment, spending, and measures of adverse selection.

Table 2.6: Average Premium by Plan Type Under Each Counterfactual Policy

	No Comm.	Community Rating		
	Rating	No RA	ACA RA	PlanPop RA
<b>Metal Tier</b>				
1. Bronze	291	285	299	291
2. Silver	362	380	371	363
3. Gold/Plat	467	543	474	465
<b>Network Type</b>				
HMO	371	404	378	369
Kaiser	378	407	385	375
NonHMO	407	451	415	408
<b>Region</b>				
NorCal	451	511	460	455
SoCal	365	393	371	362
<b>Overall</b>	389	426	396	388

Note: This table gives the unweighted mean premium under each simulation for each plan type. Plan-level premiums are based on the average in population (scaled by  $\bar{\theta}^p$ ). Plans in regions 1, 9, and 10 omitted. Units in dollars.

Before getting to the results, recall the basic predictions from Section 2.2. Community rating is predicted to drive down enrollment and increase prices by deterring low-cost consumers. These predictions hold for both the extensive margin (prices/enrollment overall),

<sup>58</sup>For the counterfactual exercises I exclude regions 1, 9 and 10 (about 10% of state enrollment). In these regions, some people only had access to one insurer in 2015. This makes the simulated prices unstable (particularly from the selection at the heart of this paper). Understanding how selection impacts these markets with very little competition is important and a good topic for future work. To keep things relatively simple, this paper removes them from the analysis.

and the intensive margin (price/enrollment for higher quality plans). Risk adjustment should be able to offset some of this by eliminating the effect of risk composition on prices. ACA risk adjustment is expected to have little or no effect on take-up. The alternative risk adjustment might be able to increase take-up but the degree is an empirical question based on the amount of residual extensive margin adverse selection.

I begin by examining the effect of each policy on prices in the market. Table 2.6 presents the (unweighted) average premiums of each policy by plan type. The premium of each plan is measured as the average premium in the population, but at the current baseline price ( $\bar{\theta}^p p_{jt}$ ). First consider the effect of community rating alone (column 2 vs. column 1). The first three rows of the table give premiums by metal tier. Going from no community rating to community rating without risk adjustment, it is clear that prices are effected as one would theorize. The average premium of a Gold/Platinum plan increases from \$467 to \$543, while Bronze plans decline slightly from \$291 to \$285. These reflect a shift of younger consumers away from high-generosity plans to low-generosity plans. For network types, one can see the premiums of all plan types increase under community rating. The average HMO premium would increase from \$371 to \$404, while that of Non-HMOs would increase from \$407 to \$451. This suggests that adverse selection impacts both plan types, though disproportionately more for non-HMOs. The last row indicates that the market as a whole is adversely selected. The average premium would increase from \$389 to \$426 with community rating.

Next consider the effect of risk adjustment under the ACA, presented in the third column of the table. Generally speaking, prices in this environment are somewhere between the prior two scenarios. The average premium of a Gold/Platinum plan would decrease with risk adjustment from \$543 to \$474, compared to pure community rating. Interestingly, the average premium for Bronze plans would increase from \$285 to \$299, even higher than under no community rating. This is because risk adjustment requires plans that attract healthier

enrollees to make payments, which increases premiums. Examining premiums by network types, all plan types experience lower premiums when adding risk adjustment. Note, however, these are unweighted by enrollment, so this is largely driven by high generosity plans that have relatively small enrollment.

Finally, consider the effect of using the alternative “PlanPop” risk adjustment, presented in the last column. Relative to ACA risk adjustment, the alternative risk adjustment generally reduces premiums for all categories. It significantly reduces premiums for HMOs, while there is a slightly smaller effect for non-HMOs. This is because this method disproportionately lowers risk adjustment payments for lower cost plans, which passes through to premiums. Notice that prices under this method are on average very similar to those without community rating due to the reduction in extensive margin adverse selection.

The effects of each policy on enrollment also match theoretical predictions. Since the price effects discussed above largely parallel many of the same patterns, I keep this discussion brief. Tables 2.7 and 2.8 present enrollment shares and counts, respectively, for each plan type under each counterfactual. Rows and columns represent the same simulations and plan types discussed in the prior paragraphs.

Beginning with shares in Table 2.7, all the patterns described on prices are present. Without risk adjustment, community rating decreases market shares of Gold/Platinum plans from 19.0% of the market to just 2.7%. It would also decrease enrollment in non-HMO plans from 48.1% to 40.8%. Note that in many areas HMOs are not available. Hence these effects are much larger within regions where HMOs are present and popular. Adding ACA risk adjustment largely closes this gap. For example, it increases the share of Gold/Platinum plans to 10.3% from 2.7% without risk adjustment—hence roughly half of the difference. ACA risk adjustment also increases the non-HMO share from 40.8% to 45.2%, which is over halfway to the 48.1% without community rating. Finally, examining the last column, one can see that the alternative risk adjustment further restores enrollment towards generous

Table 2.7: Market Shares by Plan Type Under Each Counterfactual Policy

	No Comm.	Community Rating		
	Rating	No RA	ACA RA	PlanPop RA
<b>Metal Tier</b>				
1. Bronze	22.8	40.2	26.7	26.0
2. Silver	58.2	57.1	63.0	62.5
3. Gold/Plat	19.0	2.7	10.3	11.6
<b>Network Type</b>				
HMO	25.5	30.1	27.6	27.0
Kaiser	26.4	29.1	27.2	27.1
NonHMO	48.1	40.8	45.2	45.9
<b>Overall</b>	100	100	100	100

Note: This table gives enrollment shares conditional on take-up, under each simulation for each plan type. Plans in regions 1, 9, and 10 omitted. Units in Percentages (%).

Table 2.8: Market Enrollment by Plan Type Under Each Counterfactual Policy

	No Comm.	Community Rating		
	Rating	No RA	ACA RA	PlanPop RA
<b>Metal Tier</b>				
1. Bronze	234,537	356,856	233,618	233,469
2. Silver	599,878	507,398	550,064	561,948
3. Gold/Plat	195,879	24,286	89,780	104,228
<b>Network Type</b>				
HMO	263,095	267,472	241,352	243,315
Kaiser	271,817	258,415	237,416	243,840
NonHMO	495,382	362,654	394,695	412,489
<b>Overall</b>	1,030,293	888,541	873,463	899,644

Note: This table gives total enrollment under each simulation for each plan type. Plans in regions 1, 9, and 10 omitted. Units in households.

plans as was predicted. Table 2.8 gives the impact of each policy on the extensive margin by presenting the total enrollment counts. The first column shows that without community rating, total enrollment would be just over 1 million households in the examined regions. Adding community rating decreases total enrollment to roughly 889 thousand, a 13.8% reduction.<sup>59</sup> Adding ACA risk adjustment actually further decreases total enrollment, likely due to the price increase in Bronze plans. The alternative “PlanPop” risk adjustment, conversely, can both restore shares as well as increase total enrollment. This is seen in the last column, where overall enrollment would increase from 873 to 900 thousand households, or 3.0%.

Next, I turn to the impact of each policy on transfer amounts and government spending.<sup>60</sup> Table 2.9 presents the average risk adjustment amount each plan would receive per enrollee. Notably, Under the ACA method, HMOs *pay* an average risk adjustment amount of \$8.22 per household while PPOs receive \$3.05 on average.<sup>61</sup> Using the alternative risk adjustment as opposed to the method in the ACA would lead to overall risk adjustment payments of \$15.02. This reflects adverse selection into the market as a whole. In this case, all plan types would receive larger payments (or pay less). For example, HMOs would receive \$6.22 per enrollee as opposed to making payments in the current environment.

A main result of Table 2.9 is that the alternative risk adjustment, while it can increase total enrollment and the share in higher quality plans, would require additional funding from

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<sup>59</sup>Recall that I hold the APTC *method* fixed which protects most high-cost enrollees in the case without community rating. Also, as pointed out, I do not have the framework to measure the welfare consequences of this since I underestimate the true variation in medical costs and ignore dynamics. While total enrollment has declined, community rating enables those with the highest WTPs to get access to insurance.

<sup>60</sup>I only measure risk adjustment and APTCs and ignore how CSRs change—some people might shift to enhanced silver plans from Bronze, affecting the total outlays of government spending, which I do not measure.

<sup>61</sup>The overall average ACA risk adjustment transfer is non-0 despite budget neutrality because regions 1, 9 and 10 are omitted. The fact that it is negative implies that regions 1, 9 and 10, are getting positive transfers on average—i.e. have costlier enrollees. These areas are largely rural.

Table 2.9: Risk Adjustment Receipts Per Enrollee Under Each Counterfactual Policy

	No Comm.	Community Rating		
	Rating	No RA	ACA RA	PlanPop RA
<b>Metal Tier</b>				
1. Bronze	0	0	-25.21	-11.05
2. Silver	0	0	1.49	15.98
3. Gold/Plat	0	0	36.71	68.29
<b>Network Type</b>				
HMO	0	0	-8.22	6.22
Kaiser	0	0	-4.18	12.81
NonHMO	0	0	3.05	21.53
<b>Region</b>				
NorCal	0	0	-4.19	14.55
SoCal	0	0	-0.99	15.25
<b>Overall</b>	0	0	-2.03	15.02

Note: This table gives the average risk adjustment revenue per household, under each simulation for each plan type. Negative values imply firms make payments into RA system. Plans in regions 1, 9, and 10 omitted. Units in dollars.

Table 2.10: Impact of Counterfactual Risk Adjustment on Government Spending

	APTC	RA	APTC + RA
<b>Baseline</b>			
CR + ACA RA	329,503	350	329,153
<b>Difference (<math>\Delta</math>)</b>			
CR Only	1,008	-350	658
CR + PlanPop RA	-11,377	13,166	1,789

Note: This table gives the impact of each simulation on *monthly* government spending, relative to the current baseline policies. CR is community rating. APTC is the tax credits to subsidize premiums. RA is risk adjustment. Plans in regions 1, 9, and 10 omitted. Units in \$1,000 dollars.

the government. Since premium subsidies (APTC) amounts also change between policies, I compare overall government spending in Table 2.10. The last row of the table presents the impact of switching from the current policy to the alternative risk adjustment. As can be seen, the alternative risk adjustment would require an additional \$13.2 million (monthly) in the exchange. But by increasing risk adjustment payments, it would also lower premiums and hence government spending on APTCs. APTC spending would decline by \$11.4 million, offsetting most of the spending on risk adjustment in the exchange. Hence, the overall budgetary impact of the alternative risk adjustment would be relatively small once factoring in savings from APTC.<sup>62</sup>

To summarize, in absence of any risk adjustment, community rating in the ACA would have a significant impact on the type of enrollment and coverage rates. Risk adjustment successfully offsets most of the effect on market composition—i.e. the chosen network type and metal tier—but no impact on the overall decline in take-up rates. The alternative risk adjustment further restores market shares to the no community rating equilibrium and slightly increases overall enrollment. This risk adjustment would require funding from the government, but most of it would be offset by savings in the APTCs.

### **Adverse Selection in the Market**

This section describes explicit measures of adverse selection for all plans under the different policy simulations. The discussion in the prior section is suggestive of adverse selection, but the degree is not precisely clear. The metric for adverse selection used in this study is the relative cost of the marginal consumer (standardized for age rating) compared to

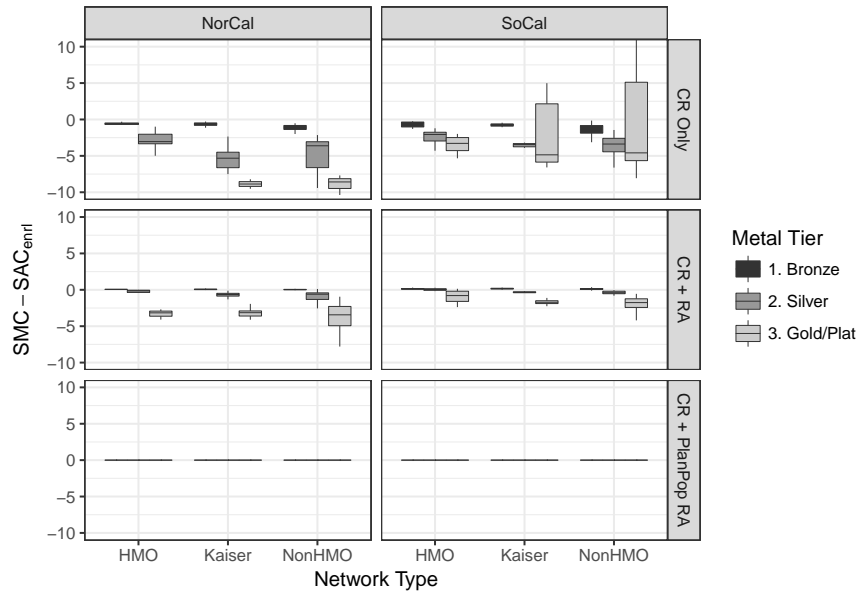
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<sup>62</sup>Recall, off-exchange plans are also combined in the same risk adjustment pool. For those plans, there is no savings in APTCs to offset any positive payments required for risk adjustment. However, the off-exchange population is higher income and likely to have very different risk composition. It could have less extensive market adverse selection, or even “advantageous” selection (Finkelstein and McGarry, 2006; Fang et al., 2008). Moreover, that group by construction has much higher WTPs for insurance. Therefore, the increases to consumer surplus from the alternative risk adjustment are likely much higher for the off-exchange population. More data on this population is needed to do a better cost-benefit analysis.



the average of all inframarginal consumers, i.e.  $SMC_j - SAC_j$ . Recall a negative value is sufficient evidence of adverse selection for that plan since the marginal consumer is relatively lower risk.

Figure 2.10: Adverse Selection Under Each Counterfactual Policy



Note: This figure plots the distributions of standardized marginal costs relative to standardized average costs for each plan. A negative value implies adverse selection into the plan, even after any risk adjustment transfers. The unit of analysis is a plan. Outlier plans and plans with fewer than 100 enrollees are excluded. As in other analyses, regions 1, 9, and 10 are also excluded.

Figure 2.10 plots the distribution of these values for all plans under each policy, omitting the No Community Rating policy which by definition has no adverse selection. The patterns are generally consistent with the prior section and theoretical predictions. First, examine the top panel which represents the market without risk adjustment. Generally, non-HMOs experience more adverse selection, as do higher metal tiers. For example, for a typical Gold/Platinum non-HMO plan in Northern California, the marginal consumer costs about \$8 less than the rest of the plan's enrollment pool. However, the spread of the box plot indicates for some plans this difference is much larger.

The exception to these patterns is for Kaiser and Non-HMOs in Southern CA, where some Gold/Platinum plans appear to positively select from the market—i.e. marginal consumers are actually higher cost. These plans have relatively low enrollment and the reason for this selection is likely from the relatively high prices as well as an income effect.<sup>63</sup> For these consumers, the income effect dominates adverse selection which leads to generous coverage among low-cost consumers (Finkelstein and McGarry, 2006; Fang et al., 2008).

Moving down to the second panel gives the impact of adding ACA risk adjustment. It is clear that risk adjustment reduces adverse selection, but does not eliminate it entirely. The previously described patterns still hold but are attenuated. For a typical Gold/Platinum Non-HMO plan, the difference between the cost of the marginal and inframarginal consumers is about  $-\$3$  after risk adjustment. The pattern on Gold/Platinum Kaiser plans described above appears to be over-corrected by ACA risk adjustment. Finally, note that the bottom panel has no adverse selection by construction of the alternative risk adjustment method.

## 2.7 Discussion

In this section, I discuss the implications of the aforementioned findings. The first implication is that the level of competitiveness in the California market is promising for health care reform. Even in markets with a small number of firms, prices are not substantially higher than costs due to the high degree of price-sensitivity. There has been much attention on the lack of insurer participation in many ACA markets.<sup>64</sup> Some have suggested this pattern is a result of adverse selection or other imperfections in the market. However, the simulations

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<sup>63</sup>The omission of unobserved heterogeneity in preferences—particularly the correlation between price elasticity and relative risk—likely plays a role in this.

<sup>64</sup>See: <https://www.kff.org/health-reform/issue-brief/insurer-participation-on-aca-marketplaces-2014-2017/> or <https://www.kff.org/interactive/counties-at-risk-of-having-no-insurer-on-the-marketplace-exchange-in-2018/>

suggest risk adjustment in the ACA is quite effective (assuming risk scores in practice are near-perfect predictors of true expected cost as in the model). Hence, these findings support an alternative hypothesis: price-sensitive consumers keep profit margins low. Beyond a relatively small number of entrants, marginal profits are too low to cover large fixed costs of operating health plans.

Moreover, the high price sensitivity in the market provides an explanation about the types of plans that exist. Given the high degree of plan substitutability for a large share of enrollees, low-cost plans (i.e. narrow networks or tightly managed care) have a strong competitive advantage. An anecdotal example is UnitedHealthcare in Covered CA. The plan entered a few markets in 2016 with relatively broad networks and hence relatively high costs and premiums. The plan garnered low enrollment and exited the following year. Ho and Lee (2017) measure the welfare implications of narrowing networks more formally. While this level of competitiveness is generally positive for the ACA, the results might not carry over to other populations (e.g. with high incomes), where elasticities are known to be lower (Ho, 2006; Ericson and Starc, 2015). Additionally, if product variety is extremely low as in some markets nationwide, it is important in and of itself regardless of prices.<sup>65</sup> More work is needed explicitly testing alternative hypotheses on why there are so few entrants and on the types of plans that enter.

Given the results in the simulations, another implication is that risk adjustment is very important in addressing adverse selection between plans. This is true regardless of using the method in the ACA or the “textbook” alternative tested in the simulations. However, risk adjustment that is tied to individual plan costs and that corrects for selection along the extensive margin could have benefits to consumers in multiple ways. First, it would reduce premiums for low-cost plans by reducing risk adjustment payments. Second, it would

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<sup>65</sup>Having a very small number of plans is also problematic in these markets where government subsidies are linked to prices (Jaffe and Shepard, 2017).

increase transfers to plans that attract sicker enrollees which could reduce residual adverse selection. It would also reduce adverse selection along the extensive margin to a small degree. It is important to note, however, that there are other efficiency considerations that I cannot measure in this framework. The current method of risk adjustment more strongly incentivizes cost reductions in the long run for high-cost plans. Hence, ACA risk adjustment could lead to more aggressive bargaining or additional medical management strategies, both of which would pass to consumers through lower premiums.

Finally, policies that can increase premiums for any particular group should be expected to reduce rates of take-up. While community rating has important efficiency and distributional effects, it is likely contributing to low rates of coverage among those with low expected health care spending. Hence, policies aimed at universal coverage should pair community rating with subsidies that target low-cost groups (Tebaldi, 2016). The use of a stronger mandate would achieve higher rates of coverage and has other benefits to consumers, such as lower markups (Ericson and Starc, 2015) or reduced adverse selection (Hackmann et al., 2015). However, this study suggests that a stronger mandate also has consequences for those that have low valuations of insurance.<sup>66</sup>

## 2.8 Robustness

The findings of this paper are within the context of the particular model employed, which is not without limitations. There are a number of simplifying assumptions needed due to data availability or tractability that impact the results. The most crucial of these is the assumption that expected spending across consumers within a plan varies only by age and

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<sup>66</sup>The overall welfare is more complicated by the fact that consumers without insurance seem to benefit from “uncompensated care” (Finkelstein et al., 2017a), which would be saved under more complete coverage. Finkelstein et al. (2017b) explore other beneficiaries of the ACA reforms, since many consumers seem to have low valuations of insurance.

gender—hence adverse selection is only caused by gender differences and age differences that exceed the 3:1 pricing ratio. I ignore all other health conditions (or preferences) that could determine expected spending. The impact of this is that I am underestimating the true variance in expected spending, which can be large due to consumers with certain chronic high-cost conditions. While this is clearly not accurate, it is less incorrect than in other contexts. The market excludes those that are covered by other government programs such as the elderly, many chronically disabled, and those in poverty—all of which would likely have higher variation in expected health spending. To the extent that I am missing significant variation, I underestimate the degree of adverse selection in the market. This is particularly relevant for the simulation of community rating without risk adjustment, and the degree of extensive margin selection under current ACA risk adjustment. In the first case of community rating without risk adjustment, there would likely be even lower coverage in generous plans. In the case of using “textbook” risk adjustment which corrects for extensive margin selection, the benefits are likely to be even larger (i.e. I currently underestimate the amount of adverse selection along the extensive margin). The government cost of the risk adjustment would also likely increase with the alternative risk adjustment method.<sup>67</sup>

In future iterations of this study, I plan to add unobservable heterogeneity in costs which can be correlated with newly added unobservable preferences. The correlation can be identified from the relationship in premiums across metal tiers (see footnote 67) and variation in premiums under varying market structures (similar to the method employed by Lustig (2010)). Adding unobservable preference heterogeneity will also make the demand side more flexible, and can be identified from adding other years of data. While the current model is im-

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<sup>67</sup>There is an important empirical finding that suggests the model is imperfectly capturing cost heterogeneity that is correlated with preferences. Once adjusting for actuarial value differences (including moral hazard), the cost of a 21 year-old should be the same across all tiers within a market-carrier. Contrary to this, I find the AV-adjusted costs is increasing in the level of coverage, which is a prediction of Rothschild and Stiglitz (1976) under hidden information. Hence, there is likely unobserved cost heterogeneity which is correlated with the preference for more generous coverage. Fortunately, this precise gap can be used in future iterations of the model to identify the degree of unobserved adverse selection.

perfect, it is still informative in getting the relative effectiveness of different risk adjustment methods, as well the direct impact of community rating on total enrollment.

Given the limitations discussed above, I do not calculate welfare comparisons with the model. Since I underestimate variation in costs and in preferences, I will be missing important tails in both of those distributions. Moreover, as highlighted by Handel et al. (2015), the benefits from community rating come from intertemporal risk smoothing. I do not model this aspect of insurance and so would not provide a complete measure of the welfare benefits. For these reasons, I focus exclusively on market outcomes. In this study, I use the adverse selection metric as a proxy for welfare. But since adverse selection is only problematic insofar as it leads to welfare reductions, more work is needed examining welfare explicitly.

Another major limitation of this work is that I assume risk scores are perfect measures for expected spending. While they have improved dramatically over time, there could still be health (Brown et al., 2014) or preference (Einav et al., 2013, 2016; Shepard, 2016) reasons that this is not the case. A violation in this assumption translates to additional adverse selection in either simulation with risk adjustment. Since this bias enters both cases, the differences should roughly cancel. It would also overestimate the benefits of risk adjustment relative to straight community rating.

Also as a practical issue, the alternative “textbook” risk adjustment described in the analysis is unattainable for a number of reasons. First, it assumes the regulators perfectly know plan costs. Using claims plus some administrative amount could help infer plan costs, but it is likely to be imperfect. In practice, risk adjustment in this style has been based on prices instead of costs, such as in Medicare Advantage. The degree of competitiveness in the market will dictate how much prices and costs differ. If there is sufficient market power, risk adjustment tied to prices could effect firm pricing incentives (Curto et al., 2014; Jaffe and Shepard, 2017). Second, adjusting for risk relative to the population requires knowledge of the risk of the uninsured households, which is not observable in claims. However, regulators

could use survey data on health conditions to approximate the relative risk of the insured and uninsured populations.

Finally, it should be pointed out once more that this study is within the context of Covered CA, which differs from other exchanges around the country. The many strategies outlined in Section 2.2.2 make the California market more competitive, and with higher quality products. If other exchanges differ in these ways, the implications of this study might be different.

## 2.9 Conclusion

The ACA establishes a number of regulatory policies aimed at granting access to coverage and minimizing any resulting inefficiencies. This is particularly true in the newly created subsidized exchanges, where private firms compete in a regulated market environment. This paper examines the regulations targeting the supply-side of that market—community rating and risk adjustment. I not only estimate a model that includes these features of the ACA, but I provide a framework to think about adverse selection in this context—a main source of inefficiency that policymakers are concerned about.

Since risk adjustment in the ACA successfully eliminates the majority of adverse selection across plans, how does this reconcile with low rates of coverage and low enrollment in more preferred plans? This study finds that consumers are highly price-sensitive and hence are drawn to low-cost options, regardless of adverse selection. Similarly, community rating, while having large welfare benefits, drives many low-cost consumers out of the market by increasing their premiums. In general, most of the reduction in enrollment from community rating cannot be recovered from risk adjustment, even when adjusting on the extensive margin. While risk adjustment can shape relative market shares to more closely represent those without adverse selection, it does little to overall take-up. This study supports prior

findings and suggests that policies aimed at universal coverage need to consider the high price-sensitivity for low-cost consumers (Tebaldi, 2016; Ericson and Starc, 2015) and the relatively low willingness-to-pay for insurance in general (Finkelstein et al., 2017a).

While this study closely examines market outcomes under each policy, there is still much to know about the welfare implications. This is an important area of future work. Both community rating and risk adjustment have clear trade-offs. Community rating redistributes across consumers. The benefits of reducing premium hikes are paired with increasing prices to low-cost consumers, many of whom will no longer buy coverage. For risk adjustment, redistribution happens across firms by “subsidizing” firms that attract high-cost enrollees and “taxing” those that attract low-cost enrollees. The benefit is that generally desirable plans that are exposed to adverse selection can remain in the market and will be affordable to consumers of all risk types. But the consequence is that low-cost products become more expensive, which can also hurt consumers. Finding the optimum for each of these policies needs further investigation and will likely be case-specific. This paper sheds light on these trade offs and sets up a framework to continue this investigation. As the U.S. government increasingly relies on the private market to deliver public benefits, these questions are increasingly important. Whether it be the ACA exchanges, Medicare, or Medicaid, this study shows these supply-side policies can have a significant impact on the health coverage people obtain.



## Chapter 3

# Frictions in Health Insurance Take-up Decisions: Evidence from a Covered California Open Enrollment Field Experiment

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## 3.1 Introduction

At any one time, 14 million people have health coverage through an exchange created by the Patient Protection and Affordable Care Act (ACA), and 22 million people have obtained ACA exchange coverage at some point since their creation in 2014. As a fraction of eligible enrollees, however, take-up is surprisingly low. Approximately 60 percent of individuals who are eligible for a federal premium subsidy—and 40 percent of lower income individuals eligible for progressive premium and cost-sharing subsidies—forgo the subsidy and remain uninsured.<sup>2</sup>

This is surprising because of the availability of federal means-tested subsidies. For individuals below 250 percent of the federal poverty level (% FPL), representing nearly half of the subsidy-eligible exchange population, a Bronze plan would typically cost \$1 to \$59 per month, representing a benefit of \$316 per month.<sup>3</sup> And an enhanced silver plan (in which cost-sharing is also heavily subsidized) would typically cost these individuals \$69 to \$146 per month, representing a premium plus actuarial benefit of approximately \$378 per month.<sup>4</sup>

The low take-up in the ACA exchanges is consistent with a well-established feature of means-tested benefits programs—namely that individuals do not participate in subsidized programs for which they are eligible (Currie, 2006). Low take-up has been observed in a number of other settings, including take-up of EITC, AFDC, food stamps, etc (Currie, 2006; Bhargava and Manoli, 2015). Standard economic models of program participation traditionally consider benefits versus costs, where costs include price, social stigma, the costs of acquiring information and other transaction costs (Currie, 2006). In the context of

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<sup>2</sup>See <https://www.kff.org/health-reform/state-indicator/marketplace-enrollment-as-a-share-of-the-potential-marketplace-population-2015/> or <https://www.kff.org/uninsured/issue-brief/estimates-of-eligibility-for-aca-coverage-among-the-uninsured-in-2016-october-2017-update/>

<sup>3</sup>Statistics based on Covered California enrollment in 2015. Bronze premium range represents per-member inner quartile range and monthly benefit is mean per-member monthly subsidy.

<sup>4</sup>Benefit based on mean premium subsidy plus the actuarial value benefit times the plan premium.

the ACA insurance exchanges, where individuals still bear net-of-subsidy premiums, the cost of insurance is the most frequently cited factor deterring take-up.<sup>5</sup> And when combined with the low value consumers place on insurance, estimated to be typically less than a quarter of the cost (Finkelstein et al., 2017a), the price of insurance would appear to explain much of the observed low take-up.

However, it's unclear if individuals are aware of their subsidy and cost sharing options. By statute, subsidies not only depend on income, but also family size and the price of the benchmark plan offered in their zip code. And subsidies for cost-sharing may be obscured by lack of knowledge about eligibility and insurance design (Bhargava et al., 2017). The low consumer willingness-to-pay estimated by Finkelstein et al. (2017a) could embed numerous informational and psychological frictions that impede take-up. Indeed, the role of frictions associated with benefit participation is evident in other programs, such as retirement saving and EITC, as a consequence of low program awareness (Smeeding et al., 2000; Chetty et al., 2013; Chetty and Saez, 2013; Bhargava and Manoli, 2015). Procrastination and inertia impact participation in employer-matched retirement savings (Madrian and Shea, 2001). And psychological frictions such as inattention (Karlan et al., 2016), complexity, and the hassle cost of claiming benefits (Bertrand et al., 2006) also influence program participation. While these frictions have not been well studied in the context of health insurance take-up, complexity (Bhargava et al., 2017; Abaluck and Gruber, 2011; Kling et al., 2012) and inertia (Ericson, 2014b) can significantly impact consumer welfare through suboptimal choice of health or drug insurance plan. These findings highlight the potential importance of informational and psychological frictions in the take-up of health insurance, and motivate tests to identify and to reduce them.

Unlike participation in EITC or retirement savings programs, insurance is a selection market where individual participation has externalities on the market as a whole. In this case,

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<sup>5</sup>See <https://www.kff.org/uninsured/fact-sheet/key-facts-about-the-uninsured-population/>

individual participation effects the market risk pool which determines equilibrium participation, especially under community-rated pricing required under the ACA. While program administrators may wish to increase take-up among eligible beneficiaries, interventions that attempt to raise participation can have ambiguous impacts on both equilibrium participation and welfare. If the marginal group that responds to an intervention is sicker—due to severe baseline lack of information—the intervention may impact those most in need of insurance, leading to negative impacts on market risk and potentially total enrollment in equilibrium. If the marginal group that responds is healthier—as would be the case if search frictions dissuade marginally healthy consumers from purchasing insurance—interventions that reduce frictions can lead to lower average risk, and potentially greater enrollment and improved market stability. Ultimately, the welfare impact of any intervention depends on the correlation between underlying frictions and beliefs, and health spending risk of the marginal respondent. The sign of this correlation, which may depend on the type of friction targeted by an intervention, is particularly important in fragile ACA markets, where the presence of adverse selection gives rise to instability (Handel et al., 2015).

In this study, we report findings from a field experiment conducted in collaboration with Covered California, the state’s health benefits exchange. In the experiment, we randomly assigned interventions to roughly 87,000 California households who were found eligible to enroll through Covered California but had not yet selected a plan. These households came from two groups: those who applied directly to Covered California, and those who were found eligible for Covered California automatically after a change in their Medicaid eligibility (usually disenrollment) was processed by their county. Each household was either assigned to a control group or one of four letter intervention treatment groups. Consumers in each treatment group received a different letter, designed to study frictions that could hinder take-up. We use differential treatment effects across interventions to infer sources of frictions in take-up decisions. We stratified the randomization by reported income, language, and

other demographic variables in order to evaluate differential experimental treatment effects by these categories, given a priori predictions about differential frictions and informational costs. The experiment included five arms:

1. **Control:** No direct intervention was given to these consumers.
2. **Reminder:** Consumers were sent a letter reminding recipients of the open enrollment deadline, and the Covered California website and telephone number where they could shop for plans. For the sample of consumers who had recently initiated the registration process, we view this treatment as a reminder that targeted inattention or procrastination (rather than lack of awareness about where to shop for plans).
3. **+Subsidy and Penalty:** Consumers were mailed the reminder plus their estimated subsidy and tax penalty for uninsurance, based on their reported income. This letter targeted lack of information or misperception about subsidy benefits, but also included the reminder.
4. **+Price Compare:** Consumers received the reminder, subsidy and penalty information, plus a table listing the Silver and Bronze plans offered in their market, with their net-of-subsidy premium. For low-income consumers eligible for the enhanced Silver plan, we showed only Silver plans. By making more salient the list of prices of available plans, this table was designed to reduce search costs and the complexity of comparing shopping.
5. **+Price and Quality Compare:** Consumers received the same information as in the +Price Compare group, but the comparison table also included plans' quality ratings. Making quality ratings salient was designed to further reduce search costs and complexity of comparing value.

Note that the letter interventions are cumulative, insofar as the Subsidy intervention includes the reminder, and the two Plan Comparison treatments include the reminder and the subsidy information. Thus, the impacts of interventions aimed at reducing the cost of obtaining subsidy and plan comparison information are estimated by netting out the impact of the reminder.

We find that a basic reminder of the enrollment deadline raised enrollment by 1.4 pp (or 16 percent) in this low-uptake population. This evidence, along with patterns of the timing of enrollment, is consistent with inattention and procrastination having an important role in take-up. It is also consistent with the role of reminder letters in reducing inactivity due to procrastination or forgetfulness found in other settings (Heffetz et al., 2016).

For the full sample, making subsidy and plan comparison information more salient did not result in increased take-up above the impact of the reminder. However, the average effect masks heterogeneity by income. Among those with the lowest incomes, the subsidy and plan comparison interventions have a slightly larger (marginally significant) impact on enrollment, above the reminder, implying that low income consumers may underestimate their subsidy benefit. However, at higher incomes (and lower subsidies reported in the letters), take-up is lower than when consumers are offered only the basic reminder—despite reminder-only recipients eventually observing their subsidies when enrolling. This pattern is consistent with consumers misperceiving subsidy benefits (where relatively low income consumers underestimating their subsidies, and higher income consumers overestimating their subsidies), and either facing transaction/hassle cost of purchase, or exhibiting reference dependence utility.

Finally, we study whether the letter interventions impact the average risk of consumers, by inducing healthier or sicker consumers into the market. As our primary measure of health risk, we use a measure of spending risk based on observed claims for the covered year. We find that the letter interventions resulted in a 5.9 percent decrease in overall average spending

risk.

Not only does the marginal respondent to the letter (“complier”) have lower risk on average than the inframarginal insured, we find that compliers are lower risk than the average marginal uninsured consumer. This implies heterogeneity in psychological frictions and/or misperceptions about subsidy benefits; the letter interventions induce take-up among compliers at different points in the health distribution, corresponding to the marginal health of heterogeneous groups. Consistent with this evidence, we find that the effects of the letters on average risk are almost entirely driven by their effect among low income consumers who are eligible for the greatest subsidies. Moreover, the impact of the reminder letter on both take-up and risk for the lowest income consumers is as large as the personalized subsidy-reporting letters, suggesting that misperception about subsidies alone isn’t responsible for the low take-up and prevailing adverse selection among this group; hence, barriers created by lack of awareness (among the Medicaid disenrolled sample) and procrastination and inattention (among prior applicants) may be larger for this group. This is consistent with information barriers in Medicaid churn, as well as evidence that the economic stress is associated cognitive load and memory impairment (Mani et al., 2013; Deck and Jahedi, 2015), which could contribute to psychological frictions that impede take-up.

The experimental results allow us to estimate the implied cost of informational and psychological barriers in insurance take-up. Using a structural demand model, we estimate that the effect of the interventions—which reduce these barriers—is equivalent to a \$41 increase in monthly premium subsidies for this population. Compared to a recent estimate of the median willingness-to-pay for insurance of roughly \$100 (Finkelstein et al., 2017a), our results indicate that informational and psychological barriers play a significant role in explaining low take-up. Moreover, the low estimates on the willingness-to-pay for insurance, and the low projected impact of increased financial assistance on increased take-up, are likely to be impacted by interventions that reduce these barriers.

These results highlight the important role that informational and psychological barriers play in the take-up of insurance, particularly among low income individuals who are eligible for the largest benefit. The distinguishing feature of this setting—in contrast to EITC and retirement savings programs where psychological barriers have also been studied—is that program participation occurs in a selection market. Our finding that reducing informational and psychological barriers can improve both equilibrium enrollment and risk pool stability highlights the importance of educational campaigns and enrollment assistance. Our results also make clear the potential destabilizing effects of recent regulatory actions to defund ACA marketing, including a 90 percent reduction in market place advertising, and 40 percent cut in community based navigator programs (Goodnough and Pear, 2017; Lodes, 2017).

Understanding how to improve decision-making in health care is also increasingly important as choice is increasingly devolved to individuals, as is the case in ACA exchanges. The design of the ACA follows recent movement in publicly-financed insurance, such as Medicare Advantage and Part D drug insurance, a model predicated on consumer choice disciplining private insurers and providers to compete on prices and quality. Success of this model depends on if—and how well—individuals make health insurance decisions.

## **3.2 Background on the ACA**

A major provision of the ACA was the establishment of regulated insurance marketplaces, or Exchanges, for the nongroup and small group markets—i.e. for those without health insurance coverage through a large employer or another public program. The exchanges rely on both insurance issuer standards and managed competition to provide access to quality plans at market determined prices. Given the complications of the individual market prior to the ACA—characterized by denials of coverage, complicated products, and low rates of en-



rollment<sup>6</sup>—this new regulatory framework sought to improve affordability, consumer choice, and stability in the market. To this end, provisions of the ACA regulate how insurers can set premiums and how plans can be designed, and provide subsidies that make premiums affordable.

The premium regulations are largely to make the market more equitable. Under the ACA, insurers can only vary premiums for a plan by age (and smoking in some states other than California), and the ratio of the premiums of the oldest to the youngest cannot exceed 3:1. Insurers also cannot deny coverage to anyone that is eligible for participation in the market—a policy known as “guaranteed issue.”<sup>7</sup> In addition to regulations on how insurers can set prices, there are also standardizing rules on the plan benefit designs. For example, all plans must be classified as one of five metal tiers corresponding to the actuarial value (AV)—i.e. the generosity of cost sharing. Plans must also include certain Essential Health Benefits such as emergency and mental health services. The advantages of these standardizations correspond to the two major objectives of the ACA: 1) providing stability in the market by minimizing cream-skimming and unraveling plans, and 2) simplifying the decision-making process by removing search frictions.<sup>8</sup>

Without the proper remedies, the above pricing regulations in the ACA would make the exchanges particularly at risk to adverse selection. To prevent the markets from “unraveling,” the law mandates that all individuals be insured. To ensure that all households can afford coverage under the mandate, the law also provides premium and cost sharing assistance, both of which increase as incomes decline. Generally, any household with an income between 100

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<sup>6</sup>See <http://www.kff.org/health-reform/issue-brief/pre-existing-conditions-and-medical-underwriting-in-the-individual-insurance-market-prior-to-the-aca/>

<sup>7</sup>Given the evolution of risk over the life cycle, these types of pricing rules can increase consumer surplus (Handel et al., 2015); however, without other mitigating policies they can also lead to adverse selection and instability in the market (Geruso and Layton, 2017).

<sup>8</sup>An additional benefit of these two objectives is increased competition through increased transparency and plan substitutability, which leads to lower premiums for enrollees.

and 400 percent of the federal poverty level (% FPL) and that isn't offered insurance through an employer is eligible for a discounted insurance on the exchange. These discounts are applied to monthly premiums using an Advanced Premium Tax Credit (APTC) based on a projected annual income. To ensure affordability in light of the variations in health insurance premiums across ages and regions, the APTC uses a complex formula to determine each consumer's unique tax credit amount, which can then be applied to any product available through the Exchange (excluding Catastrophic level coverage). One disadvantage of this complexity, however, is that it can be difficult to anticipate or communicate with ease how much each product will cost net of the APTC. As a result, consumers generally need to use an online calculator or to complete an insurance application to be able to browse through products and respective prices.<sup>9</sup> Hence, despite the goal of simplifying insurance under the ACA, the APTC introduces new complications to the decision-making process.

Despite the mandate and subsidies, and regulations that simplify insurance decision-making, there is still a relatively low rate of take-up in the exchanges. The ACA has led to a large decline in the overall rate of uninsured in the U.S.,<sup>10</sup> but only 64% of households that are eligible for the aforementioned APTCs in the exchanges actually enroll in a plan.<sup>11</sup> This low take-up has been the subject of recent health care discussions and some recent evidence has attributed it to a low willingness-to-pay (WTP) for insurance—that most households have a WTP below the price, even after government subsidies (Finkelstein et al., 2017a). However, whether it be for the rather complicated APTC schedule or other aspects of insurance decision-making, it is possible that choice frictions still explain part of this low

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<sup>9</sup>Premium credits are reconciled at the end of the year once annual income has been realized. This means that even the complex prices determined during the year may change upon filing taxes (which occurs after all health insurance has already been purchased and consumed).

<sup>10</sup>See <https://www.kff.org/uninsured/report/the-uninsured-a-primer-key-facts-about-health-insurance-and-the-uninsured-under-the-affordable-care-act/>

<sup>11</sup>See: <https://www.kff.org/health-reform/state-indicator/marketplace-enrollees-eligible-for-financial-assistance-as-a-share-of-subsidy-eligible-population>

take-up. In this case, the WTP calculated by Finkelstein et al. (2017a) will conflate the value of insurance plus these types of informational costs; if these frictions are large, then the true valuation of insurance without choice frictions could be much larger than found in that study. As noted in Section 3.1, there is evidence in similar markets on the importance of the complexity of information on decision-making.

### **3.3 Study Sample and Interventions**

#### **3.3.1 Study Sample: The Covered California “Funnel”**

The baseline population for the study is the “Funnel” into Covered California, which comes from two sources. The first source of the Funnel is households that applied directly to Covered California, were determined eligible to enroll in a plan (and, if applicable, eligible for subsidies), but never selected a plan. These consumers may have visited `CoveredCA.com` and entered information themselves, or could have worked with various Covered California Certified Enrollers, including Covered California call center employees, licensed insurance agents, navigators, or other enrollment personnel certified by Covered California to provide consumer assistance. After initiating the enrollment process, a household may not have chosen a plan for rational reasons—that the costs exceeded the perceived benefits—or for behavioral reasons that don’t necessarily indicate this cost-benefit calculation. For example, a household might be unsure of the actual benefits of insurance, plan to return later to complete the process, but have run out of time or forgotten before the deadline. In this case, the letter interventions provide consumers only some new information that the household hasn’t already seen. Instead, the letters largely serve as a reminder, and also provide concise information about the plans that may help to simplify their decision-making process. Henceforth, we refer to this population as “Open Enrollment Applicants” or “OE App” for short.

The second source of the Funnel is prior enrollees from the state Medicaid program

who had likely lost their eligibility due to changes in income. Any household that enters the Funnel from this source would have received a formal notice (letter) from their county informing them of their changed Medicaid eligibility and their new eligibility to enroll in a plan through Covered California. Many, but not all, of these consumers would also be eligible for subsidies through Covered California, depending on their new incomes, other available sources of coverage, and other eligibility conditions. For this group, the letter interventions in this study most likely would provide the first targeted information on Covered California plan options, along with corresponding price information. For this reason, the letters make information more salient and reduce the costs of acquiring plan information. These potential enrollees were referred to the Funnel by their respective counties through the Statewide Automated Welfare System (SAWS). Henceforth, we refer to this population as “County Referrals” or “Refer” for short.

Since the interventions serve different roles for these different populations, we conduct much of the analysis separately for each group, and label them “Open Enrollment Applicants” (“OE App”) and “County Referrals” (“Refer”) accordingly. Having these two sub-populations is beneficial since it allows us to better understand the mechanisms that drive the results.

The total Funnel size at the start of the study was 153,146 households. 64% of this total was County Referrals most likely from Medicaid, while the remaining 36% was the Open Enrollment Applicants. Since the Open Enrollment Applicants signaled interest in enrolling in a plan, this population is expected to have a much higher baseline rate of take-up.

### **3.3.2 Sample Selection for Randomized Control Trial**

The prior section describes the full set of households in the Funnel which were deemed eligible for the study at the time of treatment assignment. For budgetary reasons, we reduced the total sample to 126,182 random households from the full Funnel to be in the study; these

were then randomized into the 5 treatment arms using the method described below in Section 3.3.4. Since time of the treatment randomization, we have learned reasons why some of those original households were not eligible to enroll in Covered California or did not get properly exposed to the treatments. Hence, we make further restrictions to create the sample that we use for the analysis in this study. Since treatment assignment was random, these ex post exclusions have an identical effect on all treatment arms in expectation; however, we also ensure this empirically holds in the final sample (see Section 3.3.4).

The first exclusion is for households who have any members with invalid ages in the data.<sup>12</sup> Specifically, we exclude all households with any members that have either negative ages or are 100 years of age or older. The ages in the data are used to display premium information in the letter treatment arms, which would be incorrect if the ages are invalid. The second exclusion is for households who have incomes below 100% FPL. These households are generally ineligible for subsidies in ACA exchanges but are eligible for Medicaid. Hence, they are unlikely to enroll in an exchange plan. The next set of households that are dropped are those that had moved before the experiment and did not have eligible mailing addresses. In this case, households that are assigned to any of the letter treatment groups are not actually treated, effectively making them the control group.

Finally, the last group are those that come from the SAWS system and are deemed ineligible for subsidies. After implementing the original intervention, further research from Covered California indicated that a significant share of the consumers who are referred from the counties through the SAWS system (resulting in an automatic application for coverage) may have also had eligibility for other sources of coverage, such as Medicaid eligibility that is based on age or disability. According to eligibility rules for the marketplace, these consumers would have received confirmed eligibility for coverage through Covered California, but were not eligible for subsidies due to their existing eligibility for other sources of health insurance.

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<sup>12</sup>Enrollee ages are based on year of birth. Invalid ages are due to incorrect information on birth year.

Table 3.1: List of Sample Exclusions from Funnel

	Count	Take-up
All	153,146	7%
Initial Budgetary Exclusion	26,964	9%
Any Member with Invalid Age	660	0%
FPL<100	4,097	1%
Invalid Mailing Address	5,017	3%
SAWS and Deemed Subsidy Ineligible	42,471	1%
<b>Final Sample</b>	<b>87,394</b>	<b>10%</b>

Note: This table lists all exclusions made from the full Funnel which are used to create the analytical sample. The exclusion counts are not mutually exclusive and hence some overlap substantially. The far right column gives the rate of take-up for each excluded group for reference.

In a practical sense, these consumers are not considered to be actively seeking coverage through Covered California and were excluded from the analysis.

After making the above exclusions, the final sample size is 87,394 households. A summary of these exclusions and their impact on the sample size is presented in Table 3.1. Once more, even though these exclusions were made after the initial randomization, their impact on each treatment arm is the same in expectation.

### Descriptive Summaries of the Study Sample

This section presents descriptive statistics on the final study sample. We also describe how the sample relates to the 2015 Covered California enrolled population and the 2015 uninsured population in California.<sup>13</sup> We find that the study sample is roughly a mix of these other two populations. This is unsurprising given that the Funnel is largely drawn from those that were uninsured in 2015 but were likely on the margin of enrolling (see Section 3.3.1 on the Funnel definition).

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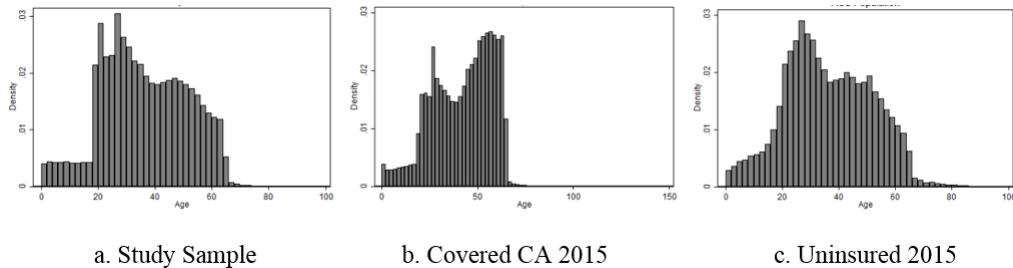
<sup>13</sup>Data on the uninsured come from the IPUMS (Ruggles et al., 2017) version of the American Community Survey (ACS). We restrict the full ACS to those that are flagged uninsured at the time of interview, not an institutional inmate, and with incomes above 100% FPL.

Table 3.2: Summary of Demographics in Each Population

	Study Sample	Covered CA 2015	Uninsured 2015
HH Age	36.96	41.74	35.71
Std. Dev.	14.27	13.25	12.41
FPL   FPL<400	215.23	210.49	211.52
Std. Dev.	65.29	66.44	78.92
Male	0.47	0.48	0.56
Female	0.53	0.52	0.44
White	0.25	0.32	0.23
Latino	0.43	0.21	0.35
Asian	0.13	0.17	0.10
Black	0.04	0.02	0.04
FPL > 400	0.21	0.10	0.19

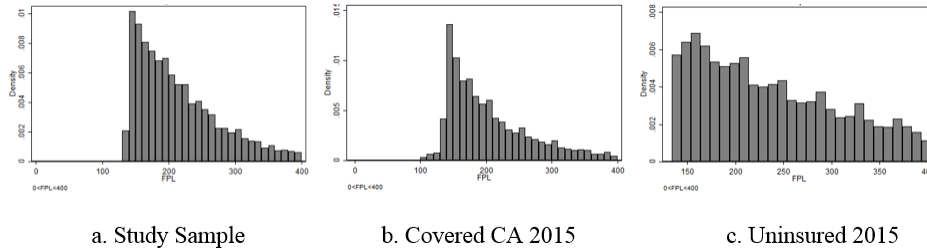
Note: This table presents descriptive summaries on the demographic information of all households in each population. Ages are based on household average. FPL measures are conditional on being less than 400, the cutoff for premium subsidies.

Figure 3.1: Age Distribution in Each Population



Note: This figure plots the full distributions of ages for each of the three populations.

Figure 3.2: Income Distribution in Each Population



Note: This figure plots the full distributions of FPL levels for each of the three populations (conditional on less than 400%).

Table 3.2 displays demographic summaries on each of the three populations. The average age in the sample is 37 years old. This is relatively younger than that of Covered California (42) but slightly older than the uninsured population (36). The full distributions of ages are displayed in Figure 3.1. The shape of these distributions confirms that the sample is more similar to the uninsured than to Covered California.

The average FPL percent in the sample (conditional on being less than 400)<sup>14</sup> is 215. This is higher than both Covered California (210) and the uninsured (212). The shapes of the distributions in Figure 3.2, however, paint a slightly different picture. The study sample is more similar to the Covered California population in that there are few households in the 100-133 FPL range. Additionally, the right tail in the uninsured income distribution is also fatter indicating that among the uninsured, there are more households in the upper income range. Regarding gender, 53% of the sample is female, which is also more similar to the Covered California population (52%) rather than the uninsured population (44%). The income and gender statistics are both evidence that the sample population is the marginally uninsured who are disproportionately eligible for subsidies and disproportionately female. Finally, 25% of the sample is White, which is similar to the uninsured but lower than in Covered California.

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<sup>14</sup>Since FPL measures are missing for much of the sample and Covered California populations, we restrict this measure to just FPL among those with FPL less than 400. This range determines the APTC level and hence the data are more complete.



In summary, relative to the rest of the uninsured population, the sample is similar in that it is younger than the Covered California population and more likely to be nonwhite. However, unlike the rest of the uninsured, the study sample is like the Covered California population in that it is lower income (when dropping the Medicaid eligible) and more likely to be female. Given the Funnel definition and these observations, we think of this sample as disproportionately being made up of the marginally uninsured. For this reason, this population is probably more likely to take up than the overall uninsured population in subsequent years.

### **3.3.3 Experimental Letter Interventions**

Subjects in the study were randomized into one of five arms: a control arm or one of four experimental intervention arms. Individuals in the control arm received no direct communication from Covered California beyond the generic outreach and marketing activities, representing the status quo interaction with consumers in the Funnel. Consumers in the control arm could still receive information through general advertising, such as Covered California sponsored newspaper, radio, and television advertisements, or outreach conducted by third parties.

Each of the four experimental letter interventions, summarized in Table 3.3, was designed to test the importance of potential behavioral friction for insurance take-up. Letters in all treatment arms were double sided, accordion style letters. When opened, the large postcard sized mailer would unfurl into a four post-card length letter. One side of the letter was uniform across all four letter interventions, and reminded the study subject in simple bold typeface about how to enroll, and the enrollment deadline. The opposite side of the unfurled letter varied according to the treatment arm, each targeting a specific mechanism, below.

*Procrastination/Inattention:* The first intervention tests whether procrastination or inattention impacts take-up. We design a Reminder Letter, which offers a salient reminder about

Table 3.3: Targeted Mechanisms and Interventions

<b>Mechanism</b>	<b>Intervention: Letter content</b>	<b>Sample</b>	<b>Description</b>
<i>Procrastination and inattention</i>	<i>Reminder Letter</i>	Open Enrollment Applicants	Reports open enrollment deadline, and the Covered California website and telephone number where consumers can purchase plans.
<i>Program awareness (search costs)</i>			
Awareness of Covered California	<i>Reminder Letter</i>	County Referrals	Same as above
Awareness of subsidy and penalty	<i>+Subsidy and Penalty Letter</i>	Open Enrollment Applicants and County Referrals (all)	Reports total annual subsidy and penalty across all registered policy members. Also reports equivalent monthly savings due to subsidy.
Plan Attributes and Choice Frictions	<i>+Price Compare Letter</i>	Open Enrollment Applicants and County Referrals (all)	Reports Silver and Bronze plans offered in subjects' market, ordered by the net-of-subsidy premium. For consumers eligible for the "enhanced" Silver plan, letter reports only Silver plans.
	<i>+ Price and Quality Compare Letter</i>	Open Enrollment Applicants and County Referrals (all)	In addition to above, table also reports plan star quality rating. For consumers eligible for the "enhanced" Silver plan, letter reports only Silver plans.

Note: This table displays the different interventions in this study and the mechanisms they identify.

the enrollment deadline, and the Covered California phone numbers and website for enrollment. Take-up patterns show peak enrollment typically occurs just prior to the enrollment deadline, which suggests procrastination or inattention may factor into enrollment decisions. Moreover, simple reminders have been shown to counter inattention and improve program adherence in other settings, such as paying municipal parking tickets (Heffetz et al., 2016). Because the sample of Open Enrollment Applicants had just weeks before initiated plan shopping and completed the income verification process, they are well-informed about the existence of Covered California, and how to initiate the purchase process. Therefore, we interpret the Reminder Letter as targeting inattention or procrastination, rather than lack of awareness about the market itself.

*Lack of Awareness about Covered California:* In contrast to the Open Enrollment Applicants, consumers who enter the Covered California Funnel through County Referrals (mostly from Medicaid disenrollment) have not taken limited if any direct action, and may be less informed about the availability of, or their eligibility for, enrollment in the individual exchange. For this subsample of the Reminder Letter arm, we view the intervention as testing the combined role of program awareness and procrastination/inattention.

*Lack of Awareness of Subsidy and Penalties:* We also test whether lack of program awareness about the subsidies and penalties impacts take-up. Conceptually, we view lack of awareness as rooted in search costs, which the letter lowers by providing personalized information of both subsidies and penalties—based on the income and family size they report during the Covered California registration process. For the County Referrals, income and family size are reported to Covered California by SAWS, using updated data from local county health administrators of the state Medicaid program. The Subsidy/Penalty Letter reported total estimated annual subsidies and penalty across all registered policy members on the initial application. The subsidy is also reported as a monthly savings due to the premium subsidy. By design, this letter (and all other treatment interventions) includes the

basic reminder. Therefore, we interpret the impact of reporting subsidy and penalty as the change take-up over and above the impact of the Reminder Letter.

*Choice Frictions and Lack of Awareness of Plan Attributes:* Finally, we test whether choice complexity and lack of awareness about plan attributes impact take-up. Previous studies have shown that making attributes of available plans salient in easily comparable leads consumers to switch to lower cost plans (Abaluck and Gruber, 2011; Kling et al., 2012) or to higher value plans (Ericson and Starc, 2016), by simultaneously reducing the cost of obtaining plan attributes and reducing choice frictions by making plan comparison simpler. We introduce two letter interventions that targets these frictions in the context of take-up decisions. The Price Compare Letter included a table that listed all available Silver and Bronze plans offered in subjects' market, along with each plan's estimated net-of-subsidy premium to the household. Plans were listed in increasing order of their net-of-subsidy premium. For consumers eligible for the "enhanced" Silver plan (that is, below 250% FPL), the Price Compare Letter reports only Silver plans.<sup>15</sup>

A second version of this intervention included each plans' quality rating, reported in a column next to the plan's net-of-subsidy premium. The quality rating is a 1-5 star rating, as rated by Covered California's Quality Rating System, computed using Consumer Assessment of Healthcare Providers and Systems (CAHPS) measures, as required under the ACA. This intervention was motivated by research showing that consumers demand higher value plans, not just lower cost (Blumberg et al., 2013), and that absent difficult-to-acquire quality information, some consumers interpret lower cost to be a signal of lower quality (Dodds et al., 1991).

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<sup>15</sup>In 2015, 89 percent of consumers in the market enrolled in a Silver or Bronze plan. Limiting the set of plans to only Silver and Bronze made plan comparison simpler, while still capturing the vast majority of plans these consumers were likely to choose. This restriction to Silver plans for the <250% FPL sample was urged by Covered California leadership, to ensure that consumers who were eligible for cost-sharing assistance subsidies did not forgo them based on a letter that primarily emphasized plan premiums.

### 3.3.4 Randomization

We assign each household in the study sample to treatment arms using stratified randomization. This method ensures that we have balanced the sample on observable characteristics, and reduces variation across treatment groups due to randomness. The observable characteristics we use for stratification are federal poverty level (FPL) category (<150, 150-200, 200-250, 250-400, 400+ or missing), race category (Latino/Black vs. other), Spanish language preference, email eligible, and whether the household used an enrollment delegate. The unit of stratification is the intersection of each of the above 5 characteristics which creates 80 stratification units. Each household is classified into one of the 80 strata and within each, households are randomly assigned to one of the 5 arms. This method ensures that households in each treatment group are on average observationally equivalent.

As described in Section 3.3.2, we impose several exclusion restrictions after the treatment randomization. Randomization ensures that, in expectation, the study arms are still balanced across arms for the final study sample. Table 3.4 presents how observable characteristics of the final study vary by treatment arms. For all characteristics, a joint F-test of equality across arms cannot be rejected at the 5% level. The p-value for age is marginally significant (at  $\alpha = 0.1$ ), but as seen in the last column, we cannot reject the average age is the same in the control arm as the combined treatment arms at any significance level.<sup>16</sup> This is evidence that the treatment will also be uncorrelated with any unobservable characteristics.

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<sup>16</sup>The age variable used here is actually the average age of the household members. Since this reduces the variance in the age variable across households, this p-value is lower than if using individual-level ages in each arm.

Table 3.4: Summary Statistics by Arm

	Treatment Arm						p-val (All Arms)	p-val (Arm1)
	Control	Letter Only	Subsidy/ Pen	SP+ Plans	SP+ PlanStars	Total Sample		
	(1)	(2)	(3)	(4)	(5)	(6)		
Letter FPL	212.40	211.98	212.45	211.89	212.52	212.25	0.86	0.74
Actual FPL	207.04	206.71	206.49	206.39	206.98	206.72	0.89	0.51
White	0.26	0.26	0.26	0.26	0.25	0.26	0.62	0.77
Latino	0.43	0.43	0.43	0.42	0.43	0.43	0.62	0.58
Asian	0.12	0.12	0.12	0.12	0.12	0.12	0.79	0.64
Black	0.05	0.05	0.04	0.05	0.05	0.05	0.33	0.52
Spanish language	0.17	0.17	0.17	0.17	0.17	0.17	0.89	0.60
HH Size	1.40	1.39	1.40	1.39	1.39	1.39	0.96	0.76
Married	0.49	0.48	0.48	0.48	0.48	0.48	0.52	0.08
Age	37.69	37.90	37.59	37.60	37.46	37.65	0.06	0.65
HH Risk Ratio	1.99	2.01	1.99	1.99	1.98	1.99	0.57	0.97
Sample Size	17378	17431	17521	17509	17555	87394		

Note: This table displays summary statistics on each study arm including the control and 4 treatment groups. Column (7) is a joint test for all arms being equal and column (8) is test that the control group the same as all the treatment arms combined.

## 3.4 Empirical Strategy

### 3.4.1 Data

There are two data sources for this study: Covered California administrative data and IBM Watson (formerly Truven) risk score data. The base Covered California data combines the two “Funnel” sources described above, Open Enrollment Applicants and County Referrals (generally from Medicaid). After the end of 2016 open enrollment, we merged this base data with the new 2016 enrollees. Households were considered to have taken up insurance if they selected a plan (and didn’t cancel prior to payment) before the end of the open enrollment deadline. Demographic variables such as age and income are based on those in that were reported in the original data from the Funnel.

We also combined the enrollment data with IBM Watson risk score data. These risk scores are based on diagnoses from claims in the 2016 enrollment year. Hence, they reflect actual “concurrent” health during the year of coverage. This measure also removes any variation due to prices of services (i.e. for specific providers) or quantities (with the exception of the presence of a diagnosis).<sup>17</sup>

### 3.4.2 Estimation Strategy

#### Experimental Impacts on Take-up

Our main outcome of interest is take-up of Covered California insurance. We exploit the random assignment to treatment arm to identify the causal impact of the four letter-based

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<sup>17</sup>The advantage of these concurrent scores is that there is complete data, whereas prior claims would be missing for anyone that was uninsured.

interventions on average take-up rate. We estimate:

$$\begin{aligned}
 Takeup_i = & \beta_0 + \beta_1 Reminder_i + \beta_2 SubPen_i + \beta_3 PriceCompare_i + \\
 & \beta_4 PriceQualCompare_i + x_i' \Gamma + \epsilon_i
 \end{aligned}
 \tag{3.1}$$

In most specifications, we include a vector of household level characteristics,  $x_i$ , that controls for family size, number of kids, age, race, language preferences, marital status, Covered California’s age-based community-rating premium ratio, and household income (as percent of the FPL). If balance is achieved by the randomization, the covariance between treatment assignment and covariates should be zero, and inclusion of controls should not markedly impact treatment effects, and serve primarily to increase precision.

Because all letter interventions include the basic reminder, the effects of Subsidy+Penalty, and the effect of the two plan comparison letters, are estimated as additional impact beyond that of the impact of the reminder letter captured by  $\beta_1$ . In some specifications, we collapse the three arms that report subsidies, or all four interventions arms, into one indicator variable.

Since the letter treatments other than the Reminder only have income-specific information, it is important to consider the possibility of different treatment effects for different income groups. Additionally, choice frictions and other search costs may differ by demographic group. On the one hand, lower income individuals may face greater barriers to acquiring program information and comparing plans due to comparatively higher language barriers, lower education, language barriers, or stress-related cognitive overload (Mani et al., 2013). On the other hand, higher wage-based value of time of higher-income consumers could imply larger cost of search. To test for heterogeneous treatment effects, we estimate equation (3.1), including interactions between treatment indicators and income. For similar reasons and more described in the following section, we also estimate the model including treatment interactions with age.



## Experimental Impacts on Market Risk

If the marginal respondent to reminders and information about insurance benefits is higher risk, then the treatment arms will increase the average market risk, which has implications for equilibrium prices. Conversely, if the marginal respondent is lower risk, the letter interventions will lower average market risk and hence prices. To test whether the interventions induce healthier individuals to enroll, we modify and re-estimate equation (3.1), interacting treatment indicators with age. Age is a strong predictor of risk, and is observed in the data.

$$\begin{aligned} Takeup_i = & \beta_0 + \beta_1 Reminder_i + \beta_2 SubsidyLetters_i + \beta_3 Age_i + \\ & \beta_4 Reminder_i * Age_i + \beta_5 SubsidyLetters_i * Age_i + x_i' \Gamma + \epsilon_i \end{aligned} \tag{3.2}$$

In equation (3.2), we combine the three subsidy letter arms into a single group, *Subsidy Letters<sub>i</sub>*, and interact treatment indicators with the mean age of the household. Negative coefficient estimates on  $\beta_4$  and  $\beta_5$  would suggest the interventions induced younger, and typically healthier, individuals to enter the market.

While age is not a direct measure of expenditure risk, it is used to regulate community rated premiums in the ACA. By statute, premiums are only allowed to vary by age, and the most expensive premiums (for consumers ages 65 and up) can be at most three times the premiums for youngest enrollees (for consumers age 21). Because the actual age-spending profile is steeper (Blumberg and Buettgens, 2013), younger consumers on average subsidize the risk pool and older consumers on average incur spending that exceeds premiums; therefore, differential take-up by observed age can have direct impacts on all premiums and the stability of the risk pool.

As a more direct measure of risk, we use claims data for covered year 2016 to test whether the letter interventions lead to differences in average expenditure risk among insureds. Our primary measure of expenditure risk is the Verisk concurrent risk score as implemented

by IBM Watson Health, the contracted claims aggregator for plans participating in the health benefits exchange. This measure is based on realized health claims and observed disease conditions during 2016, and therefore captures the impact of treatment on expected expenditures incurred during the covered year of the study.<sup>18</sup> With this data, we estimate average risk, *conditional on take-up*, by treatment arm:

$$\begin{aligned} Risk_i = & \beta_0 + \beta_1 Reminder_i + \beta_2 SubPen_i + \beta_3 PriceCompare_i \\ & + \beta_4 PriceQualityCompare_i + x_i' \Gamma + \epsilon_i \end{aligned} \tag{3.3}$$

Note that the coefficients on the treatment arms in equation (3.3) capture the impact of the interventions on *average risk of the study sample*. Under strict assumptions—that no individual is *less* likely to take-up in response to treatment—we can infer the average marginal risk of those induced to take-up from the impact on average risk.<sup>19</sup>

Finally, we also examine actual realized total expenditures and utilization during covered year 2016. Given the variance in expenditure and utilization, these specifications will generally be underpowered, but will serve as consistency checks on specifications that regress the aggregate expected expenditure risk measure on treatment arm indicators. These results are consistent with our other measures of risk, and hence are not presented in this study.

## Estimating the Costs of Choice Frictions

The letter interventions provide reminders to enroll, as well as personalized information about costs, plan availability and comparable attributes. Since they do not actually change

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<sup>18</sup>This can be thought of as a concurrent risk score, representing the risk given realized health conditions in the coverage year. It has benefits over other measures of risk in that we know the enrollee was covered during this time and hence has non-missing data.

<sup>19</sup>If the interventions caused some demographic groups to increase take-up and others to decrease take-up, the estimated coefficients in equation (3.3), together with the take-up rate, can be used to infer the average risk of the marginal respondent, including those who are persuaded and dissuaded to enroll by the letters.

the quality of the plans available, if the treatments do increase take-up, the information alone can be interpreted as valuable to consumers. This is either by reducing the amount of time and effort (i.e. search costs) required to select and purchase plans—as in the case of the subsidy and plan comparison interventions—or by lowering cognitive costs associated with remembering to purchase a plan—as in the case of the basic reminder. In this section, we describe how to estimate a structural model that allows us quantify the dollar value of the interventions to consumers.<sup>20</sup>

A natural way to conceptualize the value to consumers is in terms of the premium subsidy (APTC), since this is largely a subsidized market. The value of interest is the amount of premium subsidy that would achieve the same impact on take-up as each intervention. The rest of the section describes a model of enrollment which can be used to obtain this measure.

Consider household  $i$  with a vector of characteristics  $x_i$ , ATPC  $\tau_i$ , which receives treatment arm  $j \in \{1, \dots, 5\}$  or  $T_i^j$ . The indirect utility  $u_i$  of taking up insurance *relative to remaining uninsured* is as follows:

$$u_i = \sum_{j \neq 1} \gamma^j T_i^j + \alpha \tau_i + x_i' \pi + I_i + \varepsilon_i \quad (3.4)$$

In this specification,  $I_i$  represents the utility of all insurance plans available to the household given their zip code at the gross (unsubsidized) premiums, i.e. the “inclusive value.”<sup>21</sup>  $I_i$  implicitly includes the value of each plan given plan attributes such as the provider network.  $\varepsilon_i$  is the idiosyncratic utility of having insurance and follows a logistic distribution. The household takes up insurance if this utility  $u_i$  exceeds 0.

The object of interest in this framework is the willingness-to-pay (WTP) for treatment.

<sup>20</sup>There are still additional search costs after the intervention, so the value of treatment can also be thought of as a lower bound on the total cost to consumers of searching for a plan.

<sup>21</sup>This can be derived in a plan choice framework as  $I_i = E\{\max_k u_{ik}\}$  where  $u_{ik}$  is the utility of each individual plan.

As noted, this can alternatively be thought of as the cost of searching for a plan (or remembering to search for a plan) which is eliminated by getting the treatment. Since  $\tau_i$  is in units of dollars,  $\alpha$  is utils per dollar. Hence, the WTP for treatment  $j$  relative to the control is:

$$WTP^j = \frac{\gamma^j}{\alpha} \tag{3.5}$$

Note that to get  $WTP$ , only  $\gamma$  and  $\alpha$  are needed from (3.4) and namely the more complicated inclusive value is not needed. Therefore, we can replace  $x'_i\beta \approx x'_i\pi + I_i$  and simplify the problem by estimating a reduced-form version of (3.4) as follows:

$$u_i = \sum_{j \neq 1} \gamma^j T_i^j + \alpha \tau_i + x'_i\beta + \varepsilon_i \tag{3.6}$$

We know from the randomization that  $\gamma^j$  are identified in the data. Estimating  $\alpha$  is more complicated because APTC ( $\tau_i$ ) varies with ages and income in a nonlinear way. Specifically, the APTC is increasing and convex in age, and decreasing and convex in income. To be sure that the estimate of  $\alpha$  is not driven by functional form assumptions in (3.6), we explore many specifications for robustness.

## 3.5 Results

### 3.5.1 Average Treatment Effects

Table 3.5 reports the overall impact on coverage take-up, by treatment intervention. The average increase in take-up across the four treatment arms, compared to the control, is 1.4 percentage points. This is equivalent to an average increase by 16.3 percent (i.e. 0.014 above the control group take-up rate of 0.086). Overall, there was no differences in take-up across the letter interventions, a finding we revisit in subsequent sub-group analyses.

Table 3.5: Average Treatment Effects on Take-up

Model	OLS				Logit				
	Sample	Full	Full	OE App	Refer	Full	Full	OE App	Refer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Arm2: Reminder	0.015*** (0.003)	0.013*** (0.003)	0.021*** (0.005)	0.005* (0.003)	0.173*** (0.037)	0.161*** (0.038)	0.168*** (0.043)	0.133* (0.079)	
Arm3: Subsidy-Penalty	0.014*** (0.003)	0.012*** (0.003)	0.017*** (0.005)	0.007** (0.003)	0.163*** (0.037)	0.154*** (0.038)	0.145*** (0.043)	0.183** (0.079)	
Arm4: Price Compare	0.013*** (0.003)	0.012*** (0.003)	0.017*** (0.005)	0.008** (0.003)	0.159*** (0.037)	0.155*** (0.038)	0.137*** (0.043)	0.200** (0.078)	
Arm5: Price+Quality Compare	0.014*** (0.003)	0.012*** (0.003)	0.017*** (0.005)	0.007** (0.003)	0.168*** (0.037)	0.157*** (0.038)	0.144*** (0.043)	0.194** (0.078)	
Latino		-0.012*** (0.003)	-0.015*** (0.005)	-0.008*** (0.003)		-0.138*** (0.031)	-0.116*** (0.036)	-0.174*** (0.063)	
Asian		-0.005 (0.004)	-0.006 (0.006)	-0.003 (0.004)		-0.046 (0.040)	-0.048 (0.046)	-0.043 (0.085)	
Black		-0.029*** (0.005)	-0.038*** (0.008)	-0.020*** (0.005)		-0.348*** (0.065)	-0.315*** (0.075)	-0.460*** (0.133)	
SAWS		-0.125*** (0.003)				-1.481*** (0.032)			
FPL		-0.019*** (0.001)	-0.022*** (0.002)	-0.010*** (0.002)		-0.225*** (0.018)	-0.203*** (0.019)	-0.262*** (0.045)	
Mean of Outcome Variable	0.086	0.086	0.137	0.037	0.086	0.086	0.137	0.037	
All Controls	N	Y	Y	Y	N	Y	Y	Y	
Observations	87,394	87,394	44,248	43,146	87,394	87,394	44,248	42,800	
R-squared	0.000	0.053	0.025	0.018					

Note: This table displays coefficients from the main specification in equation (3.1). Sample “OE App” is the Open Enrollment Applicants. Sample “Refer” is the County Referrals, largely from Medicaid. Controls are mean HH age, Funnel round, race dummies, HH size, HH members, HH kids, Marital Status, Email accessible, SAWS Dummy, FPL, FPL missing,  $FPL \geq 1000$ , flagged as subsidy ineligible by Covered California, and region dummies. Logit results are model coefficients. Robust Standard Errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

The average overall impact is essentially unchanged after controlling for an extensive list of household and primary policy holder characteristics (Column 2 vs 1). The standard set of controls includes indicators for rating region, the level of geography at which plan premiums are permitted to vary, as well as race, age, income and family composition. We also find large differences in enrollment rates by consumer demographics. Black and Latino consumers are markedly less likely to take-up than White or Asian consumers. And take-up declines steadily with household income, likely due to the phase out of the premium subsidies, which by statute decline in income at a much higher rate than income rises.<sup>22</sup>

The large negative coefficient on SAWS in Column 2 reveals the stark difference between consumers who actively initiated the enrollment process (Open Enrollment Applicants) and consumers who were disenrolled from Medicaid (County Referrals). By virtue of their own engagement with the exchange, Open Enrollment Applicants have familiarity with Covered California as a market for individual coverage, whereas County Referrals are likely much less informed about Covered California. For some individuals from the County Referrals, it is possible that they are unaware of their Medicaid disenrollment, let alone their need to seek insurance coverage from the individual exchange. Because of the marked differences in program awareness as well as the interpretations of the treatments (see Section 3.3.1), we report most analyses separately by Open Enrollment Applicant and County Referral samples as one key dimension of heterogeneity.

We interpret the Basic Reminder Letter–Arm 2–in the Open Enrollment Applicant sample as operating solely on procrastination, or inattention to the deadline, given that this population is already well aware of the existence of the market. The information provided in the reminder letter simply duplicates information the consumers have already been exposed to repeatedly during their previous initiation of enrollment. As reported in Column 3, the

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<sup>22</sup>For example, the average single-policy holder at 133% FPL would face an annual net-of-subsidy premium of \$510; whereas with three times that income, right below 400% FPL (at the threshold of subsidy eligibility), the average annual net-of-subsidy premium would be \$4,600, or nearly 10 times higher.

basic reminder letter appears to have the largest effect across all treatments for the Open Enrollment Applicant sample—nearly a 17 percent increase—revealing an important role of reminders in attenuating the impact of procrastination or inattention on the failure to enroll. This is consistent with recent behavioral interventions (Heffetz et al., 2016) that show positive impacts on of reminder letters in combating procrastination.

Notably, interventions that report subsidy and plan characteristics on average do relatively less well. We posit that Open Enrollment Applicants may be aware of the existence of low income subsidies, but negatively update the subsidy amount they expect to receive. Alternatively, the lower treatment effects in the subsidy-reporting arms could be due to confusion from excessive information. We test these possible dynamics more explicitly in the next subsection.

For the County Referral population (Column 4), treatment effects, measured by percent increases in enrollment, are generally larger than for the Open Enrollment Applicant sample (with the exception of the Reminder letter). This is likely due to the very low baseline level of awareness of the program, and larger marginal impact of information. Consistent with this possibility, baseline County Referral take-up is 3.7 percent (compared to Open Enrollment Applicant take-up of 13.7 percent). Moreover, we find that providing more informative through the letters leads to higher take-up. The reminder letter, which for the County Referral population addresses both lack of information and procrastination/inattention, leads to a 13.5 percent higher enrollment over the control. In addition, providing subsidy information, leads to an 18.9 percent increase in enrollment. Further reporting available plans, conveniently ranked by price, leads to a 21.6 percent increase in enrollment. Adding quality information leads to a slightly lower increase than the prices alone, but still above the subsidy information alone. While the differences across the letter arms are not statistically different for the County Referral sample, the patterns are consistent with significant lack of information impeding take-up on that group. For the Open Enrollment Applicant sample,

procrastination, and possibly incorrect priors about benefit availability, appear to impact enrollment decisions the largest.

### 3.5.2 Heterogeneous Effects by Income

Table 3.6 reports treatment effects by intervention arm, interacted with income. In all columns, the omitted group is the Basic Reminder Letter arm and its interactions. We test the possibility that at higher incomes, personalized subsidy letters may negatively update initial consumer priors regarding expected subsidies, a possibility that would explain why the overall treatment effect for the subsidy-reporting letters are generally lower than in the Basic Reminder arm. Overall, we find that at the lowest incomes, reporting subsidies results in higher enrollment than the reminder alone—seen most clearly in the second row of coefficients. As incomes increase, the impact of subsidy-reporting letters decreases steadily. This effect appears to be driven largely by the Open Enrollment Applicant sample, as can be seen in Columns 2 versus 3 in the table, or in Figures 3.3 and 3.4.

Perhaps surprisingly, as incomes rise for the Open Enrollment Applicants, the take-up rates for the subsidy-reporting arms fall steadily to levels that are *lower than* in the Basic Reminder arm. The pattern is again most evident in columns 4-6, where the treatment arms are interacted with income bracket dummy variables, rather than the continuous income variable. It is also clear from panel (a) of Figure 3.4. The lower take-up among subsidy-reporting treatment arms is observed at higher incomes despite enrolling consumers in the Basic Reminder arm eventually observing the same information that is reported in the subsidy-reporting letters.

These pattern is consistent with higher income Open Enrollment Applicants incorrectly believing their subsidies to be higher than in reality; and, in response to updated information, they are less likely than otherwise similar consumers in the reminder arm to re-initiate and complete the enrollment process. Incorrect priors, alone, cannot explain why higher

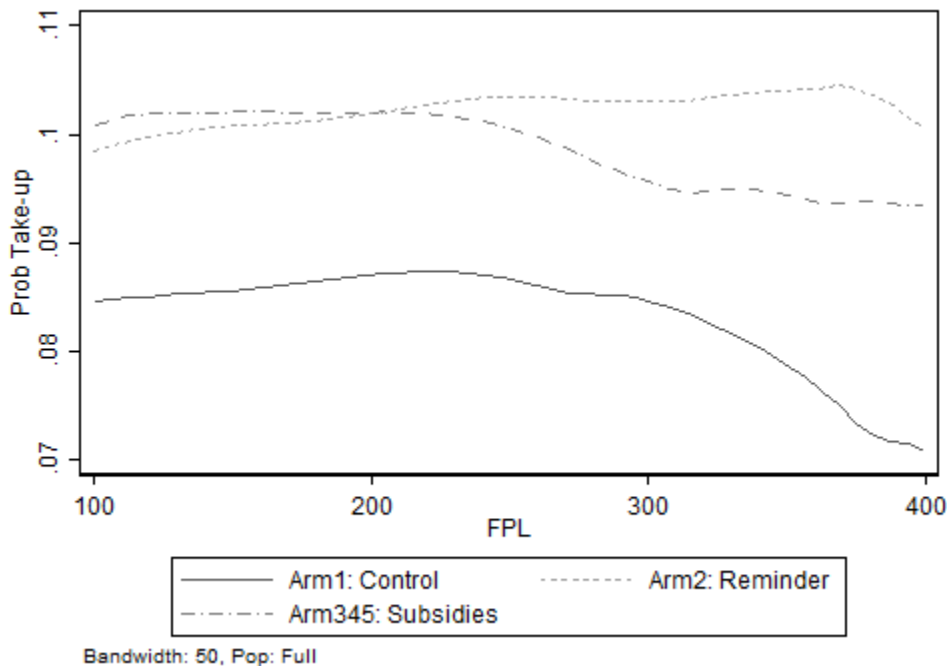


Table 3.6: Treatment Effects by FPL

Model	OLS			OLS			Logit		
	Sample	All	OE App	Refer	All	OE App	Refer	ALL	OE App
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Arm1: Control	-0.001 (0.011)	-0.027 (0.023)	0.008 (0.010)	-0.009* (0.005)	-0.026** (0.012)	0.000 (0.005)	-0.114* (0.067)	-0.177** (0.084)	0.004 (0.114)
Arm345: Subsidy Arms	0.017* (0.010)	0.028 (0.019)	0.004 (0.009)	0.006 (0.004)	0.008 (0.010)	0.004 (0.004)	0.070 (0.053)	0.053 (0.066)	0.099 (0.092)
Arm1*FPL Level*100	-0.000 (0.000)	-0.000 (0.009)	-0.006 (0.004)						
Arm345*FPL Level*100	-0.008* (0.004)	-0.015* (0.008)	-0.000 (0.004)						
FPL in [180, 250]				-0.000 (0.006)	-0.013 (0.012)	0.004 (0.005)	-0.010 (0.071)	-0.072 (0.085)	0.120 (0.133)
FPL in [250, 400]				-0.011 (0.009)	-0.020 (0.016)	-0.009 (0.007)	-0.114 (0.105)	-0.113 (0.121)	-0.220 (0.222)
Arm1 x FPL in [180, 250]				-0.009 (0.007)	-0.001 (0.016)	-0.011* (0.007)	-0.109 (0.095)	-0.021 (0.115)	-0.287* (0.172)
Arm345 x FPL in [180, 250]				-0.010 (0.006)	-0.015 (0.014)	-0.006 (0.006)	-0.118 (0.075)	-0.100 (0.090)	-0.141 (0.135)
Arm1 x FPL in [250, 400]				-0.009 (0.008)	-0.001 (0.016)	-0.006 (0.007)	-0.112 (0.107)	-0.048 (0.123)	-0.218 (0.251)
Arm345 x FPL in [250, 400]				-0.014* (0.007)	-0.028** (0.014)	0.003 (0.006)	-0.167** (0.084)	-0.209** (0.096)	0.112 (0.193)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	75,495	32,698	42,797	75,495	32,698	42,797	75,495	32,698	42,797
R-squared	0.062	0.027	0.018	0.062	0.027	0.018			

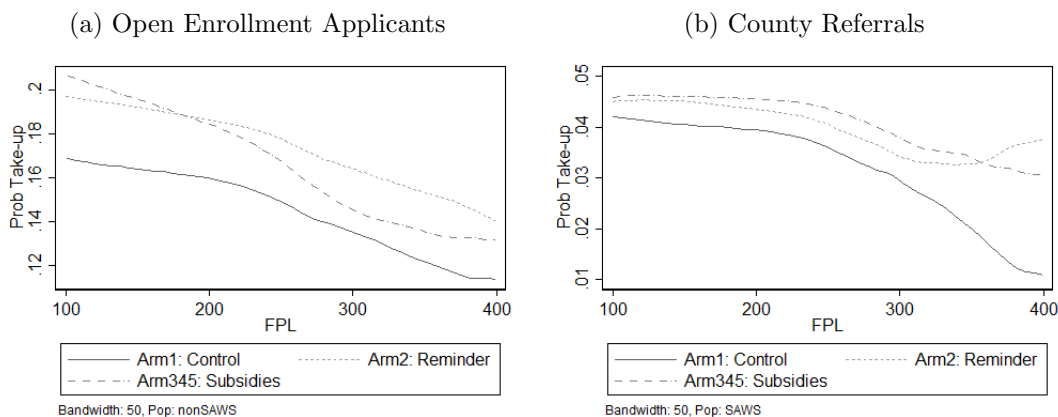
Note: This table displays coefficients from the main specification but with income interactions on the treatment effect. Common controls are mean HH age, Funnel round, race dummies, HH size, HH members, HH kids, Marital Status, Email accessible, SAWS, FPL, FPL missing,  $FPL \geq 1000$ , flagged as subsidy ineligible by Covered California, and region dummies. Logit results are model coefficients. Robust Standard Errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Figure 3.3: Take-up by Income



Note: This figure plots the probability of take-up—estimated with local regression—as a function of FPL (conditional on being less than 400). Treatment arms with targeted information (3, 4, and 5) are combined.

Figure 3.4: Take-up by Income, and Funnel Group



Note: These figures plots the probability of take-up—estimated with local regression—as a function of FPL (conditional on being less than 400), separately for the two subsamples: Open Enrollment Applicants and County Referrals. Treatment arms with targeted information (3, 4, and 5) are combined.

income consumers in the basic reminder group, who eventually see their subsidies during the enrollment process, still take-up at higher rates than consumers in the subsidy-reporting arms, despite eventually observing the same subsidy information. This pattern suggests that in addition to having incorrect priors, consumers exhibit either 1) a fixed time or hassle cost of re-initiating the enrollment process; or 2) reference-dependent utility, e.g. as modeled by Kőszegi and Rabin (2006), or both.

Consistent with Currie (2006), fixed time or hassle costs represent behavioral transaction costs, which, with the financial cost of plans, contribute to a total cost of purchasing insurance. Receiving negative updates about premiums after incurring the transaction cost of re-initiating the enrollment process would predict that higher income Open Enrollment Applicants in the basic reminder group would have a higher take-up rate than otherwise similar consumers who received the negative update in a letter, before re-initiating enrollment.

The patterns we describe above are also consistent with reference-dependence. Specifically, Kőszegi and Rabin (2006) model an “attachment effect” whereby an increase in the likelihood of buying (e.g. due to beliefs that prices would be low) increases a sense of loss of not buying, which increases the willingness to buy at a price that is higher than initially expected. Without additional interventions that shift beliefs about expected prices, or data on plan searching-through insurance brokers or visits to the Covered California website—we are unable to distinguish between transaction costs and reference dependence. However, the role of inattention/procrastination as well as the cost of obtaining information about program benefits established in Table 3.5 suggests that transactions costs at least partly explain why the reminder letter generates a larger treatment effect than the subsidy letters among relatively higher-income individuals.

### 3.5.3 Risk Selection

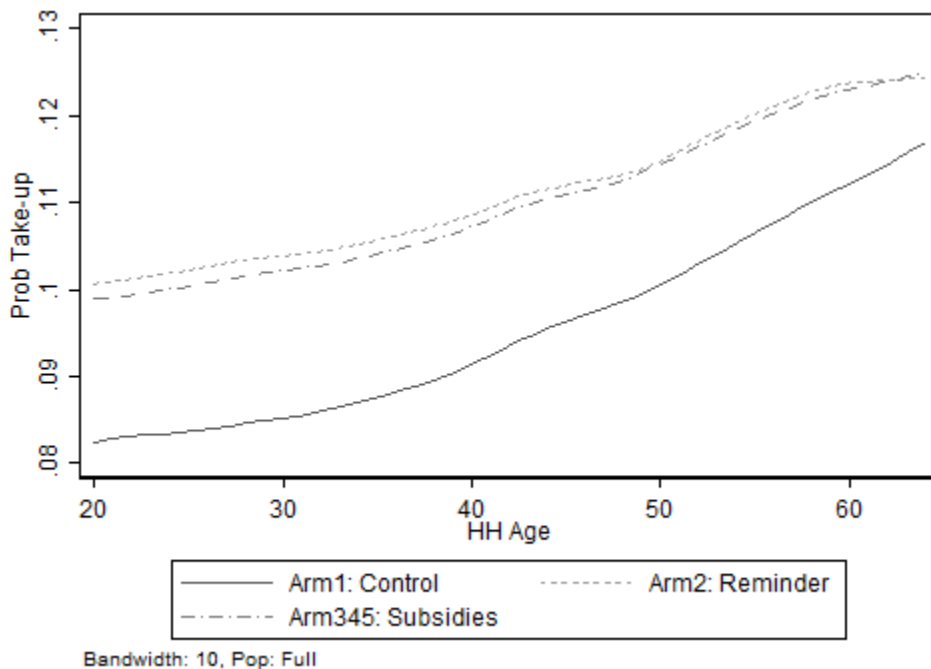
#### Take-up by Age

Figures 3.5 and 3.6 depict take-up rates by age, across the treatment arms. It is evident that age is a strong predictor of take-up. As mentioned before, expenditure risk rises sharply with age (after childhood), whereas premiums rise less steeply due to rating regulations. This leads to lower demand for medical care, and lowers the actuarial value of plans, for younger consumers. The letter interventions appear to raise take-up rates across the age distribution, with larger effects at younger ages; as evident from Figure 3.6, for Open Enrollment Applicants, this increased effect for the young is both in absolute and percentage terms, while for the County Referrals, this is as a percent of baseline take-up rates.

To explicitly estimate the differential take-up by age, we estimate equation (3.2) and regress take-up on interactions between treatment arm indicators and age. Results are reported in Table 3.7. In Column 1, we allow for a flexible non-parametric relationship between age and take-up. The non-parametric specification allows us to estimate treatment effects separately for children, for whom health spending risk is typically higher than for young adults. We find that the average treatment effect across all letters interventions is highest for the youngest adults. This finding is of considerable policy importance, given that rate regulations dictate that younger consumers are on average net subsidizer to the risk pool. The differential treatment effect declines with age, and by age 65, the differential effect by effect is one half of the effect among younger adults, and is not statistically significant.

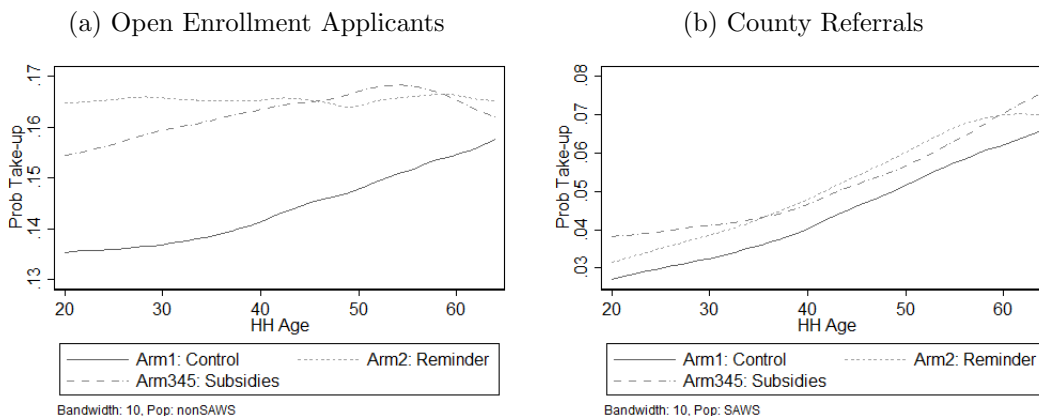
In columns 2-7, we separate the reminder arm from the subsidy-reporting arms. To reduce the number of interactions, we restrict the differential effect by age to be linear, and restrict the sample to adults, for whom the age effects appear monotonic. The linear specification also shows larger treatment effects for younger consumers, with the basic reminder leading to somewhat larger enrollment among younger consumers than the subsidy reporting

Figure 3.5: Take-up by Household Age



Note: This figure plots the probability of take-up—estimated with local regression—as a function of household age (conditional on being between 20 and 64). Treatment arms with targeted information (3, 4, and 5) are combined.

Figure 3.6: Take-up by Household Age, and Funnel Group



Note: These figures plots the probability of take-up—estimated with local regression—as a function of age (conditional on being between 20 and 64), separately for subpopulations of Open Enrollment Applicants and County Referrals. Treatment arms with targeted information (3, 4, and 5) are combined.

Table 3.7: Treatment Effects by Age

Age Sample	All	≥18					
Income Sample	All	All	≤180 FPL	180-250 FPL	>250 FPL	All	All
Funnel Sample	All	All	All	All	All	OE App	Refer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age in [18,30)	-0.035*** (0.012)						
Age in [30,45)	-0.037*** (0.013)						
Age in [45,65)	-0.035** (0.015)						
Age 65 and up	-0.123*** (0.018)						
Arm2345	-0.005 (0.011)						
Arms2345 x Age in [18,30)	0.022* (0.011)						
Arms2345 x Age in [30,45)	0.020* (0.011)						
Arms2345 x Age in [45,65)	0.013 (0.012)						
Arms2345 x Age 65 and up	0.010 (0.012)						
Age (Mean HH, 10 years)	0.013*** (0.002)	0.007*** (0.001)	0.011*** (0.002)	0.010*** (0.003)	0.001 (0.002)	0.009*** (0.003)	0.007*** (0.001)
Arm2: Reminder		0.027*** (0.008)	0.035*** (0.013)	0.029* (0.016)	0.017 (0.015)	0.047*** (0.016)	0.009 (0.007)
Arm345: Subsidy Arms		0.022*** (0.007)	0.036*** (0.011)	0.014 (0.013)	0.013 (0.012)	0.031** (0.013)	0.014** (0.006)
Arm2 x Age (10 years)		-0.004* (0.002)	-0.007** (0.003)	-0.003 (0.004)	-0.001 (0.004)	-0.006* (0.004)	-0.001 (0.002)
Arm345*Age (10 years)		-0.002 (0.002)	-0.006** (0.003)	-0.000 (0.003)	-0.001 (0.003)	-0.003 (0.003)	-0.002 (0.002)
Observations	87,394	84,688	28,764	27,938	27,986	42,848	41,840
R-squared	0.056	0.053	0.079	0.063	0.029	0.025	0.018

Note: This table displays coefficients from the equation (3.2), where we interact treatment effect with household age. Each column represents a different subsample depending on age, income level, and Funnel subsample. Common controls are mean HH age, Funnel round, race dummies, HH size, HH members, HH kids, Marital Status, Email accessible, SAWS, FPL, FPL missing,  $FPL \geq 1000$ , flagged as subsidy ineligible by Covered California, and region dummies. All results are from OLS. Robust Standard Errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

letters; as seen in columns 6 vs. 7 or Figure 3.6, this is largely driven by Open Enrollment Applicants. The effect of drawing in younger consumers is primarily contained among low income consumers, for whom we reported the largest impact on take-up. In the next subsection, we investigate further the mechanisms for why the letters induce younger—and possibly healthier—consumers into the market.

### **Impact on Average Health Spending**

To test directly the impact of the letter interventions on health spending risk, we use data from realized claims for coverage year 2016.<sup>23</sup> As described in Section 3.4.2, our key outcome variable is a measure of expected health spending. Figure 3.7 shows the distribution of log risk for the Open Enrollment Applicants, among the full subsample (panel (a)) and for the low income subsample (panel (b)). As seen in the figures, the distribution of risk is lower among the letter intervention arms, with more pronounced effects among low income consumers. In contrast, the shift in the risk distribution towards healthier consumers for the County Referrals is not apparent when comparing just control vs. all treatment arms (Figure 3.8).

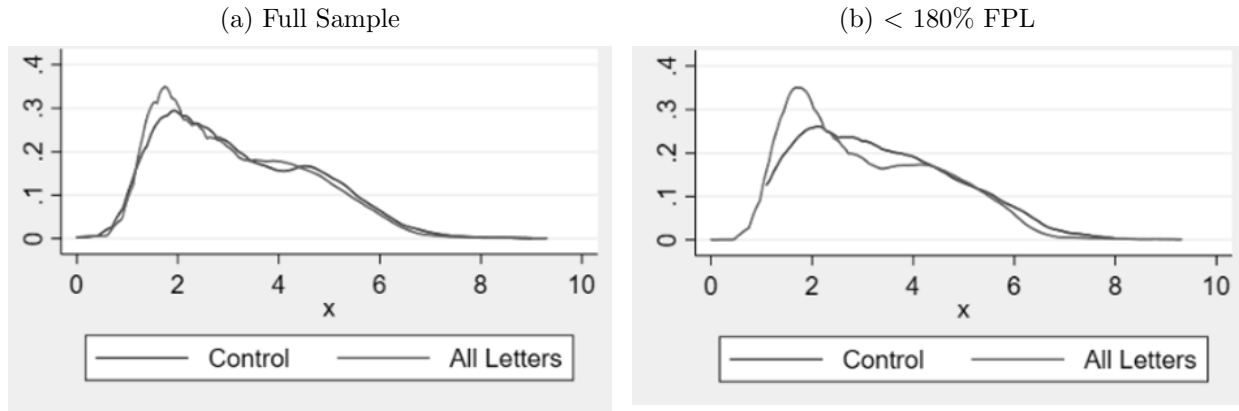
To estimate explicitly the effects of the letter interventions on average risk, we regress health spending risk on treatment arm indicators, conditional on enrollment, as specified in equation (3.3). Randomized treatment assignment allows us to interpret the coefficients on treatment arms as impact on the average risk in response to our treatments. For now, we do not control for age, in order to capture the full effect of the letter interventions on expenditure risk, including both the selection of younger consumers, and the selection of healthier consumers, conditional on age.

Results are reported in Table 3.8. Overall, the letters cause average health expenditure

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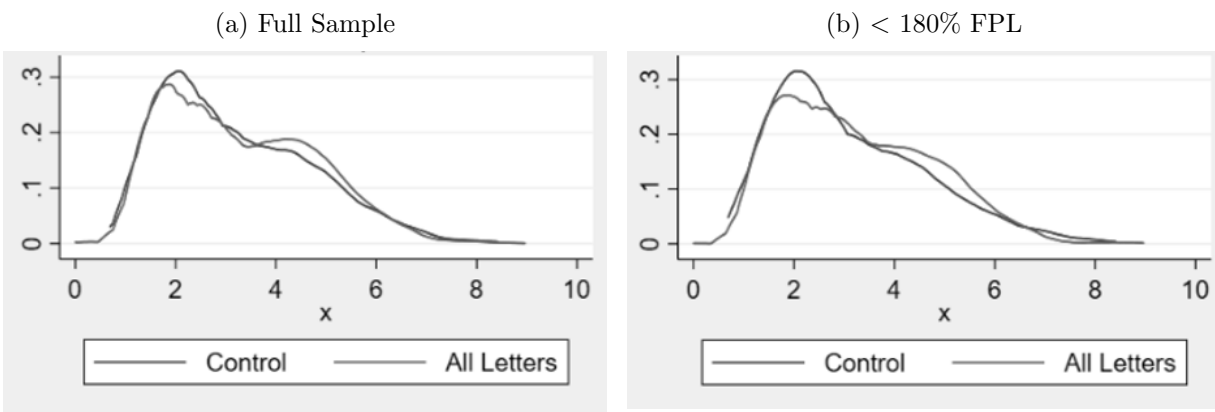
<sup>23</sup>Because claims are only available for consumers who take-up, this measure of risk is observed for enrolled consumers only.

Figure 3.7: Risk by Letter vs. Control among Enrollees, OE Applicants only



Note: These figures plots the kernel density of risk scores based on realized 2016 claims for control vs combined treatment groups, only among Open Enrollment Applicant subpopulation.

Figure 3.8: Risk by Letter vs. Control among Enrollees, Referrals only



Note: These figures plots the kernel density of risk scores based on realized 2016 claims for control vs combined treatment groups, only among County Referral subpopulation, and generally Medicaid disenrolled.



Table 3.8: Effect of Treatment on Spending Risk

Dependent Variable: ln(Spending Risk)													
Income Sample	All			≤180	180-	>250	≤180	180-	>250	≤180	180-	>250	
	Entry Path Sample	All	OE App	Refer	FPL	250	FPL	FPL	250	FPL	FPL	250	FPL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Arm2345	-0.059*												
	(0.036)												
Arm2	-0.032	-0.071	0.074	-0.062	-0.002	-0.040	-0.141	-0.023	-0.064	0.051	0.060	0.109	
	(0.044)	(0.051)	(0.089)	(0.080)	(0.079)	(0.072)	(0.101)	(0.093)	(0.077)	(0.135)	(0.151)	(0.219)	
Arm345	-0.068*	-0.114***	0.060	-0.078	-0.096	-0.044	-0.223***	-0.131*	-0.037	0.160	0.044	-0.158	
	(0.037)	(0.042)	(0.075)	(0.065)	(0.067)	(0.060)	(0.084)	(0.078)	(0.065)	(0.107)	(0.133)	(0.189)	
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	
Region Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	
Observations	11,472	11,472	8,685	2,787	3,709	3,534	4,203	2,445	2,565	3,655	1,264	969	548
R-squared	0.037	0.037	0.035	0.052	0.036	0.050	0.044	0.040	0.050	0.041	0.054	0.087	0.113

Note: This table displays coefficients from the equation (3.3), and age excluded as a control. Risk is measured from diagnoses on coverage year 2016 realized claims. Each column represents a different subsample depending on income level and Funnel sample. Common controls are Funnel round, race dummies, HH size, HH members, HH kids, Marital Status, Email accessible, SAWS, FPL, FPL missing,  $FPL \geq 1000$ , flagged as subsidy ineligible by Covered California, and region dummies. All results are from OLS. Robust Standard Errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

risk to decline 5.9 percent. This implies that the average risk of the marginal respondent to the letter interventions is 57 percent of the expected expenditure risk of the average inframarginal enrolled consumer.<sup>24</sup>

Similar to patterns we observed for differential take-up by age, we find that the positive effects on risk is largely driven by the Open Enrollment Applicants, and particularly lower income consumers within that population, a point we return to in the following section. We also find that the subsidy-reporting letters have a larger effect on healthy risk selection among the Open Enrollment Applicants than the reminder letter—a pattern which differs from take-up based on age alone where we find that the reminder captures most of the effect. And while the difference between the reminder letter and the three subsidy-reporting letters is not generally statistically significant, this pattern appears to hold across most

<sup>24</sup>A 5.9 percent decrease in total average risk based on a 16 percent enrollment increase implies an average risk among marginal responders that is  $0.572 = ((1 - .059) * 116 - 100)/16$  percent of the average risk of inframarginal consumers.

sample specifications. The marginal respondent to a simple reminder could have greater demand for health care than the marginal respondent to a letter that also reports generous subsidies. This would predict patterns that we observe in the data, where the difference in treatment effects between the reminder and subsidy-reporting letters is largest for low income consumers for whom subsidy-reporting letters are more likely to reveal larger than expected subsidies.

Finally, we examine the extent to which the impacts on average risks are captured by the marginal respondent to the letter interventions being younger, and to what extent the letters are inducing healthier consumers to enroll, conditional on age. To test this, we estimate equation (3.3) controlling for age. Results are reported in Table 3.9. Overall, we find that 40 percent of the overall treatment effect on risk is due to selection of healthier consumers, conditional on age, while 60 percent is due to attracting younger consumers into the market.<sup>25</sup> Therefore, even beyond the positive risk pooling effect of inducing younger consumers into the market (part of which is offset by the lower premiums charged to younger consumers), the letters also induce healthier consumers into the market, whose lower health spending risks contribute fully to subsidizing the risk pool. As seen earlier, there is, however, important heterogeneity across the two Funnel subsamples of the Open Enrollment Applicants and the County Referrals. Most of the lowered risk, conditional on age, is driven by the Open Enrollment Applicants. For the lowest income group of the County Referrals, the subsidy-reporting letters appear to draw in *higher* risk conditional on age. Hence, in this subpopulation, it appears the treatment effects by age and risk actually go in opposite directions, where the targeted letters draw in younger but higher risk consumers.<sup>26</sup>

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<sup>25</sup>This is using the ratio of the estimated coefficients from the two specifications, with and without age controls.

<sup>26</sup>Recall the County Referral population comes from those that were recently disenrolled from Medicaid; it's possible that they have more private information on their health spending from exposure to the Medicaid program relative to being uninsured, which could explain this difference.

Table 3.9: Effect of Treatment on Risk, Conditional on Age

		Dependent Variable: ln(Spending Risk)											
Income Sample	All				≤180	180-	>250	≤180	180-	>250	≤180	180-	>250
Entry Path Sample	All	OE App	Refer	All	FPL	250	FPL	FPL	250	FPL	FPL	250	FPL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Arm2345	-0.024 (0.034)												
Arm2	0.002 (0.042)	-0.028 (0.048)	0.076 (0.087)		-0.020 (0.077)	0.010 (0.076)	-0.001 (0.069)	-0.097 (0.096)	-0.007 (0.088)	-0.013 (0.073)	0.085 (0.130)	0.055 (0.150)	0.035 (0.213)
Arm345	-0.033 (0.035)	-0.073* (0.040)	0.082 (0.073)		-0.024 (0.062)	-0.074 (0.064)	-0.015 (0.057)	-0.172** (0.079)	-0.111 (0.073)	0.008 (0.061)	0.227** (0.102)	0.058 (0.131)	-0.240 (0.181)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,472	11,472	8,685	2,787	3,709	3,534	4,203	2,445	2,565	3,655	1,264	969	548
R-squared	0.132	0.132	0.135	0.130	0.132	0.138	0.140	0.140	0.149	0.138	0.137	0.145	0.201

Note: This table displays coefficients from the equation (3.3) with age as a control variable. Risk is measured from covered year 2016 realized claims. Each column represents a different subsample depending on income level and Funnel group. Common controls are mean HH age, Funnel round, race dummies, HH size, HH members, HH kids, Marital Status, Email accessible, SAWS, FPL, FPL missing,  $FPL \geq 1000$ , flagged as subsidy ineligible by Covered California, and region dummies. All results are from OLS. Robust Standard Errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### 3.5.4 Summarizing the Results

The above results show important heterogeneity in treatment effects by income (and subsidy), health spending risk, and reason for entering the Funnel (i.e. the role the information has). These results are consistent with differential informational barriers and psychological transaction costs faced by different segments of the study population—and hence, heterogeneous benefits of information provided by the letters. Since the letters serve different roles for the Open Enrollment Applicant and County Referral populations, below we discuss the interpretations of each separately.

#### Results for Open Enrollment Applicants

In the Open Enrollment Applicant population, which we consider to have some information about the program and existence of subsidies, there are two notable patterns of interest: the first is related to treatment effects by income, and the second is related to treatment effects

by age.

First, the effect of the Reminder letter relative to the control is uniform across income groups (as seen in column 2 of Table 3.6). This suggests the importance of procrastination/inattention is fairly common across income groups, i.e. for those with different levels of subsidies. Interestingly, and as noted above, the effect of the additional subsidy information in the letter—relative to the basic reminder—actually decreases the likelihood of take-up. Since those with the Reminder letter eventually learn the level of the subsidies, we can conclude that beliefs about the level of subsidies are imperfect upon receiving the letters.<sup>27</sup> Specifically, these results are consistent with the higher income enrollees having more optimistic beliefs about the level of their subsidies. The exact mechanism that leads to the increased take-up upon realizing the true subsidies is unclear. As we mention above, it is consistent with a fixed cost of re-initiating the enrollment process, or reference-dependent utility as modeled by Kőszegi and Rabin (2006). In either case, for those that had already initiated the Covered California enrollment process, providing the true level of the subsidy in the letter appears to decrease their propensity to enroll in a plan relative to getting a basic reminder.

The second notable pattern in the Open Enrollment Applicant population is how the treatments interact with risk. We find evidence that treatment effects of all letters are largest among the youngest consumers in the market—that is, younger consumers are more responsive to all letters. Among the youngest consumers, it appears that the Reminder letter actually has the largest treatment effect (though not statistically greater than the other letters). However, when we measure the effect on market risk, we actually find the opposite to be true—the letters with subsidies induce lower risk enrollees than the Reminder letter alone.

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<sup>27</sup>There is an alternative explanation that the effectiveness of the letters is a declining function of the total information—representing complexity. Providing the subsidies could also have simply turned off consumers to continuing the process. With the current study, we cannot identify this mechanism versus the above alternatives.

This suggests that *younger* consumers are most affected by the procrastination/inattention, while low risk (conditional on age) consumers are either likely to have higher costs of acquiring information, or likely to overestimate the costs of insurance. Combining this with the results described above, it appears the Reminder letter among the upper income households is inducing relatively higher risk enrollees into the market. Put another way, the lowest income households that are induced into the market by the generous subsidy information are those with the lowest risk. This seems reasonable given that higher risk consumers are disproportionately more likely to have already taken up insurance (given community rating).

### **Results for County Referrals**

The County Referral population comes primary from those that previously had Medicaid but were disenrolled, and hence had not previously initiated the Covered California enrollment process. For both of these reasons, this population is expected to have relatively less information about ACA subsidies and a lower propensity to enroll in a plan compared to the Open Enrollment Applicants. For the County Referrals, we find results consistent with the Open Enrollment population that the all letter interventions increase take-up. Also, as with Open Enrollment Applicants, we find important heterogeneity among the County Referrals from Medicaid.

When examining treatment effects by income among the County Referral population, we find slightly different results from Open Enrollment Applicants. The pattern described above—where providing subsidy information in the letters *lowers* take-up—is not present. It could be that those that initiated their application directly through Covered California had higher expectations about the level of subsidies, which is less likely to be the case for the County Referrals who have less familiarity with the program. In general, there does not appear to be a strong interaction between income and treatment effects for the County Referral group—the small exception being the possibility that the Reminder is most effective

among those with the highest incomes (as with Open Enrollment Applicants).

When examining the interaction of letter interventions with risk, we find quite different patterns from those among Open Enrollment Applicants. For example, we find much less heterogeneity across ages (Figure 3.6—i.e., the younger are not more responsive to letter treatments. If anything, Tables 3.8 and 3.9 suggest that the letters—particularly with targeted subsidies—actually increase ages and risk in the market among the lowest income group.

These differences relative to the Open Enrollment Applicant population are especially important when considering extrapolating the results of this study to the larger uninsured market in the U.S. As we see here, the impacts of each intervention will differ depending on consumer characteristics, such as level of income and insurance status history.

### 3.5.5 Structural Estimation of Costs

In this section, we estimate the value to consumers of these interventions, as detailed in Section 3.4.2. As noted, this can alternatively be thought of as the barriers that consumers otherwise face when making enrollment decisions, which are removed by the letters. Here, we estimate the coefficients in (3.6). As above, we combine all treatment arms with targeted subsidy information into a single arm “345.”

Recall that we are interested in the following willingness-to-pay (WTP) for each letter intervention:

$$\begin{aligned} WTP^2 &= \frac{\gamma^2}{\alpha} \\ WTP^{345} &= \frac{\gamma^{345}}{\alpha} \end{aligned}$$

where  $\gamma^j$  reflects the coefficient on each treatment dummy and  $\alpha$  is the coefficient on the monthly premium subsidy (monthly APTC).

Given standard distributional assumptions, we estimate the model in (3.6) with standard

logistic regression.<sup>28</sup> For this section only, we restrict the analysis to just individual plans (as opposed to family) to get the WTP to reflect that of a single individual.<sup>29</sup>

All results for this section are presented in Table 3.10. In each column, the rows associated with  $Arm_j$  are estimates for  $\gamma_j$  and the row associated APTC is with is  $\alpha$ .

In the main specification in column 1, the treatment effect of both groups is approximately 0.14 and the effect of APTC is 0.0035.<sup>30</sup> Interestingly, controlling for APTC, take-up is decreasing in age, a pattern which is robust across specifications and can be seen in the unsubsidized subgroup with incomes above 400% FPL (not displayed). While we would expect the value of insurance to be increasing across ages, the premiums are also increasing to represent higher costs. The decline in take-up with age suggests prices increase faster than the value of insurance for this sample. The interaction on age and income is positive which suggests this effect is attenuated for higher income households, consistent with this theory.

These results imply our estimates for  $WTP^2$  and  $WTP^{345}$  are \$42 and \$40 respectively for the whole sample. This implies that getting any letter intervention has the same effect on take-up as \$41 dollar increase in the *monthly* APTC.

As with the other results, there is notable heterogeneity in the WTP measures for different subgroups of the sample, as seen in columns 5 - 8. The WTP measures by Funnel subpopulations match those described above. Specifically, among the Open Enrollment Applicants, the WTP for the subsidy-reporting letters (\$47) is lower on average than that of

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<sup>28</sup>We conduct inference on WTP measures using the delta method with `nlcom` in STATA.

<sup>29</sup>We restrict to individuals to capture the WTP for a single person. We also tested an alternative specification using APTC *per member* to reflect this, but consistently get smaller estimates for  $\alpha$ . Hence, the current specification implies smaller and more conservative measures of WTP.

<sup>30</sup>Since the identification of  $\alpha$  comes from variation in take-up with respect to APTC (which also varies with age and income), we ensure that the results are not sensitive to the functional form of age and income. Hence, in columns 2 - 4, we allow for higher order polynomials in the measures of Risk and FPL. These do not appear to have an impact on the main results so we use the first order form as the main specification.

Table 3.10: Estimates from Structural Model

Logistic Regression (Take-up)								
Sample	All				OE App	Refer	Age [20, 45]	Age (45, 75]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Arm2	0.146*** (0.0450)	0.146*** (0.0450)	0.146*** (0.0450)	0.146*** (0.0451)	0.142*** (0.0506)	0.148 (0.0993)	0.222*** (0.0568)	0.0211 (0.0766)
Arm345	0.140*** (0.0374)	0.140*** (0.0374)	0.140*** (0.0374)	0.141*** (0.0375)	0.114*** (0.0421)	0.224*** (0.0817)	0.146*** (0.0476)	0.112* (0.0626)
APTC	0.00348*** (0.000200)	0.00389*** (0.000224)	0.00390*** (0.000233)	0.00347*** (0.000244)	0.00241*** (0.000238)	0.00602*** (0.000534)	0.00507*** (0.000364)	0.00287*** (0.000273)
FPL	-0.512*** (0.0690)	3.115*** (0.821)	3.928 (5.412)	439.5*** (117.4)	-0.504*** (0.0793)	-0.234 (0.274)	-0.538* (0.308)	-0.454** (0.204)
Risk	-3.289*** (0.312)	-1.203 (1.567)	9.943* (5.520)	60.03*** (17.23)	-2.149*** (0.388)	-6.572*** (0.813)	-4.007*** (1.555)	-2.953*** (0.562)
FPL*Risk	0.499*** (0.0518)	0.387 (0.281)	-1.654* (0.992)	-8.031*** (3.084)	0.319*** (0.0640)	1.040*** (0.147)	0.670** (0.281)	0.429*** (0.0967)
FPL/Risk Poly Order	1	2	3	4	1	1	1	1
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Region Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Observations	61,958	61,958	61,958	61,958	31,818	30,140	38,730	18,679
WTP2	41.91	37.68	37.48	42.25	59.00	24.59	43.86	7.365
SE	13.16	9.842	9.829	11.17	18.10	16.65	9.623	26.73
WTP345	40.16	36.02	35.83	40.56	47.26	37.23	28.82	39.10
SE	10.99	11.79	11.77	13.34	21.80	13.97	11.63	22.13

Note: This table displays coefficients from the equation (3.6). FPL in logs. Risk is age-based rating factor used for premium determination. Each column represents either a different specification of the functional form of risk and FPL, or a different subsample. Columns 2 - 4 have higher order terms of risk and FPL as stated. WTP measures and associated standard errors presented in the final 4 rows (p-values not indicated). \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



the basic reminder(\$59), though not statistically significant. In the County Referral sample, we see that the WTP for the subsidy information is higher than for the basic reminder with  $WTP^2$  and  $WTP^{345}$  at \$24.59 and \$37.23 respectively. Since the County Referral population is also relatively more responsive to the APTC ( $\hat{\alpha}_{Ref} = 0.006$ ), the magnitudes of both WTP measures are relatively lower than among the overall sample. The reason for the high responsiveness to APTC among the County Referrals is likely because this sample is disproportionately lower income, having come from Medicaid. Hence, changes in APTC will represent a larger share of income.

Finally, we estimate the aggregated WTP measures for 2 age groups: ages 20 - 45 (younger) and ages 46-70 (older). Among the younger sample, there is a relatively higher WTP for the basic reminder than the subsidy letters, at \$43.86 vs \$28.82. Conversely for the older sample, the WTP for the basic reminder is lower than that of of the subsidy letters at \$7.37 vs. \$39.10. Hence, the reminder alone has a relatively small impact for older enrollees, but it is equivalent to a \$44 increase in APTC per month among the younger enrollees.

These estimated values in this section have implications for cost-benefit comparisons of letter interventions, and for the relative effectiveness of financial levers (e.g. expanding subsidies) to raise take-up rates.

## 3.6 Conclusion

This study documents the existence of economically significant behavioral choice frictions in the decision whether or not buy insurance. We find evidence that both procrastination/inattention and search costs reduce take-up rates in ACA markets. Procrastination/inattention appears to be especially important among younger potential enrollees, as is seen in the population that had previously initiated the Covered California enrollment process. Since the letter interventions disproportionately induce enrollment among the lowest risk

consumers—especially among those that are aware of program benefits—these interventions have positive externalities for the whole market. The presence of search costs are also evident in both subpopulations of the sample. Among the Open Enrollment Applicants, we find that those with the lowest incomes and highest subsidies increase take-up rates when given detailed pricing information. The fact that this detailed subsidy information actually decreases take-up as subsidies decline is consistent with higher-income consumers—who initiated enrollment—overestimating the level of their benefits, or having incomplete information and facing additional search costs.

Finally, we find these letters provide significant economic value despite their relatively low cost. The effect on take-up is on average equivalent to a \$41 increase in the monthly government subsidy for this sample. Given this magnitude, it suggests measures of willingness-to-pay based on choice patterns in the data will be substantially impacted by these choice frictions. In particular, since revealed preference based approaches capture the value of insurance *net of these frictions*, these approaches will underestimate the standalone value of insurance to consumers. These significant frictions in acquiring insurance also point to the importance of program marketing. We find that program marketing not only effects individual choice behavior but can have broader benefits to the stability of the market. Particularly in ACA markets, by making information about the program more salient, overall market risk can be reduced leading to reduced premiums for all consumers. However, it should be noted that there is important heterogeneity in treatment effects described throughout the study. Policymakers and researchers should therefore consider the population of interest when extrapolating these results beyond this market.

# Appendix A

## APPENDIX

### A.1 ACS Sample

The data that identifies the uninsured population comes from the American Community Survey (ACS). Since this data is appended to the Covered CA enrollment data, there are a number of modifications I make to ensure the two data sources are consistent. These broadly fall into two categories: sample selection (i.e. who is eligible) and geographic location (to identify which plans are available). The primary concern with sample selection is to identify if the household without insurance should be considered “in the market” for Covered CA insurance. To classify households without insurance, I use whether or not anyone in the household went without insurance at any point in the year.<sup>1</sup> Since the decision unit is the household, I combine all uninsured members and assume they collectively decide whether or not to get insurance. As in the Covered CA data, I drop households with more than 4 members for simplicity. The last sample selection criteria I use for the ACS is to ensure that the individual is not eligible for other government programs, i.e. Medicaid and Medicare.

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<sup>1</sup>This is technically over-inclusive since someone can be uninsured for part of the year, and in Covered CA for another part of the year, so would be in both data sources. I extract from this possibility. I also exclude any members that were institutionalized.

To this end, I exclude households with incomes below 138 FPL (the Medicaid cutoff in CA) and members age 65 and above.<sup>2</sup>

The last modification I make to the ACS is creating geographic variables that are consistent with the plan choice sets. Namely, Covered CA plans are offered at the zip code  $\times$  county level while the ACS data is identified up to the Public Use Micro Area (PUMA) level, and only sometimes includes county. Hence, I create a mapping from PUMA to county  $\times$  zip code. I use crosswalks from Missouri Census Data Center. The complication is that individual PUMAs map to multiple zip codes, often many. My solution is to collapse these zip codes into groups that share the same choice sets and distribute the weight proportional to the population in those areas. For example, suppose PUMA A maps to zip codes X, Y and Z, each of which have equal populations. Suppose further that X and Y has plan 1 offered, while Z has plan 2 offered. My method splits any household in PUMA A into two observations, the first being offered plan 1 with  $2/3$  weight and the other offered plan 2 with  $1/3$  weight. For the purposes of calculating distances to providers, I randomly assign a zip code within the offer region with probabilities based on zip code populations.<sup>3</sup>

One outstanding problem that is unaddressed but is worth considering for future work is APTC ineligibility for undocumented workers. I assume that everyone in the ACS within the regulated FPL range is eligible for APTC subsidies when in fact there are some undocumented workers for which this is not the case. This would underestimate the value of insurance since the data would show a portion of low-income households that chose not to get insurance even though they are “eligible for subsidies” in the data. This is especially problematic if the share of undocumented is correlated with APTC, which would bias down

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<sup>2</sup>I impose these same conditions in the Covered CA data to ensure a clean sample.

<sup>3</sup>There are two problems with this method. The first is that estimation and inference ignores this dependence across observations—i.e. the sample will appear larger than it really is. The second is that there is measurement error in that this imputation that is also uncorrected in the estimation. I abstract from these nuances since the sample is relatively large compared to these effects.

the nesting parameter. Fortunately, the control function approach largely solves this type of bias. The overall bias in the value of insurance remains, but this likely has little effect since most of the results are across plans.

## A.2 PCP Model Enhancements

In this appendix, I describe how the PCP model could easily be improved with the availability of PCP utilization data. The only data that is actually needed is individual-level data on how far patients travel to visit their PCP—i.e. one variable for distance to PCP, and one variable for the patient zip code. Adding an additional column for population density to control for travel costs would also significantly improve model performance.<sup>4</sup> This type of individual-level utilization data could be acquired from Truven or the Centers for Medicare and Medicaid services.

Rather than the current form of  $EV_{ijt}^P$  which only considers PCPs within 5 miles, an improved version would consider all nearby PCPs, appropriately discounted for travel costs. One can also estimate utilization probabilities ( $\lambda_i$ ) from the same data or more easily from MEPS in the same manner as for hospitals. Given PCP utility estimates and utilization probabilities, one can calculate unconditional PCP network utilities ( $EV_{ijt}^P$ ) using (1.7).

Here is a basic overview for how to estimate PCP utilities:

1. Identify a PCP for each patient in the data—e.g. assume it is the most commonly visited physician that has a specialty code for internal medicine or family medicine.
2. Collapse the data to the zip code ( $z$ )  $\times$  distance band ( $b \in \{5, 10, 15, 25\}$ ) level, with a column for the following:

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<sup>4</sup>Imagine having many doctors within the 20-25 mile range. This is unlikely to add value to a plans network in a dense metropolitan area, but would in a rural area.

- Share of patients in  $z$  that have a PCP in band  $b$  :  $s_{zb}$
- Number of PCPs within band  $b$  of  $z$  :  $N_{zb}$

3. Letting the smallest band (e.g.  $b = 5$ ) be the normalization unit, estimate the following linear function:<sup>5</sup>

$$(\ln(s_{zb}) - \ln(s_{z5})) - (\ln(N_{zb}) - \ln(N_{z5})) = -d^b + \epsilon_{zb}$$

$\epsilon_{zb}$  is added to close the model in this form and represents unobservable (and ex ante unknown to enrollee) preferences (e.g. traffic patterns). For all values of  $b$ ,  $d^b$  are the main parameters of interest and represent the disutility of traveling to distance band  $b$  to visit a PCP. This form closely resembles other aggregate logit models without heterogeneous preferences. The difference is in the left hand side variable: rather than regressing relative shares on characteristics, we regress relative shares *relative to the number of potential PCPs* in that distance. Note that this form assumes  $d^5 = 0$ , since not all distance disutilities can be separately identified. Therefore  $d^b$  represents the cost of seeing a PCP in distance band  $b$  relative to one within 5 miles.

### A.3 Risk Adjustment in the ACA

As described in the Section 2.2, risk adjustment in the ACA is different from the textbook case in that it is benchmarked to average premiums and risk scores are relative to the enrolled population only. Specifically, the formula for risk adjustment in the ACA is:

$$T_{ij} = \left( \frac{\theta_i^c * AV_j * GCF_j}{N_{CC}^{-1} \sum \theta_i^c * AV_{ij} * GCF_j} - \frac{\theta_i^p * AV_j * GCF_j}{N_{CC}^{-1} \sum \theta_i^p * AV_{ij} * GCF_j} \right) \bar{P} \quad (\text{A.1})$$

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<sup>5</sup>Given the availability of population density values  $dens_z$ , replace  $d^b$  with the interaction  $d_0^b + d_1^b * dens_z$ .

$AV_j$  is the actuarial value for plan  $j$  based on metal tier and adjusts for moral hazard.<sup>6</sup>  $GCF_j$  is a geographic cost factor which adjusts for premiums in the rating region relative to the state.<sup>7</sup> And finally,  $\bar{P}$  is the enrollment weighted state average premium. The first term (with the premium scaling) is roughly what the plan would be expected to cost relative to the market average. The second term represents how much revenue a plan is expected to generate from a particular enrollee. Two properties that were intended in the design of this formula are: 1) it is budget neutral, and 2) it is (roughly) exogenous to any particular firm's pricing decisions. See Pope et al. (2014) and Kautter et al. (2014) for more details on the transfer formula and risk adjustment considerations.<sup>8</sup>

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<sup>6</sup> $AV_{ij}$  is the  $AV_j$  chosen by household  $i$ .

<sup>7</sup>Note that this implies a similar problem across regions as mentioned in the paper exists within region.

<sup>8</sup>This is slightly different from the actual formula. In the first term, the true formula replaces  $\theta_i^c * AV_j$  with a "plan liability risk score." This is essentially a risk score for each metal tier to account for nonlinearities in cost sharing. For this study, I do not use actual risk scores, so using  $\theta_i^c * AV_j$  is sufficient.

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