Estimating Equilibrium in Health Insurance Exchanges: Price Competition and Subsidy Design under the ACA*

Pietro Tebaldi+

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Abstract. To design premium subsidies in a health insurance market it is necessary to estimate consumer demand, cost, and study how different subsidy schemes affect insurers' incentives. Combining individual-level enrollment data and plan-level claims from the Californian ACA marketplace with a model of insurance demand and insurers' competition, I estimate demand and cost primitives, and assess equilibrium outcomes under alternative subsidy designs. I find that younger households are significantly more price sensitive and cheaper to cover. Given this, counterfactual simulations show that tailoring subsidies to age leads to equilibria where all buyers are better off and per-person public spending is lower.

Keywords: subsidies, health insurance, health reform, ACA, health exchanges

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+University of Chicago, Department of Economics. Email: ptebaldi@uchicago.edu.

1 Introduction

Despite its growing importance in the provision of government-sponsored health insurance (Einav and Levin, 2015), the response of market outcomes to the decision of how to set premium subsidies in a health insurance market is still largely unexplored. A recent and large-scale example of such market design decision is found in the low-income subsidy introduced by the 2010 US health care reform (Patient Protection and Affordable Care Act; ACA). Between 2014-2016, under this program the federal government transferred approximately $40 billion per-year to private insurers, providing discounts on health insurance premiums — under the form of tax credits — to more than 10 million US citizens. Knowledge of the relationship between subsidy design and policy-relevant outcomes such as coverage levels and public spending is critical to evaluate the success of this reform, and for the design of similar programs in the future.

In this paper I study the dependence of equilibrium outcomes on how subsidies interact with three important features of private health insurance markets: demand from low-income households, insurers' price competition, and selection — correlation between a buyer's willingness to pay and expected health cost. Characteristics of demand determine the extent to which subsidies increase buyers' participation. Pricing incentives and market power of imperfectly competitive insurers react to these changes in demand, but also to corresponding changes in average cost driven by differences in the composition of enrollment pools.

To account for these effects, and compare different subsidy designs, I combine data on enrollment and claims from the first year of the Californian ACA marketplace — in which 90% of the 1.3 million buyers (890,000 households) received federal subsidies — with a model of insurers' competition customized to include subsidies and other ACA regulations. I discuss identification and estimation of demand and supply primitives exploiting the details of the regulatory environment and variation in the composition of buyers across different contracts. I then use these estimates and a model of equilibrium pricing to carry on quantitative comparisons of different designs of subsidy programs in terms of prices, enrollment, markups, and public spending. Within this framework, my results imply that the ACA subsidy scheme leaves room for improvements that are quantitatively significant and consistent with theoretical predictions. The alternatives I consider can potentially reduce insurers' market power, and increase incentives for the participation of young buyers that directly affects average cost, prices, and public spending.

The paper makes three main contributions. First of all, I provide estimates of demand and cost primitives using detailed data from the largest ACA marketplace. Other research that evaluates the role of ACA regulations using post-reform data (see e.g. Kowalski, 2014; Dafny, Gruber, and Ody, 2015; Dickstein, Duggan, Orsini, and Tebaldi, 2015; Orsini and Tebaldi, 2015) primarily exploits cross-sectional variation in outcomes across states, or state-level variation over time, without adopting specific models for demand and cost. Here I combine individual-level enrollment data with ex-post realized insurers' cost. Thanks to the granular variation in prices induced by ACA regulations within a single georgraphic market, I can estimate demand and cost accounting for selection, product differentiation, and for important implications of the ACA regulatory framework. My main empirical result shows that, at the estimated parameters, a policy change in which subsidies to relatively older buyers (high-demand and high-cost) are lowered and subsidies for the "young invincibles" (low-demand and low-cost) are increased can make all buyers better off, increase variable profits, and lower government spending.

The second contribution consists of highlighting this mechanism from a theoretical perspective. I show how, in a market with a group of buyers who are cheaper to cover and more price sensitive than others — adverse selection — , tailoring the generosity of subsidies to favor this group can lead to an equilibrium where all groups are better off and public spending is lower. Intuitively, shifting subsidy generosity from the high-cost, high-demand group to the low-cost, low-demand group changes the relative composition of enrollment pools, lowering average cost and increasing aggregate elasticity. This puts downward pressure on equilibrium prices, and it can increase quantity purchased for all groups while also reducing public spending. Importantly, since also the group receiving a lower subsidy can be made better off, the benefits of heterogeneous subsidization can be achieved while avoiding redistributive concerns.

The third contribution comes from a more methodological perspective. Many papers in the empirical literature on selection markets identify heterogeneity in risk and preferences relying on the availability of individual-level cost data matched to enrollment information, or using external surveys (see e.g. Einav, Finkelstein, and Cullen, 2010a; Einav, Finkelstein, and Schrimpf, 2010b; Einav, Finkelstein, Ryan, Schrimpf, and Cullen, 2013; Handel, 2013; Starc, 2014). Here, instead, I formalize the conditions under which it is possible to identify cost heterogeneity (both observed and unobserved) across buyers using aggregate, contract-level cost data combined with enrollment data sufficiently granular to allow the identification of heterogeneous preferences. Although a similar estimation approach can be found in Bundorf, Levin, and Mahoney (2012), our identification strategies and empirical contexts are substantially different.[1]

The structure of my analysis is as follows. I start in Section 2 with a stylized model that highlights the theoretical implications of the design decisions I consider in the paper. The main one is whether discounted prices should be equal across all buyers with the same income, or adjusted to buyers' age; the second is whether or not price discounts should be fixed ("vouchers"), or calculated as a function of market prices ("price-linked"; this is the main focus of Jaffe and Shepard (2016)). Both decisions are closely related to the ACA design, which features price-linked subsidies by

[1] In Appendix I also show how, were claims data unavailable, cost heterogeneity can be identified assuming optimal pricing (see also Lustig, 2010) along the tradition of Rosse (1970); Bresnahan (1981); Berry, Levinsohn, and Pakes (1995). I implement both approaches, showing that cost estimates obtained leveraging on equilibrium assumptions are similar to those obtained from contract-level cost information.

which, given income, for subsidized buyers the overall level of discounted prices do not vary by age. More precisely, given income, all buyers can find a Silver plan at the same price, and indeed the data shows that the average monthly premium paid by subsidized buyers is indeed approximately constant in age. The model highlights that vouchers are less distortionary than price-linked subsidy, and that targeting subsidies in favor of younger buyers can make all buyers better off and reduce per-person public spending. Importantly, the quantitative impact of different subsidy designs depends on the primitives of the market, and particularly on the intensity of price competition and the heterogeneity in price elasticity of demand and cost across different groups. These primitives are the key estimands of the paper.

In Section 3 I present the regulatory details of ACA marketplaces: contract regulations, rating rules, and subsidies — the focus of my analysis here —, but also active purchasing, risk-adjustment, re-insurance, and risk-corridors.[2] I go on introducing data on prices, enrollment, and claims, from the first year of the Californian marketplace. This is the largest among ACA marketplaces, where subsidy eligible households can choose between different coverage options offered by a set of participating insurers. This provides me with an attractive setup to estimate demand for coverage among the low-income uninsured in the newly created marketplaces.

I combine this novel dataset with a discrete-choice model of insurance demand and insurers' expected cost in Section 4. The main demand specification is a finite-types mixed-logit model à la Berry, Carnall, and Spiller (1996); Train (2008); Fox et al. (2011).[3] Each household can be one of four types — where a type corresponds to a set of market-specific demand parameters —, and the probability of being a given type is a function of age, income, household composition, and of the geographic market of residence. This allows the distribution of willingness-to-pay for insurance to vary, in every geographic market, both across observable demographic groups and within a given demographic group. To account for selection, the second key feature of the model is to allow contract-level claims to vary not only with the characteristics of a contract (insurer, market, and level of coverage), but also with the characteristics of the contract's enrollment pool in terms of demographics and willingness-to-pay for insurance.

The combination of individual-level demographic and enrollment information with the ACA-rating rules provides two elements that one can rely on for demand identification (Section 5). First, insurers only set one baseline price for any given contract in any given market; prices are then varied exogenously across households with different age and income applying a fixed formula. Second, the characteristics of insurance contracts are standardized by the exchange, and the (unobserved) net-

[2] Although not relevant for the estimation of demand and cost parameters, I abstract away from some of these institutional details when analyzing counterfactual designs of the subsidy program. This ensures tractability of the equilibrium analysis and allows me to focus on the role of heterogeneous subsidies in controlling buyers' selection into the market.

[3] For robustness I also consider a simple logit and a nested logit where buyers first decide whether to enter the exchange and then which plan to choose.

work of providers is fixed for a given insurer within a geographic market. With an approach similar to the one of Chamberlain (1980); Ho and Pakes (2014); Geruso (2016), I exploit these two facts (and standard functional-form restrictions of the mixed-logit framework) to identify heterogeneity in preferences across buyers. The key intuition is to compare choices of a large number of different buyers who face identical choice sets within a market (the level of pricing), and whose prices differ only for regulatory reasons. Differences in choices across demographic groups identify heterogeneity in preferences across households with different age and income, dispersion of choices within groups with similar demographics identifies the heterogeneity conditional on household characteristics.

For identification of insurers' costs I rely instead on how contracts differ in the composition of their buyers in terms of demographics and willingness-to-pay for coverage. To gain intuition, once I obtain demand estimates, I can construct for every contract the composition of buyers in terms of observables (age and income) and willingness-to-pay for higher coverage (implied by the demand estimates). Heterogeneity in cost across buyers is identified by variation in realized claims corresponding to variation in composition of enrollment pools, after controlling for firm, market, and coverage-level fixed effects.[4]

In Section 6 I present the resulting estimates, which are largely consistent with previous literature focusing on age-driven heterogeneity in demand and cost in insurance market (see e.g. Geruso, 2016). For demand I find that willigness-to-pay for coverage significantly increases in household's age, and that there is a substantial degree of heterogeneity both across regions and across households with similar observables. I estimate that households whose average age is less than 30 are willing to pay (on average) approximately \$1,000 per-year to increase their coverage from Bronze to Gold (or to reduce their deductible from \$5,000 to \$0). This number is as high as \$1,600/year for buyers older than 50. This heterogeneity translates in differences in the propensity of buyers to leave (enter) the market if subsidies were lowered (raised). While I estimate that, on average, 5-7% of younger-than-30 would leave the market if all prices increased by \$100/year, this number is estimated to be 2-3% for older-than-50 buyers. The estimates also highlight that households who enter the market are more willing to pay for extra-coverage. For younger households the estimated willingness to pay to upgrade from Bronze to Gold conditional on purchasing coverage increases to \$1,500-2,000/year. The same estimate for older households is between \$2,800-3,000.

Cost estimates show evidence of adverse selection, both along observable household characteristics and unobservable preferences within households with the same observables. I find that older buyers are costlier to cover (on average 1 year of age increases expected cost by 1.6%), and the

[4]Without claims data one can follow a similar intuition after assuming optimality of prices. Marginal revenues are equal to marginal cost, which results from a combination of unobserved cost across different demographic and willingness-to-pay groups. Hence, to estimate cost heterogeneity one can compare marginal revenues/cost between contracts with differing composition of marginal buyers. This composition can be derived directly from the estimated heterogeneity in demand. The general identification result is presented in Appendix and it follows from results in Berry and Haile (2014) combined with a constructive proof partially adapted from Somaini (2011, 2015).

same is true for buyers who are more willing to pay for generous coverage (even conditional on age, income, and product chosen). I estimate that, on average, a $1,000/year increase in willingness to pay to upgrade from Bronze to Platinum corresponds — ceteris paribus — to a 19% increase in expected cost for the carrier.

These demand and cost estimates are the main inputs for my counterfactual analysis in Section 7. I start by comparing fixed vouchers to the price-linked discounts adopted under the ACA. The current scheme calculates discounts from market prices to ensure that buyers do not pay more than a predetermined amount. As a consequence, if all prices increase by $1, low-income buyers do not face any price change, while government expenditure increases by $1 per buyer. This creates incentives for insurers to set higher prices than if discounts were instead predetermined vouchers. Indeed, my simulations imply that equilibrium insurers' markups are 16% lower if the current subsidy scheme is replaced by a voucher; under this alternative discounts are of equal amount to those ACA ones but are not adjusted to insurers' decisions. This reduction in markups corresponds to an increase in coverage of approximately 8.4% (buyers face lower net-of-subsidy premiums), while government spending per-buyer is approximately unchanged.

Importantly, the comparision between vouchers and price-linked subsidies is the key focus of Jaffe and Shepard (2016), who find a quantitatively similar distortion using data from the pre-ACA Massachussets health insurance exchange. They also discuss important implementation issues of an alternative voucher system, with a key role being played by the government's ability to predict cost and demand in a market to set vouchers at the correct level. They main finding is that, even allowing for a sizable range of government's mismeasurement of market primitives, consumers and government would be better off using vouchers rather than price-linked subsidies. My analysis of the voucher vs. price-linked tradeoff is simpler, but complements theirs in measuring the distortion of price-linked subsidies in a multi-product environment — in MA insurers where only offering one coverage option —, and comparing the size of this distortion across markets with different levels of competition. Consistently with simple theoretical considerations, I find that more concentrated markets (less than 4 insurers) show a much larger distortion than the one I measure in markets with 5 or more insurers.

The more novel design decision I consider in my analysis is whether the subsidized price that a buyer pays should vary not only with her income, but also her age. Within a voucher-based system,[5] I find that, by raising vouchers to under 45 by $400 and lowering those to over 45 by $200, enrollment among the young raises by 50% while enrollment of the older is approximately unchanged. The reason is that, in equilibrium, a higher share of young enrollees reduces average cost by 15%, and markups by more than 20% (young buyers have also higher elasticity). Hence prices are lower, and this offsets the $200 reduction in the subsidy to the older group. At the same time,

[5]This significantly simplifies equilibrium computations.

per-insured government expenditure is also reduced by approximately 15% ($600 per-buyer-year).

In addition to the papers discussed earlier, my work relates to numerous studies that use pre-reform data to study regulations that closely resemble those introduced by the ACA. Many of them use data from the Massachusetts' health exchange, a setting similar to ACA marketplaces.[6,7] In this context, Hackmann, Kolstad, and Kowalski (2015) measure the welfare effect of an insurance mandate, and Ericson and Starc (2015) develop and estimate a demand-supply model to study several ACA-like regulations, with main focus on the effect of age-based price adjustments for high-income buyers. My work complements theirs by focusing on the low-income segment of the population — not making active choices in the MA context —, and precisely studying the subsidy program for these buyers. Lastly, even outside the ACA setting there is a growing literature adapting industrial organization techniques to analyze the interaction between regulations and supply behavior of private health insurers. The cases of Medicare Advantage, Medicare Part D, Medigap, and Medicaid are the main focus of, among many others, Duggan and Hayford (2013), Curto et al. (2014), Duggan, Starc, and Vabson (2014), Starc (2014), Clemens (2015), and Decarolis, Polyakova, and Ryan (2015). Notably, Decarolis (2015) shows distortions of insurers' decisions due to the design of subsidies in Medicare Part D, with design optimality (in the same market) being explicitly considered in Decarolis, Polyakova, and Ryan (2015). In a broad review of this literature Einav and Levin (2015) explicitly discuss the importance of properly accounting for market power when designing these programs.

2 Subsidy design in health insurance

2.1 Stylized framework

Consider a market with J health insurers. For now, each offers just one insurance plan $j = 1, ..., J$, with $j = 0$ denoting the outside option. I relax this assumption and consider multi-plan insurers later in the context of my application. Non-price characteristics of each plan are fixed, and their generosity of coverage is the same, so differences in demand across plans are driven by brand preferences and attributes of the provider networks.

Buyers are of one of two types, say young and old, denoted by $\tau = Y, O$, and I will use $G(\tau) \in [0, 1]$ to denote the fraction of type τ buyers in the market. Different types of buyers may

[6] See also Long et al. (2010); Ericson and Starc (2012b,a, 2013, 2014); Shepard (2014).

[7] Other studies combine theoretical results and simulations: the impact of insurance mandates and minimum coverage provisions is studied by Azevedo and Gottlieb (2014); the relationship between risk-adjustment and insurers' competition by Mahoney and Weyl (2014); the long-run welfare impact of community rating rules by Handel, Hendel, and Whinston (2015); the interaction between exchange design and labor markets by Aizawa (2015). Differently from my work, these papers abstract away from various aspects of market structure and imperfect competition observed in the US insurance market (see e.g. Dafny, 2010; Starc, 2014), and quantifications use data or estimates from employer-sponsored insurance (e.g. Einav, Finkelstein, and Cullen, 2010a; Handel, 2013).

have different health status (and thus cost for the insurer) and demand for insurance coverage. In particular, when selling coverage to a type τ buyer, insurer j expects to incur a cost equal to C_j^τ.

Demand is instead defined as follows. Each individual buyer i has willingness-to-pay for product j equal to v_j^i, and the vector $v^i = (v_1^i, ..., v_J^i)$ is drawn $i.i.d$ from the c.d.f. $F(v|\tau)$, conditionally on the buyer's type. Demand can then be represented by $\sigma_j(P, \tau)$, a function — derived from $F(v|\tau)$ — indicating the probability that a buyer of type τ chooses j when prices are $P = (P_1, ..., P_J)$. I assume that $F(v|\tau)$ is such that $\sigma_j(P, \tau)$ is strictly decreasing in P_j, and that it is continuous and differentiable. I also use $\eta_{jk}^\tau \equiv \left|\frac{\partial \sigma_j(P,\tau)}{\partial P_k}\right| / \sigma_j(P, \tau)$ to denote the semi-elasticity of demand for j by type τ buyers with respect to the price of plan k; in this section this is treated as constant.

As an extreme example of limits to price discrimination (similar to those mandated by the ACA, see Section 3), insurers cannot vary prices by τ, so each sets a single price P_j that applies to all buyers. Expected profits are then a weighted average of profits across the two types:

$$\Pi_j(P_j, P_{-j}) = G(Y) \cdot \left[\sigma_j(P, Y) \cdot (P_j - C_j^Y)\right] + G(O) \cdot \left[\sigma_j(P, O) \cdot (P_j - C_j^O)\right]. \tag{1}$$

In this sense, heterogeneity in demand and cost across types is used to model selection: even if observable, the type of a buyer is not priced, and neither the average nor the marginal cost curves of a product are necessarily constant functions of the corresponding pricing decision. To gain intuition, here I assume complete information, and that prices form a Nash Equilibrium. That is, each insurer j sets its price P_j to maximize $\Pi_j(P_j, P_{-j})$ taking P_{-j} as given.[8]

2.2 Subsidies

To consider the effect of a subsidy program, let a subsidy design be a function $S(P, \tau) > 0$, such that type τ buyers face the discounted price vector $P - S(P, \tau) = (P_1 - S(P, \tau), ..., P_J - S(P, \tau))$. This will change demand by both types, from $\sigma_j(P, \tau)$ to $\sigma_j(P - S(P, \tau), \tau)$, and will have a corresponding effect on profits, equilibrium prices, and government expenditure.

For every chosen design the equilibrium price vector (pre-subsidy) — $P^{*,S}$ — is such that, for every product, the price is the sum of average cost and markup. Characteristics of demand and cost across different types of buyers determine how average cost and markup depend on the chosen subsidy design. To see this formally, let $\alpha_j^S(P)$ be the share of young buyers of plan j when the subsidy design S is adopted and prices are P.[9] I use this to define the corresponding average cost — $AC_j^S(\cdot)$ — and markup — $MK_j^S(\cdot)$ — functions under S (see supplementary Appendix S1 for

[8] Here I also maintain the assumption that (primitives are such that) prices are strategic complements, so that equilibrium comparative-static results from Vives (1990) can be applied.

[9] $\alpha_j^S(P) = \frac{G(Y)\sigma_j(P-S(P,Y),Y)}{G(Y)\sigma_j(P-S(P,Y),Y)+G(O)\sigma_j(P-S(P,O),O)}$.

detailed derivations):

$$AC_j^S(P) = C_j^Y \cdot \alpha_j^S(P) + C_j^O \cdot (1 - \alpha_j^S(P)), \tag{2}$$

$$MK_j^S(P) = \frac{1 - \left[\alpha_j^S(P)\left(1 - \alpha_j^S(P)\right)\left(\eta_{jj}^O - \eta_{jj}^Y\right)\left(C_j^Y - C_j^O\right)\right]}{\eta_{jj}^Y \alpha_j^S(P) + \eta_{jj}^O(1 - \alpha_j^S(P))}. \tag{3}$$

Then, $P^{*,S}$ is an equilibrium under S if, for each j, $P_j^{*,S} = AC_j^S(P^{*,S}) + MK_j^S(P^{*,S})$, so that the problem of the government — if cost and demand primitives are known — amounts to choosing S knowing that prices will then satisfy this equilibrium condition, and coverage and spending will respond accordingly. For this I also let g^S be the per-insured public spending in equilibrium corresponding to a subsidy design S.

Targeted or non-targeted subsidies? A first comparison is between a non-targeted subsidy, for which the subsidy does not depend on τ, so $S(P, \tau) = S(P)$, in contrast to a targeted subsidy that does. The key result here is that, in a market with adverse selection, tailoring the generosity of subsidies to favor the cheaper-to-cover *and* more-price-sensitive group can lead to an equilibrium where all groups are better off, and the government spends less to subsidize a buyer.

Proposition 1 *If prices are strategic complements and $C_j^Y < C_j^O$, $\eta_{jj}^Y > \eta_{jj}^O$ for all j:*

(a) if S is a non-targeted voucher scheme $S(P, \tau) = V$, for which, at the equilibrium prices $P^{*,S}$, $\alpha_j^S\left(P^{*,S}\right) < \frac{1}{2}$ for all j, then there exists a $\Delta > 0$ such that, for the targeted voucher scheme $\widehat{S}(P, Y) = V + \Delta$, $\widehat{S}(P, O) = V - \Delta$, $P^{*,\widehat{S}} < P^{*,S}$;

(b) if, moreover, $P_j^{*,S} - P_j^{*,\widehat{S}} > \Delta$ for all j, then equilibrium quantities purchased under $\widehat{S}$ are higher in both groups, and $g^{\widehat{S}} < g^S$.

I prove this in Appendix A, but the intuition is as follows. The starting situation is one in which the government uses a non-targeted voucher, fixing an amount $V > 0$ such that $S(P, \tau) = V$, while the alternative is a targeted voucher for which $\widehat{S}(P, \tau) = \widehat{V}^\tau$, with $\widehat{V}^Y > V > \widehat{V}^O$. For any given P, the composition of buyers under the two schemes differs, with $\alpha_j^S(P) < \alpha_j^{\widehat{S}}(P)$ for all j because of quasi-linearity of preferences. Hence, since young buyers are cheaper to cover *and* more price sensitive, $\widehat{S}$ implies lower average cost *and* markups. Hence, replacing S with $\widehat{S}$ induces an equilibrium with lower prices (part (a)). Moreover, if these price reductions are larger than the amount by which discounts to old buyers are lowered under $\widehat{S}$ ($V - \widehat{V}^O$), coverage is higher for all buyers, and spending per-buyer is lower (part (b)).

Price-linked discounts or vouchers? A second relevant design decision is whether subsidies should be ex ante fixed by the regulator, or computed ex post as a function of market prices, as it is currently done under the ACA (see Section 3). Practically, one can consider a scheme S with price-linked discounts, for which $\frac{\partial S(P,\tau)}{\partial P_j} > 0$ (for some j), or a voucher program where instead $\frac{\partial S(P,\tau)}{\partial P_j} = 0$ for all j and all P. This is also the main focus of independent work by Jaffe and Shepard (2016), where they also discuss the welfare consequences and critical implementation issues of this policy choice under different assumptions about the government's information on market primitives.

Price-linked discounts may be desirable if the government — not knowing demand and cost primitives — is unable to predict price. Adjusting subsidies to prices reduces then the possibility that discounts are too low (or too high) than what would be necessary to induce a target coverage level. However, adjusting subsidies to prices can distort insurers' incentives, and lead to an equilibrium with higher prices and higher spending by the government than what would result if subsidies were ex ante fixed. The intuition is straightforward and clearly resembles the difference between lump-sum as opposed to proportional taxes. If price increases are partly covered by discount adjustments, insurers maximize profits as if buyers were less price sensitive, and thus have additional incentives to set higher prices. The magnitude of this distortion decreases with the intensity of price competition and with the degree of horizontal differentiation in the market. I formalize this in Proposition 2 in the supplementary Appendix S1.

Relevant primitives. This discussion considered qualitative effects of different subsidy design decisions in a simplified setting and under stringent assumptions about market primitives, and delivered a set of possibility results. Relaxing these assumptions, cost and preferences across different buyers become the key estimands one needs to determine the direction and magnitude of the differences between subsidy schemes in a specific context. Looking at the ACA marketplaces, this is my goal in the rest of the paper.

3 ACA marketplaces

3.1 Institutional context and federal regulations

As of 2013, 17 percent of US citizens younger than 65 did not have health insurance coverage (Smith et al., 2014). Affordability of the annual premium was a prominent reason why those uninsured did not purchase coverage in the private market (Tallon, Rowland, and Lyons, 2013), and this was one of the main motivations for the ACA. In 2014, the ACA instituted health insurance marketplaces in each of the fifty states. A marketplace is a market in which private insurers offer a variety of coverage options, and the federal government provides subsidies for low-income participants. Indeed, in the first two years of their operation, approximately 90 percent of buyers on these marketplaces received premium subsidies,[10] associated with annual government disbursements of

[10] See e.g. https://aspe.hhs.gov/sites/default/files/pdf/83656/ib_2015mar_enrollment.pdf.

approximately \$40 billion (see Anthony et al., 2015).

ACA marketplaces operate in each state separately, but they all follow similar institutions and regulations. Each state is divided into geographic rating regions — groups of counties or zipcodes — defining the level at which decisions by buyers and insurers take place. Every spring, insurers announce their interest in offering plans in each region in the subsequent calendar year. Entrants undergo a certification process, after which they offer different coverage options, classified into five coverage levels: Minimum Coverage, Bronze, Silver, Gold, and Platinum. Minimum Coverage indicates plans with very high deductible, which cannot be purchased by subsidized buyers, nor by buyers older than 35. The four metal tiers represent increased coverage options, and are ordered by an estimate of the actuarial value of their coverage: 60% for Bronze, 70% for Silver, 80% for Gold, and 90% or more for Platinum plans. Products and prices are set (and made public) at the end of every summer, and individuals can then compare and purchase plans in their region during the "open enrollment" period in the late months of each year. Coverage then lasts for the subsequent calendar year.

Pricing regulations. One important provision of the ACA is that insurers are not allowed to arbitrarily vary prices depending on buyers' observable characteristics. The only characteristic that affects annual premiums is the buyer's age, but even this adjustment is done in a pre-specified way (see also Orsini and Tebaldi, 2015). That is, each plan j offered in region r is associated with a single base price $b_{jr} > 0$, which is then translated to age-specific premiums using given age adjustment factors A^τ, equal for all products:

$$P_{jr}^\tau = A^\tau \cdot b_{jr}. \tag{4}$$

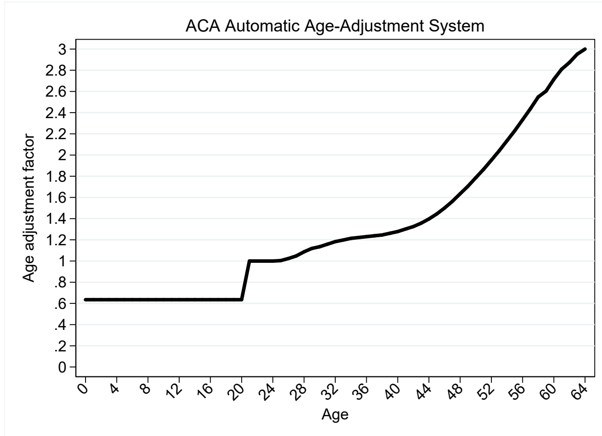
Age adjustments vary between 0.635 (up to 20-year-olds), equal 1 for 21-years-old buyers, and increase smoothly up to 3 for 64-years-old buyers. Details for all ages are shown in Figure 1.

Premium subsidies. Although P_{jr}^τ is the premium received by the seller when a τ-year-old buyer enrolls in plan j in region r, subsidies are provided for all households with annual income below four times the federal poverty level (FPL; approximately \$47,000 for a single individual).

For this, the law establishes a cap on the premium amount the household should pay for the second-cheapest Silver plan (benchmark plan) in each region. This cap is a function of the income of the household (see Table 1), ranging — for single buyers — from \$684 per-year for the lowest income group to \$4,368 for the highest income group. Importantly, given income this cap amount does not vary with the age of the buyers.

This subsidy scheme defines a premium discount for each age (τ; calculated as total age of the

Figure 1: **Age adjustment factors in ACA marketplaces**



Note: For every age τ, the line in the figure shows the corresponding factor A^{τ}, which is used to compute the price of a high-income, unsubsidized buyer (equation (4)). If the base price of the product is b_{jr}, $P^{\tau}_{jr} = A^{\tau} \cdot b_{jr}$. This is also equal to the total amount that the insurer receives when a subsidized buyer purchases the plan.

Table 1: **Price caps for subsidy calculation in ACA marketplaces**

Income as % of FPL	up to 150%	150-200%	200-250%	250-400%
Max % of income to buy 2^{nd} cheapest Silver	4%	6.3%	8.05%	9.5%
Price cap of 2^{nd} cheapest Silver (single)	\$684	\$1,452	\$2,416	\$4,368
Price cap of 2^{nd} cheapest Silver (couple+1 child)	\$1,164	\$2,472	\$4,008	\$7,392

Note: The table shows, as a function of a buyer's income, the maximum amount that can be spent on the second cheapest Silver plan in the region. For each age-income pair, the subsidy is computed as the difference between the premium of this product (after age adjustment) and the corresponding share of annual income for the buyer. The bottom row shows the corresponding price cap on monthly price for the second cheapest Silver plan in the region for singles and households of three.

household adding up all members) and income (y) in region r equal to

$$S^{\tau,y}(b_r) = \max\left\{A^{\tau} \cdot b^*_r - \overline{P}^y, 0\right\}, \tag{5}$$

where $\overline{P}^y$ is the premium cap for households with income y, and b^*_r is the base price of the benchmark plan in the region. Since the law establishes that each buyer must pay at least \$1, the price of plan j for a household with total age τ and income y in region r is equal to

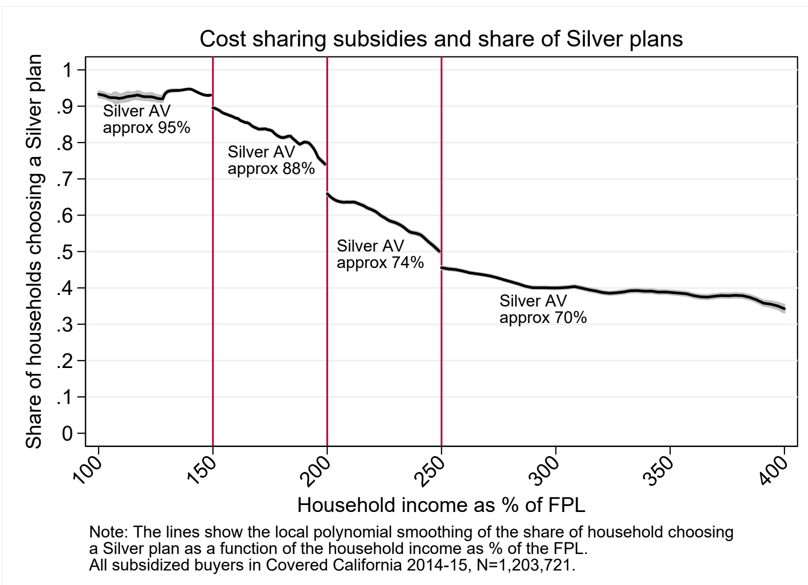
$$P^{\tau,y}_{jr} = \max\{P^{\tau}_{jr} - S^{\tau,y}(b_r), 1\}. \tag{6}$$

There are two important properties of this subsidy scheme. First, for a given income level each household can find (one) Silver plan for the same premium, independently from their age. Second, the difference in premium both across different insurers and across different levels of coverage is instead increasing in age, while it does not depend on the income of the household.

Cost-sharing subsidies. Another important regulation in ACA marketplaces is the provision of cost-sharing subsidies, available for households purchasing a Silver plan and whose income is lower than 250% of the FPL. For them, the federal government covers part of deductible and out-of-pocket expenses, increasing the actuarial value of Silver plans from 70% to 95% for income levels between 100-150% of the FPL, 88% for income levels between 150-200% of the FPL, and 74% for income levels between 200-250% of the FPL.

Cost-sharing reductions do not directly affect prices, yet make Silver plans increasingly more attractive the lower the income of the household (see also DeLeire et al., 2016). This is evident in Figure 2, showing the plan choices as observed in the Californian data that I present in details below. The share of households purchasing a Silver plan is steadily declining as income increases — from over .9 to .4 with discontinuous jumps at the discontinuities in cost-sharing — although the difference in premium between Silver and other levels of coverage does not vary with income.

Figure 2: **Cost sharing subsidies and share of households choosing a Silver plan**



A second consequence of cost-sharing reductions is that, although the insurer covers approximately 70% of the health expenses, buyers' utilization when enrolled in a Silver plan will be as if the plan provided higher coverage, and therefore likely to be higher (c.f. "moral hazard" in health insurance, see e.g. Manning et al., 1987; Einav et al., 2013).

Risk adjustment, reinsurance, and risk corridors. The ACA introduced three programs to mitigate insurers' incentives to cream skim healthy patients, and to facilitate the stabilization of the new markets. The programs are called risk-adjustment (permanent), re-insurance (2014-2016 only), and risk-corridors (2014-2016 only), often referred to as "the three R's".[11]

Risk-adjustment under the ACA determines monetary transfers from insurers with ex-ante relatively less risky enrollees to those who enroll ex-ante relatively more risky enrollees. Importantly, this is a budget neutral program. The government only calculates these transfers through a risk-adjustment formula that is being developed by the Department of Health and Human Services (see Kautter et al., 2014). If risk profiles (in terms of preexisting conditions, age, gender, tobacco use) do not differ across insurers, risk-adjustment implies no transfers, even though the overall riskiness of the market could be very high. The main role of the program is then to mitigate insurers' incentives to select the healthiest within market participants. When setting higher prices and offering more generous plans than competitors, insurers know that, even if they end up with a comparatively riskier pool, this will be (at least partly) compensated by higher risk-adjustment transfers.

Re-insurance and risk-corridors are instead temporary programs facilitating market stabilization in the early years, reimbursing insurers for the ex-post realized riskiness of their pools independently from the one of their competitors. Re-insurance collects a fixed amount for every health insurance policy sold by any issuer in any market in the US,[12] and it compensates every insurer for individual claims exceeding an attachment point ($45,000 in 2014-15, and $90,000 in 2016) until a cap of $250,000. The coinsurance rates are 100% in 2014, and 50% in 2015-16. By covering part of the right tail of risk, this program limits insurers' incentives to set high-premiums in the fear of incurring losses due to the riskiness of the newly insured.

While re-insurance reimburses the cost of covering high-cost patients, risk-corridors are intended to facilitate the targeting of a 20% (variable) profit margin. Every insurer who (across all markets served in the state) does not spend in claims and administrative costs at least 77% of premiums must pay into the program. The payment is proportional to the difference between 80% of premiums and the amount spent. Symmetrically, every insurer who spends more than 83% is eligible for reimbursement, with amounts being again proportional to the difference between spending and the 80% target. Importantly, this program is not guaranteed to pay out, since it is possible that the payments due to less profitable insurers are larger than the dues of the more profitable ones.[13]

Risk-adjustment, re-insurance, and risk-corridors are important drivers of insurers' incentives in setting prices, and interact in a complex way with other regulations. Although my focus in the rest of this paper is on the design of the subsidy program, in Section 7 I will briefly discuss how these programs could (and should) be incorporated in a richer setup and potentially affect the calculations of equilibrium outcomes under alternative regulatory frameworks.

[11] See e.g. http://kff.org/health-reform/issue-brief/explaining-health-care-reform-risk-adjustment-reinsurance-and-risk-corridors/.

[12] State high-risk pools are excluded from the program. The annual per-contract amounts were set at $63 in 2014, $44 in 2015, and $27 in 2016.

[13] For example, in 2014 insurers were due a total of $2.8 billion while only owing $362 million. Therefore the program paid only 12.5% of what was due to insurers who realized lower-than-expected variable margins.

The role of the exchanges: active purchasers and clearinghouses. In terms of management of the marketplaces, state regulators can decide whether to set up a state-based organization or whether to have local insurers offer plans through a federally-run market platform. There are two main models of governance: the exchange as active purchaser (CA, CT, KY, MD, MA, NV, NY, OR, RI, VT), and the exchange as clearinghouse (all other states, where importantly all federally-run exchanges fall in this group). As illustrated by Krinn, Karaca-Mandic, and Blewett (2015): clearinghouse models are those in which all health plans that meet published criteria are accepted, while active purchasers are those in which states negotiate conditions for entry, premiums, provider networks, number of plans, and benefits.

In California, for example, the exchange needs to approve entry of insurers in any given rating region, and if a participating insurer leaves the exchange it is not allowed to sell individual health insurance for several subsequent years. Additionally, like most active purchasers the Californian exchange imposes strict limits on the number of contracts that each insurer must offer, and opted for fully standardized combinations of deductible and co-pays within each metal tier (details in Table 2). In this situation, within a rating region insurers are differentiated only in their brand name, the structure of their provider networks, and the associated premiums. This will be important for my analysis, because deductible and co-pays are exogenous rather than insurers' decisions.

The process through which base prices (and thus premiums) are set represents a major difference between the two models. In clearinghouses, the exchange has no role: rates are set by insurers as posted prices as long as they comply with existing (federal and local) regulations of health insurance markets. On the other hand, when exchanges act as active purchasers they have an important role in the process of setting premiums for the following year of coverage. Using the words of the administrators of the Californian exchange,[14] the exchange "jawbones down premiums to the extent it can, leveraging its private information on risk mix, competitor rates, and the price elasticity of demand".[15]

Early evidence on how the chosen model of governance affects outcomes is mixed, with the usual complications arising from cross-states comparisons; see Krinn, Karaca-Mandic, and Blewett (2015) and Scheffler et al. (2016). Although not relevant for the estimation of demand and cost, it is still important to consider these institutional details when studying counterfactual designs of specific regulations. I will discuss this when introducing the simple supply model that I use for my analysis of alternative subsidy designs in Section 7.

[14] See http://healthaffairs.org/blog/2015/10/02/whither-health-insurance-exchanges-under-the-affordable-care-act-active-purchasing-versus-passive-marketplaces/.

[15] In my conversations with exchange staff members directly involved in this process, I learned that exchange researchers provide insurers with estimates of how many buyers they could expect to gain or lose upon changing base prices, as well as the corresponding risk composition. The exchange does not want insurers to be surprised, hence announces when competitors are planning to raise or decrease rates, and provides analyses that insurers can use in the process of setting their rates accordingly.

3.2 The case of Covered California

With its 1.3 million enrollees in 2014, the Californian marketplace (Covered California) is the largest among ACA marketplaces,[16] and provides a useful setup to estimate demand and supply primitives and thus quantify the effect of alternative subsidy designs. The state is divided into 19 rating regions (map in Figure 9 in Appendix), with the number of insurers active in each region varying between 3 and 6, for a total of 11 participants.

As a leading example of active purchaser, in Covered California financial details of different levels of coverage are fully standardized as shown in Table 2. Moreover, when selling plans in a region each insurer must offer one plan in each level of coverage, and although the federal law allows some premium adjustments for tobacco use, these are not allowed in Covered California.

Table 2: **Standardized financial characteristics in Covered California**

	Annual deductible	Maximum out-of-pocket	Primary care visit	Emergency Room	Specialist visit	Preferred drugs	Advertised coverage*
Catastrophic	n.a.	\$6,600	n.a.$^{(1)}$	n.a.$^{(1)}$	n.a.$^{(1)}$	n.a.$^{(1)}$	n.a.$^{(3)}$
Bronze	\$5,000	\$6,250	\$60	\$300$^{(2)}$	\$70$^{(2)}$	\$50$^{(2)}$	60%
Silver (>250% FPL)	\$2,250	\$6,250	\$45	\$250	\$65	\$50	70%
Silver (200-250% FPL)	\$1,850	\$5,200	\$40	\$250	\$50	\$35	74%
Gold	\$0	\$6,250	\$30	\$250	\$50	\$50	79%
Silver (150-200% FPL)	\$550	\$2,250	\$15	\$75	\$20	\$15	88%
Platinum	\$0	\$4,000	\$20	\$150	\$40	\$15	88%
Silver (100-150% FPL)	\$0	\$2,250	\$3	\$25	\$5	\$5	95%

Source: http://www.coveredca.com/PDFs/2015-Health-Benefits-Table.pdf
$^{(1)}$: Pay the necessary fee (negotiated between carrier and provider) until the maximum out-of-pocket is met. $^{(2)}$: After deductible is met, before pay the necessary fee (negotiated between carrier and provider). $^{(3)}$: Pay the full cost until maximum out-of-pocket is met *: These percentages are displayed to buyers when comparing products.

3.2.1 Data

In this paper I use three main data sources. The first is an extract of the official records of Covered California, obtained via Public Records Act (CA Gov §6250). This contains anonymized and non-identifiable individual-level enrollment information for every purchase in the exchange during the first open enrollment period (October 2013 - April 2014). Each record shows unique individual and household identifiers, gender, age at the date of purchase, residence information (county and 5-digit zipcode), bins for annual household income as % of the FPL, unique identifier for the selected plan (insurer, region, network type, metal tier), total premium paid by the household, and information on coverage termination (if occurred).

To use these data, I first restrict my analysis to households with less than 6 members (99.5% of the buyers are in households of 5 or less). Second, I compute a continuous measure of household income by inverting formula (6) for the subsidy calculation (I observe the discount, and all

[16] See http://kff.org/health-reform/issue-brief/data-note-how-has-the-individual-insurance-market-grown-under-the-affordable-care-act/ .

elements of the formula beside the price ceiling, which can then be mapped to the annual income of the household). This returns a complete individual-level dataset of 1,291,214 enrollment records (881,283 households),[17] summarized in panel (a) of Table 3.

The second data source is an extract of the 2013 American Community Survey (ACS) accessed via IPUMS (Ruggles et al., 2015). For the analysis I use only the Californian sample. Using household weights I construct a dataset containing individual and household identifiers, health insurance coverage information, age, gender, household annual income, and geographic area.

Importantly, I define potential buyers for Covered California as those who did not have any coverage or had individually purchased coverage at the end of 2013. This returns a dataset of 8,239,898 potential buyers (3,392,942 households),[18] summarized in panel (b) of Table 3.

The third data source consists of the rate-review filings collected by the Center for Medicare and Medicaid Serices (CMS).[19] Every year, insurers still active in the ACA marketplaces must justify their base prices (transformed in premiums as explained above) with "previous experience" in the market. In particular, pricing decisions for plans covering 2016 — taken during 2015 — must be accompained by average, plan-level claims data from coverage during 2014. For every plan still offered in 2016, the data then shows 2014 enrollment and 2014 average incurred claims for which the insurer was responsible.

From the CMS filings, I match average claims for 480 out of 490 plans offered in 2014 Covered California. These cover 98.9% of the exchange enrollment; the two missing insurers (each active in one region, for a total of 10 plans) covered only 15,313 individuals. Summary statistics for plan-level enrollment and claims are reported, respectively, in panels (c) and (d) of Table 3.

3.2.2 Descriptive analysis

Premiums and choices by age and income. Premiums that are relevant for buyers' decisions are summarized by panels (a) through (d) of Table 4, where to highlight the effect of age adjustments and subsidies I compare average premium by metal tier across 3 age groups, singles and non-singles, high-income households and households with income between 200-220% of the FPL.

Premiums for the high-income older than 50 are approximately 3 times larger than those for high-income younger than 30. These are equal to the amounts received by insurers for each house-

[17] The dataset originally contains 1,450,477 person-purchase records. For my analysis I discard all records with missing age or age over 64 (11,461), records with negative premium or subsidized premium higher than non-subsidized premium (935), records with multiple purchases per-household or different plan selection within household (61,235), records with plan selections outside the region of residence (30,942), households with more than 5 members (7,295), and records with missing variables.

[18] This construction is consistent with external sources, see e.g. the Small Area Health Insurance Estimates (https://www.census.gov/did/www/sahie/), or estimates from the California Health Care Foundation (http://www.chcf.org/publications/2016/12/californias-uninsured).

[19] See: https://www.cms.gov/CCIIO/Resources/Data-Resources/ratereview.html.

Table 3: **Data summary**

	Individual-level purchases and potential buyers									
	(a): **Covered California 2014**					(b): **ACS 2013 uninsurance or private insurance**				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Age	1,291,214	41.96	15.12	0	64	8,239,898	35.23	16.02	0	64
Gender (M=1)	1,291,214	0.47	0.50	0	1	8,239,898	0.53	0.50	0	1
Household size	1,291,214	1.87	1.01	1	5	8,239,898	2.17	1.19	1	5
FPL<400 (Yes=1)	1,291,214	0.93	0.25	0	1	8,239,898	0.60	0.49	0	1
Household income if subsidized ($1,000)	1,203,721	33.79	15.73	11.90	111.64	4,980,989	35.29	21.42	0	119.00

	Plan-level enrollment and claims									
	(c): **Enrollment in 2014 Covered CA**					(d): **2014 per-person claims ($1,000); CMS filings**				
Coverage level	N. plans	Mean	Std. Dev.	Min	Max	N. plans	Mean	Std. Dev.	Min	Max
Catastr.	80	180	225	1	1,055	78	1.969	2.088	0.283	6.432
Bronze	140	2,427	2,907	1	16,671	138	2.303	1.411	0.366	6.432
Silver	90	10,303	12,477	41	57,363	88	3.415	1.386	1.206	6.784
Gold	90	988	1,265	7	5,511	88	4.514	1.855	1.707	12.268
Platinum	90	889	1,033	8	5,555	84	8.707	5.231	1.812	20.310

hold choosing their plans. Because of the subsidy formula, however, this monotonicity does not hold for low-income households. For them, the subsidy design implies that Silver plans are available for approximately the same amount for all ages (the second cheapest Silver for *exactly* the same amount for a given income level and household composition). For lower coverage, premiums decrease in age, while the opposite is true for Gold and Platinum plans, a pattern that is mechanically implied by the formula of the subsidy scheme in (5) and (6).

The composition of potential buyers and the decision to purchase coverage are also highly heterogeneous across households with different age and income, as summarized in panels (e) and (f) of Table 4. Out of the 5.1 million households that are potential buyers according in the ACS data, 3.7 million (72%) are eligible for premium subsidies. Among the subsidized, less than one million households (approximately 23%) have average age higher than 50. The decisions to purchase coverage in the exchange is very different along these dimensions. First, the average entry rate of non-subsidized buyers is less than 10%, compared to 38% for subsidized buyers; this group then makes up for more than 90% of those purchasing plans in the exchange. Second, among subsidized households, participation rates are significantly higher when the average age is higher than 50 (53.8%) when compared to younger households (30%). Recalling that all households can find the same plans, and that Silver plans are affordable for a premium that is almost constant in age, these facts are informative about differences in willingness to pay for insurance across different groups.

To look in further details at the relationship between prices and choices among subsidized

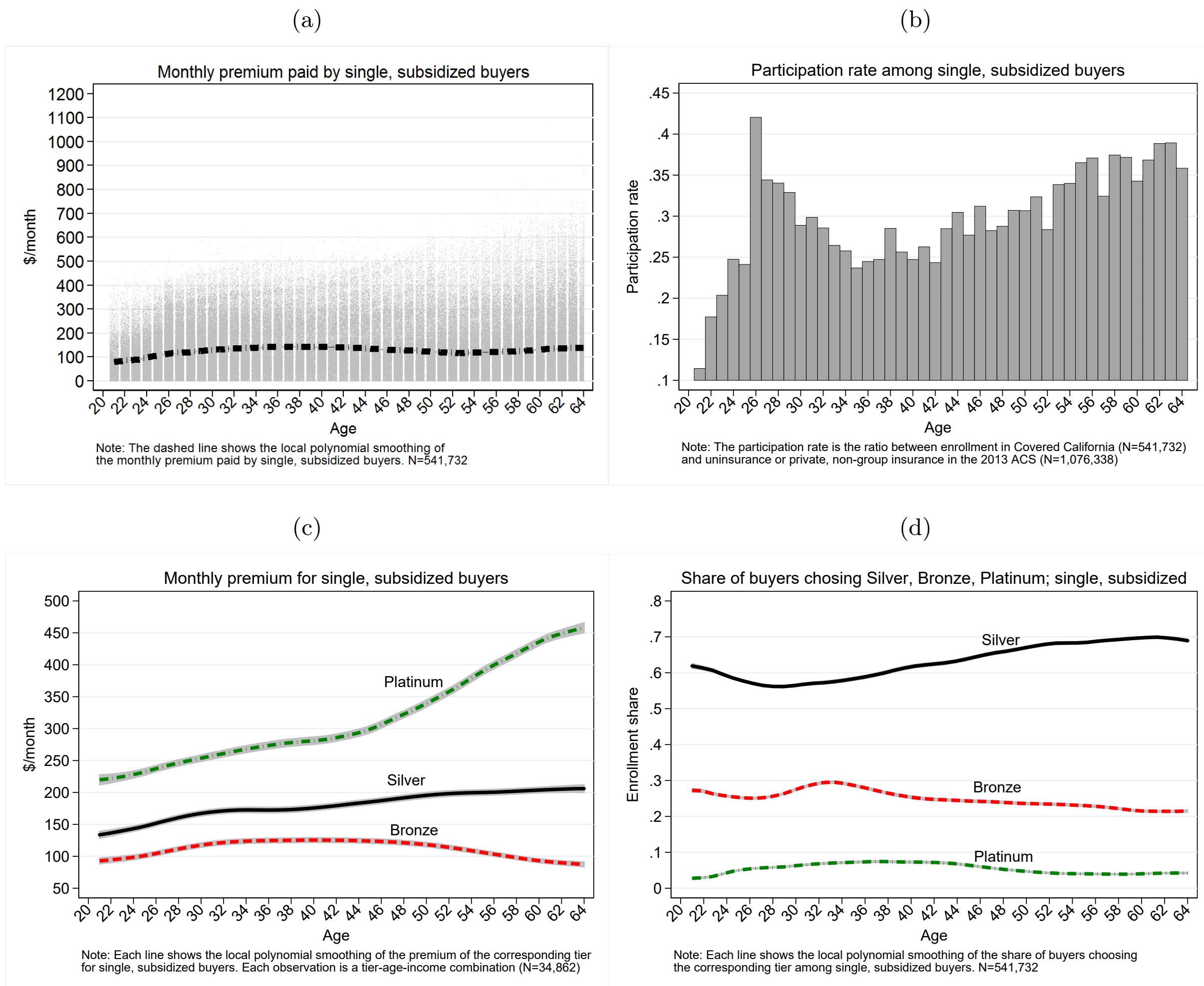
Table 4: **Prices and participation by age and income**

	Average premium for subsidized buyers (200-220% FPL, $1,000)									
	(a): **Singles**					(b): **Non-singles**				
	Coverage level					Coverage level				
Average age of household members	Catastr.	Bronze	Silver	Gold	Platinum	Catastr.	Bronze	Silver	Gold	Platinum
10-30	n.a.	1.137	1.661	2.068	2.440	n.a.	0.922	2.542	3.967	5.205
30-50	n.a.	0.758	1.691	2.383	3.027	n.a.	0.472	2.525	4.246	5.701
50-64	n.a.	0.370	1.788	3.132	4.346	n.a.	0.340	2.333	4.664	7.208
	Average premium for non-subsidized buyers ($1,000)									
	(c): **Singles**					(d): **Non-singles**				
	Coverage level					Coverage level				
Average age of household members	Catastr.	Bronze	Silver	Gold	Platinum	Catastr.	Bronze	Silver	Gold	Platinum
10-30	1.706	1.922	2.473	2.921	3.298	3.748	7.593	9.347	10.915	12.000
30-50	2.355	3.165	4.111	4.846	5.492	4.922	9.862	13.285	13.991	15.276
50-64	n.a.	6.031	7.825	9.275	10.548	n.a.	12.081	15.750	18.014	20.247
	Participation in Covered California									
	(e): **Share purchasing coverage**					(f): **Potential buyers (N. of households)**				
	Income as % of FPL					Income as % of FPL				
Average age of household members	100-150	150-200	200-250	250-400	>400	100-150	150-200	200-250	250-400	>400
10-20	0.229	0.219	0.221	0.230	0.090	225,829	373,035	217,675	328,536	205,913
30-50	0.324	0.479	0.456	0.264	0.051	321,737	500,973	320,667	547,571	610,134
50-64	0.433	0.616	0.715	0.389	0.070	154,487	278,310	160,273	268,210	648,193

buyers — key for demand estimation —, panel (a) of Figure 3 plots the premium paid by single, subsidized buyers (vertical axis) against the buyer's age (horizontal axis). The dashed line shows that the average monthly premium is approximately constant across ages. This confirms that, when deciding to participate, subsidized buyers spend on average the same amount. Yet, panel (b) shows again that such participation decision (ratio of enrollees in Covered CA to potential buyers in the ACS) is not constant in age, in particular it is steadily increasing between mid-30 and 64. This fact suggests that, on average, older buyers are more willing to pay for coverage than their younger counterparts. (Between the ages of 20 and 34 the relationship between age and participation is not monotonic. This is likely due to buyers receiving support from their parents, as suggested by the peak of participation at 26; this is the age at which dependents cannot be enrolled in the same plan as their parents.)

Considering only participating buyers, panel (c) of Figure 3 plots the monthly premium paid by single, subsidized buyers of different ages for Bronze, Silver, and Platinum plans. Enrolling in a Platinum plan rather than a Silver plan costs a 30-years-old an extra $75/month, while this difference increases to $250/month for a 60-years-old. Conversely, downgrading coverage from Silver

Figure 3: Prices and choices for single, subsidized in 2014 Covered California



to Bronze would save a 30-years-old \$50/month, while more than \$100/month for a 60-years-old. If preferences for insurance were not affected by age, these price differences would impact the shares of buyers choosing different tiers. Yet, as shown in panel (d) the share of buyers choosing Platinum coverage is approximately constant in age, and the share of those choosing to downgrade to Bronze coverage is decreasing in age. This is suggestive that, on average, older buyers are more willing to pay for more generous coverage.

Market structure. Beside prices, population, and enrollment, I will also include in my analysis variation in the combination of participating insurers and resulting distribution of market shares. The number of insurers goes from three to six, for a total of eleven participants. Four are large players — Anthem, Blue Shield, HealthNet, and Kaiser —, operating almost everywhere in the state. The remaining seven are smaller, local insurers offering coverage only in a small number of regions. Insurers are differentially attractive in different regions and for different income groups, as I summarize in Table 5. Among the four largest carriers, each captures on average between 15-36% of subsidized buyers. Yet these shares range from a minimum of 10% to a maximum of 30% for HealthNet, 50% for Kaiser and Blue Shield, and over 90% for Anthem, the largest insurer in Covered California.

Table 5: **Average market share by insurer in 2014 Covered California**

		Market share : Subsidized buyers				Market share : Unsubsidized buyers			
Carrier name	N. regions	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Anthem	19	0.363	0.229	0.070	0.909	0.426	0.211	0.100	0.908
Blue Shield	19	0.292	0.131	0.086	0.525	0.226	0.074	0.086	0.352
Kaiser	18	0.209	0.164	0.005	0.511	0.213	0.121	0.006	0.444
HealthNet	13	0.147	0.155	0.010	0.354	0.159	0.066	0.037	0.241
Molina	4	0.021	0.028	0.003	0.063	0.022	0.034	0.001	0.073
Chinese C.H.	2	0.223	0.151	0.116	0.330	0.052	0.025	0.034	0.070
LA Care	2	0.086	0.029	0.066	0.106	0.144	0.019	0.131	0.158
Western	2	0.029	0.017	0.017	0.041	0.075	0.033	0.052	0.098
Sharp	1	0.090	0.000	0.090	0.090	0.224	0.000	0.224	0.224
Valley	1	0.028	0.000	0.028	0.028	0.034	0.000	0.034	0.034
Conta costa	1	0.027	0.000	0.027	0.027	0.029	0.000	0.029	0.029

The comparison between market shares within subsidized to those within high-income buyers suggests that preferences for insurers may vary by income group. For example, while Anthem has, on average, a share of high-income buyers of approximately 43%, within subsidized this drops to 36%. In contrast, a similar difference is “gained” in the opposite direction by Blue Shield, whose share within low-income, subsidized buyers is 6% higher than within high-income. Part of these differences in the success of large insurers can be explained by the role played by small local insurers. For instance, Chinese Community Health Plan captures 33% of low-income buyers in San Francisco region 4, and 12% in San Mateo region 8; within high-income, however, this number drops to less than 7% in both regions. The opposite pattern is also observed, with Sharp — a local insurer in San Diego — enrolling 9% of low-income buyers, while 23% of buyers who pay their premiums in full.

4 Econometric model

4.1 Primitives

Markets, insurers, and products. There are R geographic markets (regions), indexed by $r = 1, ..., R$. In each r, a population of households is offered J health insurance plans by N

insurers, indexed by $n = 1, ..., N$.[20] For each n, $J_n \subset J$ is the set of products offered by n, and with a slight abuse of notation $n(j)$ will denote the seller of product j.

Households. A potential buyer i in region r is defined by a tuple $(\tau^i, y^i, h^i, v^i, c^i)$; superscripts are used throughout to index buyers (households), while subscripts index regions, insurers, and products.

The triplet $(\tau^i, y^i, h^i) \in \mathcal{T} \times Y \times \mathcal{H}$ (all finite sets) denotes age, income, and composition of household i, and it is observed by all agents. Preferences of a buyer are instead unobserved by sellers, and are described by the vector $v^i = (v^i_1, ..., v^i_J) \in \mathbb{R}^J$. This collects i's willingness to pay for each of the J products relative to the outside option $j = 0$. For buyers of type (τ, y, h), $P^{\tau,y,h}_r = (P^{\tau,y,h}_{1r}, ..., P^{\tau,y,h}_{Jr})$ denotes the "price vector" of differences between the price of each j and the price of the outside option (e.g. tax penalty for lack of insurance). Hence, i chooses j when $v^i \in \mathcal{D}_j(P^{\tau^i,y^i,h^i}_r)$, where

$$\mathcal{D}_j(P^{\tau^i,y^i,h^i}_r) = \left\{ v \in \mathbb{R}^J : \underset{k \in J}{\operatorname{argmax}} \left\{ v_k - P^{\tau^i,y^i,h^i}_{kr} \right\} = j \text{ , and } v_j \geq P^{\tau^i,y^i,h^i}_{jr} \right\}. \tag{7}$$

Note that I abstract away from how each v^i could be derived from a more primitive model of choice under uncertainty (see Einav et al., 2013, for an example of this derivation with CARA preferences).

The last element characterizing i, $c^i = (c^i_1, ..., c^i_J) \in \mathbb{R}^J_+$, collects the costs that each insurer expects to bear if i enrolls in a given product. That is, c^i_j is equal to the amount that the seller of j expects to spend to reimburse the health services of i under insurance policy j during the coverage period. Differences in c^i_j across j may reflect different underlying contracts with health providers, differences in administrative costs, differences in the generosity of coverage, or differences in expected utilization of health services.

Population. In every region, the composition of potential buyers is observed, with $G_r(\tau, y, h) \geq 0$ denoting the number of households with type (τ, y, h) in region r. Additionally, conditional on (τ, y, h), preferences and cost of buyers in region r are distributed according to the continuous density $\widetilde{f}_r(v^i, c^i|\tau, y, h)$.

Rather than the entire joint distribution $\widetilde{f}_r$, the two relevant primitives that I will focus on throughout are the marginal density of preferences conditional on household type:

$$f_r(v^i|\tau, y, h) = \int_{\mathbb{R}^J_+} \widetilde{f}_r(v^i, c^i|\tau, y, h)\, \mathrm{d}c^i, \tag{8}$$

and the vector of expected costs for each j in region r conditional on household's type and prefer-

[20] Having an equal number of insurers and products across regions is a simplification to keep notation uncluttered, this does not affect the empirical application.

ences:

$$\psi_r(v,\tau,y,h) \equiv \int_{\mathbb{R}^J_+} c^i \cdot \frac{\widetilde{f}_r(v,c^i|\tau,y,h)}{f_r(v|\tau,y,h)}\,\mathrm{d}c^i = E\left[c|r,v,\tau,y,h\right]. \tag{9}$$

In words, $\psi_{jr}(v,\tau,y,h)$ is the insurer's expected cost when covering under plan j a household of type (τ,y,h) and preferences v in region r.

Demand. The function $\sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h})$ denotes the probability that a household of type (τ,y,h) purchases j when the prices are $P_r^{\tau,y,h}$. Using the above notation this can be expressed as

$$\sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h}) \equiv \int_{\mathcal{D}_j(P_r^{\tau,y,h})} f_r(v^i|\tau,y,h)\,\mathrm{d}v^i. \tag{10}$$

4.2 Observables

The econometrician observes, for all products (j) in all regions r, the base price b_{jr}, the product characteristics (metal tier and insurer) z_j, and the realized average cost C_{jr}.

For every household i, observables include the characteristics (τ^i, y^i, h^i) and the plan selection $S^i \in \{0,1,...,J\}$, where $j=0$ denotes the outside option (no purchase). From above, for each household in region r:

$$\Pr\left[S^i = j\right] = \sigma_{jr}^{\tau^i,y^i,h^i}(P_r^{\tau^i,y^i,h^i}) \quad \text{for} \quad j>0. \tag{11}$$

4.3 Functional form and other assumptions

Finite-types mixed-logit. The following structure for preferences (similar to Berry, Carnall, and Spiller, 1996; Train, 2008) is assumed throughout:

$$v_j^i = \alpha^i z_{jr}^{y^i} + \xi_{n(j)r}^i + \varepsilon_{jr}^i, \tag{12}$$

where $(\alpha^i,\xi^i) \sim P_r(\alpha,\xi|\tau^i,y^i,h^i)$, with finite support, and ε_j^i ~Type I extreme value. The vector α^i collects the parameters on the observable product characteristics, while ξ^i collects the valuations for the insurer-region specific unobservables. The natural interpretation for this is the money-metric valuation for the network of medical providers offered by insurer $n(j)$ in region r.

If $P_r(\alpha,\xi|\tau^i,y^i,h^i)$ is degenerate and constant across regions, this model is equivalent to a standard multinomial logit with (τ,y,h)-specific parameters and insurer-region fixed effects. Importantly, in this case the unobservable term $\xi_{n(j)r}$ would affect willingness-to-pay for product j equally for all households. In the mixed-logit specification, however, households with the same observable characteristics are allowed to have different taste for coverage generosity but also different preferences for provider networks; Ho and Lee (2016) provide evidence supporting this.

Conditional on (α, ξ), the probability that household i chooses j in r is

$$\Pr\left[S^i = j|\alpha, \xi\right] = \frac{\exp\left[-P_{jr}^{\tau^i, y^i, h^i} + \alpha z_j^{y^i} + \xi_{n(j)r}\right]}{1 + \sum_k \exp\left[-P_{kr}^{\tau^i, y^i, h^i} + \alpha z_k^{y^i} + \xi_{n(k)r}\right]}, \tag{13}$$

and the age-income-household specific demand function can be re-written as:

$$\sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h}) = \sum_{\alpha,\xi} P_r(\alpha, \xi|\tau, y, h) \cdot \Pr\left[S^i = j|\alpha, \xi\right]. \tag{14}$$

To model unobserved heterogeneity, in every region (α, ξ) can take four distinct values, and each point in the support (α_{kr}, ξ_{kr}), $k = 1, ..., 4$, realizes with probability

$$P_r(\alpha_{kr}, \xi_{kr}|\tau, y, h) = \frac{\exp\left[\delta_{0r}^k + \delta_{1r}^k \tau + \delta_{2r}^k y + \delta_{3r}^k h\right]}{\sum_{\ell=1}^4 \exp\left[\delta_{0r}^\ell + \delta_{1r}^\ell \tau + \delta_{2r}^\ell y + \delta_{3r}^\ell h\right]}, \quad k = 1, 2, 3, 4, \tag{15}$$

with $\delta_{0r}^1 = \delta_{1r}^1 = \delta_{2r}^1 = \delta_{3r}^1 = 0$. The likelihood function in region r is then

$$\mathcal{L}(\alpha_r, \xi_r, \delta_r) = \prod_i \left(\sum_{k=1}^4 P_r(\alpha_{kr}, \xi_{kr}|\tau^i, y^i, h^i) \cdot \Pr\left[S^i = j|\alpha_{kr}, \xi_{kr}\right]\right), \tag{16}$$

and the region-specific parameters $(\alpha_r, \xi_r, \delta_r)$ can be estimated via EM-Maximum Likelihood (Train, 2008); this can be implemented using the command *lclogit* in Stata®, see Pacifico (2013).

Costs. For every buyer, the ex-post realized cost covered by the insurer, say $\widetilde{c}_j^i$, is the sum of its expectation c_j^i and an idiosyncratic error term κ_j^i, independent from other variables (both observed and unobserved).

Importantly, I assume that c_j^i and the idiosyncratic preference shock ε_j^i are independent. This is key to my argument for identification of cost without observing individual-level claims data. In particular, this implies that $\psi_r(v, \tau, y, h) = E\left[c|r, v, \tau, y, h\right] = E\left[c|r, \alpha, \xi, \tau, y, h\right]$.

Lastly, the cost function varies across products, insurers, and markets, as a function of product characteristics z_{jr} and demand parameters: $\psi_{jr}(\alpha, \xi, \tau, y, h) = \psi(\alpha, \xi, \tau, y, h, z_{jr})$.

Together, these three assumptions imply that

$$C_{jr} = \kappa_{jr} + \sum_{\tau,y,h,\alpha} \psi(\alpha, \xi, \tau, y, h, z_{jr}) \frac{G_r(\tau, y, h) P_r(\alpha, \xi|\tau, y, h) \cdot \sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h}; \alpha, \xi)}{\sum_{\tau,y,h} G_r(\tau, y, h) \sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h})}, \tag{17}$$

where $E[\kappa_{jr}] = 0$. In my main specification I will set $\psi(\alpha, \tau, y, h, z_{jr}) = \beta^\alpha \alpha + \beta^\tau \tau + \beta^y y + \gamma z_{jr}$, allowing cost to vary with the buyer's age, income, willingness-to-pay for low-deductible, and insurer, coverage level, and region fixed-effects.

5 Identification

Demand. Identification of demand relies on the observability of individual-level choices and demographics, and on the institutional details of Covered Calfornia. Within a region, all buyers face identical choice sets, and, most importantly, the unobservable characteristics of these products (where a primary concern arises from the unobservability of provider networks) are equal for all buyers within a rating region. At the same time, prices and the observed financial generosity of Silver plans vary significantly across households within a region, but this is not the result of supply-side decisions, but rather the consequence of rating regulations, premiums subsidies, and cost sharing subsidies.

This is then a unique setting in which one does not need to rely on regional variation in prices (which could be driven by differences in providers, or properties of demand or cost across regions) to identify the parameters of the demand system. Instead, the variation in prices within the level at which insurers engage in supply-decisions is sufficient to identify demand region-by-region, estimating directly the insurer-region specific (unobservable) fixed-effect. This closely resembles the strategy adopted by Ho and Pakes (2014); Geruso (2016), and relates to the approach originally introduced by Chamberlain (1980).

The main intuition can be seen easily in the simple multinomial logit case, where for a household with characteristics (τ, y, h) the indirect utility from purchasing a plan is in which one has $\alpha_r^{\tau,y,h}$ being the collection of demand parameters for a given household type, and $\xi_{n(j)r}$ being the insurer-region specific unobservable that is potentially correlated with the base price b_{jr}. Given a pair of competing products j and k one has:

$$\ln\left(\frac{\Pr[S^i = j|\tau, y, h, r]}{\Pr[S^i = k|\tau, y, h, r]}\right) = -\left(P_{jr}^{\tau,y,h} - P_{kr}^{\tau,y,h}\right) + \alpha_r^{\tau,y,h}\left(z_j^y - z_k^y\right) + \xi_{n(j)r} - \xi_{n(k)r}. \tag{18}$$

The empirical analog of the left-hand side is observed for all j, all k, and all (τ, y, h). Then, one can consider a second type (τ', y', h') and express the difference $\left(\alpha_r^{\tau,y,h} - \alpha_r^{\tau',y',h'}\right)$ as a function of only observables, cancelling out the unknown term $\xi_{n(j)r} - \xi_{n(k)r}$. Moreover, when the two products are offered by the same insurer, $n(j) = n(k)$, the above expression can be used directly to obtain the parameters $\alpha_r^{\tau,y,h}$. These are then identified exploiting only within-region variation.

In the richer setting in which (α, ξ) are drawn from $P_r(\alpha, \xi|\tau, y, h)$ two main assumptions are relaxed. First, independence from irrelevant alternatives (IIA) imposed by the standard-logit framework does not need to hold. Second, the model allows different households to have a different valuation for the unobserved insurer-region specific provider network.

As discussed in Berry, Carnall, and Spiller (1996), the variation underlying the identification of heterogeneity in demand parameters within similar demogrpahic groups consists of violations of IIA in the data when similar consumers face different prices (because of age-rating and subsidies) and/or different generosity of coverage for otherwise similar prices (due to the discontinuities in actuarial value induced by the cost-sharing subsidies). In particular, the standard logit framework — imposing IIA — requires that the values of (α, ξ) calculated comparing choice probabilities of Bronze and Silver plans are equal to those calculated comparing choice probabilities of Bronze and Platinum plans. When this is not the case, the residual variation in choice probabilities is informative about heterogeneity in preferences within each group.

Importantly, the functional form restriction on the way in which $P_r(\alpha, \xi|\tau, y, h)$ varies with household demographics also plays a role. If this was fully unrestricted preferences could not be identified, as there would be no variation left in prices within region and (τ, y, h) combination. Instead, I assume that the distribution of (α, ξ) evolves according to (15), a smooth and continuous function. Then, while the variation in choices and prices within similar demographics (e.g. 20-22-year-olds, single, with the same income) identifies the distribution of (α, ξ) within this group, the way in which this differs over the entire support of (τ, y, h) identifies the parameters δ, hence $P_r(\alpha, \xi|\tau, y, h)$.

Cost. A more critical challenge for identification of the model's primitives is that, differently from a market without selection, costs for insurers may not only vary by product, but also with the characteristics of the buyer. My approach here formalizes the conditions for identification of cost heterogeneity in this context, leveraging on the availability of plan-level cost information (as in Bundorf, Levin, and Mahoney, 2012). In Appendix I also provide a formal argument for identification on cost when no cost data are available, leveraging on supply-side assumptions (as in Lustig, 2010, and a previous version of this paper).

When demand is identified, the functions $P_r(\alpha, \xi|\tau, y, h)$, and $\Pr\left[S^i = j|\alpha, \xi\right]$ are known. Therefore, the expression in (17) is known up to κ_{jr} and the cost function $\psi(\alpha, \xi, \tau, y, h, z_{jr})$, which enters linearly on the right-hand side. Letting M be the dimensionality of the cartesian product $\text{supp}(\alpha, \xi) \times \mathcal{T} \times Y \times \mathcal{H}$. A set of sufficient conditions for identification of $\psi(\cdot, \cdot, \cdot, \cdot, z_{jr})$ is the following:

1. There are at least M products for which $z_{jr} = z$, for some z;
2. Within these products, the matrix in which: a row is a product j, a column is a combination $(\alpha, \xi, \tau, y, h)$, and each entry is the term

$$\frac{G_r(\tau, y, h) P_r(\alpha, \xi|\tau, y, h) \cdot \sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h}; \alpha, \xi)}{\sum_{\tau,y,h} G_r(\tau, y, h) \sigma_{jr}^{\tau,y,h}(P_r^{\tau,y,h})} \tag{19}$$

   is full-column-rank.

Under these conditions, regressing C_{jr} on the collection of (19) for all $(\alpha, \xi, \tau, y, h)$ for the group of products for which $z_{jr} = z$ returns the function $\psi(\cdot, \cdot, \cdot, \cdot, z)$.

Intuitively, the above conditions require that, within groups of products that have the same characteristics, there is a varying composition of enrollment in terms of observable buyers' characteristics and preferences for insurance. This can be driven by changes in the set of competitors, competitors' prices, or characteristics of the population in the market.

In practice, conditions 1 and 2 above can be very demanding, but one can combine the same intuition with a parametrization of ψ and a similar identification strategy follows. For instance, one may let

$$\psi(\alpha, \xi, \tau, y, h, z_{jr}) = \beta^{\alpha}\alpha + \beta^{\xi}\xi + \beta^{\tau}\tau + \beta^{y}y + \beta^{h}h + \gamma z_{jr}.$$

Then the expression in (17) simplifies to

$$C_{jr} = \kappa_{jr} + \gamma z_{jr} + \beta^{\alpha}\overline{\alpha}_{jr} + \beta^{\xi}\overline{\xi}_{jr} + \beta^{\tau}\overline{\tau}_{jr} + \beta^{y}\overline{y}_{jr} + \beta^{h}\overline{h}_{jr}, \tag{20}$$

where $\overline{\alpha}_{jr}$ is the average α among buyers of j in r, and similarly for ξ, τ, y, and h. Here the condition for identification of γ and β is that the matrix collecting $(z_{jr}, \overline{\alpha}_{jr}, \overline{\xi}_{jr}, \overline{\tau}_{jr}, \overline{y}_{jr}, \overline{h}_{jr})$ is full-column rank, requiring again variation in the composition of buyers in terms of preferences and observables after controlling for product characteristics.

6 Estimates with Covered California data

6.1 Demand

6.1.1 Logit

I start by showing estimates from a simple logit and nested logit models, in which I do not allow for unobserved heterogeneity in preferences.

Table 6 shows estimates of a standard logit with the sensitivity to premium varying with household demographics and various sets of fixed-effects. Following the derivation in Berry (1994) the estimating equation is

$$\ln\left(\frac{s_{jr}^{\tau,y,h}}{s_{0r}^{\tau,y,h}}\right) = -(\alpha^{\tau} + \alpha^{h} + \alpha^{y})P_{jr}^{\tau,y,h} + \beta AV_{j}^{y} + \xi_{n(j)r}^{0-49}\mathbf{1}[\tau < 50] + \xi_{n(j)r}^{50-64}\mathbf{1}[\tau \geq 50] + \epsilon_{jr}^{\tau,y,h}, \tag{21}$$

in which $s_{jr}^{\tau,y,h}$ denotes the share of households with demographics (τ, y, h) choosing j in region r. AV_{j}^{y} is the actuarial value of contract j (varying with the household's income), and the terms in ξ collect the insurer-region specific unobservables (network of providers). These are allowed to differ for households with average age below 50 and above 50. The error term $\epsilon_{jr}^{\tau,y,h}$ is assumed to be mean zero conditional on P, AV, and ξ.

The estimates in Table 6 show a large degree of heterogeneity in sensitivity to premium across households with different age, and composition, reflecting the variation in the data presented in

Table 6: **Standard logit estimates, equation (21)**

	$\ln(s_{jr}^{\tau,y,h}) - \ln(s_{0r}^{\tau,y,h})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Premium coefficient, all buyers							
Premium ($1,000)	-0.14***		-0.16***		-0.16***		
	(0.0067)		(0.0072)		(0.0072)		
Premium coefficient, single subsidized							
Premium ($1,000) $\times Age \in [10, 19)$		-0.37***		-0.45***		-0.44***	-0.40***
		(0.040)		(0.029)		(0.031)	(0.031)
Premium ($1,000) $\times Age \in [20, 29)$		-0.43***		-0.51***		-0.49***	-0.46***
		(0.034)		(0.021)		(0.023)	(0.023)
Premium ($1,000) $\times Age \in [30, 39)$		-0.40***		-0.47***		-0.45***	-0.42***
		(0.029)		(0.020)		(0.020)	(0.021)
Premium ($1,000) $\times Age \in [30, 49)$		-0.35***		-0.41***		-0.40***	-0.37***
		(0.023)		(0.015)		(0.016)	(0.016)
Premium ($1,000) $\times Age \in [50, 59)$		-0.24***		-0.28***		-0.27***	-0.37***
		(0.019)		(0.013)		(0.014)	(0.019)
Premium ($1,000) $\times Age \in [60, 64]$		-0.17***		-0.21***		-0.19***	-0.28***
		(0.017)		(0.013)		(0.014)	(0.015)
Difference in premium coefficient, other groups							
Non-subsidized		-0.047***		-0.048***		-0.051***	-0.047***
		(0.0090)		(0.0078)		(0.0083)	(0.0082)
Household of 2		0.076***		0.098***		0.090***	0.11***
		(0.017)		(0.013)		(0.013)	(0.013)
Household of 3		0.21***		0.25***		0.24***	0.23***
		(0.026)		(0.019)		(0.019)	(0.018)
Household of 4		0.31***		0.36***		0.35***	0.34***
		(0.032)		(0.023)		(0.023)	(0.023)
Household of 5		0.34***		0.40***		0.39***	0.37***
		(0.035)		(0.025)		(0.025)	(0.025)
Actuarial value (%)	-0.0023**	0.0026**	-0.0021*	0.0044***	-0.0032**	0.0030**	0.0027**
	(0.0010)	(0.00094)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Insurer FE	N	N	Y	Y	N	N	N
Region FE	N	N	Y	Y	N	N	N
Insurer×Region FE	N	N	N	N	Y	Y	N
Insurer×Region×over-50 FE	N	N	N	N	N	N	Y
Observations	26521	26521	26521	26521	26521	26521	26521
Adjusted R^2	0.115	0.215	0.202	0.325	0.234	0.350	0.373

Standard errors in parentheses, clustered at the region level (19 clusters).
An observation corresponds to a unique combination of (insurer-tier-region-age-income-household size).
* $p < .1$, ** $p < .05$, *** $p < .01$

Section 3. In the most conservative specification — column (7) with insurer-region fixed effects allowed to differ for households with average age higher than 50 — the premium (in \$1,000/year) coefficient decreases from -0.40 for the younger households, to -0.28 for the older ones. Moreover, huseholds with children have a higher willingness to pay, ceteris paribus.

Interpreting this estimates, one can calculate the willingness-to-pay for a 20% increase in actuarial value; this corresponds to an increase in coverage from Bronze to Gold, or a reduction in deductible from \$5,000 to \$0. This number goes from approximately \$300/year for younger-than-45 households, to \$700/year for households whose members are, on average, older than 60. Without allowing for richer heterogeneity, these estimates are likely to present a severe bias toward zero, driven by the imposition of IIA with a large fraction of households choosing to stay out of the exchange. The richer specifications I consider next relax this assumption.

6.1.2 Nested logit

Next I consider a two-groups nested logit model, in which households first decide whether to participate or not, then which plan to purchase. As discussed in Berry (1994), this is equivalent to allowing for a random coefficient on the value of the outside good, imposing IIA for products in the exchange but not between these products and the choice to not purchase coverage. I let ζ denote the nesting parameter, which represents the correlation between the utility of alternative options inside the market. As ζ goes to one, households would only choose whether or not to purchase, but would be completely indifferent between different alternatives. As ζ goes to zero, the model is equivalent to the standard logit presented above.

The estimating equation is:

$$\ln\left(\frac{s_{jr}^{\tau,y,h}}{s_{0r}^{\tau,y,h}}\right) = -(\alpha^{\tau}+\alpha^{h}+\alpha^{y})P_{jr}^{\tau,y,h}+\beta AV_{j}^{y}+\xi_{n(j)r}^{0-49}\mathbf{1}[\tau<50]+\xi_{n(j)r}^{50-64}\mathbf{1}[\tau\geq 50]+\zeta\ln(s_{jr|IN}^{\tau,y,h})+\epsilon_{jr}^{\tau,y,h}, \tag{22}$$

in which $s_{jr|IN}^{\tau,y,h}$ denotes the share of buyers with characteristics (τ, y, h) choosing j in r conditional on choosing some product in the market ($j \neq 0$).

I show the resulting estimates in Table 7. In the more conservative specification in column (7) the nesting parameter is 0.48, confirming that the choice data reveals a significant departure from IIA: the substitution patterns between inside products are different from the substitution between these products and the outside good.

This first relaxation of IIA immediately affects the estimates of premium coefficients and the resulting quantification of willigness-to-pay for coverage. For all demographics, the estimated premium coefficient is lower than in the standard logit model. This is now equal to -0.30 for the younger households, and decreases to -0.20 for the older ones. At the same time, allowing a flexible substitution pattern between outside option and products in the exchange leads a larger estimate

Table 7: **Nested logit estimates, equation (22)**

	$\ln(s_{jr}^{\tau,y,h}) - \ln(s_{0r}^{\tau,y,h})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Premium coefficient, all buyers							
Premium (\$1,000)	-0.14***		-0.16***		-0.16***		
	(0.0068)		(0.0077)		(0.0076)		
Premium coefficient, single subsidized							
Premium (\$1,000) $\times Age \in [10,19)$		-0.26***		-0.33***		-0.34***	-0.30***
		(0.037)		(0.031)		(0.032)	(0.032)
Premium (\$1,000) $\times Age \in [20,29)$		-0.29***		-0.36***		-0.37***	-0.33***
		(0.032)		(0.023)		(0.024)	(0.024)
Premium (\$1,000) $\times Age \in [30,39)$		-0.25***		-0.32***		-0.32***	-0.29***
		(0.028)		(0.022)		(0.022)	(0.023)
Premium (\$1,000) $\times Age \in [40,49)$		-0.22***		-0.28***		-0.28***	-0.26***
		(0.021)		(0.016)		(0.016)	(0.017)
Premium (\$1,000) $\times Age \in [50,59)$		-0.12***		-0.16***		-0.17***	-0.27***
		(0.017)		(0.014)		(0.015)	(0.020)
Premium (\$1,000) $\times Age \in [60,64]$		-0.069***		-0.11***		-0.11***	-0.20***
		(0.016)		(0.014)		(0.015)	(0.016)
Difference in premium coefficient, other groups							
Non-subsidized		-0.082***		-0.082***		-0.080***	-0.076***
		(0.0082)		(0.0082)		(0.0083)	(0.0082)
Household of 2		0.017		0.041***		0.043***	0.063***
		(0.017)		(0.014)		(0.014)	(0.014)
Household of 3		0.11***		0.16***		0.16***	0.15***
		(0.026)		(0.020)		(0.020)	(0.020)
Household of 4		0.20***		0.25***		0.25***	0.24***
		(0.033)		(0.025)		(0.025)	(0.025)
Household of 5		0.21***		0.27***		0.28***	0.26***
		(0.036)		(0.026)		(0.027)	(0.027)
Actuarial value (%)	0.0092***	0.0084***	0.0090***	0.0095***	0.0084***	0.0089***	0.0085***
	(0.00071)	(0.00096)	(0.00089)	(0.0013)	(0.00093)	(0.0013)	(0.0013)
Nesting parameter	0.60***	0.57***	0.56***	0.51***	0.54***	0.48***	0.48***
	(0.018)	(0.024)	(0.013)	(0.014)	(0.012)	(0.013)	(0.013)
Insurer FE	N	N	Y	Y	N	N	N
Region FE	N	N	Y	Y	N	N	N
Insurer×Region FE	N	N	N	N	Y	Y	N
Insurer×Region×over-50 FE	N	N	N	N	N	N	Y
Observations	26521	26521	26521	26521	26521	26521	26521
Adjusted R^2	0.318	0.386	0.352	0.434	0.354	0.437	0.459

Standard errors in parentheses, clustered at the region level (19 clusters).
An observation corresponds to a unique combination of (insurer-tier-region-age-income-household size).
* $p < .1$, ** $p < .05$, *** $p < .01$

for the value of generous coverage, with the coefficient on actuarial value increasing from 0.0027 to 0.0085. Consequently, as one would expect the estimates of willingness-to-pay for insurance are significantly larger than before. Younger households are now estimated to value a \$5,000 decrease in annual deductible approximately \$1,000/year, household with age between 40-50 approximately \$1,500/year, and the older group of households approximately \$3,000/year.

6.1.3 Mixed logit

The richer specification introduced in Section 4 imposes even weaker assumptions on substitution patterns, allows preferences for contract generosity to differ across markets, and introduces unobserved heterogeneity in preferences for contract generosity and provider networks within households with similar demographics in the same market.

To illustrate the results, here I primarily focus on the average posterior of wilingness-to-pay (in \$/year) for an increase of 20% of the actuarial value of the insurance coverage (WTP henceforth), or to reduce the annual deductible from \$5,000 to \$0. In Covered California this is equivalent to upgrading from Bronze to Gold, or from Silver to Platinum for buyers who are not eligible for cost-sharing subsidies.

Table 8: **Estimated WTP for +20% coverage (from \$5,000 to \$0 deductible)**

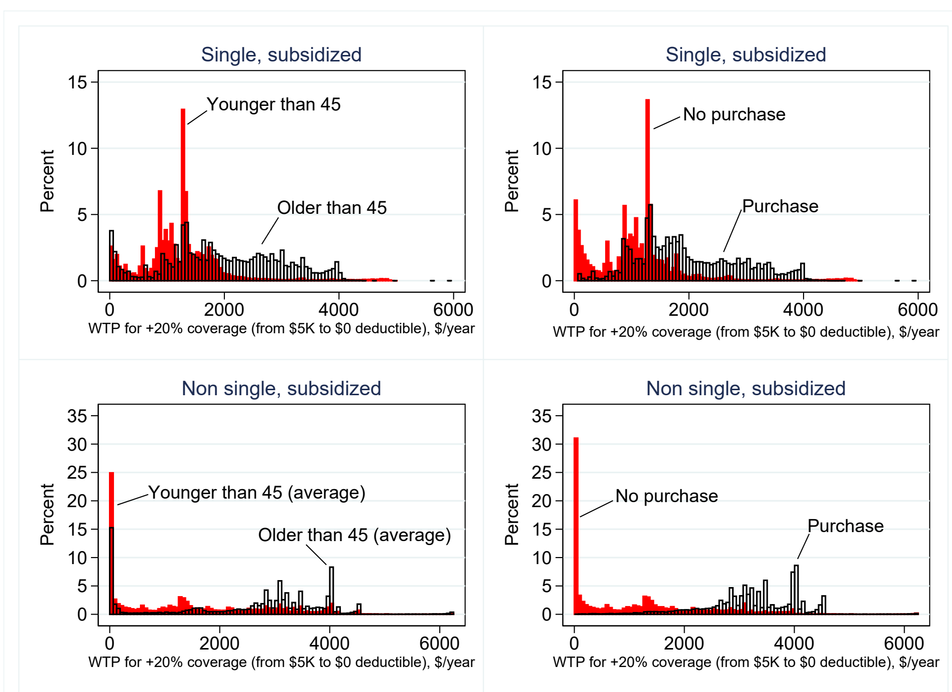
Age of household members	**Subsidized households** No purchase			Purchase in Covered CA		
	Mean	St. Dev.	Cross-region St. Dev.	Mean	St. Dev.	Cross-region St. Dev.
10-20	1,111	1,256	917	2,288	1,288	371
20-30	1,066	1,109	609	1,586	916	266
30-40	1,070	1,048	423	2,139	1,068	288
40-50	1,245	1,096	434	2,533	987	333
50-60	1,278	1,013	423	2,803	842	354
60-64	1,611	1,277	651	3,031	741	410
Insurer-Region FE		Y			Y	
	Non subsidized households No purchase			Purchase in Covered CA		
	Mean	St. Dev.	Cross-region St. Dev.	Mean	St. Dev.	Cross-region St. Dev.
10-20	405	235	210	2,924	152	131
20-30	532	210	125	2,972	196	103
30-40	600	190	118	2,926	276	98
40-50	552	177	85	2,596	634	357
50-60	634	116	21	2,691	535	230
60-64	752	71	20	2,942	210	63
Insurer-Region FE		Y			Y	

In Table 8 I summarize WTP as estimated for different groups of households, distinguishing between average age of household memebers, subsidized and not, and conditioning on the observed choice (no purchase vs. purchase in Covered California). As the table highlights I estimate that WTP is highly heterogeneous across households with different age and income, within households with the same age and income, and across regions.

Focusing on the low-income, subsidized buyers, represeting 90% of enrollees in Covered California, I find that comparatively older households are significantly more willing to pay for coverage. From \$1,600/year among 20-30-years-old households, WTP for \$0 deductible raises to \$2,800-3,000/year among households whose members are, on average, older than 50. Within each group, the standard deviation of WTP varies between \$700 and \$1,000, with 30-50% of this variation being driven by cross-region heterogeneity. The model predicts that buyers who decide not to purchase coverage have significantly lower WTP, with a difference varying between \$1,000 for the younger households and \$1,500 for the relatively older ones. For the higher-income, unsubsidized buyers this difference is estimated to be larger than \$2,000.

Figure 4 shows the estimated distribution of WTP among subsidized buyers, distinguishing between single, non-single, and highlighting differences between age groups, and differences between purchase decision. This clearly shows the large differences between these groups, and the large degree of residual heterogeneity after conditioning on choice and household age. In particular, the entire distribution of WTP is shifted to the right for older households, and for households who

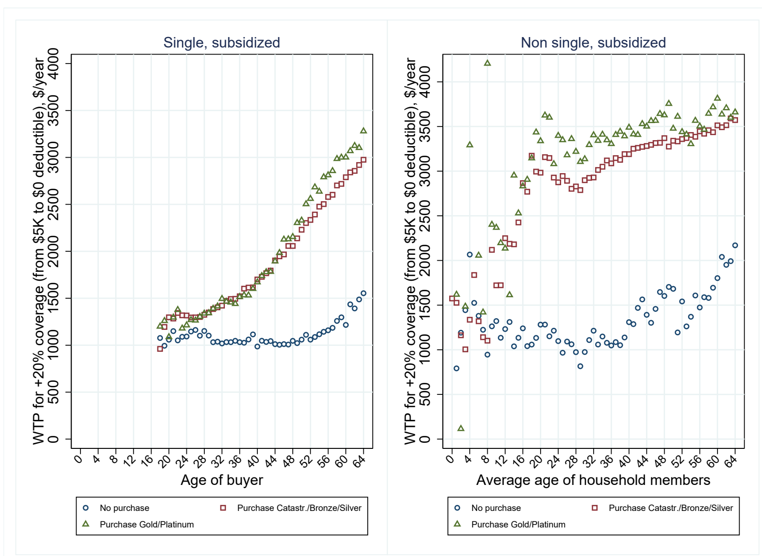
Figure 4: **Histogram of estimated WTP for +20% coverage**



chose to purchase coverage. This shift is estimated to be significantly larger for non-singles.

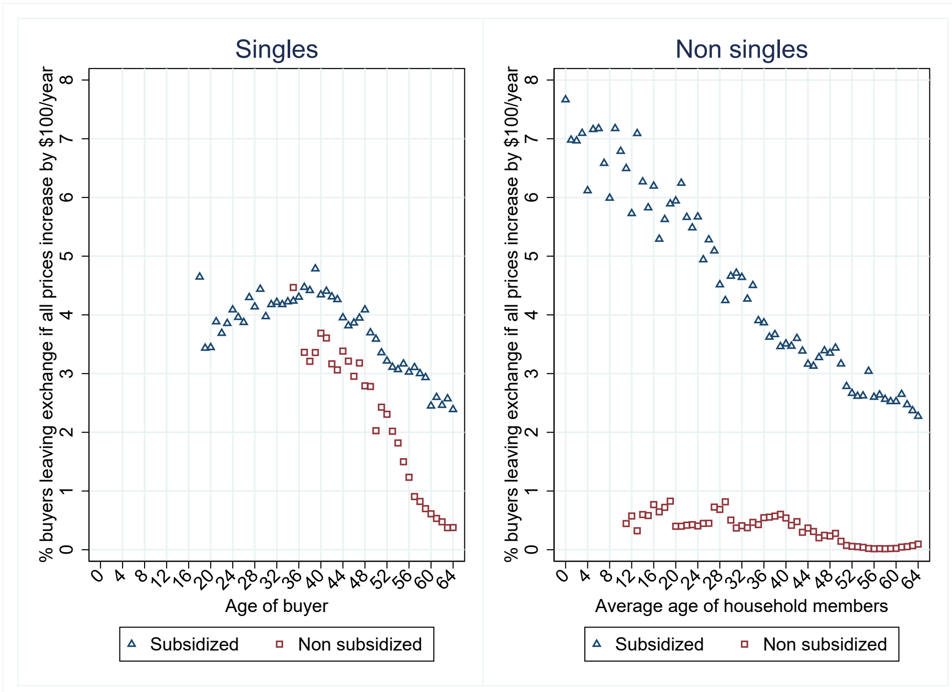
To investigate this further, in Figure 5 I plot the average WTP within each age group distinguishing between single, non single, and by coverage choice. As anticipated, older households have, on average, higher WTP, but this relationship is very different for singles and non-singles. Except for the (very few) households with exceptionally low average age (e.g. single mothers), I estimate that among non-singles who purchase coverage WTP is growing from \$3,000 for the younger households to \$3,500 for the older ones. This age-driven heterogeneity is significantly larger for single buyers, where WTP grows from less than \$1,500 to over \$3,000.

Figure 5: **Average WTP by age, household type, and coverage choice**



Essential to the analysis of the subsidy program, these estimates imply that the semi-elasticity of demand at the extensive margin, defined as total % drop in participation in the exchange due to a \$100/year increase in all premiums (equivalent to a \$100 decrease in the subsidy) is also highly heterogeneous in age. In Figure 6 I show how this varies by age and income, distinguishing again between singles and non-singles. Within each group, older households would leave the market at a slower rate if subsidies were reduced. The difference from the youngest to the oldest group is between 2% for single, subsidized (from 4.5% to 2.2%) and 5% for non-single, subsidized (from 7% to 2%). The estimated semielasticity is much lower among non-subsidized households: as discussed earlier, these are very unlikely to participate, but when doing so their are not very responsive to small price changes.

Figure 6: **Semielasticity by age, household type, and subsidy status**



6.2 Cost

Combining plan-level cost data, enrollment information, and the demand estimates described above, I obtain estimates of individual (expected) cost as a function of product, insurer, and region characteristics, but also varying with buyers' characteristics and preferences. Specifically, for any plan I regress the (log) average incurred claims on average age of buyers, average income (as % of FPL), average WTP (estimated above), actuarial value dummies, insurer dummies, and regional dummies. The results are shown in Table 9 below, where column (5) is the most comprehensive specification.

Interpreting these estimates, I find a substantial degree of heterogeneity of cost across buyers. Even after controlling for insurer, coverage level, and region fixed-effects, buyers are costlier to cover as they get older, and when they are more willing to pay for higher coverage. The magnitudes of these coefficients are robust across specifications, while this is not the case for the effect of income, vanishing when controlling for contract, insurer, and region FE.

Quantitatively, the estimated parameters indicate that, on average, a 10-years increase in average age of the enrollment pool (this number ranges from 18 to 61, with a standard deviation of 7.4) increases ceteris paribus expected average claims by 16%. Consistenly with a substantial degree of adverse selection, i.e. a positive relationship between willingness-to-pay for insurance and expected cost, a $1,000/year increase in WTP corresponds to a 20% increase in average claims.

Lastly, more generous plans have higher expected costs. In particular, the $0 deductible Plat-

Table 9: **Average cost as a function of buyers' composition and plan characteristics**

	Log Plan-level claims				
	(1)	(2)	(3)	(4)	(5)
Buyers' characteristics					
Average enrollee's age	0.058	0.029	0.017	0.014	0.016
	(0.000)	(0.000)	(0.070)	(0.076)	(0.078)
Average enrollee's income	0.004	0.004	0.001	0.000	-0.001
	(0.000)	(0.000)	(0.400)	(0.984)	(0.403)
Average enrollee's WTP for +20% actuarial value ($1,000/year)		0.441	0.216	0.215	0.195
		(0.000)	(0.002)	(0.001)	(0.021)
Product and market characteristics					
Actuarial value					
50 — Catastrophic			-	-	-
60 — Bronze			0.036	0.069	-0.004
			(0.872)	(0.718)	(0.985)
70 — Silver			0.290	0.259	0.148
			(0.304)	(0.272)	(0.593)
80 — Gold			0.582	0.622	0.573
			(0.009)	(0.001)	(0.009)
90 — Platinum			1.109	1.141	1.093
			(0.000)	(0.000)	(0.000)
Insurer FE	N	N	N	Y	Y
Region FE	N	N	N	N	Y
Obs	404	404	404	404	404
Adjusted R2	0.21	0.28	0.47	0.58	0.57

Note: Estimates obtained via OLS regression of $\ln(C_{jr})$ (columns (1)-(5)) and C_{jr} (columns (6)-(10)) on average age, income, and estimated WTP of buyers choosing j in r, actuarial value dummies, insurer and region FE. Standard errors are clustered at the region level and two-sided p-values reported in parentheses.

inum plans are for the issuer twice as costly as Bronze plans, and 80% costlier than Silver plans. Importantly for interpretation, these differences can be driven by the higher coverage for the same health-risk and utilization, but also by an increase in utilization (moral hazard). Such difference is not distinguishable in my empirical setting. Although this is not essential to study counterfactual prices and quantities under different subsidy schemes, it would be important to engage in welfare calculations. This is one of the main reasons why, although the model would allow me to do so, I choose to not discuss welfare in this paper.

7 Equilibrium under different subsidy designs [Preliminary]

Building on the theoretical insights from Section 2, and using the richer model with estimates from Covered California, I can now compare equilibrium under different designs of the subsidy program. Throughout, I will assume that insurers maximize expected profits knowing market primitives, and that base prices form a Nash equilibrium of the static pricing game.

7.1 Vouchers vs. price-linked discounts

My first comparison is between the ACA subsidy design and an "equivalent" voucher program, where buyers receive fixed discounts equal to those resulting in equilibrium under the current scheme. To start, recall that under the ACA design if base prices are b_r^{ACA} buyers receive price-linked discounts $S^{\tau,y}(b_r^{ACA})$ computed via equation (5). I compare this to the alternative design $\widehat{S}$, under which buyers receive a fixed discount ("equivalent voucher") $\widehat{S}_r^{\tau,y} = S^{\tau,y}(b_r^{ACA})$, which is *not* adjusted as insurers' pricing decisions b_r vary. Because young buyers are more price-sensitive and cheaper to cover, insurers' marginal profit functions under $\widehat{S}$ lay below marginal profit functions under S (discussion in Section 2). Therefore, even in this richer model insurers set lower base prices under the voucher scheme $\widehat{S}$ than under the ACA design, and relevant equilibrium quantities respond accordingly.

To quantify these differences I start off by computing equilibrium base prices b_r^{ACA} under the status quo subsidy design. For this, I use demand and cost estimates from Covered California, and assume that insurers use the observed age-income composition G_r to compute expected profits in each region. I then carry on the same equilibrium computation under the equivalent voucher scheme $\widehat{S}$ and compare the two equilibria in terms of enrollment by age group, average cost, average markups (difference between total per-person amount received by the insurer and average cost), and subsidy expenditure.

Table 10 reports the results of this comparison, showing that differences between the two designs are indeed sizable. In particular, under fixed vouchers equilibrium markups are 15% lower (approximately \$200 per-year). This is driven by insurers setting lower base prices, yielding to lower pre-discount premiums. At these lower premiums, because vouchers are not adjusted discounted prices are lower than under the ACA design, and enrollment is higher (+7% among under 45, and +9% for the older group). With these changes in enrollment the age-composition of buyers remains almost unaltered, and this reflects into average cost being approximately the same in the two equilibria (+1%). Markups reductions are then largely explained by a lower per-person amount received by insurers, combination of lower average subsidy provided by the government (-5%), and lower contribution paid by buyers (-11%).

Table 10: Comparison between ACA price-linked discount and vouchers

	Enrollment 20-44	Enrollment 45-64	Average cost	Average markup	Per-person subsidy	Total spending
ACA status quo levels: (endeogenous discount)	460,423	543,029	\$4,061	\$1,753	\$3,944	\$4.45 billion
Percentage change under equivalent voucher [(1)]	+7%	+9%	+1%	-15%	-5%	+3%

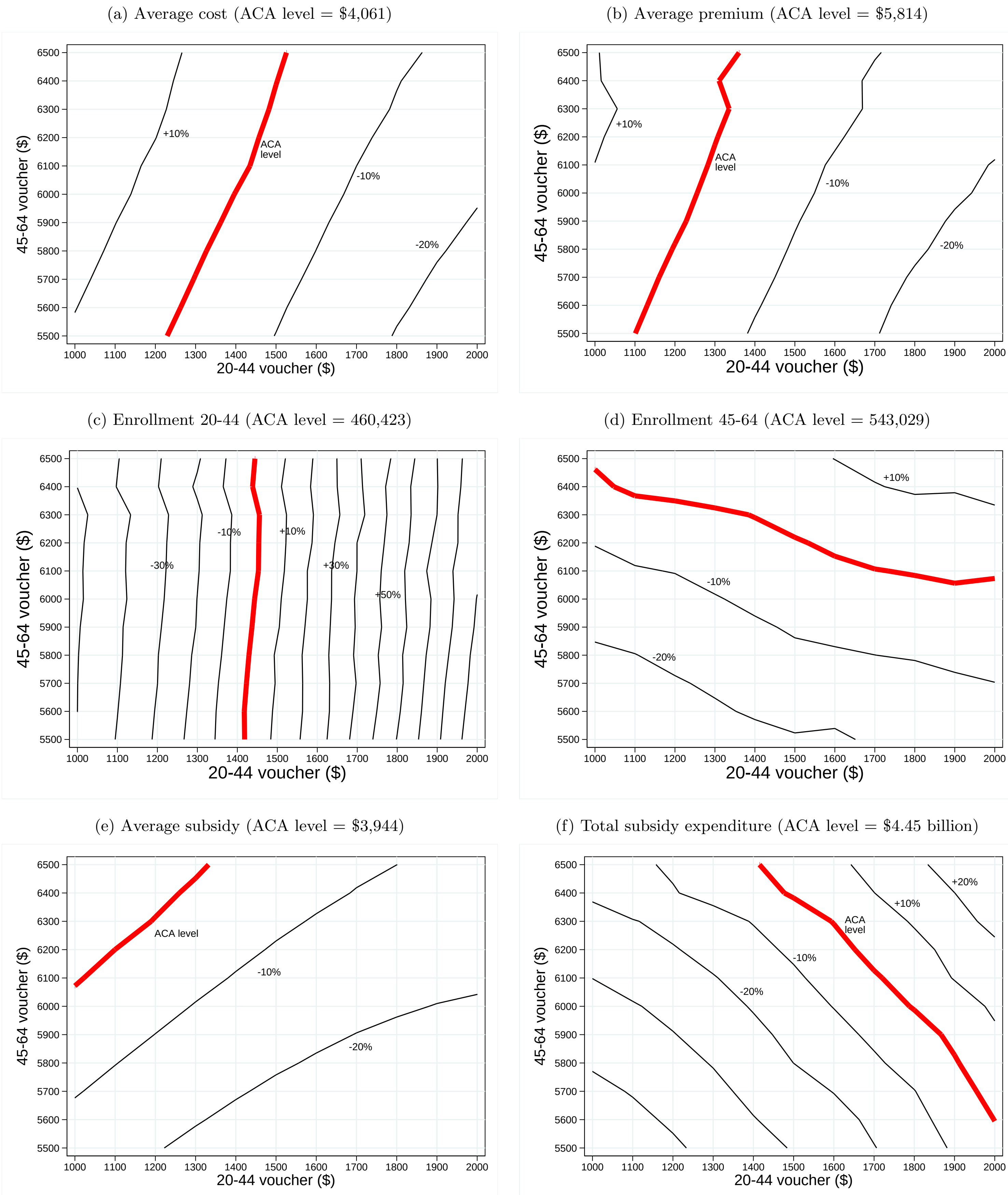
Note: Market outcomes in the simulated equilibrium under the ACA (fit of baseline model) and relative change in these outcomes in the equilibrium under a voucher program that provides, in every region, discounts equal to those resulting in equilibrium under the ACA. The average "equivalent" voucher is \$1,500 for the under 45 and \$6,500 for the over 45.

7.2 Age-adjusted vouchers

Next I quantify the difference in equilibrium outcomes induced by variations in the voucher amount across different age groups; this allows me to explore the potential gains from age-targeted subsidies. I consider fixed vouchers analogous to $\widehat{S}$, where instead of setting voucher values equal to the discounts provided under the ACA scheme, for any age group τ there is an amount $V^{\tau} > 0$ for which $\widehat{S}^{\tau} = V^{\tau}$. (I omit y from the notation since I observe only one income level in my data.) The discussion in Section 2 highlights that, within this class of subsidy schemes, reducing vouchers for the old and increasing those for the young can yield to lower average cost, higher coverage, and lower per-buyer spending. Intuitively, increasing the relative share of young buyers in enrollment pools lowers average cost and markups (by raising average elasticities), thus induces insurers to set lower prices. If this price reduction exceeds the amount by which the voucher of the older group was raised, all buyers are better off. Additionally, if the enrollment increase is sufficient to compensate the lower per-enrollee markup, also total profits are higher, so that insurers are not worse off either.

To investigate this mechanism, I simulate and report equilibrium outcomes for different pairs of voucher values $(V^{20\text{-}44}, V^{45\text{-}64})$, varying these over a two-dimensional grid of \$100 increments. In Figure 7 I plot level curves (in the space of voucher values) for equilibrium outcomes that would likely enter the government's objective: average cost, average premium received by insurers, enrollment for different age groups, and subsidy expenditure (both per-insured person and aggregate). To facilitate comparisons, for each outcome I highlight the curve corresponding to the equilibrium level under the ACA design, and each other curve corresponds to a 10% increase (or decrease) from this level. Panel (c) and (d) show how equilibrium enrollment in the two age groups varies as a function of vouchers. Because they are less price sensitive, for old buyers level curves of enrollment are significantly sparser than those of the young, corresponding to a flatter surface. In practice, a \$100 increase in $V^{20\text{-}44}$ yields to a much larger increase in enrollment among the young than the drop in enrollment among the old implied by a \$100 reduction in $V^{45\text{-}64}$. The effect of age adjustments to vouchers follows, as it is shown directly by the downward sloping curves in panel (d): one can increase $V^{20\text{-}44}$, reduce $V^{45\text{-}64}$, and obtain higher coverage for both groups, with lower cost (panel (a)) and lower per-person public spending (panel (e)).

Figure 7: Equilibrium outcomes: ACA scheme vs. age-specific vouchers



The figure shows level curves of equilibrium outcomes resulting under an age-adjusted voucher as functions of the voucher for the under 45 (x-axis) and voucher for the over 45 (y-axis). The level corresponding to the baseline ACA equilibrium (model fit) is highlighted in red, and every level curve corresponds to a 10% increase (decrease) for that level. The graph is obtained simulating equilibrium base prices — zeroing first-order conditions — as vouchers value vary over the grid in $100 increments.

In Table 11 I compare with more precision equilibrium outcomes along two level curves depicted in panel (d), with voucher values for which enrollment of the over 45 is approximately constant at either 1.08 or 1.02 times the equilibrium level under the ACA. In both situations a $400 increase in $V^{20\text{-}44}$ and a simultaneous $200 reduction $V^{45\text{-}64}$ maintain enrollment of the older group approximately invariant. At the same time, however, enrollment among under 45 increases by approximately 60%, and average cost is 10-15% lower. Since young buyers are more price-sensitive markups are also lowered, up to a 25% drop from ACA levels (approximately $448 per-person-year), and per-person public expenditure is reduced by more than 15% (or $600 per-person-year). Lastly, the large increase in enrollment compensates the reduction in per-person markup, and insurers are also better off when the markets has more young buyers; total profits go from $1.76 to $1.89 billion.

Table 11: Equilibrium outcomes under different age-adjusted vouchers

		Enrollment 20-44	Enrollment 45-64	Average cost	Average markup	Per-person subsidy	Total spending
Vouchers at which 45-64 enrollment ≈ 1.07-1.10 times the ACA level							
$V^{[20,44]}$	$V^{[45,64]}$	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)
1500$^{(1)}$	6500$^{(1)}$	1.07	1.09	1.01	0.85	0.95	1.03
1600	6500	1.22	1.10	0.98	0.83	0.93	1.08
1700	6400	1.38	1.10	0.93	0.79	0.90	1.10
1900	6300	1.70	1.07	0.87	0.79	0.85	1.16
Vouchers at which 45-64 enrollment ≈ 1.02-1.03 times the ACA level							
$V^{[20,44]}$	$V^{[45,64]}$	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)
1500	6300	1.07	1.02	0.99	0.83	0.91	0.95
1700	6200	1.40	1.03	0.91	0.79	0.86	1.03
1800	6200	1.55	1.03	0.88	0.78	0.84	1.07
1900	6100	1.75	1.02	0.84	0.76	0.82	1.10

Note: Market outcomes (relative to the ACA equilibrium in the baseline model) in the simulated equilibrium under alternative pairs of age-adjusted vouchers. Both panels show market outcomes changing as the voucher for the under 45 is raised and the voucher for the over 45 is lowered. The top panel corresponds to a level curve of over 45 enrollment equal to 102-103% of the ACA level, while the bottom panel corresponds to a level curve of over 45 enrollment equal to 107-110% of the ACA level; see also Figure 7.

7.3 ACA price-linked discounts with age-specific price caps

My results thus far suggest that the use of age-adjusted vouchers might be preferable to the current ACA scheme (price-linked discounts not tailored by age). However, price-linked discounts have the important advantage of ensuring the final price for the buyer. The government needs to know less about the determinants of insurers' and buyers' decisions, and can avoid the risk of setting vouchers that are either too high or too low. Nevertheless, even if only price-linked discounts are feasible, age adjustments might still be desirable due to age-heterogeneity in demand and cost.

In my last counterfactual I consider this, comparing the ACA scheme (where price caps used to compute discounts are equal to $1,400 for all ages) to a scheme with price-linked discounts but with premium caps varying by age. Practically, I consider a scheme $\widehat{S}$ such that

$$\widehat{S}^{\tau,y}(b_r) = \max\left\{A^{\tau} \cdot b_r^{*} - \overline{P}^{\tau,y}, 0\right\}, \tag{23}$$

in which $\overline{P}^{20\text{-}44,y} < \overline{P}^{45\text{-}64,y}$, and b_r^{*} is the second-cheapest base price of Silver plans in the region. This is then the same scheme S as implemented under the ACA (equation (5)), with the only difference being that price caps vary also by age (under S one has $\overline{P}^{20\text{-}44,y} = \overline{P}^{45\text{-}64,y} = \overline{P}^{y}$). Practically, one can also think of this as a scenario in which the government provides — on top of the current subsidy program — additional incentives for the participation of young buyers with different fiscal instruments.

The results of this comparison are reported in Table 12, where I show how equilibrium outcomes respond to progressively lower price caps for the under 45. Higher generosity of the subsidy scheme for young buyers yields again to large increases in their participation, and a corresponding reduction in average cost and per-buyer subsidy outlays. Yet, gains relative to the ACA scheme are smaller than under age-adjusted vouchers, since markup reductions are lower (from over 20% to less than 10%), a consequence of the additional distortions induced by price-linked discounts.

Table 12: Equilibrium outcomes under the ACA scheme with lower price caps for under 45

		Enrollment 20-44	Enrollment 45-64	Average cost	Average markup	Per-person subsidy	Total spending
$\overline{P}^{[20,44]}$	$\overline{P}^{[45,64]}$	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)	(ACA =1)
1400	1400	1	1	1	1	1	1
1300	1400	1.13	1	0.97	0.99	0.98	1.04
1200	1400	1.28	1	0.95	0.97	0.96	1.08
1100	1400	1.42	1	0.93	0.95	0.94	1.12
900	1400	1.75	1	0.88	0.91	0.91	1.22
800	1400	1.94	1	0.86	0.91	0.90	1.29

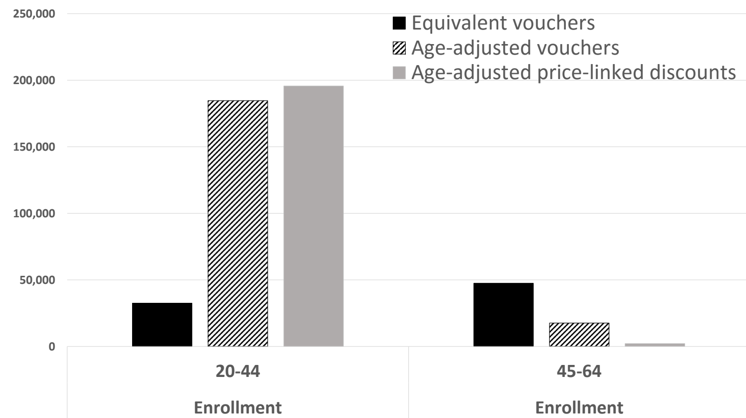
Note: Market outcomes (relative to the ACA equilibrium in the baseline model) in the simulated equilibrium under alternative pairs of age-adjusted price-linked subsidies. The table shows market outcomes changing as the price cap on the second-cheapest Silver plan in the region for the under 45 is progressively lowered.

7.4 Summary of equilibrium comparative statics under different designs

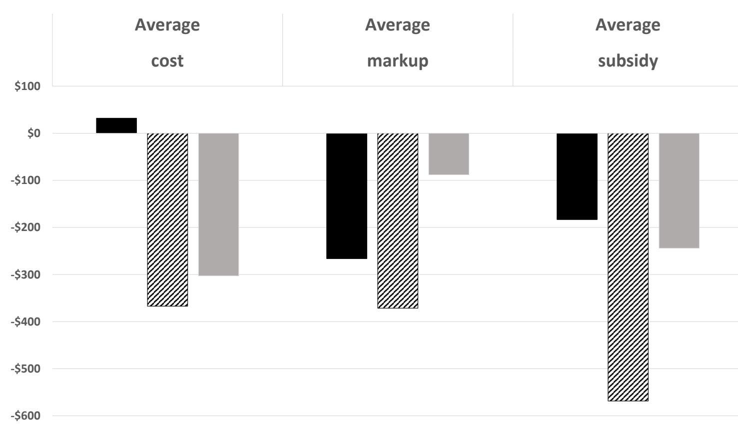
I summarize the above comparisons in Figure 8, where I express differences between the ACA design and possible alternatives in head-counts (for enrollment) and dollars (for average cost, markup, and subsidy).

Figure 8: Summary of differences between ACA scheme and counterfactual alternatives

(a) Differences in enrollment from price-linked discounts without age adjustments



(b) Differences in cost, markup, and subsidy from price-linked discounts without age adjustments



The figure summarizes the comparison between the ACA subsidy design and the three alternatives I consider in my counterfactuals: fixed vouchers with amounts equivalent to the discounts in the equilibrium under the ACA — black bars — , age-adjusted vouchers chosen to be such that over 45 enrollment is 3% higher than under the ACA — crosshatched bars — , and age-adjusted price-linked discounts where the price ceiling on Silver coverage for the under 45 is raised to have the same enrollment as under age-adjusted vouchers — shaded bars.

The bars are derived from Tables 10, 11, and 12.

The figure highlights the different role played by the two aspects of subsidy design that I focused on. On the one hand, using vouchers instead of price-linked subsidies increases price competition, and thus lowers markups and the cost for the government of covering a low-income buyer. On the other hand, tailoring discounted prices to age does not imply a redistributive trade-off, but rather is a powerful tool to affect the market average cost, insurers' markups, and per-buyer government expenditure. Importantly, the two mechanisms co-exist and either complement or offset each other under different design alternatives.

8 Conclusions [Preliminary]

The recent changes to the US health care system, primarily induced by the 2010 national reform, opened many questions for regulators and economists. Within the growing body of work on regulation of private insurance, in this paper I used an empirically tractable model of imperfect competition between insurers to study (static) equilibrium under different designs of the ACA subsidy program. The applied contribution is two-folded. First, I estimated the model in the post-reform status quo, regulated by the ACA and in which the vast majority of buyers are low-income and thus subsidy eligible. Second, my counterfactuals highlighted that the ACA subsidy scheme leaves room for possible improvements that are quantitatively significant and consistent with theoretical predictions.

In my application I used data from the first year of operations of the Californian marketplace to obtain estimates of demand and cost. Importantly, the buyers in this market belong to a segment of the population that was largely underrepresented in previous studies, and I found a large degree of heterogeneity (both in demand and cost) across buyers of different age. These estimates are the drivers of my counterfactual results. Price-linked subsidies as mandated by the ACA increase insurers' market power, implying higher markups, lower coverage, and higher spending when compared to a mechanism where low-income discounts are not adjusted to prices. I quantified this distortion to be approximately \$200 per-person-year (15%). A second result is that age-adjustments of subsidized premiums within a given income level might lead to better outcomes, both in terms of enrollment levels and efficiency in the use of public funds. This alternative might be easier to implement than exogenous vouchers, and the gains follow directly from the heterogeneity in cost across buyers: Raising the participation of "young invincibles" generates a positive externality on the entire market, reducing costs, prices, and the public spending for every insured buyer. Supporting intuition, my simulations suggested that potential gains are sizable: One can maintain enrollment among buyers who are older than 45 approximately unaltered, increase enrollment among younger buyer by more than 50%, while reducing per-insured public spending by \$600 per-year. With the government intent to increase coverage while limiting spending, a modification of the subsidy scheme to allow for age-specific premium even among low-income buyers could then improve upon the current regulation.

Looking at ACA marketplaces, here I focused on the design of the subsidy program, with a partial equilibrium analysis that holds other parts of the regulations unchanged. Subsidies are indeed only one piece of the large regulatory innovation mandated by the reform, and different rules complement each other in generating market outcomes. Versions of the model I employed here could also be used to study other ACA regulations, such as age-rating restrictions, cost-sharing support, risk-adjustment mechanisms, or tax-penalties for the uninsured.

Pricing decisions can be arguably seen as a natural starting point to analyze insurers' competition in a new institutional context. However, pricing incentives are just one part of the complex puzzle that economists and regulators need to consider. Dynamic incentives of buyers — e.g. choice inertia (Handel, 2013) — and insurers — e.g. entry and network-setting decisions (Ho and Lee, 2016) — could also play a relevant role in determining outcomes in this market. As the marketplaces are now entering the fourth year of operations, in the future it will be possible to use richer models and data to account for these additional dimensions.

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APPENDIX

Appendix A. Proof of Proposition 1

I prove part (a), and part (b) follows immediately by simple algebra.

Note that for any τ the probability that a buyer chooses j at the prices P is

$$\sigma_j(P,\tau) = \int_{\{v_j \geq P_j\} \cap \{v_j - v_k \geq P_j - P_k \forall k\}} \mathrm{d}F(v|\tau). \tag{24}$$

Then, when all prices are lowered by Δ for Y buyers:

$$\sigma_j(P-\Delta,Y) = \int_{\{v_j \geq P_j - \Delta\} \cap \{v_j - v_k \geq P_j - P_k \forall k\}} \mathrm{d}F(v|Y) > \sigma_j(P,Y). \tag{25}$$

Symmetrically, when all prices are increased by Δ for O buyers:

$$\sigma_j(P+\Delta,O) = \int_{\{v_j \geq P_j + \Delta\} \cap \{v_j - v_k \geq P_j - P_k \forall k\}} \mathrm{d}F(v|O) < \sigma_j(P,Y). \tag{26}$$

It follows that for all P $\alpha_j^S(P) < \alpha_j^{\widehat{S}}(P)$. From this, and recalling that $C_j^Y < C_j^O$, $AC_j^{\widehat{S}}(P) < AC_j^S(P)$. Moreover, since $\eta_{jj}^Y > \eta_{jj}^O$, the denominator in $MK_j^S(P)$ is smaller than the denominator in $MK_j^{\widehat{S}}(P)$. Then, if for some $\Delta > 0$, the numerator in $MK_j^S(P)$ is larger than the numerator in $MK_j^{\widehat{S}}(P)$ — at least in a neighborhood of $P^{*,S}$ —, then the right-hand side of (**??**) is lower under $\widehat{S}$ than under S, and since prices are strategic complements Vives (1990) implies $P^{*,\widehat{S}} < P^{*,S}$. To obtain the result it is then sufficient to consider the equilibrium point $P^{*,S}$, and setting $\widetilde{\alpha}_j^{*,S}(\Delta) \equiv \alpha_j^{\widehat{S}}\left(P^{*,S}\right)$ check that the function

$$\Phi_j(\Delta) = 1 - \left(C_j^Y - C_j^O\right)\left(\eta_{jj}^O - \eta_{jj}^Y\right)\widetilde{\alpha}_j^{*,S}(\Delta)\Big(1 - \widetilde{\alpha}_j^{*,S}(\Delta)\Big)$$

is decreasing in $\Delta \in \left[0, \overline{\Delta}\right]$ for some $\overline{\Delta} > 0$. Since $\widetilde{\alpha}_j^{*,S}(0) < \frac{1}{2}$, $\frac{\mathrm{d}\widetilde{\alpha}_j^{*,S}(0)}{\mathrm{d}\Delta} > 0$, one has

$$\Phi_j'(0) = -\left(C_j^Y - C_j^O\right)\left(\eta_{jj}^O - \eta_{jj}^Y\right)\frac{\mathrm{d}\widetilde{\alpha}_j^{*,S}(0)}{\mathrm{d}\Delta} < 0,$$

and the result follows.■

Appendix B. Nonparametric identification without claims data

In this appendix I provide conditions for nonparametric identification of the distribution of willingness to pay and of cost conditional on willingness to pay, assuming that observables consists of choices, prices, and products' characteristics.[21]

For this I use a model that is not tailored to my specific application, omitting subsidies and other regulations. This allows me to focus on, and highlight, the novel aspect of the identification argument, which is to use equilibrium assumptions and variation in the preferences of marginal buyers to identify cross-buyer cost heterogeneity. I provide a positive result for the case of single-plan insurers (or plan-level pricing decisions), an important simplification that leaves open questions for future work. In fact, multi-product pricing decisions introduce several complications, with the need of additional conditions, a different constructive proof, or specific functional form assumptions (e.g. those in the empirical application in this paper, or in Lustig, 2010).

B1. Model and observables

I start by adopting the model of demand used in Berry and Haile (2014) (BH), and then model supply allowing costs to vary with buyers' willingness to pay, and assuming that a Nash-in-prices equilibrium realizes in each market.

Demand (adapted from BH). Each consumer i in market r chooses a plan (or product) from a set $\mathcal{J} = \{0, 1, ..., J\}$. A market consists of a continuum of consumers in the same choice environment (e.g. geographic region). Formally a market r for the J products is a tuple $\chi_r = (x_r, p_r, \xi_r)$, collecting characteristics of the products or of the market itself. Observed exogenous characteristics are represented by $x_r = (x_{1r}, ..., x_{Jr})$, where each $x_{jr} \in \mathbb{R}^K$. The vector $\xi_r = (\xi_{1r}, ..., \xi_{Jr})$, with $\xi_{jr} \in \mathbb{R}$, represents unobservables at the level of the product-market. Finally, $p_r = (p_{1r}, ..., p_{Jr})$, with each $p_{jr} \in \mathbb{R}$, represents (endogenous) prices.

Consumer preferences are represented with a random utility model quasilinear in prices (Section 4.2 in BH). Consumer i in market r derives (indirect) utility $u^i_{jr} = v^i_{jr} - p_{jr}$ when purchasing j, with the usual normalization $v^i_{0r} = 0$, for all i, all r. Given prices, the choice of each buyer is then determined by the vector $v^i_r = (v^i_{1r}, ..., v^i_{Jr})$. For each buyer in market r, v^i_r is drawn i.i.d. from a continuous density $f_r(v)$. This satisfies the following:

D1. *BH Demand structure*: There is a partition of x_{jr} into $(x^{(1)}_{jr}, x^{(2)}_{jr})$, where $x^{(1)}_{jr} \in \mathbb{R}$, such that given indexes $\delta_r = (\delta_{1r}, ..., \delta_{Jr})$, with $\delta_{jr} = x^{(1)}_{jr} + \xi_{jr}$, $f_r(v) = f(v|\delta_r, x^{(2)}_r)$.

[21] This is the main difference between my approach and existing work on identification of demand and cost in selection markets, where the observability of costs (e.g. ex-post claims) has been assumed (c.f. Einav, Finkelstein, and Cullen, 2010a; Bundorf, Levin, and Mahoney, 2012, and many others). One exception is Lustig (2010), who like me estimates costs using equilibrium pricing conditions. While our estimators are similar, my point here is to formalize which variation is sufficient for identification.

Therefore, assuming that $\arg\max_{j\in J} u^i_{jr}$ is unique with probability one in all markets, choice probabilities (market shares) are defined by

$$\begin{aligned} s_{jr} &= \sigma_j(\chi_r) = \int_{\mathcal{D}_j(p_r)} f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v, \;\; j = 0, 1, ..., J, & (27)\\ \mathcal{D}_j(p_r) &= \{v : v_j - v_k \geq p_j - p_k, \text{ for all } k \neq j\}\,. & (28)\end{aligned}$$

Observables. Let $z_r = (z_{1r}, ..., z_{Jr})$, $z_{jr} \in \mathbb{R}^L$, denote a vector of cost shifters excluded from the demand model. The econometrician observes $(p_{jr}, s_{jr}, x_{jr}, z_{jr})$ for all r and all $j = 1, 2, ..., J$.

Supply. Let $w_{jr} = (\xi_{jr}, x_{jr}, z_{jr}) \in \mathbb{R}^{K+L+1}$ collect characteristics (observable and unobservable) and cost shifters of product j in r. When purchasing j, a buyer i with valuations $v^i = v$ in market r increases the total expected cost for the insurer by $\psi_j(v, w_{jr})$, $\psi_j : \mathbb{R}^J \times \mathbb{R}^{K+L+1} \to \mathbb{R}$.

The function $\psi_j(\cdot, w_{jr})$ is continuous and bounded for all j, and describes how the expected cost of covering the buyer varies with her vector of valuations after conditioning on w_{jr}.[22]

At the prices p_r the seller of j realizes profits in market r equal to

$$\Pi_{jr}(\chi_r) = p_{jr} \cdot \sigma_j(\chi_r) - \int_{\mathcal{D}_j(p_r)} \psi_j(v, w_{jr}) \cdot f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v. \tag{29}$$

I assume that in each market prices are set in a complete information Nash equilibrium in pure-strategies. To formalize this, the set of marginal buyers of product j can be described by

$$\begin{aligned} \partial\mathcal{D}_j(p_r) &= \{v : v_j - v_k = p_{jr} - p_{kr} \text{ for some } k \neq j\} & (30)\\ &= \lim_{\varepsilon \downarrow 0} \left\{\mathcal{D}_j(p_r) \cap \left(\mathbb{R}^J \setminus \mathcal{D}_j(p_{jr} + \varepsilon, p_{-jr})\right)\right\}. & (31)\end{aligned}$$

Then, following Uryas'ev (1994); Weyl and Veiga (2014), quasilinearity of indirect utility with respect to price implies that, in equilibrium, in every market r:

S1. *Equilibrium*: For all $j = 1, ..., J$, $mr_{jr} = mc_{jr}$, where

$$\begin{aligned} mr_{jr} &= \sigma_j(\chi_r) - p_{jr} \cdot \int_{\partial\mathcal{D}_j(p_r)} f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v, & (32)\\ mc_{jr} &= -\int_{\partial\mathcal{D}_j(p_r)} \psi_j(v, w_{jr}) \cdot f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v. & (33)\end{aligned}$$

From S1, marginal revenues are equal to marginal costs, which must be true in a Nash-in-prices equilibrium. The integrals in mr_{jr} and mc_{jr} are well defined because $f(\cdot|\delta_r, x_r^{(2)})$ and $\psi_j(\cdot, w_{jr})$ are both continuous and bounded functions of v.

[22] As in Section 4, ψ and $f(v)$ could be derived from a more primitive joint distribution $h(v, c)$ over individual preferences and cost, as shown in equations (8) and (9). If this joint distribution admits a continuous density, the resulting ψ_j is continuous in v, which here is a maintained assumption.

B2. Conditions for identification

Identification is defined as in Roehrig (1988); Matzkin (2008): if the unobservables differ (almost surely), then the distribution of observables differ (almost surely), where probabilities and expectations are defined with respect to the distribution of (χ_r, s_r, z_r) across markets.

My result is obtained combining conditions for identification of demand provided in BH — yielding to identification of ξ_r and then of $f(v|\delta_r, x_r^{(2)})$ — with a constructive proof to identify ψ_j which I adapted from Somaini (2011, 2015).[23] To simplify notation without loss of generality, as in BH I condition on $x_r^{(2)}$ — which unlike $x_r^{(1)}$ can affect the distribution of preferences quite arbitrarily — and suppress it.

Beside the demand and supply assumptions D1 and S1, I will use the following conditions:

C1. *BH Exogeneity of cost shifters*: For all $j = 1, ..., J$, $E[\xi_{jr}|z_r, x_r] = E[\xi_{jr}] = 0$.

C2. *BH Completeness*: For all functions $B(s_r, p_r)$ with finite expectations, if $E[B(s_r, p_r)|z_r, x_r] = 0$ with probability one, then $B(s_r, p_r) = 0$ with probability one.

C3. *Large support*: For every j, supp $v_r|\delta_r, w_{jr} \subset$ supp $p_r|\delta_r, w_{jr} \subset P$, with P bounded.

Condition C1 is a standard exclusion restriction, requiring mean independence between demand instruments and the structural erros ξ_{jr}. Condition C2 is a completeness assumption, requiring instruments to move market shares and prices sufficiently to distinguish between different functions of these variables through the exogenous variation in these instruments. C3 is a large support assumption, requiring cost shifters excluded from ψ_j to move prices in a set that covers the support of (conditional) valuations. This is a stronger requirement than the large support assumption sufficient to identify the distributions $f(v|\delta_r)$, which would only require supp $v_r|\delta_r \subset$ supp $p_r|\delta_r$. The stronger condition in C3 allows to prove that cost functions ψ_j are also identified. In supplementary Appendix S3 I discuss conditions for identification that do not require C3, hence — although imposing stronger restrictions on the model — are more operational in many applications.

One then has:

THEOREM **1** *Under D1, S1, C1, C2, C3, ξ_r, $f(v|\delta_r)$, and ψ_j are identified.*

Proof of Theorem 1. Condition C3 implies supp $v_r|\delta_r \subset$ supp $p_r|\delta_r$, and demand is identified:

LEMMA **1** (Berry and Haile, 2014) *Under D1, C1, C2, ξ_r is identified, and $f(v|\delta_r)$ is also identified if, additionally, supp $v_r|\delta_r \subset$ supp $p_r|\delta_r$.*

[23] This highlights the parallelism between auctions with interdependent costs and selection markets. In the former case (expected) marginal costs depend on the competitors' signals, varying with differences of bids between competitors. In a selection market (expected) marginal costs depend on the preferences of buyers choosing the plan, varying with differences of prices between competitors.

Proof. Follows from Theorem 1 and Section 4.2 in BH.□

Similarly to Somaini (2011, 2015), the rest of the proof amounts to approximating for every j, every w_{jr}, and every $\widehat{v} \in \text{supp } v_r|\delta_r, w_{jr}$, the integral of cost conditional on $\mathcal{D}_j(\widehat{v})$:

$$\Psi_j(\widehat{v}; w_{jr}, \delta_r) = \int_{\mathcal{D}_j(\widehat{v})} \psi_j(v, w_{jr}) \cdot f(v|\delta_r)\, \mathrm{d}v. \tag{34}$$

The mixed-partial J-1 derivative with respect to $\widehat{v}_{-j}$ yields then identification of the unknown cost function ψ_j, since

$$\frac{\mathrm{d}^{J-1}\Psi_j(\widehat{v}; w_{jr}, \delta_r)}{\mathrm{d}\widehat{v}_{-j}} = \psi_j(\widehat{v}, w_{jr}) \cdot f(\widehat{v}|\delta_r) \tag{35}$$

and $f(\widehat{v}|\delta_r)$ is identified by Lemma 1. This exploits the fact that price enters linearly in buyers' indirect utility, hence the set $\mathcal{D}_j(\widehat{v})$ is described by a set of inequalities which defines a cone in $\mathbb{R}^J$ with vertex $\widehat{v}$. The boundary of this cone is the set $\partial\mathcal{D}_j(\widehat{v})$ defined in (30); see also Figure 1 in BH.

To approximate $\Psi_j(\widehat{v}; w_{jr}, \delta_r)$, fix j, w_{jr}, and $\widehat{v} \in \text{supp } v_r|\delta_r, w_{jr}$. Consider then a parametric curve $\eta : \mathbb{R}_+ \to \mathbb{R}$, with $\eta(\ell) = \widehat{v}_j + \ell$, and with this define the function $\widehat{\Psi}_j(\ell) = \Psi_j((\eta(\ell), \widehat{v}_{-j}); w_{jr}, \delta_r)$. Differentiating $\widehat{\Psi}_j(\ell)$ (and using again Uryas'ev, 1994; Weyl and Veiga, 2014) yields

$$\frac{\mathrm{d}\widehat{\Psi}_j(\ell)}{\mathrm{d}\ell} = -\int_{\partial\mathcal{D}_j((\eta(\ell), \widehat{v}_{-j}))} \psi_j(v, w_{jr}) \cdot f(v|\delta_r)\, \mathrm{d}v. \tag{36}$$

The function $\phi_j(\ell) \equiv \frac{\mathrm{d}\widehat{\Psi}_j(\ell)}{\mathrm{d}\ell}$ is bounded and continuous, and hence Riemann integrable over $[0, T]$, where by C3 the upper bound T can be chosen to be such that $\widehat{\Psi}_j(T) = 0$. Therefore,

$$\Psi_j(\widehat{v}; w_{jr}, \delta_r) = \widehat{\Psi}_j(0) = -\int_0^T \phi_j(\ell)\, \mathrm{d}\ell. \tag{37}$$

The integral in (37) can be approximated with arbitrary precision. For this, one can choose a sequence $\{\ell^n\}_{n=0}^N$ for which $0 = \ell^1 < \ell^2, ..., < \ell^{N-1} < \ell^N = T$, and using C3 build a corresponding sequence $\{\chi_r^n\}_{n=0}^N \in \text{supp } \chi_r|\delta_r, w_{jr}$, such that $p_r^n = (\eta(\ell^n), \widehat{v}_{-j})$. Then, as $\max_n\{\ell^n - \ell^{n-1}\}$ becomes arbitrarily small

$$\sum_{n=0}^{N-1} \phi_j(\ell^n)(\ell^{n+1} - \ell^n) \approx \int_0^T \phi_j(\ell)\, \mathrm{d}\ell, \tag{38}$$

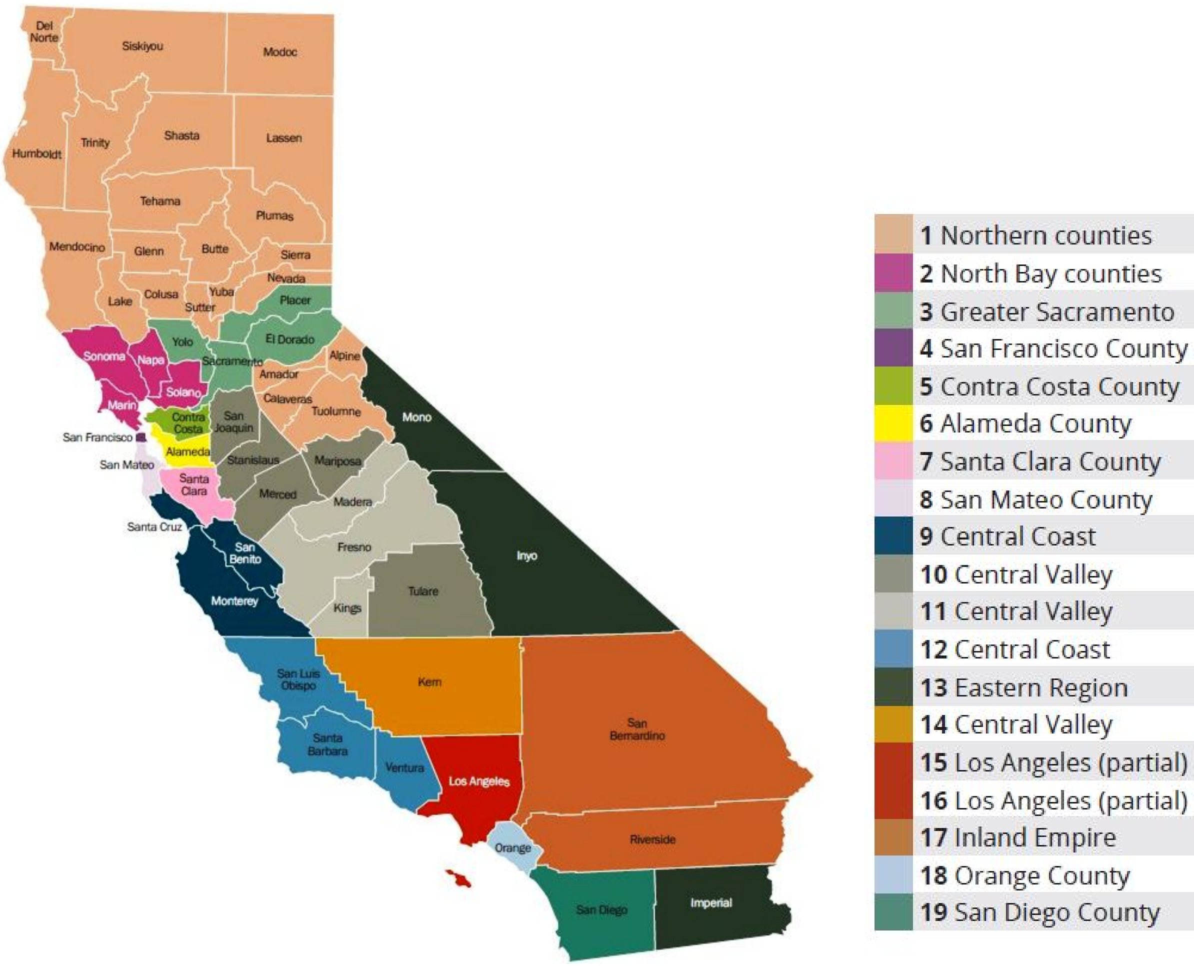
where by all the elements in the Riemann sum are identified since by S1 each $\phi_j(\ell^n)$ can be replaced by

$$mr_{jr}^n = \sigma_j(\chi_r^n) - p_{jr}^n \cdot \int_{\partial\mathcal{D}_j(p_r^n)} f(v|\delta_r^n)\, \mathrm{d}v, \tag{39}$$

which is identified by Lemma 1.■

ADDITIONAL FIGURES

Figure 9: Rating regions in Covered California



Source: www.CoveredCA.com

The map shows the 19 rating regions in Covered California. In each region, every spring insurers can announce their participation in the following year's open enrollment. The marketplace needs to authorize entry, and requires the insurer to offer five coverage levels with pre-determined financial characteristics (Table 2). In the summer insurers set one base price for every level of coverage in every region where they entered, prices and subsidies are then calculated from base prices applying ACA regulations (Section 3).

SUPPLEMENTARY APPENDIX

FOR ONLINE PUBLICATION ONLY

S1: Supplementary Appendix to Section 2

S1.1. Derivation of equilibrium condition (??)

Given a subsidy design S, rewrite the profit function for product j as

$$\Pi_j^S\left(P_j, P_{-j}\right) = Q_j^S\left(P_j, P_{-j}\right)\left(P_j - AC_j^S\left(P_j, P_{-j}\right)\right), \tag{40}$$

where $AC_j^S(\cdot)$ is defined in (3) and $Q_j^S(P) = G(Y)\,\sigma_j\left(P - S(P,Y), Y\right) + G(O)\,\sigma_j\left(P - S(P,O), O\right)$. If P^* is an equilibrium one has

$$\begin{aligned}\frac{\partial \Pi_j\left(P_j^*, P_{-j}^*\right)}{\partial P_j} &= \frac{\partial Q_j^S\left(P_j^*, P_{-j}^*\right)}{\partial P_j}\left(P_j^* - AC_j^S\left(P_j^*, P_{-j}^*\right)\right) + Q_j^S\left(P_j^*, P_{-j}^*\right)\left(1 - \frac{\partial AC_j^S\left(P_j^*, P_{-j}^*\right)}{\partial P_j}\right) \\ &= 0;\end{aligned}$$

and rearranging terms leads to $P_j^* = AC_j^S\left(P_j^*, P_{-j}^*\right) - \frac{Q_j^S\left(P_j^*, P_{-j}^*\right)}{\frac{\partial Q_j^S\left(P_j^*, P_{-j}^*\right)}{\partial P_j}}\left(1 - \frac{\partial AC_j^S\left(P_j^*, P_{-j}^*\right)}{\partial P_j}\right)$.

To simplify this further, rewrite

$$\begin{aligned}-\frac{Q_j^S\left(P_j^*, P_{-j}^*\right)}{\frac{\partial Q_j^S\left(P_j^*, P_{-j}^*\right)}{\partial P_j}} &= \frac{Q_j^S\left(P_j^*, P_{-j}^*\right)}{G(Y)\,\sigma_j\left(P^* - S(P^*,Y), Y\right)\eta_{jj}^Y + G(Y)\,\sigma_j\left(P^* - S(P^*,O), O\right)\eta_{jj}^O} \\ &= \frac{1}{\alpha_j^S(P^*)\,\eta_{jj}^Y + \left(1 - \alpha_j^S(P^*)\right)\eta_{jj}^O};\end{aligned} \tag{41}$$

$$\begin{aligned}&\frac{\partial AC_j^S\left(P_j^*, P_{-j}^*\right)}{\partial P_j} = \left(C_j^Y - C_j^O\right)\frac{\partial \alpha_j^S(P^*)}{\partial P_j} = \\ &= \left(C_j^Y - C_j^O\right)\frac{\frac{\partial\left(G(Y)\sigma_j\left(P^* - S(P^*,Y), Y\right)\right)}{\partial P_j}Q_j^S(P^*) - G(Y)\,\sigma_j\left(P^* - S(P^*,Y), Y\right)\frac{\partial Q_j^S(P^*)}{\partial P_j}}{\left(Q_j^S(P^*)\right)^2} \\ &= \left(C_j^Y - C_j^O\right)\left(\eta_{jj}^O - \eta_{jj}^Y\right)\alpha_j^S(P^*)\left(1 - \alpha_j^S(P^*)\right).\end{aligned} \tag{42}$$

Putting together (41) and (42) gives the expression for the equilibrium price in (**??**):

$$P_j^* = AC_j^S\left(P_j^*, P_{-j}^*\right) + \underbrace{\frac{1-\left(C_j^Y - C_j^O\right)\left(\eta_{jj}^O - \eta_{jj}^Y\right)\alpha_j^S\left(P^*\right)\left(1-\alpha_j^S\left(P^*\right)\right)}{\alpha_j^S\left(P^*\right)\eta_{jj}^Y + \left(1-\alpha_j^S\left(P^*\right)\right)\eta_{jj}^O}}_{MK_j^S\left(P_j^*, P_{-j}^*\right)}. \tag{43}$$

S1.2. Price-linked discounts vs. vouchers

The following proposition shows that, as long as there is a group of buyers who are more price sensitive and cheaper to cover, given price-linked subsidies it is possible to find a voucher scheme leading to an equilibrium with lower prices.

PROPOSITION **2** *Assume that prices are strategic complements, and let S be a subsidy design for which at any P, $\frac{\partial S(P,\tau)}{\partial P_j} = \delta > 0$, for some j (which may depend on P). Then, if $C_j^Y < C_j^O$, and $\eta_{0j}^Y > \eta_{0j}^O$ for all j, a voucher scheme $\widehat{S}$ such that $\widehat{S}\left(P,\tau\right) = \widehat{V}^\tau = S\left(P^{*,S},\tau\right)$ is such that $P^{*,\widehat{S}} < P^{*,S}$.*

Proof. From the equilibrium comparative static results formalized in Vives (1990), the proof amounts to show that, for all P at which all products make weakly positive profits, setting $\widehat{S}\left(P,\tau\right) = \widehat{V}^\tau = S\left(P,\tau\right)$ implies

$$\frac{\partial \Pi_j^S\left(P_j, P_{-j}\right)}{\partial P_j} \geq \frac{\partial \Pi_j^{\widehat{S}}\left(P_j, P_{-j}\right)}{\partial P_j} \text{ for all } j, \tag{44}$$

with a strict inequality for at least one j. (This immediately implies that $\frac{\partial \Pi_j^{\widehat{S}}\left(P^{*,S}\right)}{\partial P_j} < 0$ for at least one j: At the equilibrium prices under S, if the vouchers $\widehat{S}$ are adopted, at least one insurer wants to lower its price).

To show (44), given that at prices P for at least one j, $\frac{\partial S(P,\tau)}{\partial P_j} = \delta > 0$, and for all k, $P_k \geq AC_k^S\left(P\right)$, one has that for any j:

$$\begin{aligned}
\frac{\partial \Pi_j^S\left(P_j, P_{-j}\right)}{\partial P_j} - \frac{\partial \Pi_j^{\widehat{S}}\left(P_j, P_{-j}\right)}{\partial P_j} &\geq \delta\left(\frac{\partial Q_j^S\left(P\right)}{\partial P_0}\left(P_j - AC_j^S\left(P_j, P_{-j}\right)\right) - Q_j^S\left(P\right)\frac{\partial AC_j^S\left(P\right)}{\partial P_0}\right) \\
&= \delta\left(\underbrace{P_j - AC_j^S\left(P_j, P_{-j}\right)}_{>0} - \underbrace{\frac{Q_j^S\left(P\right)}{\frac{\partial Q_j^S(P)}{\partial P_0}}}_{>0}\frac{\partial AC_j^S\left(P\right)}{\partial P_0}\right).
\end{aligned}$$

Hence (44) follows if $\frac{\partial AC_j^S(P)}{\partial P_0} < 0$: raising the price of the outside good (or equivalently the subsidy) lowers average cost. This is indeed the case as long as $C_j^Y < C_j^O$, and $\eta_{0j}^Y > \eta_{0j}^O$:

$$\begin{aligned}
\frac{\partial AC_j^S(P)}{\partial P_0} &= \left(C_j^Y - C_j^O\right) \frac{\partial \alpha_j^S(P)}{\partial P_0} \\
&= \left(C_j^Y - C_j^O\right) \frac{\frac{\partial(G(Y)\sigma_j(P-S(P),Y))}{\partial P_0} Q_j^S(P) - G(Y)\sigma_j(P-S(P,Y),Y)\frac{\partial Q_j^S(P)}{P_0}}{\left(Q_j^S(P)\right)^2} \\
&= \left(C_j^Y - C_j^O\right)\left(\eta_{0j}^Y - \eta_{0j}^O\right)\left(1-\alpha_j^S(P)\right) < 0.
\end{aligned}$$

Therefore (44) holds and, by Vives (1990), $P^{*,\widehat{S}} < P^{*,S}$. ■

S3: Identification without a large support assumption

Setup.

- J products are offered in R markets.
- A buyer i in market r is a pair (z_{ir}, v_{ir}). $z_{ir} \in \mathbb{R}^Q$ is a collection of buyer-specific observables (e.g. age, income, gender, zip-code); $z_{ir} \in \mathcal{Z} = \{z^1, ..., z^T\}$, a finite set. $v_{ir} = (v_{i1r}, ..., v_{iJr}) \in \mathcal{V}$ is a vector of (money-metric) valuations collecting the buyer's willingness-to-pay for each of the J products.
- The probability that a buyer has characteristics $\widehat{z} \in \mathcal{Z}$ in market r is $\mu_r(\widehat{z}) \geq 0$; $\sum_{\widehat{z} \in \mathcal{Z}} \mu_r(\widehat{z}) = 1$.
- Conditional on $z_{ir} = \widehat{z}$, in market r v_{ir} is drawn $i.i.d$ from the density $f(v_{ir}|z_{ir}, x_r, \xi_r)$, with support $\mathcal{V}$.
  $x_r = (x_{1r}, ..., x_{Jr})$ collects observed characteristics of the J products in r, with each $x_{jr} \in \mathbb{R}^K$.
  $\xi_r = (\xi_{1r}, ..., \xi_{Jr})$ collects unobserved characteristics of the J products in r affecting preferences, with each $\xi_{jr} \in \mathbb{R}$.
- Prices are equal for all buyers in a market, and are collected in the vector $p_r = (p_{1r}, ..., p_{Jr})$, $p_{jr} \in \mathbb{R}$.
  Given prices, the set of valuations of buyers choosing j is $D_j(p_r) = \{v \in \mathcal{V} : v_j - p_j \geq v_k - p_k,\ \forall k\}$.
  Given prices, the set of marginal buyers for j is $\partial D_j(p_r) = \{v \in \mathcal{V} : v_j - p_j = v_k - p_k \text{ for some } k\}$.
- The (expected) cost for the seller when a buyer with $(z_{ir}, v_{ir}) = (\widehat{z}, \widehat{v})$ purchases j in r is $\psi_{jr}(\widehat{z}, \widehat{v})$.
  The function $\psi_{jr} : \mathcal{Z} \times \mathcal{V} \to \mathbb{R}_+$ is not assumed to be constant, thus this is market with selection.
- Setting $\chi_r = (p_r, x_r, \xi_r)$, the probability that a buyer with characteristics $z_{ir} = \widehat{z}$ chooses j in r is
  $s_{jr}(\widehat{z}) = \sigma_j(\widehat{z}, \chi_r) = \int_{D_j(p_r)} f(\widehat{v}|\widehat{z}, x_r, \xi_r)\, \mathrm{d}\widehat{v}$. Expected profits for the seller of j in r are then
  $$\Pi_{jr}(\chi_r) = \underbrace{p_{jr} \sum_{\widehat{z} \in \mathcal{Z}} \mu_r(\widehat{z}) \sigma_j(\widehat{z}, \chi_r)}_{\text{Revenues}} - \underbrace{\sum_{\widehat{z} \in \mathcal{Z}} \mu_r(\widehat{z}) \int_{D_j(p_r)} \psi_{jr}(\widehat{z}, \widehat{v}) f(\widehat{v}|\widehat{z}, x_r, \xi_r)\, \mathrm{d}\widehat{v}}_{\text{Cost}}.$$

Observables and demand identification. Let $w_r = (w_{1r}, ..., w_{Jr})$ denote product/market-specific cost-shifters excluded from buyers' preferences (e.g. service fees for hospitals and clinics covered by a given j); each $w_{jr} \in \mathbb{R}^L$. The econometrician observes, for all r, all j, and all z, the collection $(\mu_r(z), s_{jr}(z), p_{jr}, x_{jr}, w_{jr})$. Berry and Haile (2014, 2015) provide sufficient conditions under which ξ_r and $f(\cdot|\cdot, x_r, \xi_r)$ are identified. I impose these conditions and treat these demand primitives as known henceforth.[24]

Cost identification — two types. The remaining unknown primitives — one value for each $\psi_{jr}(\widehat{z},\widehat{v})$ — are more numerous than the observed supply decisions — say N, one value for each price p_{jr}.[25]

I start by considering the simple case in which cost only depends on observable characteristics of the buyer, i.e. $\psi_{jr}(\widehat{z},\widehat{v}) = \psi_{jr}(\widehat{z})$; this reduces the number of unknowns to $N \times T$. To make things even simpler, suppose that $T = 2$, i.e. $\mathcal{Z} = \{z^1, z^2\}$, so that there are only two unknowns $\psi_{jr}(z^1), \psi_{jr}(z^2)$ for each observed pair jr.

The first step is to assume that prices are set optimally by sellers, implying that $mr_{jr} = mc_{jr}$. In this expression: $mr_{jr} = \sum_{\ell=1}^{2} \mu_r(z^\ell) \left(\sigma_j(z^\ell, \chi_r) - p_{jr} \int_{\partial D_j(p_r)} f(\widehat{v}|z^\ell, x_r, \xi_r) \,\mathrm{d}\widehat{v} \right)$, while the right-hand side (marginal cost) is

$$mc_{jr} = \sum_{\ell=1}^{2} \mu_r(z^\ell) \int_{\partial D_j(p_r)} \psi_{jr}(z^\ell, \widehat{v}) f(\widehat{v}|z^\ell, x_r, \xi_r) \,\mathrm{d}\widehat{v} = \sum_{\ell=1}^{2} \psi_{jr}(z^\ell) \left(\mu_r(z^\ell) \int_{\partial D_j(p_r)} f(\widehat{v}|z^\ell, x_r, \xi_r) \,\mathrm{d}\widehat{v} \right).$$

I then assume that $\psi_{jr}(\cdot) = \psi(\cdot; x_{jr}, \xi_{jr}, w_{jr})$, letting cost functions vary only with product characteristics and cost shifters. Then, for any given triplet $(\overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})$, sufficient conditions to identify $\psi(\cdot; \overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})$ are

(i) there are at least two products jr and $\widetilde{jr}$ with $(x_{jr}, \xi_{jr}, w_{jr}) = (x_{\widetilde{jr}}, \xi_{\widetilde{jr}}, w_{\widetilde{jr}}) = (\overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})$; and

(ii) the two products have a different composition of marginal buyers in terms of z^1 and z^2:

$$\frac{\mu_r(z^1) \int_{\partial D_j(p_r)} f(\widehat{v}|z^1, x_r, \xi_r) \,\mathrm{d}\widehat{v}}{\mu_r(z^2) \int_{\partial D_j(p_r)} f(\widehat{v}|z^2, x_r, \xi_r) \,\mathrm{d}\widehat{v}} \neq \frac{\mu_{\widetilde{r}}(z^1) \int_{\partial D_{\widetilde{j}}(p_{\widetilde{r}})} f(\widehat{v}|z^1, x_{\widetilde{r}}, \xi_{\widetilde{r}}) \,\mathrm{d}\widehat{v}}{\mu_{\widetilde{r}}(z^2) \int_{\partial D_{\widetilde{j}}(p_{\widetilde{r}})} f(\widehat{v}|z^2, x_{\widetilde{r}}, \xi_{\widetilde{r}}) \,\mathrm{d}\widehat{v}}.$$

If this is the case $\left[\psi(z^1; \overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr}), \psi(z^2; \overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})\right]$ is the unique solution of the linear system describing the first-order conditions that must hold for both products:

$$\begin{bmatrix} mr_{jr} \\ mr_{\widetilde{jr}} \end{bmatrix} = \begin{bmatrix} \mu_r(z^1) \int_{\partial D_j(p_r)} f(\widehat{v}|z^1, x_r, \xi_r) \,\mathrm{d}\widehat{v} & \mu_r(z^2) \int_{\partial D_j(p_r)} f(\widehat{v}|z^2, x_r, \xi_r) \,\mathrm{d}\widehat{v} \\ \mu_{\widetilde{r}}(z^1) \int_{\partial D_{\widetilde{j}}(p_{\widetilde{r}})} f(\widehat{v}|z^1, x_{\widetilde{r}}, \xi_{\widetilde{r}}) \,\mathrm{d}\widehat{v} & \mu_{\widetilde{r}}(z^2) \int_{\partial D_{\widetilde{j}}(p_{\widetilde{r}})} f(\widehat{v}|z^2, x_{\widetilde{r}}, \xi_{\widetilde{r}}) \,\mathrm{d}\widehat{v} \end{bmatrix} \begin{bmatrix} \psi(z^1; \overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr}) \\ \psi(z^2; \overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr}) \end{bmatrix}.$$

In words: With two types of buyers which may imply different cost for the same product jr, it is necessary to observe two products with the same characteristics, and that variation in the characteristics of their competitors and/or market composition — and thus prices — induce variation in

[24]See conditions D1, C1, C2, C3 in Appendix B; or Theorem 1 and Section 4.2 in Berry and Haile (2014). Berry and Haile (2015) (see in particular Section 4.2) provide a rich discussion on the advantages of rich variation in individual level data to trace out the heterogeneity in preferences in each market relaxing specific functional form and parametric assumptions.

[25]With $\psi_{jr}(\widehat{z},\widehat{v}) \equiv c_{jr}$, i.e. assuming away selection, this would not be the case, and one could use the traditional cost-identification results discussed in Rosse (1970); Bresnahan (1981).

the composition of their marginal buyers in terms of the two types. If the two types are YOUNG and OLD, if one product has a 50:50 ratio of marginal buyers across YOUNG and OLD, it is necessary to observe another product for which (i) one assumes the same cost function and (ii) the ratio of marginal buyers across YOUNG and OLD is not 50:50.

Cost identification — general case. This approach can be extended to the general model. What follows differs slightly from Appendix B, yet the main point is conceptually the same.[26] As above I impose:

A1. For all j and all r, $mr_{jr} = mc_{jr}$, where $mr_{jr} = \sum_{\widehat{z}\in\mathcal{Z}} \mu_r(\widehat{z}) \left(\sigma_j(\widehat{z}, \chi_r) - p_{jr} \int_{\partial D_j(p_r)} f(\widehat{v}|\widehat{z}, x_r, \xi_r)\, \mathrm{d}\widehat{v} \right)$, and

$mc_{jr} = \sum_{\widehat{z}\in\mathcal{Z}} \mu_r(\widehat{z}) \int_{\partial D_j(p_r)} \psi_{jr}(\widehat{z},\widehat{v}) f(\widehat{v}|\widehat{z}, x_r, \xi_r)\, \mathrm{d}\widehat{v}$.

A2: For any j, $\psi_{jr}(\widehat{z},\widehat{v}) = \psi(\widehat{z},\widehat{v}, x_{jr}, \xi_{jr}, w_{jr})$, where x_{jr} may include the identity of the seller.

Then I restrict the number of "cost-types" to be finite, the *key assumption* for my argument:[27]

A3: There exists a finite (disjoint) partition of $\mathcal{V}$, say $\left\{\mathcal{V}^1, \mathcal{V}^2, ..., \mathcal{V}^M\right\}$ such that, for any $\widehat{z} \in \mathcal{Z}$, if $\widehat{v}, \widetilde{v} \in \mathcal{V}^m$ for some $m = 1, ..., M$, then $\psi(\widehat{z},\widehat{v}, x_{jr}, \xi_{jr}, w_{jr}) = \psi(\widehat{z},\widetilde{v}, x_{jr}, \xi_{jr}, w_{jr})$.

Using $\partial\mathcal{D}_{jr}(\mathcal{V}^m, z^\ell) = \left(\mu_r(z^\ell) \int_{\partial D_j(p_r)\cap\mathcal{V}^m} f(\widehat{v}|z^\ell, x_r, \xi_r)\, \mathrm{d}\widehat{v} \right)$ to denote the density of marginal buyers for j in r with characteristics z^ℓ and valuations $\widehat{v} \in \mathcal{V}^m$ I then have the following:

PROPOSITION **3** *Under A1-A3, $\psi(\cdot,\cdot,\overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})$ is identified if there exists a set of $H \geq T \times M$ pairs $\widetilde{jr}$ such that*

(i) *$(x_{\widetilde{jr}}, \xi_{\widetilde{jr}}, w_{\widetilde{jr}}) = (\overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})$ for all $\widetilde{jr} = 1, ..., H$; and*

(ii) *the H-by-$(T \times M)$ matrix of marginal buyers*

[26] In Appendix B I focus only on heterogeneity in cost due to differences in preferences, ignoring observable heterogeneity across buyers. I impose cross-product restrictions, and use a large support condition on prices that is extremely demanding on the data. This stronger condition allows me to provide a constructive proof for the identification of cost functions using variation in the set of marginal buyers, without assuming that selection is limited to a finite set of possible preference types. Here I impose more assumptions, but the conditions for identification become more transparent and operational.

[27] For example, suppose I was to estimate the following parametric model:
Facing prices p_r, the indirect utility that buyer i derives from j in r is

$$u_{ijr} = -\alpha_i p_{jr} + \beta_i x_{jr} + \xi_{jr} + \epsilon_{ijr},$$

where (α^i, β^i) collects random parameters drawn from a distribution $G(\alpha, \beta|z_{ir})$ with finite support $A \times B$ (similar to the demand system in Berry, Carnall, and Spiller, 1996).
Assumption A3 then holds by assuming that $\psi(\alpha, \beta, \epsilon, x_{jr}, \xi_{jr}, w_{jr}) = \psi(\alpha, \beta, x_{jr}, \xi_{jr}, w_{jr})$, requiring that the idiosyncratic preference shock ϵ is uninformative about the buyer's risk.

$$
\begin{array}{c}
h=1 \\
\vdots \\
h=H
\end{array}
\begin{bmatrix}
\partial\mathcal{D}_{\widetilde{jr}}(\mathcal{V}^1,z^1) & \partial\mathcal{D}_{\widetilde{jr}}(\mathcal{V}^2,z^1) & \dots & \partial\mathcal{D}_{\widetilde{jr}}(\mathcal{V}^M,z^1) & \partial\mathcal{D}_{\widetilde{jr}}(\mathcal{V}^1,z^2) & \dots & \partial\mathcal{D}_{\widetilde{jr}}(\mathcal{V}^M,z^T) \\
\vdots & \vdots & & \vdots & \vdots & & \vdots \\
\partial\mathcal{D}_{\widetilde{j'r'}}(\mathcal{V}^1,z^1) & \partial\mathcal{D}_{\widetilde{j'r'}}(\mathcal{V}^2,z^1) & \dots & \partial\mathcal{D}_{\widetilde{j'r'}}(\mathcal{V}^M,z^1) & \partial\mathcal{D}_{\widetilde{j'r'}}(\mathcal{V}^1,z^2) & \dots & \partial\mathcal{D}_{\widetilde{j'r'}}(\mathcal{V}^M,z^T)
\end{bmatrix}
$$

is full-column rank w.p.1 with respect to the (conditional) distribution of $\left((\mu_r, x_{-jr}, \xi_{-jr}, w_{-jr})\middle|(\overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})\right)$.

Beside the simple proof that I report below, the intuition is similar to the 2-types case analyzed earlier. To identify differences in the cost of a product j induced by differences in the type of buyer, one can use variation in the composition of marginal buyers within groups of products with otherwise (assumed) equal cost structures. This variation is induced by variation in the characteristics of opponents $(x_{-jr}, \xi_{-jr}, w_{-jr})$, or variation in the composition of potential buyers in the market $\mu_r(\cdot)$. Both induce variation in prices and choices, thus marginal buyers' composition, but do not directly affect individual cost functions for product j.

Since the number of possible "cost-types" that can be identified is bounded by the number of "preference types" distinguished by the demand system, the availability of rich individual-level observables and large variation in prices is important: Both can allow the estimation of a demand system with richer heterogeneity (see Berry and Haile, 2015), and this can then lead to the estimation of cost functions with less limits on selection.

Proof of Proposition 3

Assume that there are two functions $\psi(\cdot,\cdot,\overline{x}_{jr},\overline{\xi}_{jr},\overline{w}_{jr}) \neq \widehat{\psi}(\cdot,\cdot,\overline{x}_{jr},\overline{\xi}_{jr},\overline{w}_{jr})$ for which observables are the same with strictly positive probability. Pick for any $m = 1, ..., M$ an arbitrary $v^m \in \mathcal{V}^m$. By A1-A3, with positive probability, for all pairs jr with $(x_{jr}, \xi_{jr}, w_{jr}) = (\overline{x}_{jr}, \overline{\xi}_{jr}, \overline{w}_{jr})$

$$
mr_{jr} = \sum_{m,\ell}^{M,T} \psi(z^\ell, v^m, x_{jr}, \xi_{jr}, w_{jr}) \partial\mathcal{D}_{jr}(\mathcal{V}^m, z^\ell)
$$

$$
mr_{jr} = \sum_{m,\ell}^{M,T} \widehat{\psi}(z^\ell, v^m, x_{jr}, \xi_{jr}, w_{jr}) \partial\mathcal{D}_{jr}(\mathcal{V}^m, z^\ell),
$$

thus

$$
\sum_{m,\ell}^{M,T} \left(\psi(z^\ell, v^m, x_{jr}, \xi_{jr}, w_{jr}) - \widehat{\psi}(z^\ell, v^m, x_{jr}, \xi_{jr}, w_{jr})\right) \partial\mathcal{D}_{jr}(\mathcal{V}^m, z^\ell) = 0.
$$

Conditions (i) and (ii) imply then that $\psi(\cdot,\cdot,\overline{x}_{jr},\overline{\xi}_{jr},\overline{w}_{jr}) = \widehat{\psi}(\cdot,\cdot,\overline{x}_{jr},\overline{\xi}_{jr},\overline{w}_{jr})$ w.p.1, a contradiction.■