Spatial Disparities, Selection, and Segmentation in Health Insurance

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Job Market Paper

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Abstract

Most U.S. means-tested programs use uniform eligibility thresholds that ignore regional cost of living differences. I study whether and how adjusting eligibility thresholds to local cost of living shape selection, sorting, and segmentation in adjacent health insurance markets: Medicaid and health insurance marketplaces. I develop and estimate a model where the regulator sets eligibility rules, insurers compete on price and quality, and consumers choose or are assigned to plans. I find that adjusting eligibility thresholds for cost of living creates competing effects: it improves coverage by crowding low-income families into insurance in high-cost areas, but also reshuffles risk pools across both programs in ways that change premiums and plan quality. Counterfactual simulations using administrative data from California show that partial cost of living indexing yields higher welfare per public dollar than either uniform thresholds or full indexing. These results demonstrate how eligibility design interacts with market structure and insurer incentives in segmented health insurance systems.

Keywords: Subsidies, Health Insurance, Poverty Thresholds, Cost of Living.

JEL codes: H51, I13, L22

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All errors are mine.

1. INTRODUCTION

Nearly one in three Americans receives benefits from at least one means-tested social safety net program. Federal rules set uniform eligibility thresholds for these programs as fixed percentages of the federal poverty level (FPL), irrespective of local variation in the cost of living.[1] This uniformity across benefit allocations, although administratively simple, implies that households with identical real purchasing power may face starkly different eligibility outcomes depending on where they live. In high-cost regions, families earning modest nominal incomes may fail to qualify for public benefits, while households in similar economic conditions located in low-cost areas can receive these benefits. These geographic disparities raise a central policy question: Should income-eligibility thresholds be indexed to local living costs?

I examine this question in the context of public health insurance, focusing on two adjacent programs: Medicaid and the Affordable Care Act's individual insurance market or "Marketplace". In most states, Medicaid eligibility for non-disabled, non-elderly, single childless adults (the focal group of the paper) is set at 138% FPL.[2]Above this income threshold, individuals without employer-sponsored insurance may purchase coverage through the Marketplace. The Marketplace is open to all individuals without employer-sponsored coverage. Income-tested premium tax credits are limited to those with 100-400% FPL and cost-sharing reductions make coverage more affordable but do not determine eligibility itself.[3] Practical differences in cost sharing, network size, and benefit design further distinguish the two programs. For example, Medicaid enrollees face little or no out-of-pocket spending, whereas Marketplace enrollees may encounter significant premiums and deductibles.[4] These structural contrasts matter because they shape how individuals respond to income-based eligibility thresholds and how geographic adjustments to those thresholds affect both program participation and welfare.

From a theoretical perspective, adjusting Medicaid eligibility thresholds to reflect cost of living differences has ambiguous effects on equilibrium outcomes. For example, in high cost of living areas, higher thresholds not only alter the size of public and private insurance markets (economies of scale), but also the scope of each market by changing the demographic composition through

[1]Examples include SNAP, Medicaid, and Child Tax Credits in the US, as well as Kindergeld (Germany), Caisse des Allocations Familiales (France), and Child Benefit (Canada).

[2]Importantly, Medicaid eligibility is substantially more complex than a single 138% FPL cutoff. States determine eligibility through numerous "pathways," each defined by categorical and income criteria that differ across populations, which I expand on in the Background Section. Non-expansion states retain even lower limits for adults. As elaborated below, this paper abstracts from these complexities and focuses on the expansion-state adult group (non-elderly, non-disabled adults without dependents), for whom the Affordable Care Act standardized the income threshold at 138FPL.

[3]In other words, Marketplace plans are not "means tested"; rather, the allocated amount of federal subsidies declines with income.

[4]Marketplace plans are differentiated by actuarial value or "metal tiers," which refer to the share of expected medical costs covered by the plan. These tiers range from 60% for Bronze, 70% for Silver, 80% for Gold, and 90% for Platinum plans. Silver plans, as discussed in the Background section below, serve as the basis for cost-sharing reductions.

multiple channels.[5] In practice, three elements complicate the effects of such eligibility changes.[6] First, take-up frictions due to application costs, imperfect information, and strategic choice across programs with heterogeneous benefit structures and provider networks. Second, supply-side responses. Third, multi-layered regulation produces significant cross-sectional heterogeneity in how ostensibly uniform policies map into realized coverage outcomes.

While previous work has separately studied crowd-out in Medicaid expansions (Cutler & Gruber 1996; Gruber & Simon 2008), adverse selection in the Marketplace (Hackmann, Kolstad & Kowalski 2015; Tebaldi 2022), and geographic variation in safety net access (Finkelstein & Notowidigdo 2019; Currie & Grogger 2002), no single work combines all three. In this paper, I build and extend the existing literature in several ways. First, I develop a conceptual framework that extends standard models of insurance selection (Einav, Finkelstein & Cullen 2010) to capture how eligibility rules drive selection across programs. I provide mathematically and graphically possible channels to consider when thinking about decentralizing eligibility criteria. The key insight from this conceptual framework is that selection operates along two margins: consumer demand heterogeneity (as in standard models) and institutional eligibility rules that partition consumers across markets with distinct competitive mechanisms. Second, I provide the first joint estimates of demand elasticities and willingness-to-pay for coverage attributes in both Medicaid managed care and subsidized Marketplace plans. While Marketplace demand estimates exist (Tebaldi 2022; Ericson & Starc 2015), there are two novelties. First, demand parameters for Medicaid managed care, particularly sensitivity to plan quality and network breadth among low-income adults, are new to the literature. Second, my model includes both programs and endogenizes both federal and state regulators' decisions in equilibrium. The final contribution is the counterfactual analysis. I show that eligibility adjustment increases aggregate consumer surplus net of costs across all policy designs considered. The key mechanism that drives these results is the insurer price responses to changes in the risk pool of the potential buyers in the private market. I also show while average premiums decrease overall, welfare effects are highly heterogeneous across regions. I provide two possible explanations for such results. The first one is who becomes newly Medicaid eligible (previously uninsured vs privately-insured or selection). The second one is how much government spending is offset by savings from fewer uninsured. These results thus add to discussions about geographic equity in safety-net design and to proposals to adjust poverty thresholds for the Supplemental Poverty Measure.

To anchor the mechanisms in the data, I document three facts. First, affordability gaps between the national Medicaid threshold and local family budget standards are large and heterogeneous.

[5] First, it extends public coverage to individuals who are effectively priced out of insurance in expensive regions (Nichols & Zeckhauser 1982; Currie & Grogger 2002), and second, to those who would otherwise purchase private insurance (Cutler & Gruber 1996; Gruber & Simon 2008). Lastly, by reshaping risk pools in the private market, eligibility expansions can induce pricing and product design responses by commercial insurers, which may draw previously uninsured individuals into private coverage. Thus, the welfare effects largely depend on local selection patterns.

[6] Using American Community Survey and restricting to six most expensive metropolitan areas, I find that a back-of-the-envelope adjustment to the eligibility thresholds to adjust for local cost variation increases the eligible population by approximately 17,000 single childless adults -nearly doubling baseline levels.

Using data from the U.S. Bureau of Economic Analysis, I document that, at the state level, regional price parities (RPP) range from 85 to 118, implying that a single childless adult at 138% FPL has 20–25% less purchasing power in higher-cost states than in lower-cost states. Second, I examine whether plan premiums in California, the setting which I focus on in my empirical exercise, vary with the cost of living. I find that although Marketplace premiums rise with the cost of living, the pass-through is incomplete, producing wide dispersion in net prices across counties. Third, using the American Community Survey, I find differences in coverage distributions. As income increases, the probability of an individual being uninsured or on Medicaid decreases. However, as income rises, coverage shifts differently in high versus low cost of living areas. These facts suggest that the eligibility thresholds interact with the cost of living.

Accordingly, I develop and estimate a structural model of demand, supply, and regulation to analyze these tradeoffs. My model proceeds in four stages. First, the federal regulator sets location-specific eligibility threshold for Medicaid. In doing so, it maximizes maximizes total consumer surplus net of public expenditures while accounting for both intensive and extensive margins. Second, insurers observe the pool of their potential buyers and operate under state contracts. In my model, Medicaid plans choose quality investments to maximize their assigned share of passively enrolled, lower-cost marginal enrollees. They trade off investment costs with expected future profits, taking into account consumers' risk profiles. In the Marketplace, insurers compete on price à la Nash-Bertrand. Third and conditional on their eligibility, each consumer chooses an insurance plan from the available set following a standard static discrete choice model. Consumers' key priorities are plan quality (in Medicaid) and premiums (in the Marketplace). Lastly, the state regulator observes the share of individuals deemed eligible for Medicaid but who fail to choose a plan, and assigns them to a plan based on observed quality. [7] Using the estimated model, I evaluate the welfare effects of allowing the federal regulator to choose market-specific eligibility rules. In the model, welfare is measured in terms of consumer surplus from access to coverage or a more generous coverage, insurer profits or losses, and the fiscal cost to government, including Medicaid capitation payments and federal Marketplace subsidies.

I estimate the model using detailed administrative enrollment data as well as public and hand-collected plan information from California between 2017 and 2019. California is an ideal setting: Medi-Cal (the state's Medicaid program) accounts for roughly 15% of national Medicaid enrollment, and Covered California (the state's Marketplace) accounts for nearly 8% of national Marketplace enrollment. Two additional features of these programs in California make this problem interesting. First, standardized benefits across Marketplace plans simplify modeling firm behavior. Second, Medi-Cal's quality-based auto-assignment mechanism, which allocates enrollees to plans based on plan quality. Also, California's regions have substantial cost of living variation

[7] Medi-Cal managed care plans operate under state contracts and are expected to generate savings relative to fee-for-service care by managing utilization and negotiating provider payments. However, within the state's risk-adjusted capitation framework and medical loss ratio (MLR) requirements, pricing competition is largely fixed ex ante through negotiated capitation rates. As a result, the main margin of competition among plans is service quality and performance on state-selected HEDIS indicators, which directly affect plan assignment shares and potential penalties.

(40% real income differences across counties). All these features allow me to identify key elasticities and responses in my model. While my empirical application focuses on California, the mechanisms I identify are national in scope and portable. I find systematic differences in demand across the two programs. In Covered California, I find that price sensitivity declines with increases in income across all age groups. By contrast, in Medi-Cal, demand parameter variation is much smaller: sensitivity to network breadth is roughly constant across age groups, and quality effects, while positive, are more modest. I estimate that marginal claims costs (and Medi-Cal quality costs) vary across plans and geographic markets.

Regulators face a critical trade-off when deciding where to draw the eligibility threshold. In principle, the "optimal" policy would involve Ramsey-style transfers or smoothing subsidies across programs. However, in practice, they rarely implement such complex designs. Instead, adjustments typically occur along administratively tractable margins.[8] Motivated by this institutional reality, I evaluate the effects of alternative eligibility thresholds that reflect feasible extensions of existing practice. I consider three feasible alternatives to the uniform 138% FPL cutoff. First, I adjust the eligibility thresholds to state-level minimum wage, and second, more granularly, to the local cost of living. In all counterfactuals, I restrict the analysis to individuals with incomes below 400% FPL. All counterfactual designs, thus, are considered in these analyses to relax eligibility thresholds relative to the status quo, making these policies inherently expansionary.

I find that aggregate consumer surplus net of costs increases under all considered alternative thresholds. Quantitatively, these gains are meaningful. Benchmarking eligibility halfway towards the local cost of living yields the highest (around $40 million) total welfare for the representative population in California relative to the status quo. More importantly, I find that markets adapt to threshold changes by adjusting prices and quality. Across all alternative designs, the average premium for the benchmark plan in Covered California declines substantially. For those remaining in Covered California, average consumer surplus increases, though the gains are smaller than the corresponding premium reductions. On the Medi-Cal side, enrollment expansions are accompanied by small declines in average plan quality. One possible explanation for these results is that the quality metrics focus primarily on child-related follow-up services, whereas the population I study in this paper is childless adults. Despite these modest declines, average consumer surplus in Medi-Cal rises under all counterfactual designs. While welfare increases, aggregate results mask potential variation in welfare effects across different regions. I report consumer surplus net of costs (including uncompensated care savings) for each region under each counterfactual eligibility design. I find that gains from decentralization are uneven. I explore two possible avenues to explain these differences: (1) who becomes newly eligible (previously uninsured vs already-insured), and (2) the extent to which public spending replaces existing payments versus adds new spending.

Finally, I use the model to disentangle the welfare changes under alternative eligibility thresh-

[8] This is evident in poverty measurement and other safety net programs: the Supplemental Poverty Measure incorporates geographic adjustments for housing costs, and Medicare and HUD payments use local wage and rent indices.

olds. I consider four possible channels. First, the mass of near-threshold uninsured (targeting gain). Second, the risk and cost profile of switchers (fiscal cost), third, insurer pricing (premium response), and lastly, the passive-enrollee share in Medicaid (quality-assignment surplus). To do so, I calculate the variation in each channel by holding others fixed. I find that more than 60% of the welfare changes come from lower Marketplace premiums resulting from improved risk pooling. The remaining effects stem from modest quality adjustments in Medi-Cal's auto-assignment markets.

2. Related Literature

This paper combines and contributes to several strands of the existing literature. First, it extends work in both academia and policy emphasizing the importance of regional cost-of-living variation—not only in poverty assessment and program design, but also in the administration of social insurance programs. Since 1963, the federal standard for measuring poverty in the United States has been the Official Poverty Measure (OPM), which relies on a national threshold that does not account for local price variation. Recognizing the OPM's limitations, alternative approaches such as the Supplemental Poverty Measure (SPM) and locally anchored indices (Glaeser, 2011) have been developed to incorporate geographic variation, while others focus on consumption-based metrics (Meyer and Sullivan, 2012; Meyer et al., 2022) or comprehensive income measures (Burkhauser et al., 2024).Building on these advances, a parallel literature examines the consequences of incorporating geography into the design of public policy—including optimal tax policy (Kaplow, 1996; Albouy, 2009) and well-being assessments (Furdell et al., 2005; Chien and Mistry, 2013; Povey et al., 2016). My work bridges these strands by extending the logic of regional adjustment to the eligibility thresholds of health insurance programs. Focusing on Medicaid and the health insurance marketplaces—two adjacent programs—I show that geographically adjusted thresholds have competing effects: they can increase coverage by enrolling more low-income families in high-cost areas, but also shift risk pools in ways that affect premiums and other plan features. This approach contributes to the literature on multi-program market design and on the welfare implications of affordability constraints (Wagstaff and Van Doorslaer, 2000; Bundorf and Pauly, 2006; Bernard et al., 2009; Pauly, 2017; Ho, 2018; Kanimian and Ho, 2024), particularly given evidence that cost remains a primary barrier to coverage for many uninsured adults.[9]

Second, this paper shares a core motivation with the literature on market segmentation: understanding how changes in market structure—and the resulting re-sorting of individuals—affect welfare. Segmentation is a pervasive phenomenon across many markets, including school attendance zones (Bayer et al., 2007; Frankenberg et al., 2023), housing (Galster & Rothenberg, 1991), automobiles (Lutz, 2004), assets (Alvarez et al., 2002; Hietala, 1989), agriculture (Gil et al., 2000), service industries (Allon & Federgruen, 2009), and labor markets (Reich et al., 1973; Taubman & Wachter, 1986), with segmentation often based on demographic, geographic, psychographic, or

[9]Recent estimates suggest that nearly 70% of nonelderly uninsured adults cite high costs as the primary barrier to obtaining coverage, Kaiser Family Foundation (KFF) analysis of the National Health Interview Survey.

behavioral factors. Within health insurance, my paper is most closely related to Fleitas et al., 2025 and Dickstein et al., 2024, both of which examine the implications of merging or segmenting the small-group and individual insurance markets.[10] Fleitas et al., 2025 uses proprietary insurer data to model plan choice and simulate counterfactuals that shift small-group households to the Marketplace, distinguishing between fixed-premium and equilibrium scenarios to estimate welfare gains. Similarly, Dickstein et al., 2024 analyzes the effects of pooling small group and individual markets under the ACA in Oregon, showing that while pooling can benefit higher-risk individuals, healthier enrollees may experience welfare losses. Like these studies, my paper investigates how reallocating individuals across segmented markets impacts consumer welfare and insurer responses. However, my setting is fundamentally different: the choice sets and institutional architectures of Medicaid and the Marketplace are categorically distinct, presenting unique challenges in comparing welfare across non-aligned plans and modeling behavior under institutional constraints. Addressing these challenges allows my paper to extend the segmentation literature to settings where mechanisms of sorting and welfare differ substantially from previously studied cases.[11]

Lastly, this work contributes to the extensive literature on the crowd-out effect, which examines how public insurance expansions influence private market outcomes. Related studies have assessed the impact of ACA Medicaid expansions on private insurance markets, including Clemens, 2015, Peng, 2017, and Sen and DeLeire, 2018. More recently, Holmes, 2021 investigates how the termination of a risk-sharing program in one market can affect insurer participation, premiums, competition, and enrollment in adjacent markets lacking such a program. In a similar vein, my work underscores that policy changes targeting a specific insurance market can generate significant spillover effects in others. These cross-market effects are particularly salient given the multi-market presence of insurers, who can reallocate administrative resources, coordinate pricing, and exploit economies of scale—potentially amplifying or mitigating the impact of policy shocks. This dynamic is especially relevant in the current policy environment, as states like South Dakota and North Carolina expand Medicaid, and as over 1.5 million individuals have recently been disenrolled from Medicaid due to the unwinding of pandemic-era provisions, with many facing coverage gaps between Medicaid and subsidized exchange eligibility.[12]

[10] Similar insurance segmentation exists in other developed countries, such as Australia and Germany; see Health Plan Payment in Australia/Germany, Risk adjustment, risk sharing and premium regulation in health insurance markets (2018).

[11] Further, my work relates to research on segmentation and transitions within health insurance, such as Timmers (2023), who studies the effects of allowing Medicaid-eligible individuals to select plans on the Marketplace, finding higher premiums and reduced consumer surplus in New Hampshire, and Ackley et al. (2024), that examines increases in outpatient utilization when individuals transition from Medicaid to Medicare at age 65. These studies, together with mine, speak to broader concerns about insurance "churn"—frequent transitions between Medicaid, Marketplace, and employer coverage due to income volatility or administrative barriers. This issue is particularly salient in the context of ongoing Medicaid unwinding, as individuals move between coverage systems that are not designed to be seamlessly interoperable.

[12] Additionally, this paper contributes to the market design literature, particularly in the areas of subsidy structures, risk adjustment (see Ericson and Starc (2015); Finkelstein et al. (2019); Decarolis et al. (2020); Jaffe and Shepard (2020); Tebaldi et al. (2023)), and auto-enrollment (Geruso et al. (2023); Shepard and Wagner (2023)). My contribution is twofold: first, I evaluate an alternative subsidy design that accounts for regional cost-of-living differences; second, I ex-

3. THEORY

In this section, I introduce a stylized framework of adjacent health insurance markets. The model extends Einav, Finkelstein, and Cullen (2010) to a multi-market context, where both consumer demand and eligibility rules shape selection. The purpose of the model is not to offer a comprehensive representation of real-world insurance markets, but rather to highlight that, once eligibility thresholds are adjusted for regional cost of living differences, the welfare effects are theoretically ambiguous. This ambiguity motivates the empirical and quantitative analysis that follows.

Consider a setting in which there are two markets, L and H, each offering a single full health insurance contract.[13] In market L, the insurance contract is offered for free and in market H at a price p. I assume that if individuals want to purchase the insurance contract, they do so at the lowest price available, which is sufficient to characterize demand for insurance. Individuals are characterized by a type vector θ, and income Y. θ captures heterogeneity in risk, preferences, and expectations of healthcare use. The population follows a distribution $G(\theta, Y)$. Denote by $W(\theta_i, Y_i)$ individual i's willingness to pay (WTP) for insurance. Under this setup, I normalize outside option utility (no insurance, U) to 0, and define utility from insurance F as:

$$u_{iF} = \begin{cases} W(\theta_i, Y_i) & \text{if individual } i \text{ is in market L} \\ W(\theta_i, Y_i) - p & \text{if individual } i \text{ is in market H} \end{cases}$$

Individuals choose to enroll in the contract offered if $u_{iF} \geq 0$, that is, if their WTP for insurance exceeds insurance premium p. Lastly, I impose the following assumptions on individual preferences.

Assumption 1 (Monotonicity and Concavity in Income): $\forall\, \theta, \quad \frac{\partial W(\theta,Y)}{\partial Y} > 0 \quad \text{and} \quad \frac{\partial^2 W(\theta,Y)}{\partial Y^2} < 0.$

Assumption 2 (Multidimensional Heterogeneity): Given Y, $\exists\, \theta_i \neq \theta_j$ such that $W(\theta_i, Y) \neq W(\theta_j, Y)$.

Assumption 1 suggests that, at any fixed θ, higher income individuals value insurance more but that valuations flattens at very high income levels. Assumption 2 accentuates that individuals with the same income may have different WTP due to variations in their underlying factors or θs. Graphically, this implies that demand for insurance does not lie along a single dimensional income ladder but is instead resembles a Cantor-type set. The multidimensionality of characteristics fundamentally alters the nature of market sorting. Selection into insurance is not only shaped by income-based affordability, but rather within-income-group heterogeneity. Finally, I denote by $C(\theta_i, Y_i)$ the expected monetary cost associated with insuring individual i of profile (θ_i, Y_i). I assume the cost does not vary by market.

plicitly integrate multiple health insurance market segments into the analysis. This multi-market perspective is crucial in the U.S. context for accurately assessing welfare implications and simulating the effects of policy interventions.

[13] For exposition, I consider both markets offer same exact contract which only differs in price. The setting can be expanded to include multiple plans with different features.

I use the framework to show how imposing a uniform threshold across locations alters eligibility, enrollment, and welfare relative to the decentralized benchmark. I begin from a benchmark with decentralized eligibility thresholds across locations, and then impose a common threshold in both locations to illustrate the implications of uniform policy design. To simplify the exposition, consider two locations $l = 1, 2$ with cost of living indexes $1 = c_1 < c_2$. I assume eligibility thresholds are set as Y_1 and Y_2 in locations 1 and 2, respectively, and that thresholds are proportional to the relative indices, that is, $Y_1/Y_2 \propto c_1/c_2$. For simplicity, assume that each location has an identical distribution of individuals and insurance prices. The latter assumption is reasonable, as many counties within the same rating area exhibit no price differentiation. These assumptions serve as normalizations and are straightforward to relax, and indeed, they are relaxed in the empirical application.

Given these assumptions, aggregate demand in each location l and market L is determined by the interaction of three factors: the region capturing individuals' WTP, the income threshold Y_l, and the price p:

$$D_L = \int 1\{Y \leq Y_l\} dG(\theta, Y)$$

In market H, individuals with income above the threshold Y_l pay price p for insurance. In this case, demand for insurance compasses those whose willingness to pay exceeds the market price p:

$$D_H = \int 1\{Y \leq Y_l, W(\theta, Y) \geq p\} dG(\theta, Y)$$

Lastly, the average expected cost in each market is given by:

$$AC_L = \frac{1}{D_L} \int 1\{Y > Y_l\} C(\theta, Y) dG(\theta, Y) \text{ and } AC_H = \frac{1}{D_H} \int 1\{Y \geq Y_l, W(\theta, Y) \geq p\} C(\theta, Y) dG(\theta, Y)$$

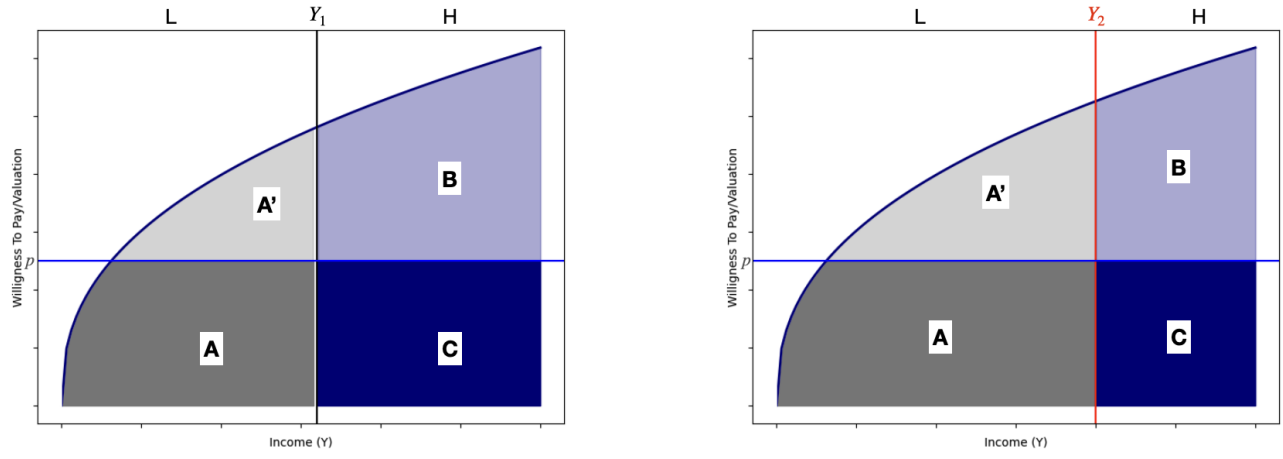


Figure 1: Baseline Sorting Under Location-Specific Thresholds: Location 1 (left) and Location 2 (right)

In Figure 1, I illustrate the WTP region against nominal income Y for locations 1 and 2, respec-

tively. Insurance price p and location-specific thresholds Y_l segment the region into 4 sub-regions. First, Regions A and A' represents all individuals with income below Y_l who are eligible for free coverage in market L. More specifically, Region A' consists of those who would have purchased insurance at price p in market L but are offered the insurance contract for free instead. Region A' emphasizes both effective targeting of high-valuation individuals and allocative inefficiency stemmed with zero prices. Second, Region B includes individuals who efficiently sort into market H due to their high WTP. This region represents the demand for the insurance contract in market H. Finally, Region C encompasses those with low WTP (relative to p) who are above the income threshold Y_l and efficiently remain uninsured.

Now suppose both locations have exactly the same eligibility threshold, Y_1. Applying Y_1 to location 2, I show, in Figure 2, that two additional regions emerge: D and E. From market L's perspective, Regions D and E include individuals who previously were eligible to free insurance coverage. The new demand for insurance in L is:

$$D^L_{new} = \underbrace{\int 1\{Y \leq Y_2\} dG(\theta, Y)}_{\text{Demand, } D_L \text{ under } Y_2} - \underbrace{\int 1\{Y_1 < Y \leq Y_2\} dG(\theta, Y)}_{\text{crowd out = D+E}}$$

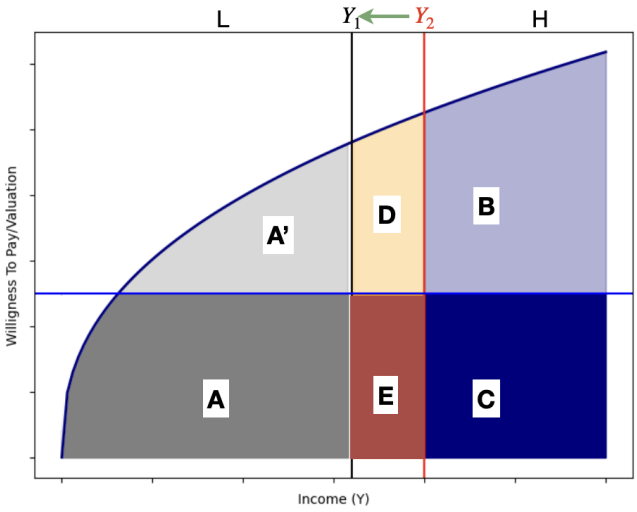


Figure 2: Sorting Under Uniform Threshold: Allocating Location 1 Threshold to Location 2

From market H's perspective, the new demand for insurance increases by region D (those with $WTP > p$) only:

$$D^H_{new} = \underbrace{\int 1\{Y \geq Y_1,\ W(\theta, Y) \geq p\}\, dG(\theta, Y)}_{\text{Demand, } D_H \text{ under } Y_2} - \underbrace{\int 1\{Y_1 < Y \leq Y_2,\ W(\theta, Y) \geq p\}\, dG(\theta, Y)}_{\text{crowd in = D}}$$

Region E represents a coverage gap that emerges from the interaction between uniform thresholds and local costs. The welfare implications here are particularly severe as these individuals may

have high WTP for insurance but find themselves priced out of both markets. The magnitude of these inefficiencies scales with the cost of living differential between locations. When this gap is large, the uniform threshold creates substantial allocative inefficiency.

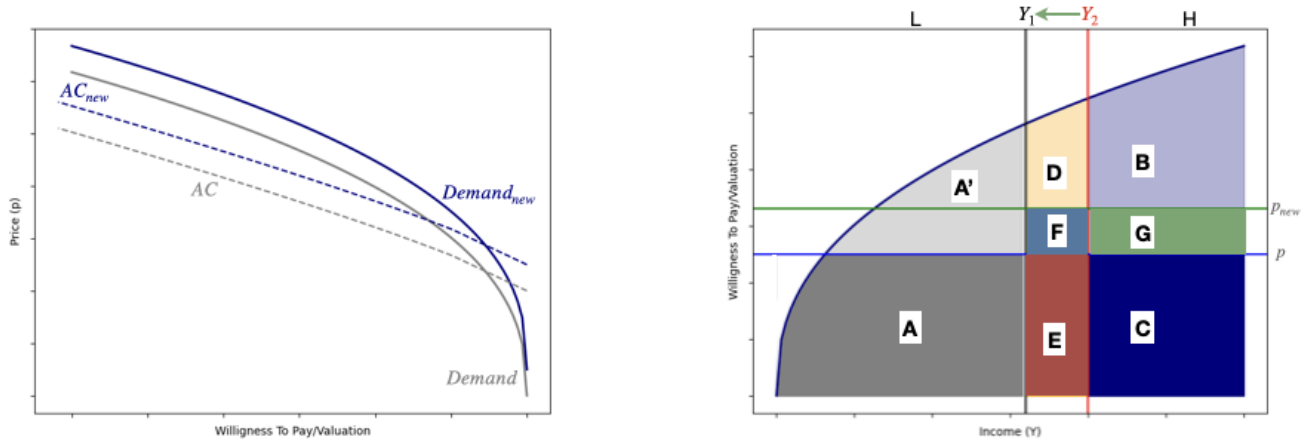


Figure 3: Cross-market Selection

If selection effects are significant across these markets, the price p may adjust in response to changes in demand. One potential direction for p is upwards as shown in Figure 3. This particularly arises from an outward shift of the AC curve to AC_{new} as Region D brings a mix of higher-risk individuals. The new premium p_{new} in market H is the intersection of $Demand_{new}$ or D^H_{new} with AC_{new}. Denote by D^{eqn}_H a possible *equilibrium demand* in market H:

$$D^{eqn}_H = \underbrace{\int 1\{Y \geq Y_1,\ W(\theta,Y) \geq p\}\, dG(\theta,Y)}_{\text{Demand, } D_H \text{ under } Y_2} - \underbrace{\int 1\{Y_1 < Y \leq Y_2,\ W(\theta,Y) \geq p\}\, dG(\theta,Y)}_{\text{crowd in = D}}$$
$$- \underbrace{\int 1\{Y \geq Y_2,\ p \leq W(\theta,Y) < p_{new}\}\, dG(\theta,Y)}_{\text{crowd out = F+G}}$$

The corresponding equilibrium average cost is:

$$AC^{eqn}_H = \frac{1}{D^{eqn}_H} \int 1\{Y \geq Y_2, W(\theta,Y) \geq p_{new}\} C(\theta,Y) dG(\theta,Y)$$

In this stylized setting, I conclude that (1) eligibility thresholds reallocate coverage across markets L and H, (2) underlying characteristics of individuals (θ) impact both premium movements and crowd-out, and (3) the direction of selection effects can flip by local conditions. However, the direction and magnitude of these changes are a priori ambiguous. Moreover, since this setting focuses on prices only, it does not reflect other margins that may adjust. In particular, equilibrium changes may arise through three channels: (i) premiums (pricing), (ii) nonprice attributes (benefit generosity, network breadth/quality), and (iii) selection and market structure (risk mix). To

disentangle these mechanisms and recover their contributions, I develop a structural model.

4. Institutional Primer and Data

4.1 Background

Individuals and households in the U.S. obtain health insurance through different market segments based on eligibility. This paper focuses on the interactions between two key segments: Medicaid (Medi-Cal) and Marketplace (Covered California) in California for several reasons. First, these segments are vital in delivering affordable healthcare to vulnerable populations and maintaining continuous coverage for millions. Second, California is often seen as a healthcare bellwether with the most significant increase in insured individuals following the ACA. Its Medicaid program, Medi-Cal, is the country's largest by enrollment and spending. Lastly, California also offers a unique advantage for model specification.

Since January 2014, individuals and households in California seeking health insurance could access coverage through two primary sources: (1) no- or low-cost coverage via Medi-Cal or (2) premium assistance through Covered California. Applicants use a single application to report their income, family size, and any source of coverage they have. Adults with income below 138% FPL generally qualify for Medi-Cal with no premiums. The application also calculates the level of financial assistance available to the applicant to purchase a Covered California plan for those not eligible for Medi-Cal but requiring coverage. In this section, I outline the key features of each segment (See Appendix C for details on the online application process).

4.1.1 Medi-Cal

Medi-Cal provides coverage for essential health benefits to historically underserved groups, and under the latest ACA expansion, to adults with income up to 138% FPL (see Appendix C.2 for different pathways of Medi-Cal eligibility). The program is administered by the California Department of HealthCare Services (DHCS) and is jointly funded as an open-ended federal commitment, with the state covering half of the program's costs. In this paper, I focus on income-based eligibility of Medi-Cal.

Medi-Cal offers both fee-for-service (FFS) and managed care options. The majority of Medi-Cal recipients are now enrolled in managed care plans, with only a limited number still accessing care through the FFS system due to specific exemptions.[14] The number and type of plans offered vary widely: 22 counties have a single public plan, 14 counties have a public and privately provided plan, and the remaining have either two or more commercial plans. While publicly run plans are organized at the local or regional level, commercial plans are contracted by the state regulator through an unknown procurement process. Historically, and more specifically during the years studied in this paper (2017-2019), procurement did not occur every year, and in all geographic

[14] Carve-outs are available for dental, mental health, and substance abuse, and drugs.

areas.[15] All Medi-Cal managed care plans provide standard benefits, including doctor and specialist visits, hospital services, prescription drugs, and prenatal and maternity care, along with limited immunizations and preventive services. Some plans may offer other services such as behavioral health, telehealth, and advise nurse services, which I elaborate in Appendix C.1. Plan cost sharing and covered services are generally standardized and follow federally and state-specified schedule with minimal cost sharing, as low as $1. Plans are compensated through a per-member, per-month payment, which is adjusted by demographic group (e.g., children, adults, seniors, persons with disabilities, and maternity) and plan county, further stratified by risk categories (lower bound, midpoint, and upper bound). All plans within a given county receive identical payments for enrollees in the same demographic and risk group. Actuaries set the compensation rates for particular geographic areas.

Participation in Medi-Cal is voluntary and requires individuals to apply to determine their eligibility. Once deemed eligible, individuals are notified and invited to choose a health plan from the available options within 30 days. If no selection is made during this period, the state assigns individuals to a plan, giving priority to plans in which a family member is already enrolled. In the absence of such connections, assignment is directed toward higher-performing plans. Plans are evaluated on predetermined quality measures by the state regulator. Quality measures are a subset of the Healthcare Effectiveness Data and Information Set (HEDIS) which include well-child visits, adolescent immunizations, prenatal and postpartum care, and follow-up after emergency department visits.[16] Between 2017 and 2019, 71.7% of newly eligible Medi-Cal enrollees actively selected a plan, while 28.3% were auto-enrolled.

4.1.2 Covered California

Covered California provides health insurance primarily for individuals and households ineligible for Medi-Cal or affordable employer-sponsored insurance.[17] Plans are offered by commercial insurers and are standardized at coverage levels, also known as "metal tiers" based on how much risk is borne by the insurer versus the consumer: Bronze plans have an actuarial value (AV) of 60%, followed by Silver plans, 70%, Gold, 80%, and Platinum, 90%.[18] Within a tier, plan features

[15] During 2014-2019, there was one expansion procurement in 2015 in Sacramento and San Diego, where two plans were added.

[16] To determine auto-assignment rates, DHCS compares each plan's performance either against peers in two-plan counties or the county's harmonic mean in multi-plan counties awarding points based on whether a plan's scores are statistically superior, equivalent, or inferior. Penalties are applied to plans that fail to meet specific requirements, and final allocations are normalized to total 100%. This default process is considered quasi-financial, as it channels passive enrollees to certain plans while also encouraging health plans to continually improve their performance. Emerging evidence suggests that defaulted beneficiaries generally exhibit lower healthcare utilization compared to those who actively select plans. See Putting Quality to Work: Rewarding Plan Performance in Medi-Cal Managed Care, California HealthCare Foundation, May 2006 and Appendix C.3 expands on the evaluation process and the metrics used.

[17] For plan years beginning in 2025, employer-sponsored coverage is considered affordable if the employee's required contribution for the lowest-cost self-only plan does not exceed 9.02% of their household income. This percentage is adjusted annually by the IRS.

[18] Catastrophic coverage is also offered for individuals under 30 years old, satisfying specific criteria. This tier accounts for only 1% of enrollment, which I abstract away from in this paper.

have the same cost sharing structure and number (see Appendix C.6).[19]

Health plans in Covered California are compensated primarily through premiums, but the process for setting these premiums is highly regulated. Insurers must adhere to a variety of rules governing how premiums are determined and who can be charged what amount. For example, insurers are required to charge the same premiums throughout all counties within a given rating area. A rating area is a county or a group of counties defined at the state level. There are 19 rating areas in California. While partial participation is allowed, any insurer entering a rating region must offer a Bronze, a Silver, and a Gold plans. Additional regulations prohibit insurers from denying coverage based on pre-existing conditions or varying premiums based on health risks. Although premiums can be adjusted by age, the age bands are predetermined and strictly limited.[20] Notably, in California, insurers cannot adjust premiums based on tobacco use, a practice permitted in some other states.[21] Given these regulations, in rating region m, each plan j is associated with a single "base" premium, say b_{jm}. This is translated to age-adjusted (pre-subsidy) premium using given age adjustment factors τ_i for consumer indexed by i, equal for all products. The premium received by the insurer for an enrollee i in plan j and market m is:

$$\underbrace{P_{ijm}}_{\substack{\text{premium collected}\\ \text{by insurer}}} = \underbrace{b_{jm}}_{\substack{\text{premium set}\\ \text{by insurer}}} \times \underbrace{\tau_i}_{\text{age factor}}$$

While P_{ijm} is the amount collected by the insurer, premium assistance is available for individuals and households in two forms. First, premium subsidies are available for those with income 100-400% FPL in the form of tax credits that can be applied to any Marketplace plan. Subsidies are on a sliding income basis and are a function of (1) age-adjusted price of the second-cheapest Silver tier plan (also known as the benchmark plan) in the market, $b_{2Sm} \times \tau_i$, and (2) maximum affordable amount (MAA), $\bar{p}(income_i)$ for consumer i with income $income_i$.[22] Formally, the subsidy received by individual i is equal to:

$$subsidy_{im} = \max\{b_{2Sm} \times \tau_i - \overline{p}(income_i), 0\}$$

and the premium paid by a consumer i to enroll in plan j in market m is:

$$p_{ijm} = \max\{b_{jm} \times \tau_i - subsidy_{im}, 0\} \tag{1}$$

[19] This structure is not typical in all states. In most cases, insurers have the flexibility to design their plans' cost-sharing features to achieve the target AV, effectively turning the process into a menu of choices.

[20] The oldest individuals cannot pay more than three times higher premiums than the youngest individuals do.

[21] In addition, insurer premiums have to satisfy the medical loss ratio (MLR), which requires insurers to pass through at least 80-85% of their margins.

[22] The MAA limit is 2% of income for consumers with incomes of 100% FPL and 9.5% of income for consumers with incomes of 400% of FPL in 2014 (these percentages change slightly each year). For example, a single consumer earning less than $31,300 in 2024 would have a contribution limit of $626 annually ($\approx$ $52 monthly), the consumer's monthly premium subsidy would be $148 if the full benchmark plan premium were $200. This $148 subsidy could be used for any metal plan (catastrophic plans do not qualify for subsidies). In an event plan, if the premium is below $148, the subsidy is reduced, so the premium is non-negative.

The second form of assistance are the cost-sharing reductions (CSRs). CSRs are available for individuals and households with income up to 250% FPL who purchase a Silver plan. CSRs do not directly affect prices but make Silver plans more attractive by increasing their AV. Specifically, if a consumer's income is below 150% FPL, the AV increases to 90; if income falls between 150% and 200% FPL, the AV rises to 88; and for those with incomes between 200% and 250% FPL, the AV increases to 74. For this group, the federal government covers part of their out-of-pocket spending, increasing the actuarial value of the plans.

4.2 Data

There is no comprehensive data to study segmentation in health insurance. The most extensive data is the state-level All-Payer Claims Databases (APCD). [23] Even with such data, meaningful (and relevant to this project) demographic information, such as income, is not reported. Hence, this paper attempts to answer the research question with the most comprehensive dataset.

4.2.1 Enrollment

Data on enrollment comes from two sources. First, Medi-Cal enrollment information is from the California Department of Health Care Services (DHCS). Enrollment data is organized by aid codes (eligibility groups, benefits, and funding sources) and aid categories (similar aid codes into broad classifications such as Seniors and Persons with Disabilities or Long-Term Care). The granular level data, however, is not publicly available. For this paper, I request custom data on individuals eligible under 42 CFR 435.119, which includes non-pregnant adults aged 19-64 with household income at or below 138% FPL.[24] For each year, county, and non-specialty managed care plan, I observe unique individual counts of Medi-Cal enrollees by age brackets (19-34, 35-54, 5-64) and income (below 138% FPL).[25] Table B1.1 summarizes unique individual-year counts by age brackets and managed care plan.[26] The majority of the enrollees are ages 19-34 (49.40%), followed by ages 35-54 (31.06%) and 55-64 (19.54%). Like many U.S. health insurance markets, Medi-Cal is concentrated. LA Care has the highest market share with 20.06% (2.52 million) enrollees, followed by Health Net Community Solutions at 13.74% (1.72 million) enrollees and Inland Empire Health Plan at 11.08% (1.39 million). The market share of the remaining insurers range between 5% and 7%.

[23] Currently, 25 states have a mandatory APCD. California's APCD, known as the Health Care Payments Data (HPD), began data collection in 2018, with applications to queue access only available since December 2024.

[24] 42 CFR 435.119: https://www.ecfr.gov/current/title-42/section-435.119. The regulation does not exclude married individuals; however, data on marital status is largely missing (99%+ in multiple years), making it unreliable for assessment. Parents or caretaker relatives qualify under 42 CFR 435.119 if their dependent child(ren) receive Medicaid, CHIP, or minimum essential coverage. For more details on the aid categories covered under this regulation, refer to Appendix C.4.1

[25] Discussions with the Information Management Division staff indicated that the DHCS places greater emphasis on whether a beneficiary's income falls within the specified range, rather than focusing on the precise income amount. Hence, precise income information is not available at this stage.

[26] All individuals are only counted once. If they have multiple plans throughout the year, their plan with the highest plan number will be represented in the table. Priority is given to Managed Care plans over FFS.

Data on Covered California enrollment is also obtained through a custom request. For every plan purchase, I observe individual and household identifiers, along with age, gender, three-digit zip code, county, rating region, plan identifier, premium paid, and income bracket. While income and age are reported in discrete bins, I use the pricing regulations to determine income with higher precision. I narrow my focus to adults aged 19–64 and beneficiaries with premium subsidies.[27] The final sample is a total of 1.16 million individuals in a given year. Table B1.3 summarizes the enrollment data in age and income brackets. Across age brackets, highest enrollment is for ages 55-64 (36.45%) , followed by 19-34 (32.79%) and 35-54 (30.80%). For income brackets, largest enrollment (31.81%) is from individuals and households with income between 150-200% FPL.[28] Four players (Anthem, Blue Shield, Health Net, and Kaiser) are present across a large number of markets, while the remaining insurers are only available in a small number of regional markets. Kaiser has the highest market share (within enrollees) with 34% of enrollees, followed by Blue Shield (28%), Health Net (11%), and Anthem (7%). In terms of metal tier, 28% of enrolled individuals choose a Bronze plan, while 61% choose a Silver plan. Gold (6%) and Platinum plans (3%) are selected more rarely.[29]

4.2.2 Supplementary Data

I supplement the main enrollment data with several other datasets. First, I hand-collect data on Medi-Cal plan network size and characteristics, which I summarize in Appendix Table C.4. Plans vary substantially in the breadth of the contracted provider networks, he scope of additional services offered (beyond the standardized Medi-Cal benefit package), and supplemental benefits (such as telehealth, behavioral health services, home health support, and CHDP (Child Health and Disability Prevention) examinations). It is worth noting that this data has two key limitations: (1) I do not observe plan characteristic data for plans operating in a single-plan county; and (2) data are unavailable or missing for some plans. I supplement missing observations using publicly available provider directories and archived plan materials. I document the coverage of these variables (Appendix C.1) and describe the procedure for how I construct a measure of network breadth (Appendix C.7). Second, and for Covered California, complement enrollment data with publicly available information on plan benefit design. To have the universe of plans offered, I combine this data with publicly available data on product prices for all health insurance companies by counties and age groups.[30]

To construct the set of potential buyers, I use the American Community Survey (ACS) via Integrated Public Use Microdata Series (IPUMS). ACS has demographic and socioeconomic infor-

[27] Since off-Covered California plans are not eligible for subsidies, excluding the unsubsidized population mitigates concerns that enrollment files may miss many individuals purchasing coverage outside the Marketplace. I also restrict my data to include individuals who stayed with a single choice of plan over a single year.

[28] Average age among subsidized single childless adults in Covered California is 44, while average income is 219.77% of the FPL, which is around $28,000 annually. Individuals pay, on average,$148 per-person, per-month or $1776.84 per-year, receiving subsidies (gross-net) that are, on average, more than 2.5 times as large.

[29] These numbers vary widely across regions and years.

[30] See Data & Research:https://hbex.coveredca.com/data-research/

mation from over 4 million people annually and is designed to be representative at the state and substate geographic levels, mainly Public Use Microdata Area (PUMA) level.[31] I first restrict ACS to PUMAs spanning California, and then to individuals with either (1) no insurance, (2) Medicaid, and (3) private insurance.[32] Table B1.4 shows health insurance coverage distribution in California from 2017-2019. In 2017, within the 19-64 demographic group and income less than 400% FPL, 10.5% of individuals (2.5 million) had no health insurance, among whom, 18.4% are qualified for Medicaid due to their income. Out of the insured, 21.4% are in Medicaid and 11.9% are in private coverage. In Appendix C.5, I expand on the sample construction.

To bound insurer costs, I use several datasets from the Center for Medicare and Medicaid (CMS) and DHCS. From CMS, and for Covered California insurers, I use realized claims information called the Rate Review Files (RRF). RRF contains average experienced claims declared by insurers per-member month. In my analysis, I use 2019-2021 RFF files since the experience period is reported with a 2-year delay. I also use Medical Loss Ratios (MLRs) as an additional information on firm claim costs (for Medi-Cal and Covered California) and quality improvement costs (Medi-Cal). MLR is a measure of how much of a health insurance company's premium revenue is spent on actual medical care and quality improvement efforts, versus the amount spent on administrative costs, marketing, and profits. I complement these data with Medical Expenditure Panel Survey (MEPS) via Integrated Public Use Microdata Series (IPUMS). MEPS collects data on health care use, health care expenses, health insurance coverage, and quality of care, among other related topics. I use MEPS to infer medical spending for individuals who are privately insured, with age and household income within the same range as those in Medi-Cal and Covered California While I observe enrolment at a granular, individual-level data, my cost measures are aggregated to a coarser level, and noisier. In Tables B1.5 and B1.6, I summarize the differences in realized average claims by insurer.

From DHCS and Medi-Cal Managed Care Performance Reports, I compile county-plan-level quality measures for Medi-Cal plans. The reported quality measure, also known as the Aggregated Quality Factor Score (AQFS), is a composite score constructed by DHCS using a subset of HEDIS measures selected to evaluate managed care plan performance. It is calculated as a percentage of the National High Performance Level (HPL), with 100% representing top national performance and 40% denoting the Minimum Performance Level (MPL) set by the state. In Figure B1.1, I show the substantial cross-plan variation in quality: while a few plans, such as Kaiser Permanente (which are excluded from the study), consistently score near the HPL benchmark, many fall near or below the statewide average of 63%. A number of plans fail to meet the state-defined

[31] PUMAs, defined by the U.S. Census Bureau, partition the United States into areas with populations of at least 100,000 and typically under 200,000 (with only the lower bound strictly enforced).

[32] ACS began collecting information on health insurance coverage in 2008. The question reads: is this person currently covered by any of the following types of health insurance or health coverage plans? - Medicaid, Medical assistance, or any government-assistance plan for those with low income or a disability. The survey's question is designed to estimate comprehensive coverage across all means-tested programs, but it does not allow for the separation of Medicaid/CHIP from other forms of means-tested coverage as well as different forms of private insurance (employer-sponsored insurance vs Covered California). In the paper, I restrict my sample to adults (which focuses on non-CHIP recipients) as well as those whose income is below 400% FPL.

minimum threshold of 40%.

Lastly, and for the counterfactual exercises, I use two data sources. First, and for the minimum wage benchmarking exercise, I use California's statutory schedule of gradual increases in the minimum wage. In 2017, the minimum wage was $10.50 per hour for employers with 26 or more employees (smaller employers were subject to a $10.00 minimum until 2018), with annual increases until reaching $15 per hour in 2022.[33] I convert hourly wages to annual earnings assuming 40 hours of work per week over 50 weeks per year. This provides a direct labor-market–based benchmark for adequacy against which to compare the FPL and cost of living measures. For the cost of living benchmarks, I use the Economic Policy Institute's (EPI) Family Budget Calculator to measure local adequacy standards, with permission. This calculator estimates, for ten different family types, the monthly income required to attain a modest but adequate standard of living. The EPI Family Budget is market-based and includes housing, food, transportation, child care, health care, taxes, and other necessities. The health care component includes both insurance premiums and out-of-pocket expenditures.[34] Compared with the FPL and SPM, the EPI budget provides a more accurate and complete measure of economic security in the U.S. Since my analysis is at the rating-area level rather than the county level, I aggregate by taking an population-weighted average of cost of living across counties in a rating area.[35]

4.2.3 Descriptive Patterns

To motivate the empirical model, I highlight three pieces of patterns observed in the data. Figure B1.3 illustrates the significant gap between the uniform eligibility limit (blue markers at $16,642.8) and the family budget (orange markers) for a single childless adult across rating areas in California. The "budget-gap" or the amount by which living costs exceed the eligibility line nearly triples as one moves from inland areas to coastal hubs. In relatively lower-cost areas like Kern or the Central Valley, the gap sits around $18,000 to $20,000, whereas in high-cost coastal areas like San Mateo or Santa Clara, that gap balloons to nearly $50,000. This suggests that a family in San Mateo could earn three times the eligibility limit and still lack the funds to cover basic regional living expenses, effectively falling into a "benefit cliff" where they are too "wealthy" for assistance but too poor to survive.[36]

In Figure B1.4, I show the annual premiums for three types of health insurance plans: Cheapest

[33]Source: CALIFORNIA INCREASES MINIMUM WAGE RATES FOR 2017 (April 2016), available at: https://tbowleslaw.com/minimum-wage-rates-2017/.

[34]The Calculator assumes families purchase coverage through ACA Exchanges. For methodology, see EPI Family Budget Calculator Documentation.

[35]In California, counties within a rating area generally have similar cost of living.

[36]I also show in Figure B1.5, the distribution of household incomes in California (for single childless adults, capped at $50,000 annually which is around 400%FPL) across three types of health coverage—Uninsured (blue), Medicaid (red), and Private Insurance (orange)—grouped by cost of living tiers: Low Cost, Mid Cost, and High Cost Areas. Across all cost of living levels, Medicaid coverage is concentrated at the lower end of household incomes. In contrast, private insurance shows a broader distribution over the income range, with higher density among higher-income households (particularly in high-cost areas) highlighting the income-dependence of private market access. The uninsured population has a wide range of incomes. In higher cost of living areas, income distributions for all groups shift slightly upward.

Plan, Second Cheapest Plan (Benchmark Plan), and Most Expensive Plan for a 21-year-old single, childless adult. While there is a general trend of premiums increasing with the cost of living, the relationship is not perfect, as premiums are influenced by multiple factors beyond just living costs. Inland Empire ($1,831 for the Cheapest Plan), for example, has one of the lowest premiums despite its relatively lower cost of living. Higher-cost counties like Greater Sacramento and San Mateo show significantly higher premiums, particularly for the Most Expensive Plan ($9,765 and $8,111, respectively).

	Uninsured	Medicaid	Private
Income	-0.006***	-0.031***	0.000***
	(0.000)	(0.000)	(0.000)
High Cost of Living	0.035***	-0.137***	0.053***
	(0.000)	(0.000)	(0.000)
Income × High Cost of Living	-0.000***	0.015***	-0.004***
	(0.000)	(0.000)	(0.000)
Year FE, Controls	YES	YES	YES
R^2	0.3559	0.4141	0.4790

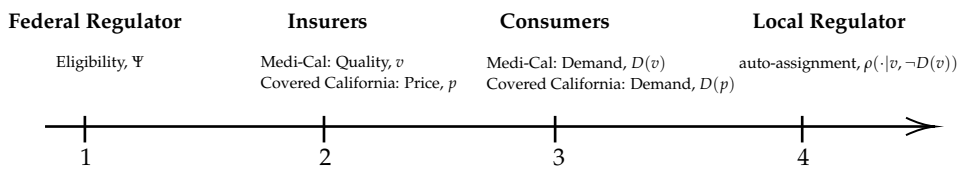
Table 1: Regression estimates for insurance outcomes. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$. Income is in $10,000 and capped at 400% FPL.

Lastly, I investigate how income and cost of living interact to shape insurance market selection. Using ACS data for Californians aged 19–64 (capped at 400% FPL), I estimate a linear probability model to determine how a region's "cost premium" affects coverage:

$$Y_{imt} = \beta_0 + \beta_1 \text{Income}_{imt} + \beta_2 \text{HighCost}_{mt} + \beta_3 \text{Income}_{imt} \times \text{HighCost}_{mt} + X_{it}'\gamma + \delta_t + \epsilon_{imt} \quad (2)$$

where Y_{imt} is a binary indicator for insurance status (Uninsured vs Medicaid or Private Insurance, Medicaid vs Uninsured, or Private vs Uninsured) for individual i in region m and year t. $Income_{imt}$ is measured in $10,000s, and $HighCost_{mt}$ is an indicator which denotes if region m in year t is the upper half of the living cost distribution. X_{it} include controls for individual demographics (e.g., age, gender, race, employment, and education) and year-level fixed effects, δ_t.[37] The results in Table 1 reveal that while higher income naturally reduces Medicaid enrollment ($\beta = -0.0311$), residing in a high-cost region exerts a powerful independent negative effect on coverage ($\beta = -0.137$). Most notably, the positive interaction term ($\beta = 0.0145$) suggests that the "income effect" on Medicaid eligibility is softened in expensive areas, likely because families remain eligible at slightly higher nominal incomes due to local adjustments, yet the overall high cost of living still pushes more individuals into uninsurance ($\beta = 0.0354$). Collectively, these findings suggest that (1) Medicaid effectively targets low-income households, (2) uniform eligibility thresholds and cost of living disparities contribute to coverage gaps, particularly in high-cost regions.

[37] I also estimate a continuous version of $HighCost_{mt}$ variable. Results remain unchanged.



Although the descriptive evidence above suggests that uniform thresholds interact with cost of living, it does not distinguish between underlying mechanisms, such as participation frictions and affordability constraints. To address this limitation, I construct a structural model that links eligibility design, consumer demand, and insurer behavior in both Medi-Cal and Covered California.

The model has four agents. In the first stage, the federal regulator sets Medi-Cal eligibility threshold Ψ, which sorts individuals into those eligible for Medi-Cal and those who have to purchase their own coverage through Covered California. In the second stage, health insurance firms observe their potential enrollee pool and choose quality (in Medi-Cal) and prices (in Covered California). In the third stage, consumers, conditional on their eligibility, they choose a plan from the set of available options to them. Finally, the state or local (county-level) regulator allocates those who pass a means-test and have not selected a plan to one with the highest quality. The novelty of the framework is that it explicitly incorporates the regulatory environment and segmentation of adjacent but different insurance markets. To simplify exposition, I start by presenting the inner loop (consumer and firm behavior) in reverse order, and then the regulators' problem. I do not impose any optimality on the regulators' decision, but instead test several alternative policies.

Define a market to be a county indexed by $m = 1, \ldots, M$. Within each market m, there are two segments s offering health insurance plans: Medi-Cal, which I denote by $s = 1$, provides no-cost coverage for those who sign up for one, and Covered California, which I denote by $s = 2$, which offers subsidized coverage for those ineligible for Medi-Cal. In each market-segment pair (m, s), there are I_{ms} potential consumers, indexed by $i = 1, \ldots, I_{ms}$. Consumers are heterogeneous in observable characteristics denoted by d_i. Consumers do not choose which segment to be in, but rather, a given market m, segment assignment (by the regulator) for a consumer i is determined by observable income. Conditional on eligibility, consumer chooses a plan from the set of available options.

5.1 Inner Loop

In this subsection, I present stages two and three. On the demand side, I develop a discrete choice framework of individual health insurance decisions. The model accommodates rich heterogeneity in consumer preferences and institutional frictions in plan selection to captures both the intensive margin of plan choice and the extensive margin of market participation. To sharpen identification, I condition on persistently enrolled individuals within a given year, thereby focusing on determinants of plan choice among non-switchers while abstracting from transitory churn.

I estimate the model separately for each insurance segment.

I model the supply side, both in Medi-Cal and Covered California, as a static Nash equilibrium in which firms optimize quality and pricing given market conditions and consumer behavior under a stable policy environment. In the Medi-Cal market, insurers offer a single managed care contract and choose an effort that maps deterministically into observed quality, up to an idiosyncratic error term. I assume a common noise distribution across firms, which enables identification of quality effort from cross-sectional variation in observed quality. In Covered California, insurers offer multiple standardized contracts. I focus on their pricing behavior under Bertrand competition, with premiums scaled by predetermined age-rating factors. Because entry and product design remain stable in both markets during my sample period, I take them as given and restrict attention to insurers' intensive-margin decisions.

5.1.1 Utility Function

Every year t, and in each market m-segment s pair, consumer i chooses a plan, among a set of available insurance plans $j \in \mathcal{J}_{mst}$, or may opt out of making choices. Let u_{ijmst} denote the indirect utility that consumer i in market m, segment s, derives from enrolling in plan j at time t. Utility depends on consumer i's characteristics d_i, plan attributes (such as premiums, quality, and network), and idiosyncratic preferences. More formally, u_{ijms} is equal to:

$$u_{ijmst} = \underbrace{-\alpha_{ist} p_{ijmst}}_{\text{premium}} + \underbrace{\beta_{ist} v_{jmst}}_{\text{quality}} + \underbrace{\gamma_{ist} x_{jmst}}_{\substack{\text{non-price/quality} \\ \text{attributes}}} + \underbrace{\delta_{ist} d_{imst}}_{\text{demographics}} + \underbrace{\theta_{ist} \omega_{ijmst}}_{\substack{\text{non-price/quality} \\ \times \\ \text{demographics}}} + \underbrace{\xi_{jmst}}_{\substack{\text{unobserved} \\ \text{preferences}}} + \underbrace{\epsilon_{ijmst}}_{\sim \text{T1EV}}$$

where p_{ijmst} is the premium a consumer i pays for plan j in market m, segment s, and year t net of any applicable subsidies. Price sensitivity, α_{ist}, varies by consumer's age and income, and consumers receive disutility from paying higher premiums. v_{jmst} is a plan performance measure based on standardized indicators from the DHCS Managed Care Accountability Set (MCAS), which includes metrics on quality, access, and timeliness of care. I interpret this performance measure as a proxy for plan effort, a realized outcome rather than an ex ante belief or subjective perception.[38] x_{ijmst} captures observable plan characteristics that are valued independently of consumer eligibility, which I elaborate below. I allow γ_{ist} to vary across individuals and over time, capturing heterogeneous tastes for these non-price attributes, including potential differences in preferences for insurer brand or network design. d_{imst} is consumer i demographics (age and income indicators) and ω_{ijmst} are the plan features that interact with demographic characteristics, which I expand below. ξ_{jmst} represents latent plan-level demand shifters that are constant across consumers in the same market and year. This term captures unmeasured factors such as provider network breadth, drug formulary design, or administrative convenience. Lastly, ϵ_{ijmst} is the id-

[38] Performance signal may not fully capture all dimensions of quality, I assume that is disseminated uniformly and observed with common noise across individuals. This avoids the need to model subjective expectations and reflects the centralized information environment of Medicaid managed care.

iosyncratic error. More specifically, the indirect utility function u_{ijmst} can be re-written as follows for each segment (with abusing the notation):

$$u_{ijmst} = \begin{cases} \beta_{i1t} v_{jm1t} + \gamma_{i1t} x_{jm1t} + \delta_{i1t} d_{im1t} + \xi_{jm1t} + \epsilon_{ijm1t} \\ -\alpha_{i2t} p_{ijm2t} + \gamma_{i2t} x_{jm2t} + \delta_{i2t} d_{im2t} + \underbrace{\theta_{i2t} AV_{ijm2t}}_{\text{actuarial value}} + \xi_{jm2t} + \epsilon_{ijm2t} \end{cases}$$

For consumers in segment $s = 1$ (Medi-Cal), utility depends on non-price attributes, quality v_{jm1t}, network breath x_{jm1t}, and unobserved quality. Here x_{jm1t} is a measure of network breadth for hospitals is the percentage of hospitals statewide that are included in the plan's network, which I elaborate in Appendix C.1. Like Medi-Cal, in segment $s = 2$ (Covered California), most plan features are observed and standardized. The second term, $\beta_{ist} x_{ijmst}$ thus reflects consumer i's preferences for non-price plan attributes like actuarial value of the plan which interacts with individual characteristics, network breadth, customer service, or administrative ease. For Covered California, x_{ijmst} is a vector including a constant term, insurer fixed effects, and an indicator for whether the plan uses an HMO network. Lastly, AV_{ijm2t} is the actuarial value of the plan with $AV_{ijm2t} = AV_{jm2t} + a \cdot \mathbf{1}\{AV_{jm2t} = 0.70\} \cdot \mathbf{1}\{Y_{im2t} \leq 250\%\,\text{FPL}\}$. For individuals with household income below 250% FPL, actuarial value increases discretely when enrolling in a Silver plan due to CSRs. To capture this, I index the actuarial value by individual i.

Alternatively, consumers can opt out of choosing a plan, which I denote by j_0. For those in segment $s = 1$ (Medi-Cal), and conditional on individuals signing up for coverage, j_0 represents the decision not to actively choose a plan. Under such scenario, the regulator assigns the individual to one of the available plans in the county. Let ρ_{jm1t} denote the probability that consumer i is assigned to plan $j \in \mathcal{J}_{m1t}$. I assume that passively assigned consumers do not derive the *full decision utility* from their assigned plan as they would if they had actively chosen it.[39] To capture this, I introduce a discount factor $\lambda \in [0, 1]$ that scales the realized utility for passively assigned consumers.[40] In segment $s = 2$, the outside option corresponds to remaining uninsured, which I normalize to 0. To summarize,

$$u_{ij_0mst} = \begin{cases} \sum_{j \in \mathcal{J}_{m1t}} \rho_{jm1t} \cdot (\lambda \cdot u_{ijm1t}) \\ \epsilon_{ij_0m2t} \end{cases} \tag{3}$$

[39] I assume this difference arises because passive assignment may result in a plan that is not well aligned with the consumer's preferences and may result to dissatisfaction or a suboptimal fit. Using this formulation, I highlight that utility includes both the inherent attributes of the plan and the alignment between consumer preferences and plan characteristics.

[40] If $\lambda = 1$, the consumer experiences the same utility as if they had actively chosen the plan. If $\lambda < 1$, they experience only a fraction of the potential utility. The use of λ can be interpreted as a reduced-form way to capture systematic differences in valuation between active and passive consumers. While the literature often emphasizes experienced utility rather than decision utility as the normative benchmark, this distinction is precisely what motivates the inclusion of λ: it provides a flexible way to empirically distinguish between consumers who express preferences through choice and those whose allocation is administratively determined.

While the structure above describes consumer behavior conditional on interacting with the managed care assignment system, a subset of eligible individuals never enroll in coverage. That is, the model must also account for individuals who ultimately remain uninsured, representing a distinct outside option at the extensive margin. This is particularly relevant in empirical settings where, despite extensive outreach and enrollment efforts (as is the case in California) there remains a persistent group of eligible individuals who do not engage with the system at all. These individuals are not captured in administrative assignment data, but their absence has important implications for estimating demand and program reach. This participation stage applies only to Medi-Cal, and while take-up in Covered California is also incomplete, I am unable to separately identify non-participation using available survey and administrative data. In contrast, omitting a participation stage in the Medi-Cal model would preclude rationalizing the empirically observed fact that a nontrivial share of eligible individuals remain uninsured despite being enrolled by default into managed care systems. To accommodate this nuance, I introduce a participation stage that precedes plan selection.[41] At this stage, individuals decide whether to enter the insurance market or remain uninsured. [42] The individual chooses to enroll in a plan if:

$$\max_{j \in \mathcal{J}_{m1t}} u_{ijm1t} - \kappa_i > \bar{u}_i \tag{4}$$

where $\bar{u}_i$ denotes the utility of remaining uninsured. Conditional on enrolling, the individual proceeds to the choice environment described above: they either actively select a plan or, failing to do so, are passively assigned. This layered structure allows the model to capture three key empirical phenomena: (i) partial take-up among eligible individuals, (ii) non-trivial passive assignment rates among enrollees, and (iii) behavioral frictions in plan valuation among the passively assigned. In Appendix table C.10, I summarize characteristics of those eligible for Medi-Cal and uninsured from ACS.

5.1.2 Supply

I begin describing the supply side with a brief accounting of payment flows and insurer profit functions (omitting market m and year t indicies). In Medi-Cal, each insurance firm f offers a single plan j and competes for enrollees through two channels: (1) active choice (demand), and (2) auto-assignment (passive consumers) by the local regulator. For each enrolled individual i and each month (for this paper aggregated at the annual level), the insurer receives a payment R_j which are actuarially determined based on historical cost trends, administrative expenses, and

[41] Enrollment in safety net programs is not automatic. Often individuals apply and demonstrate eligibility. Often, eligibility rules are complicated, application forms long, and documentation requirements substantial. Perhaps as a result, incomplete take-up is pervasive (Currie, 2006) for many reasons the literature has identified such as lack of information, transaction costs, and stigma associated with participation.

[42] Participation can be interpreted as the outcome of a latent comparison between the expected utility of entering the system (whether through active or passive plan choice) and the utility of non-participation. One way to operationalize this structure is through a "lottery" or draw from an unobserved cost distribution, κ_i, which can be interpreted as hassle cost.

risk adjustment factors. Importantly, these rates vary by geographic market m, year t, and aid code groupings that reflect eligibility category and enrollee risk level. In this project, I focus on a subset of adult enrollees under a broader aid code classification.

On the expenditure side, insurers incur two types of costs. First, the cost of providing healthcare services to enrollee i in plan j (by firm f), which I denote by C_{ij}. I distinguish between C_{ij} and $C_{ij|j_0}$, the expected cost of a passively assigned enrollee conditional on the individual having been previously enrolled in plan j_0.[43] I assume $C_{ij|j_0} < C_{ij}$ and define their ratio as $C_{ij|j_0}/C_{ij} = c = R_j^{(\text{low risk})}/R_j$. Second, insurers choose a level of quality v_f for their plan.[44] Investment in quality is costly, and firms incur cost $I(v_f)$. Quality v_f affects firm profits through two channels: (1) demand of enrollees (active choosers), and (2) state regulator choice in allocating passive enrollees to plans. Since passively assigned enrollees are empirically lower-cost, the incentive to invest in quality reflects not only active market share considerations but also the potential to secure a more favorable risk pool. I discretize both claims (marginal) and quality (investment) costs for estimation. With these assumptions, the profit function for firm f (interchangeable with plan j) in market m, segment $s = 1$ (Medi-Cal), and year t, is given by:

$$\begin{aligned}\pi_{fm1t} = \sum_{d \in D} \Big[& \underbrace{(R_{fm1t} - C_{dfm1t}) s^d_{fm1t} M^d_{mt}}_{\text{profit from active enrollees}} \\ & \underbrace{+ (R_{fm1t} - C_{df|f_0m1t}) \mathbb{E}[\rho_{fm1t} \mid v_{fm1t}, v_{-fm1t}] \quad \underbrace{(1 - \sum_k s^d_{km1t})}_{\text{share of passive enrollees}} \quad M^d_{mt} \Big]}_{\text{profit from passive assignment}} \\ & - \underbrace{I(v_{fm1t})}_{\text{investment cost}}\end{aligned} \tag{5}$$

where s^d_{fm1t} denotes the share of age-income group d that actively selects the plan offered by firm f, and M^d_{mt} is the number of individuals in group d in market m and year t who enroll in any Medi-Cal plan. Notably, M^d_{mt} excludes individuals who do not complete the eligibility-testing process; thus, it reflects a *post-participation* market size. While I do not observe non-participants or separately identify the participation margin, the model is estimated conditional on participation. The second profit component, associated with passive assignment, is only relevant in competitive counties or counties with more than one managed care plan. I assume firms choose quality v_{fm1t} before observing their passive assignment shares ρ_{fm1t}, thus they form expectation over auto-assignment. Firms however do observe their rivals' quality decisions, v_{-fm1t}. The total market

[43] Empirical evidence suggests that passively assigned individuals tend to be healthier and less costly to insure (see *Putting Quality to Work: Rewarding Plan Performance in Medi-Cal Managed Care*, California HealthCare Foundation, May 2006).

[44] I assume investment in quality maps to plan quality score reflecting observable performance measures.

share is:

$$\underbrace{S^d_{fm1t}(v_{fm1t}, v_{-fm1t})}_{\substack{\text{total market}\\ \text{share}}} = \underbrace{s^d_{fm1t}(v_{fm1t}, v_{-fm1t})}_{\substack{\text{share from}\\ \text{active enrollment}}} + \underbrace{\rho_{fm1t}(v_{fm1t}, v_{-fm1t})(1 - \sum_k s^d_{km1t})}_{\substack{\text{autoassignment}\\ \text{share}}}$$

In Covered California (segment $s = 2$), plans primarily compete on price. Prices are set at the rating area (a geographic unit that may include one or more counties m) level, $r(m)$. For each consumer i residing in $r(m)$ and in year t, plan j collects (from the consumer) a premium $p_{ijr(m)2t}$. Consumers who are not eligible for premium subsidies, this premium equals the full list price, $P_{ijr(m)2t}$. For subsidy-eligible consumers, the insurer collects a lower premium $p_{ijr(m)2t} < P_{ijr(m)2t}$ from the individual and receives a subsidy from the government such that the total revenue equals the full list price. On the cost side, insurers pay for enrollees' healthcare expenditures and administrative costs. Spending varies with consumer risk and plan generosity, though insurers typically cover only a portion of total costs due to cost-sharing arrangements.

Several institutional features allow simplification of this general formulation for Covered California. On the revenue side, insurers cannot perfectly price discriminate across consumers. While age-based pricing is allowed, it is subject to regulatory constraints: insurers must set a base premium for a 20-year-old and then scale it using a standardized age rating curve. This implies that premiums can be written (ignoring m and t indices) as the product of a plan-specific base price b_j and a regulatory age multiplier τ_i, which is common across plans. On the cost side, I discretize risk and cost interactions by age and income. Let $C_{jr(m)2t}$ denote the average marginal cost for plan j in rating area $r(m)$, segment s, and year t. I estimate how healthcare spending varies across discrete age-income groups and construct a matrix of cost multipliers, which are then combined with plan-specific baseline costs. This structure allows both demand and cost to vary by age and income, enabling the model to capture potential adverse or advantageous selection.[45] With this structure, each insurer f chooses a vector of base prices $b_{jr(m)2t}$ (subject to regulations) to maximize profits. The profit function for firm f operating in segment $s = 2$ (Covered California) is:

$$\pi_{fr(m)2t} = \sum_{j \in \mathcal{J}_{fr(m)2t}} \sum_{d \in D} \left[(b_{jr(m)2t} \times \tau^d - C_{jr(m)2t}) s^d_{jr(m)2t} N^d_{mt} \right] \tag{6}$$

$s^d_{jr(m)2t}$ denotes the share of consumers in age-income group d who enroll in plan j, and N^d_{mt} is the total number of potential Covered California enrollees in group d. Some insurers operate across both segments and jointly choose their investment levels v_{fm2t} and base prices $b_{fr(m)2t}$ to maximize total profit. In such cases, total firm profit is the sum of segment-specific profits from Medi-Cal and Covered California.

[45] Firms also receive exogenous risk adjustment transfers, denoted $T_{jr(m)t}$, which are outside the firm's control. Appendix C.6 provides additional details on how these transfers are determined and their components.

5.2 Outer Loop

In this subsection, I present stages one and four. To fix ideas, I begin with a brief accounting of how federal and state spending is structured for Medi-Cal and Covered California, although the overarching description can be modified to any state.

I denote by $G^{fed,MC}$ federal Medi-Cal spending which reflects the cost-sharing arrangement under the Federal Medical Assistance Percentage (FMAP). For the traditional eligibility groups: children, low-income parents, the aged, and the disabled—the federal government pays 50% of benefit costs. For adults covered under the Covered California Medi-Cal expansion, the federal match rate is 90% as part of the ACA. Additional enhanced rates may apply for certain populations or services, and most administrative functions receive a 50% match. The majority of benefit spending flows through capitated payments to managed care organizations, R_{fm1t}. Because the federal match applies as a constant share of these payments, adjustments for network breadth, rurality, or provider prices directly scale federal obligations.

At the state level, Medi-Cal spending ($G^{state,MC}$) is the complement of the federal share: 50% of benefit costs for traditional groups, 10% for Covered California expansion adults, and the residual for other enhanced match categories. California finances this share through general revenues, provider taxes, certified public expenditures, and intergovernmental transfers. Like the federal government, the state's obligation is proportional to per member per month rates paid to MCOs, which can vary by \$2–\$50 across plans in the same area. Any capitation rate increase affects both federal and state budgets in fixed proportions. In my counterfactual simulations, I treat these rates as fixed.

I denote by $G^{fed,CCA}$ federal Covered California spending. $G^{fed,CCA}$ has two primary components: (1) advance premium tax credits and (2) CSR subsidies. Premium subsidies are the largest and are calculated from administrative records or adjusted for enrollee composition in counterfactual scenarios. CSR subsidies reduce out-of-pocket costs for low-income enrollees in silver-tier plans. Following Polyakova and Ryan, 2019 and using CCIIO data, I compute average per-capita CSR spending by income bracket and assign these amounts to eligible enrollees, holding CSR spending constant in simulations. I assume that the state bears no direct spending obligation for Marketplace coverage.

Lastly, I assume that both federal and state regulators incur expenditures on uncompensated care arising from individuals who remain uninsured or underinsured. Following the Kaiser Family Foundation and Urban Institute 2013 report on public spending on uncompensated care for the uninsured Coughlin et al., 2014 as well as Polyakova and Ryan, 2019, I assume an average per-capita savings of \$1,827 per newly insured person, of which \$1,139 accrues to the federal budget and \$688 to the state/local budget.

In estimation, I do not impose that observed thresholds or assignment rules are optimal solutions to the respective regulators' problems. Both regulators face institutional, political, and informational constraints that can lead to deviations from fully optimal policy. I take observed policies as inputs, estimate demand and assignment primitives separately, and use the model to

simulate alternative designs. Because FPL thresholds also determine subsidy eligibility in Covered California, shifts in thresholds alter both Medi-Cal and Marketplace spending simultaneously.

5.2.1 Federal Regulator

I assume the federal regulators objective is to maximize the sum of expected consumer surplus net of governmental spending.[46] The regulator does so by choosing market m and year t specific Medi-Cal income thresholds ψ_{mt} from within a class of Ψ thresholds. Given ψ_{mt}, an individual i in market m and year t with income Y_{imt}, is eligible for Medi-Cal if $Y_{imt} \leq \psi_{imt}$. If an individual has income Y_{imt} such that $\psi_{imt} < Y_{imt} \leq \bar{\psi}_{imt}$ they are eligible for Covered California subsidies. Lastly, let $T_i^s(\psi_{mt}) \in \{0,1\}$ indicate segment assignment implied by ψ_{mt}. The federal regulator's objective in market m and year t is:

$$W_m^{\text{fed}}(\psi_{mt}) = \underbrace{CS_{mt}(\psi_{mt})}_{\substack{\text{total consumer surplus} \\ \text{in both segments}}} - \underbrace{G_{mt}^{\text{net}}(\psi_{mt})}_{\substack{\text{total costs} \\ \text{in both segments}}}, \tag{7}$$

where CS_{mt} is the total consumer surplus in market m, which is the sum of consumer surplus from Medi-Cal, $CS_{mt}^{(1)}(\psi_{mt})$, and Covered California $CS_{mt}^{(2)}(\psi_{mt})$. I define the former as money-metric surplus via a WTP mapping of plan quality:

$$CS_{mt}^{(1)}(\psi_{mt}) = \sum_{i \in \mathcal{I}_{m1t}} T_i^1(\psi_{mt}) \cdot \mathbb{1}(i \text{ enrolls in } \mathcal{J}_{m1t}) \cdot \frac{1}{|\alpha_{i1t}|} \times WTP \times \ln\left(\sum_{j \in \mathcal{J}_{m1t}} e^{\delta_{ijm1t}}\right).$$

For Covered California, I follow Small and Rosen, 1981 to define:

$$CS_{mt}^{(2)}(\psi_{mt}) = \sum_{i \in \mathcal{I}_{m2t}} T_i^2(\psi_{mt}) \cdot \mathbb{1}(i \text{ takes up insurance}) \cdot \frac{1}{|\alpha_{i2t}|} \ln\left(\sum_{j \in \mathcal{J}_{m2t}} e^{\delta_{ijm2t}}\right).$$

G_{mt}^{net} is net fiscal cost which is equal to program outlays minus uncompensated care savings ($1,139 per person). The program costs in market m in year t under eligibility rule ψ_{mt} is equal to:

$$G_{mt}^{\text{prog}}(\psi_{mt}) = \underbrace{FMAP \cdot \sum_{i \in \mathcal{I}_{m1t}} T_i^1(\psi_{mt}) \cdot \mathbb{1}(i \text{ enrolls in } \mathcal{J}_{m1t}) \cdot R_{j(i)m1t}}_{\text{Medi-Cal capitation (federal share)}} + \underbrace{\sum_{i \in \mathcal{I}_{m2t}} T_i^2(\psi_{mt}) \cdot \mathbb{1}(i \text{ takes up}) \cdot \left(\text{APTC}_i + \text{CSR}_i\right)}_{\text{Covered California subsidies}}.$$

[46] As alternative specification, I also assume the federal regulator maximizing weighted sum of consumer and producer surplus net of spending as well. Conclusions remain unchanged.

5.2.2 State Regulator

Conditional on federal eligibility (and take-up), the state assigns *passive* Medi-Cal enrollees to managed care plans in multi-plan counties using shares $\rho_{m1t} = \{\rho_{fm1t}\}_{f \in \mathcal{F}_{m1t}}$ such that $\sum_{f \in \mathcal{F}_{m2t}} \rho_{fm1t} = 1$ with $\rho_{fm1t} \in [0,1]$. Because observed assignment follows a quality-weighted formula, I allow the state regulator to exert partial control through a discretionary component ℓ_{fm2t}. With frictions, assignment takes the form:

$$\rho_{fm1t} = \frac{v_{fm2t}}{\sum_{f' \in \mathcal{F}_{m2t}} v_{f'm2t}} + \ell_{fm2t},$$

where v_{fm2t} denotes the plan's quality score and ℓ_{fm2t} captures administrative discretion, measurement error, and constraints such as the 20% annual reassignment cap. Let $\mathcal{P}_{m2t}$ denote the set of passive enrollees in market m and year t. The state regulator's objective is to choose ρ_{m1t} to maximize marginal consumer surplus and plan profits from this group, net of the state's share of capitation costs:

$$W_{mt}^{\text{state}}(\rho_{m1t}) = CS_{mt}^{\text{passive}}(\rho_{m1t}) \; + \; \Lambda \, \Pi_{m}^{\text{passive}}(\rho_{m1t}) \; - \; G_{mt}^{\text{state,passive}}(\rho_{m1t}), \tag{8}$$

where $\Lambda \in [0,1]$ is the welfare weight on plan profits, $CS_{mt}^{\text{passive}}(\rho_{m1t})$ is the consumer surplus (similar to $CS_{mt}^{(1)}(\rho_{m1t})$ above, but restricted to passive enrollees), and $\Pi_{m}^{\text{passive}}(\rho_{m1t})$ is the profit of firms from passive enrollees. $G_{mt}^{\text{state,passive}}(\rho_{m1t})$ is the net costs to the state from autoassignment which is equal to total reimbursement rates paid to firms from assigning an individual to a plan minus uncompensated care savings (remainder of $1,139).

6. Estimation and Identification

Estimating model primitives requires solving for high-dimensional, nonlinear optimization problems. On the demand side, I estimate the parameters using a control-function approach. On the supply side, I recover marginal claims and quality investment costs using equilibrium pricing conditions. I implement the Limited-memory BFGS (L-BFGS) algorithm, a quasi-Newton method. Rather than solving for optimal eligibility thresholds, I decompose the analysis on the regulators' dimension into counterfactual experiments and simulate equilibrium outcomes for each policy design.

6.1 Regulators

The federal regulator's problem is to choose eligibility thresholds $\Psi = \{\psi_m\}_m$ that maximize a welfare criterion aggregating consumer surplus, firm profits, and public budgets. In doing so, the regulator internalizes that thresholds shape equilibrium outcomes. This creates a multi-layered policy trade-off: raising thresholds expands coverage and transfers but increases fiscal costs; lowering thresholds contains spending but shifts households into higher-priced exchange plans. Understanding these trade-offs requires an equilibrium framework that jointly incorporates demand,

supply, and regulation.

Solving this problem is challenging for several reasons. First, eligibility thresholds are continuous and there are no optimality conditions to guide the problem. Second, solving for an optimal vector of eligibility thresholds requires taking a stance on regulators objective function (I avoid drawing conclusions based on aggregate welfare since taking a stance on the welfare weight on government spending in this market is complicated.) I address these challenges by structuring the counterfactual analysis as a Stackelberg game solved by backward induction. To compute equilibria, I iterate on (v, p, ρ) using a damped Gauss–Seidel procedure:

$$x^{t+1} \leftarrow x^t + \kappa(x^\star - x^t), \qquad x \in \{v, p, \rho\},\ \kappa \in (0, 1].$$

Convergence to a fixed point guarantees mutual best responses. The regulator's chosen threshold is found over a grid of values $\psi_m \in [0, 400]$, the design that best balances coverage, costs, and the distribution of responsibility across governments.

6.2 Demand

I make a few simplifications to estimate the demand parameters. First, I assume that the idiosyncratic error, ϵ_{ijmst}, follows a Type I Extreme Value distribution in both Medi-Cal and Covered California utilities. This assumption yields to a logit choice model at the consumer level. Second, I aggregate consumer demographics to 18 bins, d, made up of three age categories: 19-34, 35-54, 55-64, and six income categories: 138% FPL or less, 138% FPL to 150% FPL, 150% FPL to 200% FPL, 200% FPL to 250% FPL, 250% FPL to 300% FPL, 300% FPL to 400%. I allow the parameters to flexibly vary by segment s, year t, and across the demographic bins d as follows:

$$\begin{pmatrix} \alpha_{ist} \\ \beta_{ist} \\ \gamma_{ist} \\ \delta_{ist} \\ \theta_{ist} \end{pmatrix} = \begin{pmatrix} \alpha_{0st} + \alpha_{dst} D \\ \beta_{0st} + \beta_{dst} D \\ \gamma_{0st} + \gamma_{dst} D \\ \delta_{0st} + \delta_{dst} D \\ \theta_{0st} + \theta_{dst} D \end{pmatrix}$$

where D is an 18-dimensional vector, with entry $D_l = 1$ if $d = l$ and 0 otherwise. The scalar parameters α_{0st}, β_{0st}, γ_{0st}, δ_{0st}, and θ_{0st} measures consumers' average preference for price, quality, non-price and non-quality attributes, demographics, and non-price and non-quality attributes interacted with demographics in each segment s and year t.[47] Given this setup, the likelihood with

[47] I limit estimation to counties with multiple participating managed care plans, where plan assignment reflects meaningful competition (see Appendix C.1 for market structure in Medi-Cal). In single-plan counties, all passive individuals are assigned to one plan. While I do not observe the share of enrollees who defaulted in these single-plan counties, I do observe plan quality levels. These data are still informative for understanding broader variation in insurer quality effort across market structures, and they provide useful context for interpreting insurer incentives and regulatory design in the absence of competition.

which consumer i with product j in market m, segment s, and year t is given by:

$$s_{ijmst}(\alpha_{0st}, \beta_{0st}, \gamma_{0st}, \delta_{0st}, \theta_{0st}, \alpha_{dst}, \beta_{dst}, \gamma_{dst}, \delta_{dst}, \theta_{dst}, \xi_{jmst}) = Prob(u_{ijmst} > u_{ij'mst}, \forall j' \neq j)$$

$$s_{ijmst}(\cdot) = \begin{cases} \underbrace{\frac{e^{\delta_{ijm1t}}}{e^{\delta_{ij_0m1t}} + \sum_{j' \in \mathcal{J}_{m1t} \setminus \{j_0\}} e^{\delta_{ij'm1t}}}}_{\text{active choice}} + \rho_{jm1t} \times \underbrace{\frac{e^{\delta_{ij_0m1t}}}{e^{\delta_{ij_0m1t}} + \sum_{j' \in \mathcal{J}_{m1t} \setminus \{j_0\}} e^{\delta_{ij'm1t}}}}_{\text{share assigned}} \\ \frac{e^{\delta_{ijm2t}}}{e^{\delta_{ij_0m2t}} + \sum_{j' \in \mathcal{J}_{m2t} \setminus \{j_0\}} e^{\delta_{ij'm2t}}} \end{cases} \tag{9}$$

where $\delta_{ijmst} = u_{ijmst} - \epsilon_{ijmst}$ is the indirect expected utility of each option. Let G_{mst} be the distribution of demographic characteristics d in county m, segment s, and year t. The total enrollment in plan j is:

$$S_{jmst} = \int s_{jmst} dG_{mst}(d)$$

The sensitivity of a consumer's demand to a change in baseline quality ζ_{jmst}(in Medi-Cal) and premium (in Covered California) p_{jm2t} is given by respectively, for all plans j, k:

$$\frac{\partial S_{kmst}}{\partial v_{jmst}} = \int \gamma_{ist} \cdot s_{ikmst} \cdot \left(\mathbf{1}_{j=k} - s_{ijmst}\right) \, dG_{mst}(d)$$

and

$$\frac{\partial S_{kmst}}{\partial p_{jmst}} = \int \alpha_{ist} \cdot s_{ikmst} \cdot \left(\mathbf{1}_{j=k} - s_{ijmst}\right) \, dG_{mst}(d)$$

The elasticity between product j and k in market m, segment s, and year t are:

$$e_{kjmst} = \begin{cases} \frac{\partial S_{kmst}}{\partial v_{jmst}} \frac{v_{jmst}}{S_{kmst}} = \frac{v_{jmst}}{S_{kmst}} \int \alpha_{ist} \cdot s_{ikmst} \cdot \left(\mathbf{1}_{j=k} - s_{ijmst}\right) \, dG_{mst}(d) \\ \\ \frac{\partial S_{kmst}}{\partial p_{jmst}} \frac{p_{jmst}}{S_{kmst}} = \frac{p_{jmst}}{S_{kmst}} \int \alpha_{ist} \cdot s_{ikmst} \cdot \left(\mathbf{1}_{j=k} - s_{ijmst}\right) \, dG_{mst}(d) \end{cases}$$

For Medi-Cal, *cross-quality elasticity* captures substitution away from competitors when a plan increases its quality investments. The effect of this substitution is more pronounced in markets where plans are close in characteristics, and more importantly, consumers are responsive to quality (α is large). Because my model allows for heterogeneity in quality valuation across age or income groups (in extended specifications), these elasticities can be used to quantify *which populations drive competitive effects* and to simulate the impact of *targeted quality improvements* under incentive schemes like California's performance-based auto-assignment rules. For Covered California, *own-price elasticities* ($j = k$) decrease as market shares of plans increase and are strictly negative ($\alpha < 0$). When a plan holds a small market share, consumers tend to be more price-sensitive at the margin. As a result, even small movement in premiums can lead to significant shifts in enrollment. *Cross-price elasticities* ($j \neq k$) are positive and increasing the premium of plan j. The magnitude of the

cross-price elasticity is proportional to the share of plan j.

6.2.1 Endogeneity

A central threat to identification arises from endogeneity of key plan characteristics, most notably, quality and price. In the Medi-Cal, plan observed quality, v_{jm1t}, is likely correlated with unobserved demand shocks or latent plan attributes, ξ_{jm1t}, that are unobservable to the econometrician but known to both consumers and insurers. Similarly, in Covered California, premiums, p_{ijm2t}, are a function of both cost expectations and competitive positioning, and thus may reflect unobserved heterogeneity in plan appeal or market-specific risk selection. While product and market fixed effects absorb some of this variation, ultimately, they are insufficient in settings where unobserved shocks vary. Standard approaches to correcting for endogeneity in discrete choice models rely on sufficient within-market variation in observed market shares and assume product-level prices.[48] These conditions are not satisfied in my data: several plans, particularly those operated by smaller carriers, have sparse or zero enrollment, and Covered California premiums vary at the household level due to subsidy design. Accordingly, I adopt the control function approach introduced by Petrin and Train (2010), which offers a tractable and robust alternative in settings where the traditional approach is either infeasible or inconsistent. The control function approach simply adds new regressors to the demand specification with the idea to derive a proxy variable that conditions on the part of the endogeneous variable that depends on the error terms. I expand more on the control function approach and the instruments used in Appendix .[49] In Appendix Tables B1.7 and B1.8, I summarize the first stage estimates for Medi-Cal and Covered California. I find that a 10% increase in the share of individuals under 35 in Medi-Cal is associated with a 13.51% increase in observed plan quality. In Covered California, a similar increase corresponds to $439 reduction in base premium. These results align with the general intuition that (1) younger enrollees may be driving quality either through their choices (selecting higher quality plans), or health care needs (plans may invest differently when serving younger populations), and (2) younger enrollees have both lower utilization and higher price-sensitivity, in line with the existing literature (eg, Tebaldi, 2022).

6.2.2 Estimates

In this section I present key results for the year 2017. The full set of estimates are reported in Appendix Tables B1.9 and B1.10 for Medi-Cal and Covered California, respectively.

Table 2 summarizes the demand estimates for Covered California. More specifically, Panel A reports the estimated coefficients on plan premiums, scaled in thousands of dollars. The estimates reveal that lower-income individuals are substantially more price sensitive than their higher-income counterparts, with sensitivity decreasing notably as income rises from below 250%

[48] see Berry, Levinsohn, and Pakes (1995).

[49] As robustness, I also estimate the demand using Berry, Levinsohn, and Pakes (1995). Results remain largely unchanged.

	Age 19–34	Age 35–54	Age 55–64
Panel A: Coefficient on Premium, $1000			
Income 138–150% FPL	0.985	0.962	0.781
	(0.0312)	(0.0302)	(0.0268)
Income 150–200% FPL	0.975	0.952	0.771
	(0.0293)	(0.0282)	(0.0245)
Income 200–250% FPL	0.854	0.831	0.650
	(0.0278)	(0.0267)	(0.0228)
Income 250–300% FPL	0.780	0.757	0.576
	(0.0276)	(0.0264)	(0.0224)
Income 300–400% FPL	0.670	0.647	0.466
	(0.0208)	(0.0193)	(0.0134)
Panel B: Mean WTP for 10% Increase in AV			
Income 138–150% FPL	0.548	0.561	0.691
	(0.0200)	(0.0204)	(0.0269)
Income 150–200% FPL	0.554	0.567	0.700
	(0.0194)	(0.0197)	(0.0256)
Income 200–250% FPL	0.632	0.650	0.831
	(0.0236)	(0.0240)	(0.0328)
Income 250–300% FPL	0.692	0.713	0.938
	(0.0275)	(0.0281)	(0.0403)
Income 300–400% FPL	0.806	0.835	1.159
	(0.0322)	(0.0334)	(0.0501)
Panel C: Mean WTP for HMO (Disutility)			
Income 138–150% FPL	-1.351	-1.384	-1.704
	(0.0572)	(0.0583)	(0.0756)
Income 150–200% FPL	-1.365	-1.398	-1.726
	(0.0561)	(0.0570)	(0.0732)
Income 200–250% FPL	-1.559	-1.602	-2.048
	(0.0671)	(0.0683)	(0.0919)
Income 250–300% FPL	-1.706	-1.758	-2.311
	(0.0770)	(0.0787)	(0.1110)
Income 300–400% FPL	-1.987	-2.057	-2.856
	(0.0909)	(0.0937)	(0.1436)

Table 2: Demand Estimates: Coefficient on Premium, WTP for AV and HMO (in $1000; standard errors in parentheses)

	Age 19–34	Age 35–54	Age 55–64
Panel A: Coefficient on Quality and Hospital Networks			
Quality (%)	0.9763	0.9768	0.9776
	(0.00557)	(0.00542)	(0.00542)
% Hospitals in Network	0.5593	0.5584	0.5613
	(0.00693)	(0.00687)	(0.00687)
Panel B: 1% Increase in Quality, expressed as % in hospitals and $ WTP			
As % in hospitals	1.745	1.749	1.742
As $ per year	21.5	28.9	40.3
As $ per year (10% quality)	215	289	403

Table 3: Demand Estimates by Age Group, Medi-Cal

FPL to 250–300% FPL and again to 300–400% FPL. Within each income bin, price sensitivity also declines with age. For example, among those with incomes between 138–150% FPL, the premium coefficient falls from 0.985 for individuals aged 19–34 to 0.781 for those aged 55–64, whereas in the highest income group (300–400% FPL) the corresponding decline is from 0.670 to 0.466. These patterns suggest that older enrollees are more tolerant of premium increases, consistent with both greater expected health risk and a higher willingness to insure against adverse shocks. The estimated elasticities are broadly consistent with prior studies of demand in Covered California.

Panel B reports the implied WTP for a 10% increase in actuarial value of the plan. WTP increases almost monotonically with both age and income from $548 for younger, low-income individuals to over $1,150 among older, higher-income enrollees. In addition to higher average WTP, the dispersion in WTP also grows with age, consistent with greater heterogeneity in both health needs and financial risk among older populations. Although these estimates are somewhat larger than those reported in earlier work, they reinforce the finding that actuarial value is a salient and increasingly valued plan attribute, particularly for older adults.

Lastly, Panel C examines preferences over plan type and shows a strong and consistent disutility associated with HMO plans. Across all demographic groups, individuals are willing to pay a substantial premium to avoid network restrictions, with WTP to avoid an HMO increasing with both age and income. For instance, the estimated disutility rises from –1.351 for the youngest, lowest-income group to –2.856 for the oldest, higher-income group. These estimates indicate a growing perceived value of wider provider networks among those with complex or frequent care needs, aligning with health insurance demand predictions in the literature.

In Table 3, I report estimates from Medi-Cal. Although differences are modest across the age brackets, older consumers exhibit slightly higher marginal utility from improvements in quality, with the quality coefficient rising from 0.976 among 19–34 year-olds to 0.977 among those aged 55–64. Sensitivity to network breadth, measured as the share of all 369 acute care hospitals in California that are included in a plan's contracted network, is at roughly 0.55 or 176 hospitals statewide across all age brackets. Many county–plan combinations have statewide shares well below this: for example, the Alameda Alliance for Health, a plan that operates in Alameda County

only, contracts with just 14 hospitals (∼4% of statewide hospitals), while L.A. Care, which operates in Los Angeles County only, covers about 70 hospitals (∼19% of statewide hospitals). The estimated trade-offs imply that a 10% increase in quality is valued equivalently to expanding a plan's network by roughly 18% of hospitals statewide, or about 66 additional hospitals. In large urban counties such as Los Angeles (105 acute care hospitals), this could translate into adding 15–20 local hospitals to the network, representing a substantial increase in in-county choice. In medium-hospital-network-sized counties like Fresno (13 hospitals), the same statewide increase could involve adding all local hospitals if not already covered, or expanding into neighboring counties to enhance access to specialized services. In small rural counties with few or no acute care hospitals, much of the gain from an expanded statewide network would come from facilities outside the county, potentially affecting access for specialized or referral care rather than routine local services. This variation underscores that, even though the network measure is statewide, its practical implications for enrollee access depend heavily on local market structure and geography.

To express quality effects in monetary terms, I proceed in two steps. First, I link changes in quality to the percentage of hospitals in the network, as described above. Second, I use estimates from Ericson and Starc (2015) on willingness to pay for network breadth and adjust them to my setting.[50] For unsubsidized single enrollees with income above 300% FPL, their estimates imply WTP for a 1% network expansion of $12.31, $16.53, and $23.14 per year for the midpoints of my age bins (27, 45, 60). I then adjust these WTP amounts to my population using age-specific scaling factors derived from a monotonic nonparametric mapping of WTP for actuarial value across different income groups (see Appendix C.7). This adjustment yields to a WTP of $215 to $403 per year for a 10% improvement in quality across all age groups.

6.2.3 Demand Fit

Figures B1.6a and B1.6c plot the distribution of plan choices in the data and the corresponding implied choice shares (untargetted moments) from the logit model for Medi-Cal and Covered California, respectively. For Medi-Cal, where plan assignment is partly passive and concentrated, the model replicates the skewed distribution in favor of dominant statewide plans (plans 1-4, market shares 0.85-0.95) and marginal plans (plans 13-15, market shares 0.05-0.15), but over/under predicts for geographically constrained plans operating in distinct regional markets. The patterns indicate that while key utility parameters for quality and network density are recognized and significant, the model could improve by including geographic market heterogeneity if collinearity issues did not arise. In the more competitive Covered California market, the model reflects the flatter distribution across a broader range of plans, despite a higher-dimensional choice set and greater heterogeneity in preferences. In general, the model fits market shares well and capable of recovering meaningful heterogeneity in plan preferences. I present a full validity of the model below.

[50] Ericson and Starc (2015) estimate plan demand in the Massachusetts Health Connector and recover marginal utilities for network breadth.

6.2.4 Identification

Given the granuarity of data, there are several sources of identification. First, in Medi-Cal, the cross-market variation in plan availability and quality, even within the same insurer, allows me to compare the behavior of similar consumers facing different plan options and quality levels across markets. Second, because California uses auto-assignment rules that allocate beneficiaries based in part on plan quality scores, I observe exogenous variation in plan enrollment shares that is mechanically linked to quality. Third, the demographic composition of each county provides exogenous variation in preferences and quality investment incentives, which is useful for both demand estimation and as an instrument for potentially endogenous plan characteristics.

In Covered California, identification is attributed to (1) within-market price variation across consumers, and (2) across-market price variation due to subsidy schedules. The former is due to institutional regulations that impose age-rating constraints and income-based premium subsidies. These rules generate heterogeneity in effective prices even for identical plans. Since I observe plan enrollment by age and income bins, I exploit differential enrollment patterns across these demographic groups within the same market This variation is plausibly exogenous to unobserved preferences, provided that individuals do not endogenously sort across counties in response to local market conditions. The second source of variation arises across markets due to the way benchmark plans are priced and determined within rating areas. Although insurers set base premiums at the rating area level, the identity of the benchmark plan may differ across counties depending on which insurers offer the second-lowest-cost silver plan in each county. Since the benchmark plan determines the subsidy schedule, this creates variation in consumer-facing premiums even for identical plans. The third source of variation I use to identify the parameters leverages differences in demographic composition across rating regions to construct structural instruments for plan prices.

6.3 Supply

I assume that in both Medi-Cal ($s = 1$) and Covered California ($s = 2$), the expected medical spending (omitting market m and year t) for enrolling individual i in plan j is multiplicatively separable into a demographic-specific cost component ω^d and a plan-specific baseline (youngest and lowest income) cost c_j to capture variation in expected utilization across age-income groups.[51] The rationale behind separability serves two main purposes. First, it maintains meaningful differences in risk profiles among enrollees by allowing costs to vary across different demographic groups. Second, it simplifies the cost structure by reducing it to a manageable set of plan-level parameters c_j, which makes estimation easier in markets with numerous plans and demographic types. The costs considered include both medical and administrative expenses. In Medi-Cal, insurers also face costs associated with quality investments. I account for these quality efforts, which influence a plan's appeal under the state's passive assignment algorithm. Let v_{fm1t} represent the quality

[51] I calibrate the ω^d multipliers using data from the Medical Expenditure Panel Survey. See Appendix Table B.3.

effort of plan f in market m, segment $s = 1$, and year t. I model the associated investment costs as follows:

$$I(v_{fm1t}, \zeta_{fm1t}) = \zeta_{fm1t}(v_{fm1t} - \underline{v})^2,$$

where $\underline{v}$ is the minimum quality effort required to participate in Medi-Cal, such as the compliance standard under Assembly Bill 85.[52] The parameter ζ_{fm1t} captures plan- and market-specific variation in the marginal cost of quality effort; it governs the steepness of the investment cost function and may reflect differences in administrative efficiency or local implementation capacity. I operationalize v_{fm1t} using the Aggregated Quality Factor Score (AQFS). Scores range from 40% (the regulatory benchmark $\underline{v}$) to 100%, with a statewide average of 60%.[53] I estimate marginal and investment costs using first order conditions and MLR ratios (see Appendix B.3 for details on the estimation procedure).

		Age 19–34	Age 35–54	Age 55–64
Income ≤138% FPL (Medi-Cal)	Average Claims Cost	218.04	449.17	558.19
	Average Investment Cost	166.55	343.09	426.36

Table 4: Medi-Cal Monthly Costs by Age Group and Income (in $)

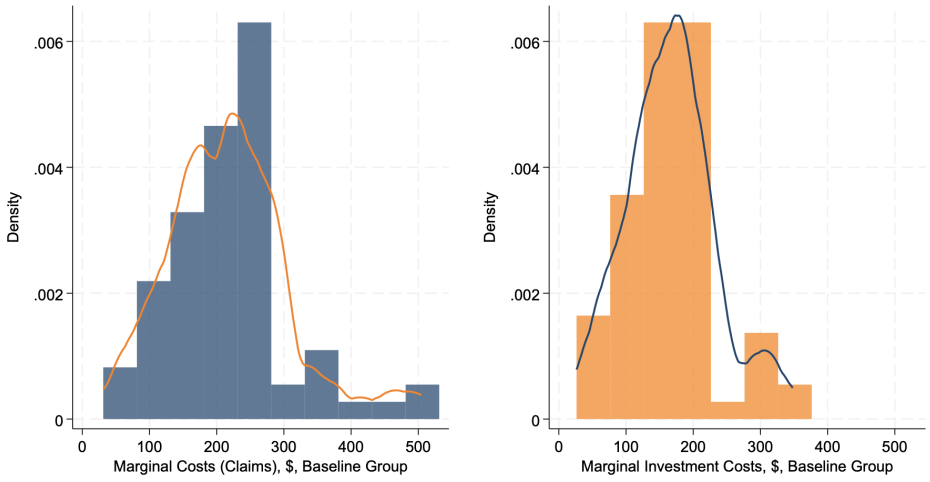


Figure 4: Distribution and Density of Medi-Cal Marginal Claims and Investment Costs, Market-Plan, Baseline Group

[52] http://www.leginfo.ca.gov/pub/13-14/bill/asm/ab_0051-0100/ab_85_bill_20130627_chaptered.pdf

[53] Observed plan quality may fall below 40% as the lower bound is imperfectly enforced. In practice, an increasing number of plans fail to meet the 40% threshold over time (see Appendix Figure B1.1)

		Age 19–34	Age 35–54	Age 55–64
Silver Plan (Cheapest)	138–150% FPL	399.57	258.81	515.35
	150–200% FPL	163.46	331.46	431.35
	200–250% FPL	161.19	483.57	622.05
	250–400% FPL	190.70	326.92	401.84

Table 5: Covered California Silver Plan Average Monthly Costs by Age and Income (in $)

6.3.1 Estimates

In this section, I summarize supply side estimates. Table 4 reports the full set of age-income adjusted marginal costs, while Figure 4 displays the distribution for the baseline group.[54] For Medi-Cal, the average plan-level marginal cost for the baseline group (individuals aged 19–34 with income below 138% FPL) is $218.04, with a standard deviation of $93.06. The corresponding investment-related component of this cost averages $166.55 (standard deviation $67.10). Estimates of the investment cost curvature parameter, ζ_{fm1t}, vary significantly. Most values are below 5, but a notable right tail extend beyond 40, likely reflecting differences in operational efficiency, and all of which affect the ease with which plans can translate investment into quality improvements. In Covered California market, I estimate the average marginal cost for silver-tier plans in the baseline group is $262.82 (standard deviation $57.96, see Table 5).[55] Figure 5 presents the corresponding distribution of costs (See Appendix Figures B1.7 and B1.8 for detailed cost distributions by market and plan).

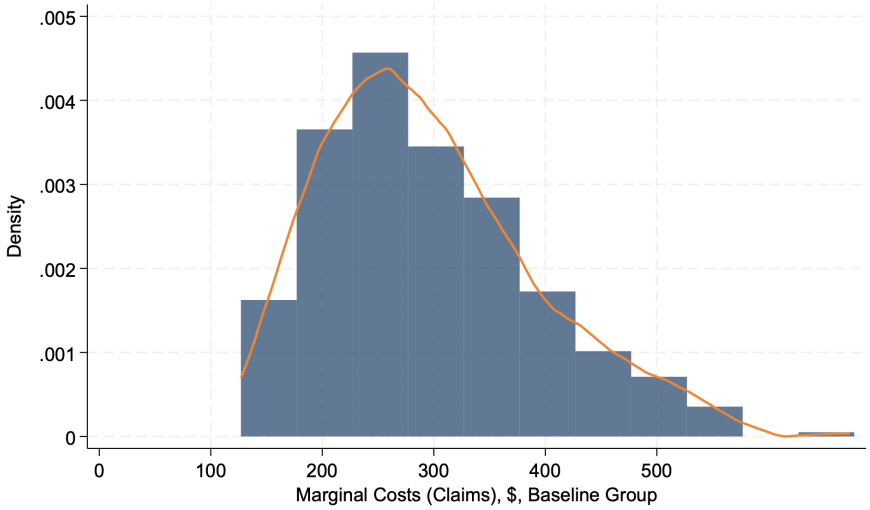


Figure 5: Distribution and Density of Covered California Marginal Costs, Market-Plan, Baseline Group

[54] See Appendix Figure B1.7 for a more detailed depiction of the cost distribution.

[55] Costs vary by actuarial value of the plans. Bronze plans average $202.31, gold plans $315.84, and platinum plans $379.35.

6.3.2 Identification

Identification of marginal costs and investment costs in Medi-Cal relies on variation in plan capitation rates, enrollment shares (active and passive), and observed quality scores across counties and years. For Medi-Cal, I exploit the variation in ρ_{fm1t} and s^d_{fm1t} to separately identify marginal cost C_{fm1t} and investment cost $I(v_{fm1t})$. More specifically, to identify the investment marginal cost ζ_{fm1t}, I use variation in plan quality scores and enrollment outcomes across markets and years. Because AQFS scores are observable, and assignment shares are a known function of relative quality, I recover plan incentives and cost parameters from the observed equilibrium mapping. For Covered California, identification hinges on observed variation in equilibrium plan prices, enrollment shares, and demographic composition across rating areas and years. Because firms choose prices to maximize profits (and set prices) subject to rating area constraints, I exploit both the (1) cross-sectional and (2) temporal variation in the demographic composition of enrollees to identify marginal costs. These demographic (age and income) characteristics differences across areas induce variation in the marginal profitability of plans which in turn affects optimal pricing decisions.

7. Effects of Alternative Eligibility Criteria

7.1 Model Validation

Before turning to counterfactual policy experiments, I first validate the model's ability to replicate key patterns of observed data. In Table 6, I show that the model matches Covered California enrollment and premium levels, as well as average Medi-Cal quality, very well; however, it slightly overpredicts Medi-Cal enrollment.

Segment	Outcome	Observed	Model
Medi-Cal	Average Enrollment Active (%)	45.68	50.14
	Average Enrollment Passive (%)	29.07	31.91
	Average Quality (%)	55.09	55.86
	Standard Deviation of Average Quality	9.39	10.09
	Average Per Member Cost ($)	–	3,351.95
	Average Consumer Surplus ($)	–	41.63
	Total Cost ($)	–	89,101,530.88
	Total Consumer Surplus ($)	–	771,704.05
	Total Firm Profits ($)	–	14,732,743.27
Covered California	Average Enrollment (%)	47.76	47.72
	Average Silver Benchmark Price ($)	3,387.28	3,424.32
	Std. Dev. of Silver Benchmark Price ($)	645.78	673.99
	Average Subsidy Per Enrollee ($)	–	5,220.01
	Avg. Cost Sharing Reductions Per Enrollee ($)	–	521.76
	Average Consumer Surplus ($)	–	945.29
	Total Subsidies ($)	–	106,015,342.20
	Total Consumer Surplus ($)	–	39,540,941.49
	Total Firm Profits ($)	–	38,770,795.63

Table 6: Model Validity

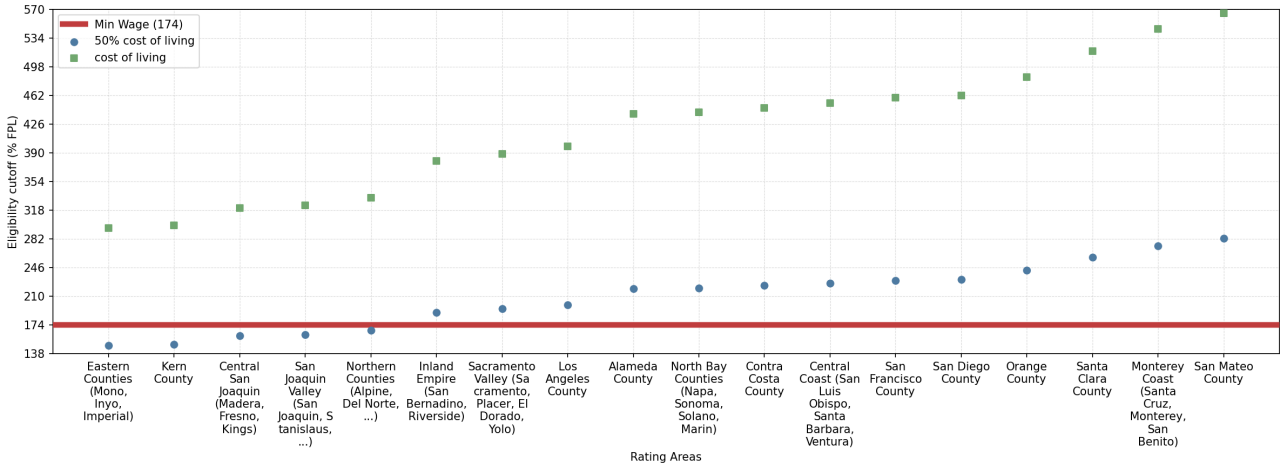
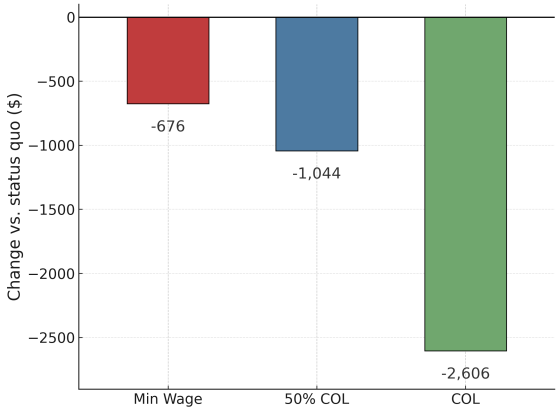


Figure 6: Uniform, Minimum Wage, and cost of living–Adjusted Eligibility Thresholds as % FPL by Health Insurance Rating Regions

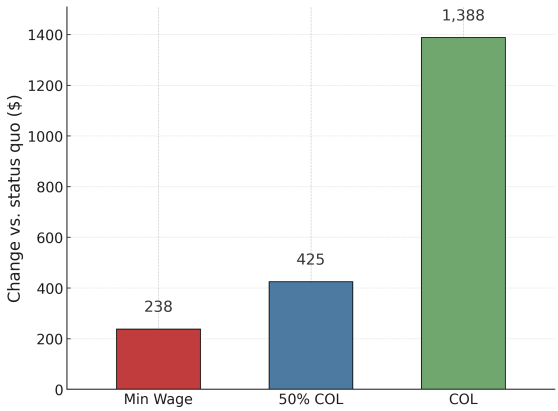
7.2 Alternative Thresholds

Next, I quantify the trade-offs associated with a tractable set of alternative eligibility designs (Figure 6). First, I examine a state-level policy that ties the Medi-Cal eligibility threshold to California's minimum wage or to prevailing labor market conditions. Second, I consider two alternatives that adjust eligibility thresholds based on the local cost of living, first halfway, and second, fully. I conduct the latter exercises at the rating area level. Rating areas are health insurance market regions within California, typically defined by geographic boundaries such as counties or groups of counties. These areas are used to set premiums and regulate insurer participation. In all counterfactuals, I restrict the analysis to individuals with incomes below 400% FPL. All counterfactual designs, thus, are considered in these analyses to relax eligibility thresholds relative to the status quo, making these policies inherently expansionary. Before solving for the equilibrium objects, I make two adjustments. First, I reclassify those who would be above the federal eligibility threshold but below the counterfactual standard from the Covered California potential buyer pool into Medi-Cal. In high cost of living areas, the eligibility expansion can be so significant that either Covered California (1) becomes thin as nearly all individuals become eligible for Medi-Cal or (2) completely eliminates the market in those regions. Second, I adjust the subsidy schedule in Covered California to align with the new eligibility thresholds. This ensures that both Medi-Cal eligibility and Covered California subsidies are consistently recalibrated in each counterfactual scenario. I then solve for equilibrium premiums consistent with firms' first-order conditions in Covered California, and quality with the joint first-order conditions and MLR constraints in Medi-Cal using the approach highlighted in the previous section. In doing so, I ensure that both pricing and quality investment decisions are internally consistent with the regulatory environment of each market segment.

Figure 7 summarizes the changes in key outcomes and consumer surplus for both Covered



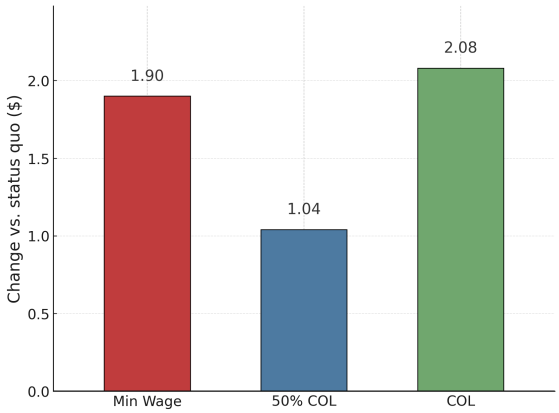
(a) Δ Average Benchmark Plan Premiums (Covered California)



(b) Δ Average Consumer Surplus (Covered California)

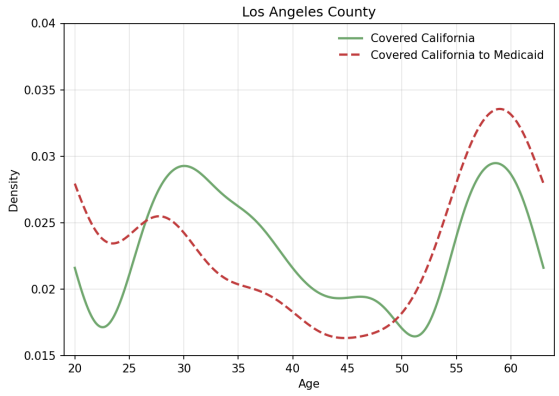


(c) Δ Average Plan Quality (Medi-Cal)

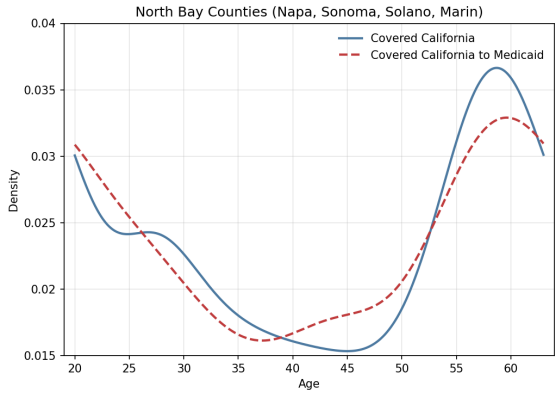


(d) Δ Average Consumer Surplus (Medi-Cal)

Figure 7: Changes in Plan Premiums, Quality, and Consumer Surplus in Covered California and Medi-Cal



(a) Δ Age Distribution in Los Angeles



(b) Δ Age Distribution in North Bay

Figure 8: Changes in Underlying Age Distribution: Los Angeles vs North Bay

California and Medi-Cal, relative to the status quo (See Appendix Table B1.14 for full results). Across all alternative eligibility designs, the average premium for the benchmark plan in Covered California declines substantially (Figure 7a). These premium reductions reflect insurers' equilibrium responses to changes in the risk pool, as healthier or lower-cost individuals transition into Medi-Cal. For those remaining in Covered California, average consumer surplus increases (Figure 7b), though the gains are smaller than the corresponding premium reductions. This difference arises because average consumer surplus aggregates across heterogeneous groups experiencing different types of adjustments. Specifically, consumer surplus changes reflect: (1) gains for previously uninsured individuals who newly obtain coverage, (2) changes in utility for individuals who remain in Covered California, and (3) gains or losses for individuals reallocated from Covered California to Medi-Cal (such as differences in plan quality and attributes). As a result, average consumer surplus reflects a net outcome that balances offsetting gains and losses across groups, rather than directly mirroring premium changes. On the Medi-Cal side, enrollment expansions are accompanied by small declines in average plan quality (Figure 7c). One possible explanation for these results is that the quality metrics focus primarily on child-related follow-up services, whereas the population I study in this paper is childless adults. Despite these modest declines, average consumer surplus in Medi-Cal rises under all counterfactual designs (Figure 7d). This surplus averages surplus from three types of individuals: (1) already in Medi-Cal, (2) moved from uninsured to Medi-Cal, and (3) moved from Covered California to Medi-Cal. The primary driver of these gains is coverage expansion, particularly among individuals who were previously uninsured and now receive some coverage. Nonetheless, the magnitude of surplus gains is muted by quality reductions and by heterogeneity in how different individuals value Medi-Cal relative to alternative coverage options.

7.2.1 Decomposing Variation

I use the model to disentangle the key mechanisms driving welfare variation. Specifically, I am interested in differences in welfare arising from (1) substitution between Medi-Cal and Covered California expansion, holding prices and quality fixed, (2) insurers' pricing responses in the exchange, and (3) quality investment responses in Medi-Cal. To understand the substitution effect, I first reclassify individuals from Covered California to Medi-Cal under each alternative threshold while keeping premiums and quality at baseline levels. For pricing effects, I fix Medi-Cal quality at baseline levels and allow premiums in Covered California to repotimize only. Finally, I allow Medi-Cal plans to adjust quality with status quo premiums. I summarize results in Appendix Figure B1.9. I find that insurers' responses to pricing in Covered California generate the largest welfare shifts, as premiums adjust sharply to changes in the risk pool's composition. While Medi-Cal quality investments yield more modest effects overall, they are significant in multi-plan markets where auto-assignment increases competition for passive enrollees.

7.2.2 Heterogeneity by Rating Area

While average premiums might decrease overall, Figure 7 may mask potential variation in welfare effects across different regions. Appendix Figures B1.10, B1.11, and B1.12 examine consumer surplus net of costs (including uncompensated care savings) for each rating area under the various alternative designs.

I explore two possible explanations for these differences. First, regions differ markedly in their demographic composition. In Figure 8, I present the age distribution of individuals who move from Covered California to Medi-Cal (dotted lines) and those who remain in Covered California under the minimum-wage eligibility threshold in Los Angeles County (consumer surplus>costs-uncompensated savings) and the North Bay counties(consumer surplus<costs-uncompensated savings). In Los Angeles County, Covered California potential buyers who stay are, on average, younger than those who enroll in Medi-Cal. This pattern indicates that Los Angeles has a younger population overall and a larger pool of uninsured or marginally insured individuals near the eligibility threshold. In contrast, in the North Bay counties, the overall age distribution is skewed towards the right, and the distinction between movers and stayers is less pronounced. Individuals remaining in Covered California in the North Bay are, on average, older than their counterparts in Los Angeles, and the group transitioning to Medi-Cal is more closely age-matched with those who remain insured through the marketplace.

Next, I focus on areas that experience net losses under alternative eligibility criteria. An area may experience net losses when one or more of the following channels dominate: increases in program costs, declines in uncompensated care savings, or reductions in consumer surplus. In Appendix Figure B1.13, I report the ratio of changes in uncompensated care savings to changes in total costs under the minimum-wage benchmarking exercise. Among the regions with consumer surplus <costs-uncompensated savings, San Diego County exhibits a substantially larger uncompensated care savings relative to cost increases than other regions. Importantly, this does not imply that San Diego experiences lower costs overall. Rather, the figure indicates that even large uncompensated care savings are insufficient to offset the magnitude of cost increases in that county. One plausible explanation is that San Diego experiences substantial movement from uninsurance into insurance coverage, which is inherently costlier than substituting or reallocating individuals between Covered California and Medi-Cal. In the latter regions, individuals were already insured, hence reallocation generates much smaller cost increases and therefore requires less uncompensated care offset to avoid net losses.

8. Conclusion

Eligibility rules are important market design levers. When programs combine public financing with private provision, designing these rules becomes especially difficult. Regulators must simultaneously pursue goals of expanding access, maintaining fiscal sustainability, and ensuring viable private participation. Currently, eligibility for these programs is set using a single nation-

wide cutoff. In this paper, I study whether and how place-based eligibility rules affect selection, sorting, and segmentation between Medi-Cal and Covered California.

I find that spatially decentralized eligibility rules are more effective than uniform national thresholds. Importantly, the analysis reveals that market structures adapt to threshold changes by altering pricing and quality. I find that the key behavioral channel affecting welfare calculations is insurer pricing responses to changes in their potential buyers. When I consider each region separately, gains from decentralization are uneven. I explore two possible avenues to explain these differences: (1) who becomes newly eligible (previously uninsured vs already-insured), and (2) the extent to which public spending replaces existing payments versus adds new spending. Although I focus on California in my empirical application, the framework is portable to other states and settings other than health insurance markets.[56] Finally, the ongoing Medicaid unwinding underscores the relevance of these results. Following the expiration of continuous coverage provisions (see Figure C.14 and C.15) emphasizes precisely the mechanisms emphasized in my analysis.

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[56] My approach also highlights the feasibility of empirical policy design: eligibility rules can be redesigned using existing inputs and phased in gradually while monitoring effects.

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A. APPENDIX

A.1 Estimation Procedure and Full Estimates

The control function methodology proceeds in two stages. In the first stage, I regress the potentially endogenous variable—plan quality in Medi-Cal or the base premium in Covered California—on a set of excluded instruments and exogenous controls. These instruments are chosen to satisfy both relevance and exclusion conditions. For Medi-Cal, I leverage demographic variation (age distribution) in adjacent counties, exploiting the fact that insurer quality investments are shaped by regional provider networks and administrative spillovers but that adjacent-county demographics are unlikely to correlate with local idiosyncratic demand shocks, conditional on fixed effects. In the Covered California setting, where premiums are uniform across counties within a rating region, I construct Waldfogel-style instruments from regional demographic composition, exploiting cross-county spillovers in actuarial pricing that are orthogonal to local preference shocks. The relevance condition holds because the demographic structure can affect the cost and quality adjustment incentives of firms through shared provider networks, workforce availability, and regional management spillovers. These factors influence a plan's investment decisions in adjacent areas and may spill over to neighboring counties via shared contracting, administrative resources, or uniform compliance with state-level quality incentives. The exclusion restriction is also plausible. While demographics affect how plans invest in quality in neighboring counties, they are unlikely to be directly correlated with unobserved demand shocks or idiosyncratic preference shocks ξ_{jmst}, conditional on local market and product fixed effects. This approach follows the logic of shift-share instruments and Bartik-style designs, where variation from adjacent or otherwise independent markets helps isolate exogenous shifts in plan incentives, rather than in plan attractiveness. The ACA marketplaces are a setting in which the presence of rating restrictions across demographic groups leads to an intuitive Waldfogel instruments.[57] These instruments use demographic characteristics of nearby markets to act as exogenous shifters of equilibrium markups. Fundamentally, the strength of these instruments depend on the assumption that prices are uniformly set at a high-level geographic area. It then follows that one's neighbor's influence the types of products and prices one is offered. In ACA marketplaces, and in Covered California, insurers set base premiums responding to the distribution of demographic characteristics in a rating region since it affects the shape of the demand and average costs. In Covered California, base premiums are set uniformly across counties within a rating region. Insurers anticipate the shape of demand and average costs based on the age-income profile of the entire rating region. As a result, variation in demographic composition outside a consumer's own county can shift prices independently of county-level demand shocks. Identification thus assumes that, conditional on buyer's age and income, preference do not depend on the distribution of demographics in the same geographic area, yet this affects base premiums, which should be higher in relatively older

[57] See Berry and Waldfogel (1999); Waldfogel (2003); Berry and Haile (2010).

regions.[58] To this end, I first regress x_j and b_j on instruments z to obtain residuals from the regressions. The residual from the first stage serves as a control function, capturing the component of the endogenous regressor that is correlated with the unobservable in the structural demand equation. The key to the control function approach is to note that under the maintained assumptions, conditional on error from first stage v, ϵ is independent of x_j (or p_j). Formally, for plan j in market m and year t, the reduced-form equation is:

$$b_{jm2t} = \eta^2_{35} \int 1[age \in A^1] dG_{m2t} + \eta_{tier} + \eta_t + \eta^2_f + v_{jm2t}$$

$$\mathrm{v}_{jm1t} = \eta^1_{35} \int 1[age \in A^1] dG_{m1t} + x_{jm1t} + \eta_t + \eta^1_f + v_{jm1t}$$

In the second stage, I include residuals v as an additional regressor in the utility function, which takes the form:

$$u_{ijmst} = \begin{cases} \gamma_{ist} v_{ijmst} + \beta_{ist} x_{ijmst} + \gamma_{ist} d_{jmst} + \xi_{jmst} + o v_{jm1t} + \epsilon_{ijmst} & \text{if } s = 1 \text{ (Medi-Cal)} \\ \alpha_{ist} p_{ijmst} + \beta_{ist} x_{ijmst} + \gamma_{ist} d_{jmst} + \xi_{jmst} + o v_{jm2t} + \epsilon_{ijmst} & \text{if } s = 2 \text{ (Covered California)} \end{cases} \tag{10}$$

where o captures the correlation between the unobserved utility component and the endogenous price. The inclusion of v corrects for endogeneity, allowing the model to recover consistent estimates of demand parameters. In the second stage, I estimate the mixed logit demand model, augmenting the indirect utility function with the first-stage residual. Under the assumption that the structural error and the residual are jointly normally distributed, the control function correction restores orthogonality between the regressors and the unobservable. Specifically, I model the structural error term as the sum of a conditional expectation and a mean-zero orthogonal component, where the conditional expectation is linear in the first-stage residual. This yields an additive correction term in the utility specification, whose coefficient captures the extent of endogeneity. The model is estimated by simulated maximum likelihood, with consumer choice probabilities computed via simulation over the random utility shocks. This approach allows for consistent estimation of demand parameters in the presence of endogenous quality and pricing, accommodates individual-level variation in premiums, and is robust to sparse product-level purchases, making it especially well-suited to the institutional features of the Medi-Cal and Covered California markets. Taking $\widehat{\xi}_{jmst}$ as given, and for each segment separately, I estimate the demand parameters $(\alpha^d_t, \beta^d_t, \gamma^d_t)$ for each demographic bin d, by maximizing the simulated log-likelihood function:

[58] See Orsini and Tebaldi (2017); Polyakova and Ryan (2019); Tebaldi (2024).

$$SSL = \sum_{i=1}^{I_t^d} \ln \left[\frac{1}{R} \sum_{r=1}^{R} \frac{e^{\delta_{ij(i)mst}}}{e^{\delta_{ij_0(i)mst}} + \sum_{j' \in \mathcal{J}_{mst} \setminus \{j_0(i)\}} e^{\delta_{ij'(i)mst}}} \right] \tag{11}$$

$$\text{with } \delta_{ij(i)mst} = \begin{cases} \gamma_t^r v_{ij(i)mst} + \beta_t^r x_{ij(i)mst} + \gamma_t^r d_{ijmst} + \xi_{j(i)mst} + ov_{jm1t} & \text{for Medi-Cal} \\ \alpha_t^r p_{ij(i)mst} + \beta_t^r x_{ij(i)mst} + \gamma_t^r d_{ijmst} + \xi_{j(i)mst} + ov_{jm2t} & \text{for Covered California} \end{cases}$$

$j(i)$ denotes the alternative chosen by individual i. Due to large sample, I estimate SSL on a sample of I_t^d individuals chosen in every year t and every demographic group d. R is the number of replications, and α_t^r, β_t^r, and γ_t^r are respectively the r-th draws from the parameter distributions. Standard errors are calculated using the variance-covariance matrix obtained as the inverse of the negative Hessian of the simulated log-likelihood function at convergence. The Hessian is calculated using numerical differentiation, the gradient is analytical.

Medi-Cal: In each year t, insurer f chooses an effort level v_{fm} to maximize profits:

$$\pi_{fm} = \sum_{d \in D} \Big[(R_{fm} - \omega^d c_{fm})\, s_{fm}^d M^d + (R_{fm} - c\,\omega^d c_{fm})\, \mathbb{E}[\rho_{fm} \mid \mathbf{v}_m]\, (1 - s_{fm}^d) M^d \Big] - \sum_{d \in D} \zeta_{fm} (v_{fm} - \underline{v})^2 M^d.$$

With $S = \sum_k v_{km}$ and $v \equiv v_{fm}$,

$$\mathbb{E}[\rho_{fm} \mid \mathbf{v}_m] = \frac{v}{S}, \qquad \frac{\partial s_{fm}^d}{\partial v} = \gamma^d s_{fm}^d (1 - s_{fm}^d), \qquad \frac{\partial}{\partial v} \mathbb{E}[\rho_{fm} \mid \mathbf{v}_m] = \frac{S - v}{S^2}.$$

The first-order condition is

$$\sum_{d \in D} \Big[(R_{fm} - \omega^d c_{fm})\, \gamma^d s_{fm}^d (1 - s_{fm}^d) M^d + (R_{fm} - c\,\omega^d c_{fm})\, \tfrac{S - v}{S^2} (1 - s_{fm}^d) M^d - (R_{fm} - c\,\omega^d c_{fm})\, \tfrac{v}{S}\, \gamma^d s_{fm}^d (1 - s_{fm}^d) M^d \Big] - 2\zeta_{fm} (v - \underline{v}) \sum_d M^d = 0. \tag{12}$$

Observed MLR spending implies

$$2\zeta_{fm} (v - \underline{v}) \sum_d M^d = \frac{2}{v - \underline{v}} \Bigg[\underbrace{\sum_d \text{num(MLR)} M^d}_{N} - c_{fm} \underbrace{\sum_d \omega^d \left(s_{fm}^d + c(1 - s_{fm}^d) \right) M^d}_{E} \Bigg].$$

Define

$$A \equiv \sum_d \gamma^d s_{fm}^d (1 - s_{fm}^d) M^d, \qquad B \equiv \sum_d (1 - s_{fm}^d) M^d,$$

$$C \equiv \sum_d \omega^d \gamma^d s_{fm}^d (1 - s_{fm}^d) M^d, \quad D \equiv \sum_d \omega^d (1 - s_{fm}^d) M^d.$$

Substituting into the FOC yields

$$R_{fm}\left[(1-\tfrac{v}{S})A+\tfrac{S-v}{S^2}B\right]-c_{fm}\left[C+\tfrac{c(S-v)}{S^2}D-\tfrac{cv}{S}C\right]-\frac{2}{v-\underline{v}}\left[N-c_{fm}E\right]=0.$$

Rearranging gives

$$\boxed{c^*_{fm}=\frac{R_{fm}\left[(1-\tfrac{v}{S})A+\tfrac{S-v}{S^2}B\right]-\dfrac{2N}{v-\underline{v}}}{C+\tfrac{c(S-v)}{S^2}D-\tfrac{cv}{S}C-\dfrac{2E}{v-\underline{v}}}}.$$

$R_{fm}\left[(1-\frac{v}{S})A+\frac{S-v}{S^2}B\right]$: marginal revenue from higher quality, via (i) *active enrollment elasticity* (A) and (ii) *passive assignment elasticity* (B). $-\frac{2N}{v-\underline{v}}$: implied marginal investment cost from observed MLR spending. C: active cost elasticity; $\frac{c(S-v)}{S^2}D$: passive cost elasticity; $-\frac{cv}{S}C$: offset when enrollees shift from passive to active; $-\frac{2E}{v-\underline{v}}$: adjustment tying the FOC to MLR-based spending.

Covered California: Firms choose base list prices $b_{jr(m)t}$ subject to ACA rating rules. The first-order condition for optimal pricing is:

$$\frac{\partial \pi_{fr(m)st}}{\partial b_{jr(m)t}}=\sum_{l\in\mathcal{J}_{fr(m)st}}\sum_{d\in D}\left[\left(b_{jr(m)t}\cdot\tau^d-\omega^d\cdot c_{jr(m)t}\right)\cdot\frac{\partial s^d_{lr(m)st}}{\partial b_{jr(m)t}}\cdot N^d+\mathbb{1}(l=j)\cdot\tau^d\cdot s^d_{jr(m)st}\cdot N^d\right]=0 \tag{13}$$

This condition characterizes the impact of subsidies on pricing behavior via demand elasticities. Rewriting in matrix form:

$$S-\Omega(B-C)=0$$

where $S_j=\sum_d \tau^d s^d_j N^d$, $(B-C)_j=\sum_d(b_j\cdot\tau^d-\omega^d c_j)$, and

$$\Omega_{lj}=-\sum_d N^d\cdot\frac{\partial s^d_j(p(b))}{\partial b_l}$$

This system can be inverted to recover plan marginal costs. I also impose the MLR condition to restrict feasible combinations of premiums, costs, and investments.

Subsidies influence both s^d_j and $\frac{\partial s^d_j}{\partial b_l}$ through the mapping:

$$\frac{\partial s^d_j}{\partial b_l}=\frac{\partial s^d_j}{\partial p_l}\cdot\frac{\partial p_l}{\partial b_l}$$

If $p_l=b_l$, then $\frac{\partial p_l}{\partial b_l}=1$. Under ACA rules, this may be zero (fully subsidized) or introduce cross-plan effects via benchmark plan pricing, creating externalities across plans.

B. TABLES AND FIGURES

B.1 Descriptive Analysis

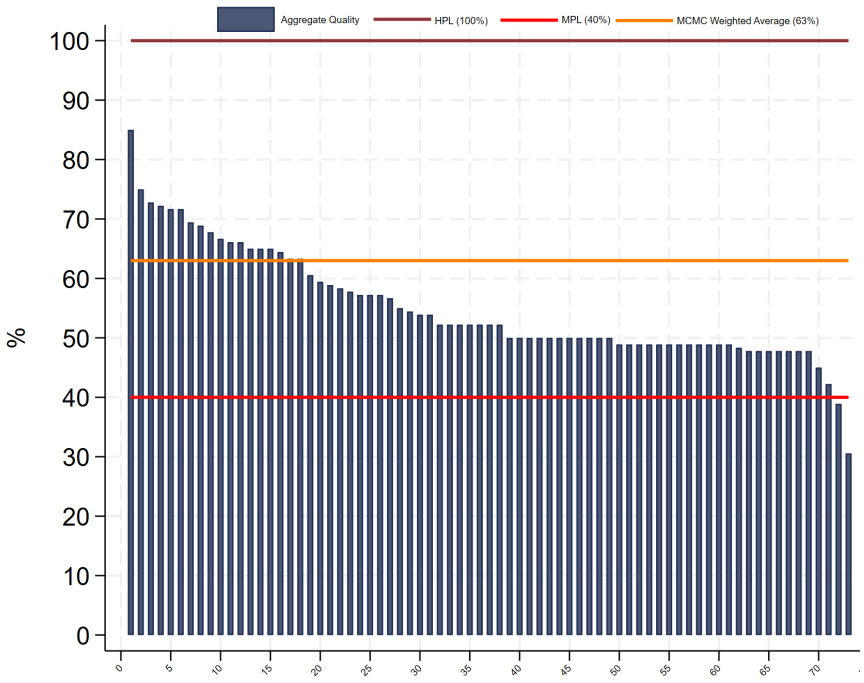


Figure B1.1: 2017 HEDIS Aggregated Quality Factor Score (AQFS)

Note: The Aggregated Quality Factor Score (AQFS) is a single score that accounts for plan performance on all DHCS-selected Health Effectiveness Data and Information Set (HEDIS) indicators. It is a composite rate calculated as percent of the National High Performance Level (HPL). The High Performance Level is 100%. The Minimum Performance Level is 40%. The State Average is 63%

B.2 Demand

	Year			
	2017	2018	2019	All
by age category (years):				
19 to 34	2,109,548	2,085,071	2,026,634	6,221,253
	(49.40%)	(49.55%)	(49.38%)	(49.44%)
35 to 54	1,330,948	1,302,096	1,265,774	3,898,818
	(31.17%)	(30.95%)	(30.84%)	(30.98%)
Age 55 to 64	829,653	820,477	812,007	2,462,137
	(19.43%)	(19.50%)	(19.78%)	(19.57%)
by insurer:				
Aetna Better Health		6,919	13,653	20,572
		(0.16%)	(0.33%)	(0.17%)
Alameda Alliance for Health	113,126	114,832	110,953	338,911
	(2.65%)	(2.73%)	(2.70%)	(2.69%)
Anthem Blue Cross Partnership Plan	341,755	328,085	317,159	986,999
	(8.00%)	(7.80%)	(7.73%)	(7.84%)
Blue Shield of California Promise	47,504	46,670	44,185	138,359
	(1.11%)	(1.11%)	(1.08%)	(1.10%)
CalOptima	324,219	320,112	313,640	957,971
	(7.59%)	(7.61%)	(7.64%)	(7.61%)
CalViva Health	123,443	121,903	120,583	365,929
	(2.89%)	(2.90%)	(2.94%)	(2.91%)
California Health and Wellness Plan	81,810	84,647	83,974	250,431
	(1.92%)	(2.01%)	(2.05%)	(1.99%)
CenCal Health	65,134	66,196	65,315	196,645
	(1.53%)	(1.57%)	(1.59%)	(1.56%)
Central California Alliance for Health	116,594	115,814	113,570	345,978
	(2.73%)	(2.75%)	(2.77%)	(2.75%)
Community Health Group	114,825	108,064	100,829	323,718
	(2.69%)	(2.57%)	(2.46%)	(2.57%)
Contra Costa Health Plan	76,224	75,697	72,743	224,664
	(1.79%)	(1.80%)	(1.77%)	(1.79%)
Gold Coast Health Plan	80,229	77,590	74,775	232,594
	(1.88%)	(1.84%)	(1.82%)	(1.85%)
Health Net Community Solutions	605,164	570,766	552,936	1,728,866
	(14.17%)	(13.56%)	(13.47%)	(13.74%)
Health Plan of San Joaquin	122,685	122,941	118,944	364,570
	(2.87%)	(2.92%)	(2.90%)	(2.90%)
Health Plan of San Mateo	49,778	48,473	44,519	142,770
	(1.17%)	(1.15%)	(1.08%)	(1.13%)
Inland Empire Health Plan	463,518	467,725	462,978	1,394,221
	(10.85%)	(11.12%)	(11.28%)	(11.08%)
Kern Family Health Care	80,367	84,095	87,074	251,536
	(1.88%)	(2.00%)	(2.12%)	(2.00%)
L.A. Care Health Plan	840,524	847,160	835,288	2,522,972
	(19.68%)	(20.13%)	(20.35%)	(20.06%)
Molina Healthcare of California	201,795	190,152	182,807	574,754
	(4.73%)	(4.52%)	(4.45%)	(4.57%)
Partnership Health Plan of California	230,627	229,650	220,645	680,922
	(5.40%)	(5.46%)	(5.38%)	(5.41%)
San Francisco Health Plan	79,831	74,422	69,099	223,352
	(1.87%)	(1.77%)	(1.68%)	(1.77%)
Santa Clara Family Health Plan	110,997	105,731	98,746	315,474
	(2.60%)	(2.51%)	(2.41%)	(2.51%)

Table B1.1: Medi-Cal Enrollment Files Summarized, Unique Individual-Year, 2017-2019

	Year			
	2017	2018	2019	All
by age category (years):				
19 to 34	153,083	122,275	123,058	398,416
	(32.53%)	(33.19%)	(32.72%)	(32.79%)
35 to 54	163,342	105,857	105,039	374,238
	(34.71%)	(28.73%)	(27.93%)	(30.80%)
55 to 64	154,200	140,318	147,960	442,478
	(32.76%)	(38.08%)	(39.35%)	(36.41%)
by income category (% FPL):				
138% FPL or less	33,788	21,246	21,214	76,248
	(7.18%)	(5.77%)	(5.64%)	(6.20%)
138% FPL to 150% FPL	66,214	60,474	57,944	184,632
	(14.07%)	(16.41%)	(15.41%)	(15.30%)
150% FPL to 200% FPL	153,808	116,532	117,016	387,356
	(32.68%)	(31.63%)	(31.12%)	(31.81%)
200% FPL to 250% FPL	83,093	66,279	67,963	217,335
	(17.66%)	(17.99%)	(18.07%)	(17.91%)
250% FPL to 400% FPL	85,606	70,105	75,988	231,699
	(18.19%)	(19.03%)	(20.21%)	(19.14%)
400% FPL to 450% FPL	6,712	4,747	5,091	16,550
	(1.43%)	(1.29%)	(1.35%)	(1.36%)
450% FPL to 500% FPL	3,566	3,668	4,012	11,246
	(0.76%)	(1.00%)	(1.07%)	(0.94%)
500% FPL to 550% FPL	3,368	1,721	2,129	7,218
	(0.72%)	(0.47%)	(0.57%)	(0.58%)
550% FPL to 600% FPL	1,780	1,579	1,873	5,232
	(0.38%)	(0.43%)	(0.50%)	(0.43%)
600% FPL or greater	6,626	5,438	6,534	18,598
	(1.41%)	(1.48%)	(1.74%)	(1.54%)
Unsubsidized Application	26,064	16,661	16,293	59,018
	(5.54%)	(4.52%)	(4.33%)	(4.80%)

Table B1.2: Covered California Enrollment Files Summarized, Unique Individual-Year, 2017-2019: Demographics

	Year			
	2017	2018	2019	All
by insurer:				
Anthem	76,869	14,866	13,612	105,347
	(16.33%)	(4.03%)	(3.62%)	(8.00%)
Blue Shield	112,454	113,370	111,535	337,359
	(23.89%)	(30.77%)	(29.66%)	(28.11%)
Chinese Community	3,912	2,683	2,509	9,104
	(0.83%)	(0.73%)	(0.67%)	(0.74%)
HealthNet	44,835	48,352	48,305	141,492
	(9.53%)	(13.12%)	(12.85%)	(11.83%)
Kaiser	148,203	131,410	136,900	416,513
	(31.49%)	(35.67%)	(36.40%)	(34.52%)
L.A. Care	9,242	20,687	24,214	54,143
	(1.96%)	(5.61%)	(6.44%)	(4.67%)
Molina	57,049	16,265	16,061	89,375
	(12.12%)	(4.41%)	(4.27%)	(6.94%)
Oscar	2,674	7,631	10,872	21,177
	(0.57%)	(2.07%)	(2.89%)	(1.84%)
Sharp	8,008	6,500	3,983	18,491
	(1.70%)	(1.76%)	(1.06%)	(1.51%)
Valley	2,573	3,810	5,321	11,704
	(0.55%)	(1.03%)	(1.41%)	(1.00%)
Western	4,806	2,876	2,745	10,427
	(1.02%)	(0.78%)	(0.73%)	(0.84%)
by metal tier:				
Bronze	142,209	115,827	113,558	371,594
	(30.22%)	(24.61%)	(24.13%)	(26.32%)
Gold	19,525	36,155	34,367	90,047
	(5.30%)	(9.81%)	(9.33%)	(8.15%)
Platinum	15,522	14,086	13,847	43,455
	(4.21%)	(3.75%)	(3.68%)	(3.88%)
Silver	293,369	202,382	214,285	710,036
	(78.01%)	(53.82%)	(56.98%)	(62.94%)

Table B1.3: Covered California Enrollment Files Summarized, Unique Individual-Year, 2017-2019: Plans

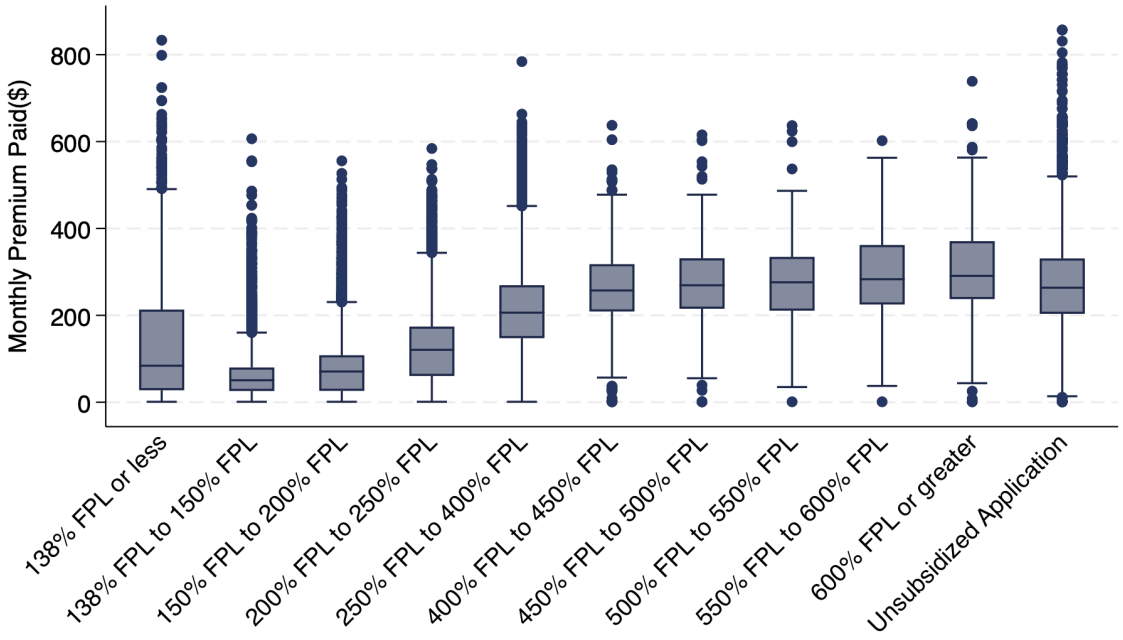


Figure B1.2: Distribution of Premium Paid (Monthly, $), by Income Brackets

year	all	Uninsured Income eligible for Medicaid	Income >138%	Medicaid	Private Coverage
2017	2,562,854 (10.5%)	703,270 (18.4%)	1,859,584 (9.0%)	5,243,073 (21.4%)	2,915,502 (11.9%)
2018	2,538,641 (11.6%)	640,576 (17.8%)	1,898,065 (9.1%)	5,212,379 (21.4%)	2,898,559 (11.9%)
2019	2,730,555 (12.7%)	597,036 (18.4%)	2,133,591 (10.1%)	4,930,589 (20.4%)	2,727,296 (11.2%)
All	7,832,050 (10.7%)	1,940,882 (18.2%)	5,891,168 (9.5%)	15,386,041 (21.1%)	8,541,357 (11.7%)

Table B1.4: Number of individuals 19-64 in different coverage types, capped at 400% FPL

Insurer	Credibility Adjusted MLR (%)	Avg Cost per Member Month($)
Alameda Alliance for Health	95.18	313.55
Anthem Blue Cross Partnership Plan	88.68	243.89
Blue Shield of California Promise	83.93	362.03
California Health and Wellness Plan	90.75	277.30
CalOptima	96.31	319.34
CalViva Health	94.39	255.34
CenCal Health	78.80	278.63
Central California Alliance for Health	97.75	251.57
Community Health Group	88.26	249.91
Contra Costa Health Plan	93.70	328.74
Gold Coast Health Plan	97.03	280.90
Health Net Community Solutions	88.48	246.71
Health Plan of San Joaquin	91.80	228.59
Health Plan of San Mateo	88.39	301.80
Inland Empire Health Plan	93.69	297.34
Kern Family Health Care	94.40	216.44
L.A. Care Health Plan	92.78	242.25
Molina Healthcare of California	86.60	272.02
Partnership Health Plan of CA	102.50	358.41
San Francisco Health Plan	90.11	297.80
Santa Clara Family Health Plan	92.79	313.16

Table B1.5: Medi-Cal MLR Summary State Fiscal Year 2017-18

	Avg Cost per Member Month($)
by insurer:	
Anthem	400.58
Blue Shield	471.50
Chinese Community	294.96
HealthNet	312.63
Kaiser	362.72
L.A. Care	205.19
Molina	137.03
Oscar	292.36
Sharp	302.73
Valley	170.86
Western	469.29
by metal tier:	
Bronze	185.32
Gold	605.17
Platinum	1517.33
Silver	300.91

Table B1.6: Rate Review Fillings, 2017

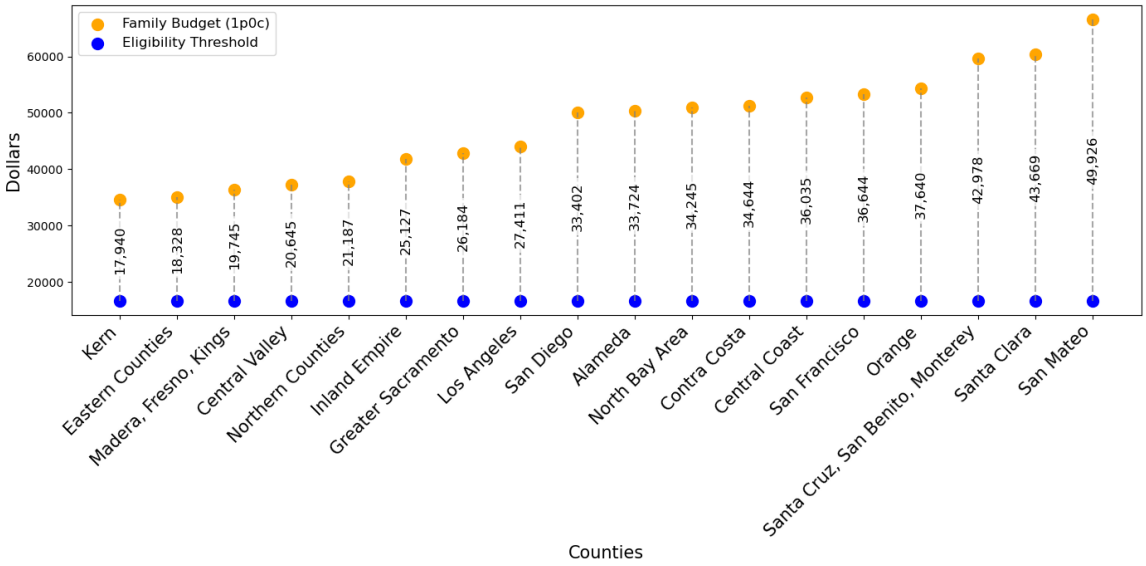


Figure B1.3: Regional Disparities in Living Costs vs. Uniform Eligibility Thresholds

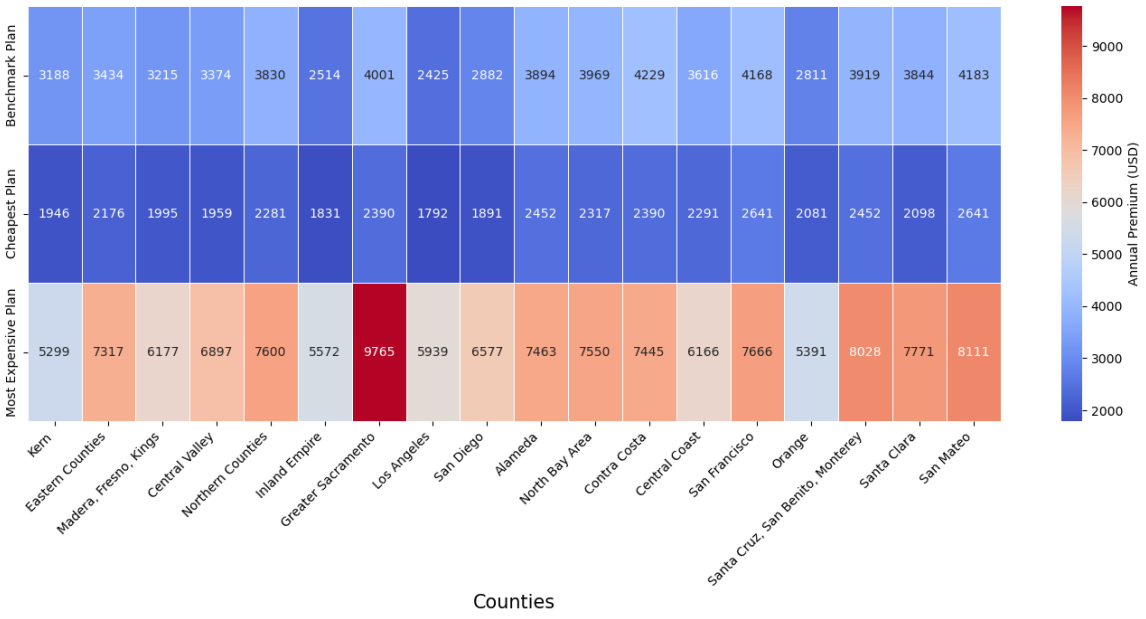


Figure B1.4: Annual Premiums for Health Insurance Plans by County (Heatmap)

Independent variable: Quality %	(1)	(2)	(3)	(4)
share under 35	37.16	18.16	15.38	13.09
	(16.01)	(12.57)	(11.34)	(10.81)
Alameda Alliance for Health				
Anthem Blue Cross Partnership Plan		-17.11	-17.16	-16.67
		(1.809)	(2.593)	(2.672)
Blue Shield of California Promise		-6.375	-6.350	-5.760
		(2.652)	(2.778)	(2.856)
CalViva		-8.422	-8.339	-8.413
		(3.644)	(4.171)	(4.177)
California Health & Wellness Plan		-23.01	-23.08	-22.12
		(1.887)	(2.616)	(2.915)
Community Health Group		8.949	8.974	9.847
		(3.803)	(5.105)	(5.205)
Contra Costa Health Plan		3.247	3.251	2.828
		(1.886)	(3.312)	(3.354)
Health Net Community Solutions		-16.84	-16.76	-16.54
		(2.836)	(3.465)	(3.681)
Health Plan of San Joaquin		-25.14	-25.07	-24.44
		(2.290)	(3.361)	(3.432)
Inland Empire Health Plan		-4.553	-4.473	-2.417
		(1.621)	(2.721)	(3.489)
Kern Family Health Care		-12.25	-12.15	-12.36
		(2.338)	(3.042)	(3.064)
LA Care Health Plan		-3.336	-3.284	4.717
		(1.559)	(2.730)	(8.980)
Molina Healthcare of California		-11.18	-11.13	-11.15
		(2.515)	(3.105)	(3.159)
San Francisco Health Plan		18.49	18.30	17.43
		(2.118)	(2.914)	(3.034)
Santa Clara Family Health Plan		-3.029	-3.090	-3.850
		(1.758)	(2.711)	(2.833)
2017				
2018			0.530	0.526
			(1.158)	(1.157)
2019			-3.884	-3.896
			(1.300)	(1.290)
% hospitals in network				-0.524
				(0.562)
Constant	36.24	61.06	63.50	66.59
	(7.627)	(6.197)	(6.079)	(6.486)
F-statistic	5.39	56.83	54.70	58.61
Prob>F	0.0212	0.0000	0.0000	0.0000
R-squared	0.0227	0.5485	0.5809	0.5885

Table B1.7: First Stage Estimates, Medi-Cal

Independent variable: Base Prices, $	(1)	(2)	(3)	(4)
share under 35	-6650.2	-6419.0	-5270.0	-4391.4
	(1334.1)	(944.2)	(816.1)	(756.8)
Bronze				
Gold		1897.8	1812.3	1836.1
		(82.61)	(72.27)	(66.12)
Platinum		3086.3	3000.8	3024.6
		(112.1)	(94.51)	(86.00)
Silver		1237.6	1152.0	1175.9
		(74.39)	(70.21)	(61.73)
Anthem				
Blue Shield			708.0	245.1
			(106.7)	(94.19)
Chinese Community			202.5	-310.2
			(140.4)	(113.6)
HealthNet			285.1	-218.3
			(131.4)	(122.0)
Kaiser			-521.1	-982.7
			(92.42)	(84.95)
LA Care			-1574.1	-2047.2
			(166.9)	(159.3)
Molina			-1154.6	-1630.5
			(126.3)	(106.3)
Oscar			-333.2	-886.8
			(160.9)	(146.3)
Sharp			-431.9	-914.1
			(178.5)	(142.4)
Valley			-938.4	-1376.0
			(142.5)	(143.8)
Western			77.24	-376.9
			(160.3)	(121.5)
2017				-776.3
				(64.75)
2018				
2019				1276.4
				(68.29)
				443.2
				(75.60)
Constant	7520.4	5994.3	5515.3	5704.9
	(563.9)	(396.4)	(358.9)	(327.5)
F-statistic	24.85	311.44	131.32	145.26
Prob>F	0.0000	0.0000	0.0000	0.0000
R-squared	0.0168	0.4591	0.5811	0.6614

Table B1.8: First Stage Estimates, Covered California

Quality (%)	0.859
	(0.00520)
Quality x Age 19-34	-0.00139
	(0.000300)
Quality x Age 35-54	-0.00112
	(0.000320)
Constant	-62.33
	(0.378)
Constant x Age 19-34	0.0704
	(0.0184)
Constant x Age 35-54	0.0668
	(0.0196)
% Hospitals in Network	0.476
	(0.00270)
% Hospitals in Network x Age 19-34	0.000762
	(0.000363)
% Hospitals in Network x Age 35-54	0.000306
	(0.000391)
Control function	0.866
	(0.00515)
Control function^2	0.00101
	(0.0000132)
Control function^3	-0.0000582
	(0.000000938)
Anthem Blue Cross Partnership Plan	12.29
	(0.0848)
Blue Shield of California Promise	1.973
	(0.0302)
CalViva Health	6.237
	(0.0411)
California Health and Wellness Plan	17.69
	(0.114)
Community Health Group	-9.792
	(0.0523)
Contra Costa Health Plan	-2.350
	(0.0178)
Health Net Community Solution	11.62
	(0.0839)
Health Plan of San Joaquin	20.08
	(0.125)
Inland Empire Health Plan	1.727
	(0.0123)
Kern Family Health Care	9.932
	(0.0623)
L.A. Care Health Plan	-5.052
	(0.0262)
Molina Healthcare of California	6.967
	(0.0562)
San Francisco Health Plan	-14.38
	(0.0871)
Santa Clara Family Health Plan	3.614
	(0.0223)

Table B1.9: Demand Estimates, Medi-Cal

Price ($1000)	0.466
	(0.0134)
Price x Age 19–34	0.204
	(0.0160)
Price x Age 35–54	0.181
	(0.0139)
Price x Income 138–150% FPL	0.315
	(0.0232)
Price x Income 150–200% FPL	0.305
	(0.0205)
Price x Income 200–250% FPL	0.184
	(0.0184)
Price x Income 250–300% FPL	0.110
	(0.0180)
AV	0.0540
	(0.000984)
HMO	-1.331
	(0.0374)
Constant	-6.311
	(0.0824)
Constant x Age 19–34	-0.616
	(0.0357)
Constant x Age 35–54	-0.317
	(0.0327)
Constant x Income 138–150% FPL	-0.615
	(0.0605)
Constant x Income 150–200% FPL	-0.159
	(0.0587)
Constant x Income 200–250% FPL	0.172
	(0.0603)
Constant x Income 250–300% FPL	0.242
	(0.0654)
Blue Shield	0.523
	(0.0303)
Chinese Community	0.705
	(0.116)
Health Net	0.973
	(0.0401)
Kaiser	1.458
	(0.0474)
L.A. Care	-0.352
	(0.0815)
Molina	0.668
	(0.0486)
Oscar	-2.665
	(0.148)
Sharp	1.542
	(0.0847)
Valley	-0.727
	(0.210)
Western	0.0971
	(0.114)
Control function	0.188
	(0.0229)
Control function^2	-0.00494
	(0.0156)
Control function^3	-0.0524
	(0.00832)

Table B1.10: Demand Estimates, Covered California

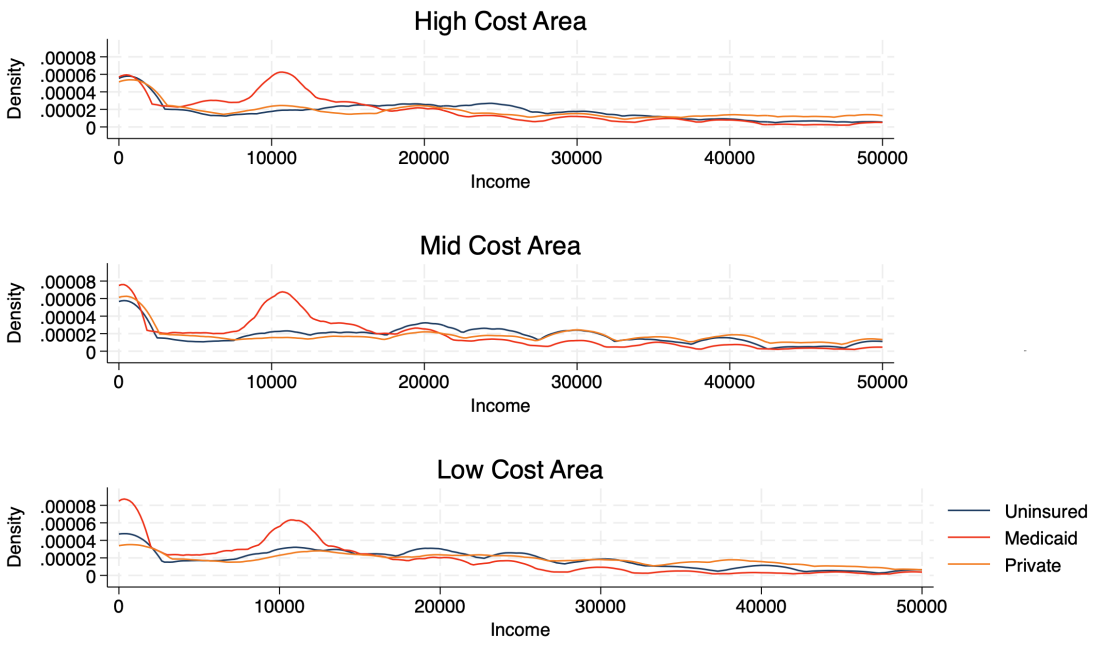
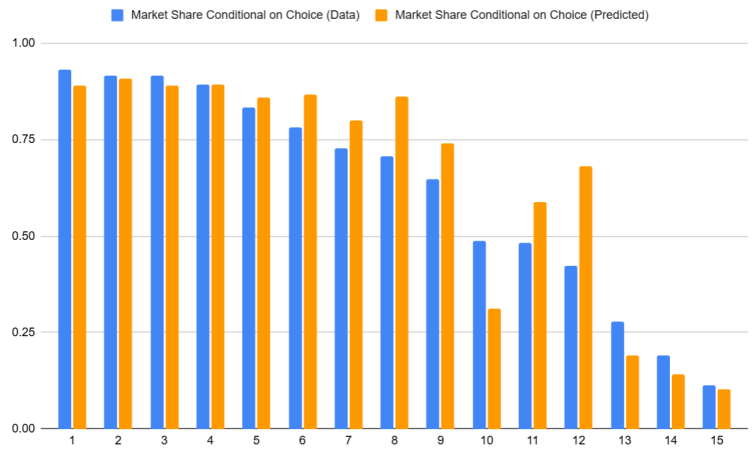
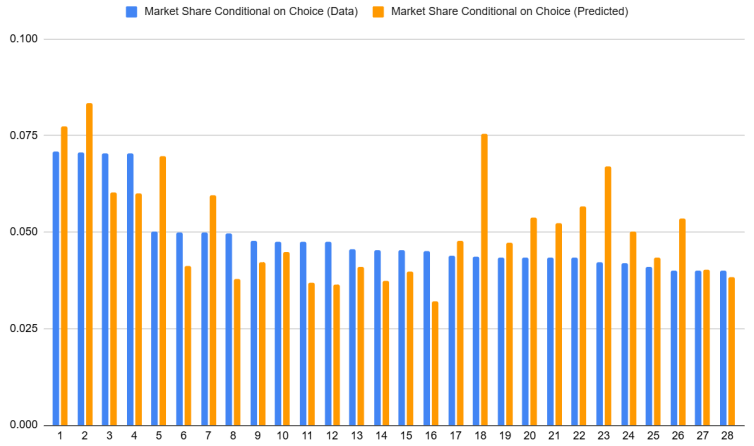


Figure B1.5: Income Distribution by Cost of Living and Coverage, Single, Childless Adults 19-64, capped at $50,000 annual income (≈ 415% FPL) 2017

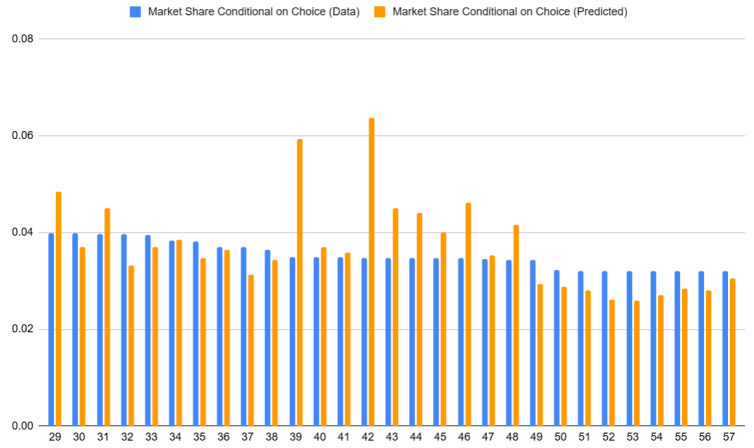
B.3 Model Fit



(a) Medi-Cal



(b) Covered California



(c) Covered California

Figure B1.6: Logit Implied Choice Distribution

Note: The dark blue bars correspond to the choice shares from data, and the light blue bars are the implied choice distribution based on logit estimates. Plans are ordered from the plan with the largest enrollment share on the left to the plans with lowest enrollment.

B.4 Marginal and Investment Costs

Coverage	Year	Income Category	Age 19–34	Age 35–54	Age 55–64
Medicaid	2017	138% FPL or less	1.00	2.06	2.56
	2018		1.00	2.89	4.23
	2019		1.00	2.74	4.00
Private	2017	138% FPL or less	1.00	1.61	3.66
		138% FPL to 150% FPL	1.76	1.14	2.27
		150% FPL to 200% FPL	0.72	1.46	1.90
		200% FPL to 250% FPL	0.71	2.13	2.74
		250% FPL to 400% FPL	0.82	1.44	1.77
		400% FPL or more	0.84	1.81	2.12
	2018	138% FPL or less	1.00	1.73	2.97
		138% FPL to 150% FPL	2.95	0.71	1.17
		150% FPL to 200% FPL	1.32	1.46	2.02
		200% FPL to 250% FPL	0.69	1.46	2.14
		250% FPL to 400% FPL	1.09	1.60	2.32
		400% FPL or more	1.00	1.77	2.63
	2019	138% FPL or less	1.00	3.94	3.43
		138% FPL to 150% FPL	1.50	5.06	2.35
		150% FPL to 200% FPL	1.06	2.10	3.44
		200% FPL to 250% FPL	1.18	2.72	3.35
		250% FPL to 400% FPL	1.39	2.27	3.13
		400% FPL or more	1.44	2.16	3.59

Table B1.11: Multipliers for Medicaid and Private Coverage

B.5 Effects of Alternative Designs

Health Plan	2017	2018	2019
Alameda Alliance for Health	313.55	292.38	331.30
Anthem Blue Cross	243.89	256.53	258.08
Aetna Better Health		294.01	359.62
Blue Shield of California	362.03	429.31	473.11
CalOptima	319.34	308.13	376.46
Central Coast Alliance for Health	251.57	297.31	368.28
Contra Costa Health Plan	328.74	356.24	378.12
CenCal Health	278.63	320.95	315.01
Community Health Group (CHG)	249.91	305.52	339.22
CA Health & Wellness	277.30	303.89	329.77
CalViva Health	255.34	267.64	299.16
Gold Coast	280.90	305.62	377.01
Health Net of California	246.71	249.12	275.34
Health Plan of San Joaquin	228.59	276.74	305.66
Health Plan of San Mateo	301.80	383.65	411.20
Inland Empire Health Plan	297.34	327.18	355.63
KP Cal	333.35	372.38	392.90
Kern Health Systems	216.44	288.42	307.19
LA Care	242.25	251.47	182.33
Molina Healthcare of California	272.02	280.78	290.34
Partnership Health Plan of California	358.41	392.76	436.83
Santa Clara Family Health Plan	313.16	263.80	435.62
San Francisco Health Authority	297.80	310.89	413.06
UnitedHealthcare		312.33	288.62

Table B1.12: Average Per-Member-Per-Month Paid Medi-Cal Claims and Quality Improvements, 2017-2019

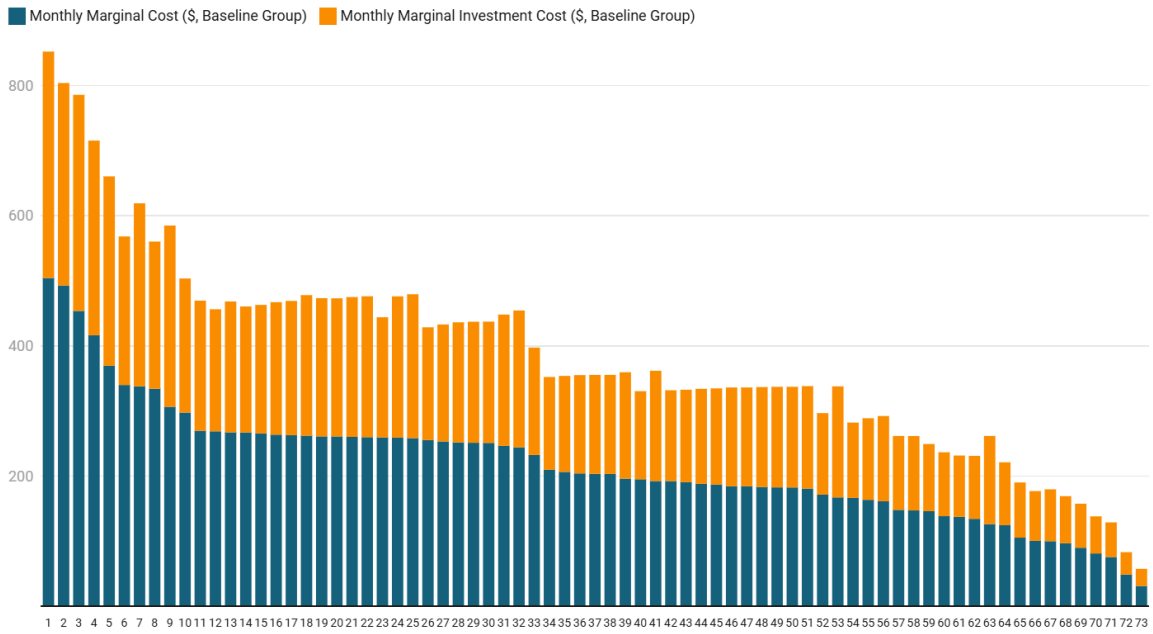


Figure B1.7: Marginal Costs and Investment Costs, Medi-Cal by Market-Plan, Baseline Group

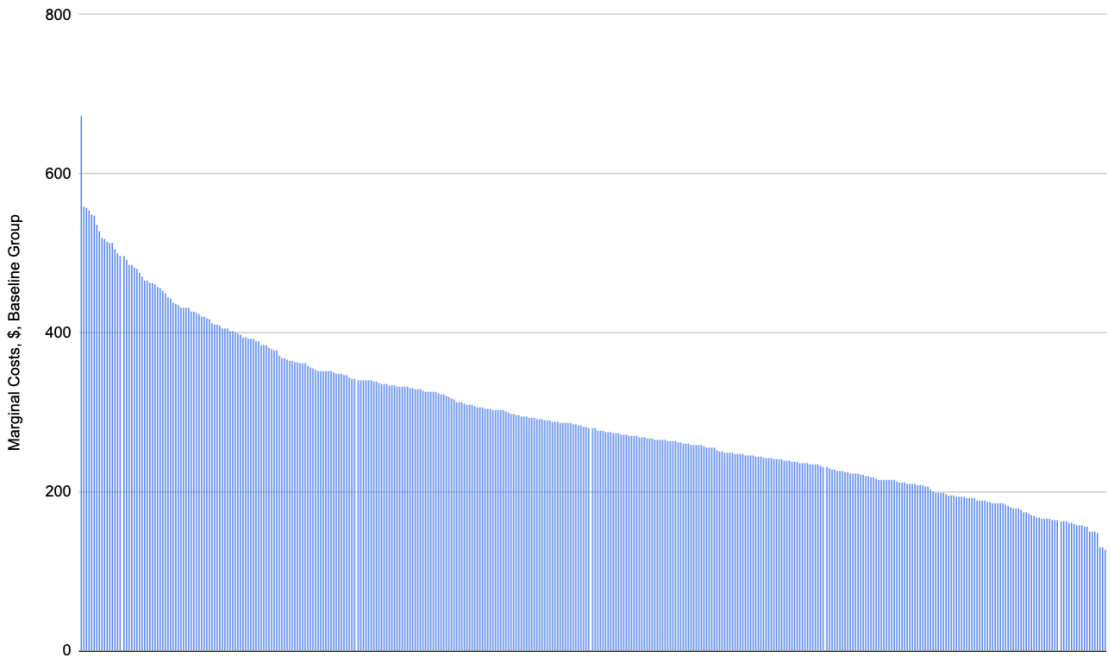


Figure B1.8: Marginal Cost Ranges, Covered California by Market-Plan, Baseline Group

Region	Change (Min Wage)	50% COL cutoff	Change (50% COL)	COL cutoff	Change (COL)
1	379,899.30	147.80225	385,957.20	295.6045	513,532.30
2	600,930.00	149.42055	707,855.00	298.8411	553,162.00
3	1,371,059.00	160.33130	1,426,283.00	320.6626	2,006,266.00
4	1,350,016.00	161.90130	1,469,823.00	323.8026	1,466,438.00
5	1,127,942.00	166.91725	1,262,345.00	333.8345	1,506,092.80
6	2,690,333.00	189.78640	2,444,684.00	379.5728	1,023,027.00
7	2,095,788.00	194.42330	2,062,775.00	388.8466	3,268,314.30
8	11,900,000.00	199.06740	16,300,000.00	398.1348	8,500,000.00
9	1,682,335.00	219.37040	2,561,883.00	438.7408	1,623,261.00
10	-403,375.10	220.33230	-492,306.56	440.6646	0.00
11	1,670,656.00	223.24440	2,257,205.00	446.4888	1,191,839.00
12	-306,682.50	226.31545	-409,935.23	452.6309	0.00
13	861,674.00	229.69650	1,569,244.00	459.3930	1,275,229.00
14	-1,910,070.00	230.97100	-669,448.00	461.9420	3,003,351.00
15	3,604,220.10	242.34870	3,060,337.30	484.6974	0.00
16	1,545,822.00	258.90260	3,224,867.20	517.8052	1,323,131.00
17	-182,824.60	272.79945	-90,612.10	545.5989	0.00
18	-242,138.20	282.73045	-151,062.20	565.4609	0.00

Table B1.13: Welfare changes under alternative eligibility thresholds, by region.

Segment	Outcome	Deviations from Baseline		
		Minimum Wage	Partial Indexing to cost of living	Full Indexing to cost of living
Medi-Cal	Average Enrollment Active (%)	9.94	6.63	11.27
	Average Enrollment Passive (%)	1.47	0.66	1.15
	Average Quality (%)	-0.11	-0.57	-0.42
	Std. Dev. Avg Quality	-1.48	-0.99	-1.27
	Average Per-Member Cost ($)	8.08	28.21	49.15
	Average Consumer Surplus ($)	1.90	1.04	2.08
	Total Cost ($)	36,503,281.38	49,873,916.87	115,277,116.14
	Total Consumer Surplus ($)	280,799.28	355,368.69	872,304.57
	Total Profits ($)	6,448,290.54	8,100,534.69	18,038,432.29
Covered California	Average Enrollment (%)	6.99	10.42	64.85
	Average Silver Price ($)	-675.86	-1,043.71	-2,605.64
	Std. Dev. Avg Silver Price	-198.59	-422.77	-558.70
	Average Subsidy Per Enrollee ($)	-1,113.83	-1,878.46	-3,809.91
	Average CSR Per Enrollee ($)	18.59	85.36	620.83
	Average Consumer Surplus ($)	238.28	424.91	1,388.21
	Total Subsidies ($)	-35,970,834.27	-49,732,028.28	-81,060,963.44
	Total Consumer Surplus ($)	-1,817,365.72	-1,567,735.79	-29,260,722.96
	Total Profits ($)	-29,282,861.43	-41,869,750.56	-32,031,133.29
Federal	Total Consumer Surplus ($)	-1,536,566.43	-1,212,367.09	-28,388,418.39
	Total Producer Surplus ($)	-22,834,570.90	-33,769,215.88	-13,992,701.00
	Total Subsidy Costs ($)	-35,970,834.27	-49,732,028.28	-81,060,963.44
	Total CSR Costs ($)	-4,608,912.00	-4,968,588.00	-17,348,304.00
	FMAP Matching Medicaid Rates ($)	18,251,640.69	24,936,958.44	57,638,558.07
	Total Costs ($)	-22,328,105.58	-29,763,657.85	-40,770,709.36
	Savings from Uncompensated Care ($)	11,235,208.66	11,275,729.70	26,228,247.50
State	Consumer Surplus (passive) ($)	5,677,146.08	6,977,959.13	16,181,693.45
	Producer Surplus (passive) ($)	8,861,702.93	6,076,602.82	23,641,834.30
	Total Surplus (passive) ($)	14,538,849.01	13,054,561.95	39,823,527.76
	FMAP Matching Medicaid Rates ($)	13,492,502.86	16,837,926.75	39,146,946.18
	Savings from Uncompensated Care ($)	2,748,681.56	3,378,491.12	7,834,627.09

Table B1.14: Counterfactual Changes by Eligibility Threshold

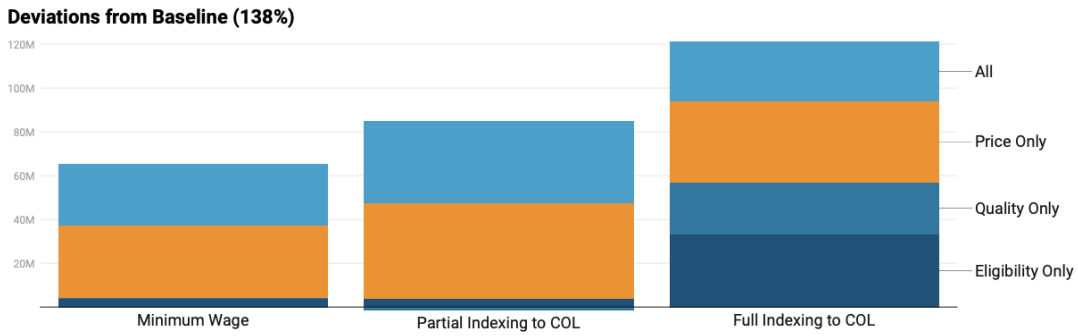


Figure B1.9: Decomposing Effects

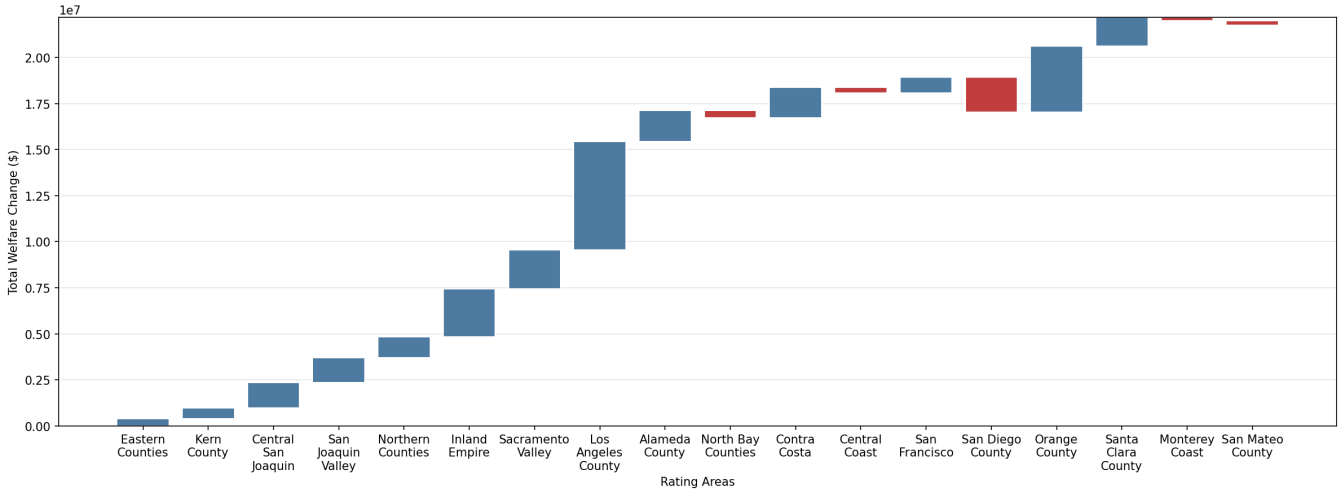


Figure B1.10: Adjusting Eligibility Threshold to Minimum Wage

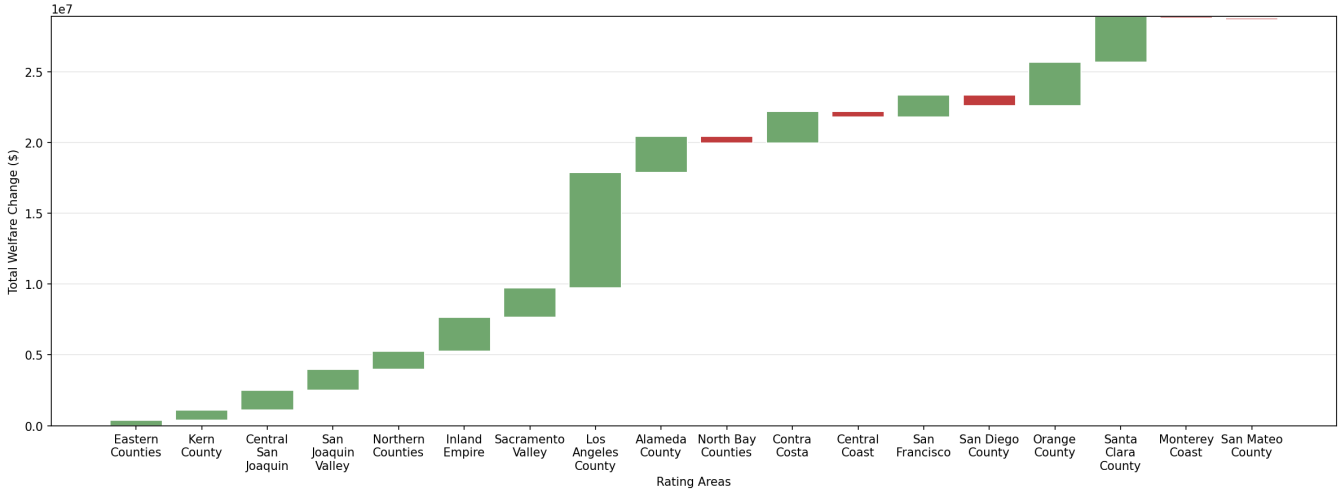


Figure B1.11: Adjusting Eligibility Threshold to Halfway Towards the Local Costs

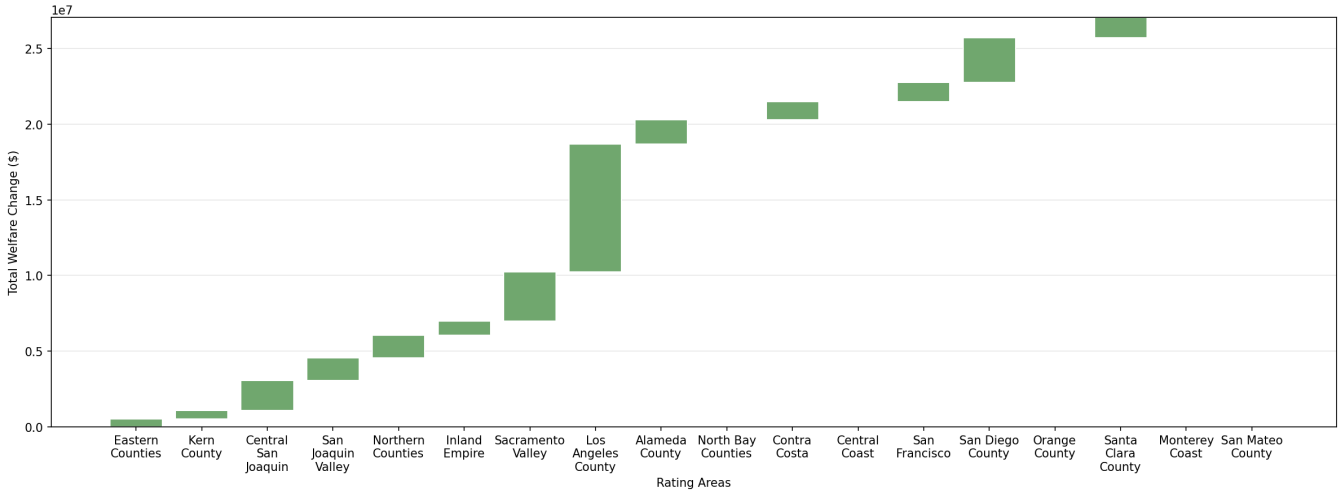


Figure B1.12: Adjusting Eligibility Threshold Fully to Local Costs

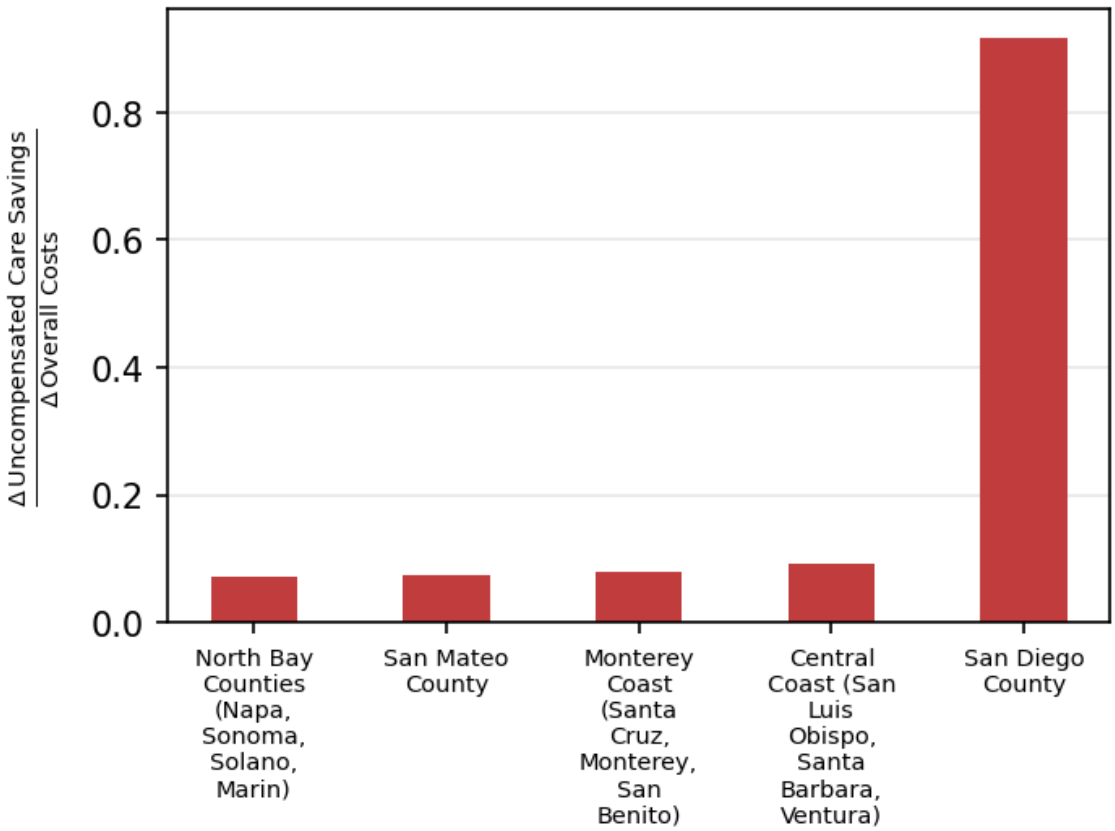


Figure B1.13: Changes in Uncompensated Care Relative to Costs For Losing Areas

C. Online Appendix

C.1 Online Application

Eligible individuals seeking coverage under Medi-Cal or Covered California may apply annually or following a qualifying life event such as job loss or a significant change in income. The online application process for both is uniform. It collects key information such as age, household income over the past 12 months, family size, and whether the applicant has access to other forms of health insurance. The state government then uses this information to determine whether the individual qualifies for Medi-Cal, for a subsidized Covered California plan, or neither. The application also enables the calculation of income as a percentage of FPL, which determines eligibility for premium subsidies. Figure C.1 depicts the user interface on CoveredCA.com that applicants encounter when initiating the enrollment process.

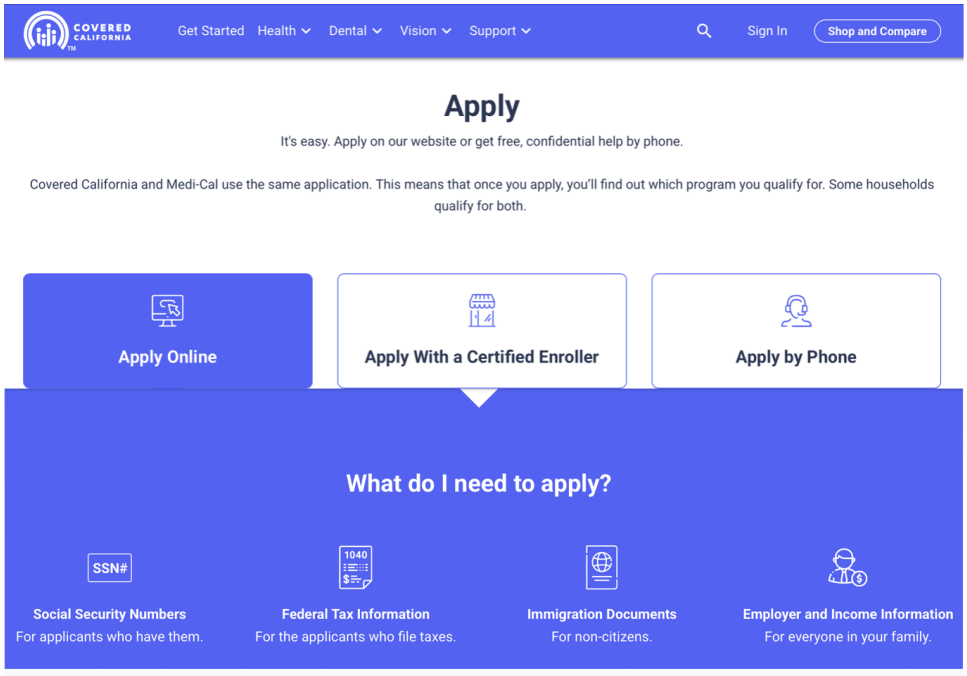


Figure C.1: Consumer interface on CoveredCA.com

Upon clicking *Apply*, individuals are directed to the options as shown in Figure C.2. The visual element simplifies the user experience by directing applicants to a tailored account setup process, which includes and verifies the information mentioned above for new applicants. The portal also provides an option for individuals to retrieve their information from a previously completed Medi-Cal application, for returning individuals, or those transitioning to Covered California. This transition application consists of two main steps: (1) retrieving a unique access code sent by the state government, example of such transition letter is Figure C.3 using identifying information to link the applicant to their pre-existing record, and (2) establishing login credentials. Individuals are then directed to a portal to view plans and compare them.

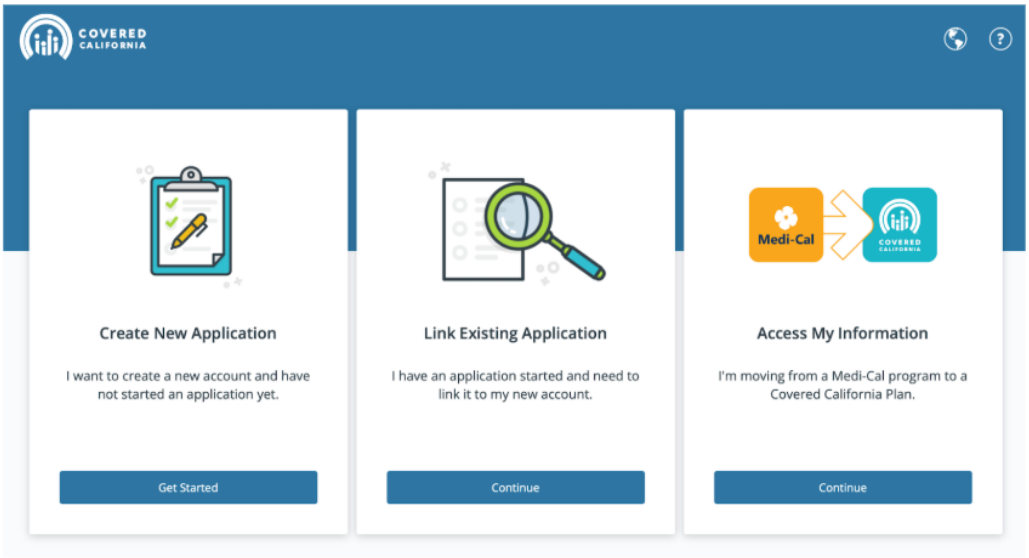


Figure C.2: Streamlined Account Creation Flow



Covered California
PO Box 989725
West Sacramento, CA 95798-9725

COVERED CALIFORNIA

Your destination for affordable healthcare, including Medi-Cal

[Mail Date]
[Case Name]
[Case Street]
[Case City], [Case State], [Case Zip]

Important news about your health benefits

Case Number: [Insert Case Number]

Dear [Insert Name]

Thank you for applying for health insurance through Covered California for you and your household members. We used the information you gave us and state and federal data to make this decision:

[Insert Decision]

Based on the change you reported:

For the next 90 days, you qualify for health insurance through Covered California. This notice says you are eligible for only 90 days because the information you provided does not match the information in the records we checked. Read the section below entitled "What to do if you qualify for 90 days" later in this notice for more information on your next steps.

Because you qualify to sign up for health insurance as a result of a qualifying life event, you have 60 days from [Insert date] to pick your health plan. Your special enrollment period ends [Insert date]

Figure C.3: Example of Transition Letter Sent by Covered California

C.2 Additional Details on Medi-Cal

Medi-Cal managed care operates under different delivery models across California's 58 counties. Table C.1 summarizes the market structure under each delivery model. Most counties (22) have a single public plan under the County Organized Health System (COHS) model, where a local public entity administers Medi-Cal managed care. The Two-Plan Model, adopted in 14 counties, features a local public plan alongside a commercial plan, providing beneficiaries with a choice between two options. Regional Expansion and Geographic Managed Care models operate in fewer counties but accommodate diverse delivery systems, including multiple commercial and nonprofit plans. Lastly, counties such as San Benito and Imperial operate under distinct models.

While most enrollees are in a managed care plan, Medi-Cal offers a fee-for-service (FFS) plan too. Table C.13 compares Managed Care and FFS across availability, market share, enrollment (both mandatory and voluntary), expenditures to Medi-Cal, covered services and mode of payment. In Table C.3, I expand list the essential, mandatory, and optional Medicaid services provided by Medi-Cal plans.

While all Medi-Cal managed care plans provide standard benefits, plans may differ in additional benefits, such as behavioral health services or diabetes care, as well as in network size. Table C.4 summarizes features of Medi-Cal managed care plans that offer additional benefits. Data on plan features in Medi-Cal is sparse and frequently incomplete. In particular, detailed plan characteristics are largely unreported and/or trivially publicly available. Each plan offers a unique combination of services beyond the standard benefits, such as behavioral health, hearing, podiatry, telehealth, and advise nurse services. Some plans, like Contra Costa Health Plan and Inland Empire Health Plan, include specialized services such as home health/in-home Support Services, durable medical equipment, and diabetes coverage. Beyond additional benefits, the number of contracted hospitals and pharmacies varies widely across plans. For instance, Alameda Alliance for Health contracts on average with 14 hospitals and 181 pharmacies, while LA CARE Health Plan has a network of 70 hospitals and a particularly wide network of 64,000 pharmacies.

C.3 Medi-Cal Eligibility Requirements

While this paper focuses on income-based eligibility for Medi-Cal and for those aged 19 to 64, there are several ways to be qualified for Medi-Cal. Tables C.5 and C.11 show who qualifies for Medi-Cal and under what conditions. Table C.5 lists the basic rules that apply to everyone, such as needing to live in California, have low income, and—until recently—not owning too many assets. It also shows that people already enrolled in certain public programs or in specific age or immigration groups may qualify automatically. Table C.11 breaks down income limits by group, with some groups—like pregnant women and children—allowed higher incomes than others. California also covers some groups that the federal government doesn't, like undocumented young adults and older adults, using state funds. Together, these tables highlight how Medi-Cal eligibility depends on many factors, creating a patchwork system where people's access to coverage can

County Model	Number of Plan(s)	Type of Plan(s)	Counties
County Organized Health System	1	local/public	Del Norte, Humboldt, Lake, Lassen, Marin, Mendocino, Merced, Modoc, Monterey, Napa, Orange, San Luis Obispo, San Mateo, Santa Barbara, Santa Cruz, Shasta, Siskiyou, Solano, Sonoma, Trinity, Ventura, Yolo
San Benito Model	1	commercial	San Benito
Two-Plan Model	2	local/public and commercial (one of each)	Alameda, Contra Costa, Fresno, Kern, Kings, Los Angeles, Madera, Riverside, San Bernardino, San Francisco, San Joaquin, Santa Clara, Stanislaus, Tulare
Regional Expansion Model	2	commercial	Alpine,Amador, Butte, Calaveras, Colusa, El Dorado, Glenn, Inyo, Mariposa, Mono, Nevada, Placer, Plumas, Sierra, Sutter, Tehama, Tuolumne, Yuba
Imperial Model	2	commercial	Imperial
Geographic Managed Care	2+ plans	local/public and commercial	Sacramento, San Diego

Table C.1: Medi-Cal Managed Care Models

vary a lot depending on their situation.

C.4 Auto-Assignment Algorithm

In Medi-Cal, as in many Medicaid programs across the country, some beneficiaries do not actively choose a health plan.[59] Consequently, the state assigns them to a plan using a random or quasi-random method to balance market share and enhance plan quality. In California, the state has developed a performance-based auto-assignment incentive that assigns beneficiaries required to enroll in Medi-Cal to a managed care plan if they do not choose one within 30 days. This process recognizes high-performing health plans and incentivizes quality improvement by directing more beneficiaries to better-quality plans.

The allocation of beneficiaries within Medi-Cal is governed by an algorithmic approach to performance evaluation. Since 2005, the program has employed various standardized Healthcare Effectiveness Data and Information Set (HEDIS) measures. Table C.7 summarizes the evolution of performance measures included by the Department of Health Care Services (DHCS) in the Auto-Assignment Incentive Program across the years 2005, 2017, 2020, and 2024. These measures are divided into two categories: quality-related HEDIS measures and safety-net support measures. The quality-related HEDIS measures focus on clinical outcomes and include metrics such as childhood immunization statuses (e.g., CIS-2, CIS-3, and CIS-10), adolescent and child well-care visits, cervical cancer screening, diabetes care (HbA1c testing and control), blood pressure control, asthma medication use, prenatal and postpartum care, and follow-up care after emergency de-

[59] Among the new enrolled, between 2017-2019, 28.3% were auto-assigned.

partment visits. Notably, certain measures, such as controlling high blood pressure (CBP) and cervical cancer screening (CCS), were excluded in 2020 due to specification changes.[60] Prior to 2024, two safety-net support measures were also incorporated: Disproportionate Share Hospital (DSH) facility discharges and safety-net provider Primary Care Physician (PCP) assignments. Recent methodological changes, have led to the separation of certain historical components. For instance, while Safety Net Primary Care Provider Assignment (as mandated by Assembly Bill 851) and Encounter Data Quality were previously integrated into incentive calculations, these elements are now monitored independently, except in cases of non-compliance with AB 85 requirements.

Figure C.4 illustrates the multi-stage algorithm that moves from performance scoring to percent allocation. First, for performance scoring, there are two types of comparisons in each county and metric: (1) plan-to-plan and (2) year-to-year. The plan-to-plan comparison compares current-year performance points among counties with two plans or against the county's harmonic mean in counties with more than two plans. Points are awarded based on whether a plan's score is statistically superior (2 points), equivalent (1 point), or inferior (0 points) to its peers or the harmonic mean. This sum of all these scores across the predetermined metrics contributes to the Current Year Score. In the year-to-year comparison, each plan's current year performance is evaluated against its performance in the previous year, with points assigned for worse performance (-1 point), no significant difference (0 points), or better performance (+1 point). This sum of all these scores across the predetermined metrics contributes to the Improvement Score. The Current Year Score and Improvement Score are then aggregated to calculate the Aggregate Score for the plan in the current year. The aggregate scores are then converted into percentage allocations for each plan. For each plan (e.g., Plan A and Plan B in county X with aggregate scores Score A and Score B), the percentage allocation is calculated using the formula

$$\%\text{Allocation for Plan A} = 100 \times \frac{\text{Score A}}{\text{Score A+Score B}}$$

$$\%\text{Allocation for Plan B} = 100 \times \frac{\text{Score B}}{\text{Score A+Score B}}$$

The maximum change in default allocation for any one plan is capped at 20% from the previous year. For example, if a plan had a 55% allocation last year and 80% this year (a 25% difference), its proposed allocation would be capped at 75%. Since 2015, plans that fail to meet specific requirements face penalties, leading to a more significant allocation of members to the County Public Hospital Health System, regardless of penalties for inadequate safety net primary care physician assignments. All penalties from capping and inadequacies are considered after the main plan-to-plan and plan year-to-year comparisons have been finalized. The final allocation is then normalized to a total of 100%. It is important to note that while single-plan counties are exempt from auto-assignment procedures, they still adhere to strict quality assessment protocols, ensuring uniform healthcare delivery standards across all jurisdictions.

[60] See Table C.8 for further information.

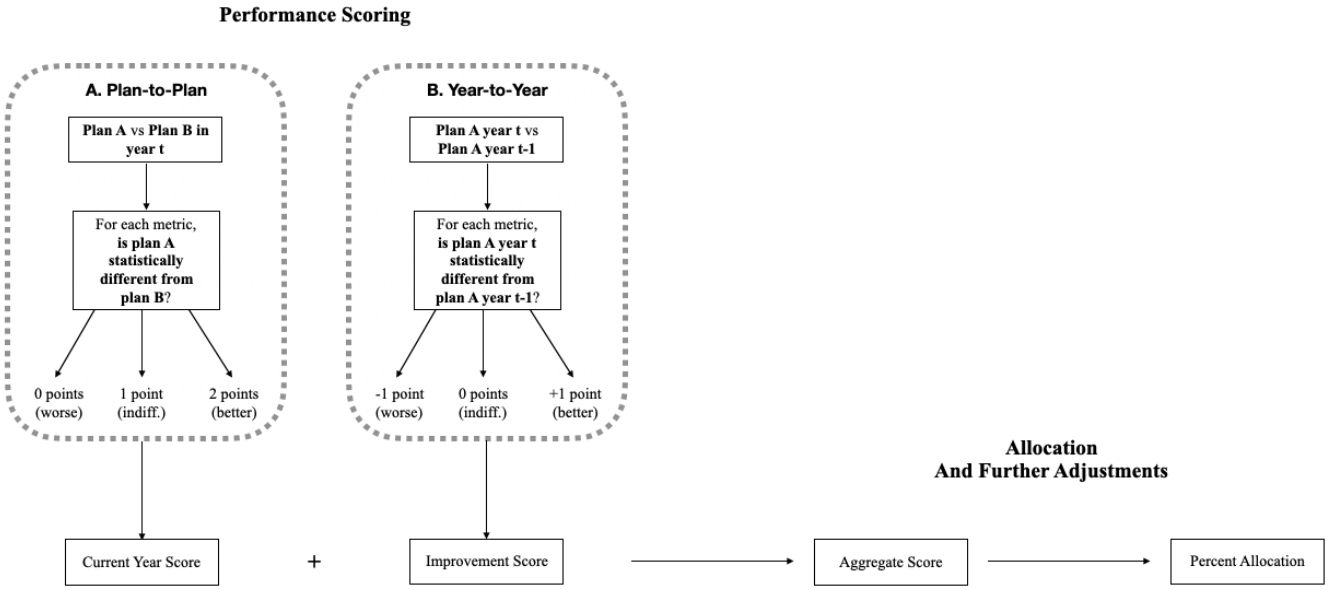


Figure C.4: Auto-Assignment Algorithm

C.4.1 Constructing Autoassignment Pool

I construct plan-level auto-assignment counts for newly eligible Medi-Cal managed care beneficiaries at the county–plan–year level using the *Medi-Cal Managed Care Newly Eligible Enrollment by Type of Enrollment* dataset. This dataset, produced in compliance with California Welfare and Institutions Code §14102.5, reports new enrollments by type (active choice versus auto-assignment) and reporting period.

For plans operating exclusively within a single county, I recover auto-assigned enrollee counts directly from the dataset. For competitors in these markets, I multiply the observed county–plan–year allocation percentage by the county's total auto-assignment count to obtain plan-specific figures; in 7 of 15 such markets, this procedure exactly reproduces reported totals, allowing the competitor allocation to be determined without additional assumptions.

For multi-county plans, where direct allocation data are unavailable, I estimate each county's auto-assignment total as the product of (i) the county's newly eligible beneficiary count and (ii) the statewide auto-assignment share of approximately 3.1%. I then distribute this county-level total across plans in proportion to their observed county–plan–year allocation percentages, calculating competitor allocations as the residual necessary to match the county total. For regionally concentrated multi-county plans, this procedure likely understates the true volume of auto-assignment, and these estimates should be interpreted as lower bounds.

After determining plan-level auto-assignment counts, I distribute them evenly across the model's

three age groups (19–34, 35–54, 55–64), assuming homogeneity in auto-assignment probabilities by age; reallocating according to the observed age distribution of new enrollees yields results that are substantively unchanged. For existing enrollees, I assume that no reallocation occurs through the auto-assignment process: beneficiaries remain in their prior-year plan unless they make an active change. In the baseline demand specification, I abstract from enrollee inertia, treating all observed choices as active while recognizing that this assumption may overstate active choice behavior in the Medi-Cal population.

C.5 Medi-Cal Aid Codes

I request that the California Department of HealthCare Services (DHCS) restrict counts related to 42 CFR 435.119, which provides Medicaid coverage for individuals aged 19 or older and under 65 with household incomes at or below 138% FPL. Under this regulation, individuals qualify if they are within the specified age range, not pregnant, not entitled to or enrolled in Medicare benefits under Part A or B of Title XVIII of the Social Security Act, not otherwise eligible for and enrolled in mandatory Medicaid coverage under the State's Medicaid plan, and have household income at or below 138% FPL for their family size. Consequently, married individuals and/or parents and caretaker relatives qualify for Medicaid under this provision only if their income exceeds 109% FPL (the Parent/Caretaker Relative group limit) but does not exceed 138% FPL (the New Adult Group limit). Per 42 CFR 435.119(c)(1), parents and caretaker relatives are only eligible under this category if their child(ren) residing in the household are covered by Medicaid, CHIP, or other minimum essential coverage. This means that a parent or caretaker relative cannot qualify for coverage unless their child(ren) are also insured. Additionally, 42 CFR 435.119(c)(2) applies specifically to California's State Plan, where the state has opted to extend Medicaid eligibility to individuals under age 21. As a result, for eligibility purposes in California, a child is defined as an individual under age 21 rather than under age 19. Table C.9 outlines all the requested codes which encompress the demographic group of Medi-Cal in this paper.

C.6 Sample Construction and Demographics from American Community Survey and Other Survey Data

I use American Community Survey (ACS) and publicly-available survey data from California to (1) summarize demographic information and (2) construct the sample of potential buyers for both Medi-Cal and Covered California. Figures C.5 and C.6 show how Californians get their health insurance and how that varies by year and age group. Figure C.5 compares the main sources of insurance between 2015 and 2021. While employer-based coverage (through small and large groups) remained the most common, Medi-Cal saw a notable increase—from 13.4 million to 14.6 million people—reflecting expanded eligibility and rising enrollment. Medicare and individual market coverage stayed relatively stable. Figure C.6 breaks this down by age group in 2021, showing that most children rely on Medi-Cal, working-age adults mostly get coverage through their jobs, and nearly all seniors are covered by Medicare. Overall, nearly half of all Californians

are covered either by Medi-Cal alone or in combination with Medicare, highlighting the critical role of public programs in the state's insurance landscape. Table C.10 provides a demographic snapshot of low-income, uninsured adults in California. The majority are between ages 19 and 54, with over half identifying as male. Nearly half have never been married, and about one-third are married and living with a spouse. More than half are not U.S. citizens, and 15% do not speak English. Most identify as White (55%), followed by Asian (9%) and Black (5%). In terms of education, nearly 69% have a high school education or less, and only 26% are in the labor force but unemployed. About 25% receive food stamps, and the average household has just over one child. On average, individuals report working about 20 hours per week, with very low reported income from social safety net programs—indicating limited engagement with benefits they may be eligible for.

Beyond checking the demographics of the population, I use ACS to construct a sample of potential consumers. I define a person eligible for Covered California if they are (1) US citizen, (2) age range 19-64, (3) income below 400% FPL, (4) not enrolled in another form of health insurance specifically employer insurance, Medicare or Tricare, and (5) not eligible for Medicaid based on income and demographic characteristics. Despite Covered California plans being available to green card holders, I cannot separately measure this subgroup because citizenship status is reported in five categories: Born in the United States, Born in Puerto Rico, Guam, the U.S. Virgin Islands, or Northern Marianas, Born abroad of U.S. citizen parent or parents, U.S. citizen by naturalization, and not a U.S. citizen. I define family income as a share of poverty level. Family income is the sum of total personal income across all members of an individual's health insurance unit (HIU). Then, I divide total income by the FPL defined in 2014 and the HIU size. The ACS does not allow to directly measure Medi-Cal eligibility.[61] Additionally, I cannot directly measure Medicaid enrollment as the ACS does not distinguish coverage under Medi-Cal from Covered California. Instead, I approximate it by restrict eligible population to US citizens. The excluded group includes undocumented immigrants and long-term green card holders. Hence, I define a person eligible for Medi-Cal if they are (1) US citizen, (2) age range 19-64, (3) income below 138% FPL, (4) not enrolled in another form of health insurance specifically employer insurance, Medicare or Tricare. This approach misses a few groups who are Medicaid eligible but whom cannot be easily measured in the ACS. One major group are children (age 0-18) since Medicaid eligibility for children extends beyond 138% of FPL. One other excluded group are the undocumented immigrants and those long-term green card holders. Other group are the pregnant women (or women with at least a child below 1 years old). Upon constraining to final eligible population for both segments of the market, I scale up to population size using the ACS person's weights. Following Finkelstein et al., 2019, I smooth the eligible population as ACS yields to noisy estimates because it is based on 1% sample and clustering in reported income at rounded numbers. To smooth the numbers,

[61] While survey data, such as the ACS, have advantages over admin data in possessing many easily accessed health, social and demographic information, one striking limitation is the discrepancy between survey and admin data counts. It has been documented that ACS undercounts Medicaid enrollment in expansion states by a relatively low percentage (Boudreaux, Noon, Fried & Pascale, HRS 2019).

I regress population count by 1% FPL bin on a quadratic polynomial in income as a % FPL. The predicted values from the regression are used in the analysis.

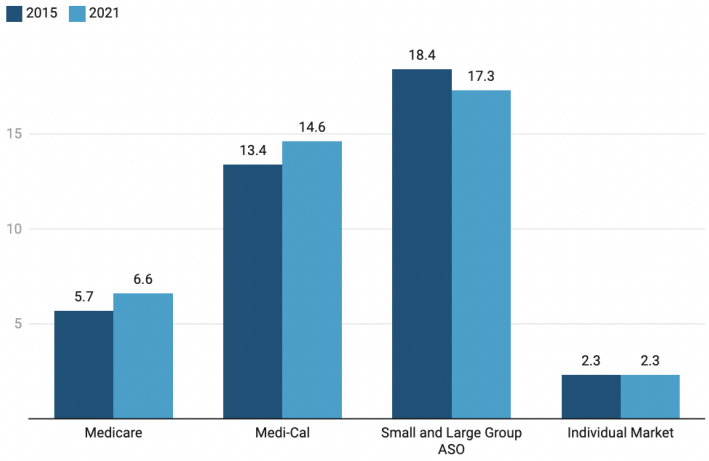


Figure C.5: Health Insurance, by Source of Coverage: California, 2015 and 2021

Source: Centers for Medicare and Medicaid Services, and California Health and Human Services Agency

C.7 Additional Details on Covered California

The Affordable Care Act (ACA) implemented the principle of *community rating*, under which premiums for a given plan must be uniform across all individuals within the same rating area and age rating band. While insurers may vary premiums based on age, this variation is subject to federal restrictions on how much more older consumers can be charged relative to younger ones (see Figure C.9). Importantly, the listed premium is not necessarily the amount consumers pay out of pocket. The ACA introduced income-based premium subsidies that cap the *Maximum Allowable Amount* (MAA) an individual or family must contribute toward coverage, depending on their income as a percentage of the Federal Poverty Level (FPL). Table C.11 summarizes these caps by income group. Each state defines its own *rating areas*, which determine the geographic boundaries of community rating pools. Federal guidance recommends that states use Metropolitan Statistical Areas (MSAs) for urban regions and group all rural counties into a single rating area. In California, the 58 counties are divided into 19 distinct rating areas (Figure C.10).

All plans offered through Covered California are standardized in terms of benefits. Within each metal tier, cost-sharing features—such as deductibles, coinsurance, and copayments—are fixed across insurers. While plans differ by brand and network composition, their benefit design remains consistent. Table C.12 summarizes the standardized plan characteristics across metal tiers.

Covered California insurers also receive federal transfers for each individual they enroll, denoted by T_{jm} for plan j in market m. In 2014, when the ACA exchanges began operating, multiple transfer mechanisms were implemented to stabilize premiums and mitigate insurer risk. Mathematically, total transfers are expressed as: $T_{jm} = RA_{jm} + RI_{jm}$.

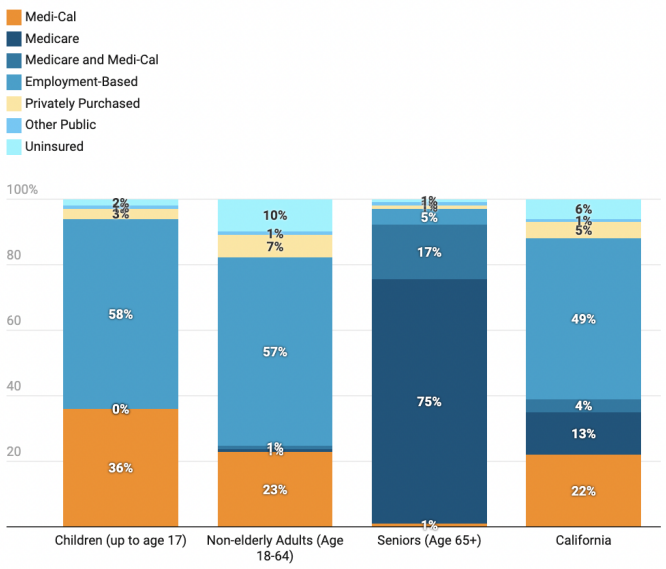


Figure C.6: Source of Insurance Coverage, by Age Group: California, 2021

Source: AskCHIS, UCLA Center for Health Policy Research

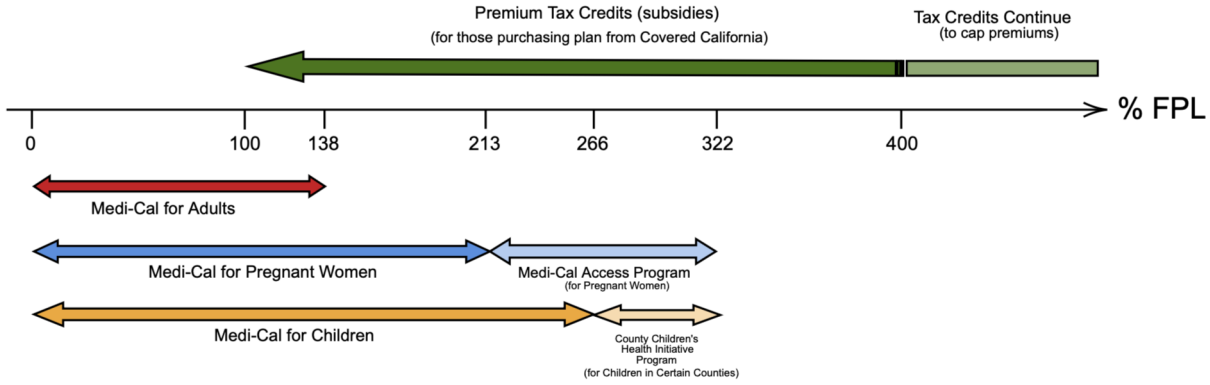


Figure C.7: Program Eligibility, by FPL

Note: The diagram shows Medi-Cal and Covered California overlapping programs (in income % FPL). Most adults up to 138% FPL are eligible for Medi-Cal. Pregnant women and children are eligible for coverage under various programs up to 322% FPL, some varying by county. Medi-Cal ineligible adults with income below 138% FPL or adults with income between 138-400% FPL are qualified for subsidies if they purchase a plan on exchanges. Tax credits continue beyond 400%, but premiums typically do not exceed MAA at 400% FPL.

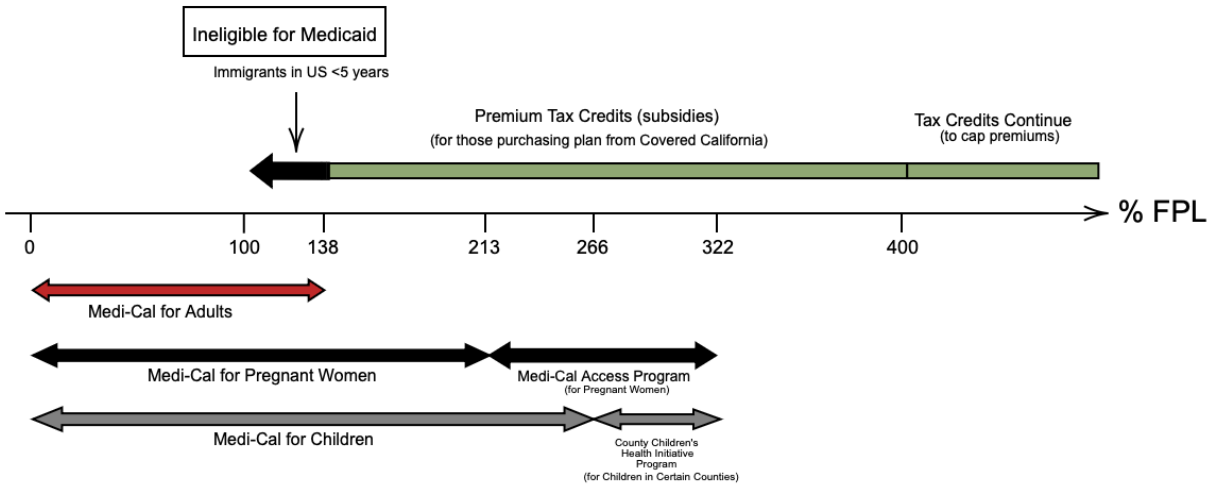


Figure C.8: Groups Identified and Focused on in Analysis, by FPL

Note: The diagram shows the groups identified and focused on in the empirical application. In black, I highlight the groups that are not identified in survey data, and in gray I point the group I do not focus on in my analysis. This leaves the analysis on the following groups: (1) adults (> 18-year olds) with income below 138% in Medi-Cal, (2) not dependent adults (> 26-year olds) with income between 100-400% FPL in Covered California, and (3) adults with no coverage.

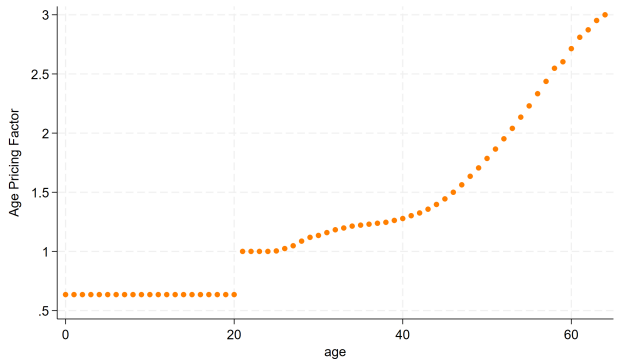


Figure C.9: Regulatory Age Pricing

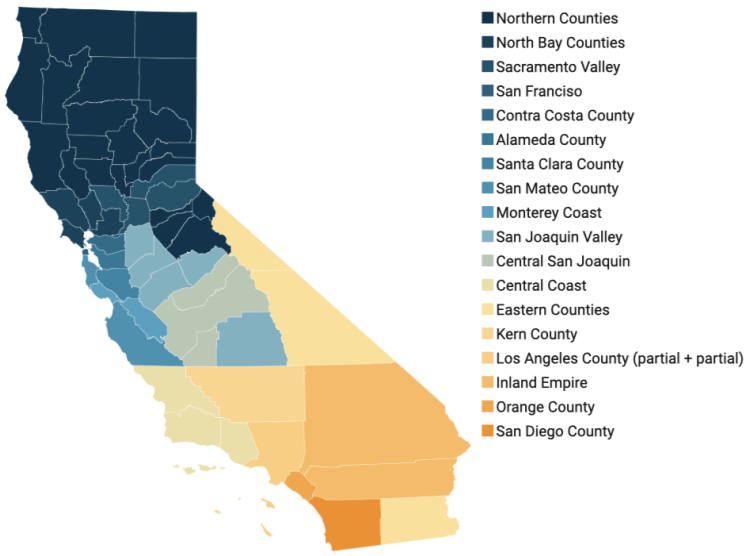


Figure C.10: Geographic Rating Areas in California

Note: Los Angeles County is split into two regions based on ZIP code. Source: CMS, "California Geographic Rating Areas." Link

The first component, *risk adjustment* RA_{jm}, is a permanent, budget-neutral program that redistributes funds across plans within a state based on enrollee risk profiles: $\sum_f RA_f = 0$. Plans with lower-risk enrollees pay into the pool, while those with higher-risk enrollees receive funds. The U.S. Department of Health and Human Services (HHS) calculates risk using enrollee demographics and diagnosis codes. Risk scores are adjusted for region and metal tier, and compared across plans within geographic and market segments. Following Pope et al., 2014, the plan-level risk adjustment transfer can be written as:

$$T_j = \left[\frac{PLRS_j \cdot IDF_j \cdot GCF_j}{\sum_k (s_k \cdot PLRS_k \cdot IDF_k \cdot GCF_k)} - \frac{AV_j \cdot ARF_j \cdot IDF_j \cdot GCF_j}{\sum_k (s_k \cdot AV_k \cdot ARF_k \cdot IDF_k \cdot GCF_k)} \right] \bar{p}_s$$

Where:$PLRS_j$ is the plan liability risk score (average enrollee risk score), IDF_j is the induced demand factor (based on cost-sharing tier), GCF_j is the geographic cost factor, AV_j is the actuarial value of the plan, ARF_j is the plan's allowable rating factor (age-based multiplier), s_k is the plan's enrollment share, and $\bar{p}_s$ is the statewide enrollment-weighted average premium.

The second component, RI_{jm}, captures two temporary transfers: *reinsurance* and *risk corridors*. Reinsurance reimbursed insurers for a share of high-cost claims. For instance, in 2014, the federal government reimbursed 80% of claim costs between $45,000 and $250,000, later increasing to 100% as funds remained unused. Risk corridors redistributed gains and losses around a target cost level $\bar{T}$, defined as:

$$\tau_f = \begin{cases} -\left[2.5\%\bar{T} + 80\%(92\%\bar{T} - C_f)\right] & \text{if } C_f < 92\%\bar{T} \\ -50\%(97\%\bar{T} - C_f) & \text{if } 92\%\bar{T} \leq C_f < 97\%\bar{T} \\ 0 & \text{if } 97\%\bar{T} \leq C_f \leq 103\%\bar{T} \\ +50\%(C_f - 103\%\bar{T}) & \text{if } 103\%\bar{T} < C_f \leq 108\%\bar{T} \\ +2.5\%\bar{T} + 80\%(C_f - 108\%\bar{T}) & \text{if } C_f > 108\%\bar{T} \end{cases}$$

By 2017, the RI_{jm} component of transfers had expired, leaving risk adjustment as the sole ongoing transfer mechanism under the ACA, unless states funded (not California to this date) their own reinsurance programs.

C.8 Network Breath and Willingness to Pay Measure for Medi-Cal

C.8.1 Constructing a Measure of Network Breath

Data on plan features in Medi-Cal is not publicly readily available and even when it is sparse and frequently incomplete. In particular, detailed plan characteristics are largely unreported; however, a review of the available information suggests that plans are broadly similar in terms of covered services. The primary observable source of heterogeneity lies in network breadth, specifically with respect to the scope of affiliated hospitals, physicians, and pharmacies.

For non-price characteristics such as network breadth (including hospitals, physicians, and pharmacies), data availability is uneven across plans, and in some cases, no quantitative network information can be recovered from publicly available sources. To construct a measure of network breath, I hand-collected data using publicly available plan comparison tools, when available. This tool typically is a one-page plan characteristic summary and are only available in counties with at least two managed care plans. Some plan summaries report the number of hospitals directly, while others provide only qualitative guidance (e.g., "contact the plan for information"), in which case no count can be recovered. The missing values were hand collected from plan provider directories. My simplest measure is the percentage of hospitals covered by the network. I compute the share of all general medical and surgical hospitals, excluding long-term care, rehabilitation, children's, and Veterans Affairs hospitals (following Ericson and Starc, 2015) in California that are included in a plan's contracted network:

$$\text{NetworkBreadth}_p = \frac{\text{Hospitals in Network}_p}{\text{Total Hospitals in CA}} \times 100,$$

where $\text{Hospitals in Network}_p$ is the number of hospitals contracted by plan p and Total Hospitals in CA is the statewide count of acute care hospitals. This measure reflects the percentage of hospitals statewide that are accessible to enrollees in plan p, providing a standardized metric that is comparable across counties and markets. Table C.14 summarizes these numbers at the plan level.

C.8.2 Translating Estimates to Willingness To Pay Measure

To express quality effects in dollar terms, I first translate aggregate quality into network breadth. Let Q denote the aggregate quality and N denote network breadth, both in percentage points. The demand estimates imply

$$\frac{\partial N}{\partial Q} \approx 0.18,$$

As an anchor for WTP, I use estimates from Ericson and Starc (2015). Ericson and Starc, 2015 measure provider coverage networks for plans on the Massachusetts health insurance exchange using (1) consumer surplus from a hospital demand system (coefficient 1.743) and (2) the fraction of population hospital admissions that would be covered by the network (coefficient 1.805) for unsubsidized enrollees all above 300% of the poverty line. For a 1% more hospitals in network, I calculate WTP for ages 27, 45, 60 to be \$12.31, \$16.53, and \$23.14 annually respectively. I denote these numbers by $\overline{\text{WTP}}_{1\%}^{\text{high},age}$.

Consumer valuation of networks may vary by context, and WTP-may be lower for lower-incomes. I use my estimates from Covered California to construct a measure of relative valuation for non-price attributes between income group studied in Ericson and Starc, 2015 and Medi-Cal (0-138% FPL). Let $\text{WTP}_{g,a}^{\Delta AV}$ denote WTP for a 1% increase in actuarial value (AV) for age a and income group $g \in \{\text{low}, \text{high}\}$, where "low" corresponds to 0–138% FPL. I define the scaling ratio

$$r_a \equiv \frac{\text{WTP}_{\text{low},a}^{\Delta AV}}{\text{WTP}_{\text{high},a}^{\Delta AV}},$$

which measures the relative valuation of non-price attributes between the low- and high-income groups. The ratios are computed from my demand estimates for Medi-Cal and constrained to be weakly decreasing in age by fitting an isotonic regression to the bin-specific estimates $\{\tilde{a}_j, \hat{r}_j\}_{j=1}^{J}$:

$$\hat{r}(\cdot) = \arg\min_{r(\cdot)} \sum_{j=1}^{J} \left(\hat{r}_j - r(\tilde{a}_j)\right)^2 \quad \text{s.t.} \quad r(a_1) \geq r(a_2) \text{ for } a_1 < a_2.$$

Figures **??** illustrate the fitted monotonic profile r_a and the mapping from quality to hospitals in network. Evaluating $\hat{r}(\cdot)$ at the age midpoints yields

$$\hat{r}(27) = 0.66, \quad \hat{r}(45) = 0.65, \quad \hat{r}(60) = 0.58.$$

Given that 1% quality $\Leftrightarrow$ 6.64 hospitals, the implied WTP for a 10% quality improvement is \$146.1, \$193.4, \$242.3 annually for ages 19-34, 35-54, 55-64 respectively.

C.9 Transitions and Medicaid Unwinding

C.10 Supplementary Tables and Figures

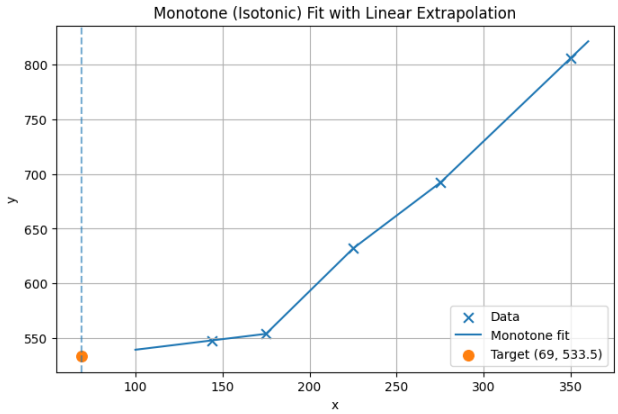


Figure C.11: Extrapolating For Ages 19-34

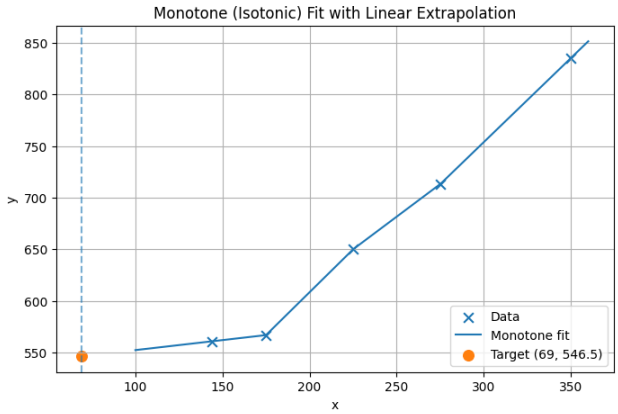


Figure C.12: Extrapolating For Ages 35-54

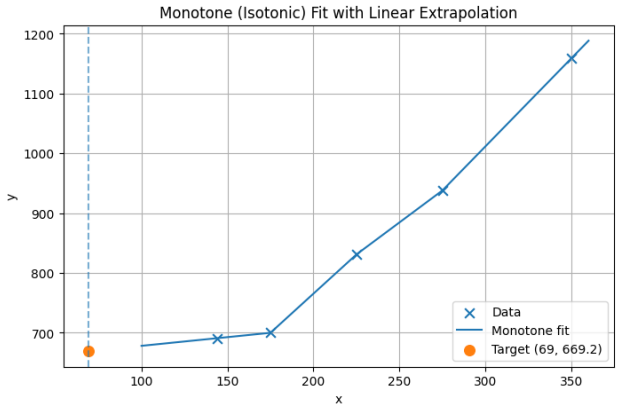


Figure C.13: Extrapolating For Ages 55-64

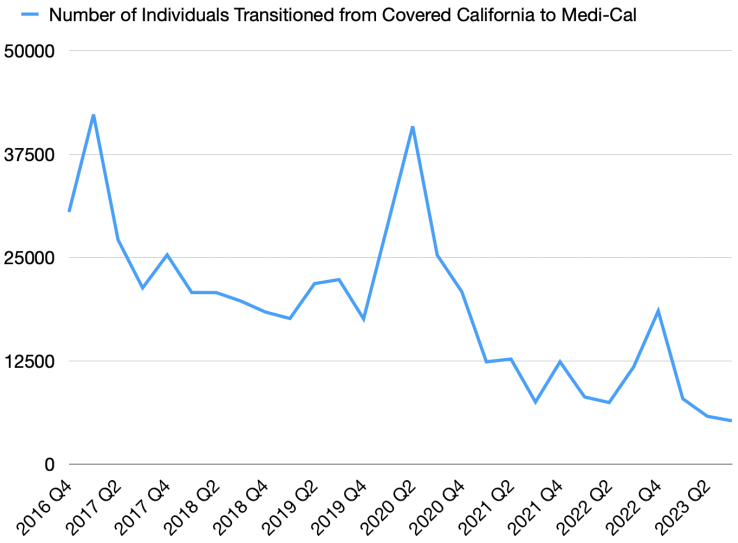


Figure C.14: Total Number of Switchers (quarterly): Covered California to Medi-Cal

Source: DHCS data on Number of Individuals Transitioned from Covered California Qualified Health Plans to Medi-Cal. https://data.chhs.ca.gov/dataset/number-of-individuals-transitioned-from-covered-california-qhps-to-medi-cal-program

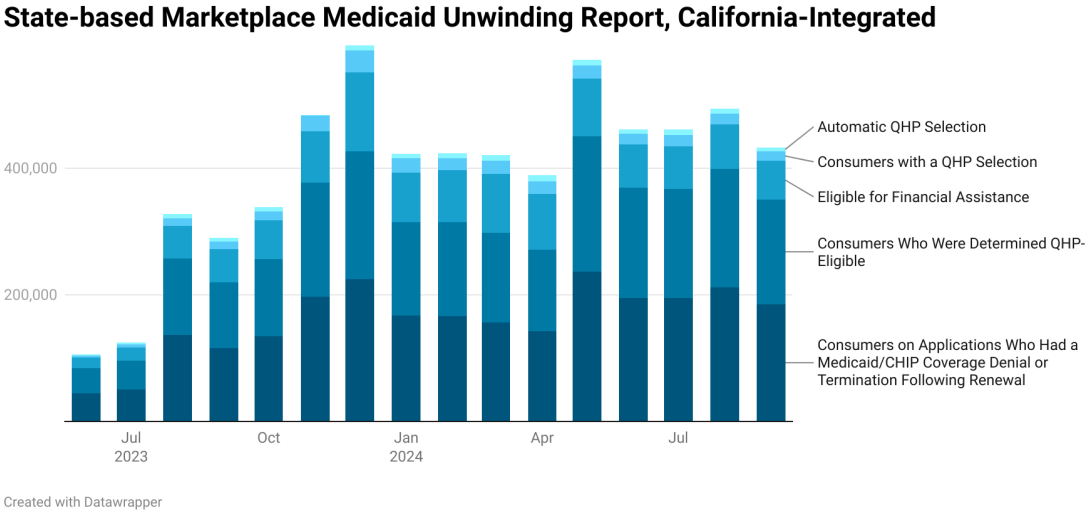


Figure C.15: State-based Marketplace Medicaid Unwinding Report, June 2023-recent

Source: CMS, Medicaid and CHIP Open Data, HealthCare.gov Marketplace Medicaid Unwinding Report. https://data.medicaid.gov/dataset/9a83ba5e-05f5-47f5-82de-f3a59233a912

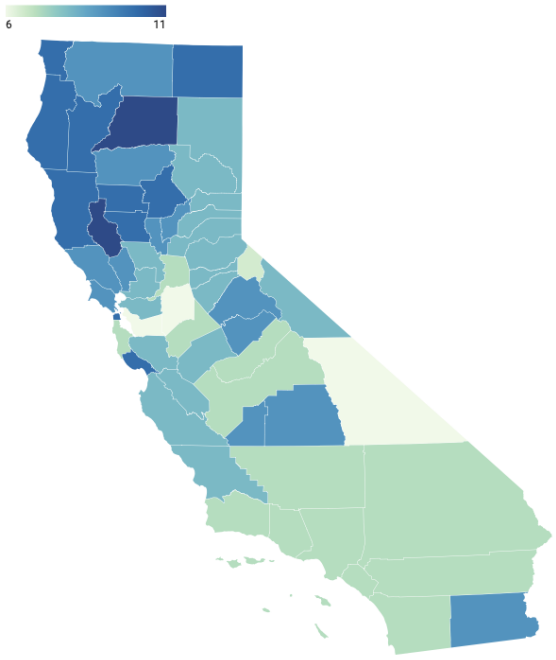


Figure C.16: Annual Median Number of Claims Per Member, Medi-Cal, 2022

Source: Healthcare Payments Data (HPD): Medical Out-of-Pocket Costs and Chronic Conditions, 2022

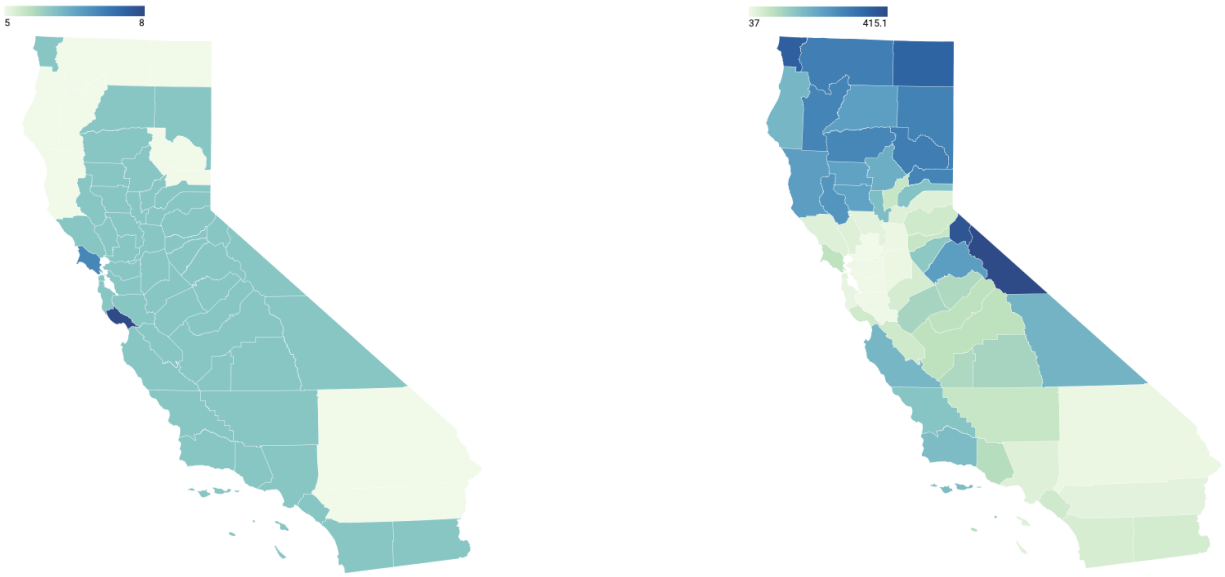


Figure C.17: Annual Median Number of Claims Per Member (left), Annual Median Out of Pocket Costs Per Member (right), Commercial , 2022

Source: Healthcare Payments Data (HPD): Medical Out-of-Pocket Costs and Chronic Conditions,

	Managed Care	Fee-for-Service
Availability	All 58 counties	All 58 counties
Market Share	85% of all enrollees	15% of all enrollees
Demographics (Mandatory)	Children Pregnant people Parents/caretaker relatives Adults without dependents Seniors and people with disabilities Enrollees in long-term care HCBS waiver enrollees Those dually eligible for Medicare Those with other health insurance American Indians & Alaska Natives (in COHS)	
Demographics (Voluntary)	American Indians / Alaska Natives (in non-COHS) Foster children and youth	Foster children and youth Share of cost (SOC) Medi-Cal enrollees (except institutional) Family PACT enrollees Other enrollees without full-scope Medi-Cal Enrollees who have received a medical exemption Enrollees with presumptive eligibility Non-citizen pregnancy-related enrollees All enrollees in San Benito County
Covered Services	All essential health benefits	Some services are carved out of managed care, including Pharmacy benefits (other than physician-administered drugs) Specialty mental health Substance use disorder services Dental services California Children's Services, for seriously ill and disabled children and youth in certain counties Most long-term services and supports (other than skilled nursing facilities)
Expenditures	48%	29%
Payment	The state pays plans a fixed monthly capitation rate per member. Plans negotiate payment rates with contracted network providers.	The state pays providers according to a fee schedule.

Table C.2: Comparison of Managed Care and Fee-for-Service

Category	Services Provided
Essential Health Benefits	Ambulatory services
	Emergency services
	Prescription drugs
	Rehabilitative & rehabilitative services and devices
	Maternity and newborn care
	Hospitalization
	Preventive, wellness services, chronic disease management
	Mental health and substance use disorder services
	Pediatric services, including oral and vision care
	Laboratory services
Additional Mandatory Benefits	Early and Periodic Screening, Diagnostic, and Treatment Services
	Nursing facility services
	Home health services
	Rural Health Clinic services
	Federally Qualified Health Center services
	Family planning services
	Nurse midwife services
	Freestanding Birth Center services
	Transportation to medical care
	Tobacco cessation counseling for pregnant women
Optional Services	Dental services for adults
	Vision services for adults
	Nonemergency medical transportation services
	Long-term services and supports
	Enhanced Care Management
	Community Supports

Table C.3: Overview of Optional Medicaid Services

Sources: " State Plan Section 3 - Services ," California Dept. of Health Care Services (DHCS), accessed June 1, 2023; " Essential Health Benefits, " DHCS, last modified May 11, 2023; " Mandatory & Optional Medicaid Benefits ," Centers for Medicare & Medicaid Services, accessed June 1, 2023; " Health Insurance Benefits, " California Dept. of Insurance, accessed June 1, 2023; " What Are the Medi-Cal Benefits ?," DHCS, accessed August 16, 2022; and Medi-Cal Provides a Comprehensive Set of Health Benefits That May Be Accessed as Medically Necessary (PDF), DHCS, January 2020. Medi-Cal is required to cover a set of mandatory benefits and has the option to provide additional benefits eligible for federal matching dollars under the Medicaid program. Medi-Cal health plans are required to cover 10 essential health benefits as outlined in the Affordable Care Act. Medi-Cal Benefits Benefits and Cost Sharing

Plan	Additional Benefits	N^{o}Hospitals	N^o Pharmacies	N^o Doctors
Alameda Alliance for Health	Diagnostic/Lab Services Behavioral Health Hearing&Podiatry	14	181	2,200
Anthem Blue Cross	Advise Nurse Service Telehealth	12	122	1,959
Blue Shield	Behavioral Health Advise Nurse Service	18	355	-
Community Health Group	Behavioral Health Advise Nurse Service	20	290	-
Contra Costa Health Plan	Advise Nurse Service Telehealth Hospice Care Home Health/In-home support services Durable Medical Equipment CHDP Examinations/Speech Therapy	11	-	-
Health Net	Behavioral Health Advise Nurse Service CHDP Examinations/Speech Therapy	19	1,395	1,903
Health Plan of San Joaquin	Advise Nurse Service	18	-	3445
Inland Empire Health Plan	Diagnostic/Lab Services Advise Nurse Service Home Health/In-home support services Diabetes Coverage Special Services	28	610	2,685
Kaiser**	Behavioral Health Advise Nurse Service	2	-	-
Kern Family Health Systems	Hearing&Podiatry	12	90	480
LA CARE Health Plan	Diagnostic/Lab Services CHDP Examinations/Speech Therapy	70	64,000	5500
Molina Health Care	Behavioral Health Advise Nurse Service	13.6	5,180	2,300
San Francisco Health Plan	Diagnostic/Lab Services Behavioral Health	9	200	2,600
Santa Clara Family Health Plan	Diagnostic/Lab Services Home Health/In-home support services Special Services	9	240	4,223

Table C.4: Medi-Cal Plan Summary Statistics, 2017

Source: California DHCS Medi-Cal Managed Care Comparison Charts via Public Records Act (PRA) request. The Comparison Charts serve as a consolidated tool that displays managed care plans in counties with at least two plans, highlighting standard benefits (which are consistent across plans) and additional benefits that vary by plan.

Eligibility Criteria	Description
Income	Household income must be below federal poverty thresholds, varying by eligibility group and household size.
Property	Some aid categories require an asset test. Exemptions exist (e.g., primary residence). The asset test was eliminated in 2024.
Citizenship and Immigration Status	Lawful residents qualify for federal funding. Undocumented individuals under 26 and over 50 can receive full-scope Medi-Cal with state funding. Restricted benefits apply to others.
Residence	Applicants must reside in California.
Public Assistance Enrollment	Automatic eligibility for enrollees in CalFresh, SSI/SSP, CalWORKS, Refugee Assistance, Foster Care, or Adoption Assistance.

Table C.5: Medi-Cal Eligibility Requirements

Source: Older Adult Expansion, California Dept. of Health Care Services (DHCS), accessed on April 7, 2023; Young Adult Expansion , DHCS, accessed on April 7, 2023; Do You Qualify for Medi-Cal Benefits?, DHCS, accessed on April 7, 2023; Ways to Apply for Medi-Cal , DHCS, accessed on April 7, 2023; and Presumptive Eligibility (PE) Programs , DHCS, accessed on April 7, 2023

Mandatory Groups	Income Threshold	Notes
Children and youth under 26 (adoption assistance or foster care)	None	—
Children under age 1	266% FPL cap	208%–266% FPL covered by CHIP
Children age 1–5	266% FPL cap	142%–266% FPL covered by CHIP
Children age 6–18	266% FPL cap	108%–266% FPL covered by CHIP
People in long-term care	100% FPL cap	Subject to ”asset test”
Parents and caretaker relatives	108% FPL cap	—
Aged, blind, and people with disabilities	Must receive SSI	Subject to ”asset test”
Pregnant women	322% FPL cap	—
Medicare enrollees with low incomes	Varies	Three categories: QMB (100% FPL), SLMB (120% FPL), QI (135% FPL)
Optional Groups		
ACA ”expansion” adults under 65	138% FPL cap	Coverage added when California expanded Medi-Cal
Parents and caretaker relatives	109%–138% FPL	Coverage added when California expanded Medi-Cal
Qualifying state and county inmates	138% FPL cap	Medi-Cal pays for hospital services
Children under age 19	134%–266% FPL	Title XXI funded Optional Targeted Low-Income Children
Children under 19 in specific counties	267%–322% FPL	Title XXI (C-CHIP)
Pregnant women, newborns, infants under 2	213%–322% FPL	Title XXI funded Optional Targeted Low-Income Children
Children under 19 regardless of immigration status	Below 266% FPL	State-only funding
Young adults (19–25) and adults (50+) regardless of immigration status	138% FPL cap	State-only funding
Undocumented persons in long-term care	100% FPL cap	Subject to ”asset test”
Aged, blind, and disabled (FPL program)	138% FPL cap	Subject to ”asset test”
Working disabled	250% FPL cap	Subject to ”asset test”

Table C.6: Medi-Cal Eligibility Groups and Income Thresholds, Mandatory Groups

Source: Theresa Hasbrouck (director, Policy Dev. Branch, California Dept. of Health Care Services [DHCS]) to all county welfare directors et al., “ 2023 Federal Poverty Levels ” (PDF), Letter 23-03, January 26, 2023; List of Medicaid Eligibility Groups: Mandatory Categorically Needy (PDF), Centers for Medicare & Medicaid Services, accessed April 7, 2023; Tricia Brooks et al., “ Medicaid and CHIP Eligibility, Enrollment, and Renewal Policies as States Prepare for the Unwinding of the Pandemic-Era Continuous Enrollment Provision, ” KFF, April 4, 2023; California Medicaid Eligibility Groups by Medi-Cal Aid Code, California Health and Human Services Agency, last updated February 1, 2023; Program Eligibility by Federal Poverty Level for 2023 (PDF), Covered California, March 2023; 2 023 Poverty Guidelines: 48 Contiguous States (All States Except Alaska and Hawaii) (PDF), US Dept. of Health and Human Services, last updated January 2022; Medi-Cal Managed Care Plans: Mandatory or Voluntary Enrollment by Medi-Cal Aid Codes — 2023 Forward (2023) (PDF), DHCS, last updated March 9, 2023; and Alison Mitchell et al., Medicaid: An Overview (PDF), Congressional Research Service, last updated February

Metric	Year			
	2005	2017	2020	2024
Quality-related (HEDIS) measures:				
Childhood immunization status: Combination 2 (CIS-2)	■	□	□	□
Childhood Immunization Status: Combination 3 (CIS-3)	□	■	■	□
Childhood Immunization Status: Combination 10 (CIS-10)	□	□	□	■
Immunizations for Adolescents: Combination 2 (IMA-2)	□	□	□	■
Well-Child Visits in 3rd-6th years (W34)	■	■	■	□
Well Child Visits first 30 Months (W30-6)	□	□	□	■
Well Child Visits 15-30 months (W30-2)	□	□	□	■
Child and Adolescent Well-Care Visits (WCV)	□	□	□	■
Adolescent well-care visits	■	□	□	□
Cervical Cancer Screening (CCS)	□	■	□	□
Comprehensive Diabetes Care: HbA1c Testing (CDC-HT)	□	■	■	□
Comprehensive Diabetes Care: HbA1c Poor Control (CDC-H9)	□	□	□	■
Controlling High Blood Pressure (CBP)	□	■	□	□
Use of appropriate medications for asthma	■	□	□	□
Prenatal care timeliness	■	□	□	□
Prenatal and Postpartum Care (PPC-Pre)	□	■	■	■
Prenatal and Postpartum Care (PPC-Pst)	□	■	■	□
Follow-Up After ED Visit: Mental Illness (FUM)	□	■	■	□
Follow-Up After ED Visit: AOD (FUA)	□	■	■	□
Safety-net support measures:				
DSH facility dischargesc	■	■	■	□
Safety-net provider PCP assignments	■	■	■	□

Table C.7: Evolution of the Measures Factored into Auto-Assignment Incentive Program

Notes: CCS and CBP were removed from consideration in 2020 due to measure specification changes, though they remain part of the Auto-assignment incentive program HEDIS measure set. Safety-net provider PCPs were defined as primary care clinicians practicing in: Federally Qualified Health Centers (FQHC), Rural Health Centers (RHC), Indian/Tribal Clinics, non-profit community/free clinics licensed as primary clinics by the state (including satellite/intermittent sites serving as plan PCP locations), and clinics affiliated with publicly owned DSH facilities. 2005 information from *Putting Quality to Work: Rewarding Plan Performance in Medi-Cal Managed Care*, California HealthCare Foundation, May 2006.

Childhood immunization status: Combination 2 (CIS-2)(retired in 2021): DTAP, IPV, MMR, HIB, Hepatitis B and VZV

Childhood immunization status: Combination 3 (CIS-3): DTAP, IPV, MMR, HIB, Hepatitis B, VZV, and PCV

Childhood immunization status: Combination 10 (CIS-10): DTAP, IPV, MMR, HIB, Hepatitis B, VZV, PCV, Hep A, RV, and Influenza

Immunizations for Adolescents: Combination 2 (IMA-2): Meningococcal, TDAP/TD, HPV

Well-Child Visits (Ages 3-6 Years): Members 3-6 years of age who had one or more well-child visits with a primary care practitioner

Well Child Visits in the First 30 Months of Life (15 Months – 30 Months) (W30-6): Assesses children who turned 15 months old during the measurement year and had at least six well-child visits with a primary care physician during their first 15 months of life.

Well Child Visits in the First 30 Months of Life (15 Months – 30 Months) (W30-2): Assesses children who turned 30 months old during the measurement year and had at least two well-child visits with a primary care physician in the last 15 months.

Child and Adolescent Well-Care Visits (WCV): Assesses members 3–21 years of age who received one or more well-care visit with a primary care practitioner or an OB/GYN practitioner during the measurement year.

Cervical Cancer Screening (CCS): Assesses women who were screened for cervical cancer using any of the following criteria: (1) Women 21–64 years of age who had cervical cytology performed within the last 3 years, (2) Women 30–64 years of age who had cervical high-risk human papillomavirus (hrHPV) testing performed within the last 5 years, (3) Women 30–64 years of age who had cervical cytology/high-risk human papillomavirus (hrHPV) cotesting within the last 5 years.

Comprehensive Diabetes Care (CDC-HT): Assesses adults 18–75 years of age with diabetes (type 1 and type 2) who had Hemoglobin A1c (HbA1c) testing.

Comprehensive Diabetes Care (CDC-H9): Assesses adults 18–75 years of age with diabetes (type 1 and type 2) who had HbA1c poor control (>9.0%).

Controlling High Blood Pressure (CBP): Assesses adults 18–85 years of age who had a diagnosis of hypertension and whose blood pressure was adequately controlled (<140/90 mm Hg).

Prenatal and Postpartum Care (PPC): Assesses access to prenatal and postpartum care: (Pre)The percentage of deliveries in which women had a prenatal care visit in the first trimester, on or before the enrollment start date or within 42 days of enrollment in the organization. (Pst) The percentage of deliveries in which women had a postpartum visit on or between 7 and 84 days after delivery.

Follow-Up After Emergency Department Visit for Mental Illness (FUM): Assesses emergency department (ED) visits for adults and children 6 years of age and older with a diagnosis of mental illness or intentional self-harm and who received a follow-up visit for mental illness within 7 and 30 days.

Follow-Up After Emergency Department Visit for Substance Use (FUA): Assesses emergency department (ED) visits for members 13 years of age and older with a principal diagnosis of substance use disorder (SUD), or any diagnosis of drug overdose, who had a follow up visit for SUD. Two rates are reported: (1) ED visits for which the member received follow-up within 30 days of the ED visit (31 total days). (2) ED visits for which the member received follow-up within 7 days of the ED visit (8 total days).

Table C.8: HEDIS Measures

Source: HEDIS Measures and Technical Resources, NCQA

Aid code	Name	Eligibility Group	Short Description
7U	Adults - Ages 19 to 64 - Express Lane Enrollment (ELE) (Obsolete)	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
8L	Adults - Ages 19 to 64 - Modified Adjusted Gross Income (MAGI) 0% to 138% Federal Poverty Level (FPL)	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K2	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - State Medical Parole	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K3	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - State Medical Parole	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.

Aid code	Name	Eligibility Group	Short Description
K4	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - Blind/Disabled - State Medical Parole	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - not newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K5	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - Blind/Disabled - State Medical Parole	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - not newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K6	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - County Compassionate Release	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K7	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - County Compassionate Release	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K8	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - Blind/Disabled - County Compassionate Release	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - not newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
K9	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - Blind/Disabled - County Compassionate Release	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - not newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
M1	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
M2	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.

Aid code	Name	Eligibility Group	Short Description
N0	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - Low Income Health Program (LIHP) - County Inmate	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
N5	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - State Inmate	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
N6	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - State Inmate	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
N7	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - County Inmate	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.
P3	Adults - Ages 19 to 64 - MAGI 0% to 138% FPL - Hospital Presumptive Eligibility (HPE)	Adult Group - Individuals at or below 138% FPL Age 19 through 64 - newly eligible	Non-pregnant individuals aged 19 through 64, not otherwise mandatorily eligible, with income at or below 138% FPL.

Table C.9: Medicaid Eligibility Aid Codes

Age	19-34	799,025 (40.82%)
	35-54	923,160 (47.16%)
	55-64	235,219 (12.02%)
Male		1,055,275 (53.91%)
Marital Status	Married with spouse present	644,254 (32.91%)
	Married with spouse absent	100,020 (5.11%)
	Separated	73,444 (3.75%)
	Divorced	154,441 (7.89%)
	Widowed	28,764 (1.47%)
	Never Married/Single	956,481 (48.86%)
Not a citizen		1,078,426 (55.09%)
Does not speak English	299,320 (15.29%)	
Race	Asian	184,153 (9.41%)
	Black	106,039 (5.42%)
	White	1,086,024 (55.48%)
Schooling	No schooling at all	105,461 (5.39%)
	At most grade 12	1,344,905 (68.69%)
	Some college	507,158 (25.92%)
Employment	Employed	999,159 (51.05%)
	Unemployed	184,310 (9.42%)
	Not in the labor force	773,935 (39.54%)
Food stamp Recipient		492,315 (25.15%)
mean FPL		75.12
		(44.11)
mean number of Children		1.15
		(1.47)
mean reported hours at work		20.01
		(19.29)
mean social security income		104.06
		(1,061.54)
mean welfare/public assistance		86.04
		(738.97)
mean supplemental social security income		5.07
		(204.77)

Table C.10: Demographic Characteristics of Individuals with Income $<$ 138% FPL and Uninsured

Federal Poverty Level	Up to 150%	200%	250%	400%
Percent of Income	4%	6.3%	8.05%	9.5%
Maximum Monthly Portion	Up to $57	Up to $121	Up to $193	Up to $346

Table C.11: MAA by Income as % of FPL

Note: Table summarizes the maximum monthly premium contribution (MAA) required based on income relative to the Federal Poverty Level. Source: Covered California Health Insurance Companies, 2014 report.

	Tier			
Coverage Category	Bronze	Silver	Gold	Platinum
Advertised AV	60%	70%	80%	90%
Annual Wellness Exam	$0	$0	$0	$0
Primary Care Visit	$75	$35	$30	$15
Specialty Care Visit	$105	$70	$55	$40
Urgent Care Visit	$75	$35	$30	$15
Annual Deductible	$6,300	$2,500	$0	$0
Annual Out-of-Pocket Max	$6,800	$6,800	$6,750	$4,000

Table C.12: Standardized Plan Characteristics, Covered California, 2017

Metal Tier	Actuarial Value (AV)	Induced Demand Factor (IDF)
Catastrophic	0.570	1.00
Bronze	0.600	1.00
Silver	0.700	1.03
Gold	0.800	1.08
Platinum	0.900	1.15

Table C.13: Actuarial Value and Induced Demand Factor by Metal Tier

Plan Name	Counties Served	Hospitals in Network	% Average Statewide Hospitals
Alameda Alliance for Health	1	14	0.04
Anthem Blue Cross Partnership Plan	26	6-21	0.05
Blue Shield of California Promise	1	18	0.05
CalViva Health	2	13	0.04
California Health and Wellness Plan	19	2-22	0.06
Community Health Group	1	20	0.05
Contra Costa Health Plan	1	11	0.03
Health Net Community Solutions	7	3-55	0.04
Health Plan of San Joaquin	2	18	0.05
Inland Empire Health Plan	2	28	0.08
Kern Family Health Care	1	12-12	0.03
L.A. Care Health Plan	1	70	0.19
Molina Healthcare of California	5	2-21	0.04
San Francisco Health Plan	1	9	0.02
Santa Clara Family Health Plan	1	9	0.02

Table C.14: Network Breath Measures by Plan

Program	Target Population	Eligibility
Supplemental Security Income Program (SSI)	Individuals 65 and older, blind or disabled adults/children	Assets cannot exceed $2,000 for individuals, $3,000 for couples
Supplemental Nutrition Assistance Program (SNAP)	All low-income individuals and families	Gross income must be **less than 130% FPL**
National School Lunch Program	School Students	Free lunch if household income **less than 130% FPL**, reduced-price lunch if household income **less than 185% FPL**
Women, Infants, and Children's Program (WIC)	pregnant/postpartum women, breastfeeding women with an infant (<1), infants (<1), and children (<5)	Household incomes **less than 185% FPL**, or be eligible through another welfare program with income eligibility **less than 185% FPL**
Medicaid	Low-income children, parents, seniors with Medicare only, disabled, nursing home residents	For adults, income **less than 138% FPL** (higher in D.C.). For children/pregnant women, income limit ranges from **133-380% of FPL**
Temporary Assistance for Needy Families Program (TANF)	Low-income families with children or pregnant women	Varies by state, **based on FPL and liquid assets**
Subsidized Housing Programs	Low-income families, single mothers and those with children are given priority	For public housing, income 80% of area median income (AMI), voucher program: maximum (gross) income of 50% of AMI.
Child Care Development Fund (CCDF)	Low-income families with children younger than 13 by federal guidelines, might vary by state	Varies by state, Family income less than 85% of the applicable state median income.

Table C.15: Eligibility For Major Federal and State-Level Means-Tested Programs in the U.S.

Notes: This table summarizes eligibility criteria for major means-tested programs in the US. Source: U.S. Department of Health and Human Services. More programs using poverty guidelines as a part of eligibility determination: https://www.hhs.gov/answers/hhs-administrative/what-programs-use-the-poverty-guidelines/index.html

	Medi-Cal	Covered California
Eligibility	Typically for low-income individuals and families, including pregnant women, children, seniors, and people with disabilities.	Available for individuals and families who don't qualify for Medi-Cal but need assistance with purchasing private health insurance.
Income Requirements	Eligibility is based on income level, with varying thresholds depending on family size and other factors.	Eligibility is based on income level, with specific thresholds determined by household size and the federal poverty level.
Benefits	Provides comprehensive health coverage, including doctor visits, hospital stays, preventive care, prescription drugs, mental health services, and more.	Offers various health plans from different insurance companies with varying levels of coverage, including essential health benefits required by the Affordable Care Act (ACA).
Cost	Typically low or no cost for eligible individuals.	Premiums, deductibles, copayments, and coinsurance vary depending on the selected plan and income level, with subsidies available for those who qualify.
Enrollment Periods	Open year-round.	Typically during open enrollment periods, unless qualifying for a special enrollment period due to life events like marriage, birth of a child, or loss of other coverage.
Application Process	Can apply online, by phone, by mail, or in person through county social services offices, health clinics, or Covered California.	Can apply online through the Covered California website, by phone, by mail, or with the help of a certified enrollment counselor or insurance agent.
Provider Network	Coverage is through the Medi-Cal network of providers, which may vary by region.	Coverage options include various private health insurance plans with different networks of doctors, hospitals, and specialists.
Special Programs	Offers special programs for specific populations, such as the Aged, Blind, and Disabled (ABD) program.	Offers financial assistance programs, including premium assistance and cost-sharing reductions for eligible individuals and families.
Administration	Administered by the California Department of Health Care Services (DHCS).	Administered by Covered California, the state's health insurance marketplace, in partnership with the state government and private health insurance companies.
Insurers	Not applicable, as Medi-Cal is a government-administered program.	Covered California contracts with private health insurance companies, such as Anthem Blue Cross, Blue Shield of California, Kaiser Permanente, and others, to offer health plans through the marketplace.
Compensation	Medi-Cal reimburses healthcare providers directly for covered services based on a predetermined fee schedule.	Insurers receive compensation through a combination of premiums paid by enrollees, subsidies from the government, and payments from Covered California based on the number of enrollees in their plans.

Table C.16: Medi-Cal and Covered California: Eligibility, Benefits, and Other Dimensions.

Note: This table compares Medi-Cal and Covered California on several dimensions. Source: Covered California, accessed February, 2024.

	Federal Role	State Role
Regulation (General)	Sets broad guidelines for Medicaid and ACA, including mandatory benefits and eligibility criteria.	Regulates insurance within the state, decides on additional benefits, and can impose more stringent requirements.
Eligibility	Establishes minimum eligibility criteria for Medicaid and ACA subsidies.	Has discretion to extend eligibility beyond federal minimums, affecting the scope of coverage and budgetary implications.
Policy Implementation	Directs overall policy objectives and funding parameters under Medicaid and the ACA.	Adapts federal policies to local contexts, with significant leeway in implementation strategies and priorities.
Medicaid Expansion	Threshold set by the fed. Covered 100% of costs for newly eligible enrollees under Medicaid expansion initially, decreasing to 90% by 2020.	Decide whether to expand Medicaid. Manage expanded enrollee populations and associated costs.
Medicaid Funding	Provides a matching percentage of Medicaid funding to states (FMAP), with no preset limit.	Responsible for a share of Medicaid funding. Uses various sources like taxes, fees, and local funds.
Health Insurance Marketplace	Facilitates health insurance exchanges in states that do not set up their own. Offering subsidies for low-income individuals.	May establish and operate their own exchanges, determining local implementation strategies within ACA guidelines.

Table C.17: Federal vs State Role: Medicaid and ACA marketplaces

Note: This table summarizes role of each federal and state regulator for each of Medicaid and ACA individual insurance exchanges.

Government	**Agency**	**Responsibilities**
Federal	Centers for Medicare & Medicaid Services	Provides regulatory oversight
		Reviews and monitors waivers to program rules
State	California Department of Health Care Services	Administers Medi-Cal
		Sets eligibility and benefits, contracts with managed care plans and other providers, and determines payments
	California Legislature	Passes legislation enabling programs, eligibility requirements, waivers, and benefits within federal law
		Provides oversight through hearings and audits, approves overall budget
County	County Health and Social Services Department	Conducts eligibility determination
		Oversees enrollment and re-certification

Table C.18: Medi-Cal Governance

Note: This table summarizes different Medi-Cal agencies and their roles.