Firm Learning in a Selection Market: The Case of the ACA Exchanges

Claudio Lucarelli[1] and Evan Saltzman*[2]

[1]University of Pennsylvania
[2]Emory University

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Abstract

Creating new markets with private sector participation has been the government's preferred mechanism for expanding health insurance. Previous analyses assume firms have full information since market inception. We study the welfare impact of firms learning about demand and cost by estimating an adaptive learning model of the California ACA exchange. We find firms' knowledge of demand and cost increases social welfare by 25% of average subsidized premiums because firms underestimated premium sensitivity, resulting in excessive markups. Taxpayers and disadvantaged subpopulations disproportionately bear the social cost of firm misinformation. Simulations indicate risk adjustment creates larger economic tradeoffs when firms are misinformed.

Keywords: Adaptive learning, adverse selection, risk adjustment, health insurance, ACA.

JEL Codes: I11, I13, L51, L88, H51

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1 Introduction

Health insurance benefits for the poor, elderly, disabled, and other vulnerable populations are increasingly being delivered in the United States through the private sector with robust public financing. The most prominent examples of publicly-supported private health insurance markets are Medicaid Managed Care for the poor, Medicare Advantage and Medicare Part D for the elderly, and the insurance exchanges recently introduced under the Affordable Care Act (ACA) for low- and middle-income people. These programs serve an increasing share of Americans. As of 2020, approximately 53.9 million people participate in Medicaid Managed Care, 24.1 million people are enrolled in Medicare Advantage, 46.5 million people have a Medicare Part D plan, and 11.4 million get health coverage through the ACA exchanges (Kaiser Family Foundation, 2020).

Implementation of these programs requires establishing new markets with active participation of private firms. A significant challenge for firms at the outset is that they have little knowledge of the relevant market characteristics for making optimal decisions, including consumer preferences and competitors' behavior. In markets with selection such as health insurance, firms face the additional challenges of forecasting cost and understanding how cost is correlated with demand. How quickly firms learn about these characteristics has significant welfare implications, particularly during the period before the new market reaches equilibrium. Understanding the effects of firm learning is critical for designing efficient markets, particularly in health insurance where new market creation is prevalent.

In this paper, we study how firm learning affects social welfare and the efficacy of regulation designed to promote efficient health insurance markets. Explicit consideration of the transition to equilibrium represents a departure from the previous literature evaluating the design of government-created health insurance markets in Medicare Advantage (Town and Liu, 2003; Lustig, 2009; Curto et al., 2020; Miller et al., 2019), Medicare Part D (Abaluck and Gruber, 2011, 2016; Ketcham et al., 2015; Decarolis et al., 2020; Fleitas, 2017), Medigap (Starc, 2014), the pre-ACA Massachusetts exchange (Ericson and Starc, 2015; Geruso et al., 2019; Hackmann et al., 2015; Finkelstein et al., 2019; Jaffe and Shepard, 2020), and the ACA exchanges (Tebaldi, 2020; Saltzman, 2021; Polyakova and Ryan, 2021; Einav et al., 2019). These studies make the common assumption in the empirical industrial organization (IO) literature that the market is in equilibrium and firms have full information. This assumption is a significant shortcoming of the current literature given the incidence of government-created health insurance markets over the last two decades. Our paper seeks to address this gap in the health insurance literature by incorporating firm learning into the standard IO modeling approach.

Our paper also contributes to the broader empirical IO literature on learning in oligopoly markets (see Aguirregabiria and Jeon (2020) for a recent review of this literature). Most of this literature focuses on how consumers learn about their demand (Ackerberg, 2003; Dickstein, 2018) or how firms learn about their cost (Benkard, 2000; Zhang, 2010; Conley and Udry, 2010; Newberry, 2016). Doraszelski et al. (2018) and Jeon (2020) use adaptive learning models to study how firms learn about their demand and about their competitors' behavior in the U.K. electricity market and container shipping industry, respectively. Doraszelski et al. (2018) find that it takes several years before firms' behavior reaches a resting point consistent with a complete information Nash equilibrium and that convergence to equilibrium is better described with learning models than with standard IO models. We extend this literature by applying adaptive learning to a selection market where firms not only need to learn about their demand and cost, but also how demand and cost are correlated.

To understand the effect of firm learning in health insurance, we study the state-based exchanges created under the ACA. Predicting who would enroll in the ACA exchanges and how much they would cost was particularly challenging for firms because potential enrollees included those with coverage in the pre-ACA individual health insurance market (i.e., the market where consumers buy insurance directly from an insurer) and those without insurance (Gruber, 2017). New ACA restrictions on risk rating that prohibited firms from using health status and limited the use of age in rating consumers created additional sources of uncertainty when predicting demand and cost (Pauly et al., 2015, 2020). For researchers, it is usually difficult to know where firms are in the process of learning, or if they learn at all, given limited data on firm forecasts. The ACA setting provides a unique opportunity to understand firm learning because (1) there exist detailed data on consumer choices and firm cost from the establishment of the exchanges and (2) participating firms must provide a prediction of expected costs, as well as their realized costs, when they submit proposed premiums for regulatory review. By comparing firms' predicted and realized costs, we can assess whether firms learn and how quickly learning occurs.

Similar to Doraszelski et al. (2018), we develop an adaptive learning model that allows firms to progressively learn about consumer preferences and the cost of insuring consumers over time. We assume firms behave as econometricians by using *available* information on consumer plan choices and costs to form expectations about the future.[1] Our framework is a straightforward extension of the standard IO approach and can be applied with data on consumer choices and firms' predicted and actual costs. We account for heterogeneous consumer preferences, adverse selection, and moral hazard. The model incorporates key ACA policies such as the individual mandate, risk adjustment, and premium subsidies, allowing us to study how learning affects the efficacy of these policies.

To estimate our adaptive learning model, we obtain data from the California ACA exchange. The California exchange is an important market for understanding how firms learn in the ACA exchanges because it accounts for approximately 13% of nationwide enrollment (Kaiser Family Foundation, 2020). Our consumer-level administrative data from California contain nearly 10 million consumer plan choices between 2014 and 2019, the first six years of the exchange. We supplement our demand data with data on firm costs from insurer rate filings. Because insurers must file both their predictions for the coming year and their past experience, we can evaluate how well firms were able to predict their costs over time. We document that over the first several years of the California

[1]The field of macroeconomics has a long history of including adaptive learning in dynamic general equilibrium models (Sargent, 1993; Evans and Honkapohja, 2001), but these insights have been brought only recently to the industrial organization literature.

exchange, firms' predictions of their costs converged to their actual realized costs. We interpret the convergence of predicted and actual costs as evidence of firm learning.

Our model parameter estimates indicate that firms substantially underestimated consumer premium sensitivity in the ACA's initial years. We compare our model cost predictions to the firms' cost predictions in the insurer rate filings and find that our model performs well in replicating firm expectations. In most cases, the difference is less than \$2 or about 0.5% of the firm's average predicted cost, and the largest difference between the firm's and model's cost prediction is just under \$10 or about 2.5% of the firm's average predicted cost.

Using our estimated model, we simulate the impact of learning. If firms had correctly predicted demand and cost, premiums would decrease by 18.4% and annual per-capita social welfare would increase by \$423, approximately 25% of the average premium paid by consumers. Annual total social welfare increases by \$1.04 billion. Welfare gains largely accrue to the government because of a reduction in premium subsidies that are linked to premiums. This finding suggests that taxpayers bear a large share of the social welfare cost of firm misinformation during the ACA's initial years. Disadvantaged subpopulations that are more price sensitive disproportionately benefit when firms learn. Average per-capita annual consumer surplus increases \$231 for Black consumers and \$195 for Hispanic consumers. This result highlights the importance of closely monitoring the welfare of disadvantaged subpopulations when creating new markets.

We also examine how knowledge of specific model parameters affects social welfare. Because firms substantially underestimated consumer premium sensitivity in the ACA's initial years, markups were excessively high. Correcting firms' expectations of premium sensitivity is one of the primary mechanisms through which learning enhances social welfare. We also find firm knowledge of cost yields substantial welfare gains.

Managing adverse selection is a key challenge in designing new health insurance markets. An important ACA policy designed to mitigate selection is risk adjustment, which transfers money from firms with disproportionately low-risk consumers to firms with disproportionately high-risk consumers. Risk adjustment limits underinsurance (i.e., consumers purchase too little coverage) due to adverse selection that may result from firms cherry-picking low-risk consumers, but may exacerbate underenrollment (i.e., too few consumers participating in the market). We use our estimated model to simulate the impact of risk adjustment with and without firm knowledge of the model parameters. When firms are still learning, risk adjustment increases the share of enrollment in the most generous plans, but total exchange enrollment declines by 1.1% or 21,000 people. We therefore find substantial evidence of the tradeoff in addressing underinsurance and underenrollment (Azevedo and Gottlieb, 2017; Geruso et al., 2019; Saltzman, 2021). In a counterfactual scenario where firms know the model parameters, risk adjustment expands the share of enrollment in the most generous plans, but decreases total exchange enrollment by only 0.3%. Our simulations indicate that risk adjustment is considerably more detrimental to exchange enrollment when firms are still learning. This result has important policy implications for the design of new markets, where firms face a learning curve.

The remainder of this paper is organized as follows. Section 2 describes the data and ACA setting. Section 3 develops a model of the ACA exchanges. Section 4 discusses estimation. Section 5 presents the model parameter estimates. Section 6 uses the model to simulate the impact of learning. Section 7 uses the model to simulate policy counterfactuals. Section 8 concludes.

2 Data and Policy Background

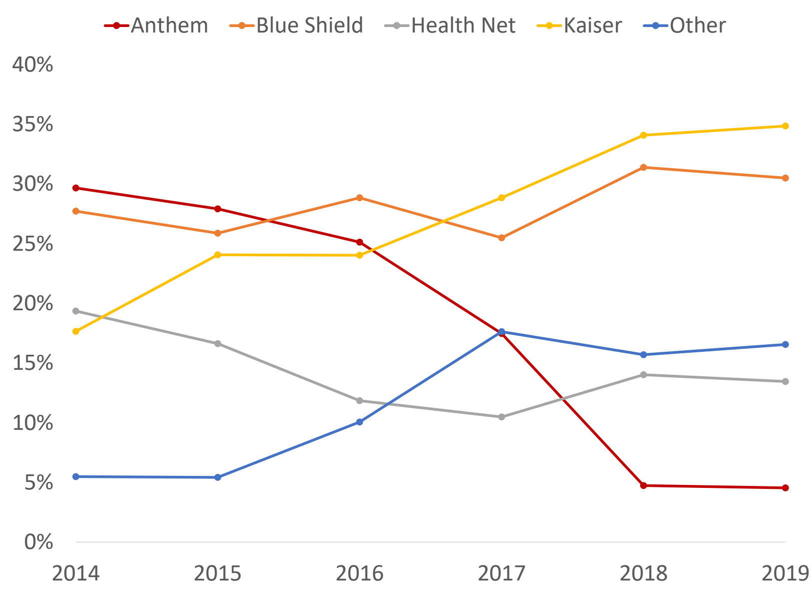
The Affordable Care Act (ACA) seeks to expand health care access coverage by promoting subsidized access to health insurance. A key mechanism for accomplishing this objective was the establishment of state-based health insurance exchanges in 2014. Eligible exchange consumers can receive subsidies to purchase health insurance from private insurance firms. Firms must comply with numerous regulations that limit risk rating of premiums.

To study these exchanges, we use two primary sets of data: (1) consumer-level data on enrollee choices from the California ACA exchang and (2) plan-market-level data on firm costs from insurer rate filings. We describe these data sources in the following two subsections.

2.1 Data on Enrollee Choices

We obtain consumer-level enrollment data from the California ACA exchange. There are approximately 10 million records in our enrollment data between 2014 and 2019. Figure 1 indicates that the California exchange has robust firm participation. There are 4 dominant firms – Anthem, Blue Shield, Health Net, and Kaiser – and 9 regional firms.[2] Anthem's decline in market share is the result of its exit from most of the state in 2018. The enrollment data indicate every enrollee's selected plan and demographic information such as age, county of residence, income, and subsidy eligibility, but do not indicate enrollee utilization.

Figure 1: Insurer Market Share By Year in the California Exchange



Our data enable us to define every household's menu of choices and calculate the precise premium the household pays for each plan in its choice set. Consumers can choose a plan from one of

[2]These firms include Chinese Community Health Plan, Contra Costa, L.A. Care Health Plan, Molina Healthcare, Oscar, Sharp Health Plan, United Healthcare, Valley Health Plan, and Western Health Advantage.

the four actuarial value (AV) or "metal" tiers, including bronze (60% AV), silver (70% AV), gold (80% AV), and platinum (90% AV). Individuals under age 30 can buy a basic catastrophic plan. Table I indicates that silver is the most commonly selected option because eligible consumers must choose a silver plan to receive cost sharing reductions (CSRs) that reduce that reduce deductibles, copays, etc. CSRs increase the actuarial value of the silver plan from 70% to (1) 94% for consumers with income below 150% of the federal poverty level (FPL); (2) 87% for consumers with income between 150% and 200% of FPL; and (3) 73% for consumers with income between 200% and 250% of FPL. Consumers with income above 250% of FPL are ineligible for CSRs. Approximately two-thirds of California consumers are eligible for CSRs.

Almost 90% of exchange enrollees are eligible for premium subsidies. Premium subsidies are available to consumers who (1) have income between 100% and 400% of the federal poverty line (FPL); (2) are citizens or legal residents; (3) are ineligible for public insurance such as Medicare or Medicaid; and (4) lack access to an "affordable plan offer" through employer-sponsored insurance. Most households in California with income below 138% of FPL are eligible for Medicaid and therefore ineligible for premium subsidies. A plan is defined as "affordable" if the employee's contribution to the employer's single coverage plan is less than 9.5% of the employee's household income in the 2014 plan year. This percentage increases slightly each year. The next section discusses the complex ACA formula used to calculate premium subsidies.

Consumers also have an outside option to forgo insurance. Although any citizen or legal resident can purchase an exchange plan, only individuals without access to public or employer-sponsored insurance purchase exchange plans in practice because of premium subsidy eligibility rules and the prohibitive cost of exchange plans relative to other insurance. Appendix B details how we construct the exchange-eligible population. For consumers who were ever enrolled in an exchange plan, we impute exchange-eligibility for years when they were not enrolled. We use panel data on transitions between different insurance statuses from the Survey of Income and Program Participation for this imputation (U.S. Census Bureau, 2019).

Table I: Choice and Demographic Distribution By Year

	2014	2015	2016	2017	2018	2019	Overall
Market Size	2,197,669	2,420,764	2,461,389	2,444,685	2,429,209	2,272,457	14,226,173
Total Enrollment	1,362,316	1,639,923	1,702,160	1,697,074	1,710,469	1,553,374	9,665,316
Metals							
Catastrophic	1.0%	0.8%	1.0%	1.1%	1.2%	1.3%	1.1%
Bronze	23.7%	25.2%	26.3%	26.7%	28.9%	28.8%	26.7%
Silver	63.9%	63.8%	63.7%	63.8%	54.7%	55.3%	60.8%
Gold	6.0%	5.5%	5.1%	5.2%	11.2%	10.9%	7.3%
Platinum	5.4%	4.7%	3.9%	3.2%	3.9%	3.7%	4.1%
Network Type							
HMO	43.1%	48.3%	46.5%	58.4%	64.3%	65.4%	54.6%
PPO	56.9%	51.7%	53.5%	41.6%	35.7%	34.6%	45.4%
Income							
138% FPL or less	4.7%	3.5%	3.3%	4.0%	4.0%	3.5%	3.8%
138% FPL to 150% FPL	14.1%	14.3%	14.6%	14.7%	14.4%	14.0%	14.4%
150% FPL to 200% FPL	32.8%	32.8%	31.9%	30.3%	28.8%	28.4%	30.8%
200% FPL to 250% FPL	16.8%	16.7%	16.3%	16.3%	16.7%	16.7%	16.6%
250% FPL to 400% FPL	22.4%	23.4%	23.6%	23.6%	25.8%	27.4%	24.4%
400% FPL or greater	9.3%	9.3%	10.3%	11.0%	10.3%	9.9%	10.0%
Subsidy Status							
Subsidized	89.6%	88.8%	87.5%	86.5%	87.3%	87.7%	87.8%
Unsubsidized	10.4%	11.2%	12.5%	13.5%	12.7%	12.3%	12.2%
Age							
0-17	5.7%	6.0%	6.2%	6.7%	7.3%	7.3%	6.5%
18-25	11.1%	11.3%	11.1%	10.7%	10.5%	10.0%	10.8%
26-34	16.3%	16.9%	17.4%	17.6%	17.7%	17.3%	17.2%
35-44	16.6%	15.9%	15.3%	15.1%	15.2%	15.1%	15.5%
45-54	24.4%	23.5%	22.8%	22.2%	21.4%	21.0%	22.5%
55+	25.8%	26.3%	27.2%	27.8%	27.9%	29.3%	27.4%
Gender							
Female	52.6%	52.2%	51.9%	52.2%	52.5%	52.5%	52.3%
Male	47.4%	47.8%	48.1%	47.8%	47.5%	47.5%	47.7%
Race							
Asian	22.8%	21.8%	22.0%	22.6%	23.0%	23.4%	22.6%
Black/African American	2.7%	2.5%	2.4%	2.4%	2.4%	2.4%	2.5%
Hispanic	27.5%	28.2%	28.0%	28.3%	28.4%	27.8%	28.0%
Non-Hispanic White	39.4%	39.5%	39.6%	38.5%	37.1%	36.8%	38.5%
Other Race	7.7%	7.9%	7.9%	8.2%	9.1%	9.6%	8.4%

Consumers without insurance may be subject to a penalty under the ACA's individual mandate. The individual mandate penalty was phased in between 2014 and 2016. The penalty for a single person was the greater of $95 and 1% of income exceeding the tax filing threshold in 2014 and the greater of $695 and 2.5% of income in 2016. The penalty was set to 0 starting in 2019 following passage of the Tax Cuts and Jobs Act of 2017. Exemptions from the ACA's individual mandate are made for certain groups, including (1) those with income below the tax filing threshold and (2) individuals who lack access to a health insurance plan that is less than 8% of their income in 2014 (this percentage changes slightly each year).

Although our focus is firm learning, a natural concern is whether consumers learn and adjust their plan choices accordingly. To study this issue, we tabulate year-to-year enrollment transitions across metal tiers and insurers in Table II. Two important features that mitigate the concern of consumer learning emerge: (1) churn is substantial and (2) switching between plans is minimal despite highly volatile premiums during the study timeframe. About one-third of consumers exit the exchange each year. High churn arises because ACA insurance is significantly more costly for consumers than other forms of insurance. Consumer participation in the ACA exchanges is closely linked to employment status changes and temporary income shocks. Among consumers that renewed coverage, 81% chose the same plan, 91% of consumers chose a plan from the same metal tier, and 88% chose a plan from the same insurer. High levels of churn suggest limited opportunities for consumers to learn and low levels of switching indicate consumers are not adjusting their plan choices over time. Hence, we do not model consumer learning.

2.2 Data on Insurer Costs

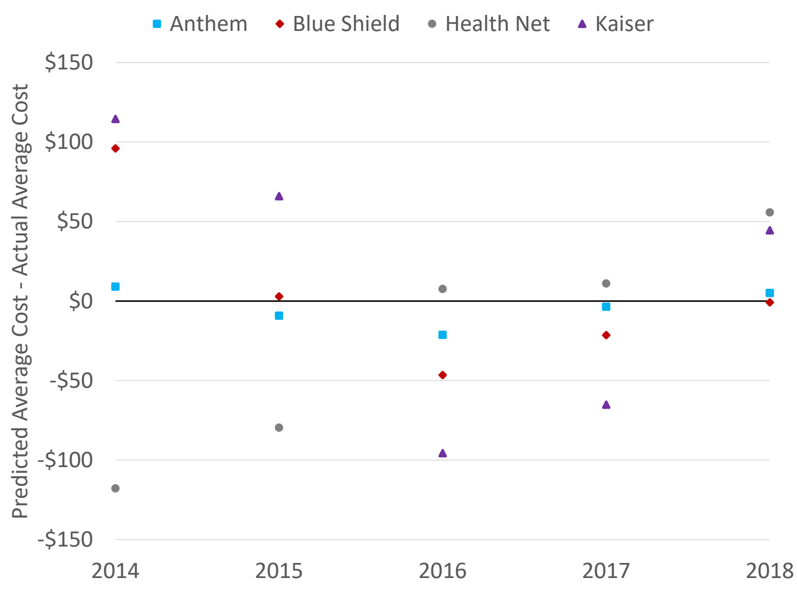
We obtain cost data from insurer rate filings. All participating California exchange insurers must submit their proposed premiums for actuarial review at the Department of Managed Health Care (DMHC). Insurers are required to include detailed supporting data justifying premium increases, including past medical claims and expected trends. DMHC does not have the authority to reject

Table II: Transition Matrices

	Cat.	Bronze	Silver	Gold	Plat.	Unins.	Inelig.
Cat.	35.6%	7.2%	2.5%	0.6%	0.3%	7.3%	46.5%
Bronze	0.1%	57.8%	4.6%	0.7%	0.2%	9.3%	27.3%
Silver	0.1%	3.0%	63.2%	1.1%	0.2%	8.6%	23.8%
Gold	0.1%	2.4%	9.8%	52.6%	1.0%	8.4%	25.7%
Plat.	0.1%	1.2%	6.6%	5.0%	53.1%	8.2%	25.8%
Unins.	0.2%	6.7%	14.0%	2.2%	0.9%	24.3%	51.7%
Inelig.	0.6%	7.1%	13.2%	2.3%	0.9%	18.1%	57.8%
	Anthem	BS	HN	Kaiser	Other	Unins.	Inelig.
Anthem	48.7%	7.5%	1.4%	3.3%	2.6%	9.0%	27.4%
BS	1.4%	62.3%	1.9%	2.0%	1.4%	7.7%	23.2%
HN	1.0%	2.9%	55.3%	1.4%	3.8%	9.9%	25.8%
Kaiser	0.3%	0.8%	0.3%	64.4%	0.7%	8.6%	24.9%
Other	0.3%	2.1%	3.5%	2.1%	56.7%	9.7%	25.7%
Unins.	2.8%	6.3%	2.7%	7.4%	4.8%	24.3%	51.7%
Inelig.	2.9%	6.5%	2.5%	7.8%	4.4%	18.1%	57.8%

Each (i, j) cell of the transition matrices indicates the percentage of consumers in state i that transitioned to state j. The first panel indicates transitions between metal tiers and the second panel indicates transitions between insurers. As described in Appendix B, consumers not enrolled in an exchange plan may be either (1) eligible for exchange coverage but uninsured or (2) ineligible for the market.

Figure 2: Cost Prediction Error By Year



Notes: Figure shows the evolution of the average cost prediction error for the four large firms. Average cost equals average claims minus the average risk adjustment transfer received and average reinsurance received.

premium increases, but can find the insurer's rate filing "unreasonable" if the supporting data do not support the rate increase and the insurer refuses to adjust their rates accordingly. Insurers must notify enrollees of an unreasonable finding. As part of the rate filing, insurers must include an independent actuarial certification which confirms its actuarial methodologies were audited by an independent firm. Because rate filings are subject to extensive scrutiny by both DHMC and independent auditors, we assume insurers truthfully report their projected costs and cannot strategically misreport in order to gain a competitive advantage.

The DMHC rate review process usually begins the summer before the new plan year when the proposed premiums take effect and can last several months. Firms submit their premiums for plan year t in the summer of year $t-1$ using experience data (i.e., supporting data) from plan year $t-2$. For example, rate filings for 2016 are submitted in the summer of 2015 and report experience from 2014, the most recent complete year of experience. The new premiums for 2016 take effect on January 1, 2016. Firms cannot adjust premiums in the middle of the plan year. Similarly, consumers can only switch exchange plans once a year during a period called "open enrollment."

Insurers did not have any experience data from the exchanges in 2014 to make projections. Most insurers developed their 2014 premium rates using experience from other lines of business, including the pre-ACA individual market and the small group market. Although these were useful starting points, a substantial portion of the potential exchange population consisted of consumers who were uninsured. Insurers had to estimate both the size and health status of the uninsured population that would enroll. As part of its rate filing, Blue Shield indicated that it used the U.S. Census Bureau's Current Population Survey (CPS) to estimate the size of the uninsured population by age, income, and geography. Blue Shield estimated the uninsured population's take-up of insurance by calibrating premium sensitivity factors with its experience data for each age-income group. The firm assumed for each age group that the health status distribution of the uninsured population was the same as the health status distribution in its experience data.

The insurer rate filings provide key plan-market-level financial information, including enrollee medical claims, reinsurance, and risk adjustment. Reinsurance was a temporary policy in effect through 2016 that helped to offset the realized claims of high-utilization consumers. Risk adjustment is a permanent policy where plans with lower-than-average risk make transfer payments to plans with higher-than-average risk. ACA risk adjustment transfers sum to zero, in contrast with Medicare Advantage risk adjustment transfers that are benchmarked to the risk of those choosing the outside option (i.e., traditional Medicare) and do not necessarily sum to zero. The objective is to disincentivize firms from cherry-picking the lowest-risk consumers to reduce cost (Handel et al., 2015; Layton, 2017; Mahoney and Weyl, 2017). Cherry-picking may result in the unraveling of the most generous, high-cost plans (e.g., plans in the platinum tier). Risk adjustment discourages strategic variation in premiums by plan generosity, but does not explicitly restrict such variation. Under the ACA's single risk pool provisions, risk adjustment occurs at the state level for all metal plans in the individual market. Catastrophic plans have a separate risk adjustment pool. In the next section, we discuss the calculation of ACA risk adjustment transfers.

A unique feature of the rate filing data is the ability to compare firms' predicted costs with their realized costs. We refer to the difference between the firm's predicted and realized average costs as the *cost prediction error*, where cost is the sum of claims, risk adjustment, and reinsurance. The cost prediction error for year t is the difference between the predicted average cost reported in the year t rate filing and the realized average cost reported in the year $t+2$ rate filing. For example, the 2016 cost prediction error uses predicted cost data from the 2016 rate filing and the realized cost data for 2016 as reported two years later in the 2018 rate filing.

Figure 2 reports the firms' cost prediction error. In the first year of the ACA exchanges, Blue Shield and Kaiser over-predicted average monthly costs by \$96 and \$115, respectively, whereas Health Net under-predicted its average monthly cost by \$118. The firms' prediction error narrowed considerably over the first five years of the exchanges. During this period, the direction of the prediction error reversed for all four firms, most strikingly for Kaiser. This reversal suggests that the firms were not strategically misleading regulators with their predictions. By 2018, Anthem and

Blue Shield were able to predict their average costs to within \$5 of their actual costs. Kaiser also had its smallest cost prediction error in 2018. Health Net reduced its prediction error by more then half from 2014 to 2018. We interpret this convergence of predicted and actual costs as evidence of firm learning. Morrisey et al. (2017) also find anecdotal evidence of substantial initial uncertainty and firm learning in interviews with insurance firm representatives from 5 states, including California.

3 Model

Consider a two-stage game where in period t (1) insurers set premiums simultaneously to maximize their expected profit and (2) consumers then select a plan to maximize their expected utility. Below we detail how we model each of these stages, beginning with consumer plan choice.

3.1 Consumer Plan Choice

Households choose the plan that maximizes their (indirect) utility function

$$U_{ijt}(p;\boldsymbol{\beta}) \equiv \beta_i^p p_{ijt}(p) + \beta_i^y y_{ij(t-1)} + x_{ij}'\beta^x + \xi_j + \epsilon_{ijt}^d \tag{1}$$

where $p = \mathbf{p}_t$ is the vector of plan base premiums set by all insurers in each market in year t, $p_{ijt}(p)$ is household i's premium for plan j in year t, $y_{ij(t-1)}$ indicates whether household i chose plan j in the previous year, x_{ij} is a vector of observed product characteristics including the plan AV, ξ_j is a vector of unobserved product characteristics, and ϵ_{ijt}^d is an error term. We allow the household's premium parameter $\beta_i^p = \beta^p + w_{it}'\phi$ to vary with household characteristics w_{it} and the household's inertia parameter $\beta_i^y = \beta^y + x_{ij}'\kappa + w_{it}'\nu$ to vary with household and product characteristics. CSRs enter utility equation (1) through the plan AV and premium subsidies reduce the household's premium $p_{ijt}(p)$. The utility of the outside option $U_{i0t} = \beta_i^p \rho_{it} + \epsilon_{i0t}$, where ρ_{it} is the household's penalty for forgoing insurance in year t.

3.1.1 Calculating Household Premiums

The household's premium $p_{ijt}(p)$ is calculated as

$$p_{ijt}(p) = \max\left\{ \underbrace{\sigma_{it} p_{jmt}}_{\substack{\text{full} \\ \text{premium}}} - \underbrace{\max\{\sigma_{it} p_{bmt} - \zeta_{it}, 0\}}_{\text{premium subsidy}}, 0 \right\} \tag{2}$$

where σ_{it} is the household's rating factor, p_{jmt} is the base premium of plan j in market m and year t, p_{bmt} is the base premium of the benchmark plan, and ζ_{it} is the household's income contribution cap. The product of the rating factor and the plan's base premium equals the household's full or unsubsidized premium. In California, the rating factor can vary by age and geographic residence of the household's members.[3] Insurers can charge a 64-year-old up to 3 times as much as a 21-year-old. Figure 3 shows the partition of California into rating areas. In each rating area, an insurer's premium must be the same for all consumers of the same age.

The household's premium subsidy equals the difference between what the household would pay for the benchmark plan ($\sigma_{it} p_{bmt}$) and the household's income contribution cap ζ_{it}. The ACA's premium subsidy is endogenous because it depends on the benchmark plan premium. The benchmark plan is the second-cheapest silver plan available to household and varies between households because of heterogeneous firm entry across markets. The income contribution cap ranged from 2% of annual income for consumers earning 100% of the federal poverty level (FPL) and 9.5% of annual income for consumers earning 400% of FPL in 2014. The contribution caps increase slightly each plan year. Subsidies can be applied to any plan except a catastrophic plan. For some low-income consumers, the premium subsidy may exceed the full premium of certain bronze plans. The subsidy is reduced in these cases to ensure the premium is nonnegative.

[3]The ACA also permits rating by tobacco usage, but California prohibits tobacco rating.

Figure 3: Premium Rating Regions in California

Notes: Figure shows the premium rating regions in the California exchange (Department of Managed Health Care, 2016). California's 58 counties are divided into 19 rating areas.

3.1.2 Calculating Demand

We assume that the vector of error terms ϵ_i has the generalized extreme value distribution so that equation (1) is a nested logit model. The first nest contains all exchange plans and the second nest contains only the outside option. This two-nest structure captures the key observed substitution pattern between the silver tier and the outside option resulting from the ACA's linkage of CSRs to the purchase of silver plans. Under the assumption that ϵ_i has the generalized extreme value distribution, the household choice probabilities are

$$q_{ijt}(p;\boldsymbol{\beta}) \quad = \quad \frac{e^{V_{ijt}(p;\boldsymbol{\beta})/\lambda}\left(\sum_j e^{V_{ijt}(p;\boldsymbol{\beta})/\lambda}\right)^{\lambda-1}}{1+\left(\sum_j e^{V_{ijt}(p;\boldsymbol{\beta})/\lambda}\right)^{\lambda}} \tag{3}$$

where $V_{ijt}(p;\boldsymbol{\beta}) \equiv \beta_i^p p_{ijt}(p)+\beta_i^y y_{ij(t-1)}+x'_{ij}\beta^x+\xi_j$ and λ is the nesting parameter. The household choice probabilities in equation (3) converge to the standard logit choice probabilities when $\lambda \to 1$.

The effect of a premium change on a subsidized consumer's demand $q_{ijt}(p)$ is given by

$$\frac{\partial q_{ikt}(p)}{\partial p_{jmt}} = \sum_{l \in J_{mt}} \frac{\partial q_{ikt}(p)}{\partial p_{ilt}(p)} \frac{\partial p_{ilt}(p)}{\partial p_{jmt}}$$

for all plans j, k in the set of available plans J_{mt}. Assuming a strictly positive subsidy that does not exceed the full, unsubsidized premium, it follows from equation (2) that

$$\frac{\partial p_{ilt}(p)}{\partial p_{jmt}} = \begin{cases} 0 & l = j, j = b \\ \sigma_{it} & l = j, j \neq b \\ -\sigma_{it} & l \neq j, j = b \\ 0 & l \neq j, j \neq b \end{cases} \tag{4}$$

For a non-benchmark plan, an infinitesimal premium increase results in consumers paying more for that plan only. An infinitesimal increase in the benchmark premium does not affect what subsidized consumers pay for the benchmark plan, but reduces what consumers pay for all other plans because of the larger subsidy. The complex relationship between insurer and consumer premiums, endogenous determination of the benchmark premium, and variation in the benchmark plan across consumers due to heterogeneous entry create significant computational challenges for estimation. We carefully model the endogenous subsidy design despite the high computational cost because of the critical role premium subsidies play in addressing adverse selection and determining which economic agents assume the cost of learning.

3.2 Firm Premium-Setting

In each period t, a risk-neutral profit-maximizing firm sets the base premium p_{jmt} for each plan j that it sells in each market m and period t to maximize

$$\begin{aligned} \pi_{ft}(p;\boldsymbol{\theta}) &= R_{ft}(p;\boldsymbol{\beta}) - C_{ft}(p;\boldsymbol{\theta}) + RA_{ft}(p;\boldsymbol{\theta}) + RI_{ft}(p;\boldsymbol{\theta}) - V_{ft}(p;\boldsymbol{\beta}) - FC_{ft} \\ &= R_{ft}(p;\boldsymbol{\beta}) - (1-\iota_{ft})C_{ft}(p;\boldsymbol{\theta}) + RA_{ft}(p;\boldsymbol{\theta}) - V_{ft}(p;\boldsymbol{\beta}) - FC_{ft} \end{aligned} \tag{5}$$

where $R_{ft}(\cdot)$ is total premium revenue, $C_{ft}(\cdot)$ is total claims, $RA_{ft}(\cdot)$ is risk adjustment received,

$RI_{ft}(\cdot)$ is reinsurance received, $V_{ft}(\cdot)$ is variable administrative cost (e.g., commissions or fees), FC_{ft} is fixed cost, and ι_{ft} indicates the AV of the reinsurance contract (i.e., the expected percentage of claims paid by the reinsurer). The model parameters $\boldsymbol{\theta} \equiv (\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\mu}, \boldsymbol{\eta})$, where $\boldsymbol{\beta}$ are the demand parameters (as defined above), $\boldsymbol{\gamma}$ are the risk score parameters, $\boldsymbol{\mu}$ are the average claims parameters, and $\boldsymbol{\eta}$ are the predicted cost parameters. The next two subsections discuss calculation of the risk adjustment transfer and the model equilibrium.

3.2.1 Calculating Risk Adjustment Transfers

Pope et al. (2014) derive the ACA risk adjustment transfer formula.[4] In our notation, the per-member per-month risk adjustment transfer $ra_{jmt}(p)$ for plan j is

$$ra_{jmt}(p) = \left(\frac{r_{jmt}(p) \sum_{m \in M, l \in J_{mt}} q_{lmt}(p)}{\sum_{m \in M, l \in J_{mt}} r_{jmt}(p) q_{lmt}(p)} - \frac{h_j \sum_{m \in M, l \in J_{mt}} q_{lmt}(p)}{\sum_{m \in M, l \in J_{mt}} h_l q_{lmt}(p)} \right) \overline{p}$$

where $r_{jmt}(p)$ is the plan risk score, h_j is an exogenous expected utilization factor set by regulation that accounts for the plan AV and any associated moral hazard, and $\overline{p}$ is the weighted average premium in the market. The plan's total risk adjustment transfer $RA_{jmt}(p)$ equals

$$RA_{jmt}(p; \boldsymbol{\theta}) \quad = \quad ra_{jmt}(p) q_{jmt}(p) \quad = \quad \left[rs_{jmt}(p) - us_{jmt}(p) \right] R_t(p; \boldsymbol{\beta}) \tag{6}$$

where $rs_{jmt}(p)$ is the plan's "risk share" of total claims, $us_{jmt}(p)$ is the plan's "utilization share" of total claims, and $R_t(p) = \sum_f R_{ft}(p; \boldsymbol{\beta})$ is total premium revenue across all plans. The total risk adjustment transfer for the firm equals the sum of the risk adjustment transfers for the plans that it sells (i.e., $RA_{ft}(p) = \sum_{m \in M, j \in J_{fmt}} RA_{jmt}(p)$, where J_{fmt} is the set of all plans offered by firm f in market m and year t).

[4] We start with Pope et al. (2014)'s transfer formula as derived in their first appendix, which allows plans to vary only by their actuarial values (and not by differences in firm efficiency, geographic costs, allowable rating factors, or moral hazard). We start with this formula because we want to capture all differences in expected risk, except for cost sharing and any associated moral hazard, in the plan's risk score (i.e., cost sharing and moral hazard are addressed through the utilization share). In contrast, the plan liability risk score $PLRS_j$ as defined in Pope et al. (2014)'s second appendix does not account for certain differences such as variation in geographic cost. Instead, Pope et al. (2014) account for these differences by applying factors in the transfer formula.

The plan's risk share includes the combined effects of adverse selection, moral hazard, and plan AV, whereas the plan's utilization share only includes the effects of moral hazard and plan AV. Thus, the difference between the risk share and utilization share captures the plan's relative risk due to adverse selection only. The risk share equals

$$rs_{jmt}(p) = \frac{r_{jmt}(p) q_{jmt}(p)}{\sum_{m \in M, l \in J_{mt}} r_{lmt}(p) q_{lmt}(p)}$$

where J_{mt} is the set of all plans offered in market m and year t, and the plan risk score $r_{jmt}(p)$ is a function of enrollee characteristics and the plan AV. We do not directly observe plan risk scores in the insurer rate filing data. However, we observe all other variables in formula (6) including each plan's risk adjustment transfer and can therefore solve formula (6) for the plan risk scores. The plan's utilization share $us_{jmt}(p)$ equals

$$us_{jmt}(p) = \frac{h_j q_{jmt}(p)}{\sum_{m \in M, l \in J_{mt}} h_l q_{lmt}(p)}$$

A positive difference between the risk share and the utilization share indicates that a plan has high risk relative to its expected utilization and results in the plan receiving a risk adjustment transfer; a negative difference indicates that a plan has low risk relative to its expected utilization and results in the plan paying a risk adjustment transfer.

3.2.2 Equilibrium

Now we find the first-order necessary conditions for a Nash equilibrium. Differentiating equation (5) yields the first-order conditions

$$MR_{jmt}(p;\boldsymbol{\beta}) + MRA_{jmt}(p;\boldsymbol{\theta}) \quad = \quad (1-\iota_{ft}) MC_{jmt}(p;\boldsymbol{\theta}) + MV_{jmt}(p;\boldsymbol{\beta}) \tag{7}$$

for all markets m in which plan j is offered by the firm in year t. We define marginal revenue $MR_{jmt}(p;\boldsymbol{\beta}) \equiv \frac{\partial R_{ft}(p;\boldsymbol{\beta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$, marginal claims $MC_{jmt}(p;\boldsymbol{\theta}) \equiv \frac{\partial C_{ft}(p;\boldsymbol{\theta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$, marginal risk adjustment transfer $MRA_{jmt}(p;\boldsymbol{\theta}) = \frac{\partial RA_{ft}(p;\boldsymbol{\theta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$, and marginal variable administrative cost $MV_{jmt}(p;\boldsymbol{\beta}) = \frac{\partial V_{ft}(p;\boldsymbol{\beta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$.

Appendix A shows that every variable in equations (5) and (7) can be written in terms of three estimable variables: (1) household choice probabilities $q_{ijt}(p;\boldsymbol{\beta})$; (2) plan risk scores $r_{jmt}(p;\boldsymbol{\theta})$; and (3) average claims $c_{jmt}(p;\boldsymbol{\theta})$. Household choice probabilities are computed using equation (3). We calculate plan risk scores as a function of observable enrollee characteristics and the plan generosity using the estimating equation

$$\ln r_{jmt}(p;\boldsymbol{\theta}) \quad = \quad \sum_{d\in D}\gamma^d s_{djmt}(p;\boldsymbol{\beta}) + MT_j'\gamma^{MT} + \epsilon^r_{jmt} \tag{8}$$

The predicted demographic share $s_{djmt}(\cdot)$ is the share of plan j's enrollment in market m and year t with demographic characteristic d, MT_j is a vector metal tier fixed effects, ϵ^r_{jmt} is an error term, and the vector of risk score parameters $\boldsymbol{\gamma} = (\gamma^d, \gamma^{MT}, \gamma^n)$. The demographic shares are computed by aggregating the household choice probabilities. We calculate plan average claims as a function of the plan risk score using the estimating equation

$$\ln c_{jmt}(p;\boldsymbol{\theta}) \quad = \quad \mu^r \ln r_{jmt}(p;\boldsymbol{\theta}) + x_j'\mu^x + \mu^l l_t + n_m'\mu^n + \epsilon^c_{jmt} \tag{9}$$

where $r_{jmt}(\cdot)$ is the predicted risk score computed using equation (8), x_j are product characteristics (not including plan AV), l_t is a linear trend, n_m' are market fixed effects, ϵ^c_{jmt} is an error term, and $\boldsymbol{\mu} = (\mu^r, \mu^x, \mu^l, \mu^n)$ are the claims parameters.

4 Estimation

In this section, we explain how we use the generalized method of moments (GMM) to estimate the parameter vector $\boldsymbol{\theta}$. We first review a standard approach in the IO literature used by Saltzman (2021). We then develop an adaptive learning approach to estimate $\boldsymbol{\theta}$.

4.1 Standard Approach

In the standard approach, the econometrician pools data from all years to estimate the demand parameters $\boldsymbol{\beta}$, the risk score parameters $\boldsymbol{\gamma}$, and the average claims parameters $\boldsymbol{\mu}$. The predicted cost parameters $\boldsymbol{\eta}$ that determine how the firm forecasts cost from its past experience are not estimated. This is because the econometrician assumes firms have full knowledge and do not need to forecast future costs. Saltzman (2021) estimates $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\mu}$ by creating four sets of moment conditions: (1) demand moments that match observed choices and predicted household choice probabilities; (2) risk score moments that match observed and predicted risk scores; (3) average claims moments that match observed and predicted average claims; and (4) the first-order conditions for profit maximization in equation (7). These moment conditions are summarized below:

$$\begin{aligned}
\frac{1}{N^{IJT}} \sum_{i\in I, j\in J, t\in T} \frac{\chi_{ijt}\partial \ln q_{ijt}(p;\boldsymbol{\beta})}{\partial \boldsymbol{\beta}} &= \mathbf{0} \\
\frac{1}{N^{JMT}} \sum_{j\in J, m\in M, t\in T} \mathbf{z}^r_{jmt}(p;\boldsymbol{\theta})\left(\ln r_{jmt} - \boldsymbol{\gamma}'\mathbf{z}^r_{jmt}(p;\boldsymbol{\theta})\right) &= \mathbf{0} \\
\frac{1}{N^{JMT}} \sum_{j\in J, m\in M, t\in T} \mathbf{z}^c_{jmt}(p;\boldsymbol{\theta})\left(\ln c_{jmt} - \boldsymbol{\mu}'\mathbf{z}^c_{jmt}(p;\boldsymbol{\theta})\right) &= \mathbf{0} \\
\frac{1}{N^M_{jt}} \sum_{m\in M} g_{jmt}(p;\boldsymbol{\theta}) &= 0, \qquad \forall j \in J_t, t \in T
\end{aligned} \tag{10}$$

where N^{IJT} is the number of plans available to all households in all years, N^{JMT} is the number of plans available in all markets and years, N^M_{jt} is the number of markets where plan j is offered in year t, χ_{ijt} indicates whether household i chose plan j at time t, r_{jmt} is the observed plan risk score, c_{jmt} is the observed plan average claims, the risk score covariates $\mathbf{z}^r_{jmt}(p;\boldsymbol{\beta}) \equiv (s_{djmt}(p,\boldsymbol{\beta}), MT_j)$, the average claims covariates $\mathbf{z}^c_{jmt}(p;\boldsymbol{\theta}) \equiv (\ln r_{jmt}(p;\boldsymbol{\theta}), x_j, u_t, n_m)$, and the first-order condition values

$$g_{jmt}(p;\boldsymbol{\theta}) \equiv MR_{jmt}(p;\boldsymbol{\beta}) - (1-\iota_{ft})MC_{jmt}(p;\boldsymbol{\theta}) + MRA_{jmt}(p;\boldsymbol{\theta}) - MV_{ft}(p;\boldsymbol{\beta})$$

Because model (10) over-identifies the model parameters, we use two-step feasible GMM to find the values of $\boldsymbol{\theta}$ that minimize the GMM objective $[\mathbf{m}(\boldsymbol{\theta})]'\mathbf{W}^{-1}[\mathbf{m}(\boldsymbol{\theta})]$, where $\mathbf{m}(\boldsymbol{\theta})$ is the vector of moment values in model (10) and the optimal weight matrix $\mathbf{W}$ is a consistent estimate of the variance-covariance matrix of the moment values.

The primary estimation challenge is to identify the effect of premiums on household choices (i.e., the parameter β_i^p). Several sources of exogenous variation are used to identify the premium parameter β_i^p, including: (1) exogenous variation in absolute premiums (i.e., relative to the outside option) that results from the phasing-in of the mandate penalty between 2014 and 2016 and zeroing out of the penalty in 2019; (2) exogenous variation in relative premiums (i.e., between plans) that results from kinks in the household premium formula (2). Because of these kinks, some bronze plans may be "free" to low-income consumers if the subsidy exceeds the full premium (i.e., the second-cheapest silver plan available to the consumer may exceed the premium of some bronze plans). The set of free plans varies by market, time, and consumer characteristics such as income, age, and household composition. Unobservables at the insurer's discretion such as provider networks and formularies may also be correlated with premiums. We address this concern by estimating equation (1) with insurer-market fixed effects. Ho and Pakes (2014) and Tebaldi (2020) follow a similar approach. Our estimates are similar when including insurer-market fixed effects.

Another identification challenge is that we lack data on patient medical conditions to predict plan risk scores. Omitting medical conditions may bias estimates of the parameter vector γ^d. To address this potential source of bias, we compute predicted demographic shares using the estimated consumer-level choice probabilities from equation (3) instead of the observed demographic shares, which are likely to be endogenous. Choice model (3) can be interpreted as the first-stage of an IV regression for computing unbiased estimates of plan risk scores. A similar empirical strategy is widely used in the hospital choice literature to compute measures of hospital market concentration (e.g., Kessler and McClellan (2000)). The identifying assumption is that the predicted demographic shares are based on exogenous determinants of consumer plan demand.

A third identification challenge is to obtain an unbiased estimate of the risk score parameter μ^r to predict plan average claims. We compute predicted plan risk scores using equation (8) instead of the observed plan risk scores, which are likely to be endogenous. If the ACA risk score perfectly captures plan claims risk, then enrollee characteristics should only affect plan average claims through the plan risk score and not directly affect average claims. Imperfections in the ACA risk score are reflected in the estimated risk score parameter.

4.2 Adaptive Learning

Now we extend the standard approach to model how firms learn about the parameter vector $\boldsymbol{\theta}$. Firm participation in a new insurance market involves two principal sources of uncertainty: demand and cost uncertainty. Demand uncertainty arises when firms do not know consumer preferences. Cost uncertainty arises when firms do not know the cost of insuring their enrollees. A defining feature of a selection market such as insurance is that demand and cost uncertainty are correlated. Our learning model accommodates this correlation.

We assume that in any plan year t, firms use data from years $2014, \ldots, t-1$ to estimate $\boldsymbol{\theta}$ and determine its predicted average cost $a_{jmt}(p;\boldsymbol{\theta})$ for year t. To capture the key features of the firm's forecast of average cost, we use the estimating equation

$$a_{jmt}(p;\boldsymbol{\theta}) \quad = \quad \left[(1-\iota_t)\left(c_{jm(t-1)}(p;\boldsymbol{\theta})+\mu^l\right)+RA_{jm(t-1)}(p;\boldsymbol{\theta})\right] x_j'\boldsymbol{\eta}+\epsilon^a_{jmt} \qquad (11)$$

where $c_{jm(t-1)}(p;\boldsymbol{\theta})$ is predicted average claims in period $t-1$ using equation (9), μ^l is the long-run linear trend from equation (9), $RA_{jm(t-1)}(p;\boldsymbol{\theta})$ is the predicted risk adjustment transfer in period $t-1$ using equation (6), x_j are product characteristics, and ϵ^a_{jmt} is an error term. The vector of predicted cost parameters $\boldsymbol{\eta}$ represents deviations from the long-run linear trend. These deviations, which vary by firm and plan network type, may be the result of anticipated technological innovations, pharmaceutical introductions, or government policy changes.

Equation 11 captures the basic idea of how firms forecast cost by applying a trend to past experience. However, it is a simplification of the lengthy actuarial justification in the rate filings of how firms trend past experience to forecast future cost. To mitigate any error introduced by this simplification, we form moment conditions that match the observed predicted average cost a_{jmt} in the rate filings with predicted average cost $a_{jmt}(p;\boldsymbol{\theta})$ as calculated in equation 11.

Define the previous period set $T_t \equiv \{2014,\ldots,t-1\}$ and denote $\boldsymbol{\theta}_t$ as the firm's estimate of $\boldsymbol{\theta}$ at time t. Let N_{ft}^{JM} be the total number of plans across all markets sold by firm f at time t. To estimate $\boldsymbol{\theta}_t$, we create the following moment conditions:

$$\begin{aligned}
\frac{1}{N^{IJT_t}}\sum_{i\in I,j\in J,\tau\in T_t}\frac{\chi_{ij\tau}\partial\ln q_{ij\tau}(p;\boldsymbol{\beta}_t)}{\partial\boldsymbol{\beta}_t} &= \mathbf{0} \\
\frac{1}{N^{JMT_t}}\sum_{j\in J,m\in M,\tau\in T_t}\mathbf{z}^r_{jm\tau}(p;\boldsymbol{\beta}_t)\left(\ln r_{jm\tau}-\boldsymbol{\gamma}_t'\mathbf{z}^r_{jm\tau}(p;\boldsymbol{\beta}_t)\right) &= \mathbf{0} \\
\frac{1}{N^{JMT_t}}\sum_{j\in J,m\in M,\tau\in T_t}\mathbf{z}^c_{jm\tau}(p;\boldsymbol{\theta}_t)\left(\ln c_{jm\tau}-\boldsymbol{\mu}_t'\mathbf{z}^c_{jm\tau}(p;\boldsymbol{\theta}_t)\right) &= \mathbf{0} \\
\frac{1}{N^M_{j\tau}}\sum_{m\in M}g_{jm\tau}(p;\boldsymbol{\theta}_t) &= 0, \qquad \forall j\in J_\tau,\tau\in T_t \\
\frac{1}{N^M_{jt}}\sum_{m\in M}x_j'\left(a_{jmt}-a_{jmt}(p;\boldsymbol{\theta}_t)\right) &= 0, \qquad \forall j\in J_{ft} \\
\frac{1}{N^{JM}_{ft}}\sum_{j\in J_{ft},m\in M}x_j'\left(a_{jmt}-a_{jmt}(p;\boldsymbol{\theta}_t)\right) &= 0, \qquad \forall f\in F \\
\frac{1}{N^M_{jt}}\sum_{m\in M}\overline{g}_{jmt}(p;\boldsymbol{\theta}_t) &= 0, \qquad \forall j\in J_t
\end{aligned} \tag{12}$$

The first four sets of moment conditions are the same as in the standard approach, except that we do not use data from year t. The fifth set of moment conditions matches each plan's observed predicted average cost a_{jmt} as reported in the rate filings with the predicted average cost from the model $a_{jmt}(p;\boldsymbol{\theta}_t)$. The sixth set of moment conditions matches each firm's observed predicted average cost with the model predicted average cost. The final set of moment conditions are the first-order conditions for year t. We compute the first-order condition values $\overline{g}_{jmt}(p;\boldsymbol{\theta}_t)$ by applying the predicted cost parameters to average claims, risk adjustment, and reinsurance.

To maintain tractability, we do not model other potential sources of uncertainty that are less relevant for our setting. Our model does not allow for structural or strategic uncertainty that arises when firms have private information about their demand and cost primitives. In this market, firms have ample access to their competitors' rate filings and the regulatory rate review process occurs over several months, providing firms numerous opportunities to learn about their competitors' proposed rates. We also assume consumers are myopic and do not learn over time. As discussed in the data section, evidence of consumer learning appears to be minimal in our setting. Consumer churn is very high and switching between plans is rare.

5 Parameter Estimates

Table III summarizes the adaptive learning parameter estimates $\widehat{\boldsymbol{\theta}}_t$ for $t \in \{2015, 2016, 2017, 2018\}$ and the standard approach estimates $\widehat{\boldsymbol{\theta}}$. Firms significantly underestimated premium sensitivity in 2015 when only data from 2014 were available. Estimates of premium sensitivity almost triple in magnitude in 2016 and are nearly identical to the standard approach estimates in 2018. A similar trend exists for plan generosity (i.e., the plan AV). Firms initially underestimated the effect of plan generosity. Learning estimates of the plan AV parameter increase over time. Firms initially underestimated inertia (i.e., the previous choice parameter), although not quite to the degree of the premium sensitivity and plan generosity parameters. Firms could not estimate inertia in 2015 because they only had data for a single year at the time. Inertia was a consideration for firms in 2015, however, because a substantial share of consumers in 2015 were enrolled in exchange plans in 2014.

Learning estimates of the supply-side parameters generally converge over time toward the standard approach estimates, although not always monotonically. Estimates of the silver and gold parameters in the risk score regression converge non-monotonically toward the standard approach estimates. As expected, platinum plans have the greatest exposure to claims risk. Estimates of the age share parameters are quite volatile in the first two years and some of the estimates do not make sense (e.g., the 35 to 54 share is positive in 2015). The standard errors are very large initially, but decline over time. Consumers of Hispanic origin have considerably less claims risk than other racial and ethnic groups, but firms substantially overestimate this effect initially. Estimates of the average claims parameters are mostly similar across years.

Table III: Main Parameter Estimates

	$\widehat{\theta}_{2015}$	$\widehat{\theta}_{2016}$	$\widehat{\theta}_{2017}$	$\widehat{\theta}_{2018}$	$\widehat{\theta}$
Demand Parameters ($\widehat{\beta}_t$)					
Monthly Premium ($100)	-0.042^{***}	-0.110^{***}	-0.145^{***}	-0.179^{***}	-0.173^{***}
	(0.015)	(0.011)	(0.010)	(0.010)	(0.009)
AV	0.336^{***}	0.785^{***}	0.992^{***}	1.156^{***}	1.136^{***}
	(0.119)	(0.072)	(0.057)	(0.051)	(0.045)
HMO	-0.004	-0.014	-0.002	-0.107^{***}	-0.087^{***}
	(0.005)	(0.013)	(0.016)	(0.012)	(0.008)
Previous Choice		0.336^{***}	0.545^{***}	0.662^{***}	0.589^{***}
		(0.068)	(0.067)	(0.067)	(0.058)
Risk Score Parameters ($\widehat{\gamma}_t$)					
Silver	0.610^{***}	0.498^{***}	0.642^{***}	0.617^{***}	0.574^{***}
	(0.070)	(0.046)	(0.046)	(0.033)	(0.028)
Gold	0.652^{***}	0.628^{***}	0.713^{***}	0.789^{***}	0.765^{***}
	(0.154)	(0.097)	(0.095)	(0.063)	(0.049)
Platinum	0.908^{***}	0.954^{***}	1.042^{***}	1.114^{***}	1.098^{***}
	(0.164)	(0.091)	(0.090)	(0.060)	(0.049)
Share Ages 18 to 34	-0.990	-0.153	-1.494^{**}	-1.265^{***}	-1.025^{***}
	(1.149)	(0.805)	(0.726)	(0.483)	(0.367)
Share Ages 35 to 54	0.150	-0.774	-0.940	-1.141^{**}	-0.999^{***}
	(2.000)	(1.029)	(0.790)	(0.528)	(0.445)
Share Hispanic	-2.831^{***}	-1.559^{***}	-1.924^{***}	-1.422^{***}	-1.438^{***}
	(0.727)	(0.389)	(0.389)	(0.245)	(0.194)
Average Claims Parameters ($\widehat{\mu}_t$)					
Log Risk Score	0.960^{***}	0.974^{***}	0.964^{***}	1.015^{***}	1.019^{***}
	(0.043)	(0.008)	(0.004)	(0.002)	(0.005)
HMO	-0.158	-0.012	-0.134^{***}	0.088^{***}	-0.100^{***}
	(0.164)	(0.030)	(0.012)	(0.010)	(0.007)

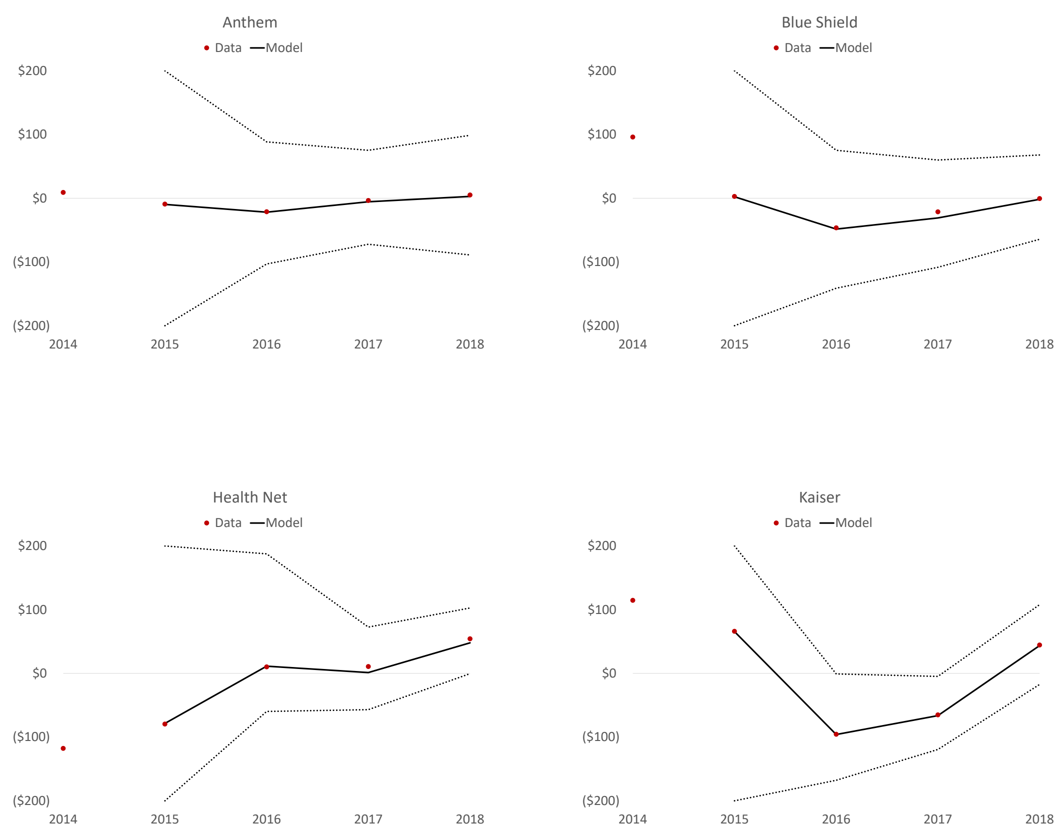
Notes: Table summarizes the adaptive learning parameter estimates $\widehat{\theta}_t$ for $t \in \{2015, 2016, 2017, 2018\}$ and the standard approach estimates $\widehat{\theta}$. Robust standard errors are in parentheses (*** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level).

To evaluate our estimated model, we compute predicted costs for each firm by year using our model parameter estimates and compare our estimates to the firms' predicted costs in the rate filing data. Figure 4 summarizes this comparison by plotting the firms' cost prediction errors. The observed cost prediction errors are the same as in Figure 2. We create 95% confidence intervals around our model point estimates of the cost prediction error by taking $1,000,000$ draws from each estimated parameter distribution[5], recomputing the cost prediction error, and finding the 2.5%- and

[5]We assume the parameter distribution is normal with mean equal to the parameter point estimate and standard

97.5%-quantiles. Our estimated learning model is effective in capturing firm learning behavior. The largest difference in the cost prediction error between the data and the model is just under $10 or about 2.5% of the firm's average predicted cost. In most cases, the difference is less than $2 or about 0.5% of the firm's average predicted cost. Observe that the 95% confidence intervals tighten over time, reflecting decreasing firm uncertainty as more data become available.

Figure 4: Cost Prediction Error By Year and Insurer



Notes: Cost prediction error for the data equals predicted average cost as reported in the rate filing data minus realized average cost as reported in the rate filing data (i.e., the same as in Figure 2). Cost prediction error for the model equals predicted average cost estimated by the model minus realized average cost as reported in the rate filing data. The dashed lines indicate the lower and upper limit of the 95% confidence interval for the cost prediction error point estimates from the model. The confidence interval limits are capped at $-\$200$ and $200 for presentational purposes.

deviation equal to the standard error in Table III.

6 Impact of Learning

Now we use our estimated model to simulate the impact of learning. We first replace the firms' learning estimates $\widehat{\theta}_{2016}$ for the year 2016 with the "full information parameters," which we assume are the estimates $\widehat{\theta}$ obtained using all available data (i.e., the last column in Table III). We then solve for the vector of premiums that satisfy the firms' first-order conditions in equation (7). Our main analysis uses the learning estimates for 2016 because it is the first year that the individual mandate penalty was in full effect and the firms had multiple years of data for estimation. In Appendix C, we simulate replacing the firms' learning estimates $\widehat{\theta}_{2015}$ for the year 2015 with the full information parameters and find qualitatively similar results.

For each simulation, we compute total social welfare in year t as

$$SW_t \quad = \quad CS_t + \pi_t - \delta GS_t$$

where CS_t is total consumer surplus, π_t is total firm profit, and GS_t is net government spending adjusted by the deadweight loss of taxation δ that results from distortions in prices and consumer behavior. The deadweight loss of taxation corresponds to the additional compensation consumers need in order to obtain their original utility levels (i.e., before government spending on the premium subsidies, CSRs, etc.) at the distorted prices (Hausman and Poterba, 1987). Following Hausman and Poterba (1987) and Decarolis et al. (2020), we multiply government spending by a factor of 1.3 to account for the deadweight loss of taxation. We compute total consumer surplus

$$CS_t \quad = \quad -\sum_{i \in I} \frac{1}{\beta_i^p} \ln \left(\sum_{j \in J} \exp\left(V_{ijt}(p; \boldsymbol{\beta}_t)/\lambda\right)^{\lambda} + \exp\left(\beta_{it}^p \rho_{it}\right) \right) + \sum_{j \in J} \left[q_{ijt}(p) * \frac{\beta_{ij}^y * y_{ij(t-1)}}{\beta_i^p} \right] \qquad (13)$$

where the first term of equation 13 is the standard nested logit formula for consumer surplus and the second term "corrects" the first term to remove gains in welfare that result from inertia. Total firm profit is $\pi_t = \sum_{t \in T} \pi_{ft}(p; \boldsymbol{\theta}_t)$, where $\pi_{ft}(p; \boldsymbol{\theta}_t)$ is defined in equation (5). Net government spending GS_t equals the sum of spending on premium subsidies, CSRs, and uncompensated care for the uninsured minus revenue collected from the mandate penalty. Premium subsidy spending is the sum of subsidies received by each consumer in equation (2). Spending on CSRs is computed as

$$CSR_t = \sum_{i \in I, j \in J} s_j^g q_{ijt}(p) c_{jmt}(p; \boldsymbol{\theta}_t)$$

where s_j^g is the expected share of claims paid by the government for plan j.[6] We calculate spending on uncompensated care by multiplying the number of uninsured that we estimate in each scenario by \$2,025, the estimated annual uncompensated care cost per uninsured[7], and a factor accounting for the change in the uninsured population's risk score. Penalty revenue collected by the government equals $\sum_{i \in I} q_{i0t} \rho_{it}$, where q_{i0t} is the household's probability of choosing the outside option.

Table IV summarizes how learning affects premiums, enrollment and social welfare. We first compare the base scenario, which uses the learning estimates $\widehat{\theta}_{2016}$, with scenario (6), which uses the full information parameters $\widehat{\theta}$. Learning the full information parameters results in a 18.4% reduction in monthly average unsubsidized premiums from \$420 to \$343. Subsidized premiums, however, decline by only \$14 from \$143 to \$129. Average bronze premiums decline the most from \$349 to \$232. As a consequence, bronze enrollment as a share of total exchange enrollment increases by 4.3 percentage points, whereas enrollment in the more generous metal tiers falls. Total enrollment increases slightly by 0.4 percentage points or about 10,000 additional people insured.

These changes in premiums and enrollment lead to a \$423 net increase in annual per-capita social welfare, equal to 8.4% of the average unsubsidized premium and 24.7% of the average subsidized premium in the base scenario. Learning the full information parameters increases total annual social welfare increases by \$1.04 billion. Welfare gains accrue mostly to the government because

[6]Ignoring moral hazard, the government's expected outlay is $94 - 70 = 24\%$ of claims for the 94% CSR plan, $87 - 70 = 17\%$ of claims for the 87% CSR plan, and $73 - 70 = 3\%$ of claims for the 73% CSR plan. To account for moral hazard, we follow Pope et al. (2014) and assume there is no moral hazard for consumers in the 73% plan, while consumers in the 87% and 94% plans increase consumption by 12%. Including moral hazard, the $s_j^g = 26.88\%$ for the 94% CSR plan, $s_j^g = 19.04\%$ for the 87% CSR plan, and $s_j^g = 3\%$ for the 73% CSR plan.

[7]We multiply the per-capita amount of medical costs that are paid on behalf of the nonelderly uninsured as estimated by Coughlin et al. (2014) by an inflation factor using data from the National Health Expenditure Accounts to adjust the estimates to the timeframe of this study (Centers for Medicare and Medicaid Services, 2018).

federal premium subsidy spending is reduced when premiums fall. Consumers realize more limited average gains in welfare because of the shift in enrollment from more to less generous plans and the relatively small reduction of $14 in average subsidized premiums. The ACA's endogenous subsidy design largely shields subsidized consumers from the welfare benefits of premium decreases.

Table V indicates the increases in consumer surplus from firm learning are heterogeneous across the exchange population. Households with income exceeding 400% of FPL gain the most consumer surplus because they are ineligible for subsidies and are therefore exposed to the full decline in premiums when firms learn. More disadvantaged subpopulations that are more price sensitive also realize substantial gains in welfare. Average annual consumer surplus increases $231 and $195 for Black and Hispanic consumers, respectively. Other demographic groups that disproportionately benefit include males single households.

In Table VI, we consider replacing the ACA's endogenous subsidy with an exogenous subsidy or voucher that does vary with premiums. For all of these scenarios, we fix every household's subsidy at its level in the base scenario. With an exogenous subsidy, we find that the average subsidized premium declines by $46 from $143 in the base scenario to $97 in scenario (6) where all parameters are known. As a result, annual per-capita consumer surplus increases by $462, but per-capita government spending on premium subsidies declines by only $77. Therefore, firm learning still enhances social welfare, but welfare gains primarily accrue to consumers rather than the government.

An interesting policy issue is whether focusing on certain parameters would accelerate the beneficial impact of learning. In scenarios (1)-(5) of Table IV, we conduct counterfactuals assuming firms know a subset of the model parameters. The largest change in social welfare occurs from knowledge of the cost parameters, which increases annual per-capita social welfare by $281 (i.e. comparing scenario base and (1)). This welfare increase is driven by a 10.0% decrease in average premiums. Learning the full information premium sensitivity parameters (i.e., comparing scenarios (5) and (6)) decreases average premiums by 9.6% and increases annual per-capita social welfare by $124 because firms initially underestimated premium sensitivity, leading to excessively high markups. The welfare effects of learning the other model parameters are mostly positive, but small. These results are robust to changing the subsidy to a voucher.

Taken together, the results reported in Tables IV and VI suggest that firm learning is beneficial to society. During the transition to equilibrium, taxpayers bear a large share of the social cost of firms not knowing the full information parameters when subsidies are endogenously-determined. Exchange consumers bear the primary social cost of firms not having full information in a counterfactual scenario where subsidies are exogenously-determined. Learning is therefore more beneficial for the lower- and middle-income population that participates in the ACA exchanges when subsidies are exogenous, but more beneficial for higher-income taxpayers when subsidies are linked to premiums. This result highlights the redistributional impact of the subsidy design when firms are learning.

7 Policy Simulations

The efficacy of government regulations that are enacted upon creation of new insurance markets may depend on whether firms are still learning. We now study how learning affects the impact of key ACA policies, including risk adjustment and the individual mandate. We simulate the elimination of risk adjustment by removing the marginal risk adjustment transfer $MRA_{jmt}(p; \boldsymbol{\theta})$ from equation (7) and solving for the vector of premiums that satisfy the resulting first-order conditions. We simulate the elimination of the individual mandate by setting the penalty ρ_{it} to zero in equation (1) and solving for the vector of premiums that satisfy the firms' first-order conditions in equation (7). We conduct these simulations for the year 2016, the first year the mandate penalty was in full effect.

Table VII presents our simulation results. Scenarios base and (3) in Table VII are the same as scenarios base and (6) in Table IV, respectively. Our simulation results reveal substantial evidence of the tradeoff between underinsurance and underenrollment in addressing adverse selection. Eliminating risk adjustment increases the share of exchange enrollment in bronze and silver plans by 6.8

Table IV: Simulation Results

	Base	(1)	(2)	(3)	(4)	(5)	(6)
Full Inf. Parameters							
Cost		✓	✓	✓	✓	✓	✓
Risk			✓	✓	✓	✓	✓
Other Demand				✓	✓	✓	✓
Inertia						✓	✓
Premium					✓		✓
Monthly Premiums							
Bronze	$349	$277	$271	$247	$215	$280	$232
Silver	$425	$393	$396	$380	$357	$394	$362
Gold	$501	$497	$499	$488	$467	$497	$477
Platinum	$539	$512	$517	$487	$485	$509	$527
Anthem	$428	$355	$351	$353	$323	$366	$322
Blue Shield	$416	$361	$361	$341	$321	$358	$328
Health Net	$383	$471	$475	$455	$436	$484	$462
Kaiser	$464	$468	$474	$438	$407	$471	$445
Other Insurer	$372	$306	$310	$270	$240	$299	$258
HMO	$417	$410	$415	$381	$351	$407	$373
PPO	$422	$358	$356	$344	$320	$361	$324
Average	$420	$378	$378	$359	$332	$379	$343
Subsidized Avg.	$143	$134	$132	$129	$124	$134	$129
Enrollment							
Total Enrollment	1,834,789	1,841,717	1,841,649	1,847,392	1,851,189	1,840,914	1,843,207
% Enrolled	74.5%	74.8%	74.8%	75.1%	75.2%	74.8%	74.9%
Bronze	18.9%	22.0%	22.7%	23.4%	24.1%	21.9%	23.2%
Silver	71.1%	68.6%	68.4%	67.4%	67.7%	68.8%	69.4%
Gold	5.3%	4.0%	3.7%	3.8%	3.5%	3.7%	3.1%
Platinum	4.7%	5.4%	5.2%	5.4%	4.7%	5.5%	4.3%
% Switching	0.0%	13.8%	14.4%	13.1%	13.1%	14.0%	15.3%
Annual Welfare Changes							
Cons. Surplus		$111	$116	$137	$170	$112	$136
Profit		($211)	($190)	($334)	($542)	($189)	($446)
Government Spending							
Prem. Subsidies		($284)	($268)	($407)	($596)	($282)	($558)
CSRs		($8)	($8)	($12)	($10)	($7)	($4)
Penalties		($2)	($2)	($4)	($5)	($2)	($2)
Uncomp. Care		($3)	($3)	($6)	($9)	($2)	($4)
Social Welfare		$281	$286	$351	$421	$299	$423

Notes: Table shows the impact of firms learning the full information parameters of the model. The first panel indicates which parameters are known to the firm, including (1) the parameters from the average claims and predicted cost equations; (2) the parameters from the risk score equation; (3) all parameters in the utility equation except the inertia and premium parameters; (4) the inertia parameters in the utility equation; and (5) the premium parameters in the utility equation. The second panel shows the effect on enrollee-weighted average premiums by metal tier, insurer, and plan network type. The third panel reports the impact on insurance coverage. The fourth panel shows the change in annual per-capita social welfare relative to the base scenario.

Table V: Change in Average Annual Consumer Surplus by Household Charactistics

	Base	(1)	(2)	(3)	(4)	(5)	(6)
Full Inf. Parameters							
Cost		✓	✓	✓	✓	✓	✓
Risk			✓	✓	✓	✓	✓
Other Demand				✓	✓	✓	✓
Inertia						✓	✓
Premium					✓		✓
Overall		$111	$116	$137	$170	$112	$136
Income							
0-250		$78	$86	$69	$87	$82	$81
250-400		$137	$144	$195	$214	$136	$144
400+		$253	$235	$418	$577	$242	$459
Age							
0-17		$149	$143	$215	$251	$154	$190
18-34		$84	$89	$97	$137	$84	$120
35-54		$115	$124	$141	$164	$110	$136
55+		$128	$128	$161	$203	$138	$146
Gender							
Female		$101	$105	$116	$150	$100	$116
Male		$121	$127	$157	$190	$124	$155
Household Size							
Single		$118	$123	$146	$191	$118	$159
Family		$105	$109	$129	$149	$106	$113
Race/Ethnicity							
Asian		$76	$84	$157	$189	$100	$118
Black		$186	$185	$227	$222	$178	$231
Hispanic		$174	$183	$161	$201	$164	$195
White		$100	$101	$132	$177	$103	$144
Other		$198	$195	$177	$207	$169	$196

Notes: Table shows the impact of firms learning the full information parameters of the model on average annual consumer surplus. The first panel indicates which parameters are known to the firm, including (1) the parameters from the average claims and predicted cost equations; (2) the parameters from the risk score equation; (3) all parameters in the utility equation except the inertia and premium parameters; (4) the inertia parameters in the utility equation; and (5) the premium parameters in the utility equation. The second panel shows the change in average annual per-capita consumer surplus by household characteristics (income, age, gender, household size, and race/ethnicity) relative to the base scenario. The “Overall” row is the same as the “Cons. Surplus” row in Table IV.

Table VI: Simulation Results with Exogenous Subsidy

	Base	(1)	(2)	(3)	(4)	(5)	(6)
Full Inf. Parameters							
Cost		✓	✓	✓	✓	✓	✓
Risk			✓	✓	✓	✓	✓
Other Demand				✓	✓	✓	✓
Inertia						✓	✓
Premium					✓		✓
Monthly Premiums							
Bronze	\$349	\$284	\$279	\$248	\$229	\$283	\$244
Silver	\$425	\$399	\$401	\$387	\$371	\$396	\$372
Gold	\$501	\$502	\$503	\$494	\$479	\$498	\$478
Platinum	\$539	\$515	\$521	\$495	\$485	\$514	\$530
Anthem	\$428	\$369	\$363	\$371	\$356	\$377	\$346
Blue Shield	\$416	\$367	\$366	\$342	\$324	\$358	\$332
Health Net	\$383	\$474	\$478	\$464	\$451	\$490	\$473
Kaiser	\$464	\$474	\$480	\$450	\$437	\$479	\$454
Other Insurer	\$372	\$311	\$317	\$278	\$263	\$300	\$268
HMO	\$417	\$416	\$421	\$394	\$383	\$413	\$391
PPO	\$422	\$367	\$365	\$353	\$336	\$367	\$338
Average	\$420	\$387	\$386	\$369	\$354	\$384	\$358
Subsidized Avg.	\$143	\$117	\$118	\$105	\$95	\$116	\$97
Enrollment							
Total Enrollment	1,834,789	1,863,629	1,859,654	1,880,097	1,896,622	1,863,771	1,884,759
% Enrolled	74.5%	75.7%	75.6%	76.4%	77.1%	75.7%	76.6%
Bronze	18.9%	20.2%	20.8%	20.4%	19.4%	19.8%	19.4%
Silver	71.1%	70.0%	69.9%	69.9%	70.7%	70.6%	72.4%
Gold	5.3%	4.1%	3.9%	4.1%	4.3%	4.0%	3.5%
Platinum	4.7%	5.7%	5.4%	5.6%	5.5%	5.6%	4.7%
% Switching	0.0%	13.6%	14.2%	13.1%	13.4%	14.3%	15.0%
Annual Welfare Changes							
Cons. Surplus		\$273	\$262	\$380	\$486	\$295	\$462
Profit		(\$187)	(\$165)	(\$327)	(\$485)	(\$193)	(\$408)
Government Spending							
Prem. Subsidies		(\$30)	(\$38)	(\$57)	(\$75)	(\$36)	(\$77)
CSRs		\$2	\$2	\$4	\$9	\$5	\$15
Penalties		(\$13)	(\$11)	(\$20)	(\$27)	(\$13)	(\$21)
Uncomp. Care		(\$22)	(\$19)	(\$35)	(\$48)	(\$22)	(\$39)
Social Welfare		\$135	\$154	\$141	\$114	\$154	\$159

Notes: Table shows the impact of firms learning the full information parameters of the model where in all scenarios, consumers receive a subsidy equal to the subsidy in the base scenario. The first panel indicates which parameters are known to the firm, including (1) the parameters from the average claims and predicted cost equations; (2) the parameters from the risk score equation; (3) all parameters in the utility equation except the inertia and premium parameters; (4) the inertia parameters in the utility equation; and (5) the premium parameters in the utility equation. The second panel shows the effect on enrollee-weighted average premiums by metal tier, insurer, and plan network type. The third panel reports the impact on insurance coverage. The fourth panel shows the change in annual per-capita social welfare relative to the base scenario.

percentage points when firms do not know the full information parameters and by 5.6 percentage points when firms do know the full information parameters. Total exchange enrollment increases by 1.1% or about 21,000 when firms do not know the full information parameters and by 0.3% or 6,000 when firms do know the full information parameters. Eliminating risk adjustment creates greater enrollment distortions when firms are still learning because the average baseline premium (i.e., the average premium in scenario base versus scenario (3)) is higher and consumer premium sensitivity is increasing in premiums.

Risk adjustment also has a substantial impact on premiums. Eliminating risk adjustment decreases average subsidized premiums by 22.2% when firms do not know the full information parameters and by 16.4% when firms do know the full information parameters. Average bronze premiums fall by 33.8% and average platinum premiums increase by 65.5% when firms do not know the full information parameters. Average bronze premiums decline by 38.7% and average platinum premiums increase by 118.7% when firms do know the full information parameters. Eliminating risk adjustment therefore results in significant average premium declines, but increases premiums for the most generous plans.

Because eliminating risk adjustment increases underinsurance but also increases enrollment, the net welfare impact of risk adjustment is not obvious. Table VII indicates that eliminating risk adjustment increases per-capita annual social welfare by $239 (column (2) compared to Base) when firms do not know the full information parameters and by $302 when firms do know the full information parameters (column (5) compared to (3)). Learning therefore has a sizable effect on the net welfare impact of risk adjustment. The main beneficiary of eliminating risk adjustment is the government, which saves $311 per consumer per year in subsidy spending when firms do not know the full information parameters and $368 per consumer per year when firms do know the full information parameters. Consumers also benefit; per capita annual consumer surplus increases by $154 when firms do not know the full information parameters and by $100 when firms do know the full information parameters.

Table VII: Policy Counterfactuals

	Base	(1)	(2)	(3)	(4)	(5)
Scenario Definitions						
Full Inf. Parameters				✓	✓	✓
Individual Mandate	✓		✓	✓		✓
Risk Adjustment	✓	✓		✓	✓	
Monthly Premiums						
Bronze	$349	$353	$231	$232	$236	$142
Silver	$425	$428	$385	$362	$366	$329
Gold	$501	$505	$479	$477	$485	$532
Platinum	$539	$543	$891	$527	$535	$1152
Anthem	$428	$431	$353	$322	$325	$253
Blue Shield	$416	$419	$355	$328	$331	$278
Health Net	$383	$387	$303	$462	$467	$390
Kaiser	$464	$467	$431	$445	$449	$428
Other Insurer	$372	$377	$265	$258	$262	$187
HMO	$417	$421	$352	$373	$378	$315
PPO	$422	$426	$349	$324	$327	$263
Average	$420	$423	$350	$343	$346	$280
Subsidized Avg.	$143	$143	$111	$129	$130	$108
Enrollment						
Total Enrollment	1,834,789	1,755,197	1,855,378	1,843,207	1,774,789	1,848,950
% Enrolled	74.5%	71.3%	75.4%	74.9%	72.1%	75.1%
Bronze	18.9%	18.8%	26.9%	23.2%	23.1%	30.4%
Silver	71.1%	71.2%	69.9%	69.4%	69.6%	67.8%
Gold	5.3%	5.3%	2.2%	3.1%	3.1%	1.2%
Platinum	4.7%	4.7%	0.9%	4.3%	4.2%	0.7%
% Switching	0.0%	1.7%	11.6%	15.3%	14.7%	21.8%
Annual Welfare Changes						
Cons. Surplus		$318	$154	$136	$446	$236
Profit		($30)	($325)	($446)	($446)	($727)
Government Spending						
Prem. Subsidies		($77)	($311)	($558)	($605)	($926)
CSRs		($10)	$4	($4)	($11)	($6)
Penalties		($283)	($8)	($2)	($283)	($3)
Uncomp. Care		$55	($15)	($4)	$44	($7)
Social Welfare		($39)	$239	$423	$375	$725

Notes: Table shows the impact of eliminating the individual mandate and risk adjustment in 2016. The first panel indicates whether the firm knows the full information parameter estimates $\widehat{\boldsymbol{\theta}}$ or must rely on the learning estimates $\widehat{\boldsymbol{\theta}}_{2016}$. The panel also indicates whether the individual mandate and risk adjustment are in place. The second panel shows the effect on enrollee-weighted average premiums by metal tier, insurer, and plan network type. The third panel reports the impact on insurance coverage. The fourth panel shows the change in annual per-capita social welfare relative to the base scenario.

In contrast to eliminating risk adjustment, learning has minimal effect on the efficacy of the individual mandate. Eliminating the individual mandate reduces total exchange enrollment by about $80,000$ or 3.2 percentage points when the mandate is repealed and firms do not know the full information parameters and $68,000$ or 2.8 percentage points when firms do know the full information parameters. The mandate has slightly less effect on enrollment when firms know the full information parameters because equilibrium premiums are lower prior to its elimination (i.e., comparing scenarios base and (3)). Repealing the individual mandate increases average monthly premiums by only 0.9% from $\$420$ to $\$423$ when firms do not know the full information parameters (i.e., comparing the base scenario and scenario (1)) and 1.1% from $\$343$ to $\$346$ when firms do know the full information parameters (i.e., comparing scenarios (3) and (4)). Despite minimal effects on equilibrium premiums, eliminating the mandate penalty increases per-capita annual consumer surplus by $318 because marginal consumers are not compelled to purchase insurance. These gains in consumer surplus are almost entirely offset by a decline in government revenue from penalty collections. Repealing the mandate therefore has little effect on per-capita annual social welfare, which falls by $\$39$ when firms do not know the full information parameters and $\$48$ when firms do know the full information parameters. The limited effectiveness of the individual mandate is consistent with the observed impact between 2018 and 2019 when the mandate penalty was set to zero. The relatively small penalty combined with robust price-linked subsidies that shield consumers from premium shocks limit the mandate's impact.

8 Conclusion

Recent public health insurance expansions have been implemented by creating new markets with private sector participation. In new markets, the standard IO assumptions of market equilibrium and complete information might be unrealistic (Doraszelski et al., 2018). We study the effects of relaxing these standard assumptions by estimating an adaptive learning model with data from the California ACA exchange. Our setting is appealing because we observe the creation of a new market and can exploit data on firms' predicted and actual costs. Our finding that learning enhances social welfare suggests that in new markets, short-run evaluations assuming market equilibrium and complete information may overstate social welfare. Ignoring firm learning may also lead to understating the social welfare cost of regulation commonly introduced in health insurance markets.

Although the primary focus of our study is firm learning, a natural concern is whether consumers also learn and adjust their plan choices accordingly form year to year (Ketcham et al., 2012; Miravete, 2003; List, 2003, 2004, 2006; List and Millimet, 2008). A significant feature of the ACA exchanges is high consumer churn due to exogenous reasons, such as job status changes or substantial income shocks. We also find minimal evidence of consumers switching plans despite highly volatile premiums during our study period. Hence, consumers have limited opportunities and incentives to learn in our study setting. A useful extension of our study may consider both consumer and firm learning.

We expect the establishment of new insurance markets to be an increasingly important mechanism for expanding access to health insurance and reducing health care costs, especially under recent proposals to transform Medicare into a premium support or defined contribution program. The methods used in this paper might be useful for analyzing the potential impact of these markets and the impact of proposed regulation while firms are still learning.

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A Mathematical Formulas in ACA Exchange Model

In this appendix, we write the variables in equations (5) and (7) in terms of three variables and associated partial derivatives: (1) the household choice probabilities $q_{ijt}(p)$; (2) the risk scores $r_{jmt}(p)$; and (3) plan average claims $c_{jmt}(p)$.

Household Choice Probabilities:

The household choice probabilities as defined in equation (3) are

$$q_{ijt}(p;\boldsymbol{\beta}) \quad = \quad \frac{e^{V_{ijt}(p;\boldsymbol{\beta})/\lambda}\left(\sum_j e^{V_{ijt}(p;\boldsymbol{\beta})/\lambda}\right)^{\lambda-1}}{1+\left(\sum_j e^{V_{ijt}(p;\boldsymbol{\beta})/\lambda}\right)^{\lambda}}$$

The (k,j) element of the Jacobian matrix of the household choice probability is

$$\frac{\partial q_{ikt}(p;\boldsymbol{\beta})}{\partial p_{ijt}} = \begin{cases} \beta_i^p q_{ijt}(p;\boldsymbol{\beta})\left[\frac{1}{\lambda}+\frac{\lambda-1}{\lambda}q'_{ijt}(p;\boldsymbol{\beta})-q_{ijt}(p;\boldsymbol{\beta})\right] & k=j \\ \beta_i^p q_{ijt}(p;\boldsymbol{\beta})\left[\frac{\lambda-1}{\lambda}q'_{ijt}(p;\boldsymbol{\beta})-q_{ijt}(p;\boldsymbol{\beta})\right] & k\neq j \end{cases} \tag{14}$$

where $q'_{ijt}(p;\boldsymbol{\beta})$ is the probability of choosing j, conditional on choosing a plan. Household i's demand partial derivative with respect to the firm's base plan premium p_{jmt} is

$$\frac{\partial q_{ikt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} = \sum_{l\in J_{mt}} \frac{\partial q_{ikt}(p;\boldsymbol{\beta})}{\partial p_{ilt}(p)} \frac{\partial p_{ilt}(p)}{\partial p_{jmt}}$$

where $\frac{\partial p_{ilt}(p)}{\partial p_{jmt}}$ is given in equation (4).

Plan Risk Scores:

We define the plan risk score in equation (8) as

$$\ln r_{jmt}(p;\boldsymbol{\theta}) = \sum_{d\in D} \gamma^d s_{djmt}(p;\boldsymbol{\beta}) + MT_j'\gamma^{MT} + \epsilon_{jmt}^r$$

The (k,j)-element of the Jacobian matrix of the plan risk score equals

$$\frac{\partial r_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}} = \frac{r_{kmt}(p;\boldsymbol{\theta})}{q_{kmt}(p;\boldsymbol{\beta})} \sum_{d\in D} \gamma^d \left[\frac{\partial q_{dkmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} - s_{dkmt}(p;\boldsymbol{\beta}) \frac{\partial q_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right] \tag{15}$$

Plan Average Claims:

We define log average claims in equation (9) as

$$\ln c_{jmt}(p;\boldsymbol{\theta}) = \mu^r \ln r_{jmt}(p;\boldsymbol{\theta}) + x_j'\mu^x + \mu^l l_t + n_m'\mu^n + \epsilon_{jmt}^c$$

The (k,j)-element of the Jacobian matrix of plan average claims equals

$$\frac{\partial c_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}} = \mu^r \frac{c_{kmt}(p;\boldsymbol{\theta})}{r_{kmt}(p;\boldsymbol{\theta})} \frac{\partial r_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}} \tag{16}$$

Plan and Firm Demand:

Total plan demand $q_{jmt}(p;\boldsymbol{\beta})$ and total firm demand $q_{ft}(p;\boldsymbol{\beta})$ equal

$$q_{jmt}(p;\boldsymbol{\beta}) = \sum_{i\in I} \left(\mathbb{I}_{i,m,t}\right) q_{ijt}(p;\boldsymbol{\beta})$$

$$q_{ft}(p;\boldsymbol{\beta}) = \sum_{i\in I, k\in J_f} q_{ikt}(p;\boldsymbol{\beta})$$

The plan and firm demand partial derivatives are

$$\frac{\partial q_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} = \sum_{i\in I}\left(\mathbb{I}_{i,m,t}\right)\frac{\partial q_{ikt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}$$

$$\frac{\partial q_{ft}(p;\boldsymbol{\beta})}{\partial p_{jmt}} = \sum_{i\in I,k\in J_f}\frac{\partial q_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}$$

Firm Revenue:

Total premium revenue earned by the firm is

$$R_{ft}(p) = \sum_{i\in I,k\in J_{fmt}}\sigma_{it}p_{kmt}q_{ikt}(p)$$

and marginal revenue $MR_{jmt}(p;\boldsymbol{\beta}) \equiv \frac{\partial R_{ft}(p;\boldsymbol{\beta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$ is

$$MR_{jmt}(p;\boldsymbol{\beta}) \;\; = \;\; \left(\frac{\partial q_{jmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right)^{-1}\sum_{i\in I,k\in J_{fmt}}\sigma_{it}\left(q_{ijt}(p;\boldsymbol{\beta}) \; + p_{kmt}\frac{\partial q_{ikt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right)$$

Firm Claims:

Total claims paid by the firm are

$$C_{ft}(p) = \sum_{k\in J_{fmt}}c_{kmt}(p)q_{kmt}(p)$$

Marginal claims $MC_{jmt}(p;\boldsymbol{\theta}) \equiv \frac{\partial C_{ft}(p;\boldsymbol{\theta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$ is

$$MC_{jmt}(p;\boldsymbol{\theta}) \;\; = \;\; \left(\frac{\partial q_{jmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right)^{-1}\sum_{k\in J_{fmt}}\left[c_{kmt}(p;\boldsymbol{\theta})\frac{\partial q_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} + q_{kmt}(p;\boldsymbol{\beta})\frac{\partial c_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}}\right] \tag{17}$$

Firm Variable Administrative Cost:

Total variable administrative cost is

$$V_{ft}(p) = v_{ft}q_{ft}(p)$$

where v_{ft} is the variable administrative cost per-member per-month. Marginal variable administrative cost $MV_{jmt}(p;\boldsymbol{\beta}) = \frac{\partial V_{ft}(p;\boldsymbol{\beta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$ is

$$MV_{jmt}(p;\boldsymbol{\beta}) \;\; = \;\; v_{ft}\frac{\partial q_{ft}(p;\boldsymbol{\beta})/\partial p_{jmt}}{\partial q_{jmt}(p;\boldsymbol{\beta})/\partial p_{jmt}} \tag{18}$$

Firm Risk Adjustment:

The firm's risk adjustment transfer is

$$RA_{ft}(p) = R_t(p) \sum_{m\in M, k\in J_{fmt}} [rs_{kmt}(p) - us_{kmt}(p)]$$

The marginal risk adjustment transfer $MRA_{jmt}(p;\boldsymbol{\theta}) = \frac{\partial RA_{ft}(p;\boldsymbol{\theta})}{\partial q_{jmt}(p;\boldsymbol{\beta})}$ is

$$\begin{aligned} MRA_{jmt}(p;\boldsymbol{\theta}) &= \left(\frac{\partial q_{jmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right)^{-1} \sum_{k\in J_{fmt}} \left[\frac{\partial R_t(p;\boldsymbol{\beta})}{\partial p_{jmt}} \left(rs_{kmt}(p;\boldsymbol{\theta}) - us_{kmt}(p;\boldsymbol{\beta})\right)\right. \\ &\quad + \left. R_t(p;\boldsymbol{\beta}) \left(\frac{\partial rs_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}} - \frac{\partial us_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right)\right] \end{aligned} \tag{19}$$

where

$$\frac{\partial R_t(p;\boldsymbol{\beta})}{\partial p_{jmt}} = \sum_{l\in J_{mt}} MR_{lmt}(p;\boldsymbol{\beta}) \frac{\partial q_{lmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}$$

$$\begin{aligned} \frac{\partial us_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} &= \left(\sum_{m\in M, l\in J_{mt}} h_l q_{lmt}(p;\boldsymbol{\beta})\right)^{-1} \left[h_k \frac{\partial q_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right. \\ &\quad \left. - \frac{h_k q_{kmt}(p;\boldsymbol{\beta})}{\sum_{m\in M, l\in J_{mt}} h_l q_{lmt}(p;\boldsymbol{\beta})} \sum_{l\in J_{mt}} h_l \frac{\partial q_{lmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}}\right] \end{aligned}$$

$$\begin{aligned} \frac{\partial rs_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}} &= \left(\sum_{m\in M, l\in J_{mt}} r_{lmt}(p;\boldsymbol{\theta}) q_{lmt}(p;\boldsymbol{\beta})\right)^{-1} \left[\left(r_{kmt}(p;\boldsymbol{\theta}) \frac{\partial q_{kmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} + q_{kmt}(p;\boldsymbol{\beta}) \frac{\partial r_{kmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}}\right)\right. \\ &\quad \left. - \frac{r_{jmt}(p;\boldsymbol{\theta}) q_{jmt}(p;\boldsymbol{\beta})}{\sum_{m\in M, l\in J_{mt}} r_{lmt}(p;\boldsymbol{\theta}) q_{lmt}(p;\boldsymbol{\beta})} \sum_{l\in J_{mt}} \left[r_{lmt}(p;\boldsymbol{\theta}) \frac{\partial q_{lmt}(p;\boldsymbol{\beta})}{\partial p_{jmt}} + q_{lmt}(p;\boldsymbol{\beta}) \frac{\partial r_{lmt}(p;\boldsymbol{\theta})}{\partial p_{jmt}}\right]\right] \end{aligned}$$

B Construction of the Uninsured Population

We model switching both between plans and into and out of the exchange market using six years of longitudinal data on exchange customers. Previous studies of the exchanges have treated demand as static, merging administrative data on exchange enrollees with survey data such as the American Community Survey (ACS) on the uninsured to form the universe of potential exchange consumers

(Tebaldi, 2020; Domurat, 2017; Saltzman, 2019). The sample of uninsured in the ACS is limited and ACS geographic identifiers are difficult to match with those in our administrative data. In contrast, we form the uninsured population using data on consumers in the California data for years in which they did not have exchange coverage. For example, consumers with exchange coverage in 2015 and 2016 are considered uninsured in 2014, 2017, and 2018 if they remained eligible for the exchange market. Consumers might lose exchange market eligibility if they gain access to employer-sponsored insurance or public insurance (e.g., Medicaid or Medicare).

Because our data do not indicate when enrollees lose exchange market eligibility, we use data from the Survey of Income and Program Participation (SIPP) to impute consumer eligibility. The SIPP is well-suited for the imputation because (1) it asks the insurance status of respondents for every month over a three-year period (2013-2015) and (2) it includes detailed information on the chief reasons for consumers' coverage status, such as whether the respondent obtained or lost an offer of employer-sponsored insurance, moved in or out of California, or became eligible or ineligible for Medicare or Medicaid. For SIPP respondents who newly obtained or gave up individual market coverage, we construct a *transitioned* variable that indicates whether the respondent gained or lost eligibility for the individual market. The *transitioned* variable takes value 1 if the respondent (1) belongs to a household that obtained or lost an offer of employer-sponsored insurance; (2) moved out of or into California; (3) the respondent turned 65 and qualified for Medicare; and (4) the respondent became eligible for Medicaid following a drop in income. We estimate a logit model regression of the *transitioned* variable on the demographic variables available in both the SIPP and the California data, including age, income, gender, race, and household size. We use the estimated logit to predict whether California consumers observed for only some years of the study timeframe transitioned into or out of the exchange market. Consumers transitioning into or out of the exchange market are removed from the study population during years when they are not enrolled in an exchange plan.

C Additional Simulation Results

Table A1: Simulation Results (2015)

	Base	(1)	(2)	(3)	(4)	(5)	(6)
Full Inf. Parameters							
Cost		✓	✓	✓	✓	✓	✓
Risk			✓	✓	✓	✓	✓
Other Demand				✓	✓	✓	✓
Inertia						✓	✓
Premium					✓		✓
Monthly Premiums							
Bronze	$337	$206	$257	$278	$215	$310	$204
Silver	$417	$306	$334	$345	$287	$371	$280
Gold	$443	$288	$359	$374	$319	$415	$367
Platinum	$471	$454	$466	$419	$418	$431	$389
Anthem	$426	$608	$455	$389	$345	$434	$267
Blue Shield	$418	$256	$301	$316	$259	$330	$273
Health Net	$337	$426	$463	$406	$453	$441	$382
Kaiser	$427	$295	$312	$329	$269	$374	$279
Other Insurer	$402	$405	$414	$439	$375	$429	$358
HMO	$392	$300	$319	$342	$278	$385	$288
PPO	$424	$290	$332	$339	$282	$359	$269
Average	$409	$293	$327	$341	$281	$368	$276
Subsidized Avg.	$121	$91	$110	$120	$110	$117	$107
Enrollment							
Total Enrollment	1,788,442	1,785,341	1,775,771	1,785,599	1,784,404	1,790,514	1,792,952
% Enrolled	73.9%	73.8%	73.4%	73.8%	73.7%	74.0%	74.1%
Bronze	17.1%	16.2%	17.6%	15.9%	17.6%	14.7%	17.8%
Silver	70.4%	69.5%	71.3%	71.7%	72.4%	72.5%	72.8%
Gold	6.4%	10.3%	7.8%	7.0%	6.9%	6.3%	4.7%
Platinum	6.1%	4.0%	3.4%	5.4%	3.1%	6.5%	4.7%
% Switching	0.0%	33.5%	27.3%	18.8%	23.8%	20.2%	18.3%
Annual Welfare Changes							
Cons. Surplus		$143	$62	$49	$75	$81	$109
Profit		($761)	($446)	($436)	($855)	($224.)	($979)
Government Spending							
Prem. Subsidies		($759)	($646)	($602)	($1040)	($319)	($1051)
CSRs		($3)	$3	$7	$11	$10	$17
Penalties		($2)	$1	($2)	($2)	($2)	($4)
Uncomp. Care		$3	$10	$2	$3	($3)	($4)
Social Welfare		$365	$439	$383	$552	$260	$475

Notes: Table shows the impact of firms learning the full information parameters of the model. The first panel indicates which parameters are known to the firm, including (1) the parameters from the average claims and predict cost equations; (2) the parameters from the risk score equation; (3) all parameters in the utility equation except the inertia and premium parameters; (4) the inertia parameters in the utility equation; and (5) the premium parameters in the utility equation. The second panel shows the effect on enrollee-weighted average premiums by metal tier, insurer, and plan network type. The third panel reports the impact on insurance coverage. The fourth panel shows the change in annual per-capita social welfare relative to the base scenario.