Consumer Inattention and Insurer Incentives in the ACA Exchanges

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Abstract

In markets with significant persistence in consumer choices over time, how do changes to product characteristics affect consumer attention and inertia? I address this question in the context of individual health plan selections on the insurance exchanges established under the Affordable Care Act. Using data on returning enrollees propensity to actively select a plan rather than automatically re-enroll in their previous choice, I find that both premium increases and changes to the structure of provider networks make consumers more attentive. Estimates from a structural model of plan choices imply that switching costs for returning consumers are significantly reduced following a large premium increase by their previously chosen plan. I find no evidence that switching costs are lower following changes to provider networks.

1 Introduction

Consumers in many markets demonstrate significant inertia or persistence in product choices over time. One such market where inertia has been shown to be important is health insurance plan selections (Handel, 2013; Ho et al., 2017; Ericson, 2014; Polyakova, 2016; Heiss et al., 2021; Abaluck and Gruber, 2016).[1] Individuals in the United States commonly choose between competing private health insurance plans that are characterized by many complex features which are difficult to compare across plans, including cost-sharing rules, prescription drug coverage formularies, and provider networks. Consumers in these markets also often have a default plan option that does not require an active plan choice, typically the plan they were enrolled in during the previous year.

Perhaps for these reasons, there is significant inertia in plan choices across many health insurance settings. This inertia could be the result of persistent unobserved heterogeneity in individual preferences over plans or switching costs associated with changing insurers, but may also arise from inattention where consumers with a default option do not always actively consider alternatives in every enrollment period. Prior research has shown that inertia has meaningful financial consequences for consumers, whether in the form of plan choice "mistakes" such as choosing a dominated plan option (Abaluck and Gruber, 2016), or from insurers exploiting inertia with higher long-run premiums (Ho et al., 2017). A significant gap in the current literature is understanding the effect of inertia, particularly resulting from inattention, on the non-price characteristics of plans offered by insurers.

One important non-price characteristic is the network of providers that a plan contracts with, at which the plan's enrollees are reimbursed for medical care. These networks are generally formed through a bargaining process that simultaneously determines payer-specific reimbursement rates for the various procedures offered by the hospital or physician. While insurers may have secondary screening or steering incentives to engage in selective contracting, network exclusion (or the threat thereof) is primarily used to negotiate price concessions from providers. If changes to the provider network make returning consumers more attentive (and thus more likely to switch plans), then plans may be more reluctant to engage in network exclusions, which would decrease insurer bargaining leverage. Therefore, inattention may impact the provider networks offered by insurers and/or negotiated provider prices.

Understanding the relationship between consumer inattention and the selective contracting incentives of downstream firms in vertical markets is important for several reasons. Within the context of healthcare, a major question is why are large insurers not able

[1] For a review, see Handel and Ho (2021).

to negotiate lower prices from providers? This question is particularly relevant in assessing policy and the overall performance of the healthcare sector, as provider prices are the most important contributor to high healthcare spending in the United States (Cooper et al., 2019). Additionally, the interaction of consumer inattention and selective contracting may play an important role in other markets. For instance, cable television providers choosing their channel lineups face similar bargaining incentives (Crawford and Yurukoglu, 2012) and features of consumer demand, with consumers exhibiting high switching costs and potentially becoming more attentive in their subscription decision following alterations to the channel lineup (Shcherbakov, 2016).

In this paper, I study the effect of changes to plan characteristics on consumer attention and the relative importance of these attention responses on insurer pricing and provider network decisions. I begin by developing a theoretical framework that shows how the incentives of downstream firms to engage in selective contracting are affected by consumer attention responses to the set of contracted upstream firms. This theoretical framework is illustrated with a simple example where the downstream firm is an insurer whose primary motivation for excluding an upstream firm from the network is steering patients to lower cost health care providers.

The setting for the empirical analysis is the individual health insurance exchanges established under the Patient Protection and Affordable Care Act of 2010 ("Affordable Care Act", "ACA") that began operating in every US state in 2014. I combine data on plan enrollment and characteristics with measures of consumer attention constructed using county-level data on the enrollment activity of consumers returning to the exchange with a default option based on their enrollment in the previous year. The primary measure of attention is the percentage of returning enrollees that actively select a plan on the enrollment website rather than being automatically re-enrolled in their default option.

Using panel regressions with county and year fixed effects plus a rich set of controls for other potential attention shocks, I find a positive association between the magnitude of year-to-year changes to the characteristics of the most popular returning plans and the percentage of returning enrollees that actively select a plan. The two plan characteristics I focus on as possible attention shocks are the monthly base premium and whether the plan uses a tiered provider network, a form of partial selective contracting by the insurer. I estimate that a $100 average increase in the monthly pre-subsidy premium of returning plans (weighted by lagged enrollment) is associated with a 1.88 percentage point increase in active re-enrollment, which is a 2.7 percent increase over the mean active re-enrollment percentage of 67.3. For the use of tiered provider networks, I estimate that all plans changing the tier structure of their network is associated with a 1.15 percentage point increase in active re-enrollment.

Motivated by the theoretical framework and descriptive evidence, I estimate a structural model of plan choices to understand the relative importance of attention responses to plan changes for insurers when designing plans. I estimate that for returning enrollees, the utility gain from remaining in the same plan is almost 80 percent lower if their plan increases the monthly base premium by $100 from the prior year. A plan switching to or from a tiered provider network does not substantially impact switching costs for returning enrollees. These results suggest that premium increases may act as an attention shock that meaningfully affects the behavior of returning consumers, while changes to the provider network appear to have little impact on an individual's likelihood of making an active plan selection when a default option is available. Counterfactual simulations reveal that roughly half of the decline in enrollment for plans that increase premiums comes from reduced consumer inertia rather than directly through consumer preferences for lower premiums.

This paper contributes to three areas of research in health economics and industrial organization. The first is the literature on inattention and incomplete consideration in individual health insurance choices, most notably Ho et al. (2017), Heiss et al. (2021), and Abaluck and Adams-Prassl (2021). Ho et al. (2017) use a two-stage demand model of attention and plan choices to evaluate the presence and effect of inattention in Medicare Part D, finding premiums would be significantly lower if all consumers were fully attentive. Heiss et al. (2021) develop a richer two-stage model of attention and plan choices to distinguish inattention from switching costs. The more general framework of Abaluck and Adams-Prassl (2021) includes a "default-specific consideration" model of inattention, which they apply to the Medicare Part D setting. Due to data limitations, I implement an alternative estimation procedure to estimate how inertia differs in response to potential attention shocks. This estimation method requires only aggregate data on plan market shares when paired with the county-level data on returning consumers use of the enrollment website to actively re-enroll in a plan, similar to the approach developed by Petrin (2002) and Berry et al. (2004). I also consider changes to the provider network of a plan as a possible attention shock, whereas Ho et al. (2017) and Heiss et al. (2021) focus on just the financial features of plan designs.

This paper also contributes to the area of research on the incentives for health insurers to engage in selective contracting. The current literature has focused on three primary incentives for health insurers to exclude or threat to exclude hospitals or physicians from their provider network: bargaining (Ho, 2009; Ho and Lee, 2019), screening/selection (Lavetti and Simon, 2018; Shepard, 2022), and steering (Gruber and Mcknight, 2016). The theoretical framework I develop posits that consumer attention responses may be a countervailing disincentive to use selective contracting in some of these cases. However, the empirical evidence from the ACA exchanges suggests this effect may be limited in practice for insurer decisions to use tiered provider networks. Recent work in this area that is especially relevant is Tilipman (2022), which studies equilibrium provider networks in the group employer market. Importantly, he includes inertia in plan choices through both insurer and provider switching costs, although his setup does not allow for attention responses or differences in inertia following changes to provider network. A main finding is that insurers over-provide network breadth and under-provide narrow network plans with high levels of inertia in plan choices even before considering attention responses.

Finally, this paper is related to the growing body of research on the functioning of the health insurance marketplaces established under the ACA, specifically related to consumer inertia and valuation of provider networks (Drake, 2019; Saltzman, 2019; Tebaldi, 2022). Of these papers, Saltzman et al. (2021) is the one most closely related to this paper. They estimate a model of plan demand and supply in this setting to study the interaction of consumer inertia with insurer market power and adverse selection. They find significant inertia, with estimated plan switching costs of nearly half of annual premiums paid by consumers. They estimate that eliminating inertia, while worsening adverse selection, would substantially lower average premiums by reducing insurer market power. I add to their findings by showing returning consumer inertia is lessened substantially in response to premium increases of consumers default option, which would limit the ability of insurers to exercise this market power over inertial consumers.

The rest of the paper is organized as follows. Section 2 presents a theoretical framework for understanding the potential interaction between consumer inattention and the use of selective contracting by insurers. Section 3 discusses the data and summary statistics. Section 4 presents descriptive evidence on the relationship between changes to the characteristics of returning plans and the attentiveness of returning enrollees. Section 5 outlines the empirical model of plan choices, the estimation routine and results, and the counterfactual simulations. Section 6 concludes.

2 Theoretical Framework

To build intuition, I develop a simple theoretical model where consumer inattention can affect the incentives of a downstream firm to engage in selective contracting. This example focuses on the "steering" incentive of downstream firms to exclude high-cost providers using selective contracting.

Consider a market with two hospitals, A and B, with exogenously heterogeneous costs. The market has individuals $i = 1, ..., N$ that receive stochastic health shocks requiring hospital treatment. For each condition g, individual i requires treatment with probability θ_{ig}. For simplicity, I assume there is no individual heterogeneity in health risk, which rules out adverse selection, so that $\theta_{ig} = \theta_g$ for each individual i.[2] The costs of each hospital for a treatment episode of each condition are given by the vectors C_A, C_B where it is assumed $C_A \ll C_B$, so that hospital A is the "low-cost" provider and B is the "high-cost" provider. If requiring care for condition g, the indirect utility of individual i receiving treatment at hospital h is given by

$$u_{ihg} = \gamma\, dist_{ih} + q_{hg} + \eta_{ihg}$$

where $dist_{ih}$ is the distance between the individual and provider h, q_{hg} is vertical provider quality for the given condition, and η_{ihg} is an idiosyncratic taste shock. Each individual is characterized by a location $x_i \sim U([0, 1])$, with distances $dist_{ih} = |x_h - x_i|$ calculated based on provider locations $x_A = 0$, $x_B = 1$.

For simplicity, I assume there is a single health condition and that the provider taste shocks η_{ih} are independently distributed Type 1 Extreme Value. With these simplifying assumptions, the ex ante utility of an individual i requiring treatment with access to the provider network $G_j \in \mathcal{P}(\{A, B\})$ is given by

$$WTP(G_j, x_i) = \log \sum_{h \in G_j} \exp(\gamma\, dist_{ih} + q_h).$$

I refer to this as the network value for individual i for the set of providers G_j.

Individuals choose between a monopolist insurer j and a non-strategic outside option for insurance coverage. A reduced form representation of individual preferences for insurance coverage given their location x_i and health risk θ is given by

$$u_{ij} = \beta_0 + \beta_1 prem_j + \beta_2 WTP(G_j, x_i) + \varepsilon_{ij}$$

where u_{ij} is the indirect utility of individual i enrolling with the insurer, $prem_j$ is the premium charged by the insurer for complete insurance against health expenditures, and $WTP(G_j, x_i)$ is the ex ante utility of individual i for the provider network chosen by the insurer as defined above. To model consumer (in)attention, I assume that individuals

[2] If insurers use network exclusions as a selection device against high-risk consumers as in Shepard (2022), then the incentive to engage in selective contracting would be exacerbated by network changes acting as an attention shock, since the insurer would want the high-risk consumers to be more attentive.

enter the period affiliated with either the insurer j or the outside option based on their prior enrollment decision. For individuals affiliated with j, they make an active choice about their insurance coverage in the current period only if

$$\alpha_0 + \alpha^P \Delta^+ prem_j + \alpha^N \Delta^- WTP(G_j, x_i) + \nu_{ij} > 0$$

and automatically re-enroll with j otherwise without considering the outside option. The attention shocks $\Delta^+ prem_j$ and $\Delta^- WTP(G_j, x_i)$ are the differences in plan characteristics from the previous year, although individuals are assumed to only respond to utility-decreasing changes (premium increases and network value decreases). Individuals affiliated with the outside option make an active insurance coverage choice with probability $\tilde{\alpha}$.

Provider prices are assumed to be set administratively and equal to exogenous per patient costs of each provider C_A, C_B. Given individual preferences over providers and insurance coverage, the insurer's problem is to maximize profits by choosing a network G_j and premium $prem_j$:

$$\max_{prem_j, G_j} \quad \pi(prem_j, G_j) = prem_j \cdot s(prem_j, G_j) - \theta \cdot \bar{c}(G_j) \cdot s(prem_j, G_j).$$

The insurer's profit is a function of their enrollment share $s(prem_j, G_j)$, which depends on both consumer preferences and attentiveness, and the utilization-weighted average cost paid by the insurer for each treatment episode required for their enrollees based on health realizations. With logistic errors ε_{ij}, ν_{ij} and affiliation share s_{j0}, the market share for the insurer is then

$$s(prem_j, G_j) = a_i \cdot \frac{\exp(\beta_0 + \beta_1 prem_j + \beta_2 WTP(G_j, x_i))}{1 + \exp(\beta_0 + \beta_1 prem_j + \beta_2 WTP(G_j, x_i))} + (1 - a_i) \cdot s_{j0}$$

where a_i is the probability that individual i makes an active choice at time t given their initial affiliation y_{i0}:

$$a_i = \frac{\exp(\alpha_0 + \alpha^P \Delta^+ prem_j + \alpha^N \Delta^- WTP(G_j, x_i))}{1 + \exp(\alpha_0 + \alpha^P \Delta^+ prem_j + \alpha^N \Delta^- WTP(G_j, x_i))}.$$

With no heterogeneity in health status (and therefore no selection into coverage by risk), the utilization-weighed average cost of the insurer given network G_j is just the costs of all providers included in the network weighted by the overall provider market shares implied by consumers preferences for hospitals.

I now consider a numerical simulation of the model that varies α^N, the attention response of consumers to provider network exclusions. Figure 1 shows that past a certain threshold of attention response, insurers forgo excluding the high-cost provider from the network, which is otherwise optimal with no attention response. The "Baseline" scenario in Panel (b) shows the optimal network size for the model parameters used in Panel (a). This shows that the optimal network excludes the high-cost hospital B when the attention response to a network change is relatively low, up to a "network exclusion threshold".

Insurer profits are highest with no attention response to network changes, as this allows them to exclude the high-cost provider without "awakening" any of their potentially inattentive affiliated consumers. Since the number of inattentive consumers affiliated with the insurer following a network exclusion falls as the attention response increases, profits gradually decline up to the point where the insurer does not alter the network. The insurer's profits are lowest when the attention response is high enough that it is optimal to not narrow the provider network to restrict hospital B, reflecting higher input costs. Similarly, the optimal premium charged by the insurer gradually falls over the range of attention responses where the insurer still excludes B from the network due to more attentive consumers given the exclusion. However, given the higher costs from not excluding B, premiums are higher past the network exclusion threshold than with no attention response.

The figure in Panel (b) also shows how the network exclusion threshold is affected by changes to other model parameters. Relative to the baseline parameters, lower overall attentiveness (a decrease in α_0), a larger difference in costs between providers (an increase in $C_A - C_B$), and a reduced importance of network value in consumer preferences relative to other factors (a decrease in β_2) all raise the network exclusion threshold, meaning the insurer is more willing to exclude B from the network. For example, as the cost differential between providers becomes larger, the cost savings from excluding hospital B outweigh the costs of greater attention for a larger range of attention responses to network changes.

This example shows that if consumers with default options increase their attentiveness in response to provider network changes, this affects the incentives of firms with market power over inattentive consumers to engage in selective contracting. In this example, sufficiently large attention responses to network changes lead to higher premiums and overall spending. Although this example exclusively considers the steering incentive for using selective contracting to push enrollees towards lower cost providers, the same intuition applies to the use of selective contracting as a mechanism to negotiate lower prices from providers. In this case, network exclusion is again used to lower input costs, but the threat of network exclusion to gain price concessions becomes less credible if such an exclusion would awaken the firms inattentive consumers. This example also only considers a single period of static price setting by the insurer, but attention responses to network changes may actually be more important with dynamic pricing since the costs of waking up affiliated consumers is greater.

3 Background and Data

3.1 Setting

A key component of the Affordable Care Act was the creation of individual health insurance marketplaces ("exchanges") in all 50 US states that began operating in 2014. Each state can administer their own exchange or use the federally-facilitated marketplaces (FFM) where consumers select plans on the federal healthcare.gov website. On the exchanges, private health insurers offer plans with regulated benefit designs that consumers can purchase using income-based subsidies.

States are divided into geographic rating areas, typically groups of counties or zip codes. Within rating areas, pre-subsidy premiums are subject to adjusted community rating and do not vary across individuals except by age and, in some states, smoking status. For a given plan, insurers set a single base premium within each rating area that is adjusted by age according to a set formula common to all plans. Subsidy eligibility depends on household income, and the subsidy amount a household receives towards a specific plan is a function of household income and the plan's base premium relative to the "benchmark" plan in that rating area, which is the second-cheapest "Silver" metal level plan.

Plans are grouped into four metal levels based on the generosity of coverage. Plan generosity is measured using actuarial value (AV), an estimate for the fraction of annual health spending that is paid for by the insurer. These metal tiers are Platinum (90% actuarial value), Gold (80% AV), Silver (70% AV) and Bronze (60% AV). Silver plans are the most popular, and for some analyses I focus solely on these plans.

Although many aspects of plan benefit design are regulated, insurers have significant discretion over provider networks for hospitals and physicians. Narrow networks that exclude a significant number of providers in a geographic market weighted by capacity are common (Graves et al., 2020). As would be expected from the incentives of insurers to use selective contracting, plan transitions to a narrow network are associated with lower premiums (Dafny et al., 2017).

The network decision that I focus on in this paper is the use of tiered provider networks by insurers. In a tiered provider network, the amount of cost-sharing borne by the consumer at a given provider depends on the tier placement of the provider within the insurer's network. Thus, providers can be partially excluded from a plan's network by being placed in a lower tier where consumers face higher out-of-pocket costs. Because of this, tiered networks are essentially narrower than a full provider network but typically more inclusive than narrow network plans. As a result, a plan transitioning to a tiered network may represent either a broadening or narrowing of the network compared to the prior year, so it is ambiguous as to whether the change increases or decreases the value of the network to consumers holding premiums and other plan features constant. The incentives for adopting a tiered network for the insurer are similar to the motivations for excluding providers entirely from a network, such as steering patients towards lower-cost providers or to increase bargaining power with providers by threatening a lower tier placement.

3.2 Data Sources

To construct measures of returning consumer attention, I use the County-Level Open Enrollment Period (OEP) Public Use Files published by the Centers for Medicare & Medicaid Services (CMS). Consumers returning to the exchanges are "crosswalked" into a default plan based on their previous plan selection. If possible, this is the exact plan that they were enrolled in during the prior year. Returning enrollees can be crosswalked and automatically re-enrolled into a different plan with the same issuer and metal level as their previous choice if their previous plan is no longer available. Since I focus on year-to-year changes to plan characteristics in this paper, I restrict attention to individuals whose default option is the exact same plan as the previous year based on the administrative plan identifier. Returning enrollees are automatically re-enrolled in their crosswalked plan by default during the open-enrollment period unless they discontinue coverage or make an active plan selection on the website.

The OEP files have county-year level data on enrollment across all plans from 2015-2020. This includes the total number of enrollees, the number of new vs. returning enrollees, and the number of returning enrollees that actively select a plan vs. automatically enroll in their crosswalked plan. From 2018-2020, I also observe the number of active returning enrollees that actually switch plans, i.e. selecting an exchange plan other than their crosswalked default option.[3]

[3]Some consumers that do not want to switch plans may need to make what is classified as an active selection to adjust their reported income for premium subsidies. Others may may actively shop and compare plans but ultimately select their default option.

I complement the OEP files with data from CMS on total enrollment for each exchange plan by state and year. For each plan on the FFM, I also observe characteristics including the metal level, pre-subsidy premium by age, deductible amount, cost-sharing amounts for various services, and a limited set of provider network summary measures from HIX Compare. The provider network summary variables include an indicator for whether the plan uses a tiered network. An important limitation of these data on plan characteristics is that it does not provide any information on the size or breadth of provider networks.

3.3 Variable Definitions and Summary Statistics

Table 1 shows summary statistics for plans and counties. The state-level plan characteristics in Panels A and B are averages across rating areas in the state where the plan is offered, weighted by rating area population. The average monthly, pre-subsidy premium for Silver plans in the sample is \$566. Roughly 16 percent of plans over the full sample have a tiered provider network and 45 percent of plan-years were available in the previous year. Focusing on just these returning plans, the average change in the pre-subsidy monthly premium from the previous year is \$69. Around 5 percent of returning plans had a change in the tier structure of the networks (transitioned from multi-tiered to single-tiered or vice versa).

From the county-level OEP, the average percentage of returning enrollees actively selecting a plan is 67.3. The average percentage of returning enrollees who switch plans during the 2018-2020 period is 29. Figure A.1 and Figure A.2 show that there is significant dispersion in the fraction of returning enrollees making active selections and/or switching plans across county-years. Across counties and years, the average share of plans available to consumers that are returning to the exchanges is 0.62.

Since the measures of re-enrollment activity are only available at the county-year level rather than by plan, I need to construct similarly aggregated measures of plan characteristic changes. I do this by weighting the change in each plan's premium (or other characteristic) by the plan's popularity in the previous year, averaging across all plans that are available in the county during both the current and previous year. For any plan characteristic x, the county-year level measure of changes to that characteristic for returning enrollees is

$$\Delta x_{ct} = \sum_{j \in J_{c,t,t-1}} (x_{jt} - x_{j,t-1}) \cdot \omega_{jc,t-1}$$

where ω_{jct} is a plan's enrollment share for a given county-year and $J_{c,t,t-1}$ is the set of plans available in county c in years t and $t-1$. The primary measure of returning consumer attention is the share of re-enrollees that make an active plan choice:

$$y_{ct} = \frac{ActiveReturningEnrollees_{ct}}{ReturningEnrollees_{ct}}.$$

Summary statistics for these county-year level exposures to plan changes are shown in Panel C. The popularity-weighted average change in premiums of returning plans has an average of \$38 and a standard deviation of \$50, with the full distribution shown in Figure A.3. The average across county-years for the fraction of returning enrollees experiencing a change to the tier structure of their default plan was 0.06.

4 Descriptive Evidence

I start the empirical analysis by examining whether and to what extent changes to the characteristics of returning plans are accompanied by higher levels of attention by returning enrollees. This analysis is done at the county-year level.

Returning consumer attention is measured by the percentage of returning enrollees that actively select a plan on the website rather than being automatically re-enrolled in their default plan. County-year level measures of changes to plan characteristics are constructed as described in Section 3. For county c in year t, $\Delta Premium_{ct}$ is the average change in the pre-subsidy premium from year $t-1$ to year t for all plans available in county c during both years, weighted by plan enrollment during year $t-1$ for the state containing county c. Similarly, the measure of exposure to changes in the use of tiered networks is the expected share of returning enrollees for a given county-year whose default option changed the tier structure of its provider network.

The relationship between premium changes experienced by returning enrollees and their propensity to make an active plan selection is shown in Figure 2. This figure is a binned scatter plot of the conditional mean of the active re-enrollment percentage for each bin of $\Delta Premium_{ct}$, where both variables are residualized and recentered using the method of Cattaneo et al. (2022). Specifically, these absorb county and year fixed effects and control for other potential attention shocks such as the fraction of plans in each observation that are returning from the previous year and changes to other plan features (e.g., network tiers, deductible amount, cost-sharing).[4]

[4]The raw relationship between premium changes and active re-enrollment is shows in Figure A.4. This shows an interesting but perhaps misleading symmetric relationship between premium changes (increases or decreases) and returning consumer attention. However, most of the within-plan premium declines occurred between the first and second year of the exchanges, when high levels of consumer attention may have been more related to the immaturity of the market rather than related to changes to plan features.

The relationship in Figure 2 provides suggestive evidence that premium increases act as an attention shock for returning customers. Active re-enrollment is higher in county-year observations where returning enrollees experienced premium increases on average for their default plan. Additionally, there is no evidence of differences in attention between observations with no change in returning plan premiums compared to those that experienced a decrease. This suggests premium changes are an asymmetric attention shock, increasing attention only when the change from the previous year is a "negative" from the consumer's perspective (i.e., a premium increase).

I extend this approach to examine other potential attention shocks, particularly changes in whether plans use a tiered provider network, by estimating regressions of the form

$$y_{ct} = \lambda_c + \tau_t + \beta_1 \, \Delta Premium_{ct} + \beta_2 \, |\Delta Tiered_{ct}| + \Delta X'_{ct}\gamma + u_{ct}.$$

Here λ_c are county fixed effects, τ_t are year fixed effects, $\Delta Premium_{ct}$ and $|\Delta Tiered_{ct}|$ are the premium and tiered provider network attention shocks described above, and $\Delta X'_{ct}$ is a vector of other county-year level attention shocks, including the fraction of plans that were available in the previous year.

Estimates from these regressions along with standard errors clustered by county are shown in Table 2. In Panel A, the dependent variable is the active re-enrollment percentage for each county-year. Focusing on Column 4, which includes the full set of controls and fixed effects, there is again evidence that both premium increases and changes to the tier structure of provider networks are associated with higher levels of attention from returning enrollees. The estimate $\widehat{\beta}_1 = 1.88$ implies that a \$100 average increase in the monthly pre-subsidy premium of returning plans (weighted by lagged enrollment) is associated with a 1.88 percentage point increase in active re-enrollment, which is a 2.7 percent increase over the mean active re-enrollment percentage of 67.3. The estimate $\widehat{\beta}_2 = 1.15$ implies that all plans changing the tier structure of their network is associated with a 1.15 percentage point increase in active re-enrollment.

In Panel B, the dependent variable is percentage of returning enrollees that switch plans from their default option. Although these estimates are smaller and not statistically significant, the sign of the estimates for both premium and tiered network changes suggest both make returning enrollees more likely to switch plans. This would be expected if consumers are more attentive and potentially become aware of plans that are superior to their default option.

While these results should not be interpreted as the causal effect of plan changes on consumer attention, they are consistent with the idea that alterations to plan characteristics do serve as attention shocks that affect the likelihood of returning enrollees automatically returning to their default option without considering alternatives. This is the case for not only salient plan characteristics like the base premium, but also for characteristics that are less easily observed but potentially important to consumers, in this case whether the plan uses a tiered provider network. Given the theoretical framework described in Section 2, the latter acting as an attention shock could have significant implications for the incentives of insurers when designing plans.

5 Empirical Model of Plan Choices

Motivated by the evidence in the prior section and the theoretical framework in Section 2, I develop a structural model of plan choices that can be estimated using the aggregate enrollment data for the ACA exchanges. The goal of this model is to jointly estimate the importance of plan changes for consumer inertia and consumer preferences over plan characteristics to determine the relative importance of the these channels for insurers when designing plan features. For example, a change to the characteristics of a plan will have a direct effect on plan choices through consumer preferences and also a potential indirect effect on the plan choices of returning consumers by making them more likely to actively shop for a plan instead of automatically re-enrolling in their default option. If this indirect effect is large relative to the direct effect, then attention/inertia responses are an important factor in insurers' incentives when redesigning plans with affiliated consumers. In the case of premium increases, returning enrollees being more likely to actively select a plan in response would mean these consumers are essentially more elastic than if inertia did not depend on changes to plan characteristics. For changes to the provider network, this would mean insurers would be more reluctant to exclude high-cost providers and may be limited in their ability to negotiate lower provider prices by threatening network exclusion.

Ideally, these would be separately identified by estimating a two-stage model of attention and plan choices that uses individual-level data on plan selections over time (Ho et al., 2017; Heiss et al., 2021). Given that I only observe aggregate plan enrollment, I take a different approach that is similar to Petrin (2002) and Berry et al. (2004) that uses the county-level OEP data on returning consumer re-enrollment activity and plan switching to help identify the inertia parameters. After obtaining estimates of the model parameters related to consumer preferences and inertia, I simulate counterfactuals aimed at understanding the relative importance of the indirect effect (via inertia) of plan changes on enrollment behavior.

5.1 Model

Due to data limitations on the level of observation of plan enrollment, I define a market m as a state-year. A consumer i in market m chooses between the J_m exchange plans offered in market m and an outside option (health insurance not through an exchange plan or being uninsured). Her indirect utility from choosing plan $j \in J_m$ is given by

$$u_{ijm} = \underbrace{X'_{jm}\beta + \xi_{jm}}_{\delta_{jm}} + Z'_{ijm}\kappa + \varepsilon_{ijm}.$$

The vector X_{jm} includes plan characteristics such as the pre-subsidy premium for a 50 year-old, whether the plan has a tiered provider network, the plan type (HMO/PPO), and the metal level categorizing plan generosity based on actuarial value, plus a constant for each year capturing the value of the outside option and issuer (firm-state) fixed effects. ξ_{jm} is an unobserved demand shock at the plan-market level that does not vary across consumers, while ε_{ijm} is a Type 1 Extreme Value idiosyncratic taste shock.

Inertia is modeled as an incremental benefit associated with remaining in the same plan as in the previous year. This does not distinguish between different underlying mechanisms for inertia, but captures both avoiding adjustment costs from switching insurers and the possibility of avoiding search costs by automatically re-enrolling with a default option. The parameter κ is a vector governing inertia that depends on a vector of potential attention shocks Z_{ijm}. Specifically, for returning plans Z_{ijm} is a vector of a constant, the increase in premium from the previous year $\Delta^+ P_{jm} = \max\{premium_{jst} - premium_{j,s,t-1}, 0\}$, and an indicator for whether the tier structure the plans network is changed from the previous year $|\Delta Tier_{jm}|$, all interacted with an indicator for whether individual i was enrolled in plan j during the previous year:

$$Z_{ijm} = 1(j = y_{i,t-1}) \cdot \begin{pmatrix} 1 \\ \Delta^+ P_{jm} \\ |\Delta Tier_{jm}| \end{pmatrix}$$

For new plans, $Z_{ijm} = 0$ for all individuals.

The market share for plan j in market m can then be written as

$$s_{jm} = \int \frac{\exp(\delta_{jm} + Z'_{ijm}(y_{i,t-1})\kappa)}{1 + \sum_k \exp(\delta_{km} + Z'_{ikm}(y_{i,t-1})\kappa)} d\, F(y_{i,t-1}),$$

which is the predicted market shares for each affiliation state integrated over the affiliation weights. The affiliation weights for each market $\gamma_m \in \mathbb{R}^{J_m+1}$ are determined by the distribution of lagged plan choices $y_{i,t-1}$ and the set of plans available in the current year. For each plan $j = 1, ..., J_m$,the affiliation share γ_{jm} is the number of enrollees for plan j in the previous year (which is zero if plan j is not a returning plan) divided by the market size M_{st}. The unaffiliated weight γ_{0m} is the fraction of individuals in the market who were not previously enrolled in a returning plan.

$$\gamma_{jm}=\begin{cases} \frac{enrollment_{j,s,t-1}}{M_{st}} & j = 1, ..., J_m \\ 1 - \sum_{j=1}^{J_m} \gamma_{jm} & j = 0 \end{cases}$$

To most accurately construct the affiliation weights without data on individual plan choices, I define the market size as the number of new enrollees (which is observed in the OEP data) plus total enrollment in the state during the previous year. This may bias the estimates of parameters related to the value of exchange plans relative to the outside options, but I am primarily interested in modeling the decisions of consumers returning to the exchanges with a default option.

For any value of the parameters $\theta =(\beta, \xi, \kappa)$, the model gives predicted choice probabilities for each of the $J_m + 1$ affiliation states for all J_m plans in the market. For a given market (dropping the m subscript), these make up the $J \times J + 1$ matrix $\hat{S} = S(X, Z, \theta)$ where the element in row j and column k is $\hat{s}_{jk}$, which is the probability that someone with affiliation state k chooses plan j.

$$\hat{s}_{jk} = \begin{cases} \frac{\exp(\delta_j)}{1+\exp(\delta_k+Z_k'\kappa)+\sum_{j'\neq k}\exp(\delta_{j'})} & j \neq k \\ \frac{\exp(\delta_j+Z_j'\kappa)}{1+\exp(\delta_j+Z_j'\kappa)+\sum_{j'\neq j}\exp(\delta_{j'})} & j = k \end{cases}$$

Given a $J + 1 \times 1$ vector of affiliation weights γ, then $\hat{S} \cdot \gamma$ gives the $J \times 1$ vector of predicted market shares for each alternative.

5.2 Estimation

The model is estimated using the generalized method of moments. It adapts the "micro BLP" approach (Petrin, 2002; Berry et al., 2004) for demand estimation to a unique type of auxiliary data on individual choices. The primary estimation challenge is separately identifying β, which are the parameters governing individual preferences over plan characteristics, from κ, which are the parameters governing inertia. The inertia parameters capture how much of a utility bump returning enrollees obtain from remaining with their previous plan choice and how this incremental utility bump varies as a function of changes to plan characteristics.

I use the county-level OEP data to construct targeted "micro-moments" that match market-level plan switching rates predicted by the model, which are implied by the values of the off-diagonal entries of $S(X, Z, \theta)$, to those observed in the data. These micro-moments also attempt to match the covariance between plan-level changes in characteristics (for returning plans) with the fraction of returning enrollees that switch plans in the given market. Specifically, these additional (sample) moment conditions are

$$\frac{1}{M}\sum_{m=1}^{M}\widehat{switch}_m - \frac{1}{M}\sum_{m=1}^{M} switch_m = 0$$

$$Cov(\widehat{switch}, \Delta P) - Cov(switch, \Delta P) = 0,$$

$$Cov(\widehat{switch}, \Delta Tier) - Cov(switch, \Delta Tier) = 0$$

where $switch_m$ is the observed fraction of returning enrollees that switch plans away from their default option in market m, $\widehat{switch}_m$ is the model prediction for this fraction at a given value of the parameters, $switch$ and $\widehat{switch}$ are vectors collecting these fractions for each plan-market observation, and ΔP, $\Delta Tier$ are vectors of plan characteristic changes at the plan-level as described above in Section 5.1.

These micro-moments are stacked in the estimation routine with the sample analogue of the moment condition

$$E[\xi_{jm} Z_{jm}] = 0$$

where ξ_{jm} is the unobserved demand disturbance and Z_{jm} is a $1 \times K$ vector of instruments. The set of instruments Z_{jm} includes all non-premium plan characteristics included in the utility specification. The excluded instrument that I use for plan premiums is the average affiliation share of all competing plans in a market.[5] The motivation for this instrument comes from how insurer pricing incentives are affected by consumer inertia with default options. If a plan is competing against only new plans (so the average competitor affiliation share is zero), the number of individuals making an active choice between plans will be higher than when most plans are returning. If the variation in this instrument comes mostly from the national strategies of large insurers in the ACA exchanges, this would

[5] Tebaldi (2022) and Saltzman (2019) provide more convincing instruments that leverage regulation-induced variation in base premiums and post-subsidy premiums at the individual level. For instance, Tebaldi (2022) uses Waldfogel instruments that are motivated by the age-adjusted community rating regulation on the exchanges. Unfortunately, these approaches require individual-level data on plan choices.

lead to exogenous variation in the composition of new and returning plans competing in different markets. However, a natural concern with this instrument is that competitors entry and exit decisions in the previous period determine the average affiliation share of competitors in the next period, and these entry and exit decisions may be correlated with ξ_{jm}.

5.3 Results

Results from the estimation are shown in Table 3. The top panel shows estimates for the inertia parameters and selected preference parameters. The bottom panel shows the annual switching costs for a returning consumer with a default option implied by the model parameters with different subsidy amounts and changes to the characteristics of their default option.

The estimate for κ_0 of 3.08 indicates significant inertia in the absence of any changes to premiums or the tier structure of the provider network for individuals default option, as this implies the utility gain from remaining in the same plan is roughly equivalent to a \$300 decrease in the monthly base premium. However, the estimate for κ^P implies that this utility gain from remaining in the same plan is almost 80 percent lower if the plan increases the monthly base premium by \$100 from the previous year. One possible explanation for this is that much of the observed inertia is a result of consumer inattention, with substantial premium increases acting as an attention shock. The level of inertia is hardly affected by changes to the tier structure of the provider network, as the estimate for κ^N is near zero. This suggests that altering the provider network has little impact consumer attention, at least in the current period.

The main preference parameter to note is the sign of the parameter on the value of a tiered provider network. This indicates that consumers prefer a tiered network to non-tiered networks, suggesting that tiered networks are in most cases more broad than alternative provider networks. Given the prevalence of narrow networks on the exchanges, this is unsurprising since tiered networks offer at least partial coverage at some providers rather than the full exclusion of many providers in narrow networks.

Based on the estimated parameters, specifically the inertia parameters the the preference parameter on monthly base premiums, individuals are willing to pay almost \$4,000 per year to stay in their current plan rather than switching to an alternative with the exact same characteristics if all consumers received no premium subsidies. Since most enrollees pay significantly less than the base premium after subsidies, this overstates the true switching costs. Assuming individuals pay half of the base premium after subsidies, which still may overstate consumer expenditure on premiums (Tebaldi, 2022), the estimates imply the annual switching cost is roughly \$2,000. With the same subsidy amount, the annual switching cost falls to \$415 if the individual's previous plan increases the monthly base premium by \$100 from the previous year. This means the consumer is only willing to pay \$415 to remain with their current plan rather than switching to an alternative with the exact same characteristics as their default option does *after* the premium increase. As would be expected given the estimate for κ^N, annual switching costs only decrease slightly if an individual's previous plan changes the tier structure of the provider network.

5.4 Counterfactuals

To understand the effect of consumer attention responses to changes in the base premium or tiered network of their default options, I conduct two counterfactual simulations. Each counterfactual involves altering the characteristics of a single plan in a given market and simulating enrollment choices using the estimates from the structural model. To isolate the indirect effect of these plan changes through changes to inertia/attention, I simulate choices for two different sets of parameters for each counterfactual: once with the exact estimates for all parameters and once with the relevant inertia response parameter (κ^Por κ^N) set to zero depending on the characteristic that is altered for the counterfactual. As would be expected from the parameter estimates in Section 5.3, the indirect effect of premium changes on enrollment choices through inertia is meaningful relative to the direct effect through preferences while the indirect effect of tiered network changes is negligible.

For the first counterfactual, I increase the monthly base premium by 5 percent for the largest (by lagged enrollment) returning plan in each state for the final year observed in the data. I then simulate enrollment choices for the markets with an affected plan, first using the full set of estimates from the structural model and then setting $\kappa^P = 0$ to shut off the inertia response to premium increases. For the set of affected plans that have a premium increase in the counterfactual, the distribution of the absolute change in market share under the counterfactual relative to the baseline from the actual data is shown in Panel (a) of Figure 3. The shift to the right of the distribution of these enrollment declines when κ^P is set to zero suggest that a large part of the enrollment responses to the premium increase of affected plans comes from lower inertia following the premium increase rather than just from the direct effect through preferences. As shown in Table 4, plans affected in the counterfactual experience a 35 percent decline in enrollment on average following the 5 percent premium increase with both inertia and preference responses, but this falls to a 19 percent average enrollment decline when the inertia response is removed. Total enrollment in the affected plans declines by 31 percent relative to baseline when choices are simulated using the estimated inertia parameters but only declines by 16 percent relative to baseline when $\kappa^P = 0$. This suggests that roughly half of the total enrollment decline following the premium increase of affected plans is due to the inertia response.

For the second counterfactual, I change the largest returning tiered network plan in each state during the final year of the data to a non-tiered provider network, which the estimates from Section 5.3 imply is a change that is disliked by consumers and would lead to enrollment declines all else equal. In this case, I simulate enrollment choices both at the estimated parameters and with κ^N set to zero to eliminate the inertia response from the network change. Unsurprisingly given the small absolute size of the estimate for κ^N, enrollment at affected plans is only slightly higher when the inertia response is shut off as shown by the overlap in Panel (b) of Figure 3. Total enrollment at plans affected by the counterfactual declines by 8.7 percent with the inertia response and 8.1 percent with the inertia response removed.

6 Conclusion

In this paper, I test whether consumers with a default option for health insurance become more attentive in response to plan changes. I focus on attention responses to changes in two important plan characteristics for my empirical setting: the monthly base premium of each plan and whether the plan uses a tiered provider network. Attention responses to the latter would have important implications for provider access and prices in markets where insurers bargain with providers over network inclusion and reimbursement rates.

The empirical setting that I study is the individual health insurance exchanges established under the ACA. Using data on the enrollment activity of individuals returning to the market with their previously chosen plan as a default option, I find a strong association between county-level exposure to changes in these plan characteristics and the likelihood that returning enrollees make an active plan selection rather than being automatically re-enrolled in their default option. I estimate that a $100 average increase in the monthly pre-subsidy premium of returning plans (weighted by lagged enrollment) is associated with a 1.88 percentage point increase in active re-enrollment, which is a 2.7 percent increase over the mean active re-enrollment percentage of 67.3. For the use of tiered provider networks, I estimate that all plans changing the tier structure of their network is associated with a 1.15 percentage point increase in active re-enrollment.

I then estimate a structural model of plan choices that includes consumer inertia which varies based on the magnitude of changes to an individual's default plan. Estimates from the model show that consumers exhibit significantly lower switching costs when their previously chosen plan increases premiums compared to the prior year, but switching costs are mostly unaffected by a change to the tier structure of the provider network of their default option. Counterfactual simulations reveal that roughly half of the decline in enrollment for plans that raise premiums by 5 percent would come from reduced switching costs rather than directly through consumer preferences for lower premiums.

These results suggest that insurers in this market may have significantly less market power over returning enrollees than would be implied by estimates from models that do not account for inertia or attention responses to premium increases. They also suggest that attention responses to changes in provider networks may have little effect on the incentives of insurers to use selective contracting to lower input costs, at least for this specific example of insurers implementing tiered provider networks. In future research, I intend to use more granular data on individual plan choices and more detailed data on the composition and breadth of provider networks to provide a more definitive answer to this question.

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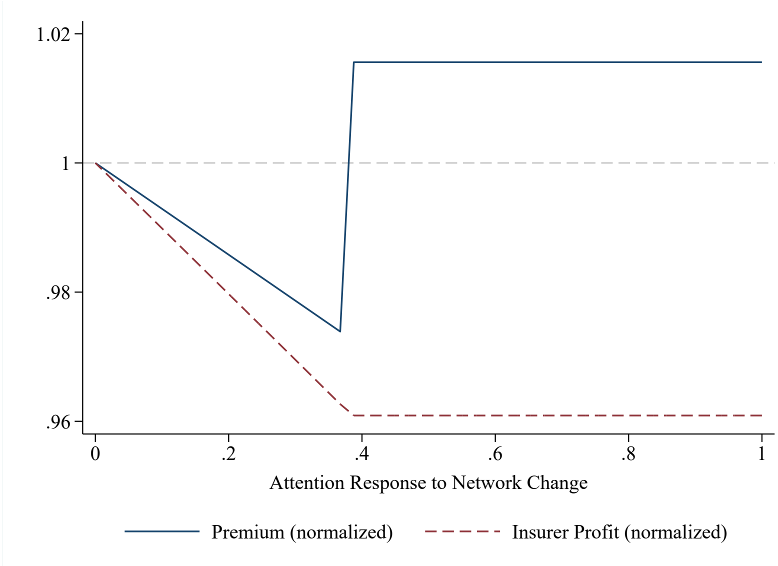
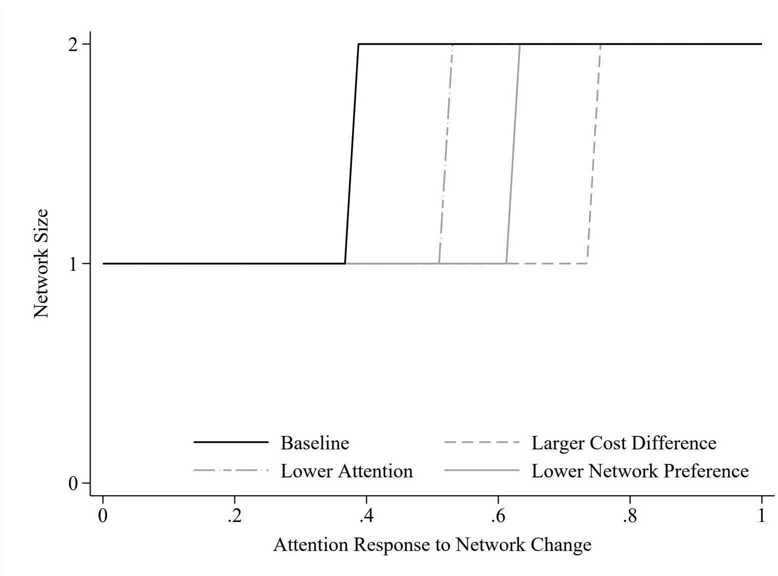
Figures and Tables

Figure 1: Theoretical Framework: Numerical Examples

(a) Insurer Outcomes with Varying Attention Response

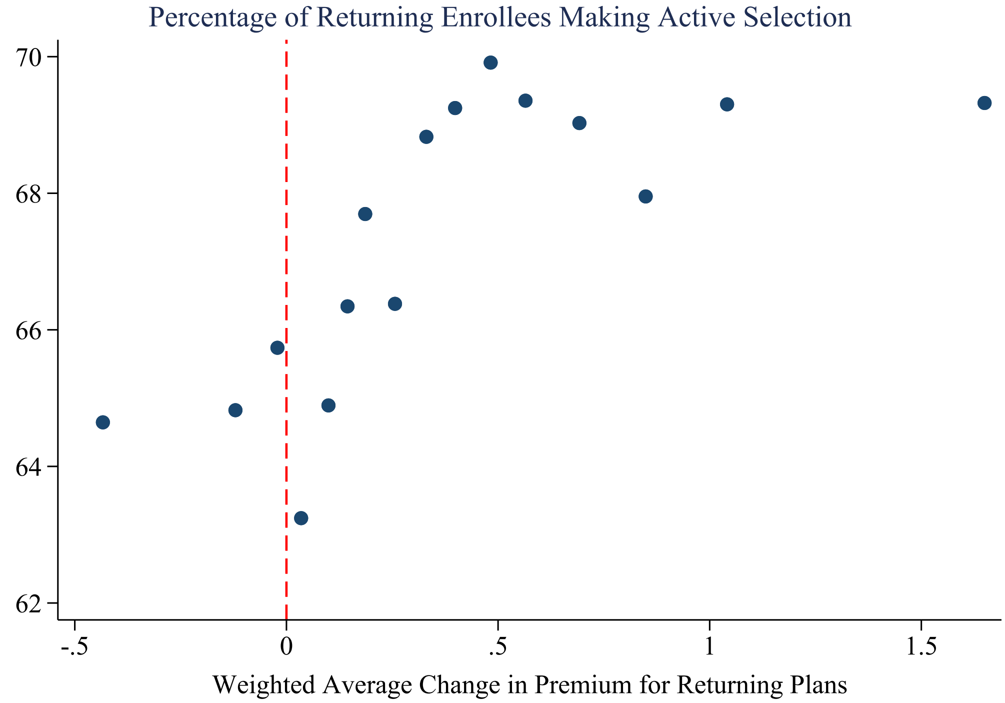


(b) Optimal Network Size



Notes: Panel (a) shows insurer profit and optimal premium with different values of consumer attention response to changes in network value ($x = -\alpha^N$), relative to no attention response ($x = -\alpha^N = 0$) . Panel (b) shows insurer's optimal network size (whether to exclude the high-cost provider B or not) for different values of consumer attention response to changes in network value. "Baseline" is the same as Panel (a). "Lower Attention" scenario decreases the overall attentiveness of consumers (decrease in α_0) relative to baseline. "Larger Cost Difference" increases the relative cost of providers (increase in $C_B - C_A$) relative to baseline. "Lower Network Preference" scenario decreases the importance of network value relative to other factors in consumer tastes (decrease in β_2) relative to baseline.

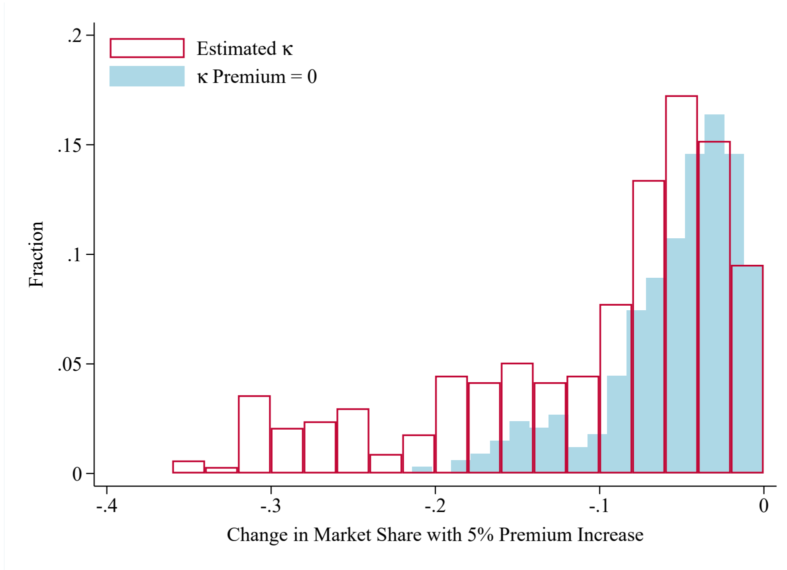
Figure 2: Premium Changes and Active Re-Enrollment



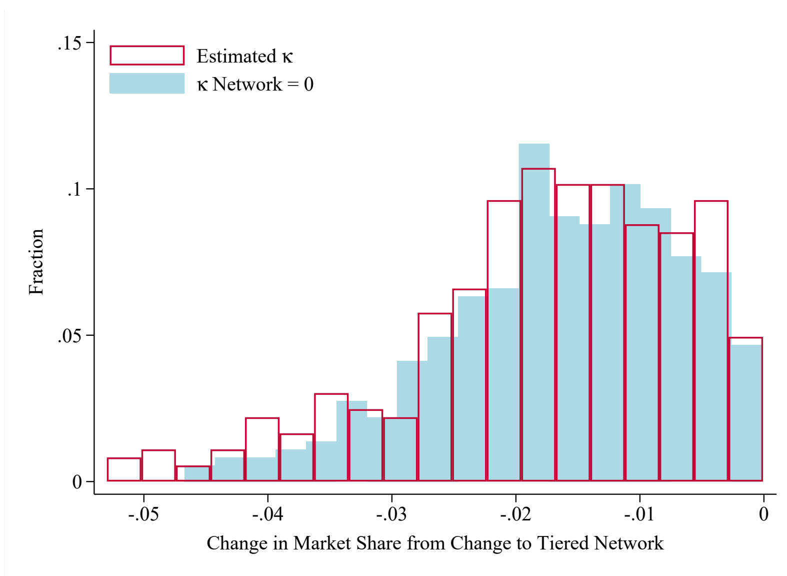
Notes: Unit of observation is a county-year. Sample is all counties in FFM states from 2015-2020. Figure shows conditional mean of dependent variable for each bin of the independent variable, which are residualized and recentered using the method of Cattaneo et al. (2022). Controls include the fraction of plans that are returning, changes to other financial plan features (deductible, cost-sharing), plus county and year fixed effects

Figure 3: Counterfactuals

(a) 5% Increase in Base Premium



(b) Change to Tiered Network



Notes: Each figure shows the difference in market share for affected plans between the counterfactual simulation and the observed data. In panel a), the base premium of the largest returning plan in each state for the final year in the data is increased by 5 percent over the observed premium. In panel b), the largest returning plan in each state during with a tiered network in the previous year is changed to a non-tier network for the final year of the data. For each counterfactual, I simulate market outcomes assuming consumers behave according to the estimated parameters and assuming no attention response (κ^Por κ^N set to zero).

Table 1: Summary Statistics

	N	Mean	SD	10th	50th	90th
Panel A: All Plans						
Premium ($100s)	7943	5.66	1.76	3.70	5.28	8.08
1(Tiered)	7943	0.16	0.37	0.00	0.00	1.00
1(Returning Plan)	7943	0.45	0.50	0.00	0.00	1.00
Plan Age	7943	1.82	1.20	1.00	1.00	3.00
Panel B: Returning Plans						
Premium ($100s)	3598	6.13	1.79	3.99	5.99	8.51
1(Tiered)	3598	0.18	0.38	0.00	0.00	1.00
$\Delta Premium$	3598	0.69	0.83	0.00	0.40	2.00
$\lvert\Delta Tiered\rvert$	3598	0.05	0.22	0.00	0.00	0.00
Plan Age	3598	2.81	1.17	2.00	2.00	5.00
Panel C: Counties						
Re-Enrollees Active (%)	11853	67.31	10.68	53.42	68.40	79.47
Re-Enrollees Switch (%)	6228	29.00	13.06	14.78	26.48	46.56
Avg. $\Delta Premium$	11853	0.38	0.50	-0.09	0.30	1.01
Avg. $\lvert\Delta Tiered\rvert$	11853	0.06	0.28	0.00	0.00	0.23
Returning Plan Share	11853	0.62	0.25	0.29	0.63	0.96

Notes: For Panel A and Panel B, the unit of observation is a state-year-unique plan. For Panel C, the unit of observation is a county-year. The sample for Panel A is all "Silver" tier plans offered on the FFM state exchanges from 2014-2020. The sample for Panel B is limited to returning plans. The sample for Panel C is all counties in FFM from 2015-2022. The county-year level (weighted) average changes in plan characteristics are calculated as described in Section 3.

Table 2: Regression Results: Plan Changes and Returning Enrollee Attention

	(1)	(2)	(3)	(4)
Panel A: Active Re-enrollment Percentage				
$\Delta Premium_{ct}$	1.91***		1.84***	1.88***
	(0.178)		(0.181)	(0.182)
$\lvert\Delta Tiered_{ct}\rvert$		1.13***	0.84**	1.15***
		(0.287)	(0.293)	(0.301)
Returning Plan Share				-1.52***
				(0.332)
$\Delta Deductible_{ct}$				0.012
				(0.0212)
$\Delta OoNCoinsurance_{ct}$				-0.021***
				(0.00350)
Constant	66.6***	67.2***	66.5***	67.1***
	(0.0681)	(0.0290)	(0.0710)	(0.215)
Observations	11810	11810	11810	11810
Panel B: Re-Enrollee Switching Percentage				
$\Delta Premium_{ct}$	1.52***		1.39**	0.83
	(0.436)		(0.456)	(0.482)
$\lvert\Delta Tiered_{ct}\rvert$		1.22*	0.83	0.56
		(0.589)	(0.622)	(0.647)
Returning Plan Share				-6.91***
				(0.892)
$\Delta Deductible_{ct}$				-0.36***
				(0.0554)
$\Delta OoNCoinsurance_{ct}$				-0.010
				(0.00740)
Constant	28.4***	28.7***	28.3***	33.8***
	(0.150)	(0.0851)	(0.159)	(0.682)
Observations	5885	5885	5885	5885
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses are clustered by county. Unit of observation is a county-year. Sample is all counties with any returning plans in FFM states from 2015-2020 (2018-2020 for Panel B). ** p<0.05 ** p<0.01 *** p<0.001*

Table 3: Parameter Estimates for Empirical Model of Plan Choices

Parameter	Estimate	Standard Error
Inertia		
κ_0	3.08	0.0388
κ^P	-2.42	0.0263
κ^N	-0.042	0.0093
Preferences		
Monthly Pre-Subsidy Base Premium ($100)	-0.954	0.0701
Tiered Provider Network	0.249	0.0956
Deductible Amount ($100)	0.0024	0.0019
Inpatient Out-Of-Network Coinsurance	0.0014	0.0012
Plan Type = PPO	-0.545	0.1119
Plan Type = HMO	-0.955	0.0942
Plan Type = POS	-1.032	0.1333
Annual Switching Costs		
No Subsidy		$3,877
50% Subsidy		$1,939
50% subsidy, $100 increase in base premium		$415
50% subsidy, change to tiered network		$1,912

Notes: See Section 5 for details on model and estimation. Annual switching costs calculated as $-12 \cdot \frac{\kappa_0}{\beta^P} \cdot \$100 \cdot subsidy$ if no change to default option.

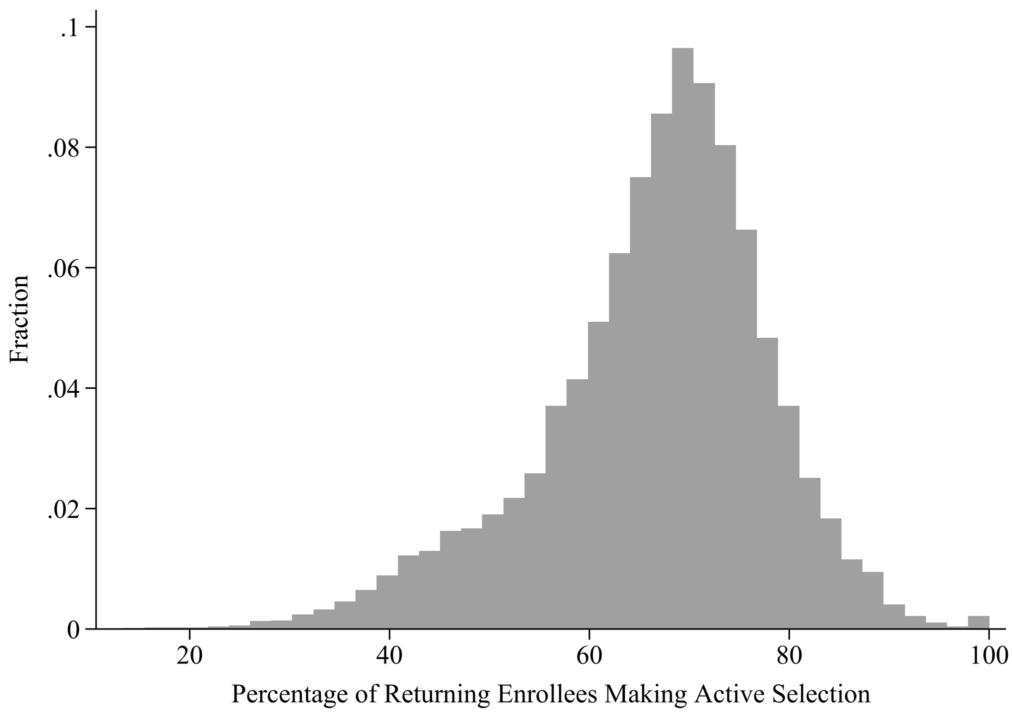
Table 4: Counterfactuals

	(1) 5% Premium Increase	(2) Change to Non-Tiered
Average Δ Market Share		
Estimated Parameters	-0.10	-0.018
No Attention Response	-0.05	-0.016
Average $\%\Delta$ Market Share		
Estimated Parameters	-0.35	-0.114
No Attention Response	-0.19	-0.110
Total Enrollment Relative to Baseline		
Estimated Parameters	0.69	0.913
No Attention Response	0.84	0.919

Notes: Table shows changes in outcomes between counterfactual simulations and observed data for plans with characteristics changed under the counterfactual. For counterfactual 1), the base premium of the largest returning plan in each state for the final year in the data is increased by 5 percent over the observed premium. For counterfactual 2), the largest returning plan in each state during with a tiered network in the previous year is changed to a non-tier network for the final year of the data. For each counterfactual, I simulate market outcomes assuming consumers behave according to the estimated parameters and assuming no attention response (κ^P or κ^N set to zero).

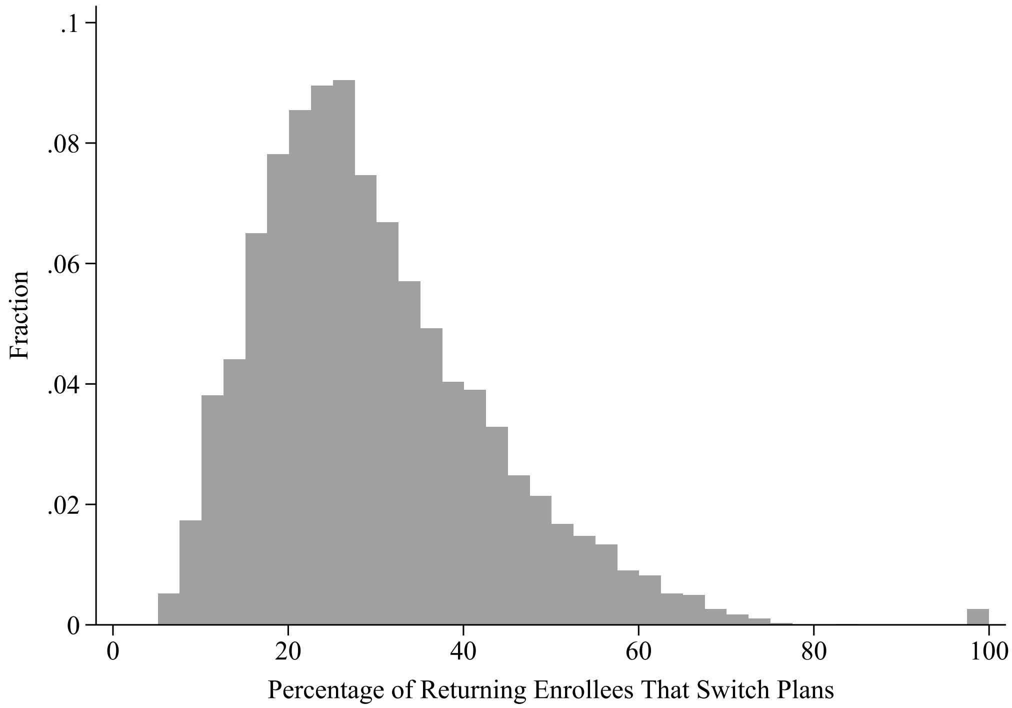
A Other Figures and Tables

Figure A.1: Distribution of Active Re-Enrollment Percentages



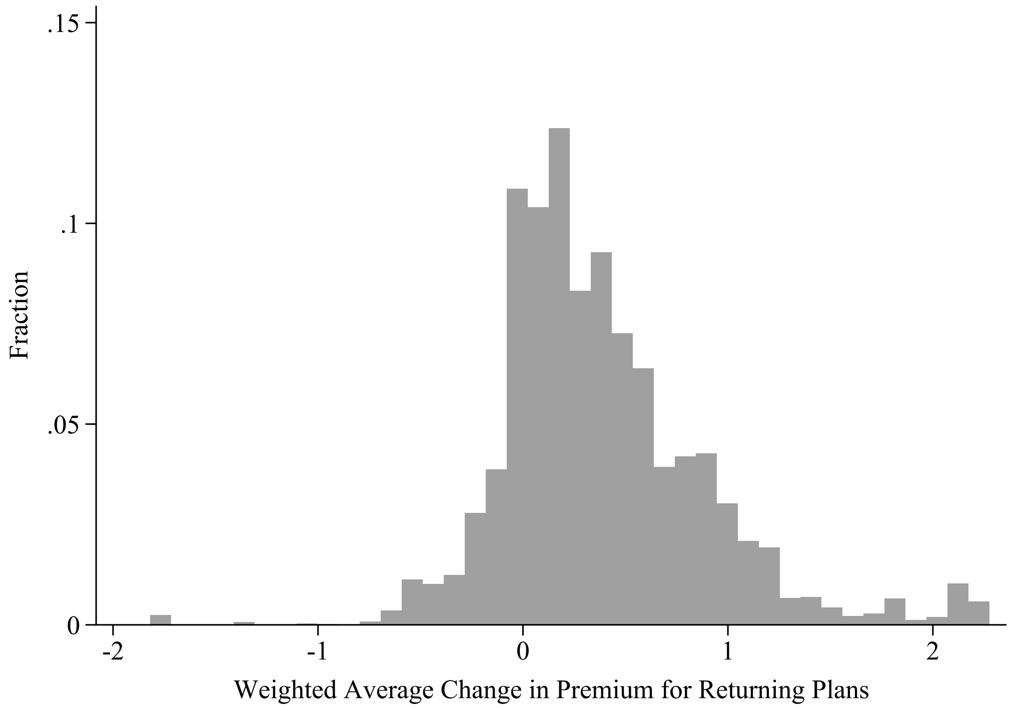
Notes: Data source is the County Open Enrollment Period Public Use Files. Unit of observation is a county-year. Sample covers all counties in FFM states from 2015-2020.

Figure A.2: Distribution of Plan Switching Percentages



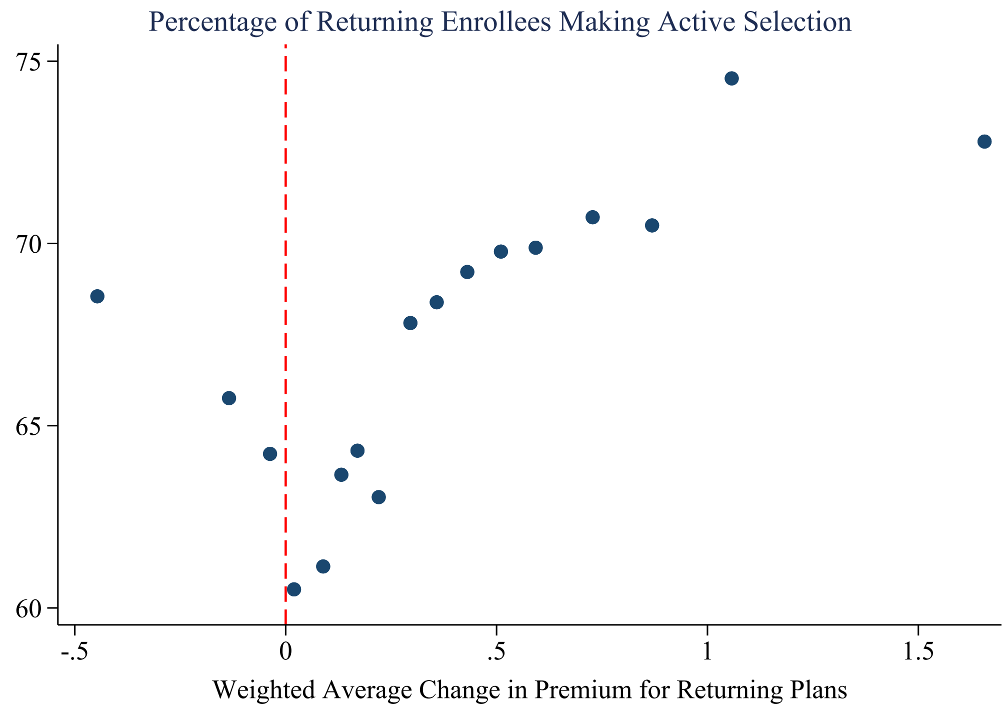
Notes: Data source is the County Open Enrollment Period Public Use Files. Unit of observation is a county-year. Sample covers all counties in FFM states from 2018-2020.

Figure A.3: Distribution of Average Returning Plan Premium Changes



Notes: Calculated from data on plan enrollment and premiums for returning plans, as described in Section 3. Unit of observation is a county-year. Sample covers all counties in FFM states from 2015-2020.

Figure A.4: Premium Changes and Active Re-Enrollment, No Controls



Notes: Unit of observation is a county-year. Sample is all counties in FFM states from 2015-2020. Figure shows mean of dependent variable for each bin of the independent variable.