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Essays in Health Economics

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in

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by

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2024

The Dissertation of Zachary Christian Hall is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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ABSTRACT OF THE DISSERTATION

Essays in Health Economics

by

Zachary Christian Hall

Doctor of Philosophy in Economics

University of California San Diego, 2024

Professor Jeffrey Clemens, Chair
Professor Itzik Fadlon, Co-Chair

This work examines consumer and producer responses to market dynamics resulting from various policy changes in the individual health insurance market under the Affordable Care Act (ACA). Chapter 1 investigates dominated plan choice manifesting as inertia in California, finding that fewer than 40% of enrollees who should switch plans do so. Further, this chapter examines the relationship between these choice errors, publicly available enrollment assistance, and active plan choice. Chapter 2 delves into nationwide pricing dynamics that result in two pricing anomalies: dominated plan choice and free plans. I find robust evidence of dominated plan choice and suggestive evidence of inertia. Chapter 3 documents and analyzes changes to

Essential Health Benefits, which serve as benefit mandates, and examines margins that insurance issuers adjust their plans in response to being bound by these mandates. These margins include changes to premiums and cost-sharing structure. I find that insurance issuers who are newly bound to these benefit mandates increase premiums by 2% per benefit relative to those who already provided them.

Chapter 1

Costly Inertia, Information Frictions and Enrollment Assistance: Evidence using Dominated Plan Choice in the California Individual Health Insurance Market

In 2018, a federal legal decision regarding the Affordable Care Act (ACA) individual market fostered a natural experiment during which premiums for health insurance plans with mid-tier coverage exceeded those with high-tier coverage for middle-to-high income enrollees. In California, this put nearly 35,000 individuals at risk of re-enrolling in a previously chosen plan that was now dominated by a lower-premium, higher-coverage plan. I study a clean case of inertia and other choice errors by examining choice of this plan throughout the state: 64.3% of these enrollees remain in the dominated plan. These inert individuals forgo at least $5 million in aggregate, or $320 per full-year enrollee, though the actual consumer loss is larger for most enrollees and affects a larger subset of enrollees. I also examine how seeking help in the form of government or corporate (issuer-based) assistance interacts with this behavior. Overall, governmental help is associated with the lowest rates of inertia, though corporate assistance corresponds to marginally better outcomes as well. Given that unassisted enrollees make an active choice only 40% of the time, much of this difference is driven by attention differences between the assisted and unassisted. No form of assistance fully or nearly eliminates these choice errors that are clear ex-ante. Given higher rates of assistance among groups with higher inertia

rates, assistance is associated with amelioration of disparities across demographic groups. Finally, I find evidence that enrollees with low health insurance literacy are those who generally receive help; yet, there is also likely selection into seeking assistance as a response to observing that silver plans were dominated.

The process of selecting a health insurance plan is one that is rife with uncertainty about future health care utilization and difficulty understanding how two health insurance plans will differ given variation in this utilization. Whether it be the misvaluing of healthcare services (Baicker et al., 2015), an excess of choices on a plan menu (Schram & Sonnemans, 2011), improper weighting of plan characteristics (Abaluck & Gruber, 2011), or simple lack of understanding of health insurance (Collier & Williams, 2022), inefficient plan choice may lead to direct loss among enrollees, including those with low incomes or high healthcare costs. An oft-studied manifestation of behavioral failure in this realm is inertia in plan choice. I contribute to this literature by measuring the frequency of dominated plan choice and quantifying its cost to beneficiaries in an important setting, namely the individual marketplace in the state of California, the second largest market for individual health insurance in the United States. Furthermore, I examine whether information interventions provided by both government and corporate entities play a role in mitigating plan choice stickiness that leads to undesirable outcomes.

The landscape of health insurance markets across the United States shifted dramatically beginning in 2010 with the passage of the Affordable Care Act (ACA). Colloquially referred to as "Obamacare", this sweeping piece of legislation intended to, and did, lead to increased accessibility and affordability (Frean et al., 2017), including in California, which chose to operate their own health insurance exchange. Besides a unified interface for comparing and choosing plans, the California marketplace also provided or otherwise facilitated additional resources for aiding plan choice and combating information frictions commonly associated with health insurance decisions. These included government-funded service centers (available via telephone and internet) and in-person enrollment counselors, also known as Navigators, as well as resources provided by the health insurance issuers themselves, namely certified insurance agents.

At the heart of this paper lies a 2018 case study on plans offered by Kaiser, a prominent health insurer in the California individual health insurance market, responsible for covering the second highest number of enrollees across California. While the decision to purchase health insurance generally involves some trade-off between upfront costs (premiums) and marginal costs for additional utilization of health services (cost-sharing), two plans offered in this year violated this norm; specifically, when comparing the two plans, one plan provided both a lower premium *and* cost sharing that is more beneficial to the consumer. More strictly speaking, the choice of one plan *dominated* the other, meaning that at all states of healthcare utilization, total expenditure on health services (premiums plus total cost-sharing) would be lower under one plan as compared to the other (see Figure 1.1). Importantly, this strict dominance could be established because the two plans came from the same *insurance product*, meaning that other possible differences between plans, including networks, plan benefits, benefit limits, and healthcare issuer, were identical between the two plans. Thus, the *only* differentiation between the two plans were financial characteristics, meaning dominance of choice could be established regardless of consumer characteristics.

Because of this unique situation, identification of a choice mistake in this setting does not require a measure of risk preferences, network or physician preferences, or health care utilization actualizations/expectations. Thus, unlike settings that require assumptions and models to quantify/document inertia, this natural experiment provides a clean setting that allows a nonparametric methodology to be employed, using a simple proportion calculation. From a neoclassical perspective, all enrollees should avoid this dominated plan, including those who were enrolled in the plan in the previous year. Still, nearly 65% of enrollees remain in this dominated plan, giving up $27 per month in premiums on average. These inert enrollees account for at least $5 million in consumer loss from premiums alone; this amounts to $269 per inert enrollee per year or $320 for those who were enrolled the entire calendar year. An additional $800,000 of consumer welfare loss, or $207 per enrollee, was incurred due to choice mistakes by individuals who had not previously chosen this newly dominated plan. Because the government subsidizes lower-income families, inert enrollees also contributed to a minimum of $186,000 in additional government spending, amounting to $9.9 per inert enrollee. Overall, this means that at least $6.38 million in total loss to consumers/government was incurred; this loss was seen as an equal and opposite increase in revenue for Kaiser. This consumer/government loss (and issuer gain) is only made more severe for those with non-zero healthcare utilization.

Heterogeneity in inertia rates across demographic strata reveal disparities that, from a policy perspective, have distributional implications and may need tempering. As age increases, at-risk enrollees are more likely to remain in their dominated plan despite both facing larger total and relative potential savings of switching and having a higher likelihood of requiring and utilizing costly health procedures. Those above age 55 are nine percentage points more likely to remain in the dominated plan compared to those under 35. Lower income enrollees below 400% of the federal poverty line are also most likely to remain in their plan, and are about nine percentage points more likely to be inert than those above 400% FPL. Finally, Hispanic enrollees are about 3 percentage points more likely than white enrollees to be inert.

Given the prevalence of costly choice errors in this important setting, it is relevant to understand whether external provision of information is associated with reduction of costly choice errors and to what extent this relationship can be characterized as causal. Among all types of "assistance," the modal group is those who are unassisted, making up for 47% of at-risk enrollees, followed by those receiving help from a certified insurance agent (35%), service center representative (14%), and Navigator (3%). While over 70% of unassisted enrollees are inert, fewer than 45% of those receiving government help remain in the strictly dominated plan; those receiving "private" assistance from an insurance agent are inert 65% of the time. These figures indicate that service channels do not eliminate costly inertia entirely. These relationships are consistent when splitting the data by race/ethnicity, income, and age while controlling for geographic variation.

A heterogeneity analysis on differences in costly inertia across different types of assistance reveals a few patterns. Firstly, generally speaking, demographic groups with higher levels of observed inertia are more likely to receive help. Across race/ethnicity, Asian enrollees see the smallest decrease in inertia associated with receiving either type of help, while Hispanic enrollees see the greatest. Across age groups, corporate help is associated with greater reductions in inertia rate for enrollees over 45 than those under 45. Finally, effects across income groups are not heterogeneous, though receipt of some subsidy, which is tied to income level, does render heterogeneous responses. Because generally demographic groups with higher levels of baseline inertia are those receiving more help, simple counterfactual exercises show that this pattern of higher utilization of assistance channels moderately decrease disparities across race/ethnicity and age groups despite somewhat minimal heterogeneity in treatment effects.

Despite measuring a reduction in inertia associated with various service channels, these measures are not causal, as service channel is not randomly assigned. Threats to identification include the fact that assistance in the previous year is predictive of current assistance channel; this relates to selection concerns, both generally (reflective of health insurance literacy) and acutely (as a response to the natural experiment). To address this, I examine how switching behavior is associated with differential outcomes. I find evidence that those who switched into receiving government help are not necessarily better off than those who already were; however, those who switched into receiving private help are nearly 30 percentage points less likely to be inert than those who were already receiving corporate help. Finally, I consistently find that those who previously received assistance of *any* kind but are now unassisted are more likely to be inert than those who remain unassisted. These results do not substantially vary across race/ethnicity, age, or income groups.

These results on switching behaviors' interaction with inert behavior reveal a few things. Lack of large differential findings between those newly receiving government help and those already receiving government help is consistent with slight evidence for selection of assistance as a response to exposure to dominated plan choice. With this in mind, differential findings with respect to corporate help lend credence to differential care given to new clients rather than acute consumer selection into receiving this assistance. Considering high retention rates of consumers in non-governmental help (>95%), insurance agents may lack the incentive to revise plan choice on a yearly basis, leading to millions of dollars of consumer loss. The final finding that newly unassisted enrollees are measurably worse off than those who were previously unassisted is consistent with the notion that, generally, low literacy types seek out government help. This also indicates that the slight differentiation between new and existing receivers of government help may be driven by one's type, as those previously unassisted are marginally better off. A final implication of these findings is that insight gained from information received from assistance channels is not persistent across enrollment years. Thus, consistent, effective yearly assistance may be necessary for those who need help understanding their insurance plan.

Inattention as a source of inertia is able to be directly observed in our dataset by considering whether enrollees made an active enrollment choice. Only 54% of individuals at risk of remaining in a dominated plan made an active enrollment decision, meaning nearly half of enrollees were inert by default. Of those who made an active plan choice, 65.5% switched into a different plan. While unassisted enrollees were least likely (40%) to make an active plan choice, they were the most likely to switch given that they did so (72%). On the other hand, those receiving assistance from a service center made an active plan choice in all cases; yet, their switching rate was lowest among all service channels at only 60%. Those who received assistance from Navigators and insurance agents constitute both attention rates and conditional switching rates that lie between these bounds. Thus, given that service center representatives do not likely cause enrollees to be *less* likely to switch plans, and given that receiving this assistance is a signal of attention in and of itself, this provides evidence that enrollees with less insurance competence (yet are attentive) tend to seek this service channel.

An additional analysis on the relationship between switching between being assisted and unassisted, as well as its relationship to inattention as a driver of inertia, provide further evidence on selection bias. In finding that those who previously received assistance but are newly unassisted are more likely to be inert than those who were unassisted in both periods, these enrollees both are less likely to make an active plan choice and less likely to switch given that an active plan choice was made. This strengthens the argument that those who receive assistance have lower levels of insurance literacy. Finally, as new assistees appear to largely drive any gains measured by insurance agent assistance, these individuals are also much more likely to make active enrollment choices, this speaks to selection into receiving this assistance as well as inattention of insurance agents as a result of having repeated interactions with clientele.

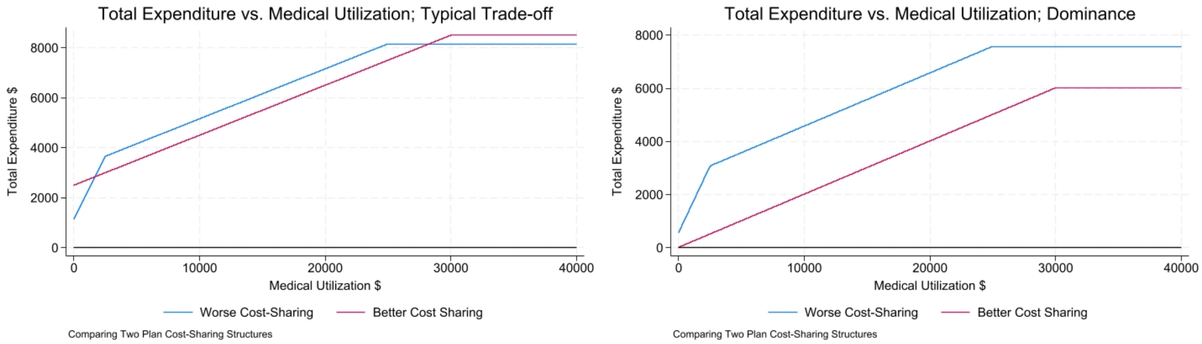
Finally, I propose Navigator program funding variation as an instrument for Navigator take-up. Despite navigator funding being generally associated with higher levels of Navigator assistance take-up, the measure lacks power in the subset of enrollees who are at risk of being inert.

The remainder of this paper proceeds as follows. In Section 1.1, I provide institutional information and a breakdown of the policy event that creates the natural experiment of interest. Section 1.2 details the data used for the analysis, documents inertia, and quantifies its impact. We also examine switching behavior and other choice mistakes. Section 1.3 examines how information interventions interact with choice mistakes, specifically delving into a heterogeneity analysis across race/ethnicity, age, and income. Section 1.4 provides supplemental analyses, including accounting for switching across service channels and website activity; I also provide robustness checks to alleviate additional selection concerns and possible data quality issues. Section 1.5 provides discussion, and Section 1.6 concludes.

1.1 Background

1.1.1 Institutional Background

Passage of the Patient Protection and Affordable Care Act, also known as the ACA, standardized U.S. health insurance offerings along numerous dimensions, including in the individual health insurance market. Firstly, requirements for provision of benefit categories ensured that a wide range of benefits (e.g. chemotherapy) were provided by all plans within a state. These minimum benefit requirements largely standardized benefits for plans and ensured that bare bones plans were not available. As such, decisions would then be made by consumers on the intensive margin of plan benefits, with metal tiers established to correspond to actuarial values (AV), including Platinum (90% AV), Gold (80% AV), Silver (70% AV) and Bronze (60% AV). As actuarial value describes the percentage of incurred health costs covered by the insurer,



(a) **(b)**

Figure 1.1. Total Consumer Expenditure Schedule over All Levels of Medical Utilization: Typical Trade-off vs. Dominated Plan Choice

Note: The above graph demonstrates total consumer expenditure over all levels of medical utilization using a simplified plan representation a la Ericson et al. (2021). Panel (a) shows a typical trade-off between two plans; one provides better cost sharing at a higher up-front cost, while the other provides worse cost sharing at a lower premium. Thus, enrollees with low expected utilization would choose the lower premium plan. Panel (b) shows the natural experiment at play: the plan with *better* cost-sharing also has a *lower* premium. Because plans are equivalent on all non-financial dimensions, we can say that the better cost sharing plan "dominates" the other, as costs are lower at all levels of utilization. The difference in total expenditure is minimized at $0 of medical utilization and maximized at the point that the worse cost-sharing plan reaches its out-of-pocket maximum. This example is the actual expenditure schedule for 2017 (panel (a)) and 2018 (panel (b)) for a 64 year old enrollee in a single household located in zipcode 94002, with an annual income of $34,371.

the ordering of these plans is clear to consumers, and thus plan premiums are generally ordered accordingly. Given these plan requirements, then, insurance issuers were encouraged to compete for enrollment by offering plans at competitive prices (premiums).

Given the ACA's purported purpose of ensuring affordability to consumers, including those with high healthcare costs, modified community rating was instituted. This requirement allowed plans to differ only by geographic area (known as rating area) and the age of the enrollee. Along with guaranteed issue – or the inability to deny coverage to any enrollee – this policy ensured that premiums faced by healthy and unhealthy individuals in the same area and at the same age were equalized[1]. The modified community rating schedule was then consistently

[1] As a result, this policy generally makes health insurance more affordable for less healthy enrollees, and thus less affordable for more healthy enrollees. Along with minimum benefit requirements, this may theoretically create an adversely selected enrollment pool (Akerlof, 1970; Rothschild & Stiglitz, 1976). Though it is not relevant to this work, this was the reasoning behind the "individual mandate" or the legal requirement of individuals to purchase insurance from the individual marketplace if otherwise uninsured. See Buchmueller & Dinardo (2002) and Einav & Finkelstein (2011) for a discussion; for a perspective that considers the individual mandate in the absence of community rating, see Enthoven & Kronick (1989).

applied to all plans (see Appendix Figure 1.A.1); for example, an enrollee aged 64 faced premium costs that were three times that of an enrollee aged 21.

A final relevant provision of the ACA is the health insurance exchanges, which were established in order to centralize the menu of plans available to each enrollee and provide ease in consideration and comparison of plans. While some states opted to use the health insurance exchange run by the federal government, other states, including California, chose instead to create and operate their own online exchanges. California thus established *Covered California*. Besides the exchange, which will be discussed further below, California has instituted other measures within their individual marketplaces, though these do not change the basic elements of the markets or our understanding of policy changes during our period of interest. Firstly, California is the only state that requires that all plans fit a "standard" plan design. This means that cost sharing structure between plans of the same metal tier and type (copay vs. coinsurance) match exactly across issuers and plan offerings. This allows issuers to compete along the dimension of benefits, pharmaceuticals, provider networks, and customer service. The state was also an early Medicaid Expansion state, meaning that Medicaid covers those with incomes up to 138% of the Federal Poverty Level. The state has taken a handful of other measures, but most apply only in later periods[2] Still, as opposed to a state like New York, whose health insurance markets mandate strict community rating and employ higher maximum Medicaid levels, California's market is comparable to those in most states across the country.

1.1.2 ACA Affordability Mechanisms

Premium Tax Credits

Two other measures of the ACA further ensured plan quality and affordability for low-income enrollees. Understanding these policies and their role under the ACA is crucial both for identifying dominated enrollees and understanding the policy change and its effect on premiums

[2]This includes a re-institution of the "individual mandate" that was removed federally in 2019, and a state-funded subsidy to increase premium tax credits; both of these were instituted in 2020.

that consumers faced in 2018. The first mechanism was *Premium Tax Credits* (PTC), which reduced the effective cost of premiums paid by individuals and families with incomes between 100% and 400% of the Federal Poverty Line (FPL). Premium Tax Credits tied the cost of a "typical" silver plan – the second lowest cost silver plan (SLCSP) in the market – to some percentage of one's income level. For example, an individual with an income of 150% FPL would be expected to contribute about 4% of their income, while an individual with an income of 400% FPL would be expected to contribute about 9.5% of their income (see Chapter 2 for further discussion and graphs of expected contribution). These maximum contributions are capped at these levels, meaning that if SLCSP is less than these amounts, enrollees will simply pay the cost of their selected plan and remain unsubsidized.

A few details regarding PTC are worth explicitly noting. Firstly, though PTC are tied to SLCSP, enrollees could then take their PTC and apply it to *any* plan offered in the marketplace. Thus, all plans' premiums were reduced by this amount, including more rich gold plans and less rich bronze plans. Secondly, because expected contribution is tied to income level, individuals across age groups (with the same income level) will pay the same amount for SLCSP. Thus, older enrollees will be receiving higher PTC in order to offset the higher listed premium cost. As a corollary, all else equal, older individuals will pay more for plans with premiums above SLCSP (gold and platinum), but pay less for those with lower premiums (bronze). Finally, PTC received cannot exceed the gross premium of a selected plan; in other words, an enrollee cannot be paid to enroll in a plan. If PTC exceeds a plan's premium, an enrollee will only receive a portion of the PTC they qualify for, and will pay $1 for their plan[3].

Cost Sharing Reductions

While Premium Tax Credits could be applied to all on-exchange plans, a second provision, *Cost Sharing Reductions* (CSR), applied only to silver plans. Specifically, for enrollees with

[3]Due to federal regulations, during this period PTC could not cover abortion services, which were required to be provided in the state of California. As a result, minimum plan cost equalled $1. In other states, where abortion services were either not covered or explicitly outlawed, zero-premium plans were often available.

incomes between 100% and 250% of FPL, CSR enhanced the cost-sharing richness of silver-tiered plans by providing actuarial values exceeding 70% for the following groups:

- 100-150% FPL: 94% AV
- 150-200% FPL: 87% AV
- 200-250% FPL: 73% AV

Thus, while higher income (>250% FPL) enrollees receive silver plans at a standard 70% AV, those between 100% and 200% FPL receive any silver plan with AV markedly exceeding Gold plans while still paying a "silver" premium. Those between 200% and 250% also receive a small boost in the cost sharing associated with enrollment in a silver plan. This makes silver plans more attractive to low-income enrollees, who are able to take advantage of both CSR and PTC to reduce healthcare expenditure. To offset the expense of providing this coverage, the cost of providing CSR was initially paid by the federal government, allowing premiums to reflect provision of 70% AV.

These affordability mechanisms promote affordability in two different manners. Both of these mechanisms make enrollees (weakly) better off than if they had not received them. Premium Tax Credits reduce the upfront cost of holding an insurance plan. Cost Sharing Reductions instead reduce the cost incurred by consumers for marginal utilization of health services. Furthermore, it lessens deductibles and out-of-pocket costs, reducing maximum financial loss. This thus alleviates overall costs to the consumer at any level of utilization of health care visits, procedures, services, or goods. While consumers generally face a trade-off between cost-sharing and premiums in choosing a health insurance plan, these mechanisms give silver plans greater value for low-income individuals, including relative to Gold and Platinum plans. As a result, in 2017, about 65% of enrollees in the California individual market were enrolled in silver plans.

1.1.3 Policy Change

In late 2017, after years of partisan disagreement over apportionment of funding for various facets of the ACA, the Trump Administration announced that funding for Cost Sharing Reductions would no longer be paid to health insurance issuers who provided them; this new policy would take hold starting in 2018. Yet, these payments were still expected to be provided to low-income enrollees in the individual markets. In California, like many other states, insurers were instructed by the exchange to "silver load" premiums, meaning they were to load the cost of providing Cost Sharing Reductions onto silver plans premiums provided on the exchange[4]. Put simply, silver loading involves pricing the silver plans for the coverage they provide (aggregated over multiple income groups); because a large portion of silver plan enrollees (approximately 60%) receive silver plans at 87% or 94% AV, the true actuarial value provided by the plan is somewhere above 70%, and thus premiums would reflect that. As such, silver plans in 2018 saw substantial premium increases relative to non-silver plans. Still, for those receiving PTC, net amount paid on a silver plan was largely unchanged, and non-silver plans became less expensive (See Chapter 2 for a more thorough explanation).

1.1.4 Plan Dominance

In choice theory, dominance dictates that all economic agents choosing between two goods should choose one over the other, even when accounting for potential behavioral biases. One clear example is the choice over money: all individuals would prefer to receive $10 over $5, as long as no other benefits or costs are involved. In practice, however, strict dominance of one product over another is often impossible to establish, as non-financial characteristics are difficult to quantify and preferences thereof are often unfeasible to fully document. However, in this highly standardized environment, this shift in premiums creates a clear-cut example of an offered plan being dominated by another, which provides an opportunity to study choice inconsistencies,

[4] In reality, insurers were required to file rates by the end of June, so insurers loaded two sets of rates: one that assumed CSR would be subsidized by the government and one that did not. The exchange's guidance and news release are available online.

including inertia. In this instance, beginning in 2018, some silver plans in the market had higher listed premiums than comparable gold plans. Since plan dominance provides a clear view of a choice mistake, it is necessary to rigorously establish that these silver plans were dominated by the comparable gold plans, and that selection of these plans, both ex-ante and ex-post, can be viewed as a behavioral mistake or indication of some information friction.

Suppose two plans can be obtained for the *same* monthly premium payments. In this context, in order to establish (weak) dominance, it must be the case that in all possible states of utilization an individual would (weakly) prefer to be enrolled in one plan over another. Since various non-financial, fundamentally unmeasurable characteristics of enrolling in a plan (e.g. customer service) may vary depending on issuer, it is not possible to establish true dominance between plans from different health insurance companies. In focusing on comparing two plans offered by the same issuer, we establish that plans may be differentiated on two extensive margins: physician networks and plan benefits. Enrollees are likely to have preferences over physicians and other providers due to variation in quality, convenience, and cost. Without detailed data on these dimensions, dominance can only be established with an equal or strictly more expansive network[5]. Benefits that a plan offers may vary as well; for example, one plan could hypothetically offer coverage for cancer treatment, while the other does not. In practice, however, the ACA largely standardizes this extensive margin of benefit offerings within states, requiring all plans to offer certain benefits. Plans on the exchange generally do not vary greatly in their plan offerings, especially within issuer, although plan differentiation does exist (e.g. adult dental benefits). Individuals with strong preferences for certain benefits may be willing to pay a higher premium for a certain procedure or prescription drug.

We account for both of these dimensions by establishing dominance between plans that are from the same product offering. Based on the rules of the ACA, a product is a "discrete

[5] Dahl & Forbes (2023) find that doctor switching costs account for a large share of inertia in plan choice, as individuals enrolled in employer-provided insurance have a strong taste for continuity of care. This is also discussed in Drake et al. (2022); our approach abstracts away from this. Preferences for continuity of care are not necessarily a behavioral failure, but may reflect imperfect information. Continuity of care has been shown to improve health outcomes (Sabety, 2020).

package of health insurance coverage benefits that are offered using a particular product network type (such as health maintenance organization, preferred provider organization, exclusive provider organization, point of service, or indemnity) within a service area." (CFR § 144.103) This package of benefits includes limitations to services (such as a maximum number of services allowed per year). Thus, plans on the same product include the same plan benefits and network type (HMO vs. PPO etc.). In California, in all years of analysis, plans within a product also generally have the same exact network; the only exception to this is SHARP Health Plan, whose product is split into two networks. When comparing between gold and silver plans in this policy environment, these conditions are met when comparing plans from the same product and with the same network. On the extensive margins of plan benefits, then, these plans are indistinguishable.

Consequently, plans from the same product and network can only vary on the intensive margin of plan benefits, known as the cost-sharing structure of the plan. Each plan is appropriately classified as a certain metal tier, which is mapped to various actuarial values provided by a plan. Still, the exact cost-sharing structure varies even among plans with the same metal tier. Because we assume that an individual receiving care will have the same experience regardless of the exact name of their plan[6], dominance is established such that if a medical procedure is obtained, it will leave the individual with more money left over for other expenditures (or future medical expenditures) at all levels of medical utilization.

Each facet of the cost-sharing structure of a plan will affect total expenditure on medical services at different junctures of healthcare utilization. If a plan has a non-zero deductible, the enrollee will be responsible for initial medical costs up to that amount on services to which the deductible applies. Once the deductible is exhausted (and for services to which the deductible does not apply), marginal cost-sharing on services may either be in the form of coinsurance or copayments. Coinsurance establishes the percentage of a medical bill that an enrollee is responsible for; a coinsurance rate of 20% means that the enrollee must pay for 20% of services

[6]This work does not consider the moral hazard problem often discussed in health insurance, namely that individuals enrolled in plans with more favorable cost-sharing will obtain more medical services as a result, possibly leading to over-utilization of healthcare services. For a summary of this, see Einav & Finkelstein (2018).

while the issuer must pay 80%. A copayment, on the other hand, is a flat fee paid for a single visit or procedure. For each plan benefit, either coinsurance or a copay is to be paid (including a $0 copay/0% coinsurance). Combined expenditures on deductibles and marginal cost-sharing is bounded by a *maximum out-of-pocket amount* (MOOP). Once this amount has been spent on services, the issuer will cover all additional costs for the remainder of the plan year.

Below, I state and justify three sufficient conditions, which together establish dominance at all levels of expenditure for plans with the same premium. The first condition is a (weakly) lower deductible. If deductible is lower, then the enrollee is responsible for 100% of medical costs for a smaller range of expenditure. Supposing that the deductible applies to all services for simplicity, cost-sharing will only begin once the deductible is met. All else equal, plans with lower deductibles have lower levels of expenditure for utilization levels that involve cost-sharing, as the first marginal dollar to which cost sharing applies is earlier in expenditure (See Appendix Figure 1.A.2; panel (a)). The second condition is that cost-sharing is (weakly) lower for all services. Lower cost sharing (either in the form of a lower coinsurance percentage or smaller copay amount) equates to lower marginal expenditure per service, which in turn equates to lower total expenditure if all else is equal (See Appendix Figure 1.A.2; panel (b)). Finally, the third condition is that maximum out-of-pocket amount is (weakly) lower. All else equal, a (weakly) lower MOOP caps expenditure at a lower amount, meaning that at high levels of utilization, the lower MOOP plan is preferred (See Appendix Figure 1.A.2; panel (c)). Together, these three conditions ensure that, at all levels of utilization, total expenditure on medical services will be (weakly) lower. For strict dominance, at least one of these weak conditions must be strict.

Once strict dominance in terms of cost-sharing is established by a one plan over another, an individual offered both plans at the same premium should choose the dominant plan in an environment free from information frictions and transaction costs. This dominance is strong, as it establishes a clear choice, irrespective of any prior on medical utilization (ex-ante). When this is the case, offering the dominant plan at a lower premium will only serve to strengthen the incentives to purchase the dominant plan: this difference can be thought of as the lower bound for the amount of money saved by choosing the dominant plan. This amount will be experienced when there is zero utilization (and other utilization levels that produce the same consumer costs). As a result, if all cost-sharing characteristics are equal, the plan with the lower premium will dominate (See Appendix Figure 1.A.2; panel (d)). This difference in premium paid can then be used to quantify the minimum loss among individuals with a choice error.

In the California individual market in 2018, Kaiser offers one set of plans under a single product, including one silver plan and two gold plans, one of which (the "Gold Coinsurance" plan) we consider below. For individuals receiving the standard 70% AV silver plan, the silver plan's deductible ($2500), drug deductible ($130), and out-of-pocket maximum ($7000) are each strictly larger than both gold plans' ($0, $0, and $6000, respectively). For the set of Kaiser plans, for each plan benefit, in all instances where both plans have either coinsurance or copay, the Gold Coinsurance plan's rate is weakly lower than the silver's. The only possible ambiguity with respect to dominance comes about due to a small number of categories for which a silver plan has one cost-sharing type while the gold plan has the other. This occurs for only two benefit categories for the Kaiser plans. A discussion of these differences, and the likelihood of them inducing a violation of dominance is discussed in detail in Appendix section A.1. Despite this ambiguity, the above argument for dominance is at least as strong as many other papers in this sphere. Liu & Snydor (2022), for example, use simplified plan representations introduced by Ericson et al. (2021), which transforms more detailed financial characteristics – deductible and out-of-pocket maximum; coinsurance and copayments often split by service type – into a simple representation with a deductible, maximum out-of-pocket amount, and flat coinsurance rate. Dominance as established in this paper is at least as strong, as marginal cost-sharing is weakly higher for *all* of these benefits, with just two exceptions that do not strictly violate the rule but introduce a small amount of ambiguity. Simplified plan representations of these two plans are compared and discussed in Appendix A.1 for thoroughness. For those who do not receive cost-sharing reductions (over 250% FPL), then, dominance is well-established by the *Gold Coinsurance* plan over the silver plan of the same product offered by Kaiser.

Besides the high income individuals, it may be useful to understand costs incurred by another group: those who receive a 73% AV silver plan (200-250% FPL). These enrollees would seemingly also be enrolled in plans that would be dominated by a lower-premium, 80% AV gold plan. However, all silver 73% AV plans have an out-of-pocket maximum ($5850) that actually is *less than* that of gold plans ($6000). As a result, at very high levels of expenditure, holding the gold plan could cost the individual up to $150 more in medical bills in a given year[7]. Still, besides this discrepancy, the standard methodology shows that these plans will have lower levels of overall spending up until that maximum is hit. While the premium difference for a higher income individual represents the financial cost of their choice mistake, the premium difference here can make up for the difference in MOOP. If an individual pays more than $150 extra on the silver plan, then total expenditure will *still* be lower at *all* levels of medical utilization under the gold plan. In practice, this requires the monthly premium difference to be somewhat large and for enrollment to last most (or all 12) months; for an enrollee who stays for 12 months, the premium difference must be at least $12.50. Since premiums vary by rating area, the age for which this occurs is different for each area. However, all individuals of age 28 and above save at least $12.50 with the gold plan; thus, I choose to analyze (as a supplementary exercise) those in this age group who remain enrolled for the entire 12 months of 2018. This subsample of lower income enrollees suffers from selection bias, but this is not necessarily to the detriment of the study. While silver enrollees with higher incomes experience ex-ante dominance of plans, these enrollees are only experiencing ex-post dominance. Though the composition of this group is different, we can still look at dominated enrollees and inertial tendencies, especially as a robustness check. Since the higher income enrollees are dominated regardless of their final premium expenditure, I refer to this group as the “ex-ante” at-risk/dominated individuals, while those with lower income whose premiums must be considered as “ex-post” at-risk/dominated individuals. I analyze these enrollees in section 4.4 as a robustness check on results.

[7] Because the gold plan has lower marginal cost-sharing and no deductible, this maximum of $5850 will occur at an earlier point of medical utilization under the silver plan than the gold plan.

1.1.5 Information Frictions, Information Interventions, and the Health Insurance Exchange

One source of plan choice insufficiencies is information frictions, which affect plan choice in welfare-relevant ways, making plan differentiation more difficult and understanding future spending more unclear (Handel & Kolstad, 2015). As marketplaces were established to foster transparency, *Covered California* provides a centralized location to compare health insurance choices from a single menu based upon one's location. This allows consumers to avoid the hassle costs of manually finding health plans at separate locations and putting the information together. Plans can be listed in any selected order, displayed based upon criteria, and compared side-by-side. Figure 1.A.3 shows the main pieces of information: Monthly contribution (premium net premium tax credits) is listed, along with the monthly savings (PTC), primary care and generic drug copays, and plan deductibles. Also clear is the issuer, the metal level, the network type (HMO vs. PPO), and the plan AV (e.g. Silver 70 HMO). If desired, consumers can find more detailed financials, and even compare plan characteristics side by side (Figure 1.A.4). Still, despite plan information accessibility, health insurance enrollees have been known to misunderstand their health plan (Collier & Williams, 2022).

Various human resources are provided by, or facilitated through, the state of California to address these information gaps and avoid choice mistakes. These "assisters," who may supplement the knowledge of enrollees and facilitate the enrollment process, can come from a variety of *service channels*. The *Navigator Program*, which is federally mandated in all states, provides funds to community-based organizations to provide assistance and outreach within the state. These enrollment counselors must not be tied to any health insurance company; instead, funding is provided to small organizations that provide enrollment, re-enrollment, and post-enrollment support. These navigators must be partnered with community-based organizations such as nonprofits, and are intended to provide in-person help to those who seek it. Besides navigators, service centers were also established in California for enrollees to call for help while enrolling. These service centers provide an opportunity to submit consumer inquiries and obtain help for enrollment over the phone or online, and are available in 14 different languages. A final government-funded service channel is the county eligibility worker. These state employees determine eligibility for California Medicaid, and review all applications when this transfer is made from the marketplace. This makes up for a low proportion of overall enrollment ($<1\%$).

Besides resources provided by the government, insurance companies also provide resources. Typical to the insurance domain is Certified Insurance Agents; to sell in the individual market in California, agents must pass state insurance courses and a licensing exam, and must be approved by the Department of Insurance. These agents represent the health insurance companies that appoint them, and thus have a different incentive structure (e.g. commission) as compared to navigators or service center representatives. For the remainder of this chapter, except where noted, I group the three types of government help together, and I group certified insurance agents along with plan-based enrollers (an additional, sparsely used non-governmental resource) as "private" help. It should be the case that these helpers, especially those provided by the government, reduce choice errors; this can be empirically evaluated.

1.1.6 Literature Review

The post-ACA landscape has been rife with opportunities to analyze both premiums and consumer behavior. This work contributes to a vast literature that studies the ACA and its consequences. Several early works analyze the initial implementation of the ACA's effect on insurance coverage, some of which explore differential effects in family enrollment as a result of Medicaid expansion status (Frean et al., 2017; Courtemanche et al., 2016), while others explore the effect of the immediately implemented policy that plans must cover dependents under age 26, using both labor (Slusky, 2017) and health (Barbaresco et al., 2015) outcomes. As a response to the *House v. Burwell* case, multiple works from policy institutes (Blumberg et al., 2016; Levitt et al., 2017; Yin & Domurat, 2017) predicted loading of cost sharing costs onto silver plan premiums across many states.

There are four main papers that use individual-level data from California to study responses to price changes due to silver loaded premiums. Rasmussen et al. (2019) finds that gold plans became more enrolled in as a result of these price changes, and that overall plan selection was sensitive to these shifts. Drake et al. (2022) and Saltzman et al. (2021) study inertia in these markets, but do so without reference to dominated plan choices; instead, they use structural models to estimate inertia costs. The former work differentiates between inattention, hassle costs, and tastes for provider continuity as sources for inertia as a result of the pricing shifts; the latter work models both demand and supply side factors and incorporates pricing models to examine how inertia interacts with market power and adverse selection. The work that most closely resembles ours is Rasmussen & Anderson (2021), which studies dominated plan selection, finding that enrollees who were previously in a newly dominated silver plan have 8 times greater odds of choosing a dominated plan than a new enrollee, demonstrating metal-tier stickiness. My work differs in that it more accurately assesses dominance as occurring to those above 250% FPL (rather than 200% FPL), more completely describes losses as being shared by both consumers and the government, and, most notably, ascribes mitigation of inertia to external information asymmetry interventions and active plan choice.

More broadly, this work contributes to a literature that focuses on choice inconsistencies and behavioral failures within health insurance markets. A large portion of this literature examines pharmaceutical plan choice within the context of Medicare Part D, which generally serves individuals over 65. Abaluck & Gruber's seminal work from 2011 provides evidence about perceived trade-offs between cost-sharing and premiums, finding that this older demographic overweights premium savings relative to cost-sharing savings when selecting Part D plans. This work also finds that plan characteristics are considered moreso than those characteristics' actual effect on overall spending. Ketcham et al. (2012) find that many of these behavioral failures are corrected over time, with the greatest improvements made by those who overspent most; Abaluck & Gruber (2016), on the other hand, find little learning over time[8].

[8] Unfortunately, our identification method, which relies on the presence of dominated plan choice, does not

Initially coined in the economics literature as "status quo bias" by Samuelson & Zeckhauser (1988) – and later explored by Kahneman et al. (1991)[9] and Ritov & Baron (1992) – the term inertia has been used more in recent years to more broadly describe repeated choices of defaults either due to inaction or repeated choices; study of this persistence has seen a surge of work in the study of health insurance in recent years. Early studies of inertia within this space, including Strombom et al. (2002) and Royalty & Solomon (1999), attribute inertia in health plan choice to switching costs. More recently, inertia has been found in some of the studies within the above Medicare prescription drug sub-literature, with a specific focus on inattention and switching costs/frictions as a source of inertia (Heiss et al., 2021; Ho et al. 2017; Ericson, 2014; Polyakova, 2016), identifying inertia by assuming that new employees have similar preferences to existing employees (Strombom et al., 2002). Handel (2013) also does this, while additionally using choice of dominated plans to identify inertia. Other works, including Bhargava et al. (2017) and Sinaiko & Hirth (2011) examine dominated plan choice irrespective of some default choice. Unlike this chapter, these previous dominated plan choice settings involve a low-deductible plan that is dominated by a high deductible plan due to large premium differences. Given that enrollees often focus on certain plan attributes rather than total spending (Abaluck & Gruber, 2011), my setting provides a more stark and salient example of plan dominance. My work further expands upon previous papers by examining information interventions and their relationship with decision making in the health insurance space. The works that most closely examine information frictions have been Handel & Kolstad (2015) and Bhargava et al. (2017). However, external, human sources of information have not yet been examined in the literature as a mitigating factor for choice errors.

persist over multiple years, and thus choice over time cannot be evaluated.

[9]This work describes status quo bias as being closely related to the endowment effect (Thaler, 1980); both concepts are manifestations of loss aversion (Kahneman & Tversky, 1984). However, evidence of an endowment effect requires estimates for willingness to accept vs. willingness to pay, which does not directly relate to health insurance markets. Mirroring results of Ketcham et al. (2012), List (2003) finds that the endowment effect ameliorates over time with greater market experience.

1.2 Data and Preliminary Analysis

1.2.1 Data

While data from federal exchanges are unavailable due to federal regulations, California provides individual-level enrollment data to researchers. Individual-level enrollment data was provided by Covered California for the years 2014-2021. This file includes plan choices for all enrollees in health insurance plans purchased on the HIX in these years. Individual and household choices are tracked over time, with information on gross (listed) premium and net (subsidized) premium. Enrollment date, coverage start and end dates, and enrollment status (enrolled, terminated, or cancelled) are also listed, along with whether an individual receives any sort of Cost Sharing Reduction. Geographical information, though not on a zip code or county level, provides both three-digit zip code (TDZ) and rating area. Basic demographic information such as age, gender, and race/ethnicity are also variables. Finally, subsidy-determining variables, including household size and income relative to federal poverty level, are included. One of the few weaknesses of the data is that the latter measure, income, is only measured in coarse groupings[10]. Since wealth is both a determinant of premium tax credits and a vital explanatory variable, I find it useful too deduce household income, which I detail in subsequent paragraphs.

In addition to the individual-level data, I supplement my analysis with public use files from the CMS, which mirror the rate, plan attribute, and service area files used in the national analysis in Chapter 2. Though service area files describe areas, including the full state, counties, or county-zipcodes that a plan is offered, there is some ambiguity as to how zipcodes match to counties and vice versa. As a result, I rely on historical website data from the Covered California website. Specifically, I scrape the website for each zipcode-county pairing available in each year, and store the plans that are explicitly offered on the website in each area. I can then use this to establish the possible set of rating area - three-digit zipcode - plan combinations. This

[10]The listed categories are: under 138% FPL; 138% FPL to 150% FPL; 150% FPL to 200% FPL; 200% FPL to 250% FPL; 250% FPL to 400% FPL; 400% FPL to 600% FPL; unsubsidized.

menu, matched with rating area-specific prices, is then cross-referenced with individual enrollees' gross premia to ensure that listed premia match possible plan price and geographical location. Households with individuals whose plans are not offered in their geographical areas or whose gross premium does not match menu prices are removed from the analysis.

In addition to the errors above, other lines of data are removed for various reasons. Firstly, households with Native Americans, who receive special plans with low cost sharing, are excluded. Household intracacies, such as individual switches into different households, households that move geographical regions, and multiple geographical regions within a single home, are flagged and removed. Finally, individuals with other data issues, such as a household size of 0 or no FPL information, are removed. All of the aforementioned issues are classified as data errors. As such, when conducting multi-year analyses, households with an error in any year of the analysis are disincluded from all years of the analysis. Besides errors, I remove all enrollees under the age of 26 from the dataset[11], as these enrollees are less likely to make their own health insurance decisions. The final step is to remove plans that were cancelled. These do not constitute an error, but rather a non-enrollment, and should be treated as such. While these are discarded, "selection" of cancelled plans may inform our understanding of enrollment in future iterations of this work.

Besides verifying plan choice, an auxiliary function of establishing plan offerings on a county-zip code level is determining the second-lowest cost silver plan (SLCSP) in each county-zip code combination. If the SLCSP is consistent across all zipcodes within a TDZ-rating area pairing, then income level can be backed out using actual net premium paid for most enrollees. This provides an opportunity for a more finely-tuned heterogeneity analysis by income on a restricted sample of the enrollment population. To do this, I first use household size to establish the federal poverty line in dollars. Then, net premiums and PTC across the distribution of candidate FPL levels within the listed appropriate interval (e.g. 250% to 400% FPL) are matched with the premium tax credit as defined by the difference between gross and net premium. The

[11]Under the Affordable Care Act, employer sponsored plans must provide dependent coverage to employees' children under the age of 26. Thus, age 26 provides a sort of discontinuity of possible new enrollees in the individual market.

weakness of this approach is that within many county-TZD pairings, SLCSP is not constant among all zipcodes. Still, without more finely constructed geographical information, income level cannot be deduced more broadly. This is, again, another way to verify the premium and income data; if a PTC match does not exist within an individual/household's listed income interval, there may be an error in the entry. Thus, I remove households that have individuals with non-matches on income level from this restricted dataset. Because we can only accurately pinpoint income for individuals receiving a premium tax credit – namely those whose PTC does not exceed their gross premium – this subsample only represents these subsidized enrollees. For a more thorough explanation and example, see Appendix section A.2.

1.2.2 Preliminary Descriptive Statistics

Of the 755,000 enrollees who fit the above criteria of this study (e.g. aged 26 or over) and were enrolled in both 2017 and 2018, about 262,000 of these enrollees (34.7%) are above the 250% FPL cutoff and thus did not receive CSR in 2018. Over 34,500 of these enrollees were enrolled in a newly dominated Kaiser plan in the previous year and are thus considered "at-risk" of being enrolled in a dominated plan. This is about 4.5% of all re-enrollees. Among these at-risk enrollees, over 78% have incomes between 250% and 400% of the Federal Poverty Level. Split into broad racial/ethnic categories, 37% are white, 2% are black, 18% are Hispanic, and 16% are Asian, among those who responded (20% do not disclose this information). Females consistute 54% of this subsample. The proportion of enrollees over the age of 55 (36%) is about equal to the proportion that are between the ages of 26 and 45. Just over a quarter are between 46 and 55. The average number of years in the market prior to 2018 is approximately 2.66 years. Finally, among at-risk individuals, nearly 50% are unassisted in their enrollment, while 35% use a certified insurance agent and 14% use service centers. Finally, just under 3% of enrollees access services provided by Navigators.

Besides basic descriptive statistics, it is useful to compare these measures against comparison groups in order to establish any differences related to enrollment choice; any differences may be indicative of selection bias and should be accounted for or examined in subsequent analyses that use other enrollees as counterfactuals. Based upon Table 1.1, enrollees previously in silver plans, columns (1) and (3), are more likely to be female than those previously not in silver plans, columns (2) and (4). Furthermore, silver enrollees tend to be less likely to be white, more likely to be hispanic, and less likely to be in a younger age group. This latter finding is due to higher enrollment among young individuals in bronze plans, the second most commonly chosen plan tier. Silver enrollees also tend to be more likely to be in the lower income category, and much less likely to be an "unsubsidized" enrollee. These individuals are also less likely to be unassisted, more likely to use government help, and more likely to use a certified insurance agent.

We can also compare Kaiser enrollees, columns (1) and (2), to non-Kaiser enrollees, columns (3) and (4). Kaiser enrollees are about twice as likely to be black; they are also less likely to be non-respondent to the survey of race/ethnicity. Kaiser enrollees are also more likely to be between ages 26 and 35, and less likely to be over 46. Most starkly, Kaiser enrollees are much likelier to be unassisted than non-Kaiser enrollees, as well as more likely to receive help from a service center. They are less likely to receive help from navigators or insurance agents, the latter of which accounts for a significant proportion difference in enrollees.

There are a few demographic categories upon which the relationship between silver and non-silver, as well as Kaiser and non-Kaiser, does not fully explain the relationship between these 4 groups. In terms of racial categories, while Asian individuals make up a greater portion of non-silver Kaiser enrollees than at-risk Kaiser enrollees, they make up a lesser portion for non-silver enrollees in non-Kaiser plans (compared to silver ones). This may be due to differential targeting of certain demographic groups by Kaiser compared to other issuers. Another noteworthy observation is that the silver vs. non-silver differential for service center utilization for Kaiser enrollees is much greater than that for non-Kaiser enrollees. Similarly, the inter-metal disparity in non-utilization of service channels is much higher among Kaiser enrollees than non-Kaiser enrollees. Unlike the discrepancy for race/ethnicity, which is pre-determined, this difference may be *due* to the dominance occuring, as service centers may have received an increase in calls in *response* to consumers being at risk. This will be addressed in section 4. With respect to differences in predetermined demographic characteristics, these threaten the external validity of findings of this study.

1.2.3 Examining the Price Shock

The year 2017 saw substantial premium increases across all metal tiers within the California individual market. Those enrolled in the Kaiser Silver plan in 2017 saw, on average, a monthly premium increase of $134, or a 23% increase on average. Non-silver Kaiser plans increased at or slightly below 10% in price. Those enrolled in non-Kaiser silver plans saw an even larger increase of $165 on average, or an approximately 32% increase. Non-silver plans from these other issuers also increased substantially, over 19% for each metal tier. This helps explain why the Kaiser silver plan became dominated: a large silver premium increase and a much smaller gold premium increase (See Figure 1.2). In 2017, prior to the policy change, the Gold Coinsurance HMO (Gold HMO) was just $61 ($90) more expensive per month than the Silver HMO plan, or about or about 11% (16%). Meanwhile, non-Kaiser Gold plans were on average $121, or 23% more expensive than the Silver plans with the same benefits and network. As a result, Kaiser's Gold Coinsurance HMO (Gold HMO) plans became 3.7% less expensive (1.3% more expensive) than the Kaiser's Silver HMO plan in 2018, while non-Kaiser Gold plans remained 12% more expensive than their counterpart Silver plans[12]. While the gap between the two plan types was closed for non-Kaiser enrollees, a trade-off still existed between Gold and Silver plans.

[12]Despite intratemporal savings in choosing a Kaiser Gold Coinsurance HMO plan, this plan was still, on average $108, or 19%, more expensive than the previous year's Silver plan, as it saw a $46 increase on average. Still, those switching from a non-Kaiser silver plan to a comparable gold plan would see an average of a $251 increase, or approximately 47%.

Table 1.1. Characteristics of At-Risk Enrollees, with Reference Groups for Comparison

	At-Risk	*Other Kaiser Enrollees*	*Comparable Enrollees*	*All Other Enrollees*
Female	0.540	0.499	0.534	0.501
White	0.365	0.398	0.360	0.393
Black	0.0213	0.0187	0.0114	0.0112
Hispanic	0.180	0.150	0.175	0.153
Asian	0.160	0.174	0.160	0.148
Other	0.0720	0.0704	0.0602	0.0561
Nonresp	0.202	0.189	0.234	0.239
Age 26 to 35	0.184	0.247	0.154	0.179
Age 36 to 45	0.182	0.198	0.178	0.187
Age 46 to 55	0.270	0.250	0.292	0.287
Over Age 55	0.363	0.305	0.377	0.348
250-400% FPL	0.781	0.665	0.772	0.683
400-600% FPL	0.108	0.136	0.0915	0.104
over 600%	0.0378	0.0526	0.0392	0.0488
Unsubs. App.	0.0733	0.146	0.0970	0.164
Years of Experience	2.667	2.520	2.722	2.726
Unassisted	0.470	0.621	0.324	0.436
Service Center	0.137	0.0637	0.0870	0.0667
Navigators	0.0299	0.0177	0.0420	0.0307
Certif. Ins. Agent	0.352	0.293	0.544	0.464
N	34,521	60,573	89,429	77,425

Note: The above table gives summary statistics for enrollees who are re-enrolling in 2018 and, in 2017 were (1) enrolled in the newly dominated plan, (2) enrolled in a separate Kaiser plan, (3) enrolled in some silver plan offered by a different issuer, and (4) other enrollees (non-silver, non-Kaiser plans). This analysis is limited to those who are not eligible for cost-sharing reductions (above 250% FPL) and aged 26 or older.

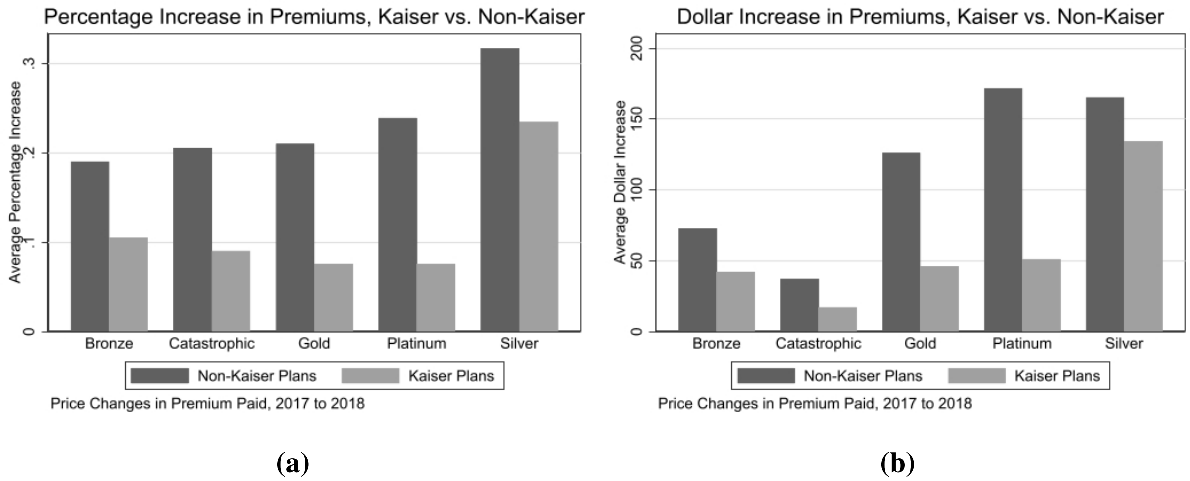


Figure 1.2. Average Premium Changes of Kaiser Plans vs. Non-Kaiser Plans, 2017 to 2018
Note: The above graph shows average changes in prices of premiums between 2017 and 2018. Panel (a) shows the percentage increase in premiums by metal tier; panel (b) shows the dollar increase in premiums by metal tier. Each graph is split to compare Kaiser (dominated silver in 2018) vs. Non-Kaiser plan premium changes. Graphs show the measured average changes in actual dollars paid in the case that no switches were made in 2017; in other words, averages are weighted by 2017 enrollment.

1.2.4 Documenting and Investigating Costly Inertia

Individual-level data allows us to establish inertia, as an initial choice is necessary for one to be inert. Because dominance occurs, identification of inertia is clean; at-risk enrollees who do not switch from the dominated plans are inert. Of the 34,526 at-risk individuals who remained enrolled in the individual market, only 12,338 (35.7%) switched plans; in turn, 64.3% of these enrollees make *dominated* plan choices and exhibit costly inertia. On average, those who switch plans are paying about $248 per month, while inert enrollees pay approximately $282. Those who chose not to switch to the dominant gold plan could have saved nearly 10% on their premiums per month ($27) *and* switch to a more favorable plan. In all, the result is that for a year of health coverage, individuals who did not switch could have saved an average of $325 per year on premiums alone.

Controlling for geographical area, comparing inert and non-inert individuals can shine light on possible inequalities that merit further scrutiny with respect to information interventions and create opportunity for heterogeneity analysis. Firstly, females are slightly less likely to

Table 1.2. Inert vs. Non-Inert Enrollees; Premium and Demographic Characteristics, 2018

	Inert	***Switched***
Observations	22,185	12,336
	64.3%	*35.7%*
Average Gold-Silver Kaiser Gap	$27.11	$25.86
Average Gross Premium	$681.33	$572.02
Average Net Premium	$281.52	$247.77
Regression Results: Demographic Characteristics		
Female	-0.0223***	
	(0.00391)	
Age 36 to 45	0.0525***	
	(0.01100)	
Age 46 to 55	0.0679***	
	(0.01056)	
Over Age 55	0.0887***	
	(0.01029)	
400-600% FPL	-0.0931***	
	(0.01132)	
over 600%	-0.0416***	
	(0.01499)	
Unsubs. App.	0.0339***	
	(0.01180)	
Black	-0.0240	
	(0.01800)	
Hispanic	0.0278***	
	(0.01021)	
Asian	0.00885	
	(0.01238)	
Other	0.0120	
	(0.01011)	
Nonresp	0.0440***	
	(0.00794)	

Note: The above table compares enrollees who remained in their dominated plan to those who switched from it. The subsample of enrollees is those over age 25 who were enrolled in the Kaiser silver tier plan in 2017 and have incomes above 250% FPL. The top panel gives the number that falls within each category as well as premium information, including both net and gross average premium, as well as the average premium difference between the dominated silver plan and the dominant gold plan. The bottom panel provides coefficients from a linear regression, where all explanatory variables are binary, and the response variable is being *inert*. The regression includes area (Three-Digit-Zip by rating pair) fixed effects.

remain in a dominated plan. Additionally, the least likely age group to be inert is those under 36, while those most likely are above 55; a consistent positive gradient for likelihood of inertia exists across all age groups. Despite a possible prior belief that lower-income individuals are more likely to interact with the system, we see that those under 400% FPL are more likely to be inert than those who are wholly ineligible for premium assistance (400% FPL and above). Finally, Hispanic individuals are slightly more likely to be inert than those who are white; those who do not indicate their race/ethnicity are most likely to be inert relative to classified racial/ethnic groups.

One advantage to this natural experiment is that we can quantify loss in consumer surplus as a result of inertia. Generally, these losses may be difficult to quantify without detailed claims data; here, we can use the difference in premium paid between the dominated and dominant plan and aggregate over each month of enrollment and all inert or otherwise dominated enrollees. This serves as a lower bound for welfare loss for three reasons. Firstly, because the gold plan has more favorable cost sharing, all non-negative levels of medical utilization under that plan will include non-negative number of dollars saved on medical care compared to the dominated plan. Secondly, the dominant gold plan may not be the option that maximizes utility. It may be the case that, for example, the bronze plan offered by Kaiser would minimize costs. Furthermore, plans offered by other issuers may exceed plan value along a combination of financial and non-financial dimensions. Thus, on a per-person basis the measure serves as the minimum amount of money to be potentially saved by a consumer by enrolling in the dominant plan, because the intensive margin of savings is not fully captured. Still, the measure acts as an appropriate average premium forgone per person by specifically not switching to the dominant gold plan. Thirdly, on the extensive margin, we do not necessarily capture all dominated individuals. This is due to standard data exclusions, as described above, which are due to data issues, as well as other data inconsistencies that are not considered in the general analysis, such as premium misreporting, as described in the following paragraph[13]. Thus, any aggregated measure of total surplus loss is an

[13] Besides this, we exclude any of these mid-to-high income enrollees whose plans are listed in the data as having

underestimate.

In order to calculate the total gross premium forgone by each individual who chose the dominated plan, one can simply calculate the difference in the listed plan premiums, and sum over the number of months enrolled. Still, in terms of net premiums, this loss is not borne entirely by the consumer. Consider, for example, an individual whose Kaiser silver plan already costs $1 per month[14]. In switching to the Gold Coinsurance HMO plan, the individual does not stand to save any money on premiums, as this plan would also cost $1 per month. Still, under the gold plan the government will have to pay less to the insurance company to compensate for the difference. Thus, the government will bear the entire premium cost of not switching[15]. More generally, the cost of any change in premiums past the point of $1 per person is borne by the government. Because this requires use of net premiums paid, enrollees whose net premiums are found to be mislisted are not included in the separate calculation of consumer and government surplus loss. However, for the combined surplus lost between the two, we can include these enrollees. On the other side of the market, these combined losses equal pure surplus gain among insurance producers. As with the additional relative loss that comes with marginal utilization of medical services for consumers, producers, who pay for these services, see equal and opposite surplus gain, as they provide less coverage for silver plans. Thus, this again serves as a lower bound both for individual and aggregate calculations of consumer/government loss and pure producer profit increase.

In 2018, this consumer welfare loss due to individuals remaining in their previously selected, newly dominated plan is at least $5,086,017. This amounts to approximately $269 per inert enrollee. For those who remain enrolled for all twelve months of coverage, the average

73%, 87% or 94% AV. These are not excluded from the general analysis. See section 4.4 for further discussion on this issue. It is unclear whether these are data entry mistakes or features of the enrollment process system.

[14]In a market where the Kaiser Silver plan has a premium below SLCSP, some enrollees will likely qualify for the plan for $1 per person. This is especially true for families with multiple enrollees, older enrollees, and lower-income enrollees. Due to California law and federal policy, California plans are bound at a minimum of $1 per month to pay for abortion services. See Dissertation Chapter 2 for a more in-depth discussion of plan choice and premium tax credits.

[15]Though net premium for each consumer would be equal under the dominant and dominated plans, switching would still be ideal, as costs would still be lower with any non-zero level of medical utilization.

yearly premium loss is equal to \$320. Among those newly enrolled in the dominated plan (new enrollees and switchers), minimum welfare loss is equal to $\$789,695$, or \$207 per person (\$310 per full-year enrollee). In all, this is a loss of at least \$5.875 million among individual market enrollees. Inert enrollees account for a loss in government surplus of $\$186,300$, while those who are newly enrolled contribute to approximately $\$25,000$ of additional loss. This is approximately \$9.9 per enrollee, or \$12.5 for each full year enrollee. For those newly enrolled, these figures are \$6.6 and \$11, respectively. In all, including enrollees who were excluded from the previous calculations, the total combined loss in consumer and government surplus has a lower bound of \$6.38 million, or \$269 per enrollee, among those in dominated plans. Again, Kaiser, the provider of the plans, will see this as a direct increase in revenue/profit[16]. Had no enrollees switched from their dominated plan, the estimated measure of total loss would have increased by about \$3.159 million[17].

1.2.5 Switching Behavior

Because preferences and expectations are heterogeneous across enrollees, plan selection among switchers is not limited to Kaiser's dominant Gold (Coinsurance) Plan. As seen in Table 1.3, nearly all (93%) of those who switch plans remain in a Kaiser plan. Approximately one-third of these individuals choose the dominant gold plan, while 26% choose the higher cost gold plan. Nearly 35% opt for less robust coverage in selecting one of two bronze plans. The remaining enrollees choose either the platinum plan (6%) or minimum coverage (1%). Of the few enrollees who switched from Kaiser, two-thirds chose a silver plan.

For those who remained in Kaiser plans (see Appendix Table A1), and using the dominant gold plan as the reference group, Hispanic and Asian enrollees were less likely than White

[16]While ACA risk adjustment programs transfer premium dollars between insurance companies for the health status of their enrollees, adjustments are not made based upon metal tier enrollment differential or premium differential.

[17]This does *not* represent the lower bound for the consumer surplus recovered by those who switched, as those who switched may have chosen a "worse" plan along either financial or non-financial margins. Among those who chose the dominant gold plan, however, we can quantify this avoided loss to be \$1.011 million.

enrollees to instead switch to the other gold plan. This relationship also holds true for selection of bronze plans. Additionally, as age increases, enrollees are less and less likely to choose a bronze plan compared to the dominant gold plan. Similarly, high income enrollees favor the bronze plan relative to lower income ones. Among those who did change issuer, the only significant, meaningful results (found in Appendix Table A2) are that females and Black enrollees are less likely to choose bronze plans[18].

1.3 Information Interventions, Choice Mistakes and Heterogeneity

Table 1.4, which summarizes inertial behavior by service channel, shows that the most inert group is those who receive no assistance, with over 70% remaining in the dominated plan; those who enroll without assistance account for nearly half of all at-risk enrollees. Assisters that are provided by the insurance companies themselves constitute the next most inert enrollees, both of which remain in the dominated silver plan about 65% of the time. This is made up almost entirely of those who receive help from certified insurance agents, who make up over a third of the sample. Finally the three least inert enrollee groups, on average, are those who receive assistance from government-provided assisters: the least inert group are helped by service center representatives – also the largest of these groups, accounting for nearly 15% of at-risk enrollees. Over 60% of these enrollees appropriately switch from the dominated plan. Unlike with the issuer-provided assisters, there is a substantial gap between the inertia rates among the assisters, as navigators switch plans only 41% of the time. The total proportion of those receiving help from a Navigator is less than 3%. The two least-used forms of assistance, plan-based enroller and county eligibility workers, help fewer than 1% of enrollees in the sample combined.

While a causal analysis of inertia requires further scrutiny, these results stand alone for

[18] Large negative coefficients for choosing minimum coverage plans regressed on age variables are not meaningful, as these plans are only available to those under 30 years old.

Table 1.3. Switching Behavior among Non-Inert Enrollees

	Switched Within Kaiser				
Total Obs.			***11,500***		
	Gold (Dom)	***Gold (Other)***	***Bronze***	***Plat***	***Minimum***
Observations	3,729	3,025	3,970	656	120
	32.4%	*26.3%*	*34.5%*	*5.7%*	*1.0%*
Average Gold-Silver Kaiser Gap	$27.09	$26.98	$24.27	$26.32	$14.34
Average Gross Premium	$654.60	$677.82	$396.76	$745.31	$211.88
Average Net Premium	$262.71	$265.42	$215.55	$304.84	$211.88
	Switched From Kaiser				
Total Obs.			***836***		
	Gold	***Silver***	***Bronze***	***Plat***	***Minimum***
Observations	79	578	151	11	17
	9.4%	*69.1%*	*18.1%*	*1.3%*	*2.0%*
Average Gold-Silver Kaiser Gap	$21.34	$26.36	$23.80	$24.20	$13.74
Average Gross Premium	$556.92	$606.72	$421.06	$822.37	$189.39
Average Net Premium	$325.55	$217.50	$212.65	$507.86	$189.39

Note: The above table gives basic descriptive information regarding the switching tendencies of those who did not remain in the dominated Kaiser plan. The top panel summarizes the distribution of enrollees within Kaiser plans, including the dominant gold plan, the other gold plan, and other metal tiers. The bottom panel summarizes selection of plans among those who switched from Kaiser; both the top and bottom panels include gross and net premium, as well as the average premium difference between the dominated and dominant Kaiser plans.

Table 1.4. Costly Inertia Rate by Service Channel

	Proportion Inert	***Total Proportion of At-Risk Enrollees***
Unassisted	0.714	0.470
	(0.452)	(0.499)
Plan-Based Enroller	0.678	0.00863
	(0.468)	(0.0925)
Cert. Ins. Agent	0.648	0.352
	(0.477)	(0.478)
Navigator	0.585	0.0299
	(0.493)	(0.170)
County-Elig. Worker	0.509	0.00165
	(0.504)	(0.0406)
Service Center Rep	0.396	0.137
	(0.489)	(0.344)

Note: The above table shows, in column 2, the total proportion of at-risk enrollees who receive each service channel. Column 1 states the proportion of these enrollees who are inert. The service channels are ordered by proportion inert.

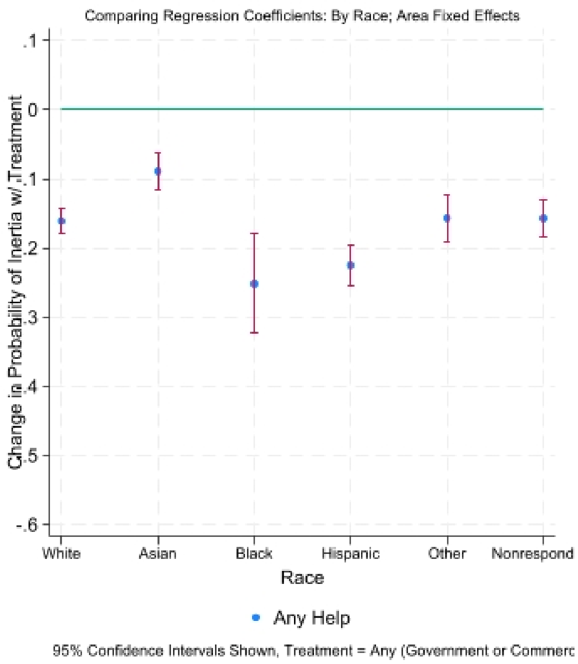
two reasons. Firstly, those receiving help, especially from a governmental resource, are less likely to remain in the dominated plan. While these raw differences may be driven by selection issues or omitted variable bias, they at least suggest that those receiving resources are less likely to make this choice mistake. Secondly, enrollees who receive help from assisters are still inert, with the *least* inert group only switching 60% of the time. This should be concerning to Covered California: while ex-post choice errors are impossible to eliminate due to uncertainty, these errors that can be evaluated ex-ante should ideally be wholly eliminated among enrollees. While this choice error is to be expected among uninformed, unassisted enrollees, its existence among those receiving direct enrollment assistance from governmental resources demonstrates a clear inefficiency and indicates that other mistakes are likely pervasive across assistance types and prior enrollment statuses.

In evaluating how service channels are correlated with inertia in health insurance choice, a heterogeneity analysis provides an opportunity to study these results across groups. This allows us primarily to demonstrate the relationship between likelihood of inertia and receipt of some service channel, specifically comparing governmental and non-governmental help. Secondarily, we can also evaluate differences in rate changes corresponding to these service channels and how this may relate to inequalities that exist in observed data. Panel (a) in each of the following three figures shows the change in probability associated with any governmental or non-governmental service channel assistance as compared to those who enroll without assistance; each confidence interval is a coefficient obtained from a regression conducted on the sub-population of interest. The three categories across which heterogeneity analyses were conducted is race/ethnicity, age, and income. Panel (b) of these figures results from a similar regression, but one whose treatment is split into governmental and non-governmental types. Across panel (a) of all figures, there is a consistent result of a decreased chance of inertia associated with receiving some form of assistance. Panel (b) demonstrates a consistent difference in effect size (between treatment types) across these demographic groups, with enrollees helped by government resources less likely to be inert than those receiving enroller-based help. Subsequent counterfactual exercises consistently find that, while the actual service channel choices of enrollees is consistently associated with inertia rates that are lower than in a world without any assistance, full utilization of government resources, as they exist now, would result in a significant reduction in inertia, bringing choice mistakes of re-enrollees to under 50%. While estimates are not causal and thus these figures, including the counterfactual, are subject to selection bias, they serve as a benchmark on which to compare further analyses.

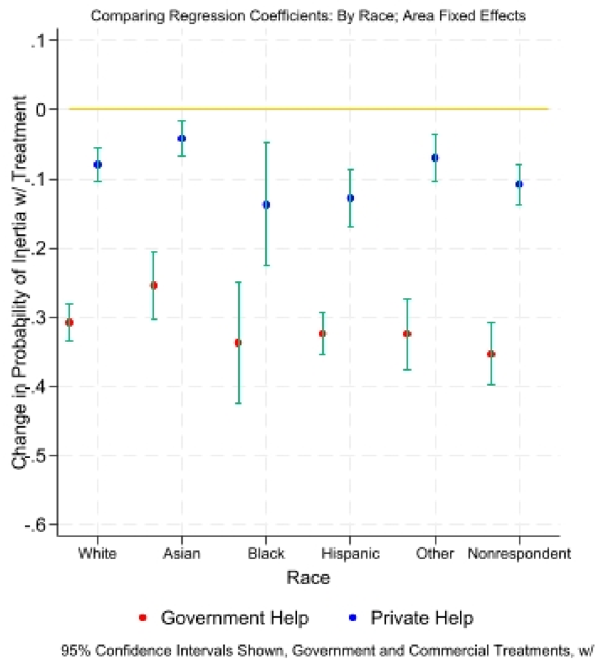
Race/Ethnicity

Firstly, takeup rates of assistance type by race/ethnicity, available in table 1.A.3, reveals a great deal of variation across groups in their uptake of service channel. For example, black and Hispanic individuals receive government help over 26% of the time, while white and Asian individuals do so less than 15% of the time. Asian individuals are the most likely race/ethnicity to receive corporate help at nearly 47%; black individuals receive this less than 19% of the time, and white and Hispanic individuals 26% and 27% of the time, respectively. This means that while the most (least) unassisted group is white (Asian) individuals, there is variation across receipt of these different types.

Across race/ethnicity, mean "effect sizes" vary; Figure 1.3 reveals that the group with the lowest inertia differential between assisted and unassisted individuals is Asian enrollees. Hispanic and black individuals constitute those with the highest differential, though the black group is not large and thus the effect size is imprecisely measured. White individuals, the largest of these groups, have coefficients between these two. These differences across Asian, white, and Hispanic individuals are statistically significant. These relationships hold when we split treatment to two types. While differences are not as stark, the coefficient for Asian and Hispanic individuals are significantly different for both treatment types. Asian individuals see the least gain in choice associated with both treatment from the government and the issuer – and the coefficient for private help for Asian individuals is not significant at the 5% level. More generally, intra-race/ethnicity differences between the inertia rate changes for the two treatments are significant for all races/ethnicities, and the magnitude of the differences between these groups



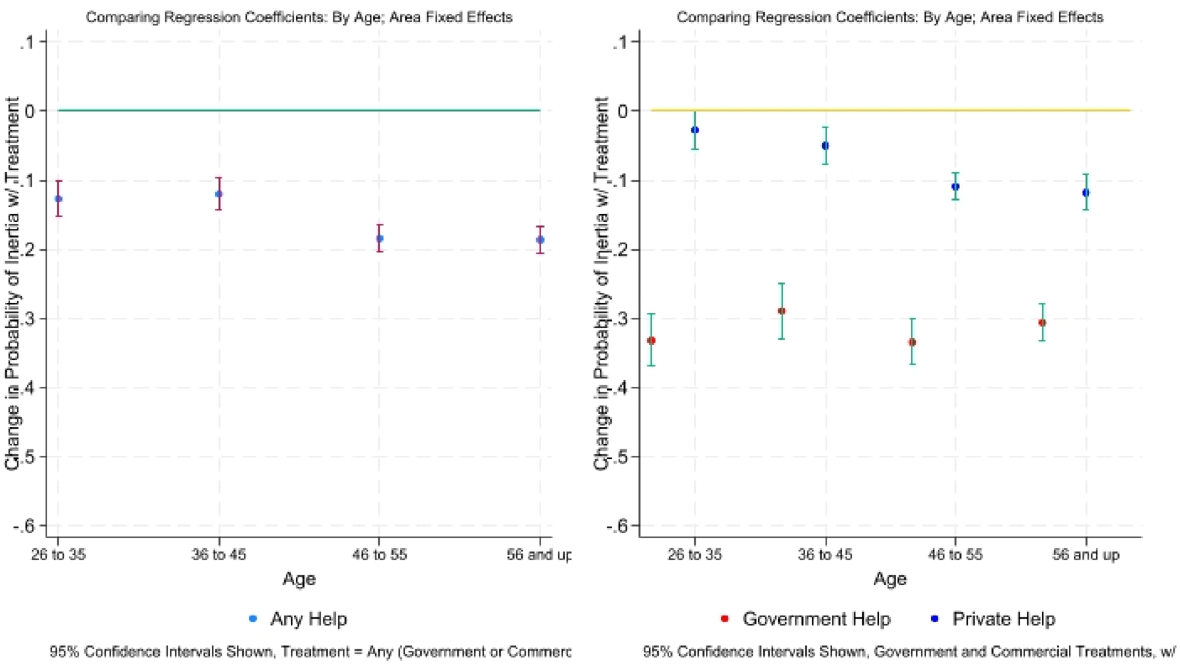
(a)



(b)

Figure 1.3. Difference in Inertia Rates between those Receiving Assistance and those not Receiving Assistance, Split by Race/Ethnicity Group

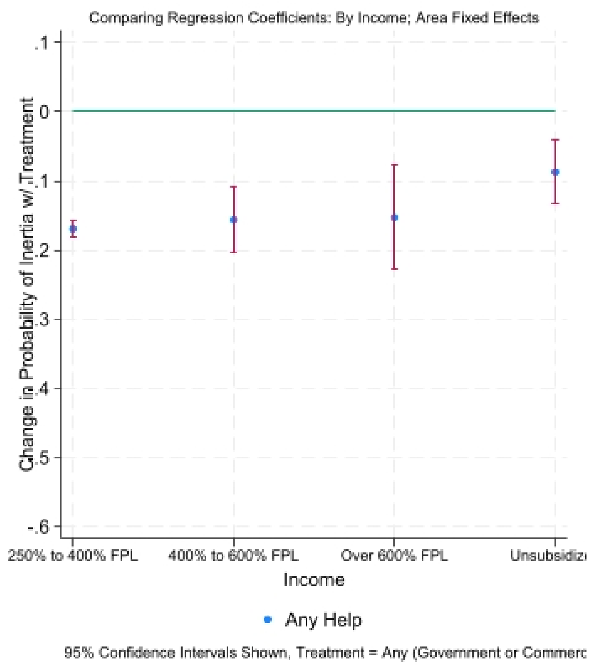
Note: The two figures above show the difference in inertia between those receiving assistance and those not receiving assistance, split by racial group (or non-classification). In panel (a), treatment is receiving *any* assistance; in panel (b), treatment is split into receiving government or private (issuer-provided) assistance. Coefficients are obtained by running separate regressions for each subgroup, controlling for age group, income group, and geographic area.



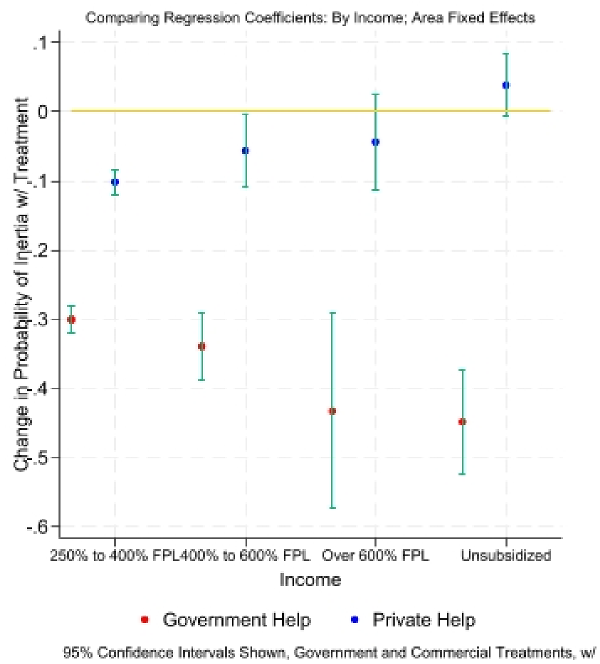
(a) **(b)**

Figure 1.4. Difference in Inertia Rates between those Receiving Assistance and those not Receiving Assistance, Split by Age Group

Note: The two figures above show the difference in inertia between those receiving assistance and those not receiving assistance, split by age group. In panel (a), treatment is receiving *any* assistance; in panel (b), treatment is split into receiving government or private (issuer-provided) assistance. Coefficients are obtained by running separate regressions for each subgroup, controlling for racial group, income group, and geographic area.



(a)



(b)

Figure 1.5. Difference in Inertia Rates between those Receiving Assistance and those not Receiving Assistance, Split by Income Group

Note: The two figures above show the difference in inertia between those receiving assistance and those not receiving assistance, split by income group (or non-classification). In panel (a), treatment is receiving *any* assistance; in panel (b), treatment is split into receiving government or private (issuer-provided) assistance. Coefficients are obtained by running separate regressions for each subgroup, controlling for age group, racial group, and geographic area.

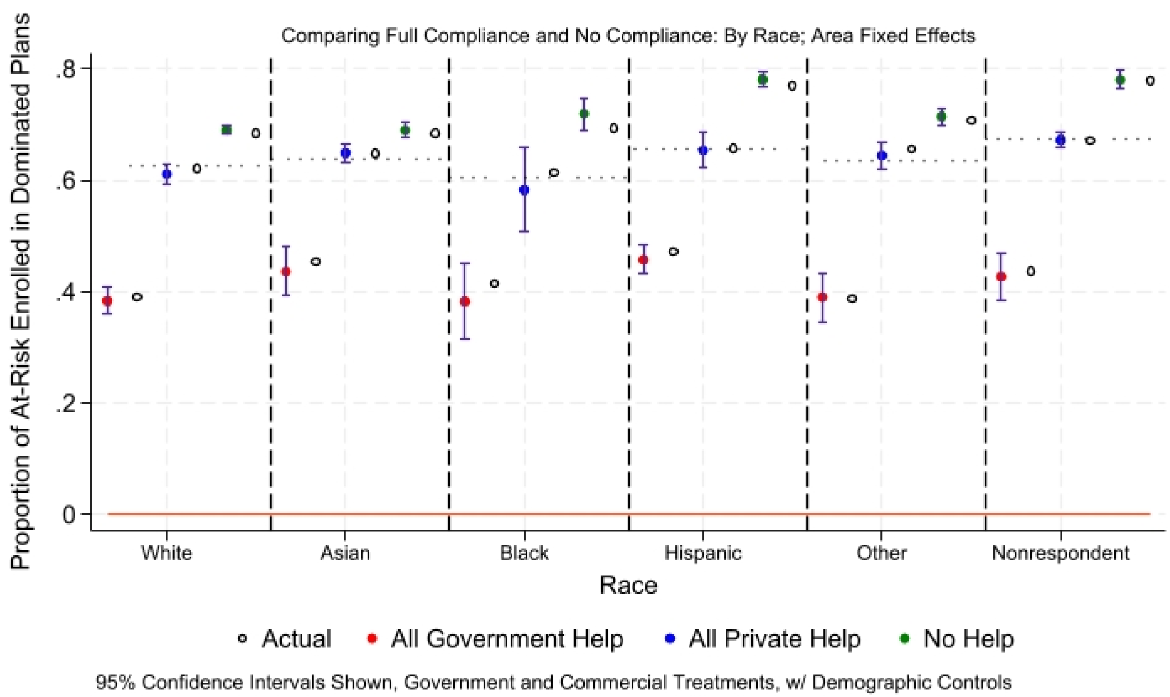


Figure 1.6. Counterfactual Exercise Estimating Inertia Rates given Full Takeup of Assistance Types, Split by Race/Ethnicity Group

Note: The above graph shows various counterfactual estimates for inertia rates across racial groups (or non-classification). For each racial group, the counterfactual estimates are: (1) all enrollees receive government help (red), (2) all enrollees receive private (issuer-based) help (blue), and (3) all enrollees receive no help (green). Actual inertia rates are in the hollow circles, repeated three times for direct comparison. This was constructed using estimates from Figure 1.3, panel (b). Clear dots represent actual levels of inertia for these assistance types. The dotted horizontal line shows unconditional enrollment for each racial group.

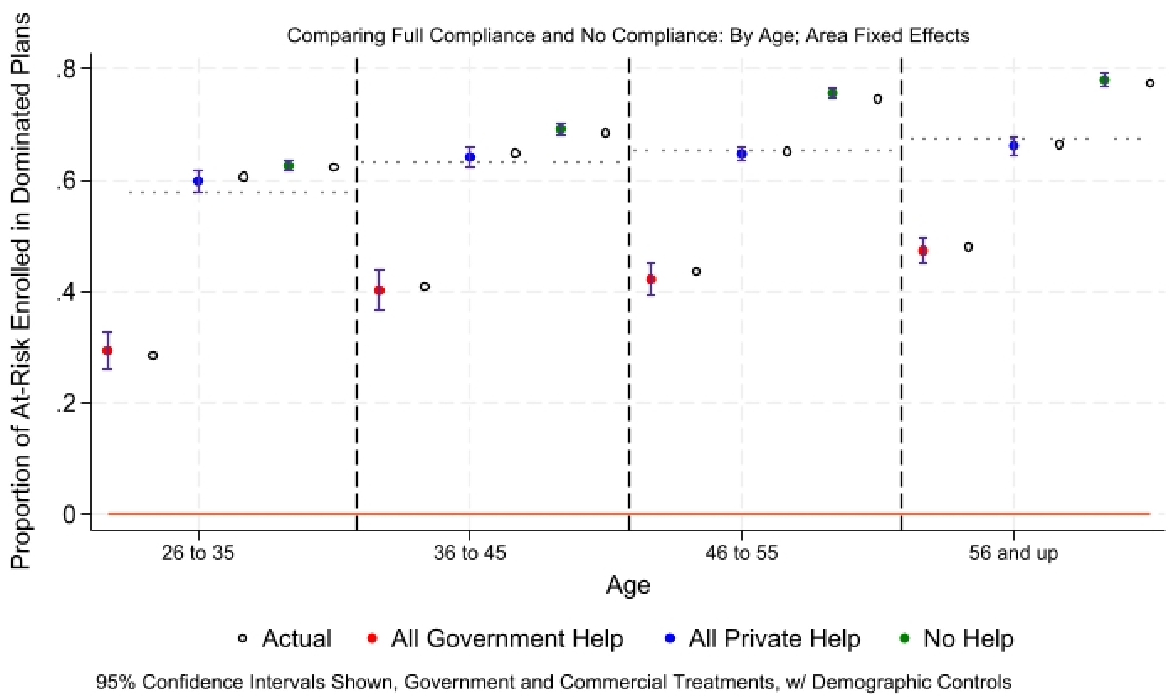


Figure 1.7. Counterfactual Exercise Estimating Inertia Rates given Full Takeup of Assistance Types, Split by Age Group

Note: The above graph shows various counterfactual estimates for inertia rates across age groups. For each racial group, the counterfactual estimates are: (1) all enrollees receive government help (red), (2) all enrollees receive private (issuer-based) help (blue), and (3) all enrollees receive no help (green). Actual inertia rates are in the hollow circles, repeated three times for direct comparison. This was constructed using estimates from Figure 1.4, panel (b). Clear dots represent actual levels of inertia for these assistance types. The dotted horizontal line shows unconditional enrollment for each age group.

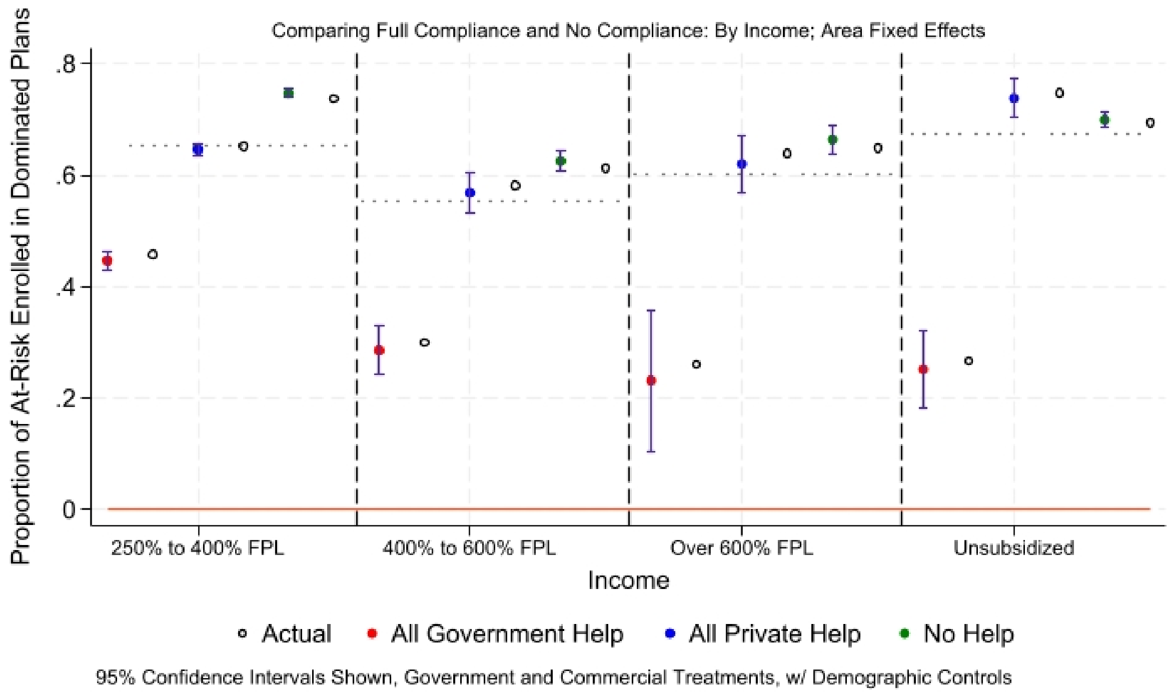


Figure 1.8. Counterfactual Exercise Estimating Inertia Rates given Full Takeup of Assistance Types, Split by Income Group

Note: The above graph shows various counterfactual estimates for inertia rates across broad income groups. For each income group, the counterfactual estimates are: (1) all enrollees receive government help (red), (2) all enrollees receive private (issuer-based) help (blue), and (3) all enrollees receive no help (green). Actual inertia rates are in the hollow circles, repeated three times for direct comparison. This was constructed using estimates from Figure 1.5, panel (b). Clear dots represent actual levels of inertia for these assistance types. The dotted horizontal line shows unconditional enrollment for each income group.

is relatively consistent for both types.

A basic counterfactual exercise (see Figure 1.6) for each race/ethnicity estimates inertia rates in the case that a group received *all* government help, *all* private help, or no help, compared to actual rates. These counterfactual estimates are subject to the caveat that estimates assume causality, which we argue is not likely. We find that, in the absence of service channels, the gap between Hispanics and other groups would be exacerbated as compared to current levels, with an inertia rate at over 78% among Hispanics. This aligns with the rate among unassisted Hispanic enrollees, which is approximately 10 percentage points above the other racial groups. If all enrollees had received private help, no estimates differ from current inertia rates more than marginally; further, Asian enrollees would be marginally worse off. Full takeup of government help would bring all groups to a lower inertia rate, though disparities are not necessarily reduced from baseline on a racial basis. In fact, compared to actual inertia rates, full takeup among all race/ethnicity groups would widen the gap between white and Hispanic enrollees.

Age

The group that receives help the least is the lowest age group, enrollees between 26 and 35, who receive assistance only 40% of the time (see Table 1.A.4). Uptake of assistance, both generally and separated by type, are monotonically increasing in age. Those over 55 receive government help in over 20% of cases, while those under 35 do so less than one-eighth of the time. Similarly, those over 55 receive corporate help over 38% of the time, while those under 35 do so nearly 28% of the time. This pattern holds true in all years, as receipt of help is correlated positively with age.

Across age groups, the estimated inertia differential between those who receive government help and those who receive no help is not starkly heterogeneous (Figure 1.4). However, outcome differences among those receiving private help are larger among older enrollees; point estimates for those receiving private help exceed negative ten percentage points for those over 45, while those under 45 are only marginally below 0. This difference for private enrollees, as well as high use of private help among older enrollees, mechanically drives differences in estimates from panel (a).

Counterfactual estimates (Figure 1.7) indicate that in the absence of any assistance, the gap in inertia would widen to approximately 15.5 percentage points, whereas the observed gap is closer to 10 percentage points. This gap is consistent with the gap among unassisted enrollees, which is also about 15 percentage points. Further, this gap would be slightly widened if all enrollees received government help, if these estimates are correct. Due to heterogeneity in private help's coefficient, older individuals with full compliance to private help would be marginally better off, while younger ones would be marginally worse off.

Income

As with age, takeup rates are monotonic across broad income groups (see Table 1.A.5): probability of either type of assistance is decreasing with income, and unassistance rates are increasing in income. Further, the unclassified, "unsubsidized" group, many of whom are likely high income, have the highest rate of non-assistance, with nearly 70% of enrollees operating without help. These enrollees receive help only 24% of the time from corporations and 8% of the time from the government, the next lowest being 31% and 11%, respectively.

If only considering assistance as a binary treatment variable (panel (a) of Figure 1.5), results are not notably heterogeneous across groups. When looking to panel (b), however, we see distinct heterogeneity. While lower income enrollees may have 10 percentage points lower probability of inertia when receiving non-government help, higher income enrollees are less helped, with those over 600% FPL and unsubsidized enrollees with effect sizes not statistically distinct from 0. Conversely, those in higher income groups have a greater income gap at higher income levels. Unlike across race/ethnicity and age, the gradient for private and government help are distinctly in opposite directions when considering inertia gaps. Unsubsidized individuals are particularly of note, as government help is associated with the greatest inertia gap, while non-government help may be associated with slightly higher rates of inertia.

A counterfactual exercise across income levels finds that, despite the difference in inertia gap for private help, high uptake among lower income enrollees diminishes the measured gap in inertia rates with unsubsidized enrollees (See Figure 1.8): whereas inertia rates among those with no assistance the gap is 4.5 percentage points in favor of the unsubsidized, the observed difference is approximately 2 percentage points in favor of the low income enrollees. However, unlike across other demographic groups, full utilization of government help across all income groups would seemingly severely exacerbate disparities, both due to differences in observed uptake and heterogeneity in the inertia gap. While the current inertia gap between lower income and middle income (unsubsidized) enrolles is currently 10 (-2) percentage points, under full utilization of government help the gaps would be 21.5 (19) percentage points. Furthermore, unsubsidized enrollees are the only demographic groups whose outcomes under full utilization of corporate help are statistically worse than at current levels. While there are differences even across observed income groups, all above 400% FPL are unsubsidized, and these differences could be due to the selective nature of not receiving a subsidy[19].

Since income is not measured on a fine scale in the original data, and *all* subsidized enrollees fall within the 250% to 400% FPL income boundaries, it is possible that differential results across these income groups is reflective not of an income gradient, but rather reflects an inherent difference between subsidized and non-subsidized enrollees. To investigate this, I turn to the restricted sample of enrollees; Appendix Figure 1.A.5 reveals no gradient across finer income groups among enrollees receiving some premium reduction. Similarly, Figure 1.A.6 shows that if we group instead by total dollars of income rather than income as a percentage of FPL, the same result holds. Further, we see that results associated with those not receiving subsidies holds for those without subsidies between 250% and 400% of FPL. Namely, help from an insurance agent does not provide for differential outcomes when compared to no help, and outcome associated with government help are at least marginally better. Though these are generally higher income, the unsubsidized have show a clear departure from those subsidized

[19]Specifically, only those who pay disproportionate attention to their plan choice would seek assistance, especially among those who do not receive a subsidy. Since receiving a subsidy involves a greater chance of needing to verify one's income and thus interact with the Covered California website, these individuals may be less likely to receive assistance without exhibiting greater investment in plan choice relative to other income groups.

that also have higher incomes.

In conclusion, across age and race/ethnicity groups, those groups with the lower baseline levels of inertia are less likely to receive help, with the exception of Asian enrollees. This is especially true across age groups. As a result, disparities in inertia seem to be addressed naturally through differential take-up of assistance. While those in the low income group are both most dominated at baseline and have the highest rates of assistance, unsubsidized enrollees have the lowest rates of assistance and the second highest rates of baseline inertia. This is likely due to the nature of the unsubsidized group; these are those across all income categories that did not report income, and thus are less likely to be engaged with the process as much as another enrollee. Still, those under 400% FPL that do not receive a subsidy exhibit similar coefficients, so this may reflect other characteristics of not receiving help. This also means that, since unsubsidized enrollees exist within the 250% to 400% FPL group, these estimates are slightly skewed by the presence of the unsubsidized. While counterfactual estimates are to be taken with a grain of salt due to issues with selection bias associated with choice of assistance channel, given that reductions in disparities are attributable to differential takeup rates, these estimates are still informative.

Back of the Envelope Calculation: Savings under Universal Government Assistance

Though there is likely selection bias with respect to whom is receiving help from which channels, it is valuable to have a sense of the potential amount of money that could be saved by stakeholders in the California individual health insurance market if receiving assistance. Since government assistance appears to be most effective, we consider a back-of-the-envelope calculation of the amount of money that could be saved if all individuals received help from either a service center representative or a navigator. In order to fully account for differentials in dollars saved across age groups due to premium factors, I use estimates of inertia differentials across age groups to calculate this. Inherent to this calculation is the assumption that likelihood of switching is equal across all inert enrollees in some age group, regardless of area and race/income. Of the $5.52 million left on the table in premium savings – a loss shared by both consumers and the government, but mostly incurred by enrollees – \$1.88 million could have been saved if enrollees were required to receive assistance from one of these government resources. This would mean that about 34.1% of these losses would not have been incurred[20].

1.4 Supplemental Analyses and Robustness Checks

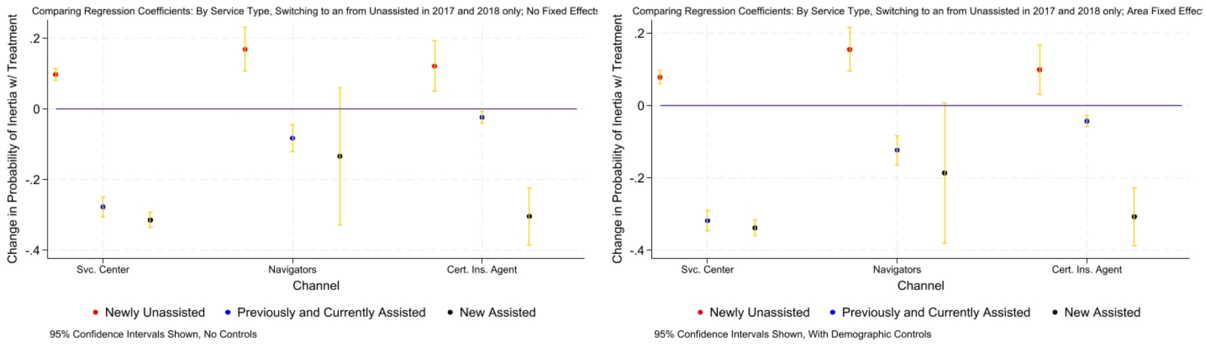
In an ideal experimental setting, service channel would be randomly assigned across at-risk participants and changes in inertia rates could be interpreted as causal estimates of decreases in these choice mistakes as a result of receiving these types of assistance. However, various biases exist that threaten this interpretation at the given point in this work. Firstly, various enrollees may select into service channels based upon unmeasured characteristics. For example, it may be the case that information seeking types are more likely to call a service center or insurance agent for help with selecting their plan. Conversely, those with high health insurance literacy may instead have a more firm grasp on the health insurance setting and thus do not need to seek help from a third party. *A priori*, it is not clear which direction this bias is likely to take. Secondly, selection of service channel may, in some cases, be a direct *response* to noticing that one's plan choice is dominated. It may be the case, for example, that a previously unassisted enrollee accesses the Covered California website and discovers that a gold plan is available for less than a silver plan. He may, then, call an additional resource such as a service center for confirmation of this seemingly anomalous occurrence and receive guidance thereof. This would, then, mean that current estimates of effects overestimate the effect of receiving help from a service center. Finally, there may be differential targeting of enrollment resources or simply variation in access to these service channels. While this is not likely for service centers, navigators and insurance agents may only be available in certain areas, or have a different capacity to help certain types of enrollees.

[20] Full compliance to government help results in a 49.2%, 36.5%, 35.4%, and 29.6% reduction in inertia among the four age groups (Ages 26 to 35, 36 to 45, 46 to 55, and 56 and up) respectively. This means that estimated savings among these groups are equal to these percentages as well. However, this final proportion is about 34% because the eldest age group is the largest in terms of both number of inert individuals and premiums paid per enrollee.

1.4.1 Service Channel Switching and Inertia

To address selection into information channels by enrollee type, both generally and in response to our policy situation, I conduct a similar analysis to the previous section, but additionally consider previous service channel in order to examine how switching between service channels relates to inertial outcomes. To do this, I look at inertia differentials across four different treatment statuses instead of two. For each service channel type, these treatment types are (1) unassisted in both years [baseline], (2) previously assisted but newly unassisted, (3) assisted in both years, (4) previously unassisted but newly assisted. Unlike with the previous analysis, I conduct analyses for each service channel type as a separate regression with three binary treatment variables, with the dataset restricted to those who fit one of the three criteria, or are otherwise always unassisted.

Figure 1.9 shows these results for the three most commonly utilized service channels. Note that this graph of the raw differences in panel (a) (without geographical or demographic controls), mirrors that of panel (b), which includes controls. This graph reveals three noteworthy observations. Firstly, enrollees who are newly assisted by a government-related service channel have slightly larger magnitude estimates than those who were already receiving that help, though these differences are not statistically significant. This indicates that there may be some selection by unassisted enrollees into government help after seeing that they are at-risk; still, this difference is marginal, and lack of power disables us from finding significant differences, especially among those receiving assistance from navigators. More decisively, there is a large, economically and statistically significant difference between those who are newly receiving help from a certified insurance agent and those who already did. While those newly receiving this corporate help have a 32 percentage point lower probability of inertia than baseline, those who already received this help in the previous year see only a 5 percentage point difference in inertia compared to always unassisted enrollees. If this was driven entirely by selection bias, it would mean (1) that this selection bias is substantial and creates a stark difference in outcomes, magnifying the



(a) **(b)**

Figure 1.9. Measured Differentials in Inertia Rate compared to Baseline (Always Unassisted), from 2017 to 2018 across Assistance Channels

Note: The above graphs show measured differentials in inertia rate compared to the baseline (0) or being unassisted in both 2017 and 2018. The sample of enrollees is at-risk enrollees, and the response variable is change in probability in being inert. Panel (a) is a raw comparison without controls; panel (b) include area fixed effects and age, income, and race/ethnicity indicator variables. For each graph, the leftmost section is run on the subsample of individuals who were either unassisted or received service center help in both years; the center section is run on the subsample of individuals who were either unassisted or received navigator help in both years; the rightmost section is run on the subample of individuals who were either unassisted or received navigator help in both years. Within each section, the left dot (red) represents those who were previously assisted and are now unassisted; the middle dot (blue) represents those who are assisted in both years, and the right dot (green) represents those who are newly assisted.

probability gains 6-fold, and (2) the selection of corporate help as a result of being at risk is much more common than the selection of government help, as we do not see anything near this stark of a pattern among government-assisted enrollees. Both of these findings, which relate to triggering of information seeking, merit further investigation. A more likely explanation is that insurance agents face costs in evaluating all of their clients' plan choices and are thus less likely to make an active plan choice as compared to government-provided resources. This finding, paired with the previous finding, also speaks to the nature of insurance agent assistance (high probability of retention) compared to service center agent assistance (requires an independent choice to receive help on a yearly basis).

A final observation from Figure 1.9 is that those who are newly unassisted are more inert than those who continue to be unassisted. This result is consistent across assistance channels. This provides indirect evidence on selection more generally: under no assistance, those who normally do not receive assistance have better outcomes than those who normally do. In other words, this is evidence that those who are generally unassisted may disproportionately include those with a more sophisticated understanding of health insurance as compared to those who are generally assisted. Similarly, rather than sophistication, it may instead reflect types in terms of attention (i.e. those who are normally assisted are less likely to pay attention when re-enrolling on their own). This will be discussed in the subsequent subsection. While this is not the only interpretation, its argument is strengthened by the fact that under random assignment, those who previously received help should be *at least* as well off as those who were previously unassisted. This is because information obtained in a previous period could (and ideally *should*, from a policy evaluation perspective) be persistent and inform decision making in future periods. Either selection is so strong as to counteract any measurable persistence of this knowledge, or it is not appropriately transmitted in the first place (i.e. enrollees are not taught to understand their health plan selection process but are rather instructed on their "best" options given their preferences). This lack of persistence may again be a result of those who are able to retain such information not selecting into receiving help. If it is the case that enrollees with low health insurance literacy are those who receive help, coefficients from section 3 may underestimate the causal effects of service channels. I further parse some of these findings out by directly measuring attention in the following section.

1.4.2 Inattention and Other Causes of Inert Behavior

A descriptive analysis that distinguishes between active and passive re-enrollment among at-risk enrollees can provide additional illumination on inattention as a source of inertia, the selective pressures at hand for those who receive assistance from some service channel, and the pool of those who receive each type of assistance. To keep enrollment continuous, health insurance marketplaces under the ACA facilitate automatic re-enrollment for individuals who do not either disenroll from their plan or choose a new plan at the beginning of the calendar year. While various marketplace factors could cause an automatic re-enrollee to be placed in a different plan[21], Kaiser enrollees do not see plan choices differ, and thus passive enrollment always results in remaining in one's previous plan. This exemplifies the integral role of active enrollment in plan choice and provides a measure of inattention, which plays a unique role in driving costly inertia, as, constranstingly, first time enrollees must always make an active plan choice.

When considering the entire set of at-risk enrollees who were previously in the newly dominated Kaiser Silver plan, only 54% made an active enrollment choice. Thus, 46% of enrollees were inert by default. Among those who made an active decision, 65.5% switched from the dominated plan. In other words, the *switching* rate among those who switched closely resembles the unconditional *inertia* rate in these markets. Inactivity was (expectedly) most prevalent among unassisted enrollees, as only 39.7% of these individuals made active plan choices. On the other hand, those who received assistance from a service center representative made active choices in virtually all (99.93%) cases. Meanwhile, 56% of those who receive help from a certified insurance agent and 63% of those who receive help from a navigator make active plan choices. Thus, these disparities in inertia rates are largely driven by active enrollment numbers, as website activity and inertia rates are ranked accordingly across service channels.

Still, differences in switching rates among the active of these groups also drive inertia and draw suggestions about the composition of each group. While the unassisted are the least attentive in terms of website activity, those who make an active choice are the most likely to switch, with over 72% enrolling in a different plan. Meanwhile, those who receive help from a service center switch only 60.4% of the time, despite receiving direct assistance. Meanwhile, 63% of those who receive assistance from an insurance agent and 65.6% of those who receive help from a community navigator appropriately switch plans. This, then, supports the notion that unassisted enrollees consist disproportionately of individuals with a high acuity for health insurance decision making. Another potential reason for this disparity would be that service

[21] If one's previous plan is no longer offered by an insurance issuer, they will be automatically enrolled in a similar plan offered by the provider (e.g. a different silver plan). If the issuer pulls out of the market entirely, a similar plan from a different provider will be issued to the enrollee.

center representatives are providing poor or even detrimental information to these enrollees. Since receiving assistance from a service center requires some level of attention in the first place, it follows that these low observed rates of inertia are related directly to high levels of attention and not necessarily effectiveness of assistance.

Though active enrollment indicates that attention is not entirely absent, the presence of an active enrollment does not wholly capture one's attention, and an active enrollee may still be inattentive to some degree. Inattention levels can be further parsed by examining switching rates among re-enrollees who were not enrolled at the end of the previous year. Though these individuals were still technically re-enrolling from their previous plan, the dynamic is different from those whose plan choice was continuous, since there is a clear disenrollment that occurs before December 31 of the the previous enrollment year (2017). Of these previously "terminated"[22],84.8% made an active plan selection. Moreover, among those making an active decision, 77% appropriately switch plans. Again, this pair of descriptive statistics reflects the nature of this decision, namely that the discontinuity in coverage induces a greater likelihood of presuming that an active choice must be made. Furthermore, this same dynamic may cause individuals to pay more attention to their plan choice, even conditional on having made an active choice, as compared to those without an interruption in their coverage. Assuming that those who previously disenrolled are not fundamentally different from those who remained in their coverage[23], this result of the presence of attention (active enrollment) and a higher degree of attention (higher switching rate) is consistent across all service channels. Since not all enrollees who experience a discontinuity in coverage necessarily must make an active choice, higher rates

[22]Our analysis data shows enrollee status at the end of a year as "Enrolled", "Terminated", or "Cancelled". The former two classifications are considered enrollments, and the 2017 variable was used to determine this status.

[23]One possible departure from this assumption would be that enrollees who previously terminated coverage may have had strong foresight that they would not need health insurance for the remainder of the calendar year, and thus disenrolled to save money on premiums. This may mean that this group is disproportionately full of those with higher insurance competence. Another possibility is that they experienced liquidity constraints and thus had to disenroll, and thus gave additional care to their re-enrollment in order to examine if they could save additional money. Finally, they may have been dissatisfied with coverage, and thus disenrolled with intentions of switching plans in the new year. A situation that would affirm this assumption would be that termination is more exogenous; an example would be an opportunity for employer-sponsored health insurance causing disenrollment.

active enrollment rates likely further enhance the argument that greater care in choice (rather than a required decision) may be induced by the discontinuity.

Active vs. passive enrollment can also be valuable by providing additional context to the analysis of the previous section (4.1), which analyzes switching service channels and costly inertia. Firstly, we compare newly unassisted to those who were previously unassisted and continue to be so. Those who are newly unassisted have both a lower probability of making an active choice (30.5% vs. 42.7%) and a lower probability of switching conditional on making an active choice (66.5% vs. 73.4%). Thus, higher inertia rates among the newly unassisted is attributed to both a higher proportion of those who are wholly inattentive and a greater switching rate among those who were at least somewhat attentive. A simple narrative for the former would be that newly unassisted individuals assume that they have made an efficient choice after previously receiving assistance, and thus feel less of a need to make an active choice in this year. The latter finding may also reflect this, but may further signify a lower ability to make these decisions as compared to those who had made an active, unassisted choice in previous periods.

The large disparity between those newly receiving assistance from a certified insurance agents and those who were already in this group also deserves prodding. Newly assisted individuals make an active choice 82.4% of the time, while those who were persistently assisted only do so 54.6% of the time. Moreover, among the newly assisted, switching rates are higher conditional on making an active choice (76.2% vs. 61.8%). This speaks to greater attention given by an insurance agent to actively enroll (or encourage their client to actively enroll) and greater care given to the decision when that is done. This relationship also holds true for new and existing receivers of navigator assistance, though the disparities are less stark. Finally, since basically all of those who receive assistance from a service center actively enroll, the small, insignificant enhancement in decision making between those who are newly in this service channel is attributed to a higher switching rate among active enrollees. Again, this may or may not be attributed to some degree of acute selection in response to the dominated plan choice.

Another simple analysis to conduct is a heterogeneity analysis of attention with respect to our demographic variables; this may illuminate further reasons behind inattention and other potential drivers of inertia. Across age and income strata, disparities in costly inertia rates appear to be driven both by active enrollment rates and differential switching rates conditional on making an active choice. The youngest age group of 26-35 is both most active and most likely to switch given they make an active choice; a negative gradient exists for both measures as age increases. Across incomes, while monotonicity is not as clear, those in the lowest income group (250% to 400% FPL) have both the lowest active enrollment rate and the lowest rate of switching conditional on accessing the website. While conditional switching rates hold across all service channels, a few have different patterns with respect to active enrollment. Firstly, though this has been previously noted, it is worth reiterating that service center representative assistance facilitates active plan choice in 100% of cases; thus overall, since both older individuals and low income individuals are more likely to receive this assistance, their active website enrollment rates are largely equalized when not conditioning on service channel type. Secondly, certified insurance agents appear to induce a situation where both older and lower income individuals have slightly higher website activity rates. This does not appear to be driven by any sort of switching, as older individuals and lower income individuals to not newly seek an insurance agent's help more often than other demographic groups. Again, these groups have higher takeup rates, which further equalizes overall unconditional inertia rates.

Across racial classifications among unassisted enrollees, we find that while conditional switching rates are similar, Hispanic individuals are markedly less likely to make an active plan choice. Furthermore, conditional switching rates among Hispanic enrollees are lower than other groups racial groups when receiving assistance from a service center representative. Finally, it appears that white individuals have the highest switching rates conditional on making an active choice, but only when they receive assistance, both from private or government resources. Still, their takeup rates of assistance are the lowest of all racial groups, and their active enrollment rate is low when receiving help from an insurance agent. Thus, despite higher takeup of assistance that largely equalize active enrollment rates, differences between these two groups in overall inertia is largely driven by differences in switching probability.

1.4.3 Geographic Variation in Funding

Because the choice of service channel is an endogenous one, measured treatment effects of these service channels does not give the decrease in probability that is *caused* by some service channel; the relationship is correlational, and various above techniques are intended to address some of these concerns to fully understand where selection may be an issue. In an ideal experimental setting, some service channel would be randomly assigned to each at-risk enrollee, and treatment effects as measured above could be documented. In order to econometrically simulate this, I suggest using geographic and racial variation in Navigator program funding as a potential instrument for navigator takeup in a two-stage least squares (2SLS) regression.

The Navigator program, which is federally mandated to be provided by all states running their own exchange, is intended to provide community-based organizations with a stake in local welfare with funding to provide assistance to enrollees who need additional enrollment assistance. For the 2018 plan year, California's Navigator program dispersed $6.425 million in funding across 43 different entities, many of which operated in multiple counties and rating areas. While access to service center help does not vary by geographic region insofar as phones and internet are equally available, access to a navigator may depend on one's physical address. This is because Navigators, also known as "Certified Enrollment Counselors", provide *in-person* guidance for health insurance plan choice. In the most extreme case, enrollees in geographic regions without any local Navigators would incur greater costs (e.g. travel, searching costs) to obtain assistance from one of these entities. On the intensive margin, entities with greater levels of funding may be able to provide assistance to a greater number of enrollees and/or provide more effective help thereto.

Publicly accessible[24] information on organizational navigator funding provides the number of dollars provided to each navigator entity that applied, as well as their counties of service.

[24] Funding information is available at https://hbex.coveredca.com/navigator/grant/

In addition to this, the ethnicity of people that are intended to be served is listed. Assuming that funding is distributed across counties by each entity based upon county population, I can measure total navigator funding provided to each county. Moreover, using overall enrollment numbers, I can calculate amount of funding per enrollee (see Appendix section 6.3 for a detailed explanation on this process). Geographic variation in navigator funding on a county level is seen in Figure 1.10 below. Areas with high levels of funding per enrollee include Kings ($29), Kern ($21), and Tulare ($17) counties. Meanwhile, 18 different counties received no funding. While these unfunded areas are generally low-population counties, it also includes mid-sized counties (such as Shasta and Madera) and excludes some small counties (such as Glenn and Colusa). The median county funding is approximately $1.50 per enrollee, which is the case in Riverside, the fourth most populace California county.

A priori, one may expect that areas with higher levels of funding would see greater uptake of navigator assistance; this is documented in Appendix Table 1.A.6. This analysis, run on the entire population of enrollees in years 2016 to 2019, shows that higher funding per enrollee is consistently correlated with higher levels of navigator help: each additional dollar per enrollee is associated with about a 0.15 to 0.3 percentage point increase in the probability of one receiving help from this service channel. No statistically significant relationships are found between funding levels and service center or certified insurance agent assistance.

While this is promising for the relevance of funding as an instrument for navigator assistance, running this same regression on only the at-risk population (and those higher-income Kaiser enrollees in some silver plan in other enrollment years), findings are not as strong (Appendix Table 1.A.7). While coefficients remain positive, the relationship is less statistically significant, and coefficients are not as large (approximately 0.1 percentage points on average). This places into question the relevance of this instrument. Thus, I argue that the setting does not provide sufficient power for use of navigator funding as an instrumental variable in a 2SLS regression.

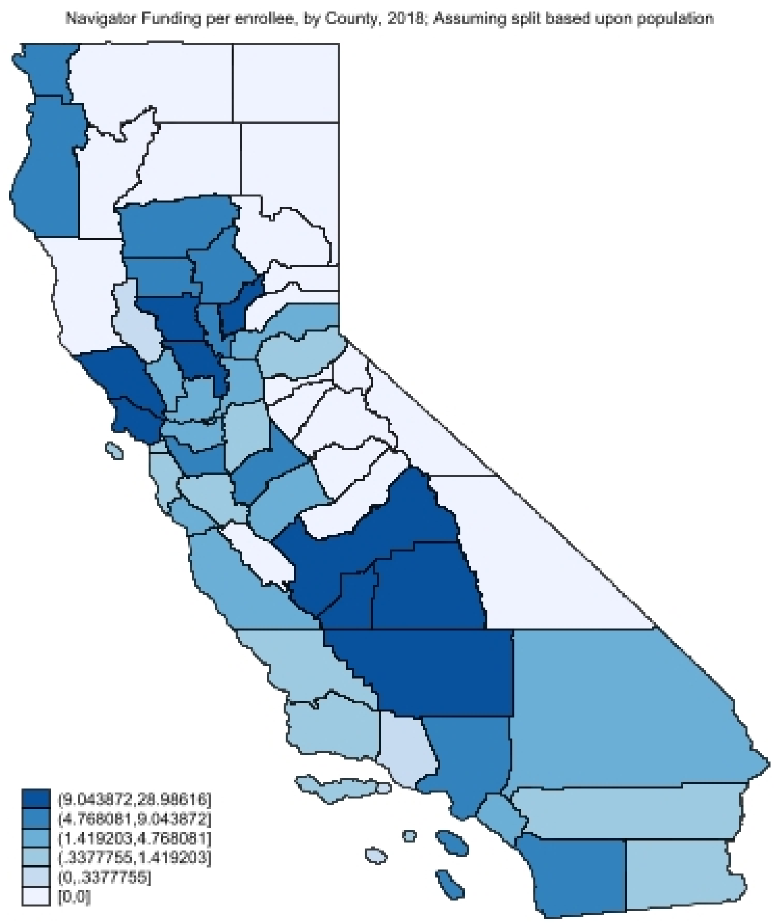


Figure 1.10. Estimated Navigator Program Funding per Enrollee in each California County
Note: The above figure shows estimated Navigator program funding per enrollee in each California county. The methodology for calculating this is found in Appendix Section 6.3.

1.4.4 Robustness Checks and Expanded Population

Unverified Plan Choice

As I have iterated, the presence of cost sharing reductions makes examining those above the 250% FPL cutoff necessary, as these are the *only* individuals who would receive a silver plan at the standard 70% AV. Still, examinations of the data find that, while classified as above 250%, some enrollees are still shown as enrolled in a plan that is receiving some level of cost-sharing reductions. For example, in 2018, across all enrollees in silver plans above this cutoff, 3.5%, 5.1%, and 2.2% of enrollees (about 11% in total) are listed with 73%, 87%, and 94% AV in their plan, respectively. While simply removing these individuals from the data would partially solve this issue in our main analyses, we would face an additional issue; namely, that we are not able to observe the CSR that would be listed for each enrollee who in fact *did* switch to a non-silver plan. If we were to remove those silver enrollees, we would only be removing those from the inert group. This presents a trade-off between the two approaches of likely underestimating or overestimating inertia. Instead, I propose using the restricted sample as a robustness check, as mismatch rates are substantially reduced after matching income levels. Fewer than 0.31% of silver enrollees are classified as receiving either 73% (0.19%), 87% (0.07%), or 94% (0.05%) actuarial value. Main descriptive statistics on inertia, which mirror Table 1.2, are available in Table 1.5; here, we see very close to the same proportion of enrollees inert as in the main analysis (64.6%), and similar coefficients on likelihood of measurable demographic characteristics.

Other (Possibly) Dominated Plans

Although not discussed in the main parts of the paper, two other plans offered in California in 2018 were silver plans whose corresponding gold plan within their product was available for a lower premium. SHARP Health Plan, which only operates in San Diego, offers two separate insurance products with distinct networks, both sets of which are priced with lower gold premiums than silver. While these would provide additional power to examine at-risk enrollee behavior, I exclude these from the main analysis of choice of dominated plans for two reasons.

Table 1.5. Inert vs. Non-Inert Enrollees; Premium and Demographic Characteristics, 2018; Restricted Sample with Verified Income Levels

	Inert	***Switched***
Observations	9,741	5,347
	64.6%	*35.4%*
Average Gold-Silver Kaiser Gap	$27.02	$25.17
Average Gross Premium	$679.12	$558.96
Average Net Premium	$300.97	$259.75
Regression Results: Demographic Characteristics		
Female	-0.0289***	
	(0.00608)	
Age 36 to 45	0.0713***	
	(0.01552)	
Age 46 to 55	0.102***	
	(0.01503)	
Over Age 55	0.130***	
	(0.01657)	
Black	0.00979	
	(0.02571)	
Hispanic	0.0230	
	(0.01544)	
Asian	0.0121	
	(0.01875)	
Other	0.00903	
	(0.01438)	
Nonresp	0.0452***	
	(0.01191)	

Note: The above table compares enrollees who remained in their dominated plan to those who switched from it. The subsample of enrollees is those over 25 who were enrolled in the Kaiser silver tier plan in 2017 and have incomes above 250% FPL. Two additional restrictions exist: (1) all enrollees come from geographic areas where SLCSP is consistent across all counties and zip codes, and (2) all enrollees have either a verified income that matches with their PTC or are within a range that is possible (e.g. if they have income listed below 400% FPL and there exists some interval below 400% FPL for which he would not qualify for PTC). This table's contents mirrors the results from Table 2.

Firstly, these enrollees come from one county, and thus there is minimal geographic variation that can be accounted for within this company. If differential resources were specifically provided to these enrollees compared to those under Kaiser, controlling for geographic variation may instead reflect differences across issuers within the county. Secondly, and possibly more importantly, the two sets of plans do not provide the clean dominance that the Kaiser plans exhibit. For one product, the silver and gold plan exactly match the cost sharing structure of the Kaiser product[25]. For the other product, though, dominance is not able to be rigorously established as with the Kaiser plans. This is due to a greater number of benefit categories that are not directly comparable (coinsurance vs. copayment). While a simplified plan representation would still indicate that dominance is established, this creates a less clean environment to study inertia, as edge cases are a greater cause for concern. For the main analysis, I simply do not include these enrollees. However, it is clear that individuals in San Diego have a set of choices that include multiple dominated plan choices, which could affect results within the county. As a result, I re-run my main analysis without San Diego (Appendix Table 1.A.8); results do not substantively change.

Enrollees receiving CSR

One may question why individuals receiving 73% CSR are not included in the group that is at-risk of enrolling in a dominated silver plan, since gold plans have an actuarial value of 80% and still available at a lower premium. However, this 73% AV plan does not pass the rigorous test for dominance, as for two drug categories (Tier 2 and Tier 3), copay is $50 under the silver plan and $55 under the gold plan. While a simplified plan representation can demonstrate that a plan is as-good-as dominated, this will not hold up; the maximum out-of-pocket amount under the silver plan is $5,850, while it is $6,000 under the gold plan. This means that enrollees with very high utilization will have greater out-of-pocket costs under the gold plan than the silver plan. While reaching this high of utilization is likely to occur only for a very small proportion of

[25] In California, plan offerings must come from a "standardized" list of plans. As a result, many plans across issuers match in this dimension.

these silver enrollees, its existence violates the dominance that makes our approach clean.

To examine this data, we must then only consider enrollees whose premium difference exceeds the \$150 difference in out-of-pocket maximum, as this represents that "maximum" difference of OOP costs under gold plan minus OOP costs under silver plan. The difference between these two plans' premiums on a monthly basis is anywhere between \$11.79 (*26 year olds in Los Angeles*) and \$46.71 (64 year olds in San Francisco). Enrollees must both pay a high enough premium difference per month and be enrolled over enough months to make up for this difference. Thus, for this analysis I further restrict the dataset to enrollees over the age of 30 (inclusive) who are enrolled in the health insurance plan for the entirety of the year. This ensures that premium differential is greater than OOP differential. Thus, we conduct the analysis with the caveat that our notion of dominance is not as strong, but does stand under simplified plan representations.

Table 1.A.9, which mirrors Table 1.2, shows that 77.7% of these enrollees are inert in 2018. Note that these enrollees pay about half as much in premiums for their dominated plan (\$146) as compared to those receiving a standard silver plan (\$282), due to higher levels of premium tax credit subsidies. Thus, savings as a percentage of net premium are nearly doubled as compared to the higher income group, as enrollees can save on average about 19% of their premium. As with those who are at risk ex-ante, females are less likely to be inert. Though there is nearly a positive age gradient for inertia, it tapers off in the highest age group and is not statistically significant.

1.5 Discussion

While differential uptake in assistive services may be at least partially indicative of differential targeting of demographic groups by both governmental and private assisters, disparate baseline unassisted rates of inertia suggest differential acuity in health insurance choice between these groups. One way to simplify this model is to assume that every demographic group has some mixture of "high competence" and "low competence" enrollees, where high competence enrollees are less likely to make costly mistakes like choosing a dominated plan. In this context, "competence" could refer to the acuity with which one grasps their insurance options and prices therof, either due to familiarity with non-linear insurance contracts or an ability to learn about them; however, it could also describe an individual who pays more attention to their plan choice. Lack of attention could be attributed to either an unfamiliarity with the possibility of changing options and relative prices within healthcare markets (i.e. low competence), a high opportunity cost of reviewing one's plan choice, or simple apathy. In section 4.2 I am able to differentiate between inattention and plan choice competence given that one is attentive. While these are likely to be correlated and directly related[26], I differentiate between these for the purpose of discussion.

Given that some proportion of high- and low-competence enrollees will seek help, it follows that groups with higher rates of costly inertia among the unassisted have more low-skill types. Across ethnic groups, those with Hispanic origin are the most inert when unassisted. Given that, especially in California, many Hispanic individuals experience language barriers[27], many may have difficulties navigating insurance contracts. Across age groups, it may be expected that younger and thus less experienced enrollees would be composed of more low-skill enrollees. Yet older individuals are more inert when unassisted, exhibiting less attention and less health insurance literacy. One may posit that, on average, younger individuals have a lower opportunity cost of taking the time to make this decision. Further, due to repeated interactions with health insurance decisions, older individuals may not expect such a pricing anomaly to occur, and thus may be more likely to be inattentive. Another argument would be that because older individuals are more likely to have employer-sponsored coverage, those who are enrolled in the individual

[26] As noted, if one is more familiar with health insurance, then they may be more likely to review their plan choice due to knowledge that market conditions may change. Evidence for this in this work is that demographic groups with high activity rates (e.g. younger and higher income ernollees) also have higher switching rates given that they make an active choice.

[27] According to the Public Policy Institute of California, 27% of the state's population was foreign born (the highest share of any state), and 51% of immigrant households speak Spanish at home.

market are, on average, less likely to make rational economic decisions. This is striking, as older individuals have a greater likelihood of having health claims, and thus can benefit even more by switching, not to mention that they can save more in premium costs due to premium multipliers[28]. Finally, when examining income, those at the lower end of the income distribution make more mistakes when unassisted. This could be reflective of those with higher incomes being generally more able to make economically sound decisions, which is a natural inclination. This is also evidence against the argument that those with a higher opportunity cost of time are more likely to be inert due to inattention, as higher income enrollees are more likely to make an active choice.

Equity concerns between high skill and low skill types are likely addressed by these service channels through uptake (rather than differential effects). In the case of service centers, these disparities are addressed by forcing enrollees to make an active choice, eliminating the prospect of full inattention. While calling a service center is itself a signal of attention, making an active plan choice is an additional extent of attention. Still, among those who make an active choice, switching rates are higher among the unassisted compared to those who receive assistance from the service center. This reinforces the notion that those receiving assistance are lower-competence types, especially given the added context that the demographic groups with worse baseline outcomes are also more likely to seek assistance. Given that their active choices are measureably worse than the unassisted's active choices, and assuming that service centers do not make one *more* likely to be inert, these enrollees, who were already attentive enough to seek help, may show that high and low competence enrollees who are attentive sort into enrolling actively (high) and seeking help (low). This is again consistent with previous findings, including that which shows that those who previously received help are more likely to make costly mistakes if newly unassisted (see Section 4.1).

[28]Given that older individuals are able to save more by switching, this is worth examining further. While those not receiving premium assistance would have proportionate differences (e.g. 10% of their premium can be saved regardless of age), those who receive Premium Tax Credits can also save a higher proportion of their income by switching (compared to those who are of younger age).

While repeated interactions with service center representatives are desirable from a policy perspective, it is clear that repeated "assistance" is not necessarily beneficial in all cases. As seen in Figure 1.9, a repeated interaction with an insurance agent is not statistically different from receiving no help when it comes to curbing this costly error. Meanwhile, repeated interactions with government-funded assistance are only marginally different from first-time interactions, which is likely due to selection bias rather than differential effectiveness. This speaks to the inherent difference between these service channels and the nature of these relationships. Interactions with an insurance agent are highly likely to take place over multiple years: the survival rate of insurance agent assistance in each year is over 97% among those who remain enrolled. This is ostensibly due to the incentive structure that insurance agents face (commission, etc.) as well as the existence of in-person interactions. Whereas reaching a service center requires action on behalf of the enrollee, an agent will have a list of their clients who they reach out to after initial contact. As such, the likelihood of receiving service channel assistance in an additional year is just over 50%. This high incidence of repeated interaction likely makes it difficult for an insurance agent to make proactive decisions on behalf of all enrollees unless specifically prompted to do so. Furthermore, the high likelihood of retaining a customer theoretically disincentivizes an agent from needing to review plan choices for all clients. Thus, the role of inattentive party may be passed from the enrollee to the agent. Contrastingly, repeated assistance from a service center involves help that could be considered independent from the previous year, as the likelihood of receiving the same service center agent is low, and a true interaction must actually occur. Moreover, these service channels have entirely different incentives for helping enrollees[29]. As those receiving help from a certified insurance agent for the first time make an active choice over 80% of the time and switch over 75% of the time when making that active choice, these individuals receive help that is as effective as service center assistance on average. Thus, it is likely that these agents possess the skills to make appropriate decisions but lack the

[29]Certified Insurance Agents generally receive commissions, and thus higher premiums translate to higher income. Still, California law prohibits insurance agents from charging consumers a fee for their services. Meanwhile, Service Center Representatives are unlikely to have perverse incentives, and act as agents with a desire to do social good.

incentive.

Navigators serve as an intermediate case between these two service channels. Because it involves face-to-face interaction, retention level is high, as over 80% of enrollees who sought a navigator in a previous year do so again the following year. While repeated interactions are likely, the incentive structure for Navigators differs from certified insurance agents. Given their community ties, Navigators have a stake in their enrollees making good insurance choices, as this could have positive externalities within the community. Furthermore, they are able to more accurately identify and address the needs of the community that they serve, as well as have a more intimate understanding of possible idiosyncracies of an area (e.g. providers) relative to service center representatives. Still, it appears that interactions with navigators are less "effective" than interactions with service center reps and (first-time) interactions with certified insurance agents. This may be because navigators serve multiple purposes, and thus may be less literate of complicated insurance contracts.

This highlights the importance of differences in effective policy prescriptions across these service channels that could strengthen their likelihood of helping consumers avoid these costly choice errors. As service centers' high switching rates still fall below those of active, unassisted enrollees, the state of California would benefit from ensuring that all agents are aware of any pricing anomalies that would put enrollees at risk of making an unambiguous choice error. Insofar as the state hopes to bridge gaps across unmeasurable characteristics (namely insurance literacy), this requires well-trained employees. For Navigators, this would also be important, while other decisions could be strengthened by requiring these workers to prove their knowledge of health insurance plans. Finally, it may be favorable to, along with correspondence, issue some sort of penalty to insurance agents who allow their clients to make these choice errors. This would help counteract the perverse incentives that may exist. Across the board, regardless of assistance status, both enrollees and assisters would benefit from nudges or requirements to make an active plan choice and reminders that market conditions are subject to change on a yearly basis.

Is it possible to formulate an instance where an individual is better off choosing the more expensive silver Kaiser plan? In theory, one could construct a rational agent with perfect foresight who is certain that they will receive no medical care in the following year. If the individual has a very high opportunity cost of their time, it may not be worth it for them to review their plan options and make a selection; this gives them a very high switching cost. Still, if this were the case, it would likely be more favorable for this individual to forgo insurance altogether, even in the presence of the mandate that levied fines against those without insurance. This is especially true since cancelling one's plan takes a fraction of the time of reviewing plan options and making a conscious, measured decision[30]. Even so, if switching costs were too high to review plans, hiring a third party to make this decision on one's behalf would still save an enrollee money. When instead considering potential market-wide positive impacts of inertia, such as curbing adverse selection as described in Handel (2013), these are unlikely because 1) this phenomenon only lasts for one year of plan choice and 2) risk pools for premium setting are based on enrollment into all plans offered by an issuer rather than a single plan[31].

Thus, it is highly unlikely that any individual is truly better off having chosen the Silver Kaiser plan than the dominant Gold Kaiser plan. Still, this assumption requires that utilization is unaffected by plan choice; this has been demonstrated to not be the case, as moral hazard is a commonly studied phenomenon in health economics. If one switches to a gold plan, they may utilize more health services than if they had chosen the comparable silver plan. The most clear demonstration of this is for elective items/procedures when comparing an insured vs. uninsured individual, as one with insurance is much more likely to utilize the service at a much lower cost. This also theoretically holds when comparing different levels of insurance. Thus, in practice, one with a gold plan may end up spending more on health goods/services than if they had chosen the silver plan. Still, augmented utilization may have positive health externalities and result in better

[30]Gabaix (2014) models inattention using a "sparsity-based" that considers that individuals make decision that are only of first-order importance.

[31]It could also be the case that high utilization type are likely to switch from other issuers into the Gold Kaiser plan, which would increase premiums for all Kaiser plans if priced accordingly

overall health; this provides for better long term economic gains and longer lifespan/healthspan.

1.6 Conclusion

While substantial redesign of the individual health insurance markets across the United States under the Affordable Care Act has increased accessibility to, and affordability of, health insurance plans for those who otherwise would not be able to find or afford plans, there still exists asymmetries in information, differences in health insurance literacy, and lack of attention that create excess costs for consumers and the government alike. These frictions cause plan choice errors, often manifesting as costly inertia, which is exemplified clearly by erroneous selection of dominated plans. When evaluated ex-ante, these plans should not be chosen by any individual or family, regardless of expectations surrounding healthcare utilization or preferences across various plan characteristics. Thus, selection of this plan is likely a signal that behavioral errors are more widespread; choices that involve trade-offs between up front and marginal costs introduce uncertainty regarding spending that is likely to exacerbate choice hazards.

Though resources exist to help close information gaps and increase understanding of health plans, these resources do not wholly eliminate choice mistakes and do not necessarily provide longstanding understanding to apply to decisions in future years. Furthermore, perverse incentives may exist among resources provided by insurance issuers. This speaks to the distinction between incentives, information, and expertise in health insurance markets. Given the stated purpose of the individual market, and its catering to low-income, under-served communities, it is likely desirable for the state of California to ensure that these human resources are properly trained and provide a full picture of insurance choices, especially when the correct – or, more accurately, incorrect – choice is clear ex-ante. As a policy prescription, one reform the exchanges might productively undertake is to notify *all* enrollees and assisters of any dominated plan offered on the exchange. This will increase attention levels for consumers and vigilance of assisters. Fully effective personnel, as well as an informed enrollee base, will help address both equity and efficiency concerns associated with dominated plan choice.

Chapter 1, in part is currently being prepared for submission for publication of the material. Hall, Zachary. The dissertation author was the primary investigator and author of this material.

1.A Chapter 1 Appendix

1.A.1 Addressing Ambiguity with respect to Strict Dominance

When comparing the *Silver 70* and *Gold Coinsurance 80* plans offered by Kaiser, deductibles and out-of pocket-maximums for each respective offering favor the gold plan; furthermore, each benefit category for which cost-sharing type is comparable (copay vs. coinsurance) sees the Gold plan with *at least as favorable* cost-sharing as the Silver plan. For example, rehabilitative speech therapy under the Gold plan involves a $25 copay, while under the Silver plan the copay is $35. For benefits paid by coinsurance under both plans, coinsurance rate is 20% for all categories; however, most of these categories, including all inpatient services and skilled nursing facilities, require deductible payments under the silver plan. As such, all of these benefits include *weakly* lower total spending on medical services. However, two benefit categories threaten the strict notion of dominance established in section, specifically due to their cost-sharing type. I detail these discrepancies below and provide arguments for strict dominance not being violated.

Home Health Care

Home Health Care services are covered at a 20% coinsurance rate under the Gold plan, but with a $45 copay under the silver plan. This would mean that a charge of $225 dollars would produce equal cost sharing under both plans. Generally, home health care is billed on an hourly basis. According to a 2022 report by Genworth conducted in August 2021, the hourly median cost of home health services was $32 per hour. Also reported is a a daily median cost of $201. Adjusted for medical inflation according the the BLS, using a total inflation factor of about 8.6% over this period, these numbers translate to about $29.50 per hour and $185 per day. This implies that most people in California who receive home health care will be better under the Gold plan in 2018. Still, those with high usage may actually pay less with a $45 copay than a 20% coinsurance rate.

I argue that this is unlikely to result in higher spending for many cases for three reasons.

Firstly, those who have a high utilization rate of home health services are less likely to be enrolled in individual market plans. Generally speaking, those who receive home health care are those with chronic conditions who live in single households. In all, higher age, especially those above 65, is positively correlated with both having a chronic condition and living in a single household (National Research Council, 2010). Disabled individuals are also more likely to receive this home care; these individuals qualify for Medicaid in California. An example of a chronic condition that would likely receive home medical care is End-Stage Renal Disease; these individuals qualify for Medicare.

Secondly, those receiving home health care are often more likely to have expenses outside of this care. As opposed to those who go for routine medical visits, which may not include further or prior medical costs, home health care utilization is often undertaken after being discharged from a hospital or Skilled Nursing Facility– inpatient visits and SNF visits are much more affordable under the Gold plan, as no deductible must be met (as compared to a $1000 deductible). Besides this, patients are likely receiving prescription drugs and other services, which are again more financially favorable under the Gold plan. Taking these two prior facts into account gives the third reason that individuals who receive home health care are likely to have high total health utilization: as a result, these individuals are more likely to hit their yearly maximum out-of-pocket limit on health care expenditure. Those who reach this upper limit are better off under the Gold plan.

Imaging

Imaging, which includes CT/PET scans and MRIs, is covered at a 20% coinsurance rate under the Gold plan, but with a $300 copay under the Silver plan. This means that if a medical provider charges $1500 or more for this service, the silver plan could provide more affordable care. According to New Choice Health, a website that aggregates healthcare costs across facilities, the range of an MRI cost in Los Angeles is about $360 to $950 for a foot MRI (least expensive) and $1100 to $2,775 for a cardiac MRI (most expensive). The overall average for an MRI in Los Angeles is about $873. CT scans are slightly more expensive, with an average cost of about \$1,352. PET scans, are much more expensive, with an average cost of \$2,914.

While the high costs of scans, especially PET scans, is concerning and threatens our strict notion of dominance, I argue two reasons why these are not likely to result in higher costs. Firstly, for the same reason described for home health care, those receiving these imaging, *especially high cost imaging like PET and CT scans*, are much more likely to be incurring a great deal of other costs, including inpatient hospital stays. A final reason couple of reasons to temper our worries applies to both of these benefits. Firstly, we consider the *other* Gold plan offered by Kaiser in this period. Despite having a higher premium, this other gold plan has a *lower* actual value (78.5%) as compared to the Kaiser plan (82%). For both benefits, this other gold plan has a slightly lower copay for each service (\$30 and \$275, respectively), as compared to the silver plan. This strengthens the argument that expected costs for these services will be lower under the gold plans. Finally, costs found online are the out-of-pocket costs for an individual without insurance. In practice, lower rates are generally paid to the hospitals, as insurance companies, especially those offering HMOs (which Kaiser plans are classified as), negotiate lower overall costs.

1.A.2 Matching Enrollees to Income Levels

This section describes the process for matching individuals within families to their income level and details data restrictions that must be made to do so. The key to doing this is using an individual's premium tax credit (PTC) and the second-lowest cost silver plan (SLCSP) in their area in order to "back out" the appropriate income level with respect to the federal poverty line (FPL). Also important for this is one's household size, which affects the number of dollars that constitute the FPL. Since PTC is determined by SLCSP and income level, this process can be reversed to find income level. The first restriction is that only individuals receiving premium tax credits (PTC) can have their incomes determined. For example, a household with an income above %400 FPL will receive \$0 in PTC. This is also the case for enrollees under 400% FPL who still do not qualify for PTC due to market conditions (e.g. low SLCSP cost). Similarly, we cannot determine income for individuals who qualify for a greater PTC than they receive;

these individuals pay the minimum allowed cost for a plan of \$1. For example, if an individual qualifies for \$300 PTC and chooses a plan that costs \$200 monthly, they will pay a net premium of \$1 for the plan, leaving \$101 on the table and only receiving \$199 in premium tax credits. These issues come down to the fact that both those who receive no SLCSP or pay \$1 for their plan have no gradient in their PTC. Thus, these households' income levels may be bounded but not determined in any precise manner.

With full access to one's geographical location, it is simple to determine these enrollees' income levels. The issue at hand is that geographical information provided in the data includes rating area (generally a county or set of counties) and three digit zip code (TDZ) (the first three digits of one's zipcode; this unit of geographical area is also used to break up Los Angeles into two rating areas). Insurance issuers are allowed to offer their products across the entire state, vary their offering by county, or further vary their offerings by zipcode within a county. The data's lack of indication of county, as well as the grouping of multiple zipcodes together, means that two individuals with the same geographical information, some TDZ-rating area pairing, may face a different set of plan choices. This could mean that they face differing SLCSP within their respective markets. As a result, the restricted dataset that includes income information on a finer scale is restricted to individuals living in TDZ-rating area combinations where SLCSP is consistent across the entire area. Based upon zip code population, 62.4% of the population of California live in areas that fit this criteria.

1.A.3 Navigator Funding Calculation

Calculations for Navigator funding for an individual were constructed using files provided to the public by the state of California. This data is not particularly granular; the funding is provided to various entities that often operate in multiple counties. As a result, we must make assumptions about how these funds were distributed across areas by each of these groups. We make the basic assumption made that funds are distributed to each county according to its population[32]. As such, larger counties receive a larger portion of funds distributed to an entity. Once total Navigator funding dollars is established for each county, the next target measure is to have dollars per enrollee within a county. For this, we need to estimate the total number of enrollees in a county. In order to do this, I assume enrollment is distributed according to populations within three-digit-zipcodes that span across county lines. Once enrollment counts per county are established, we divide by this number to establish approximate per-enrollee funding for each county. This is the measure that is represented in Figure 1.10. For conducting regressions on an individual level, this number must be established for each individual in some TDZ-rating area. For those whose geographical areas span across multiple counties, a weighted average is created based upon population share of each TDZ within each county. For areas that are fully within a single county, the county measure is used, as we assume that access provided by these funds are distributed evenly throughout the county to the enrollees.

An additional dimension that can be considered is race/ethnicity: Navigator funding files state the targeted ethnicities that each entity plans to target. To do this, I conduct the same process as above, with a few tweaks. Firstly, I assume that Navigators split dollars evenly between race/ethnicity groups. The above process is then conducted, but split by race/ethnicity. Finally, funding numbers will differ within each TDZ-rating area by race/ethnicity. Using this measure provides slightly better power and a slightly more significant first stage, but results are still not strong enough to conduct a 2SLS regression.

1.A.4 Tables

[32] Two alternatives to this measure are to assume that funds are distributed based upon county enrollment or distributed equally. Using either of these two alternatives does not affect these results.

Table 1.A.1. Switching Behavior Among Non-Inert Enrollees, Switching to Other Kaiser plan

	Switched Within Kaiser				
Total Obs.	***11,500***				
	Gold (Dom)	***Gold (Other)***	***Bronze***	***Plat***	***Minimum***
Observations	3,729	3,025	3,970	656	120
	32.4%	*26.3%*	*34.5%*	*5.7%*	*1.0%*
Average Gold-Silver Kaiser Gap	$27.09	$26.98	$24.27	$26.32	$14.34
Average Gross Premium	$654.60	$677.82	$396.76	$745.31	$211.88
Average Net Premium	$262.71	$265.42	$215.55	$304.84	$211.88
Regression Results: Demographic Characteristics					
Female		-0.0148	-0.00752	-0.0106*	0.000144
	(.)	(0.01005)	(0.00855)	(0.00616)	(0.00475)
Age 36 to 45		-0.00137	-0.0594***	-0.0280	-0.143***
	(.)	(0.01650)	(0.01871)	(0.02323)	(0.01375)
Age 46 to 55		0.00201	-0.102***	-0.00345	-0.140***
	(.)	(0.01992)	(0.01786)	(0.01868)	(0.01338)
Over Age 55		-0.00123	-0.170***	-0.00676	-0.140***
	(.)	(0.02087)	(0.01806)	(0.02737)	(0.01333)
400-600% FPL		0.00713	0.286***	-0.0105	0.0615**
	(.)	(0.01789)	(0.02340)	(0.02248)	(0.02399)
over 600%		-0.0354	0.127***	0.0572*	0.0109
	(.)	(0.04199)	(0.04088)	(0.03037)	(0.01828)
Unsubs. App.		0.0203	0.197***	-0.0349	0.0237
	(.)	(0.04109)	(0.03365)	(0.03033)	(0.02048)
Black		-0.0642	-0.00425	-0.0312	0.0220
	(.)	(0.05335)	(0.03171)	(0.03692)	(0.02760)
Hispanic		-0.105***	-0.0867***	-0.0132	0.00988
	(.)	(0.02105)	(0.01533)	(0.01548)	(0.00779)
Asian		-0.0810***	-0.0257	-0.0430***	-0.0000648
	(.)	(0.02725)	(0.01558)	(0.01537)	(0.00894)
Other		-0.0411	-0.0276	0.00793	0.00587
	(.)	(0.03474)	(0.02647)	(0.03255)	(0.01300)
Nonresp		-0.0471***	-0.0364**	-0.0226	0.000188
	(.)	(0.01633)	(0.01622)	(0.01701)	(0.00873)

Note: The above table mirrors Table 2, evaluating those who switched to a different Kaiser plan. In the regression panel, the reference group is those who switched to the dominant Gold plan.

Table 1.A.2. Switching Behavior Among Non-Inert Enrollees, Switching to Non-Kaiser Plan

	Switched From Kaiser				
Total Obs.	***836***				
	Gold	***Silver***	***Bronze***	***Plat***	***Minimum***
Observations	79	578	151	11	17
	9.4%	*69.1%*	*18.1%*	*1.3%*	*2.0%*
Average Gold-Silver Kaiser Gap	$21.34	$26.36	$23.80	$24.20	$13.74
Average Gross Premium	$556.92	$606.72	$421.06	$822.37	$189.39
Average Net Premium	$325.55	$217.50	$212.65	$507.86	$189.39
Regression Results: Demographic Characteristics					
Female		0.0181	-0.125**	0.134***	-0.101
	(.)	(0.01624)	(0.04658)	(0.04487)	(0.06840)
Age 36 to 45		-0.0484	-0.0552	-0.0742	-0.462***
	(.)	(0.05865)	(0.12588)	(0.10630)	(0.06902)
Age 46 to 55		0.0748	0.0256	-0.101	-0.368*
	(.)	(0.04873)	(0.10492)	(0.12104)	(0.18458)
Over Age 55		0.0676*	0.123	0.0257	-0.340***
	(.)	(0.03908)	(0.09734)	(0.12601)	(0.11198)
400-600% FPL		0.00200	0.149	-0.428**	0.242
	(.)	(0.06043)	(0.08911)	(0.19173)	(0.17204)
over 600%		0.000561	0.0703	-0.160	0.250
	(.)	(0.06987)	(0.16339)	(0.11770)	(0.19767)
Unsubs. App.		-0.132	-0.0140	-0.0482	-0.0455
	(.)	(0.09020)	(0.12205)	(0.09901)	(0.12078)
Black		0.0691	-0.745***	0.242	-0.125
	(.)	(0.04290)	(0.09266)	(0.16371)	(0.12402)
Hispanic		0.0328	-0.0496	-0.0678	-0.170
	(.)	(0.04053)	(0.11504)	(0.04778)	(0.13453)
Asian		0.0470	0.101	-0.0283	0.0146
	(.)	(0.04612)	(0.10362)	(0.08285)	(0.08907)
Other		0.0125	-0.0587	0.157	-0.334*
	(.)	(0.06198)	(0.13851)	(0.12555)	(0.16263)
Nonresp		0.0429	0.158	0.0359	-0.121
	(.)	(0.05313)	(0.15990)	(0.12011)	(0.13251)

Note: The above table mirrors Table 2, evaluating those who switched to a non-Kaiser plan. In the regression panel, the reference group is those who switched to the some non-Kaiser Gold plan.

Table 1.A.3. Assistance Uptake, by Race/Ethnicity

	Unassisted	***Any***	***Government***	***Private***
White	0.590	0.410	0.144	0.265
Asian	0.393	0.607	0.133	0.474
Black	0.548	0.452	0.262	0.190
Hispanic	0.450	0.550	0.277	0.273
Other	0.492	0.508	0.167	0.341
Nonrespondent	0.318	0.682	0.137	0.546

Note: The above table shows, by race/ethnicity (1) the proportion unassisted, (2) proportion receiving any assistance, (3) proportion receiving government assistance, and (4) proportion receiving private help. The sample of enrollees is those at risk of re-enrolling in the dominated silver Kaiser plan; all individuals are above the age of 25.

Table 1.A.4. Assistance Uptake, by Age Group

	Unassisted	*Any*	*Government*	*Private*
Age 26 to 35	0.600	0.400	0.121	0.280
Age 36 to 45	0.507	0.493	0.139	0.354
Age 46 to 55	0.431	0.569	0.182	0.387
Age 56 and up	0.416	0.584	0.199	0.385

Note: The above table shows, by age (1) the proportion unassisted, (2) proportion receiving any assistance, (3) proportion receiving government assistance, and (4) proportion receiving private help. The sample of enrollees is those at risk of re-enrolling in the dominated silver Kaiser plan; all individuals are above the age of 25.

Table 1.A.5. Assistance Uptake, by Income Group

	Unassisted	*Any*	*Government*	*Private*
250% to 400% FPL	0.443	0.557	0.182	0.375
400% to 600% FPL	0.514	0.486	0.161	0.325
Over 600% FPL	0.583	0.417	0.112	0.305
Unsubsidized	0.679	0.321	0.0787	0.242

Note: The above table shows, by income level (1) the proportion unassisted, (2) proportion receiving any assistance, (3) proportion receiving government assistance, and (4) proportion receiving private help. The sample of enrollees is those at risk of re-enrolling in the dominated silver Kaiser plan; all individuals are above the age of 25.

Table 1.A.6. Funding Per Enrollee vs. Receipt of Assistance, 2016-2019, All Enrollees

	(1)	(2)	(3)	(4)
Response Variable: Government Help				
Funding Per Enrollee	0.00197**	0.00300***	0.00375***	0.00109**
	(0.00097)	(0.00114)	(0.00129)	(0.00053)
Response Variable: Commercial Help				
Funding Per Enrollee	-0.00277	-0.00223	-0.00287	-0.000874
	(0.00302)	(0.00296)	(0.00281)	(0.00104)
Response Variable: Any Help				
Funding Per Enrollee	-0.000800	0.000764	0.000882	0.000219
	(0.00260)	(0.00270)	(0.00276)	(0.00105)
Response Variable: No Help				
Funding Per Enrollee	0.000800	-0.000764	-0.000882	-0.000219
	(0.00260)	(0.00270)	(0.00276)	(0.00105)
Response Variable: Navigator Help				
Funding Per Enrollee	0.00153**	0.00327***	0.00360***	0.00148***
	(0.00065)	(0.00085)	(0.00087)	(0.00038)
Response Variable: Service Center Help				
Funding Per Enrollee	0.000540	-0.0000705	0.000343	-0.000313
	(0.00051)	(0.00047)	(0.00056)	(0.00021)
Observations	361,381	367,123	392,105	169,191
Year	2016	2017	2018	2019

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The above table shows a "first stage" regression with the funding per enrollee in an area the explanatory variable; the response variable differs by row. Columns (1) - (4) are years 2016 - 2019, respectively.

Table 1.A.7. Funding Per Enrollee vs. Receipt of Assistance, 2016-2019, Silver Kaiser Enrollees

	(1)	(2)	(3)	(4)
Response Variable: Government Help				
Funding Per Enrollee	0.000959	-0.0000905	0.000535	-0.000358
	(0.00092)	(0.00138)	(0.00143)	(0.00089)
Response Variable: Commercial Help				
Funding Per Enrollee	0.000298	0.000614	0.000427	-0.000665
	(0.00248)	(0.00259)	(0.00239)	(0.00108)
Response Variable: Any Help				
Funding Per Enrollee	0.00126	0.000523	0.000962	-0.00102
	(0.00240)	(0.00218)	(0.00222)	(0.00096)
Response Variable: No Help				
Funding Per Enrollee	-0.00126	-0.000523	-0.000962	0.00102
	(0.00240)	(0.00218)	(0.00222)	(0.00096)
Response Variable: Navigator Help				
Funding Per Enrollee	0.00133***	0.00119	0.00165**	0.000971
	(0.00045)	(0.00089)	(0.00074)	(0.00059)
Response Variable: Service Center Help				
Funding Per Enrollee	-0.000339	-0.000944	-0.000762	-0.00132***
	(0.00081)	(0.00069)	(0.00090)	(0.00042)
Observations	24,718	28,656	34,521	9,496
Year	2016	2017	2018	2019

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The above table shows a "first stage" regression with the funding per enrollee in an area the explanatory variable; the response variable differs by row. Columns (1) - (4) are years 2016 - 2019, respectively. The sample of enrollees is those who are enrolled in the silver Kaiser plan in the previous year.

Table 1.A.8. Inert vs. Non-Inert Enrollees; Premium and Demographic Characteristics, 2018; San Diego County Excluded

	Inert	***Switched***
Observations	20,867	11,508
	64.5%	*35.5%*
Average Gold-Silver Kaiser Gap	$27.24	$26.03
Average Gross Premium	$684.88	$577.27
Average Net Premium	$277.90	$245.60
Regression Results: Demographic Characteristics		
Female	-0.0235***	
	(0.00398)	
Age 36 to 45	0.0550***	
	(0.01170)	
Age 46 to 55	0.0658***	
	(0.01110)	
Over Age 55	0.0875***	
	(0.01088)	
400-600% FPL	-0.0956***	
	(0.01184)	
over 600%	-0.0403**	
	(0.01619)	
Unsubs. App.	0.0360***	
	(0.01254)	
Black	-0.0241	
	(0.01818)	
Hispanic	0.0262**	
	(0.01070)	
Asian	0.0104	
	(0.01274)	
Other	0.00793	
	(0.01015)	
Nonresp	0.0483***	
	(0.00774)	

Note: The above table compares enrollees who remained in their dominated plan to those who switched from it. The subsample of enrollees is those over age 25 who were enrolled in the Kaiser silver tier plan in 2017 and have incomes above 250% FPL. The top panel gives the number that falls within each category as well as premium information, including both net and gross average premium, as well as the average premium difference between the dominated silver plan and the dominant gold plan. The bottom panel provides coefficients from a linear regression, where all explanatory variables are binary, and the response variable is being *inert*. The regression includes area (Three-Digit-Zip by rating pair) fixed effects. Enrollees from San Diego County are excluded do to the presence of other possibly dominated plan choices.

Table 1.A.9. Inert vs. Non-Inert Enrollees; Premium and Demographic Characteristics, 73% CSR Qualifiers, 2018

	Inert	***Switched***
Observations	11,064	3,169
	77.7%	*22.3%*
Average Gold-Silver Kaiser Gap	$28.26	$27.90
Average Gross Premium	$729.18	$679.54
Average Net Premium	$146.09	$123.86
Regression Results: Demographic Characteristics		
Female	-0.0175***	
	(0.00524)	
Age 36 to 45	0.0138	
	(0.01426)	
Age 46 to 55	0.0212	
	(0.01714)	
Over Age 55	0.0178	
	(0.01730)	
Black	0.0119	
	(0.02122)	
Hispanic	-0.000922	
	(0.01206)	
Asian	0.00266	
	(0.01297)	
Other	0.00977	
	(0.01605)	
Nonresp	0.0271**	
	(0.01206)	

Note: The above table compares enrollees who remained in their dominated plan to those who switched from it. The subsample of enrollees is those who were enrolled in the Kaiser silver tier plan in 2017 and have incomes between 200% and 250% FPL. Additional restrictions are a full year of enrollment and above the age of 29. The top panel gives the number that falls within each category as well as premium information, including both net and gross average premium, as well as the average premium difference between the dominated silver plan and the dominant gold plan. The bottom panel provides coefficients from a linear regression, where all explanatory variables are binary, and the response variable is being *inert*. The regression includes area (Three-Digit-Zip by rating pair) fixed effects.

1.A.5 Figures

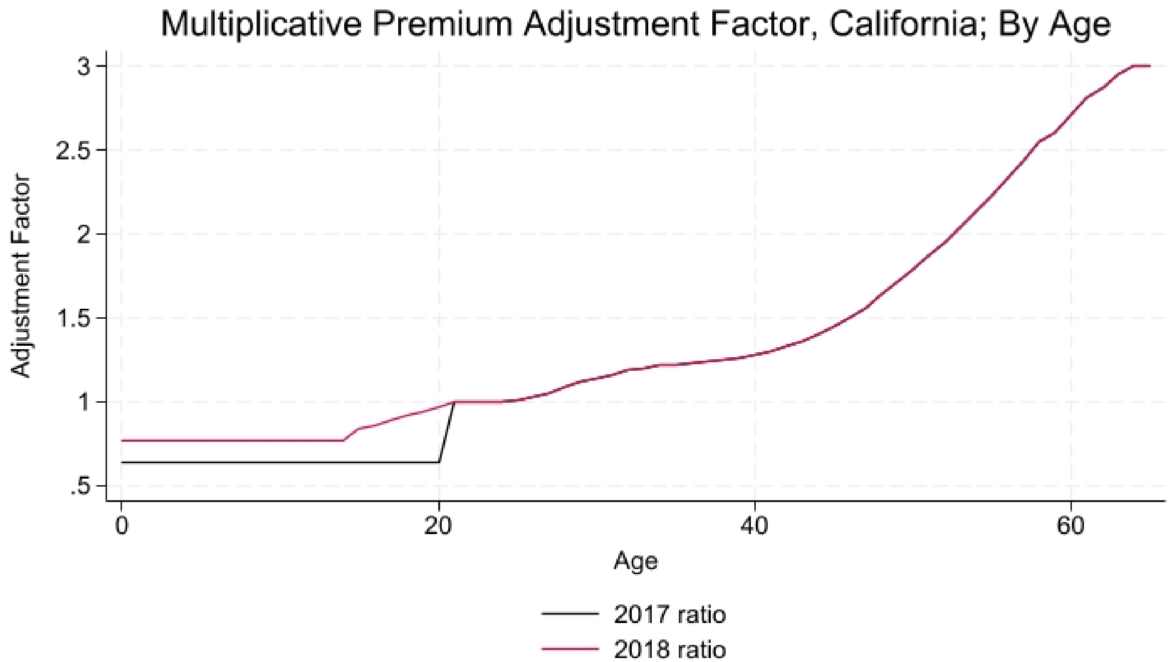
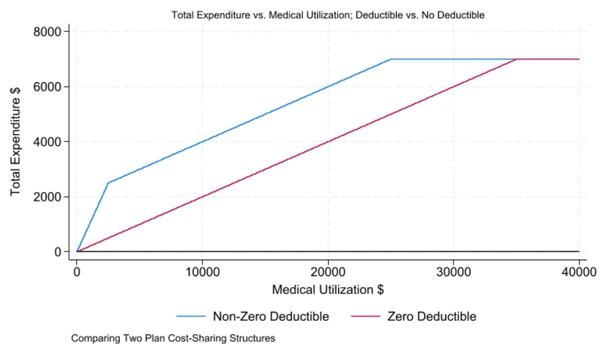
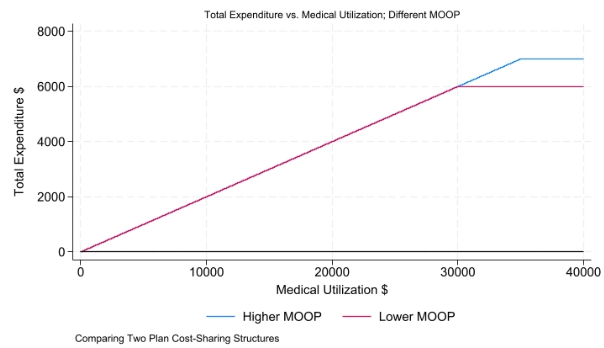


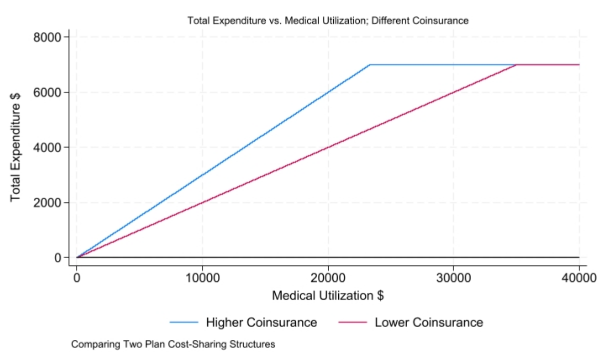
Figure 1.A.1. Premium Adjustment Factor, 2017 (and Prior) and 2018 (and After)
Note: This graph shows the premium adjustment factor, which is multiplied by the 21-year old's premium to determine an individual's premium, across ages. Note that in 2018, this standard payment schedule changed in most states, including California. This change only affected ages 0-20, who are not a part of this study.



(a)



(b)



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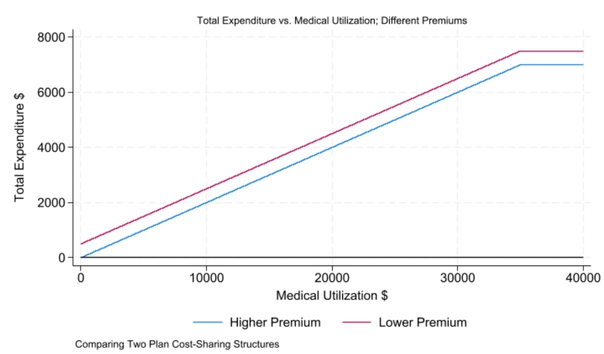


(d)

Figure 1.A.2. Total Consumer Expenditure Schedule between Plans Differentiated by various Financial Characteristics

Note: The above graph demonstrates total consumer expenditure over all levels of medical utilization using a simplified plan representation a la Ericson et al. (2021). Panel (a) shows plans differentiated only by deductible. Panel (b) shows plans differentiated only by coinsurance rate. Panel (c) shows plans differentiated only by maximum out-of-pocket costs. Panel (d) shows plans differentiated only by premium.

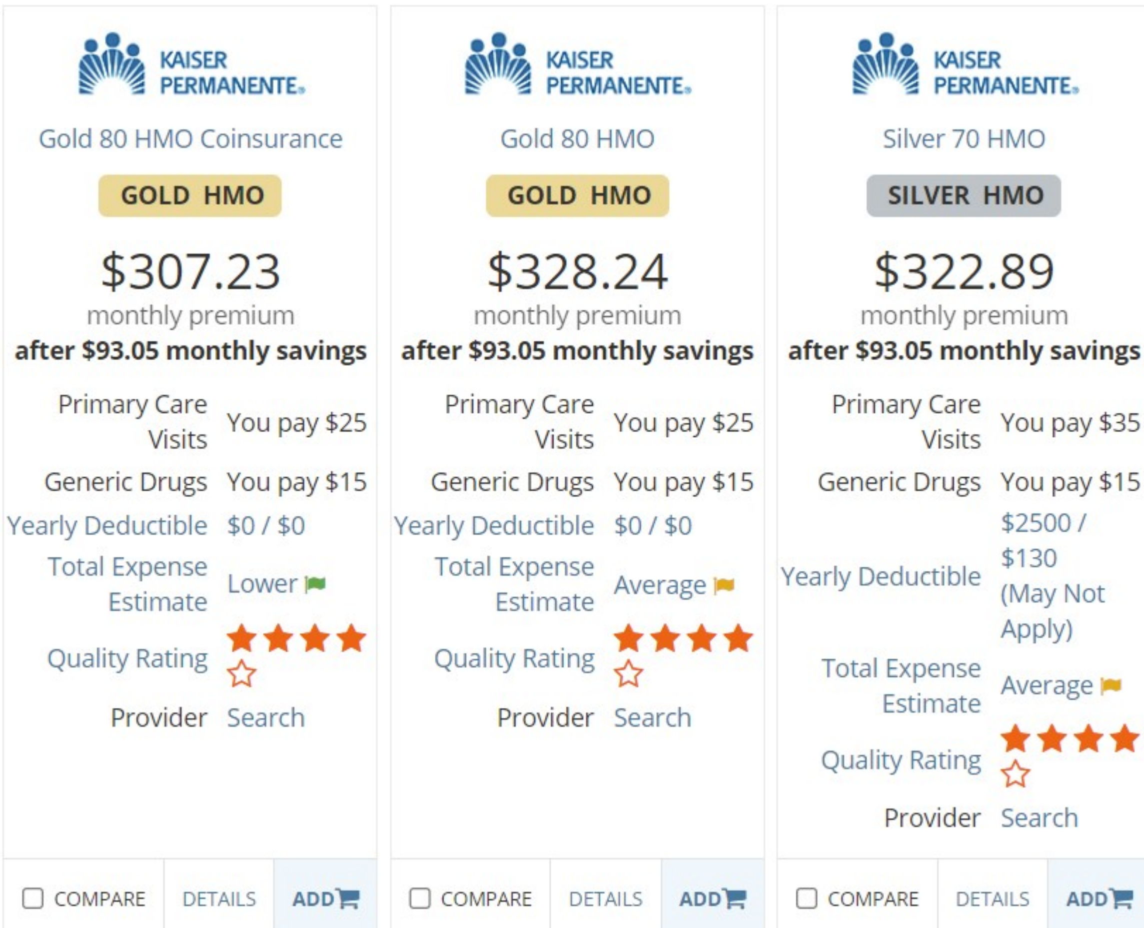


Figure 1.A.3. Example of Menu of Choices on Covered California Website
Note: This shows the menu of choices for an individual choosing from plans on the Covered California Website in 2022, though the interface was the same in 2018 (it has since changed). This shows plans, sorted by some criteria, and filtered by some or no criteria. It clearly states the plan issuer, metal tier, monthly premium monthly savings (PTC), and basic financial/cost-sharing information. Individuals eligible for Cost-Sharing Reductions (CSR) see an indication of this when looking at a silver plan.

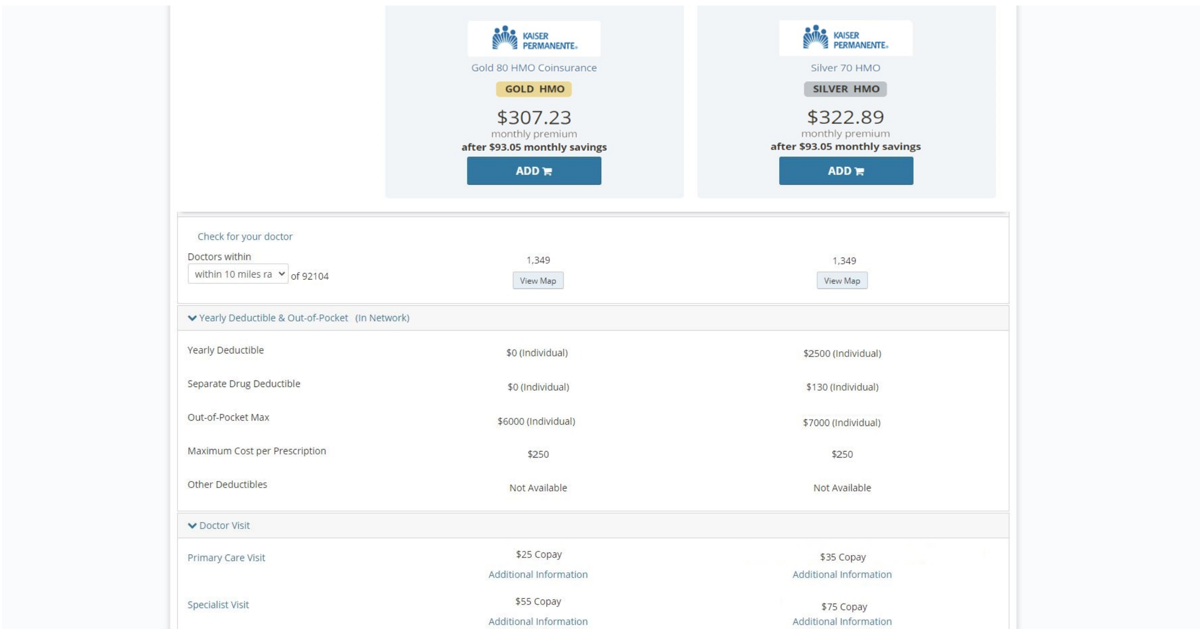


Figure 1.A.4. Example of Side-by-Side Comparison of Two Plans on Covered California Website

Note: This shows the side-by-side comparison available on the Covered California Website. besides premium and basic cost-sharing and metal tier/issuer information, which could be compared previously, this provides a more in-depth comparison. First, deductibles and maximum out-of-pocket amounds are listed. Then, we see the beginning of the specific cost sharing by plan benefit. An individual can then scroll down to find other plan benefits.

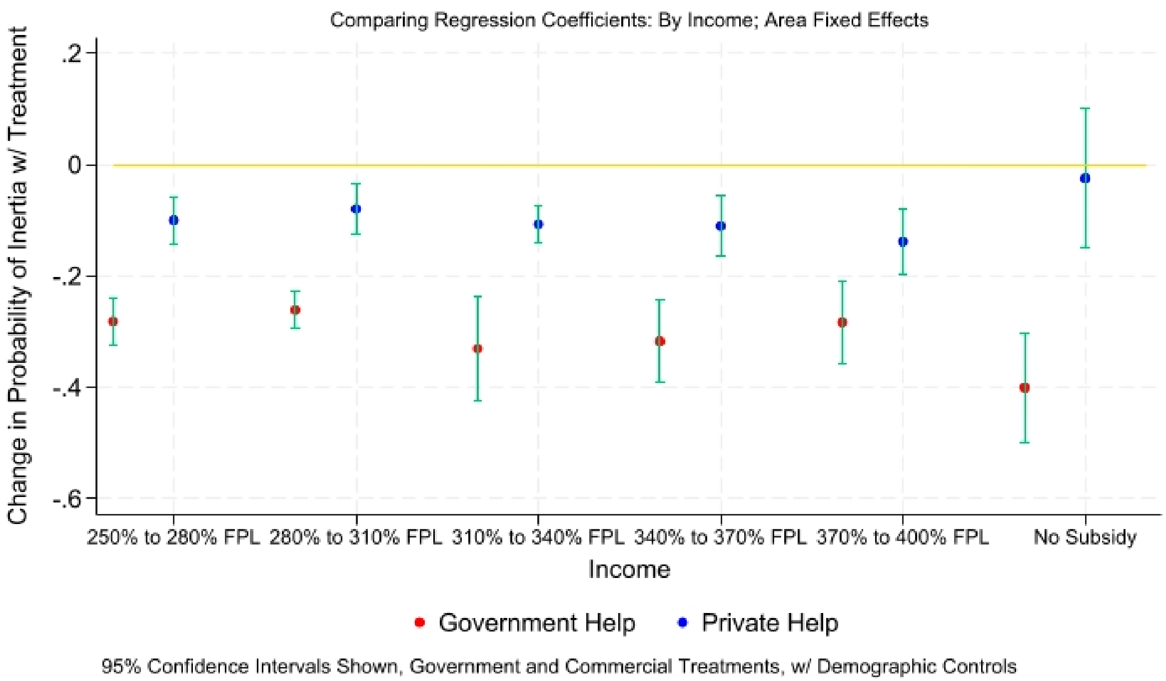


Figure 1.A.5. Difference in Inertia Rates between those Receiving Assistance and those not Receiving Assistance, split by Fine Income Groupings between 250% and 400% FPL
Note: The figure above shows the difference in inertia between those receiving assistance and those not receiving assistance, split by income group based upon percentage of the federal povery level (FPL); treatment is split into receiving government or private (issuer-provided) assistance. Coefficients are obtained by running separate regressions for each subgroup, controlling for age group, racial group, and geographic area. The subsample that this analysis is conducted on is those from rating area-three digit zip codes with a single SLCSP. Those classified as “no subsidy” are under 400% FPL but do not receive a premium tax credit. This analysis is limited to those who pay more than $1, as those who pay $1 have undetermined incomes.

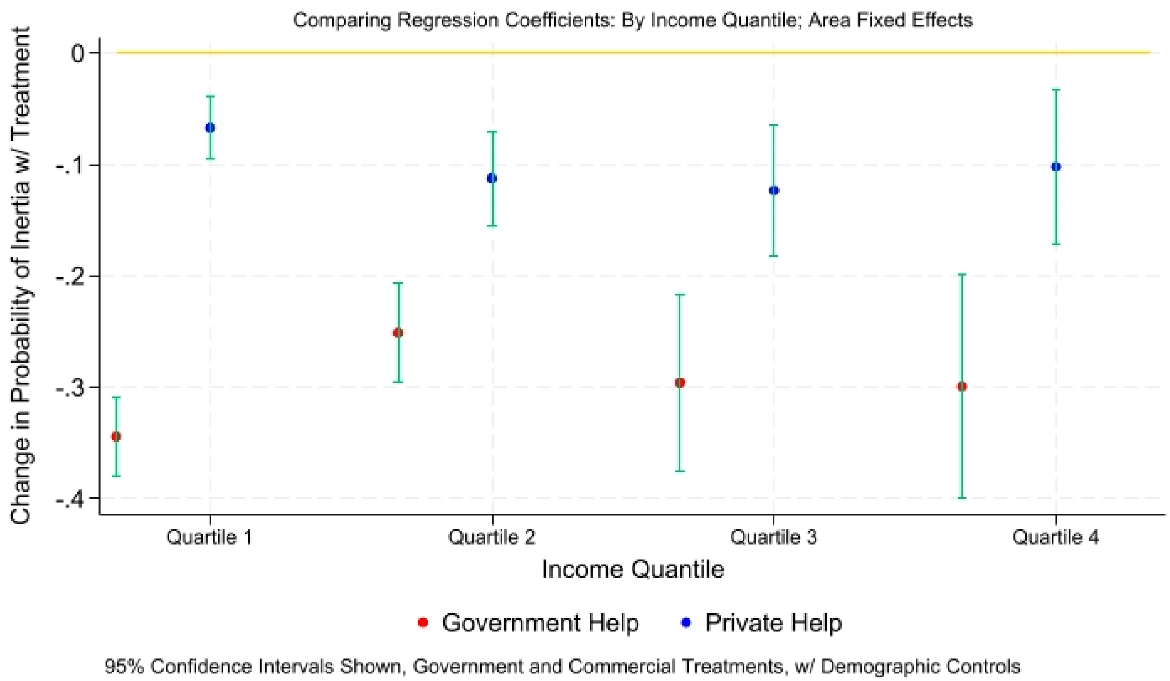
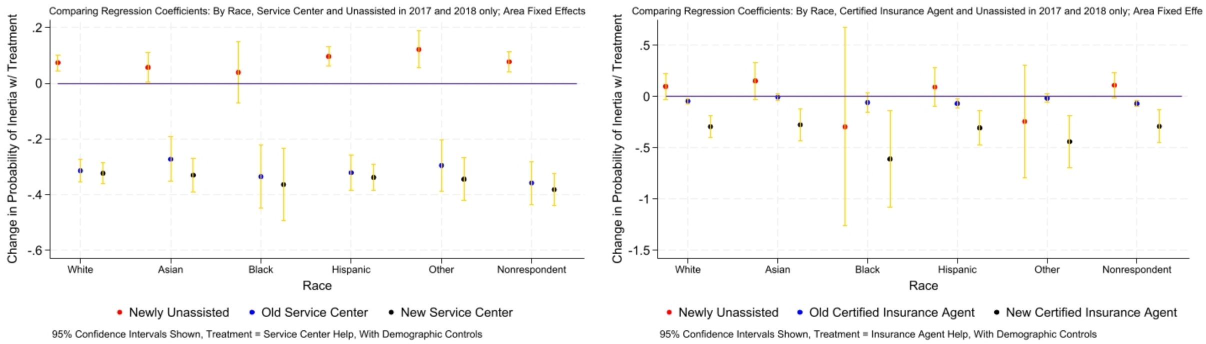


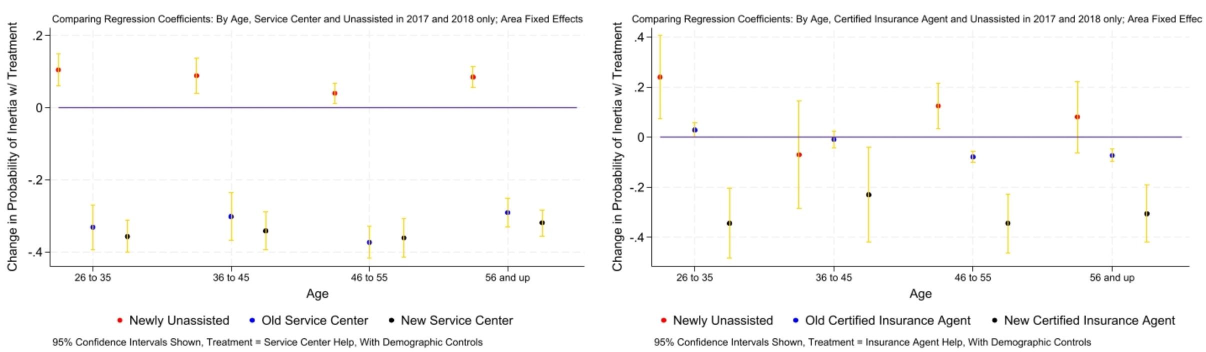
Figure 1.A.6. Difference in Inertia Rates between those Receiving Assistance and those not Receiving Assistance, Split by Income Quartiles between 250% and 400% FPL

Note: The figure above shows the difference in inertia between those receiving assistance and those not receiving assistance, split by income in dollars, split by quartile; treatment is split into receiving government or private (issuer-provided) assistance. Coefficients are obtained by running separate regressions for each subgroup, controlling for age group, racial group, and geographic area. The subsample that this analysis is conducted on is those from rating area-three digit zip codes with a single SLCSP. This analysis is limited to those who are receiving some premium tax credit, as those who do not have undetermined incomes. It is also limited to those who pay more than $1, for the same reason.



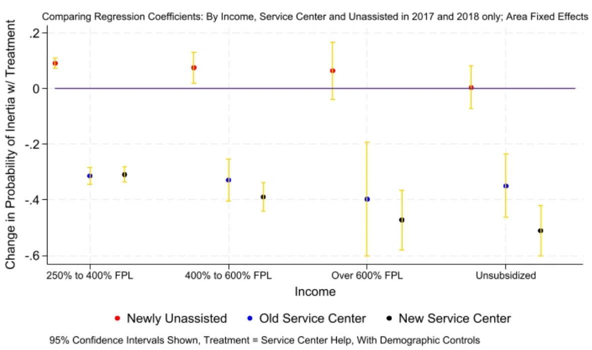
(a) **(b)**

Figure 1.A.7. Measured Differentials in Inertia Rate Compared to Baseline (Always Unassisted), from 2017 to 2018 across Assistance Channels; by Race/Ethnicity Group
Note: The above graphs show measured differentials in inertia rate compared to the baseline (0) of being unassisted in both 2017 and 2018; sample is separated into race/ethnicity groups. The sample of enrollees is at-risk enrollees, and the response variable is change in probability in being inert. Panel (a) is run on the subsample of individuals who were either unassisted or received service center help in both years. Panel (b) is run on the subsample of individuals who were either unassisted or received certified insurance agent help in both years. Each race/ethnicity group is analyzed separately. For each race/ethnicity group, the left dot (red) represents those who were previously assisted and are now unassisted; the middle dot (blue) represents those who are assisted in both years, and the right dot (green) represents those who are newly assisted. Demographic controls (age group, income group) and area fixed effects are included.

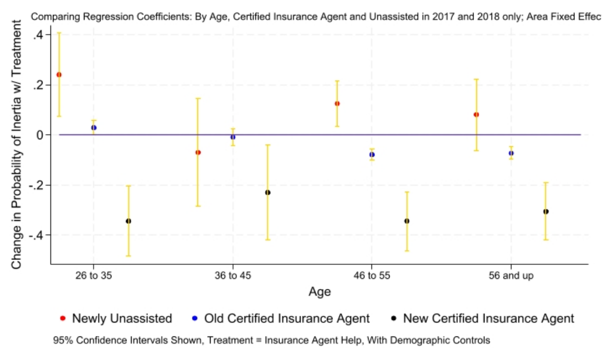


(a) **(b)**

Figure 1.A.8. Measured Differentials in Inertia Rate Compared to Baseline (Always Unassisted), from 2017 to 2018 across Assistance Channels; by Age Group
Note: The above graphs show measured differentials in inertia rate compared to the baseline (0) of being unassisted in both 2017 and 2018; sample is separated into age groups. The sample of enrollees is at-risk enrollees, and the response variable is change in probability in being inert. Panel (a) is run on the subsample of individuals who were either unassisted or received service center help in both years. Panel (b) is run on the subsample of individuals who were either unassisted or received certified insurance agent help in both years. Each age group is analyzed separately. For each age group, the left dot (red) represents those who were previously assisted and are now unassisted; the middle dot (blue) represents those who are assisted in both years, and the right dot (green) represents those who are newly assisted. Demographic controls (race/ethnicity, income group) and area fixed effects are included.



(a)



(b)

Figure 1.A.9. Measured Differentials in Inertia Rate Compared to Baseline (Always Unassisted), from 2017 to 2018 across Assistance Channels; by Income Group

Note: The above graphs show measured differentials in inertia rate compared to the baseline (0) of being unassisted in both 2017 and 2018; sample is separated into income groups. The sample of enrollees is at-risk enrollees, and the response variable is change in probability in being inert. Panel (a) is run on the subsample of individuals who were either unassisted or received service center help in both years. Panel (b) is run on the subsample of individuals who were either unassisted or received certified insurance agent help in both years. Each income group is analyzed separately. For each income group, the left dot (red) represents those who were previously assisted and are now unassisted; the middle dot (blue) represents those who are assisted in both years, and the right dot (green) represents those who are newly assisted. Demographic controls (age group, race/ethnicity) and area fixed effects are included.

Chapter 2

Dominated Plan Choice, Free Plan Availability, and Aggregate Behavioral Failures: A study of the Affordable Care Act Individual Market

In 2017, the Trump Administration announced that the United States government would no longer provide subsidies for Cost Sharing Reductions (CSR), a federally-funded provision of the Affordable Care Act (ACA) which ensured that low-income enrollees had access to rich plans in the individual market. As these improvements to copayments and coinsurance were still lawfully required in individual insurance markets, states took varying approaches in instructing and allowing issuers to load the cost of CSR onto their plan offerings. Due to the presence of another mechanism from the ACA, Premium Tax Credits (PTC), this actually made plans more affordable for many enrollees. In tandem with greater affordability, other phenomena occurred in a plethora of markets, including increased accessibility to zero-premium bronze plans among varying income groups and to gold plans that were less expensive than comparable silver plans. After theoretically considering the dynamics associated with the presence of these, I test the claims empirically on aggregated data, finding robust evidence of aggregate market failures associated with individuals choosing dominated plans. Suggestive evidence shows that this is partly attributable to inertia, caused by inattention and status quo bias, though other behavioral failures or informational frictions are likely. I also find no evidence of a zero-price effect, which *may be attributed to the use of the county-level, rather than individual-level, data.*

The decision to purchase health insurance is an action that has seen plentiful study in the health economics literature. This choice on the extensive margin reflects the trade-offs that an individual must consider when deciding whether or not to purchase a policy to protect against major medical expenses, provide for access to prescription drugs, and facilitate necessary primary care and other forms of treatment. It is also of key interest to the designers and supporters of the Affordable Care Act (ACA), which was signed into law in 2010. This piece of legislation was intended to create plan affordability and accessibility; the literature shows its measures achieved just that (Frean et al., 2017; Duggan et al., 2019). Also of interest and consequence, though, is the intensive margin of purchasing, or choice of health insurance plan. As market conditions change, individuals may have an incentive to switch plan type in the cost-sharing dimension in order to maximize their expected utility. This decision similarly involves considering the trade-offs between paying a higher price for better health care coverage and receiving greater protection against health-related costs. Besides an individual's demand elasticity to price changes, various phenomena may also be introduced into markets as the result of some economic shock; these present an opportunity to study violations of, or deviations from, predictions of basic expected utility models popularly implemented to describe rational agents. Whereas plan choice is a core tenant of the ACA, policy makers may be directly interested in responses to these shocks due to pecuniary results, health implications, and labor market factors.

In order to ensure affordability and access to rich health insurance plans, the ACA instituted two programs. Cost-sharing reductions (CSR) were provided to individuals with a marginal adjusted gross income (MAGI) between 100% and 250% of the Federal Poverty Level (FPL); these automatically adjusted the actuarial value received from enrolling in a plan from the silver metal tier, a plan of intermediate richness. A second product of the ACA was the introduction of Premium Tax Credits (PTC), which ensured that individuals can afford their silver plan premiums based upon their income level. These credits, which were tied to silver plans' prices in the market, could then be used to purchase more rich (gold) or less rich (bronze) plans. Initially, both programs were directly paid for by the federal government. Still, the policies were a subject of debate and demure, as opponents of the ACA argued that congress had not apportioned funds for the purposes of paying for CSR subsidies to health insurers.

In this paper, I study the effects of the announcement by the Trump Administration to cancel CSR payments from the federal government, a possibility that many states and insurers expected. Specifically, I examine the dynamics of plan enrollment type that occurred as a result of various state and insurer responses to the policy change. As cost-sharing adjustments were still expected to be made by insurers, many states' insurers began loading these costs onto the silver plans that provided them, which caused silver plans to increase in price. This made non-silver plans more affordable relative to silver plans, both for subsidized and unsubsidized marketplace participants.

Besides this, two other resulting market phenomena may have made non-silver plans more desirable. The first is the growing prominence of the availability of zero-premium bronze plans among subsidized enrollees, which become an option when one's Premium Tax Credit exceeds a listed bronze plan's premium. This presents the opportunity to study the presence of a zero-price effect (Shampanier et al., 2007), which may be signaled by increased bronze enrollment. The second is the emergence of gold plans that are less expensive than all available silver plans in a market. This presents a situation in which the gold plan may *dominate* all silver plans in the market for a subset of enrollees; in this case, these enrollees should switch into non-silver plans. Given the salience of price on the healthcare.gov website, deviations from this may be indicative of behavioral failures, including status quo bias and inattention (Heiss et al., 2021; Ho et al., 2017; Ericson, 2014), which may cause inertia (Handel, 2013), or metal-tier stickiness, in plan selection.

In order to conduct this study, I use Public Use Files from the Center for Medicare and Medicaid Services, including rate, open enrollment, and plan attribute files. This allows me to construct county-level data on metal tier enrollment and estimates of zero-premium bronze plan exposure and dominated silver plan exposure. Unfortunately, individual-level data is not available, so behavioral failures cannot be identified, only observed in the aggregate. We thus cannot identify inertia, though additional tests are run to show correlational evidence of inattention and/or status quo bias.

Results of this study indicate that, when examining the 36 states on the healthcare.gov platform, enrollees respond to dominant gold plans offered in a market. However, the proportion that moves is less than would be expected by a rational agent under full information and no market frictions. This may indicate behavioral failures or information frictions. This result is robust to multiple definitions of dominance which account for tastes for insurance issuer, taste for continuity of care, and taste for specific services and prescriptions. I also find that areas with high levels of active re-enrollment see fewer signs of behavioral failures; this also holds true for areas with more new enrollees. These indicate specifically that inattention and status quo bias may play a part in the behavioral failures seen in the aggregate. These results are robust to the inclusion of a handful of time-varying county-level market and health control variables

On the other hand, evidence of a zero-price effect is limited. Though increased zero-premium bronze plan exposure is associated with increased plan enrollment, this increase is eliminated when we control for price changes within a market. In fact, there is slight evidence that a zero-premium bronze plan availability may decrease bronze plan enrollment. This may be because individuals see free plans as a signal of poor quality, or that the PTC ceiling leaves forgone consumer surplus to be extracted. This may also be because individuals do not see a plan as free; they may take into account all of the costs that will be associated with having that plan.

The paper proceeds as follows: Section 2.1 describes the background of this project, including institutional information, a description of market phenomena, and a literature review. Section 2.2 describes data and the data cleaning process, as well as treatment variables. Section 2.3 describes the empirical formulation employed, and section 2.4 describes results of these estimations. Section 2.5 discusses results. Section 2.6 presents supplemental analyses, while Section 2.7 concludes.

2.1 Background

2.1.1 Institutional Background

Following the passage of the Patient Protection and Affordable Care Act (ACA) in 2010, both individual and small group (fewer than 50 employees) markets for health insurance faced substantial redesign in the United States. First and foremost, marketplaces known as Health Insurance Exchanges (HIXs) were established to provide easy access to insurers' plans and information thereof. In both markets, plans both on and off the exchanges, known as Qualified Health Plans (QHP), became standardized along various dimensions: for example, metal tiers were established to clearly represent varying levels of actuarial value (AV), including Platinum (90% AV), Gold (80% AV), Silver (70% AV), and Bronze (60% AV). Since AV represents the proportion of medical costs that an individual's plan will likely cover, higher actuarially-rated plans involved less patient cost-sharing in the form of lower copays or coinsurance, lower deductibles, and lower overall out-of-pocket costs. Generally, these plans are also naturally ordered in the same way as above with respect to premiums, as a plan that provides less rich coverage is less expensive to obtain. Essential Health Benefits (EHB), which all plans within a state are required to cover, ensured that bare-bones plans were not available on or off the HIX. This generally standardized the richness of plans along the extensive margin of benefit coverage, with most variation in coverage due to varying dental benefits. Thus, the ACA limits most variation in benefit coverage richness to the intensive margin through metal tier selection.

In order to ensure affordability for high-risk enrollees, modified community rating, which allows a plan's premium to vary only by an individual's age and geographic area, was also instituted. These geographic areas, known as rating areas, were established on a state-by-state basis, and defined as sets of counties or zip codes. This policy, along with guaranteed issue of insurance regardless of health status, partially equalized premiums faced by unhealthy and healthy individuals who purchased the same plans and made insurance generally more affordable for unhealthy enrollees. This measure, along with provision of EHB, theoretically may create an adversely selected enrollment pool (Akerlof 1970; Rothschild & Stiglitz 1976)[1] , wherein only unhealthy individuals purchase health insurance, driving up costs. Along this line of reasoning, an individual mandate was instituted, requiring individuals to purchase insurance from the individual market if they had not received it from their employer or otherwise face a fine. Modified community rating established by the ACA uses a specific schedule with a multiplicative factor by age. For example, 65 year-old enrollees pay 3 times as much as a 21 year-old enrollee for the same plan (See Appendix Figure 1.A.1 from Chapter 1 for the schedule of multiplicative factors).

2.1.2 Premium Tax Credits and Cost Sharing Reductions

Premium Tax Credits

Two other measures of the ACA, which only applied to on-exchange plans offered on the individual market, further ensured plan quality and affordability for low-income enrollees. The first mechanism, *Premium Tax Credits* (PTC), are reductions in the premiums any individual with modified adjusted gross income (MAGI) between 100% and 400% of the Federal Poverty Line (FPL) faces when purchasing health insurance. Some of these are taken as Advance Premium Tax Credits (APTC), which directly reduce the premium cost up front. Ultimately, any unpaid PTC or differences between APTC and PTC are reconciled when taxes are filed[2]. The premium tax credit that an individual receives depends upon 2 things: (1) her income level as a percentage of the Federal Poverty Level (FPL) and (2) the premium of the second-lowest cost silver plan (SLCSP) that she has access to. These PTC ensure that, based upon a sliding scale, enrollees will contribute only a certain percentage of their income toward the premium of a SLCSP. For example, an individual with an income of 100% FPL would be expected to contribute a maximum

[1] This concept was applied to health insurance markets in relevant ways by Buchmueller & DiNardo (2002), which discussed the adverse selection problem created by minimum benefit requirements and community rating regulations. Einav & Finkelstein (2011) discuss this in more depth theoretically. Enthoven & Kronick (1989)'s work on managed competition argues on the other hand that in the absence of community rating, regulating coverage helps deal with selection concerns, allowing for competition over other dimensions like quality and premiums.

[2] See https://www.irs.gov/instructions/i8962 for information on Premium Tax Credit Form 8962.

of just 2% of their income to purchase the SLCSP, while an individual with an income of 350% FPL is expected to contribute a maximum of 9.5% of their income.

Graphs showing dollars paid versus income and proportion of income paid versus income FPL level are shown in Figure 2.1. In general, the premium tax credit can be thought of as the difference between the determined income you are expected to contribute to your health insurance plan and the listed yearly cost of the second lowest price silver plan in the market. Thus, if an individual with income i must contribute at most X_i% of their income, then the premium tax credit they pay, PTC_i is defined by

$$SLCSP_{i,m} = \text{contribution}_{i,m} + PTC_{i,m},$$

where

$$\text{contribution}_{i,m} = \min(X_i\%\text{of income}, SLCSP_{i,m}).$$

Here, if the yearly SLCSP premium is lower than the expected contribution, an individual will be expected to simply pay the full price for the plan. In this case, premium tax credit would be zero, meaning an individual is fully unsubsidized. After premium tax credit is determined as a function of one's age, income, and second lowest cost silver plan in a market, an enrollee may take this premium tax credit and apply it to any individual marketplace plan that is available to them, including less rich bronze plans or more rich gold and platinum plans, as well as other silver plans. These payments directly reduce the upfront cost of obtaining a health insurance policy.

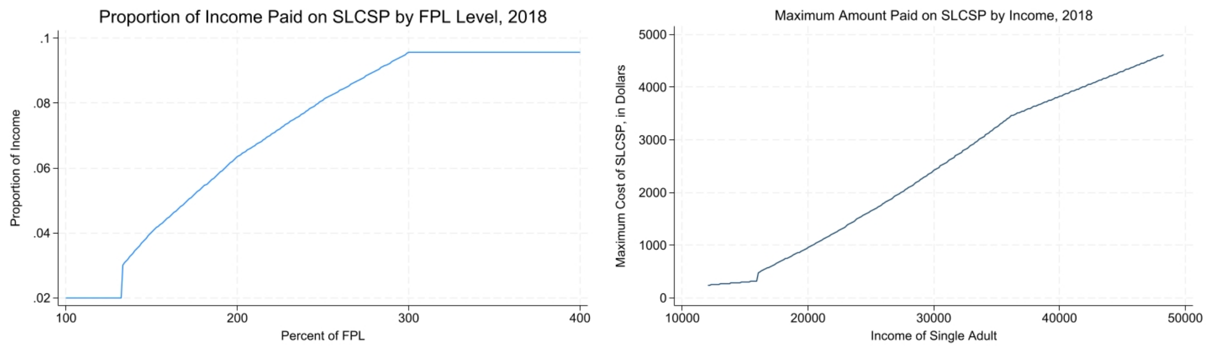
Simple Dynamics of PTC

A few facts about premium tax credits are worth fleshing out. Firstly, subsidized individuals pay a constant amount for SLCSP, regardless of how large its premium becomes. This amount depends only on income. However, some individuals may remain unsubsidized, in which case they pay less than this amount and do not receive a PTC. Secondly, when a SLCSP premium increases, premium tax credits of the subsidized shift by that exact amount. Similarly, many unsubsidized individuals will become subsidized, newly capped at the income-determined amount (see Appendix Figure 2.A.1). As a result, plans within the market that did *not* shift become *more* affordable by the amount of the PTC change for the subsidized. This means that shifts in silver premiums directly affect the affordability of other QHP through this public finance mechanism. For an illustration of this shift and its effect on plan cost across the income distribution of enrollees, see Appendix Figure 2.A.2.

Also of importance is the relationships between age and premium tax credit. While expected contribution does not vary by age, listed premiums are higher for older individuals due to community rating standards. Thus, when comparing two enrollees with the same income level, the older individual will be receiving a higher premium tax credit to offset the difference for their higher premium. This also means that younger individuals may not receive subsidies while older individuals with the same income do. Relatedly, when there are shifts in SLCSP premia, older individuals will see the greatest shifts in PTC due to the multiplier on the plan premia. The relative shift in PTC (and thus the *ceterus paribus* shift in affordability of other plans) between two differently-aged individuals at the same income level is equal to the ratio of their age multipliers. One implication of this is that while SLCSP have an equal net premium, plans with premiums listed above SLCSP plans (gold and platinum) will cost *more* for older individuals, while plans with premiums listed below SLCSP plans (bronze) will cost *less* for older individuals. This is discussed in greater detail below.

Cost Sharing Reductions The second on-exchange provision, *Cost Sharing Reductions* (CSR), improved the richness of *only silver plans* enrolled in by individuals with incomes between 100% and 250% of FPL. Specifically, actuarial values for all silver plans were adjusted as follows for the following income groups:

- 100-150% FPL: 94% AV
- 150-200% FPL: 87% AV



(a) **(b)**

Figure 2.1. Maximum Contribution by Income for Single Adult Enrollees receiving Premium Tax Credits (PTC)

Note: Panel (a) of the above figure shows the proportion of income one must spend yearly on SLCSP versus their income (expressed as a percentage of the Federal Poverty Line (FPL). Panel (b) shows the yearly dollar amount paid for the second lowest cost silver plan (SLCSP) versus income for a single adult in the continental United States (excluding Alaska and Hawaii) under the federal Premium Tax Credits program. This figure reflects the policy environment of 2018, though these charts do not change markedly year by year. Both charts assume that the total amount paid does not exceed the actual yearly SLCSP Premium, in which case this premium amount would be paid by all households with higher incomes. This would be represented by a flat line in panel (b) and a downward sloping line in panel (a).

- 200-250& FPL: 73% AV

Thus, very low-income enrollees could obtain plans with more favorable cost-sharing than platinum plans (90% AV) for the price of a silver plan. Other low-income individuals were eligible to receive plans with better cost-sharing than a gold plan or slightly better than standard silver. Thus, low-income individuals, who already qualified for premium tax credits, received further cost-saving/quality enhancing assistance in the form of CSR. Unlike PTC, CSR are only available on silver plans on the exchange. This makes silver plans more attractive to low-income enrollees, as those who enroll can take advantage of two forms of government assistance for medical costs. Like Premium Tax Credits, these reduction subsidies were to be paid for by the government directly to health insurance issuers to offset their costs of providing more rich coverage.

These two forms of government assistance foster affordability in two different respects. Premium Tax Credits directly cut the cost of holding a health insurance policy, either immediately or when taxes are filed. Cost Sharing Reductions, on the other hand, reduce the cost of each medical procedure, service, or drug on a per unit or per visit basis. They also reduce maximum out-of-pocket costs and deductibles, meaning costly medical events, or those that may include a long string of medical treatment, will have a less detrimental maximum financial effect. Just as Platinum plans may be more attractive to unhealthy individuals than Silver plans (depending on the premium of the plans), Silver plans with CSR applied dominate those Silver plans without CSR, as their premium is equal. While consumers generally face a trade-off between cost-sharing and premiums in choosing a health insurance plan, these mechanisms give silver plans greater value for low-income individuals. As a result, in 2016, about 71% of enrollees in the individual market on the federally run exchange were enrolled in silver plans.

2.1.3 Policy Change

In October of 2017, the Trump Administration announced that, beginning in 2018, the federal government would no longer be providing subsidies to pay for Cost Sharing Reductions[3]. The payments had already been controversial, as they were the subject of a landmark circuit court decision in *House v. Burwell*. Though funds would no longer support CSR, these reductions were still expected to be provided to enrollees, as specified by the ACA. Though this was just over two weeks prior to the start of the open enrollment period in the individual market, policymakers and insurers alike in many states had already planned for this action in their pricing strategies; other states allowed emergency changes to insurance filings.

What resulted in many states and by many insurers has often been referred to as "silver loading." Aptly named, this act consisted of loading the cost of Cost Sharing Reductions onto the premiums of individual silver plans. This took two flavors: some issuers loaded these costs

[3] A joint statement was issued by the Secretary of Health and Human Services and the Administrator of Centers for Medicare & Medicaid Services, stating that the Obama administration had failed to receive proper appropriation of funds from Congress for these payments. The statement emphasized the unconstitutionality of these payments still being made. Following a legal opinion from the Attorney General, as well as a 2016 federal court case ruling against federal CSR payments, these payments were discontinued immediately. There have been similar political arguments and controversies surrounding Premium Tax Credit payments.

onto the premiums of all silver QHP offered in the individual market (*general silver load*); other issuers loaded these costs only onto plans that were offered *on* the exchanges (*pure silver load*). Issuers in some states chose instead to load the cost of providing CSR across all offered metal tiers, resulting in a more uniform gross premium increase across plans as a result of this policy change. While this *broad loading* strategy may seem like an appropriate way to spread out the cost of CSR, pure silver loading is simply actuarially pricing the on-exchange silver plans for the coverage that they provide, despite its forced, distortionary nature. Broad loading, on the other hand spreads some of this cost to individuals who do not contribute to the increased costs borne by an insurer due to CSR cuts. General silver loading, on the other hand, is an intermediate case, which spreads some of the premium hike to off-exchange plans. We can thus posit that, all else equal, on-exchange silver plans' premia rose the most for insurers who instituted the pure silver-loading policy, followed by slightly smaller increases from general silver-loaded insurers; broad loading would create the least severe price hike. The severity of these changes depends on the health status of enrollees in various metal levels, the distribution of incomes of enrollees in silver plans, and the number of enrollees on off-exchange silver plans[4]. More importantly, pure silver load sees the greatest silver premium increase relative to non-silver plans. Meanwhile, general silver loaded markets see a weaker silver premium increase. Broad loads, on the other hand, see no increase in silver plans *relative* to non-silver plans, as increases are applied evenly. See Figure 2.2 below, where premium changes by metal tier reflect this prediction.

Decisions made by insurers in many states were affected by rulings of policymakers. In North Dakota, for example, insurers were not allowed to price their plans as if CSRs would not be paid. This meant that insurance issuers were not allowed to increase any of their premiums for that purpose, and simply had to eat the CSR payments as a loss[5]. As a general rule, states' regulatory bodies for insurance provided either loose guidance or firm direction on how to load

[4]It is possible that a general silver load could lead to less drastic increase in silver premia than broad loading in the same market if silver plan off-exchange enrollment was very large and on-exchange non-silver enrollment was very small

[5]This led one of the state's insurance issuers, Medica, to remove itself from the individual market in 2018. They re-entered in 2019 when insurers were allowed to begin silver loading.

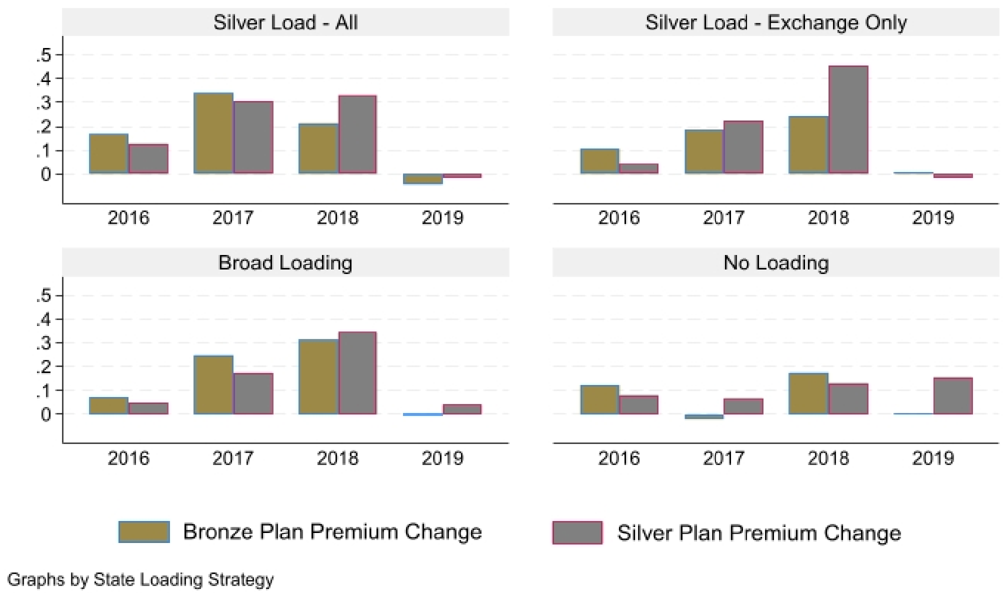


Figure 2.2. Percent Change in Premiums across State Loading Strategies, 2016 to 2019
Note: This figure shows the percent change in premiums from the previous year, grouped by a state's loading strategy chosen for the 2018 plan year. For pure silver loads, silver plan premia increased most relative to bronze plans. For general silver loads, silver plan premia increased moreso than bronze plans. Broad loading strategies led to relatively similar silver and bronze plan premia increases. In North Dakota, where insurers were required to eat the cost of their cut CSR payments, increases were close to zero (before silver loading in 2019).

the cost of CSR. Thus, many states' insurers used the same strategies when pricing their plans.

2.1.4 Silver-loading, Plan Affordability and Consumer Surplus

Although silver-loading makes premiums of silver plans more expensive, the effect that this move has on the cost of insurance for various consumers is tied directly to premium tax credits. Consider, for example, any individual enrolled in SLCSP and receiving PTC. All else equal, if all issuers in the market silver load and increase their premiums appropriately, the individual will pay the same proportion of their income on SLCSP. Thus, when SLCSP premium skyrockets, the premium tax credit that an individual receives will increase dollar for dollar. Those enrolled in *non-silver* plans, however, will actually see their cost of obtaining the plan *decrease*: if the PTC increases substantially but the premium of a plan stays the same, then the plan becomes more affordable. For a simple illustration of this, see Appendix Figure 2.A.2, with an explanation in the description. Thus, *ceterus paribus*, if a market is silver-loaded in a typical fashion, all non-silver plans will be less expensive than they would be in a non-silver-loaded market; all silver plans are about as expensive as before[6]. See Table 2.1 below for a summary of various scenarios and the ceteris paribus consumer surplus implications of these scenarios.

In Table 2.1, we see discussion of each individual's consumer surplus of a subsidized individual with income i enrolling in metal tier m, $CS_{i,m}$; I model this very simply as: $CS_{i,m} = WTP_m - [P_m - (PTC_i)] = WTP_m - [P_m - (SLCSP - z_i)] = WTP_m - P_m + SLCSP - z_i$. Here, we see that consumer surplus for enrollment in metal level m is equal to an enrollee's willingness to pay for this plan minus what he pays. This payment is equal to the difference between the premium he would pay if unsubsidized P_m, and the amount of the premium tax credit, which is equal to the second lowest cost silver plan premium minus a pre-set amount of one's income, z_i. I do not include personal characteristics in this equation because I am only considering how each

[6]One caveat to both of these results is that we must have a uniformly-loaded market. If some issuers broad-loaded, then SLCSP may not have increased much. This would instead make all silver enrollees in silver-loaded plans *worse* off, and enrollees in non-silver plans may only be slightly better off than before, depending on which issuer the plan is from.

individiual is affected, assuming none of their tastes, which would affect WTP, have changed. This simple formulation reflects intuitive results: one's consumer surplus is increasing in their willingness to pay and in the premium for the SLCSP, while their consumer surplus is decreasing in their own premium cost. Table 2.1 then reflects how this equation fares in various theoretical market responses to CSR cuts.

Examining Table 2.1 yields a few observations. Firstly, if all issuers in a market act perfectly in tandem, all consumers end up at least as well off as they would have been if CSR payments had not been cut. Specifically, when a broad load occurs, all enrollees are approximately as well off as they would have been otherwise (depending on how the loading exactly occurs); when all plans silver load, silver enrollees end up approximately the same, while non-silver enrollees are better off. Mixed strategies yield different results. Though results vary: 1) enrollees in silver plans from issuers who silver load are either worse off or about the same in the presence of mixed loading; 2) non-silver plan enrollees of silver-loaded issuers will be better off than they would have been without CSR cuts; and 3) When silver loading does not occur, silver and non-silver plans can be analyzed in the same way, and in mixed policy environments enrollees are either better off or the same. Though the table does not cover all possible intricacies of mixtures of strategies, its insights can be used to extend the findings[7].

While the simple analysis above assumes that enrollees do not switch issuers or metal levels, these consumer surplus changes, along with a potential outcomes framework, can help us draw conclusions about utility maximizing metal tier enrollment patterns following various CSR loading market responses. We can then consider all four additive elements of consumer

[7]Two scenarios as examples are the following: (1) Suppose some issuers do a pure silver load while the others do a general silver load. In this case, CSR adjustments will be the same as a mixed market, but with all changes less pronounced. (2) If some issuers do not load premiums at all (and issuers eat the loss), this would be similar to when they broad load, except CS increases are greater due to having no price change. It may be that the final row is interpreted as a situation where those who broad-loaded already had very high premiums for their silver plans. It could alternatively be the case that the issuer is the only issuer that did not silver load, it only offers one silver plan, and it was already the least expensive silver plan in the market. Note also that when there are multiple broad and/or multiple silver-loading plans, all enrollees will have similar CSR responses across issuers within strategy-metal level; however, the position of each of these loaders and non-loaders is what decides which situation we are in (which row).

Table 2.1. Loading Strategy vs. SLCSP, Consumer surplus, and Premiums; Theoretical

State Loading Strategy	Silver plans		Non-Silver Plans	
	Silver Loaded Issuer	Non-Silver Loaded Issuer	Silver Loaded Issuer	Non-Silver Loaded Issuer
Uniformly Silver Loaded Market	CS: ~same SLCSP: + P_S: +		CS: better off SLCSP: + P_B: same	
Uniformly Broad Loaded Market		CS: ~same SLCSP: + small P_S: + small		CS: ~same SLCSP: + small P_B: + small
Mixed: Some Broad, Some Silver:				
Broad was SLCSP before, still is	CS: Worse SLCSP: + small P_S: +	CS: ~same SLCSP: + small P_S: + small	CS: at least slightly better off SLCSP: + small P_B: same	CS: ~same SLCSP: + small P_B: + small
Broad was not SLCSP before, now is	CS: Worse SLCSP: +? P_S: + larger	CS: at least slightly better off SLCSP: +? P_S: + smaller	CS: better? (severity) SLCSP: +? P_B: same	CS: about at least slightly better off SLCSP: +? P_B: + smaller
Broad was not SLCSP, still isn't	CS: ~same SLCSP: + P_S: +	CS: better SLCSP: + P_S: + small	CS: better SLCSP: + P_B: same	CS: better SLCSP: + P_S: + small

Note: This table explains the various differential consumer surplus changes experienced by consumers who are enrolled in various plan types in various loading situations by state. The leftmost column represents various scenarious, including scenarios where all insurers in a state act in a similar fashion, and others where there is less harmony in insurers' actions. An same result means that as long as the price increase is the same as the SLCSP increase, which is not necessarily true in all cases. A question mark means that the severity is may vary depending on the situation.

surplus: variation in z may allow us to compare across income groups, or between those who do and do not receive PTC. A bit more complex is willingness to pay, which will reflect one's preferences for various plan metal tiers. These preferences are a function of a few things. Firstly, they are a function of health, or more specifically one's expected health care utilization while holding the policy. Unhealthy individuals, as well as those who live more reckless lifestyles and prefer strong coverage, will have a larger WTP gradient when looking across actuarial plan values. More specifically, the marginal increase in willingness to pay for a 10 percentage point change in actuarial value (by upgrading metal tier) is greater for those with greater expected health expenditures. Secondly, WTP is a function of one's income status. For reasons discussed in neoclassical economics, individuals with low incomes may have much lower willingness to pay than those with very high incomes. More relevant, though, is differences in WTP due to differential access to CSR across income groups. This then becomes relevant with respect to metal tier choice, as CSR, which has a positive relationship with WTP, is only applied to silver plans.

It now becomes useful to define a couple of objects before proceeding. I define Gold-Silver WTP gap as the difference between some consumer's WTP for a gold plan and their WTP for a silver plan. This represents the maximum number of dollars an individual would spend to replace their silver plan with a gold plan. I can then define analogous WTP gaps (Silver-Bronze WTP gap and Gold-Bronze WTP gap). A couple observations are worth noting. First, due to CSR, the Gold-Silver WTP gap between similar plans is smaller for enrollees between 200 and 250% FPL than others, and the WTP gap is negative for those at 100-200% FPL. Second, for the same reason, Silver-Bronze WTP gap is larger for enrollees between 100 and 250% FPL; it decreases in income group. These CSR payments create discontinuities in WTP at the borders of these income groups, as well as at the 400% FPL mark. Furthermore, we can similarly define CS gaps. The plan metal tier that is chosen by a consumer is the one which creates positive CS gaps between it and other possible metal tier selections.

We can then use these simple observations to make predictions about enrollment behavior in various loading contexts by comparing consumer surplus across metal tiers (and possibly issuers) before and after CSR payments are cut. For example, consider a market with homogeneous silver loading. All silver plan enrollees face no change in their consumer surplus from before to after the loading occurs. However, non-silver plan enrollees are better off. If the increase in consumer surplus for a silver plan enrollee to switch to a non-silver plan is greater than the pre-load Silver-Other CS gap, then the individual will choose the non-silver plan. The non-silver plan that was the next best alternative will become chosen, since PTC is the only object that has shifted. If all issuers broad load then all CS are approximately the same, and no enrollment changes are necessarily induced.

When we instead consider a mixed loading environment, we see varying responses by enrollees depending upon their issuer's decision and their metal tier. See Table 2.1 for breakdown by situation. Note that all non-silver-loaded issuer plans can be treated identically since all CS responses are effectively the same. This is the only situation where some enrollees may be clearly worse off (silver loaded enrollees). In all three situations, non-silver enrollees of loaded issuers see greater increases in CS than all other plans. So, in all situations these individuals would not be induced to switch plans. This also means that enrollees in other types of plans may be induced to switch to these plans. Furthermore, since enrollees in plans from non-loaded issuers see more positive CS changes than silver-loaded plans, enrollees in the latter may switch to the former. Thus, regardless of placement of SLCSP in a mixed market, responses can be expected to be similar in terms of enrollment shifting. The above discussion is purely hypothetical, and variation in pricing strategies and risk pools between insurance issuers will muddy up expected price shifts within these markets.

2.1.5 Resulting Market Phenomena

Besides the dynamics described above, there are two other price-related phenomena that began to occur with the emergence of silver-loaded markets. The first phenomenon is that in many rating areas, silver plans' premia began to exceed those of gold plans within the market.

Moreover, markets emerged where one or a handful of gold plans were less expensive than *all* silver plans offered in the area. This change in metal premium ordering changes incentives for enrollees. Assuming that WTP is higher for gold plans than silver plans, gold plans now *dominate* silver plans for all enrollees outside of 100-200% FPL, including those who are not subsidized. This means that, in the absence of market frictions due to behavioral failures or information assymetry, all of these enrollees should switch from silver plans into whichever alternate non-silver plan was a previous best alternative non-silver plan, which may or may not be a gold plan. Low-income individuals on the other hand still may prefer to enroll in a silver plan, since WTP for silver plans is higher than gold (or platinum). Prior to the introduction of cheap gold plans[8], silver plans dominated gold (or platinum) plans for these enrollees due to higher WTP and lower prices. Thus, although silver plans are not dominated, silver plans no longer dominate these markets, meaning that some subsidized low-income individuals may now be inclined to switch metal tiers[9]. Results of markets with cheap gold plans line up with dynamics of markets with silver loading; namely, in markets where this occurs silver enrollees are induced to switch while non-silver enrollees are induced to stay. Prior to 2018, no counties in this study had experienced conditions where the least expensive gold plan was less expensive than all available silver plans.

Dominance in the health insurance context does not simply require that a gold plan be less expensive than a silver plan. Although plan standardization reduces across-plan variability along most dimensions plans can still vary across a few dimensions. Some insurance issuers may

[8]I generally use the term "cheap gold plans" to signify a rating area or state where gold plans are less expensive than all silver plans. I interchangeably will also use the phrase "dominated silver plans" and "dominant gold plans," which more specifically refer the experience of cheap gold plans by those with incomes above 200% FPL.

[9]Note that the discussion about dominated plan choices relies on the assumption that plans are not differentiated across issuers. Certain measures of the ACA, including Essential Health Benefits (EHB) (Chapter 3 of this dissertation), created greater uniformity across plans in markets, specifically in terms of plan benefits offered in the case of EHB. Still, even if benefits are similar, coverage of the benefits may differ in idiosyncratic ways (slightly more services, different wording). More concerning is differences in networks of plans. If this difference in WTP due to issuer-specific characteristics is greater than the difference between WTP of silver and gold plans (and assuming both are uniform regardless of issuer) plus the price difference between the silver candidate switch plan and the gold cheap plan. Thus dominance may be impacted if taste for an insurer is substantive. I explore this further in my secondary analyses.

be preferred for reasons related to customer experience, such as customer service. Moreover, insurers may differ in the networks they offer or the benefits (and pharmaceuticals) that they cover. These latter differences may also exist among plans *within* an issuer, as it is not uncommon in the ACA markets for issuers to offer multiple sets of plans that vary along these dimensions. However, by law, all insurance products offered must be offered with at least one ”silver” variation and one ”gold”. These insurance products differ *only* in their metal tier, with the same network, formulary, and benefit package, as well as the same insurance issuer.

The second, less anomalous artifact that occurred in many markets was the emergence of zero-premium, or *free*, bronze plans. When premium tax credits rose due to silver loading, this made many individuals’ PTC greater than bronze plans in their rating area. As a result, these individuals could then obtain a bronze level plan with 60% actuarial value for no up front cost. While availability of cheap gold plans is based only upon market, access to free bronze plans also depends upon one’s income level in relation to FPL[10] and one’s age. For a simple illustration of this, see Appendix Figure 2.A.3, with an explanation in the description. As discussed above, PTC is greater for older individuals, so bronze plans are less expensive for old individuals. Thus older folks will qualify for free bronze plans when younger ones of the same income level do not. There may then be a cutoff age for each income level where all aged above the cutoff qualify for free bronze and all below do not. This same logic can be applied to income levels at a given age. When we look directly at the CS formula, a ceteris paribus increase in required contribution (from an increase in income) will lead to that exact decrease in effective price paid. Thus, similarly, there may be a cutoff age for each age where all with income below the cutoff qualify for free bronze plans and all with incomes above do not. If we were to graph all cutoffs in the age-income space, the line would be positively sloped. While free bronze plans were available for many low-income enrollees prior to the policy change, they became more widely available to individuals with higher incomes in 2018. For example, in 2017, the median county

[10]Technically, this depends upon both one’s income and family size, as the latter affects the threshold for the federal poverty line. Since information on raw income and family size are both unavailable in my datasets, only income as a percentage of FPL can be considered.

cutoff for receiving a free bronze plan for a 30-year-old enrollee was 151% of FPL; in 2018, this rose to 207% of FPL.

2.1.6 Age, PTC, and Market Phenomena

As discussed above, two individuals of the same relative FPL level will pay the same amount for SLCSP, regardless of their age. In general, old folks pay lower prices for bronze plans and higher prices for gold plans (as compared to younger enrollees). Thus, at the baseline it may seem that this market force may hypothetically be counteracting older individuals' natural tendency to choose more rich plans due to having greater health risk. However, this is not how the dynamics associated with loading sort out. When silver loading occurs, potential consumer surplus gain associated with gold plan enrollment increases by more for older individuals than younger ones[11]. The same holds true for bronze plans. These greater surplus gains among older enrollees, which come about as a direct result of greater affordability, mean that an older individual with a small Gold-Silver or Bronze-Silver CS gap would more easily be induced to switch plans; this means that enrollment changes that come about as a result of silver loading might be exacerbated by old age, as price shifts are more drastic.

In fact, the price paid can be reduced to the following equation:

$$P_{plan} = X_i + (p_{plan} - p_{SLCSP}) * m_a$$

where P_{plan} is net premium, X_i is expected contribution for an individual with income i, p_{plan} and p_{SLCSP} are baseline plan price and baseline SLCSP price (not multiplied by age factor), respectively, and m_a is the multiplier for individual of age a. In the case that an individual is not receiving a premium tax credit, X_i can be replaced with $p_{SLCSP} * m_a$, terms cancel out, and individuals pay listed plan price multiplied by the age factor. This simple equation shows that plan cost is dependent on expected contribution (and whether PTC is received), the premium

[11] Specifically, $\frac{CS_{older}}{CS_{younger}} = \frac{PF_{older}}{PF_{younger}}$, where PF is the premium factor associated with each age. For example, if we were comparing 21 year olds with 65 years olds the ratio would be 3.

difference between SLCSP and one's plan choice, and their age multiplier. This also means that, given PTC continue to be given, shifts in SLCSP and plan price need not be considered individually; only the difference is needed. There are two exceptions to this: 1) if SLCSP decreased by some amount such that PTC went from positive to 0, in which case net premium shifts would not be as large; or 2) prices shift so that now $P_plan = 0$. Another way to think about this is that price differences are determined by actual listed price differences (and all premium differences are larger for older individuals); the actual location of these prices is determined by the SLCSP's listed premium and whether it is greater than the maximum contribution as required under the ACA.

If two individuals have the same income:

- Net Premium of SLCSP:
  - If both qualify for PTC: old and young pay the same net premium for SLCSP
  - If neither qualifies for PTC: older pays higher listed premium, while younger pays lower listed premium
  - If only older individuals qualify for PTC, older individuals pay weakly higher net premiums
- If selecting a more expensive plan relative to SLCSP (e.g. typical gold plan), older individuals always pay higher premium, regardless of PTC status
- If selecting a less expensive plan relative to SLCSP (e.g. typical bronze plan):
  - If both qualify for PTC, older individuals pay less for less expensive plans
  - If only older individuals qualify for PTC, these plans are less expensive for younger individuals only if the plan premium is sufficiently close to SLCSP; as the premium decreases, the enrollee receiving PTC's premium will approach $0.
  - If neither qualify for PTC, younger individuals pay less for less expensive plans.

- As a result:
  - This (always) means that old qualify for free plans at higher income levels than younger ones.
  - Plan net price differences between any two plans are (weakly) larger for older individuals, unless both plans are on the lower bound (and have $0 premiums).
  - The Center point (net price of SLCSP) is determined by income level (through a maximum contribution amount) and the SLCSP listed age-adjusted premium relative to that cutoff
- When considering shifts in SLCSP and other plan choices,
  - A shift in difference of listed prices = A shift in difference of paid net premiums
  - This is true unless:
    - SLCSP crosses the bound of equaling the maximum contribution OR
    - SLCSP is sufficiently high and bronze plan premium is sufficiently low such that net premium is equal to $0.
  - These shifts are larger for older individuals, regardless of income level.

Larger price shifts, however, do not necessarily ex ante imply greater switching among older enrollees. Various studies have shown that older individuals have lower price elasticities of demand as compared to younger ones (Royalty & Solomon, 1999; Strombom et al., 2002). Other works studying private health insurance markets in Chile and Spain find increasing elasticity as a function of age (Costa & Garcia, 2003; Fernandez, 2012). Relatedly, Strombom et al. (2002) and Schmitz & Ziebarth (2011) find that individuals with worse health are less sensitive to price changes than healthier individuals. Still, this result is not consistent across the literature (see: Parente et al., 2004). Based upon the literature, it is likely that older enrollees have lower price elasticities, which would partially temper switching among older individuals in environments where price changes faced are larger.

Consider finally the pricing anomaly of dominated silver plans. In a market where metal tiers are appropriately ordered, the price gap between silver and gold plans is larger for older individuals due to the larger multiplier. At equal income levels, this would partially offset the higher demand levels for a gold plan among older individuals. However, when this ordering changes, dominant gold plans may now be *less* expensive for older individuals if the gold plan is less expensive than SLCSP. In this case, the larger price difference may simply be more salient, despite the silver plan being a dominated choice regardless of age. Relatedly, other works have found that poorer households have higher price elasticities[12].

2.1.7 Implications of Dominated Silver Plans and Zero-Premium Bronze Plans

Both of these phenomena provide an opportunity to study patterns associated with individual behavioral responses. The emergence of dominated silver plans provides an opportunity to study behavioral failures within these health insurance markets. In a setting with full information and rational agents, price shifts that cause silver plans to be dominated should cause all enrollees with incomes above 200% FPL to disenroll from silver plans and enroll in gold plans. However, various frictions may inhibit this change from occurring. The first is status quo bias, a well-documented cognitive bias, which involves individuals preferring their current choice over potentially better alternatives, making them less likely to switch (Samuelson & Zeckhauser, 1988). This is closely related to the *endowment effect* (Thaler, 1980), where an agent's willingness to accept exceeds his willingness to pay. Both of these behavioral anomolies are manifestations of *loss aversion*, or disutility associated with giving up a good which is greater than the utility of acquiring it (Khaneman et al., 1991). A few possible explanations for this status quo bias in this context are hassle costs of switching plans and inattention to new plan

[12]For a summary on price elasticities and heterogenity thereof across socioeconomic strata, see the review by Pendzialek et al. (2016).

availability. Each of these may result in *inertia*, defined as persistence of choice despite better offerings (Dube et al., 2010). Over time and with active market experience, it could be the case that such biases are ameliorated (List, 2003). Besides inertia in switching from dominated plans, general choice failures may exist for market newcomers as well. These behavioral failures are more likely due to information asymmetries or behavioral failures that are independent from making an initial choice.

The spreading of the prevalence of the availability of zero-premium bronze plans to higher income populations also presents an opportunity to study enrollee behavior. Augmented choice of zero-premium bronze plans may occur for various behavioral reasons. The zero-price effect suggests that perceived benefits associated with free products may be higher than products with a non-zero price (Shampanier et al., 2007). This may be explained by the affect heuristic, which suggests that psychological feelings influence decision making [13]. A tendency to favor a zero-premium plan may also be related to the concept of transaction utility (Thaler, 1985), where an individual gains utility from the perceived "deal" they are receiving from their transaction. Since the price that an individual expects to pay is weakly greater than 0, there will be weakly positive transaction utility for all individuals who purchase a bronze plan. In some contexts, another possible explanation for a zero-price effect is regret (Loomes & Sugden, 1982; Bell 1982): individuals who anticipate regret know that if they consume a free item they will not regret having paid some price for it if it does not create a great deal of utility gain. However, this may not apply in this setting, as choosing a free plan does not mean that no other costs will be incurred. Obtaining insurance plans for free may, however, be particularly attractive due the free nature of the plans being up front. One's present bias, or one's tendency to overvalue the present when considering intertemporal trade-offs (Laibson, 1997), may cause potential enrollees to further weigh the zero-premium decision when purchasing insurance, neglecting its impact on

[13] Epstein (1994) describes affectiveness as a feature of the experiential system of one's information processing system in one's mind. This experiential system system contrasts with the rational system, which focuses on logic, analytics, and justification for decisions. He describes the affective attribute as "what feels good"; Samson & Voyer (2012) describe it as representing "a reliance on good or bad feelings experienced in relation to a stimulus". Decisions made upon these judgements are often quick, natural, and automatic (Slovic et al., 2002).

future costs.

Another feature of zero-premium plans could make them *less* attractive to purchase in some circumstances. Premium tax credits are capped at one's total premium. This mechanically prevents individuals from getting monetarily compensated for having health insurance. This means that a bronze plan is as attractive as it will ever be when PTC becomes large enough for it to be free (unless WTP changes). Thus, even if SLCSP were to shift further still, no more CS could be gained by a bronze plan enrollee. This means that when SLCSP is sufficiently high and an enrollee is sufficiently poor, gold plans (which will not be loaded on) may be preferential to bronze plans for some individuals. This may even be for individuals who would have never otherwise enrolled in a gold plan. On the other hand, individuals who are the marginal group who qualify for a free bronze plan (the richest) are maximizing their CS gap with a possible added transaction utility from receiving a free product. A final reason that free plans may be less attractive to consumers is that prices act as a signal of quality[14]. In an environment where literacy of plan quality may be low, this is more likely to be the case. An additional consideration is that, in this context, zero-premium plans are mostly available to those who qualify for large cost sharing reductions on silver plans. This may mean that zero-price effects may be less effectual on these enrollees, whose plans feature disproportionately favorable cost sharing.

It is important to point out that evidence of a zero-price effect does not necessarily imply a behavioral failure. In a simple context where health care utilization is deterministic, a behavioral failure would consist of choosing a product where the net returns of making a different choice is higher. There would be heterogeneity between individuals on whether net return is minimized with any given choice, as demand for health services varies. When we introduce the fact that health utilization is stochastic, we see that this is also determined by health shocks; this component makes evaluation of plan choice failure more difficult. Whereas choice of a dominated plan involves (weakly) greater spending at every level of health care utilization, this

[14]The opposing forces of the zero-price effect and "price-quality inference" are discussed in Niemand et al. (2019). Raghubir (2004) and Kamins et al. (2009) find that consumers are willing to pay less for an individual product when it has been offered for free as part of a bundle with another product.

is not the case for selection of all bronze plans. Those with low levels of demand for health services may be receiving some transaction utility of choosing a free plan while also minimizing yearly health care spending relative to other plan choices. To deal with this, using detailed claims data, we could define ex-ante choice mistakes using the previous year's data and ex-post choice mistakes using actual utilization under the plan, similar to Abaluck & Gruber (2011). Obviously, these two measures of health care utilization will differ; if plan selection does not affect behavior, this disparity may be due to unanticipated health events or other demand shocks. To add to the disparity between ex-ante and ex-post utilization may be moral hazard, where in this context choosing a higher metal level may induce greater healthcare utilization, and vice versa (Einav & Finkelstein, 2018). In ACA markets, free bronze plans may induce individuals to curb their health care spending. This drives down premiums, but may have negative effects on an individual's health long term. This, as well as individuals' awareness of their own moral hazard (Einav et al., 2013), makes welfare analysis of free bronze plans untenable. Even if the claims data was available, private information available to an individuals which informs their expectation of future plan choice is fundamentally unobservable to an econometrician. Even so, claims data is not realistic in this context; thus, I treat selection of zero-premium bronze plans as a behavioral anomaly rather than a behavioral failure. Because of this and other data-related reasons that will be discussed, this matter is of secondary interest compared to selection of dominated silver plans.

2.1.8 Information Frictions and the Health Insurance Exchange

Health insurance exchanges were established with the purpose of facilitating health insurance purchases and providing a one-stop, easily accessible platform to do so. A majority of states chose to run their exchanges through the Federally Facilitated Marketplace (FFM), meaning that individuals in all of these states used the same website to select health insurance. Besides ease, marketplaces were intended to foster transparency and provide clear information on premiums, benefits, and other plan features. Appendix Figure 2.A.4 shows what an enrollee sees during plan selection. They are presented with a plan name, metal tier, network type, and basic cost-sharing information. The premium that an individual must pay is also listed, along with the listed premium and premium tax credit applied to the plan. This means that any individual actively re-enrolling is likely to visually see a plan available for $0. They will also be able to directly compare prices of plans without having to investigate the plans further. Individuals are thus aware of the premium tax credit they are receiving, given that they are enrolling in a plan. Besides this, the website also directly states whether an individual will receive extra savings on out-of-pocket costs (CSR) under the ACA (see Appendix Figure 2.A.5). Still, there are features of the FFM that may create frictions. Specifically, enrollees may choose not to actively enroll in years after their initial choice; this means that consumers may be simply not *choosing* at all, but rather automatically enrolling in the same plan as before.

2.1.9 Literature Review

This paper contributes to a few distinct literatures. The first is those papers which study the effects of silver loading. Other works, mostly in short articles published by policy institutes, have investigated silver loading and its various effects. The phenomena was first discussed as a possibility in early 2016 in an article from the Urban Institute (Blumberg et al., 2016), when CSR payments were first facing serious threats, specifically the *House v. Burwell* case. This article, as well as two others (Levitt et al., 2017; Yin & Domurat, 2017) predicted silver loading by insurers and substantial premium increases. Besides collecting loading decisions and magnitudes by issuer from SERFF (Kamal et al., 2017), other works looked at the effect of these changes. Drake & Anderson (2020) find that overall enrollment in areas where zero-premium plans emerged increased more than in those that did not have zero-premium plans available, specifically among those enrollees between 151% and 200% of FPL. Rasmussen et al. (2019) use individual-level enrollment data from California to find that gold plans became more enrolled in as a result of price changes due to silver loading, and that overall plan selection was sensitive to these market changes. Rasmussen & Anderson (2021) use enrollment data from California to study dominated silver plans, finding that enrollees who were previously in a newly dominated silver plan have 8 times greater odds of choosing a dominated plan than a new enrollee, demonstrating metal tier stickiness. I contribute to this small literature by empirically examining plan choice in many markets; this is the first work to look at the effects of dominated plans across the U.S. and the first to study these various phenomena associated with CSR cuts jointly.

A second, broader literature that this paper contributes to focuses on choice inconsistencies and behavioral failures within health insurance markets. A large portion of this literature examines pharmaceutical plan choice within the context of Medicare Part D, which generally serves individuals over 65 years of age. Abaluck & Gruber's seminal work from 2011 provides evidence about perceived trade-offs between cost-sharing and premiums, finding that this older demographic overweights premium savings relative to cost-sharing savings when selecting Part D plans. This work also finds that plan characteristics are considered moreso than those characteristics' effect on overall spending. Ketcham et al. (2012) find that many of these behavioral failures are corrected over time, with the greatest improvements made by those who overspent the most; Abaluck & Gruber (2016), on the other hand, find little learning over time. Inertia has specifically been found in some of the studies within this Medicare drug prescription sub-literature, with specific focus on inattention and switching costs and frictions as a source of the status quo bias (Heiss et al., 2021; Ho et al., 2017; Ericson, 2014; Polyakova, 2016). Dominated plan choice is used to identify choice inadequacy in various works as well (Bhargava et al., 2017; Sinaiko & Hirth, 2011; Handel, 2013).

Work on the zero price effect in the health insurance context is more limited, though evidence of zero-price effects have been found in tourism (Nicolau & Sellers, 2012), retail (Chen et al., 2012), and telecommunications (Driouchi et al., 2011). In the health insurance context, zero price plans can act as a reference point for consumers when comparing products (Buchmueller & Feldstein, 1997): this is another way that the zero-price effect has been characterized. Douven et al. (2020) find zero-price effects in hypothetical health insurance demand response scenarios[15].

[15] Other works, such as Pizer et al. (2003) have looked at benefit richness in Medicare plans, finding that benefit

2.2 Data

While some previous works on plan selection have used individual enrollment data, this is not available to me at a national level[16]. Instead, I utilize enrollment data that is aggregated in various manners in order to protect individuals' privacy. This data is available both on a state and county level. On a state level, enrollment numbers are available by metal tier-FPL status. These numbers are also available by metal tier-age group. These state-wide files are only available for 2017 through 2019, which limits the scope of this study. Another drawback of this data is the fact that observations are on a state level, wherein markets vary substantially. County-level data is unfortunately aggregated in a less granular fashion. Enrollment totals are available by metal level, FPL status, and age, all separately. Still, this dataset is available for 2015-2019 and provides greater detail of metal level enrollment – state level plans only identify silver and bronze enrollment in their most disaggregated data. County level data is also more precise, as much of the state level data is defined as an integer number percentage of a total. Both files are public use files available from the Center for Medicare and Medicaid Services (CMS).

My primary analysis uses Marketplace Open Enrollment Period Public Use Files from the Center for Medicare and Medicaid Services (CMS)[17]. These files provide enrollment numbers in the 36 states that run a Federally-Faclitated Marketplace (FFM) for those who enroll during the Open Enrollment Period (OEP), which generally runs between early November and late December. Enrollees of this period are then counted in the enrollment numbers for the following year. In order to capture variation of outcomes and regressors within states, I utilize county-level public use files from 2015 to 2019. Since individual-level data is not publicly available for states

generosity responded more to payment rate changes in zero-premium plans, meaning that benefits in zero premium plans are inefficiently high. This work, along with Stockley et al. (2014), recommend allowing premium rebates in order to achieve efficient equilibria of premiums and benefits. However, this is not of concern to this study, as benefit generosity is largely standardized in our setting.

[16]Nationwide MIDAS data from Branham & DeLeire (2019) is individually identified, but one of the co-authors informed me that external researchers cannot access MIDAS data for analyses due to federal constraints.

[17]These files are available at https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Marketplace-Products

on the federal exchange, this county-level data ensures that I can observe a large number of counties facing a variety of market conditions. From these files I obtain county-level enrollment breakdowns by age and income level; this determines a county's exposure to various market phenomena. County enrollment is also broken down by metal tier, which is used to measure plan selection. Cost sharing reduction numbers are also provided at a county level, though they are only available for the 2016 plan year.

Data on plans' characteristics were also obtained from Public Use Files (PUFs) from the CMS on states that participate (or partner with) the Federally-Facilitated Marketplace (FFM). I utilize yearly PUFs on rate (premium) by plan-rating area, plan characteristics, and service area of plans. These plans are available for all years of the ACA's implementation, 2014-2021. With this information, along with additional resources from the CMS on rating areas by state, we can establish which plan is the SLCSP in a market. Since SLCSP is established on a county level, I establish unique SLCSP by county-year. I then use the same files to establish whether an individual in that county faces a cheaper gold plan or whether some individuals qualify for free bronze plans. This information is then combined with enrollment numbers from 2015-2017 to establish treatments, described more below. I exclude Alaska and Nebraska from the analysis, as their ratings areas are established by zipcode rather than county. A few counties in South Dakota are also excluded, as rating areas were shuffled among a small handful of counties in 2019. Finally, some county measures are censored due to low cell value (≤ 10). Discussion of the handling of counties with relevant censored values in the applicable years is below. Only counties that offered Bronze, Silver, and Gold plans in every period of the study are considered for this analysis.

2.2.1 Enrollment Breakdowns and Masked Data Points

In the enrollment data discussed above, some county enrollment measures are censored due to low cell value (≤ 10). Masked enrollment values may occur for any relevant demographic characteristic or choice within a county, such as CSR status, FPL level, age, or metal choice.

Masking occurs in the following fashion: if any cell has enrollment less than or equal to 10, this cell is masked. If only one cell has been masked, then the second least enrolled cell is also masked, which disallows direct imputation given county enrollment totals. As a result, many cells with enrollment greater than 10 are also masked. Proper handling of these masked enrollment numbers is crucial because if counties with any masked value in any year are disincluded, fewer than 15% of available counties would be used in the final analysis. I discuss each breakdown file below; a more detailed discussion of the data cleaning process, including year-by-year discrepancies in enrollment files, is in in the Appendix Section 8.3. As a general rule, in handling masked values, I weigh the trade-off between measurement error introduced by imputing values and small sample size from not imputing values.

Metal Tier

Outcome variables of interest for this project are extracted from files that list enrollment by metal tier: Gold, Silver, Bronze, Catastrophic, and Platinum. Catastrophic enrollment is below 1% of the total population in each year[18]. Platinum plan enrollment, which began as 2.5% of total enrollment in 2015, dropped to less then 0.8% of total enrollment in 2016 and by 2019 was less than 0.2% of enrollment. This can at least partially be attributed to a massive decrease in the availability of Premium plans: between 2015 and 2016, Platinum plans went from unavailable in 27% of counties to over 63% of counties; by 2019, fewer than 15% of counties offered platinum plans. Of the three main metal tiers, Gold plans account for the least enrollment, with between 3 and 7% each year. Silver plans are the most popular, with over 60% of enrollees in each year, while bronze are the second most popular. This breakdown is available in Table 2.2.

The evolution of aggregate enrollment in the main metal tiers over time tells a story that relates to the emergence of silver loading and anomalous market mechanisms. Despite steady enrollment between 2015 and 2017, bronze plan enrollment increases by nearly seven percentage points in 2018. The year 2018 also sees silver plan enrollment drop by nearly nine

[18]Catastrophic plans require individuals to either be under 30 years old or receive a special hardship waiver. Premium tax credits cannot go toward these plans.

percentage points. These measurements also become more spread out in later years, implying that greater variation is created as a result of silver loading in 2018 and 2019. Also noteworthy is the evolution of gold plan enrollment: in 2017, gold enrollment is nearly halved; it then spikes back up nearly to its 2016 level the next year, and continues to grow to its highest level in 2019. While this dip may be concerning, the standard deviation shrinks, meaning that this drop was likely common among many counties, after which the standard error increases, which may be due to effects of differential silver loading.

Masking of enrollment tracks tightly with the above patterns. Platinum and Catastrophic plans are the most commonly masked. In counties where all plan types are offered, this generally means that, unless overall enrollment is high, both Catastrophic and Platinum plan enrollment may be masked due to one or both having enrollment of fewer than 10 individuals. However, when either of the two alternative plan types are not offered, gold plans, most often the next least enrolled in, may become masked. This causes masking of gold plans to increase from 36% of counties to over 55% of counties from 2015 to 2019. This number actually decreases by 2019, which may be due to a decrease in Catastrophic plan availability, which, when paired with having no Platinum plans offered, unmasked gold enrollment. Overall, masking of gold plans effects 73% of candidate counties.

In order to avoid eliminating nearly three-quarters of our counties due to this file alone, I develop the following rule for imputing gold metal enrollment. Of the counties that offer at least one Bronze, Silver, and Gold plan, I first eliminate all counties that, in any year, mask more than one of the Bronze, Silver, and Gold enrollment. These tend to be smaller counties whose contribution to the analysis would be negligible. If, in any year, one of Gold, Silver or Bronze is masked, along with both Catastrophic and Platinum, I disinclude this from the analysis, as these are also small counties where gold enrollment is less than 10. Removing these two types of counties removes 389 of the 2301 possible counties. For counties where Gold and one non-main metal plans are masked in some year, I look over the period of analysis to examine

Table 2.2. Enrollment in Metal Category by Year; Non-Offering Rate Among Platinum and Catastrophic Plans

	2015 Mean	***2016*** Mean	***2017*** Mean	***2018*** Mean	***2019*** Mean
Bronze Enrollment	0.211	0.212	0.215	0.282	0.305
	(0.0712)	(0.0749)	(0.0803)	(0.0984)	(0.104)
Silver Enrollment	0.691	0.711	0.742	0.652	0.617
	(0.0737)	(0.0809)	(0.0845)	(0.112)	(0.123)
Gold Enrollment	0.0636	0.0594	0.0328	0.0577	0.0694
	(0.0369)	(0.0311)	(0.0223)	(0.0696)	(0.0743)
No Platinum Plans Offered	0.279	0.639	0.827	0.862	0.860
	(0.449)	(0.481)	(0.378)	(0.345)	(0.347)
No Catastrophic Plans Offered	0.0192	0.0344	0.0880	0.213	0.206
	(0.137)	(0.182)	(0.283)	(0.410)	(0.404)

Note: The top panel of this table shows the proportion of individuals enrolled in each of the three main metal tiers in years 2015 through 2019. These proportion means are weighted by county enrollment in order to represent total enrollment into these plans. The bottom panel of this table shows the proportion of counties that do not offer platinum and catastrophic plans, which may affect masking of main metal tiered enrollment.

gold enrollment when listed. If Gold enrollment is masked in all years, I remove the county from the analysis, as I cannot confirm the baseline ratio of gold enrollment to other plans. For counties where gold enrollment is listed in at least one year, I keep all counties where gold enrollment is non-zero in all years. For county-years where gold is masked, I assume that the non-main metal tier is causing the masking: thus, I assign an enrollment of 5 to the non-main metal tier and the remaining enrollees to gold. I then repeat this entire process for the small number of counties with the analogous case for bronze or silver enrollment. All other plans, including those where both Platinum and Catastrophic enrollment are masked, do not require imputation and are included. This allows us to only impute enrollment in counties where the ranking from year to year is clear and not likely to change, and allows us to keep 1757 counties (about 76% of the original sample of counties); this contrasts with the 26% remaining if this imputation is not allowed. This sets a baseline of counties that will continue to be peeled from due to other masking issues in explanatory variables.

Age

In each year, enrollment numbers within counties are reported for the following age intervals: under 18, 18 to 25, 26 to 34, 35 to 44, 45 to 54, 55 to 64, and over 65. Over all analysis years, the most enrolled age group is age 55 to 64, with over 25% of total enrollees. Enrollment weakly decreases monotonically as age group decreases, down to 9% of total enrollees in the under 18 age group. Less than 1 percent of all enrollees are over the age of 65, as these people are eligible for Medicare. If county enrollment emulated overall enrollment then, on average, a county would need about 1100 enrollees each year to avoid having masked values, which is the case for only about 45% of county-years. Additionally, over 65 enrollment is the lowest cell in all but two fully unmasked county years. As a result, I choose to impute enrollment for counties where only over 65 and *one other age group* is masked, which minimizes the introduction of measurement error while providing for the inclusion of more counties. If this is the case, I assume that over 65 enrollment triggered the masking (≤ 10), and I assign a value of 5 to over 65 enrollment; I then assign the remaining enrollment amount to the other masked category. I then exclude counties that would require any other imputation. This removes an additional 101 counties from the analysis.

Income

Income enrollment files are organized by ranges of enrollees' income as a percentage of the federal poverty level (FPL): 100% to 150% of FPL, 151% to 200% of FPL, 201% to 250% of FPL, 251% to 300% of FPL, 301% to 400% of FPL, and those who do not receive any premium tax credit assistance. A plurality of enrollees, 35%, come from the between 100% and 150% of FPL. An additional 36% fall between 151% and 250% of FPL, and thus also qualify for CSR on silver plans. About 16% of enrollees are betwen 251% and 400% of FPL, while the remaining 11%, who remain unsubsidized in all market conditions, are outside of these groups. Depending on the year, masking of categories affects between 11% and 19% of counties. After an imputation on a small number of cells with logic similar to above (see Appendix for full explanation), an additional 142 counties are removed.

Cost Sharing Reductions

Data on cost sharing reduction status by county is also utilized in our main analysis for creating treatment variables. This information is available by county for 2016, listing the number receiving any cost sharing reduction, as well as a breakdown into CSR tier, those being 73% AV, 87% AV, and 94% AV. In this year, 58.9% of enrollees receive some type of CSR. Of those who receive CSR, 55.2% (32.5% of total) receive 94% AV, 30.6% (18% of total) receive 87% AV, and 14.2% (8.3% of total) receive 73% AV. For the purposes of my analysis, I need to know the number of individuals whose CSR actuarial value is greater than 80%; thus, I only include counties where this information is given or can be directly calculated. This leads to the removal of only 3 additional counties.

After removing counties that do not offer all three types of plans, as well as those which require more than the described imputation in any year, we are left with an analysis of 1,511 counties over 5 years. With respect to the trade-off between the measurement error introduced by imputation and power issues given a small sample size, I only impute values in situations where approximate enrollment can be adequately estimated; this minimizes the amount of measurement error introduced while still handling a large portion of masking cases. It is worth noting that measurement error is already a feature of treatment variables, which I will describe below. Error introduced by imputation is likely negligible compared to this. Additionally, counties with masked values are generally the smaller counties. Thus, excluded counties are not likely to make a great contribution to the final results of a weighted regression analysis. Analysis using a smaller dataset is used as a robustness check to ensure that using different counties or imputing values is directly altering results; no changes are found to results.

2.2.2 Constructing Treatment Variables

Consider two separate treatment variables intended to capture the intensity of phenomena within a market. The first represents the availability of zero-premium bronze plans to consumers in a county in a certain year. On an individual basis, this depends upon an individual's county, as well as their age and income. Thus, to measure market exposure, we must consider age and income distributions of counties. Calculating the exact number of individuals exposed to bronze plans is impossible for two reasons. Firstly, age and income distributions within a county are not listed jointly. Secondly, age and income are listed in course categories; these distributions, upon which free bronze plan exposure depend, are not fully observed. To calculate the treatment variable despite these issues, I begin by calculating the SLCSP premium and the least cost bronze plan premium within a county for the midpoint of each of the 7 age groupings. Using this information I then find, for each age group, the FPL level for which PTC is equal to the least cost bronze plan premium. This is the cutoff income for which all individuals below qualify for a free bronze plan. I then use this cutoff, as well as the distribution of income, to determine the approximate proportion of individuals of this age who qualify for free bronze plans. I then use these proportions to calculate final proportion or final number of enrollees in a market by summing over the age distribution within the county. Inherent in these procedures is an assumption that both age and income are marginally uniformly distributed within categories and independent of one another. This is likely to introduce a small amount of measurement error. Ex ante, I suggest that this measure slightly overestimates the total number exposed to free bronze plans. If, given that an individual is not insured by their employer, older individuals are more wealthy, then older demographics, namely those in the 45 to 64 range, would be less exposed to free bronze plans as a plan choice. Younger demographics, on the other hand, would see more exposure to free bronze plans. Since age distributions are negatively skewed, the effect on older demographics may outweigh those of the younger as compared to assuming independent distributions. Regardless, with this measurement, areas with a greater number of low-income individuals and greater individual premium tax credits will have greater treatment intensities. While my discussion focuses on this number calculated as a proportion, denoted $p^f_{c,t}$, I also utilize the total number of enrollees.

Free bronze plans are available to at least some low-income enrollees in most county-years (see Figure 2.3). In pre-treatment periods, measured free bronze total exposure is between 36% and 42%. In 2018, this rises to about 62%. Prior to 2018, the distribution of measured exposure is close to normal. In 2018 and 2019, a shift occurs in many counties, causing increased access to free bronze plans, which persists in 2019. Also, interestingly, a handful of counties saw no zero-premium bronze availability in 2019, which was an increase from previous years.

The second treatment variable measures market exposure to dominant gold plans i.e. gold plans that are less expensive than all silver plans in the market. Since all enrollees with incomes above 200% FPL should prefer these gold plans to the silver ones, I aim to measure the proportion of enrollees who *should* change insurance plans from a silver plan to another. In order to do this, I first find the total number of individuals receiving a 94% and 87% AV cost sharing reduction. By definition, these individuals are enrolled in silver plans whose actuarial values exceed gold plans. Thus, subtracting this from the total number of silver plan enrollees results in the total number of enrollees, all enrolled in silver plans, who would switch plans in a frictionless, full information environment[19]. I denote this group of potential switchers as

[19]This also assumes that taste for insurance provider, which includes a package of specific doctors or health

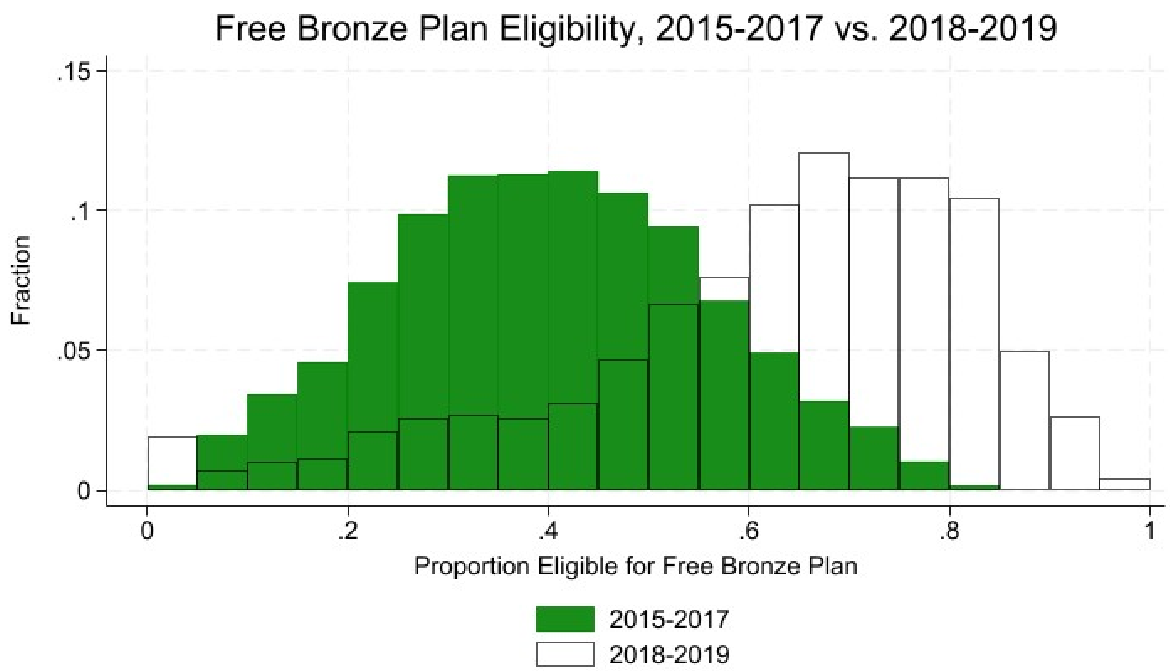


Figure 2.3. Distribution of Free Bronze Plan Exposure by County; 2015-2017 vs. 2018-2019
Note: This figure shows the distribution of free bronze plan exposure by county; these are separated into 2015-2017 and 2018-2019 time periods. This shows that between these two time periods, free bronze plans became available to more enrollees, particularly those who are younger and have higher incomes.

$p^{d*}_{c,t}$. Note that because I do not have this information for all years, I use the proportion of 2016 enrollees who fit this condition. I then define $p^d_{c,t}$ as

$$p^d_{c.t} = \begin{cases} p^{d*}_{c,t} & \text{if LCGP } < \text{SLCSP} \\ 0 & \text{otherwise} \end{cases},$$

where LCGP is the lowest cost gold plan premium. Thus, my treatment variable measures the proportion of individuals who are enrolled in silver plans that have become dominated in year t and county c.

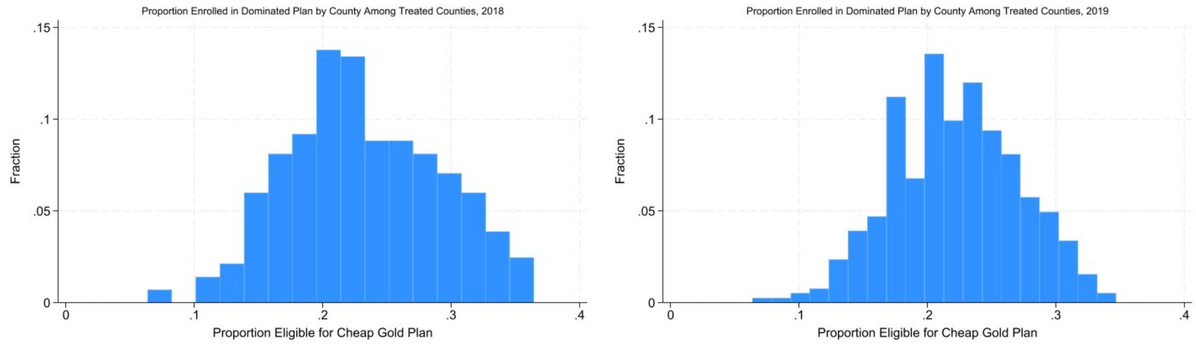
In years 2015 through 2017, $p^d_{c.t}$ is equal to 0 in all counties, as no market experienced dominant gold plans prior to the onset of widespread silver loading. In 2018 and 2019, 283 (18.8%) and 383 (25.3%) of 1511 counties, respectively, saw a gold plan with a lower premium than all silver plans. This meant that approximately 160,000 total enrollees were enrolled in what we consider dominated plans at the beginning of 2018. In 2019, some counties that previously saw cheap gold plan status reverted to the expected plan price ordering; still, by 2019, approximately 164,000 enrollees were (or had been in 2018 and remained in the treated condition) enrolled in dominated plans. This could mean that larger counties resolved their pricing anomalies while smaller ones persisted.

2.3 Empirical Formulation

Consider then the following regression:

$$Y_{c,t} = \beta_f p^f_{c,t} + \beta_d p^d_{c,t} + \lambda X_{c,t} + \gamma_c + \mu_t + \varepsilon_{c,t}, \tag{2.1}$$

networks, are not equal. This is investigated further in the supplemental analysis.



(a) 2018 **(b)** 2019

Figure 2.4. Distribution of Dominant Gold Plan Exposure by County, 2018 and 2019
Note: This figure shows the distribution of dominant gold plan exposure by county; panel (a) shows proportion exposed in 2018; panel (b) shows proportion exposed in 2019. These are not the same counties, though many are the same; thus, the 2019 panel does not necessarily represent the total who begin the enrollment period enrolled in a dominated plan, as many will have switched already at this point.

where $p^f_{c,t}$ is a policy variable that represents the proportion of individuals that are eligible for a free bronze plan, and $p^d_{c,t}$ represents the proportion of individuals who are previously enrolled in newly dominated silver plans. Both time and county fixed effects are included in the formulation. Our three outcome variables, denoted by $Y_{c,t}$, measure proportion of county enrollment into bronze, silver, or gold plans. Coefficient β_f measures the effect of free bronze-plan availability on metal tier enrollment, while β_d is the change in enrollment in some metal tier for each percentage point change in the proportion of individuals who become eligible to leave dominated silver plans. Counties are weighted by a simple average of their 5-year total enrollment so that weights are not endogenous yet reflect market size. These regressions are also repeated with counts rather than proportions, which may help account for consumer entrance and exits in ways that are not possible with proportions.

Evidence of a zero-price effect will come from our estimate of β_f when bronze enrollment is the outcome variable. A positive coefficient under all specifications would provide evidence of a zero-price effect. This coefficient will tell us the approximate change in proportion of enrollees in bronze plans associated with a change in proportion eligible for a zero-premium bronze plan. Evidence of behavioral failures are represented by inference on β_d. For silver enrollment as an outcome variable, the coefficient represents the proportion change in silver plan enrollment associated with some proportion of total enrollees who *should* switch from silver plans. Thus, a coefficient of different from zero means that there is a change in enrollment associated with this, while a coefficient of zero would mean that enrollees are not responsive to relative price changes on the intensive margin of plan choice. Also interesting from an economic perspective is whether the coefficient differs from -1; a coefficient of -1 implies a decrease in silver enrollment commensurate with the proportion of dominated enrollees. If the estimate is between -1 and 0, this is consistent with some individuals remaining in (or otherwise enrolling in) dominated silver plans. This is evidence of a behavioral failure on an aggregate level. A similar comparison to positive 1 can be made when using gold plan enrollment as an outcome variable. Thus, all three metal tier's enrollments can be used to find suggestive aggregate evidence of behavioral anomalies.

Unfortunately, the aggregated nature of the county data does not tell us how different income groups would respond to actually having access to free bronze plan or cheap, dominant gold plan. If data was split in the same way it is at the state level (metal by FPL level), we could draw more decisive conclusions. Instead, we can see which counties had greater exposure to these treatments overall based upon the composition of their enrollees and see how this distribution affects aggregated enrollment behavior. This is of course at the expense of drawing sound conclusions about individual behavior, as doing so using aggregated data is not possible. For example, while inertia is of interest as a behavioral failure, inertia cannot be measured without observing initial choices and following them over time. Instead, we can only find evidence of aggregate behavioral failures which, in the presence of other contextual factors, may suggest inertia as an explanation. Another drawback of the data is that we cannot consider non-market effects, which have interactions with the type of loading strategy employed. That is recommended for future study if an appropriate data set is available.

Measurement error and endogeneity concerns:

Suppose that measurement error is not a concern. Overall exposure to free bronze plans within a market depends upon the following: (1) the proportion of overall enrollment across age and income distributions; and (2) the set of maximum income cutoffs for each age that qualifies for a free bronze plan. Changes in the age and income distribution of enrollees may reflect shocks to economic conditions; for example, increased demand for young workers in an area could cause more young enrollees with few health conditions to enter a market. In this case, risk pools would become healthier and cause premiums to decrease. If these individuals all enroll in bronze plans (which healthy young people are more likely to do), then effects of free bronze exposure may be positively biased, as young people are exposed to free bronze plans at much lower income levels than older enrollees. Besides shifts in demographics, age and income level pair eligibility is determined by relative prices of bronze and silver plans within a market and how this interacts with federal Premium Tax Credit pricing rules. This is a direct result of silver loading strategy and other price determining factors. This means that exposure to free bronze plans is mechanically positively correlated with shifts in the bronze-silver premium gap. By nature, this gap has a causal effect on enrollment if we assume that individuals are sensitive to price shifts. Since individuals are sensitive to price shifts[20], this will have a direct measurable effect on enrollment.

Effects of exposure to dominant gold plans also face endogeneity concerns. Recall that regardless of income, premium price rankings are universal, so access to a gold plan that is cheaper than all silver plans in a market does not depend on income or age. However, exposure to a *dominant* gold plan does depend on income, as only those above 200% of FPL experience this dominance. This treatment suffers from similar concerns about unobserved demographic shifts described above. Moreover, because the treatment variable measures potential switchers from silver plans, selection into these plans is also a cause for concern. Similar to the other treatment variable, its status is also directly a result of relative price levels and shifts. Here, though, presence of any treatment is triggered by gold-silver premium gap reaching a threshold

[20]Liu & Chollet (2006), reviews this literature, finding that in the individual market price elasticity of demands are estimated to be between -0.2 and -0.6. While this demand measure is probability of receiving coverage (extensive margin), coverage may also shift in plan type (intensive margin).

(of zero); this is different from free bronze exposure, whose intensity changes upon a continuum depending on premium changes. Still, this association can be thought of in a similar fashion, just in a slightly less monotonic manner.

Measurement error of both explanatory and response variables is an additional concern. Free bronze exposure faces measurement error due to the courseness of enrollment breakdowns and ambiguity of the relationship between age and income among enrollees; these both require distributional assumptions, the implementation of which compromises the precision of our measurements. Dominant gold plan exposure faces measurement error issues because treatment is measured in 2016 rather than immediately before the treatment period. If overall enrollment shifted in 2017, this could bias our estimate upward or downward, depending on the shift. Our outcome variables also experience measurement error due to imputation; this also affects a portion of explanatory variables.

2.3.1 Control Variables

Among the most pressing of these endogeneity concerns is the direct relationship that each treatment variable has with relative prices. If, for example, there is no zero-price effect, we will most likely still precisely estimate a positive coefficient on p_f because free plan prevalence is a direct consequence of bronze plans becoming less expensive relative to silver plans. Dominant gold prevalence follows similar logic, but with relation to gold and silver prices. When the gap between gold and silver premiums decreases, this may lead to silver plans becoming dominated for some enrollees. Still, some of these individuals would have shifted with a lesser price shift. Thus, it is important to control for this shift for one or both main explanatory variables.

In my regressions I include a county level regressor intended to capture the shift in relative value of market plans based upon paid premium and actuarial value. First, for each age-income group pair, I calculate the difference in paid premium (generally listed premium less PTC) between the least expensive silver plan and the least expensive bronze plan offered in a market, and find the difference between these two numbers. This will generally equal the difference in premiums unless the bronze plan is available for free, in which case it is equal to whatever is the paid price of the silver plan. Secondly, I take this gap and, for each income group, divide by the actuarial difference between these two plans. This ranges from a difference of 34 percentage points (100% to 150% FPL) to 10 percentage points for those who do not qualify for CSR. Third, I compute a weighted average for each income group using age enrollment distributions. Fourth, I compute a weighted average over the different income groups. This measure is intended to capture the average cost of 1 additional percentage point of actuarial value when comparing bronze and silver plans. The coefficient on this control variable, then, is designed to capture how changes in the value difference between silver and bronze plans affect enrollment. I can also include a similar measure that captures the actuarial value cost of gold plans relative to silver plans. These controls aim to reduce bias in estimates caused by treatment variables' direct relationship to price shifts which individuals are elastic to. Though it is impossible to control for all price dynamics within a market, these act as a proxy for the changes that many are experiencing in relative value of different plans. Consistent with noted shifts in silver plan value, these variables both experience a general positive shift among counties as bronze and gold plans become more affordable relative to silver ones.

An additional set of time-varying county-level controls which may affect the intensive margin of benefit coverage are also included. The first is an indicator variable equal to 1 if the state has passed Medicaid Expansion legislation. Two others indicate whether platinum plans or catastrophic plans are offered in an area. We control for this because potential enrollees in platinum plans, for example, may be more likely to enroll in gold plans when platinum plans are unavailable. Finally, I include a set of county health indicator measures from the County Health Rankings & Roadmaps[21]. I include variables that control for county smoking, obesity, and physical inactivity rates, as well as an average number of poor health days in the county.

While controlling for value changes and other market and health factors may address some omitted variable bias, there is a still concern about the effect of shifting demographics and

[21] https://www.countyhealthrankings.org/health-data

how this biases estimates. Furthermore, there is a moderate deal of concern with measurement error within this framework. In order address this concern for both regressors, I run a two-stage least squares regression using a simulated instrument approach (Currie & Gruber, 1996; Cutler & Gruber 1996). To do this, I use the observed age and income distribution of *all* enrollees in the 2015 set of counties with a federally-run exchange. For a simulated measure of free bronze plan exposure, I calculate the proportion eligible for free bronze plans in each county given that their enrollment distribution directly emulates that of the 2015 nationwide enrollment distribution. The use of this instrument is intended to eliminate bias that is created due to population shifts in demographics, which ultimately impact eligibility.

In brief, coefficients for both treatment variables likely suffer from endogeneity due to omitted variable bias, both due to correlations with price changes and demographic-related shocks. Measurement error adds to this concern.

2.4 Results

Tables 2.3A, 2.3B and 2.3C show the main results of our weighted least squares analysis for bronze enrollment, silver enrollment, and gold enrollment, respectively. Column (1) in each table shows results without including control variables besides county and year fixed effects. This specification reveals that a 10 percentage point increase in free bronze plan eligibility is associated with a 1.2 percentage point increase in bronze plan enrollment and a 1.3 percentage point decrease in silver plan enrollment among county enrollees. It also shows that a 10 percentage point increase in individuals enrolled in dominated silver plans is associated with a 6.1 percentage point increase in gold enrollment and a 5.3 percentage point decrease in silver enrollment. I also find a slight negative association with bronze enrollment similar in magnitude to the coefficient on free bronze eligibility; however, this coefficient is imprecisely measured. Estimates are not noticeably affected by the inclusion of variables that control for various market and county-level health factors. The two which are effected most, the effect of dominated silver plan enrollment on both gold and silver enrollment show that not including these factors may bias the our estimates away from zero slightly. One explanation for this change may be that negative health shocks are positively correlated with increased gold enrollment *and* with dominant gold plan availability[22].

More interesting, though, is the bias revealed from including price/value controls. Estimates on enrollment effects of eligibility for free bronze plans appears to suffer from serious endogeneity in both regressions where effects were significant. In both cases, effects are of similar magnitude but with switched signs. These results are marginally significant. Because of the clear correlation between the price-value calculation and the proportion of individuals who qualify for free bronze plans, it is *a priori* expected that the coefficient on free bronze availability would be lower than normal; however, the marginally significant opposite coefficient is noteworthy. Effects of cheap gold plan eligibility also adjusted toward zero in our final specification, albeit not enough to change the significance of previously significant results. This effect on silver plan is reduced by about one-third. Its effect on gold plan enrollment, on the other hand, is mostly unchanged by the price inclusion. However, bronze enrollment now has a significant negative coefficient. Within these final regressions, coefficients on the value-price measure are mostly as expected. When silver plans become more expensive relative to bronze plans, bronze plans receive more enrollees while silver plans receive fewer enrollees. When silver plans become more expensive relative to gold plans, it also appears that bronze plan enrollment increases, while the effect on gold enrollment is possibly negative. While this marginally significant effect is not easily explainable, its effect on the coefficient of interest (effect on gold enrollment) is negligible.

In an additional set of regressions, in Appendix Tables 2.A.1, 2.A.2 and 2.A.3, we run

[22]Though it is not clear why this would be, one potential explanation is that areas with a negative health shock may differentially increase their silver plan prices moreso than gold plans.

Table 2.3A. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Bronze Enrollment, by County

VARIABLES	(1) Prop. Bronze	(2) Prop. Bronze	(3) Prop. Bronze
Proportion Eligible for Free Bronze Plan	0.116**	0.118**	-0.0984**
	(0.0530)	(0.0518)	(0.0475)
Proportion Eligible for Cheap Gold Plan	-0.110	-0.129	-0.281***
	(0.0842)	(0.0913)	(0.0868)
Silver-Bronze $/AV Gap			0.00380***
			(0.000427)
Silver-Gold $/AV Gap			0.000586
			(0.000358)
Observations	7,555	7,555	7,555
R-squared	0.771	0.773	0.846
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	None	Health and Market Factors	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a bronze plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are included in column (3). County and year fixed effects are included in all regressions. Observations are weighted by a simple average of total enrollment.

Table 2.3B. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Silver Enrollment, by County

	(1)	(2)	(3)
VARIABLES	Prop. Silver	Prop. Silver	Prop. Silver
Proportion Eligible for Free Bronze Plan	-0.133***	-0.136***	0.0717*
	(0.0472)	(0.0424)	(0.0384)
Proportion Eligible for Cheap Gold Plan	-0.527***	-0.494***	-0.332***
	(0.0719)	(0.0810)	(0.0608)
P (β_d = -1)	[0.0000]	[0.0000]	[0.0000]
Silver-Bronze $/AV Gap			-0.00366***
			(0.000326)
Silver-Gold $/AV Gap			-9.54e-05
			(0.000354)
Observations	7,555	7,555	7,555
R-squared	0.826	0.829	0.882
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	None	Health and Market Factors	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a silver plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are included in column (3). County and year fixed effects are included in all regressions. Observations are weighted by a simple average of total enrollment.

Table 2.3C. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Gold Enrollment, by County

VARIABLES	(1) Prop. Gold	(2) Prop. Gold	(3) Prop. Gold
Proportion Eligible for Free Bronze Plan	0.0216	0.0235	0.0323
	(0.0199)	(0.0201)	(0.0243)
Proportion Eligible for Cheap Gold Plan	0.613***	0.606***	0.595***
	(0.0917)	(0.0997)	(0.0981)
P (β_d = 1)	[0.0002]	[0.0004]	[0.0002]
Silver-Bronze $/AV Gap			-0.000129
			(0.000381)
Silver-Gold $/AV Gap			-0.000490
			(0.000363)
Observations	7,555	7,555	7,555
R-squared	0.750	0.751	0.756
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	None	Health and Market Factors	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a gold plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are included in column (3). County and year fixed effects are included in all regressions. Observations are weighted by a simple average of total enrollment.

the same regressions but using enrollment count data rather than proportions[23] under Ordinary Least Squares rather than Weighted Least Squares. These results mostly mirror previous results. Regressions which do not control for price shifts have coefficients on free bronze plan exposure that are more positive for bronze enrollment and less negative for silver enrollment. While coefficients on cheap gold exposure are (about one-fourth) smaller for gold plans, they do not differ greatly for silver enrollment. Introduction of price controls had similar effects on coefficient estimates, except that eligibility for free bronze plans now has a significant positive effect on silver plan enrollment. For silver plan enrollment, the coefficient estimate on cheap gold plan eligibility is also affected, decreasing by nearly 40%. It is also worth noting that the R-squared is larger for this model in all specifications. This is probably because this specification handles enrollment dynamics on the extensive margin more easily.

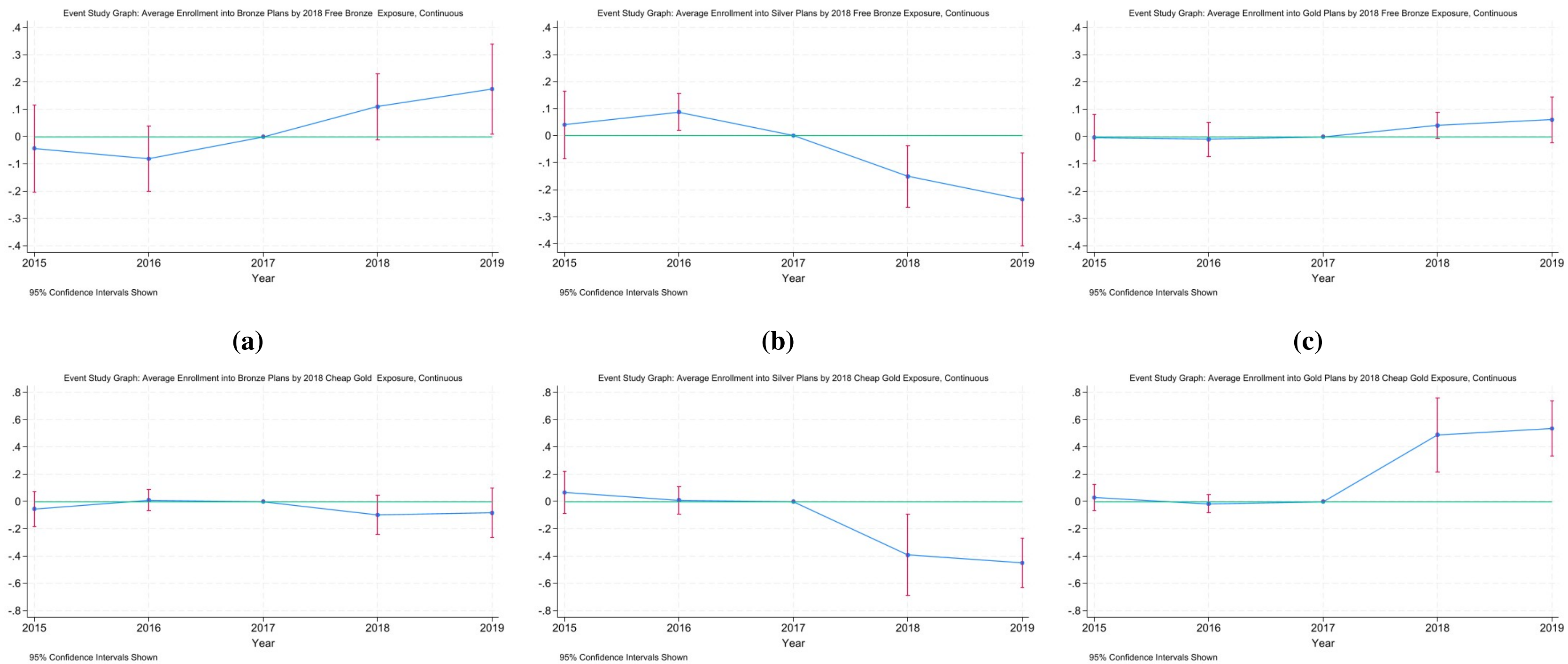
2.4.1 Evaluating and Addressing Endogeneity Concerns

One concern about the above saturated regression is that it could be overcontrolling for price shifts, especially in terms of controlling for bronze plan prices. This is mainly because the decisive factors (lowest bronze premium, silver plan premiums, and age/FPL distributions) that determine these measurements are similar for both the control variable and free bronze exposure. Thus, I examine endogeneity concerns in both specifications. To do this, I use a dynamic difference-in-difference (event study) specification to observe if there are any violations of the ”pretrends” assumption that treated counties and untreated counties would have evolved similarly in the absence of treatment. This model is similar to my normal specification above but with a different set of treatment variables dependent on time from treatment. For exposure to cheap gold plans, our measured treatment variables are time dummies interacted with measured treatment intensity. I take treatment timing as occuring in 2018, disincluding 2017 treatment variables from the regression as our base year. Treatment intensity is assigned to the variable

[23] Some control variables are also adjusted: health measures enter as total numbers rather than proportion of total. Furthermore, price/value measures are multiplied by total enrollment in order to directly relate to the size of the enrollment pool.

if dominant gold plans are available in 2018 *or* 2019. For bronze availability, I use the same base year of 2017; however, I establish the treated measure as the difference between the average free bronze availability from 2015 to 2017 and the average free bronze availability from 2018 and 2019. I do this because this dynamic treatment shifted most heavily in 2018 (as shown previously in Figure 2.3), though there were minor shifts in other periods as well. I then interact this measure with an indicator for year.

Figures 2.5(a)-(f) and 2.6(a)-(f) show event study estimation results of our three outcome variables and two treatment variables, disincluding and including price controls, respectively. In the first specification, pretrends indicate a potential threat to our equal trends assumption. Specifically, silver enrollment may have been slightly trending up among groups that saw large increases in free bronze eligibility. Response to dominant gold plans, however, presents less of a concern, as pre-periods contain stable enrollment prior to the emergence of dominated silver plans, where gold and silver plan enrollment show a clear effect. This persists when price controls are included, as in the regular specification.

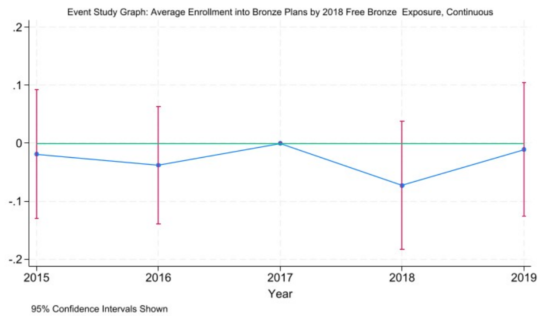


(a) (b) (c)

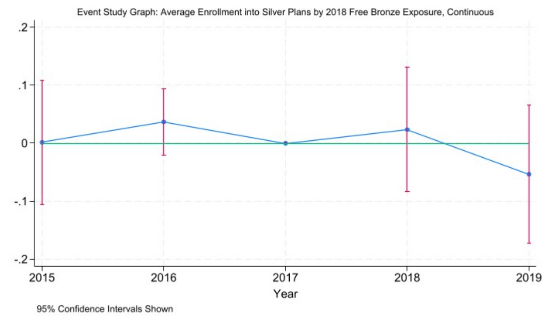
(d) (e) (f)

Figure 2.5. Dynamic Difference-in-Difference (Event Study) Estimates without Control Variables

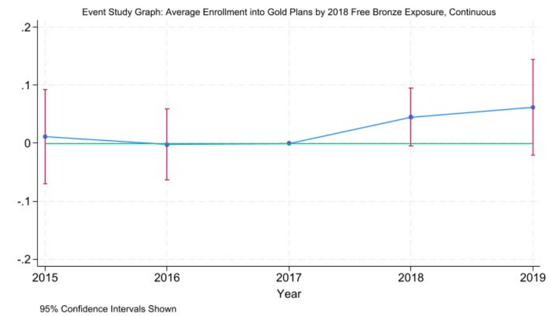
Note: Panels (a) through (f) show dynamic difference in difference (event study) estimates and 95% confidence intervals for time periods of two years prior to two years after the base year. Estimation is conducted *without* control variables. The base year is set at 2017, which signifies the last year before markets were shocked. The y-axis on each graph is proportion change in enrollment for some change in treatment variables. The top row of graphs shows enrollment response of bronze (panel (a)), silver (panel (b)), and gold (panel(c)) plans to exposure to free bronze plans, which is measured as an aggregated change from 2015-2017 through 2018-2019. The bottom row of graphs shows enrollment response of bronze (panel (d)), silver (panel (e)), and gold (panel (f)) plans to exposure to dominated gold plans, which is measured as the proportion of total enrollees in dominated gold plans in 2018 or 2019.



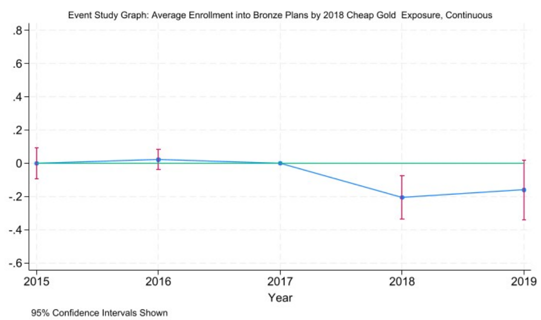
(a)



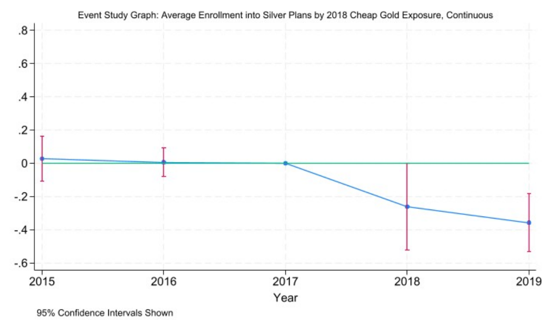
(b)



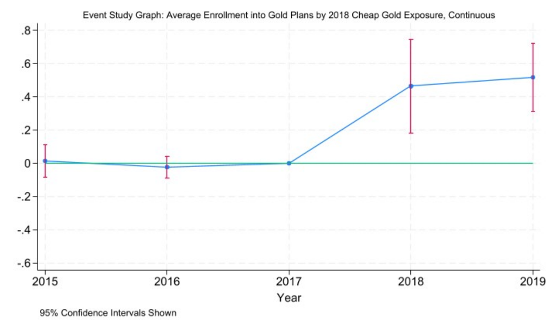
(c)



(d)



(e)



(f)

Figure 2.6. Dynamic Difference-in-Difference (Event Study) Estimates with Control Variables
Note: Panels (a) through (f) show dynamic difference in difference (event study) estimates and 95% confidence intervals for time periods of two years prior to two years after the base year. Estimation is conducted *with* control variables for catastrophic and platinum plan availability, Medicaid Expansion status, health variables, and price controls. The base year is set at 2017, which signifies the last year before markets were shocked. The y-axis on each graph is proportion change in enrollment for some change in treatment variables. The top row of graphs shows enrollment response of bronze (panel (a)), silver (panel (b)), and gold (panel(c)) plans to exposure to free bronze plans, which is measured as an aggregated change from 2015-2017 through 2018-2019. The bottom row of graphs shows enrollment response of bronze (panel (d)), silver (panel (e)), and gold (panel (f)) plans to exposure to dominated gold plans, which is measured as the proportion of total enrollees in dominated gold plans in 2018 or 2019.

2.5 Discussion

Two-stage least squares results using a simulated instrument, located in the Appendix (Tables 2.A.4 and 2.A.5, with no controls and all controls, respectively) mirror results from above, and results can refer to either of the two regressions interchangeably. In terms of using the results to determine the marketwide presence of a zero-price effect or dominated plan choices, we were more successful in the latter than the former. When examining specifications without price-value controls, evidence shows that increased free bronze plan availability is associated with higher relative levels of bronze enrollment and lower relative levels of silver enrollment. However, without controlling for price shifts, this is likely to be capturing the effects of price shifts of plans within markets, as free bronze enrollment is tightly correlated with bronze plans becoming less expensive relative to silver plans. When we attempt to control for this, results are basically reversed. This may be because we are now *overcontrolling* for price shifts, which may capture a great deal of variation in free bronze enrollment.

However, there are other scenarios that plausibly justify these results. One possible explanation is that individuals may see a zero-price tag as a signal of poor quality; this especially applies in scenarios where imperfect information is a concern (Wolinsky, 1983; Dawar & Parker, 1994). Since receiving perfect information involves time and effort, this is often an issue in health insurance markets, even in the context of the ACA. A second possibility relates to the fact that, by design, when a plan is acquired for free, an individual's premium tax credit is capped at the listed premium of their selected plan. Thus, plans that have high free bronze exposure also face higher levels of lost consumer surplus that could have been acquired by receiving a greater premium tax credit from the government. Both of these explanations are in fact consistent with a decrease in bronze enrollment. Hossain and Saini (2015) find that that the zero-price bounce is enhanced for hedonic products but subdued for utilitarian ones; as this product is "life and death", it falls in the latter category. This directly relates to the affect heuristic, which is often cited as the driving force behind the zero price effect. Theory states that affect is most induced when thought is not present. Since these health insurance plans are important, and often involve a lot of thought, a zero-price effect could be minimal if present.

Still, these results are also likely explained by issues presented by examining aggregated data. Because we cannot specifically examine *who* is experiencing free bronze plans, who is moving plans, and whether free bronze plans themselves are being enrolled in, measured effects may capture a handful of possibilities. For example, it may be that high income enrollees are those who are most likely to enroll in bronze plans, especially since they do not qualify for CSR. This may mean that more wealthy enrollees are responding to price changes that make bronze plans more attractive. Thus, once price shifts are controlled for, these regressions may pick up FPL distribution changes. Thus, this measurement may be capturing enrollment income changes, which show that less wealthy individuals are more likely to pick a silver plan due to its CSR advantages. It is worth noting that when controlling for prices, the reversed coefficients are significant only at the 5% level, and other small specification changes make them only significant at the 10% level.

Regardless of the meaning behind the results, aggregated data seems to severely inhibit our ability to examine the zero-price effect, and different specifications seriously affect our estimates. On the other hand, estimates of effects of enrollment in newly dominated plans on are much more robust across the three specifications. As expected, the presence of dominated silver plans is associated with an increase in gold plan enrollment and a decrease in silver enrollment. Regardless of the specification, Tables 2.3B and 2.3C provide evidence of behavioral failures by health insurance enrollees. Firstly, silver plan enrollment decreases are not commensurate with what is to be predicted by standard economic theory, as our coefficient differs from -1; instead, coefficients are consistent with a group of enrollees nearly half the size of the dominated plan enrollees continuing (or newly) enrolling in silver plans. Change in gold enrollment also differs from what could be expected, though a coefficient less than 1 does not necessarily constitute a behavioral failure or inertia, since dominated enrollees may switch to bronze or other plans instead.

These results on gold enrollment are robust to including price control variables, meaning that not observing price shifts is not affecting results. Bronze and silver plan enrollment response to dominated plans, as well as their respective adjustments in the presence of control variables, tell an interesting story when discussed in relation to gold plan enrollment. In terms of the expected coefficients and their relationship to one another, it may be expected ex ante that the coeffecient on silver plan enrollment would have the largest magnitude: the emergence of dominated silver plans should cause *all* silver enrollees (to which dominance applied due to CSR status) to exit, most of whom would enroll in gold plans, but some of whom would enroll in bronze plans. This would also translate to a small positive coefficient on bronze plans. However, this is not the case. Instead, our coefficients are consistent with an alternative story: the presence of dominated silver plans may be attracting individuals from bronze plans to enroll in gold plans. In this case, the decrease in bronze enrollment would be fully crowding out any increase due to gold dominance. This decrease in bronze plans is largest when we include price change variables, which control for decreasing bronze prices. These results lend more credence to the inertia story, as the coefficient on gold plan enrollment may not just be including switchers from silver plans but from bronze plans as well, causing the coefficient to be larger by accounting for switchers from bronze plans rather than only those from silver plans.

2.6 Supplemental Analyses

A few supplemental analyses can help address certain weaknesses in my initial regression. These analyses focus mainly on evidence of behavioral failures while neglecting free bronze plans, as these results are more robust and identifiable given current data. The first issue is the notion of dominance. While health insurance plans do not tend to differ greatly in the plan benefits offered, they may still vary slightly; other plan characteristics may further compromise the validity of our previously established notion of dominance. A few examples include network characteristics[24] (such as type and scope) or specifically covered prescriptions. Moreover, enrollees may have a taste for a specific insurance issuer for reasons besides continuity of care, imperfect information, or status quo bias; they may prefer to keep their insurance provider due to intangible characteristics such as customer service. Furthermore, different metal tiered plans offered within the same insurance products, which generally defines the set of covered benefits and drugs[25], are consistent across all characteristics except for actuarial value. This includes dental benefits, which are the benefits most likely to vary between plans. If we intend to find evidence of behavioral failures, we must account for these neoclassically permitted features of agents' utility functions based upon plan features.

We define dominance in four alternative manners. First, we define dominance as occurring when one gold plan offered by an issuer is less expensive than all of its silver plans. While important plan characteristics vary both within and across issuers, consistency in network and coverage is more likely when switching plans within an issuer. This also accounts for the possibility of having a taste for one's insurance issuer. Second, we define dominance as occurring when one gold plan offered by an issuer is less expensive than all silver plans with the same network, including network type (HMO, PPO, etc.). This further restricts dominance, allowing for individuals to have continuity of care preferences. Thirdly, we define dominance as occurring when one gold plan offered by an issuer is less expensive than all silver plans within the same network and product. This attempts to control for small differences between insurance product designs, such as fringe benefits, drug benefits or out-of-network rules. On the federal exchange, individuals are able to add prescription drugs and medical providers to their application in order to choose the appropriate plan. Thus, this information is directly available to consumers. All three of these approaches will offer a more strict definition of dominance and will likely show

[24]Dahl & Forbes (2023) find that individuals enrolled in employer-provided insurance have a strong taste for continuity of care when choosing insurance plans. Continuity of care is addressed as a source of plan choice inertia in Drake et al. (2022). Still, this is not necessarily a behavioral failure, as it is a rational to prefer one's doctor over others. Still, this preference *may* be a result of imperfect information and uncertainty associated with other doctors. Regardless, continuity of care has recently been shown to improve health outcomes (Sabety, 2020).

[25]The CMS states that plans "are the pairing of the health insurance coverage benefits under the product with a particular cost sharing structure

larger effect sizes. If these estimates also differ significantly from one, there will be more evidence of aggregate behavioral failures.

Treatment variables for all specifications are constructed in the following fashion. For our first treatment definition, I first establish within each county which issuers experience dominated silver plans. I then establish the proportion of enrollees within each county that enroll in the issuer by dividing issuer-county enrollment by total county enrollment. I then multiply this proportion by the initial treatment variable and sum over all appropriate issuers. This results in a treatment variable that is weakly less in all counties than in the main specification. For the second and third specification, I also use total plan enrollment within a state to establish approximate proportion of enrollees within an issuer are enrolled in a certain plan. Herein introduces one drawback of this method, which is that data is not fine enough. To conduct this without measurement error would require us to have enrollment across plans within a county. Without this, additional measurement error is introduced due to assumptions of enrollment distributions being the same across all counties. This further necessitates the use of individual data for future works.

Since the prior analysis has established the relationship between gold, silver, and bronze enrollment in relation to each other, and since the effects are clear, this exercise can be used as an additional robustness test for the aggregate behavioral failure. Thus, we need only to examine gold enrollment as an outcome variable and the estimated coefficient's closeness to one. Table 2.4 shows this result. Regardless of dominance definition, our estimated coefficients show that for every 10 percentage point increase in dominated plan enrollees there will be about a 7.8 percentage point increase in gold plan enrollment on average. Despite the inflated value compared to the initial specification, this coefficient still differs statistically from 1, which is the benchmark for a market without frictions, imperfect information, or behavioral failures. However, this difference is now only significant at a 5% for two of three dominance definitions. Still, silver plan enrollment effect still differs significantly at the 0.1% level from -1, meaning that behavioral failures are still likely. Also noteworthy is that this increased coefficient in these specifications may indicate that individuals may have a taste for specific insurance providers.

By no means does the previous regression eliminate the possibility that true dominance is not being measured, even in the absence of measurement errors. Abaluck & Gruber (2011) found that individuals tend to weigh plan characteristics; so things like copay vs. coinsurance or applicability of a deductible for a certain item could affect preferences. Still, it is unlikely that a silver plan would have *more* advantageous cost sharing structures within an issuer than a gold plan.

It is likely that all measures of dominance, including in the initial specification, are actually *understating* the exposure of enrolled plan dominance within a marketplace, at least with respect to the assumptions presented in defining dominance. This is because individuals may be in dominated plans without being measured as such. Take, for example, a marketplace with a heavily enrolled silver plan that has a major price increase. In this case, there may now be a gold plan in the market that is less expensive than the silver plan. However, if the gold plan is not less expensive than *all* silver plans, then the county is not considered to be treated. Thus, each of the above definitions of dominance understate what they purport to say. Still, these enrollees would not necessarily switch to non-silver plans, as they may choose to enroll in a different silver plan within the market or issuer. This is an additional issue with these alternate specifications. Unfortunately, enrollment data is not available even on a county-plan level to help distinguish levels of enrollment into various plans. Still, it shows that each of the above coefficients *could* actually be biased toward one due to the systematic undermeasuring of the prevalence of dominated plan enrollment. This means that evidence of coefficients that differ from 1 are more convincing.

2.6.1 Heterogeneity by Enrollment Status

My next approach leverages additional information available on the enrollment status of individuals by county. County enrollment files include a breakdown of the counts belonging to

Table 2.4. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Gold Enrollment, by County; w/ Alternative Definitions of Dominance

	(1)	(2)	(3)
VARIABLES	Prop. Gold	Prop. Gold	Prop. Gold
Proportion Eligible for Free Bronze Plan	0.0208	0.0134	0.0156
	(0.0228)	(0.0225)	(0.0218)
Proportion Eligible for Cheap Gold Plan	0.771***	0.797***	0.790***
	(0.100)	(0.106)	(0.101)
P (β_d = 1)	[0.0287]	[0.0625]	[0.0454]
Observations	7,398	7,398	7,398
R-squared	0.791	0.806	0.806
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	All	All	All
Dominance	Issuer	Network	Network & Product

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a gold plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls, which are included in all regressions, are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are also included. County and year fixed effects are included in all regressions. Column (1) defines dominance as occurring when all silver plans offered by an issuer are more expensive than some gold plan. Column (2) defines dominance as occurring when all silver plans offered by an issuer with some network are more expensive than some gold plan with the same network. Column (3) defines dominance as occurring when all silver plans offered by an issuer with some network and product are more expensive than some gold plan with the same network and product. Observations are weighted by a simple average of total enrollment.

each of the following groups: new consumers, active re-enrollees, and automatic re-enrollees. This presents two opportunities. Firstly, we can examine whether areas with high levels of active re-enrollment see results closer to unity. If this is the case, inattention may be playing some role in the issue. This is somewhat more direct evidence that inertia is occurring; though it is still correlative, its result implies that less inattentive areas are experiencing fewer aggregate behavioral failures. This creates a more specific link to inertia occurring, since passive enrollment is only possible among re-enrollees. Secondly, we can examine whether areas with high levels of new enrollment see less of a difference from unity in their estimates. If an area has a large proportion of new enrollees, these individuals are likely to sway main regression results. Introduction of dominant gold plans creates a menu of plans where new enrollees have dominated options. As these enrollees may not have a taste for an issuer and are attentive, areas with many new enrollees should see larger increases in gold plan enrollment and larger decreases in silver plan enrollment. There are two things we can learn from this. Firstly, results may provide evidence for metal tier stickiness as an explanation for behavioral failures, as areas with fewer re-enrollees (who can be inert) have may have fewer failures. This suggests that the re-enrollees are making the ones making the dominated choice. If there is no difference, then behavioral failures have less plausibility as being related to only inertia in re-enrollees. Secondly, if estimates between gaps are substantially larger than when comparing across active/passive enrollment status, this may provide additional evidence of status quo bias, which, in addition to inattention, is less likely to be a characteristic of new enrollees' decision making.

For this analysis, I restrict my sample to the years 2017 and 2018 in order to focus the analysis only on the changes in enrollment over this period. For the year 2018, active re-enrollment rate among re-enrollees is close to normal, with a mean of about 0.71 . Total county new enrollment rate is also approximately normal, with a mean of about 25% of applicants. I split counties approximately into thirds and group by low, medium, and high levels of active re-enrollment. I then run my main specification with control variables on each subsample separately. I then stratify by new enrollment levels and do the same.

Comparing estimates across the three subsamples represented by columns in Table 2.5, estimates appear to monotonically increase as as a group of counties' mean active re-enrollment rate increases. This suggests that high active enrollment levels are associated with fewer aggregate behavioral failures. Inattention has been cited as a reason for inertia, and automatic re-enrollment may indicate that an individuals is not observing their set of plan options. Thus, part of this behavioral failure may be attributed to inattention, which can be differentiated from status quo bias due to switching costs or other antecedents to imperfect information. Besides the increase in estimates, standard errors also increase substantially as active enrollment rates increase. The high active enrollment group estimate has a standard error that is nearly 7 times that of the low active enrollment group. This could mean that there is unobserved heterogeneity at higher levels of active re-enrollment. This may be related the exchange's use of *navigators* and assistors, both of whom provide guidance to enrollees. As there is variation in the use of these servants by county, it is likely that some of the areas with a high level of active enrollees would include navigators, who may decrease the chance of a behavioral failure *and* increase active enrollment.

Results in Table 2.6 also describe evidence that areas with larger portions that are new have fewer behavioral failures. This difference is much more stark than comparing across levels of active re-enrollment. Here, areas with high levels of new enrollees have an estimate that is about 17 percentage points larger than the middle tercile. This may mean that status quo bias is playing a slightly larger role in the aggregate than inattention[26]. It may be that these biases are due to switching costs, which I investigate as a possible explanation in the next section. While this may be too concrete of a conclusion given the data at hand, these correlations are informative, as they suggest that costly inertia may be at the root of these aggregate errors. See Chapter 1 of this dissertation for an examination of costly inertia in the presence of dominated plans.

[26]Despite the possibility of these behavioral tendencies which cause inertia, it may still be the case that new enrollees *also* make poor decisions for different reasons. They may lack knowledge of health insurance issuer qualities or experience otherwise. This may mean that new enrollees are more responsive to price differences due to lack of taste for a particular insurer.

Table 2.5. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Gold Enrollment, by County; Heterogeneity by Proportion Active Re-Enrollees

VARIABLES	(1) Prop. Gold	(2) Prop. Gold	(3) Prop. Gold
Proportion Eligible for Free Bronze Plan	0.0440	0.0433	-0.0549
	(0.0481)	(0.0475)	(0.0482)
Proportion Eligible for Cheap Gold Plan	0.657***	0.672***	0.712***
	(0.0219)	(0.0746)	(0.135)
P (β_d = 1)	[0.0000]	[0.0000]	[0.0418]
Observations	1,212	1,168	1,168
R-squared	0.933	0.894	0.904
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	All	All	All
Active	Low	Medium	High

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a gold plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls, which are included in all regressions, are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are also included. County and year fixed effects are included in all regressions. Column (1), (2), and (3) are run on the low, middle, and third tercile of county active re-enrollment rates, respectively. Observations are weighted by a simple average of total enrollment.

Table 2.6. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Gold Enrollment, by County; Heterogeneity by Proportion New Enrollees

VARIABLES	(1) Prop. Gold	(2) Prop. Gold	(3) Prop. Gold
Proportion Eligible for Free Bronze Plan	0.123*	0.0838	-0.0287
	(0.0641)	(0.0591)	(0.0267)
Proportion Eligible for Cheap Gold Plan	0.615***	0.626***	0.792***
	(0.117)	(0.0776)	(0.0662)
P (β_d = 1)	[0.0025]	[0.0000]	[0.0038]
Observations	1,186	1,184	1,178
R-squared	0.909	0.899	0.911
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	All	All	All
New Enrollee Level	Low	Medium	High

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a gold plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls, which are included in all regressions, are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are also included. County and year fixed effects are included in all regressions. Column (1), (2), and (3) are run on the low, middle, and third tercile of county new enrollee rates, respectively. Observations are weighted by a simple average of total enrollment.

2.6.2 Heterogeneity by County Education Level

An additional exercise of interest is to examine whether county education levels have a relationship with aggregate enrollment decisions. *Ex ante*, it seems that areas with a more educated populace would be more likely to have measured aggregate behavioral failures. However, this is not the case, as shown in Appendix Tables 2.A.6 and 2.A.7. When stratifying our sample by the proportion of individuals who do not have a high school diploma, the more highly educated areas are those whose responses are furthest from unity. Meanwhile, the areas with the most individuals without a high school degree have the greatest estimated coefficient. This monotonicity does not hold, however, when stratifying counties instead by proportion that has completed at least a bachelor's degree. Instead, areas in the second tertile are those with the estimated aggregate response close to that which would be expected without behavioral or market failures. As with before, the most highly educated counties with respect to this measure have the lowest regression estimate.

This result does not necessarily indicate that low-education and mid-education individuals are choosing better than highly educated ones. It is likely that individual market enrollees, who are of a lower income level than the total population of a county, see a different distribution of education statuses. However, this challenges the simple notion that more highly educated individuals make more sound decisions regarding plan choice. Instead, it could be that highly educated individuals, whose opportunity cost of time may be more valuable, choose not to actively re-enroll or examine plan options. This supports status quo bias due to switching costs as an explaining factor for market-wide enrollment failures. A different explanation is that areas with low education are those targeted most by navigators and other assistors.

2.7 Conclusion

To conclude, suggestive evidence of behavioral failures in the individual market under the Affordable Care Act provide motivation to study these markets further. Regardless of definition of dominance or inclusion of control variables, there is a clear increase (decrease) in gold (silver) plan enrollment when gold plans dominate all silver ones within a market, issuer, network, or product. While this means that at least some enrollees are responsive to relative price changes within a market, fewer enrollees adjust than what is expected. Along with evidence that areas with more active enrollees see fewer behavioral failures, it is likely that inattention and/or status quo bias play a role in these enrollments that create deadweight loss. Furthermore, while works like Drake & Anderson (2020) find that zero-premium bronze plans increased insurance enrollment, I find that their prevalence does not necessarily induce bronze enrollment. Instead, the approximately 10 percentage point increase in bronze plan enrollment may be attributed to relative price shifts. This may mean that bronze plans and silver plans may be more able to be substituted for one another, especially among a healthy set non-CSR-receiving subsidies.

Chapter 2, in part is currently being prepared for submission for publication of the material. Hall, Zachary. The dissertation author was the primary investigator and author of this material.

2.A Chapter 2 Appendix

2.A.1 Tables

Table 2.A.1. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Bronze Enrollment Count, by County

VARIABLES	(1) Bronze Enrlmnt	(2) Bronze Enrlmnt	(3) Bronze Enrlmnt
Number Eligible for Free Bronze Plan	0.195***	0.186***	-0.0258
	(0.0124)	(0.0146)	(0.0314)
Number Eligible for Cheap Gold Plan	-0.0473	-0.0455	-0.241**
	(0.0557)	(0.0497)	(0.100)
Silver-Bronze $/AV Gap			0.00391***
			(0.000898)
Silver-Gold $/AV Gap			-0.000859
			(0.000696)
Observations	7,555	7,398	7,398
R-squared	0.970	0.972	0.979
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	OLS	OLS	OLS
Controls	None	Health and Market Factors	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the number of individuals that enroll in a bronze plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are included in column (3). County and year fixed effects are included in all regressions.

Table 2.A.2. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Silver Enrollment Count, by County

VARIABLES	(1) Silver Enrlmnt	(2) Silver Enrlmnt	(3) Silver Enrlmnt
Number Eligible for Free Bronze Plan	-0.0943**	-0.0806***	0.316***
	(0.0353)	(0.0250)	(0.0792)
Number Eligible for Cheap Gold Plan	-0.545***	-0.481***	-0.277*
	(0.102)	(0.115)	(0.155)
P (β_d = -1)	[0.0001]	[0.0001]	[0.0000]
Silver-Bronze $/AV Gap			-0.00634***
			(0.00141)
Silver-Gold $/AV Gap			-0.00161
			(0.00216)
Observations	7,555	7,398	7,398
R-squared	0.991	0.992	0.994
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	OLS	OLS	OLS
Controls	None	Health and Market Factors	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the number of individuals that enroll in a silver plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are included in column (3). County and year fixed effects are included in all regressions.

Table 2.A.3. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Gold Enrollment Count, by County

VARIABLES	(1) Gold Enrlmnt	(2) Gold Enrlmnt	(3) Gold Enrlmnt
Number Eligible for Free Bronze Plan	-0.00731	0.00145	0.0323*
	(0.00759)	(0.00548)	(0.0177)
Number Eligible for Cheap Gold Plan	0.451***	0.478***	0.500***
	(0.0606)	(0.0654)	(0.0684)
P (β_d = 1)	[0.0000]	[0.0000]	[0.0000]
Silver-Bronze $/AV Gap			-0.000535*
			(0.000281)
Silver-Gold $/AV Gap			1.25e-05
			(0.000370)
Observations	7,555	7,398	7,398
R-squared	0.853	0.883	0.887
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	OLS	OLS	OLS
Controls	None	Health and Market Factors	All

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the number of individuals that enroll in a gold plan. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables, which control for market price shifts, are included in column (3). County and year fixed effects are included in all regressions.

Table 2.A.4. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Enrollment, by County; Simulated Instrument Results without Control Variables, 2015-2019

VARIABLES	(1) Prop. Bronze	(2) Prop. Silver	(3) Prop. Gold
Proportion Eligible for Free Bronze Plan	0.168***	-0.179***	0.0204
	(0.0510)	(0.0465)	(0.0186)
Proportion Eligible for Cheap Gold Plan	-0.128	-0.510***	0.613***
	(0.0837)	(0.0720)	(0.0921)
Observations	7,555	7,555	7,555
R-squared	0.038	0.204	0.404
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	2SLS	W2SLS	W2SLS

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a bronze, silver, and gold plan from a simulated instrument approach. Here the instrumental variable is a simulated measure of free bronze plan exposure. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. County and year fixed effects are included in all regressions. Other time-varying county-level controls are not included. Observations are weighted by a simple average of total enrollment.

Table 2.A.5. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Enrollment, by County; Simulated Instrument Results with Control Variables, 2015-2019

	(1)	(2)	(3)
VARIABLES	Prop. Bronze	Prop. Silver	Prop. Gold
Proportion Eligible for Free Bronze Plan	-0.0663	0.0439	0.0325
	(0.0534)	(0.0439)	(0.0240)
Proportion Eligible for Cheap Gold Plan	-0.275***	-0.334***	0.591***
	(0.0835)	(0.0600)	(0.0978)
Observations	7,398	7,398	7,398
R-squared	0.360	0.466	0.419
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	2SLS	W2SLS	W2SLS

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a bronze, silver, and gold plan from a simulated instrument approach. Here the instrumental variable is a simulated measure of free bronze plan exposure. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables control for market price shifts. County and year fixed effects are included in all regressions. Observations are weighted by a simple average of total enrollment.

Table 2.A.6. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Gold Enrollment, by County; by High School Graduation Level

VARIABLES	(1) Prop.Gold	(2) Prop.Gold	(3) Prop.Gold
Proportion Eligible for Free Bronze Plan	-0.0127	0.0156	0.0719
	(0.0232)	(0.0238)	(0.0454)
Proportion Eligible for Cheap Gold Plan	0.689***	0.642***	0.507***
	(0.0626)	(0.0761)	(0.119)
P (β_d = 1)	[0.0000]	[0.0001]	[0.0002]
Observations	2,495	2,385	2,675
R-squared	0.834	0.780	0.725
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	All	All	All
Education Level	Low	Medium	High

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a bronze, silver, and gold plan from a simulated instrument approach. Here the instrumental variable is a simulated measure of free bronze plan exposure. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables control for market price shifts. County and year fixed effects are included in all regressions. Observations are weighted by a simple average of total enrollment.

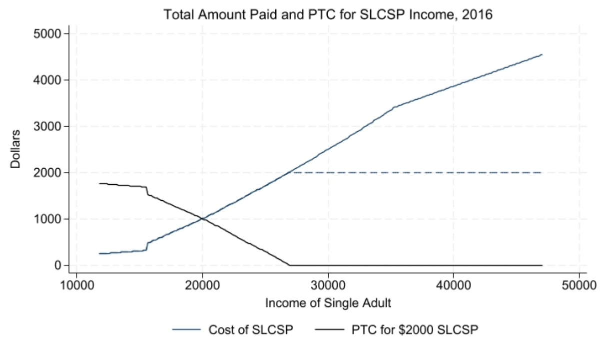
Table 2.A.7. Relationship between Free Bronze Plan and Cheap Gold Plan Exposure on Bronze Enrollment, by County; by College Graduation Level

VARIABLES	(1) Prop.Gold	(2) Prop.Gold	(3) Prop.Gold
Proportion Eligible for Free Bronze Plan	0.0519*	-0.0208	0.0502*
	(0.0299)	(0.0313)	(0.0277)
Proportion Eligible for Cheap Gold Plan	0.589***	0.693***	0.510***
	(0.0703)	(0.0975)	(0.0931)
P ($\beta_d = 1$)	[0.0000]	[0.0036]	[0.0000]
Observations	2,525	2,470	2,560
R-squared	0.769	0.807	0.757
Fixed Effects	County & Year	County & Year	County & Year
Years	2015-2019	2015-2019	2015-2019
Type	WLS	WLS	WLS
Controls	All	All	All
Education Level	Low	Medium	High

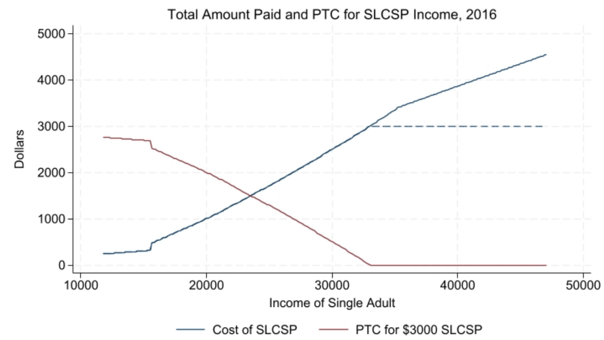
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows estimated effects of free bronze plan exposure and dominated silver plan exposure on the proportion of individuals that enroll in a bronze, silver, and gold plan from a simulated instrument approach. Here the instrumental variable is a simulated measure of free bronze plan exposure. Standard errors were calculated using the wild cluster bootstrapping technique (see Wald bootstrap-t method in Cameron et. al. (2008)), clustered by state; these are listed under estimates in parentheses. Time-varying health and market controls are state Medicaid expansion status and county-level variables: platinum plan offering status, catastrophic plan offering status, percent obese, percent smokers, average number of poor health days, and percent physically inactive. Price variables control for market price shifts. County and year fixed effects are included in all regressions. Observations are weighted by a simple average of total enrollment.

2.A.2 Figures



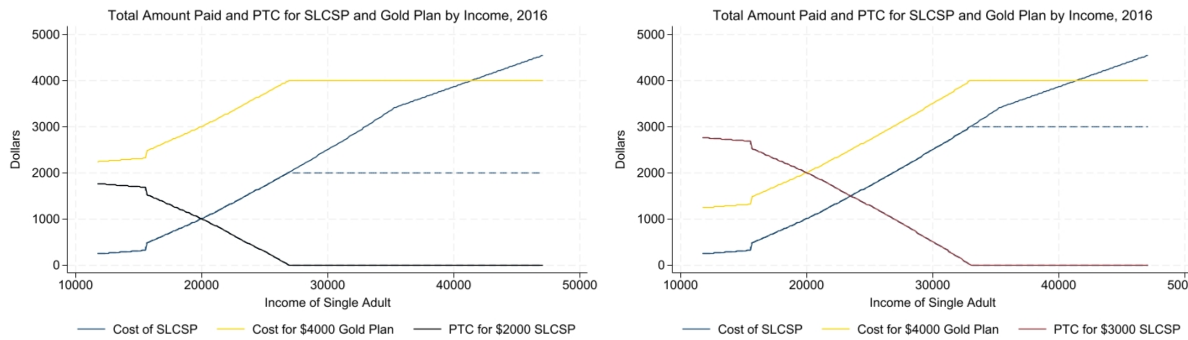
(a)



(b)

Figure 2.A.1. Change in Second Lowest Cost Silver Plan (SLCSP) Premium vs. Premium Tax Credit (PTC) across Income Levels

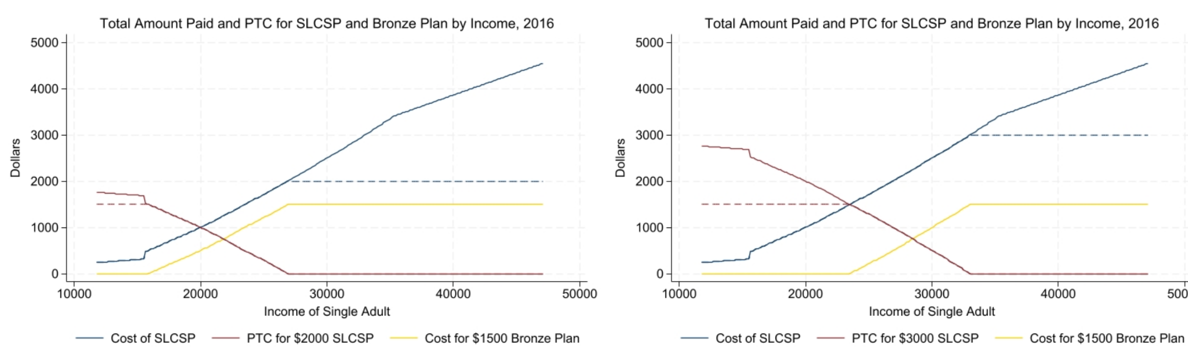
Note: This set of figures shows how different income levels (at a given age) experience shifts in the premium tax credit given a shift in the listed premium of a market's Second Lowest Cost Silver Plan (SLCSP). In panel (a), when SLSCP premium is $2,000 for a certain age group-market pair, individuals with incomes up to 229% of the Federal Poverty Level (FPL), equivalent to an individual income of $27,200, receive a positive Premium Tax Credit (PTC). When this SLCSP increases to $3,000, shown in panel (b), individuals with incomes up to 280% FPL, or about $33,260, receive a positive PTC. Others remain unsubsidized. This $1,000 increase in SLCSP translates to a $1,000 increase in PTC for previously subsidized individuals. These individuals will be as well off purchasing SLCSP as before. Those who were unsubsidized, however, will pay a higher price than before, though if they've become subsidized, this change will be less than the $1,000 shift.



(a) **(b)**

Figure 2.A.2. Change in Second Lowest Cost Silver Plan (SLCSP) Premium vs. cost of non-SLCSP plan with Higher Premium across Income Levels

Note: This set of figures shows how different income levels (at a given age) experience shifts in the premium tax credit given a shift in the listed premium of a market's Second Lowest Cost Silver Plan (SLCSP). Specifically, we see the Premium Tax Credit (PTC) can be applied to a more expensive Gold plan. In panel (a), when SLSCP premium is $2,000 for a certain age group-market pair, individuals with incomes up to 229% of the Federal Poverty Level (FPL), equivalent to an individual income of $27,200, receive a positive Premium Tax Credit (PTC). This means they receive a "discount" on a more expensive gold plan as well. When this SLCSP increases to $3,000, shown in panel (b), individuals with incomes up to 280% FPL, or about $33,260, receive a positive PTC. Others remain unsubsidized, and pay full price for a gold plan in both situations. All subsidized individuals are better off than before the SLCSP premium increase.



(a) **(b)**

Figure 2.A.3. Change in Second Lowest Cost Silver Plan (SLCSP) Premium vs. cost of non-SLCSP plan with Lower Premium across Income Levels

Note: This set of figures shows how different income levels (at a given age) experience shifts in the premium tax credit given a shift in the listed premium of a market's Second Lowest Cost Silver Plan (SLCSP). Specifically, we see the Premium Tax Credit (PTC) can be applied to a less expensive bronze plan, for which some individuals may experience zero-premium cost. In panel (a), when SLSCP premium is $2,000 for a certain age group-market pair, individuals with incomes up to 229% of the Federal Poverty Level (FPL), equivalent to an individual income of $27,200, receive a positive Premium Tax Credit (PTC). Individuals up to 134% FPL, equivalent to an individual income of about $15,900, qualify for this bronze plan for free, meaning their PTC is capped at $1,500. When this SLCSP increases to $3,000, shown in panel (b), individuals with incomes up to 280% FPL, or about $33,260, receive a positive PTC. Individuals up to 199% FPL, equivalent to an individual income of about $23,600, qualify for this bronze plan for free. Free bronze plan availability has increased. Some individuals still remain unsubsidized.

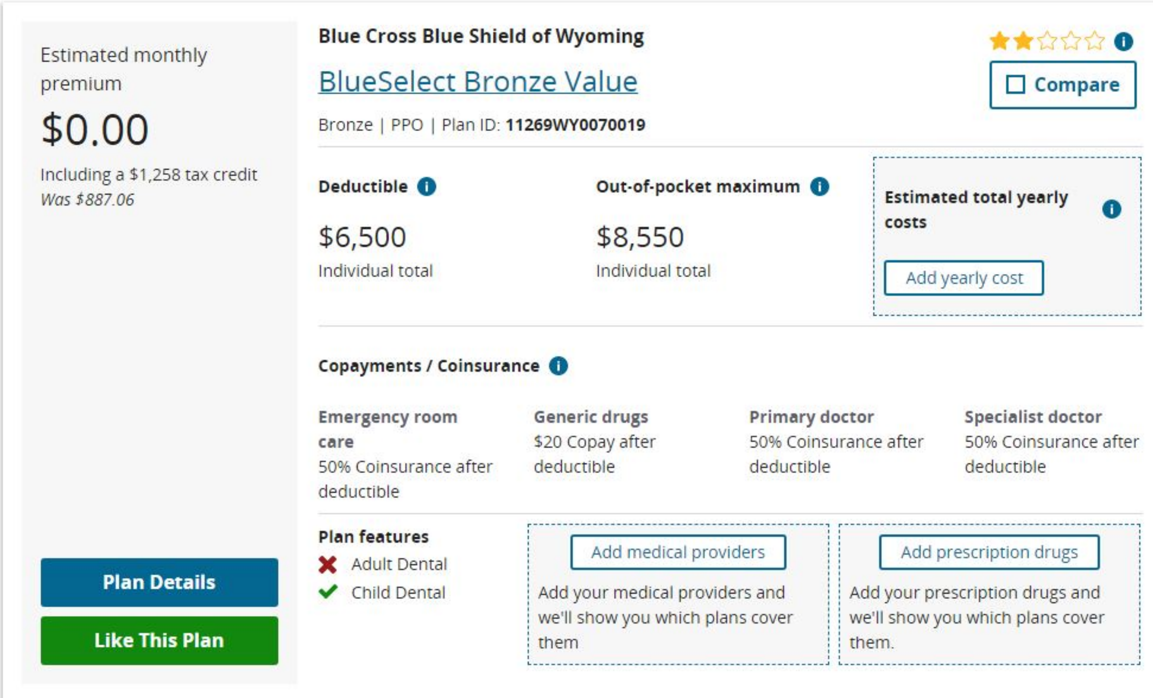
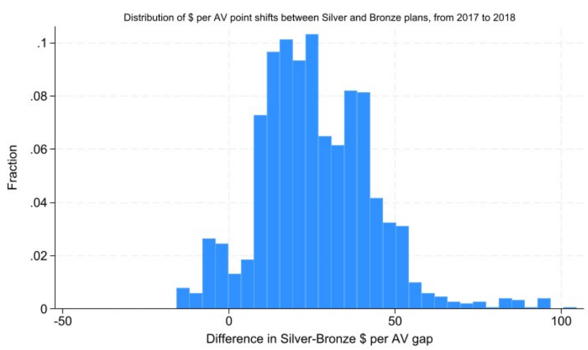
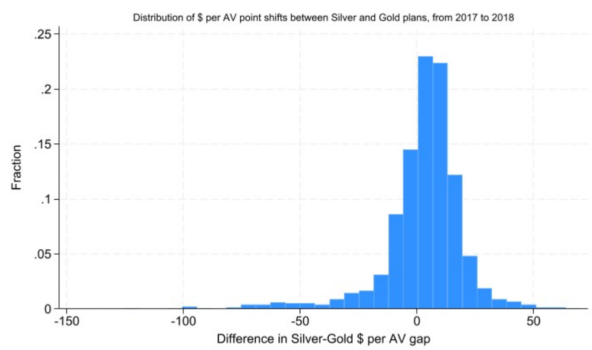


Figure 2.A.4. Federal Exchange Plan Information from Menu of Health Plans
Note: This screenshot of the ACA website shows what is directly visible to users of healthcare.gov. One's estimated monthly premium is shown in the top left corner, along with a Premium Tax Credit (PTC) amount and the baseline premium of individuals without PTC. It also states the insurance issuer name, metal tier, network type, and cost-sharing information, such as deductible, maximum out-of-pocket amount, and copayment/coinsurance of typical medical treatments. An individual may choose to compare this plan with another or view more plan details. They may also add medical providers and prescription drugs to see if the plan covers them.

Figure 2.A.5. Sorting Options and Information on Federal Exchange
Note: This screenshot of the ACA website shows what is directly visible to users of healthcare.gov. At the top, individuals may sort by lowest premium or lowest deductible. They may also toggle between health and dental plans. Finally, if they are eligible for cost-sharing reductions, they are reminded that these apply only to silver plans.



(a) Silver-Bronze $ per AV change, 2017-2018



(b) Silver-Gold $ per AV change, 2017-2018

Figure 2.A.6. Changes in $ per Actuarial Value (AV) Gap by County between (a) Silver and Bronze plans; and (b) Silver and Gold plans; 2017-2018

Chapter 3

Mandated Benefits and U.S. Health Insurance Premiums under the Affordable Care Act

Provision of Essential Health Benefits (EHBs) was one of the many policies resulting from the passage of the Affordable Care Act. These benefit requirements act as mandates and ensure that certain benefits are provided by each plan offered in the U.S health insurance exchange. I exploit between- and within-state variation in EHBs to analyze the incidence of mandated coverage on health plans in the individual market. I find that each additional mandated benefit is associated with a 2% increase in premiums among plans that are newly bound to a mandate, while rolling back benefits is not associated with premium decreases. I also find slight evidence that deductibles increase by $100 with each added benefit, though overall actuarial value of plans are unaffected. This work provides a first attempt at fully documenting EHB changes and analyzing their consequences related to plan costs; this speaks to the tension between provision of quality health care and affordability for enrollees.

The Patient Protection and Affordable Care (ACA), known colloquially as Obamacare, leveled widespread change in the health insurance market in the United States. As regulations were put in place, the innovations created a rich area for evaluation of policy in the health insurance industry (Frean et al. 2017; Antwi et al. (2013)). While the ACA's resulting mandates, policies and restrictions should be taken in harmony, I look specifically at Essential Health Benefits (EHBs) and their incidence on cost and coverage for consumers in the individual market. Although benefit mandates have long been the subject of both theoretical (Summers, 1989; Buchmueller & DiNardo, 2002) and empirical (Gruber, 1994) investigations in health insurance markets, especially with respect to premiums, positive externalities, and adverse selection, they have seen limited study in the context of the ACA. Given the legislation's goal of providing high quality plans at affordable premiums, my work examines market-wide impacts of EHB provision.

While a handful of Essential Health Benefit categories must be covered by every state, the ACA afforded each state's Department of Insurance to designate a plan which defined the benefits that must be covered in that state. These state-specific EHBs, along with any state-mandated benefit that held prior to the ACA, define the services which *must* be covered by all Qualified Health Plans (QHPs) in that state. This was done with the hope of ensuring that the marketplace did not offer any "bare-bones" plans; otherwise, this can spur an environment where adverse selection of high quality plans may occur (Akerlof 1970; Rothschild & Stiglitz 1976). This policy creates between-state variation that can be exploited in order to examine how EHBs affect premiums of health insurance plans; further, other measures of cost, such as deductibles, maximum out-of-pocket costs, and overall actuarial value can be analyzed with respect to mandated benefit changes.

Basic economic modeling will lead one to conclude that issuers must adjust their plans on some margin when a benefit is newly mandated and directly affects coverage. As the cost of providing insurance increases, all else equal, premiums will increase. Using a difference-in-difference approach, I do not find that state-by-state net EHB changes are associated with price increases across these markets. However, using a dataset from the Center for Medicare and Medicaid Services, I am able to utilize coverage data in order to exploit rich variation in coverage and investigate the differential effects of mandates on plans that are newly bound to these requirements compared to those that already provided coverage. This method loosely mirrors an approach used in the minimum wage literature (Clemens & Wither, 2019) that differentiates between states bound and not bound by federal policy changes. This analysis shows that new classification of each EHB is associated with an approximate 2% increase in plan premiums across various plan types relative to those that were unaffected. Declassification of benefits is not associated with any premium decreases, even among providers who roll back benefit coverage. The differences in results between these two methodologies speaks to the importance of using coverage data to identify treated health insurance plans and allow for state-specific shocks. This is a particular innovation of this paper relative to the current literature on state-mandated benefits.

Changes in premiums do not fully capture the changes in these markets, as EHB upheavals are associated with a $100 increase in deductible per benefit added, though this finding is not as statistically significant. Additionally, I find that each additional benefit mandated is associated with an $80 decrease in maximum-out-of-pocket costs of plans among plans that were newly bound to these policy changes. Despite no change in overall actuarial value of these plans, increasing a plan's deductible will increase health-related costs among lower-utilization enrollees while potentially decreasing these costs among high utilization types.

This work proceeds as follows: Section 3.1 provides institutional background on the Affordable Care Act and provision of Essential Health Benefits, as well as summarizing the literature on mandated benefits. Section 3.2 describes the data wrangling process and the process of documenting Essential Health Benefit levels and changes. Section 3.3 provides a brief theoretical treatment of the margins that insurance issuers may adjust plans in response to additional mandated benefits. Section 3.4 provides an analysis of the market-wide relationship between EHB changes and premiums in the year 2017, as well as the differential effects of plans that are newly bound to these policy changes in relation to those that are not. Section 3.5

examines other response margins related to enrollee cost-sharing. Section 3.6 provides additional discussion. Section 3.7 concludes.

3.1 Institutional Background

3.1.1 Passage of the Affordable Care Act

President Barack Obama signed the Patient Protection and Affordable Care Act (ACA) into law on March 23, 2010. The bill's text amended the Public Health Service Act of 1944 and stipulated various restrictions and requirements in the United States health insurance markets. These policies most commonly affected both individual and small group markets[1], the latter of which refers to employer-sponsored insurance (ESI) policies provided by a company with fewer than 50 employees. While existing plans in these markets were "grandfathered" in, only plans that fit the new standards established by the ACA could be sold beginning in 2014. Health insurance marketplaces, known as exchanges, were also created in order to create transparency and facilitate the sale of these Qualified Health Plans (QHPs) to individuals and small-groups alike[2]. In order for consumers to more easily identify a plan's cost-sharing richness, metal-tiers for QHPS were established, with each metal level (Platinum, Gold, Silver, Bronze, and Catastrophic) requiring different actuarial values of coverage.

The ACA was introduced and executed as a law that attempted to enhance both the *accessibility* and *affordability* of *quality* health insurance plans available in the United States[3]. With regards to affordability, institution of modified *community rating* regulations allowed enrollee premiums to vary only by age and geographic area[4]. This policy was intended to spread risk among individuals by equalizing the premiums faced by healthy and unhealthy

[1]One exception to this was the new rule that "large" employers must offer health insurance to its employees.

[2]QHPs include standard QHPs, as well as Child-Only Health Insurance Plans, Catastrophic Plans, Consumer Operated and Oriented Plans (CO-OPs) and Multi-State Plans (MSPs). All of these variants besides Child-Only plans are included in the analysis of this paper. Requirements of QHPs as a consequence of the ACA can be found in the United States Code of Federal Regulations, Title 45, Subtitle A, Subchapter B.

[3]A brief report by the National Conference of State Legislature (NCSL) can be found here: https://www.ncsl.org/portals/1/documents/health/HRACA.pdf

[4]This differs from non-modified community rating regulations, which do not allow pricing variation by age.

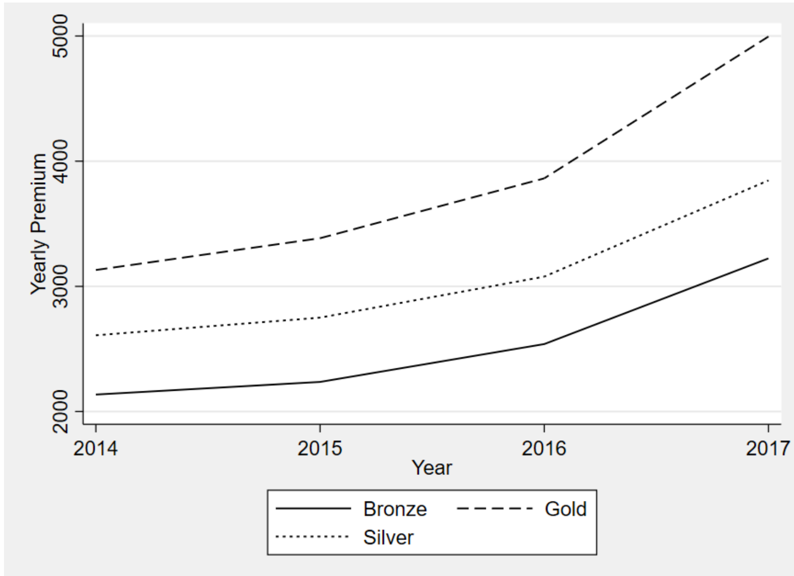


Figure 3.1. Average Yearly Premium of a 21-year old Enrollee in the U.S. Individual Health Insurance Market; 2014-2017
Note: This graph shows the average yearly premium paid by a 21-year old non-smoking enrollee in the U.S. individual health insurance market from 2014 to 2017.

policyholders. Prior to passage of the ACA, insurers could vary premiums of plan offerings based upon a policyholder's observable characteristics, including any pre-existing conditions. The ACA disallowed this and, further, required *guaranteed issue*, which barred health insurance issuers from denying coverage based on pre-existing conditions. As a result of these policies, premiums were set according to a preset age-based ratio relative to the premium for a 21 year old enrollee[5] (Orsini & Tebaldi, 2017). These ratios are mostly consistent between states, though Utah has different community rating standards[6]. States were also partitioned into "rating areas," the geographical areas for which community rating holds. The number of rating areas in a state ranges from one in New Hampshire, New Jersey and Delaware, to 67 in Florida (one rating area per county).

The combination of community rating and guaranteed issue are policies that ensure that

[5]For example a 64 year old may have a premium that is a maximum of 3 times that of the 21 year old. Those below 21 pay 0.635 times the 21 year old rate.

[6]Outside of the 35 states included in this study, Massachussetts, Minnesota and Washington D.C. all also had their own schedule of adjustment factors. New Jersey, a state included in this study, required a different schedule for its small group market.

unhealthy enrollees who seek health insurance can access any policy available within the market at a premium that is more affordable than if their plans had been individually underwritten. While this is beneficial for unhealthy types, those who are healthy face higher premiums than they would without the regulation. As unhealthy individuals enroll in coverage, this may drive out healthy individuals from the risk pool – increasing premiums may cause healthy individuals to disenroll, as the expected value of insurance no longer outweighs the price of enrollment. This can result in a "death spiral" in which healthy individuals disenroll due to high premiums, which causes prices to increase, and the cycle continues (Buchmueller & DiNardo, 2002). In order to temper this adverse selection problem[7], the law calls for an *individual mandate* requiring all individuals to purchase health insurance from the individual market if they were otherwise uninsured. Those who did not have health insurance would face a fine, known as a "shared responsibility payment", of \$95 per adult per year in 2014, which was to become a penalty of \$695 per adult per year by 2016 (78 Federal Register 53646). In requiring healthy individuals to purchase health insurance, this can lead to decreased premiums and costs, as well as welfare gains, as evidenced by work studying the implementation of an individual mandate in Massachusetts in the mid-2000s (Hackmann et al., 2015).

Another major regulatory measure of the ACA, as well as its relationship to community rating, should be mentioned. In order to increase access to affordable care, the text of the law increased the threshold for qualifying for Medicaid, expanding the pool of eligible enrollees from those who make under 100% of the Federal Poverty Level (FPL) to those who make under 138% of the Federal Poverty Level. If high cost types are drawn out of the pool of potential private market participants, Medicaid expansion can help alleviate adverse selection problems within community rated markets (Clemens, 2015). Though Medicaid expansion was initially intended to be a requirement for all states, a U.S. Supreme Court decision *National Federation*

[7] As explained and modelled in Einav & Finkelstein (2011), adverse selection occurs due to a downward sloping marginal cost curve. This is unique because the marginal cost curve and average cost curves are inherently linked to the demand curve; an inefficiency is created by insurance issuers being unable to price based upon an individual's type.

of Independent Business v. Sebelius made the expansion optional on a state-by-state basis. States that chose to implement Medicaid expansion saw higher levels of enrollment growth during the early stages of the policy period (Courtemanche et al., 2017). The effects of the aforementioned policies, as well as other rules established by the ACA have been investigated recently by a handful of papers[8].

While various other important mandates and restrictions were set forth by the ACA, this paper focuses on *Essential Health Benefits* (EHB). According to the U.S. Code of Federal Regulations Title 45, starting in 2014, all QHPs would be required to provide coverage in 10 statutory benefit categories. This list includes commonly covered categories such as Emergency Services and Hospitalization while also including coverage for Mental Health and Substance Abuse Disorder services. Additionally, states at this time were required to choose a *base-benchmark* plan from a list of candidates issued in 2012: i) one of the three largest small group products by enrollment; ii) one of the three largest state employee benefit plans by enrollment; iii) one of the three Federal Employees Health Benefit Program (FEHBP) plan options; or iv) the largest HMO in the state. The base-benchmark plan defines the state-specific Essential Health Benefits; benefits covered in the base-benchmark plan must be covered in all non-grandfathered QHPs. All statutory categories that are not covered by a base-benchmark plan selection must be supplemented by adding that benefit category in its entirety from another candidate base-benchmark plan (or alternatively, for pediatric oral and vision services, from Federal Employees Dental and Vision Insurance Program (FEDVIP) or the state's Children's Health Insurance Program (CHIP) plan). Provision of coverage of Essential Health Benefits, plus the supplemented categories, define the *EHB-benchmark plan* for a state. The scope of covered benefits and associated limits of a health plan offered by an issuer is known as the state's *EHB package*. Provision of EHB is defined by being at least substantially equal in covered benefits and limitations on coverage. Furthermore, annual and lifetime dollar limits are not allowed for EHB,

[8]See Frean et al. (2017) for discussion of premium subsidies, medicaid expansion and the individual mandate; see Antwi et al. (2013) for an analysis of the dependent coverage mandate, which requires coverage of enrollees children up to age 26 under ESI.

though these limits may be converted into actuarially equivalent coverage limitations. Finally, some benefits, including non-necessary orthodontia and routine non-pediatric dental services, cannot be EHB[9]. Allowing states to establish their own EHB was intended to allow for flexibility in coverage for states while ensuring that scope of coverage is rich for those purchasing a QHP (77 Federal Register 70644). A further result of regulations set forth was that the cost of all state-mandated benefits passed into law after 2012 – which by definition are not EHBs– would be defrayed by state governments (45 CFR § 155.170).

3.1.2 Economics Literature on Mandated Health Benefits

Essential Health Benefits are simply state-mandated benefits that have been put in place as a result of the Affordable Care Act, applying to all issuers and plans alike. Summers (1989) emphasizes that positive externalities, in the form of increased public health, may arise from mandating certain benefits. Further, these benefits may be considered *merit goods*, which individuals either underestimate the probability of having to use or simply value too little. Thus, requiring them to be covered may be best for policyholders. Furthermore, mandating that plans cover certain benefits may mediate further adverse selection that can occur in the markets: despite low-cost individuals' requirement to enroll, if some plans offer a benefit while others do not, the pool of enrollees in those richer plans may be adversely selected. Issuers could then differentiate plans in order to price discriminate through the benefits that are offered. This would defeat the purpose of the community-rated markets, which intended to provide coverage at affordable rates to low cost types[10]. A key trade-off in what many of these key policies address is between coverage accessibility, richness and affordablility for high-cost types and affordability for low-cost types that may not "need" coverage at all, let alone rich coverage.

Work within the literature has found that specific benefit mandates may increase utiliza-

[9]For more information on Essential Health Benefits, see 45 CFR § 156

[10]Buchmueller & DiNardo (2002) mention that mandated benefits create an environment in which the "death spiral" mentioned previously is more likely (in the absence of an individual mandate) because low-cost enrollees would otherwise purchase "lower quantities" (i.e. fewer benefits) when faced with higher prices. This separating equilibrium is not possible when "bare-bones" plans are not allowed to issued.

tion of services; this includes mandates for Autism Spectrum Disorder (ASD) treatment (Barry et al. 2017), Mental Health Treatment (Harris et al. 2006), Infertility Treatment (Bitler & Schmidt, 2006; Hamilton & McManus, 2012) and Telehealth (Grecu & Sharma, 2019). Theoretically, negative externalities may arise from this in the form of *over*-utilization (moral hazard), as individuals who do not value a medical procedure may be induced take up a service due to its reduced cost. Still, increased utilization does not necessarily imply overutilization, and increased use of certain services may be the direct purpose of many of these policies.[11] Besides utilization, state-mandated benefits may affect other margins, including health outcomes,[12] spending[13] and insurance coverage.[14]

Premiums have also been studied within the policy context of state-specific insurance mandates. Generally speaking, works have examined three types of mandates as originally defined by Gruber (1994): (1) *benefit* mandates require coverage of certain services at a certain level; (2) *provider* mandates ensure that certain provider types are covered by insurance plans; and (3) *coverage* (or person) mandates stipulate that certain individuals must be covered. The literature usually looks at these mandates both collectively and separately. Kowalski et al. (2008) finds that these mandates are associated with about a 0.5% increase in average premiums using a cross-sectional analysis. Gohmann and McCrickard (2009) use premium data on plans sold in Metropolitan Statistical Areas that cross state borders, exploiting having the same insurance sold in markets with different policies; they analyze a handful of mandates individually (instead of collectively) and find mixed results depending on the mandate. Limitations of both of these

[11]Mandell et al. (2016) finds that states that implemented ASD insurance mandates saw an increase in the number of children diagnosed with the disorder; however, the number of diagnoses, even after treatment, was much lower than community prevalence in these states, even after 3 years of implementation.

[12]Schmidt (2005; 2007) finds that Invitro Fertilization (IVF) mandates increase fertility, while Bitler (2008) finds that IVF mandates are associated with higher rates of twinning among older mothers. Telehealth mandate results on health outcomes are more mixed, and may depend on metropolitan status (Grecu & Sharma, 2019).

[13]Candon et al. (2018) finds that ASD mandates increase spending on ASD-specific outpatient services, especially for those who on the high end of the spending distribution. Barry et al. (2017) also finds an increase in spending on ASD-specific services especially among younger children.

[14]Li & Ye (2017) find that mental health parity laws reduce ESI coverage among veterans, a drop which is largely offset by their increased enrollment in public insurance. Gruber (1994) famously looks at five high cost state mandates in the ESI market and finds no evidence that mandates cause employers to stop offering ESI to their employees.

studies include endogeneity that likely exists between policies in certain states and other factors that influence premiums. Though the latter work alleviates this concern by using areas within the same metropolitan area, other regulations that differ between states are not accounted for; further, the mandates analyzed may be non-representative. LaPierre et al. (2009) uses survey data on premiums over a six year period and find little effect on premiums by benefit mandates. Both Bailey (2014) and Bailey & Blascak (2016) use Medical Expenditure Panel Survey (MEPS) data from 1996 to 2011 to examine premiums in the ESI market. These works find that both benefit mandates and provider mandates increase insurance premiums.

My work offers improvements on the previous literature in a handful of ways. Firstly, this is the first work that studies the effect of benefit mandates on premiums (and other variables) after the implementation of the Affordable Care Act. Works that study many different mandates have only studied pre-ACA time periods, while those that include 2014 look at specific mandates only. This makes the work more policy relevant, as all changes in mandated benefits whose costs are borne by individuals and issuers will be EHB changes moving forward.[15] Furthermore, the ACA's regulations create more uniform rules between states, including community ratings standards, individual mandates and dependent coverage mandates. This creates more comparable environments between states in terms of state-by-state regulation and how this evolves over time. Since many of these uniform regulations include our *other* mandate types (provider and coverage mandates[16]), we can isolate the effect of benefit mandates specifically. Secondly, this work is the first to employ a regression that utilizes coverage data, as prior work that include data across multiple years only look at the affect on markets as a whole rather than directly affected plans. Finally, I am also able to look at other plan responses due to availability of a detailed data set

[15]As mentioned previously, all state-mandated benefits passed after December 31, 2011 must have their costs defrayed by the state on behalf of the enrollee (45 CFR § 155.170).

[16]For example, "Nurses and Other Practitioners" are covered as an EHB by all states in all years, so its study is not relevant. Further, CMS guidance has maintained that both provider mandates and coverage mandates are not considered state-required benefits for the purpose of EHB. The dependent coverage mandate, which was instituted as part of the ACA beginning in 2010, required all plans in the individual and group market to provide coverage to enrollees' children under the age of 26. See Antwi et al. (2013), Barbaresco et al. (2015), or Mulcahy et al. (2013) for a discussion of this policy.

created from Public Use Files released by the CMS.

3.1.3 Implementation & Evolution of Essential Health Benefits

The text of the ACA states that "[t]he Secretary (of Health and Human Services) shall ensure that the scope of essential health benefits... is equal to the scope of benefits provided under a typical employer plan, as determined by the Secretary." Thus, the U.S. Department of Health and Human Services (HHS) was tasked with ironing out the timing and implementation of EHB beginning with the 2014 policy year. Despite receiving differing guidance from the Institute of Medicine (IOM)[17], the HHS released a bulletin in late 2011 describing their intent to use a state-by-state benchmark approach in order to achieve coverage similar to those offered by employers. Following submission of benchmark plans, the CMS released summaries of EHB packages with reference to 45 potential essential health benefits, with each categorized as "Covered" or "Not Covered". Besides these *core* EHB, other benefits that did not fall within these benefits were also listed. These summaries, which were created by CMS, were paired with documents listing state-required benefits that exist in each state independent of EHB.

In submitting plans for certification to CMS, health insurance issuers were required to fill out a Plans & Benefits Template. These templates included each of the 45 core benefits, as well as 23 other benefits, along with classification of EHB for each. These benefits that were additionally listed (such as Chemotherapy) were classified as EHB if they had been explicitly listed in the CMS documents under "other" benefits. This standardized list of 68 benefits make up the set of EHB to be addressed by all plans and all issuers in their plan filings provided to the federal government in all years of this study.

Loosely following a recommendation from the IOM, the initial plan of the HHS was to allow for each state to revise their EHB package in 2016 (78 Federal Register 12834), but this timing was pushed back to the 2017 plan year for undisclosed reasons (80 Federal Register

[17] See Health Affairs Blog post at https://www.healthaffairs.org/do/10.1377/hblog20111014.014449/full/ for a summary. The report recommends that EHB be defined based upon premium targetting, and that states should be allowed to adopt variants of a federal EHB package. These recommendations were largely ignored.

10750). For this policy year, states were able to again choose from the same list of candidate plans; this time around, though, they chose from plan designs implemented in 2014 rather than 2012. This provides for a planned and executed policy change between the years 2016 and 2017. Although a handful of states did not change their base-benchmark plan choice, EHB may have still shifted slightly, as this choice was to be from the 2014 plan year (as opposed to 2012 for the initial plan). The intention of this change was to "ultimately create efficiencies for issuers in designing plans."

Still, this is not the only time that EHB packages may have changed. A second "revision" to EHB packages occurred on June 19, 2014, when revised EHB benchmarks were posted by the Centers for Medicare and Medicaid Services (CMS). These documents, which were initially sent out to issuers on May 15, 2014, list state- and CMS-identified corrections to each state's Essential Health Benefits package along with instructions to provide coverage in these updated categories. These EHB changes are fundamentally different from the those that occurred in 2017 because the base-benchmark plan did not change. Instead, the CMS was issuing a correction to some benefits' EHB designation due to prior misclassification or omission. Though this creates a more plausible exogeneity story, this does not necessarily mean that these shocks reflect experimental variation: some benefits, such as Diabetes Education and Well Baby Care & Visits, were first established as EHBs by many states with this revision, and had not been addressed in previous versions. This may have been due to the CMS overlooking these specific benefits systematically. Although the PUFs indicate changes in requirements in the 2016 plan year due to the revised EHB packages being released, coverage changes indicate that these shifts were actually effective in 2015.

The change in EHB packages from 2014 to 2015 presents greater context for the true nature of EHB changes in general; evolution of EHB indicated by the CMS may not actually be due to a change in base-benchmark plan coverage, even for the 2017 policy change. While CMS produces EHB summary documents and requires issuers to submit plan designs, under 45 CFR 140.201, states are primary enforcers of the PHS act which the ACA falls under. This creates a potential disconnect between the *de jurre* coverage requirements of issuers and *de facto* enforcement by each state. It is possible, then, that EHB changes as documented in CMS' official files and documents are not changes at all. Furthermore, the CMS website states that the EHB packages that evidently held for 2015 and 2016 were those that applied for 2014-2016, and the revision is not mentioned in any official documents. Its existence is only documented in archived web pages and public use data from 2014. Still, since enforcement of EHB is done on a state-by-state basis, it is unclear if these changes did in fact affect issuers' perception of what was required of them, or states' enforcement of EHB[18]. Because of the inconclusivity of 2015 EHB package changes, I disinclude the 2014 plan year from this analysis and do not examine these potential shifts in requirements. Furthermore, scrutiny must be levied against many 2017 policy changes that are clearly documented in EHB benefit documents. The known extent of these issues will be discussed further later in this paper, including in the Appendix. As a result, a comprehensive understanding of EHB changes and their effect on benefit coverage required a deep dive into both EHB documents and public use files. While coverage data and treatment understanding required additional care, premium, deductible, and other plan data such as actuarial value are straightforward and do not require adjustment.

3.2 Data

The CMS's Center for Consumer Information and Insurance Oversight (CCIIO) provides a handful of publicly-available data resources pertaining to the Affordable Care Act. One of these pages provides EHB package summaries for each state, as previously mentioned. Using archived versions of these web pages, EHBs can be tracked over time. Another one of these pages provides public-use files (PUFs) pertaining to costs & benefits, plan attributes, enrollment

[18] Conflicting evidence, even within states, exists on this. Arizona's 2015 EHB package added dialysis and infusion therapy coverage, among others. Correspondence with the state Department of Insurance and Financial Institutions (DIFI) indicates that "DIFI enforces compliance with the state benchmark, not the state summary, so our review of plans for compliance with the benchmark would not have changed based on the change to the CMS summary (in 2015)." Still, official documents from SERFF indicate a direct change in the EHB requirements that Arizona used to certify QHP from 2014 to 2015, specifically with respect to these benefits. This discrepancy, as well as others, has not yet been resolved.

numbers, and premium rates. The Costs & Benefits PUF is compiled from all issuers' completion of the Plan and Benefits Template filled out by issuers during plan certification. This file provides coverage data on each of the 68 standardized benefits, any state-mandated benefits, as well as any additional benefits that a plan may choose to list. This information, cross-referenced with the CMS summaries, defines the policy changes required for conducting an analysis. The latter three PUFs were combined to create plan-specific premium data, along with estimated frequencies for weighting in regressions and summary statistics. For my analysis on premiums, I focus specifically on premiums for a 21 year old non-smoker in the individual insurance market. Since each state is partitioned into ratings areas within which premiums cannot differ, each observation is on the plan-ratings area level. I focus on the 35 states that have used a federally-run or federally facilitated exchange, as these are the states whose plans, rate, and enrollment data are available. This analysis focuses on the years 2014 to 2017 due to the high volume of policy changes that occurred and differentially affected states beginning in 2018.[19]

Summary statistics for plan premiums (Table 3.1) illustrate the rising premiums across states since full implementation of the Affordable Care Act. Regardless of metal level, the average price paid for plans increased between 2014 and 2017 at a magnitude that is economically significant. Catastrophic, Bronze, and Gold plan premiums increase by over 50%, while those of Silver plans increase by less (41%) and Platinum plans increase by more (80%). Over this period of time, Platinum plans saw decreasing enrollment, moving from 4% of total enrollment in 2014 to less than 0.5% of total enrollment in 2017. The declining popularity of these plans may be tied to their sharp price increase. Enrollment in Bronze and Silver plans increased while enrollment in Gold plans decreased over this time frame, indicating that rising premiums saw

[19]The main reason that I do not include 2018 and on in this analysis is that the Trump administration announced that it would no longer pay of cost sharing reduction (CSR) subsidy payments to issuers, which was announced in late 2017. This led to a practice known as "silver loading," where insurers loaded the cost of providing CSR onto their silver plans. This practice varied by state, but generally led to skyrocketting silver plans, and in turn increased federal premium tax credit (PTC) amounts, which are tied to the second-lowest priced silver plan in each market. See this Disseration's Chapters I and II or https://www.healthaffairs.org/do/10.1377/hblog20190913.296052/full/ for a discussion of this. The 2018 plan year also saw the introduction of Expanded Bronze plans. Furthermore, 2018 saw a change to the federal premium adjustment schedule in all states except for Mississippi and Alaska. The repeal of the individual mandate for the 2019 plan year is another major policy that affects analyses.

enrollees shift to cheaper plans with less rich coverage.

3.2.1 Individual Market Premium Weights and Controls

Analysis of premiums, as well as subsequent secondary analyses, are conducted for plans in the individual market only. This is done for two primary reasons. Firstly, each state included in the analysis has a functioning individual market in each year, meaning that data is available for plans of this type. In 2014, all but three states offered small group plans on the health insurance exchange. By 2020, this number grew to 26 states that only offered individual plans in the marketplace[20]. Secondly, enrollment numbers included in PUFs are only available for insurance products offered in the individual marketplace from 2014 to 2017. The data from these yearly PUFs can be used to construct frequency weights for conducting analyses and to create both state and rating area level controls for use in regressions.

When examining the effect of policy on premiums, it is desirable to create weights based upon enrollment in those plans. This will ensure that plans that are rarely or never purchased do not hold equal influence over results as those that are bought frequently. Since premiums are priced at a rating area level, it would be ideal to have the enrollment of each plan in each rating area. However, this information is not available. Instead, I construct *estimated* enrollment frequencies based upon state-plan level enrollment and county-issuer level enrollment. This was completed under the assumption that the relative distribution of enrollments among plans provided by an issuer is the same on a state and county level. Since rating areas in most states are groups of full counties, I could then sum estimated county-level enrollment to estimate enrollment in a plan by rating area. Controls for inclusion in the analyses herein could also be created from these data files. On a county-issuer level, demographic breakdowns of enrollment are available. These characteristics include gender, age group, and income relative to the Federal Poverty Level. We can then use this information to control for the demographics of enrollees

[20] Some of these states, including Arkansas, Mississippi, and Utah, run their own Small Group exchange.

Table 3.1. Descriptive Statistics for Premiums of Plans Offered on the Individual ACA Marketplace, 2014-2017

	2014		***2015***		***2016***		***2017***	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Yearly Premium	2496.97	574.20	2631.53	587.92	2843.97	631.93	3468.94	890.78
Prop. Bronze	0.15	0.36	0.20	0.40	0.21	0.40	0.21	0.40
Prop. Silver	0.71	0.46	0.70	0.46	0.72	0.45	0.75	0.43
Prop. Gold	0.09	0.29	0.07	0.25	0.06	0.24	0.03	0.17
Prop. Platinum	0.04	0.20	0.03	0.16	0.01	0.08	0.00	0.05
N	16,901		21,340		18,085		12,089	
Catastrophic Premium	1472.77	341.40	1712.57	305.49	1854.58	370.05	2318.88	446.33
Bronze Premium	2011.45	435.28	2167.22	424.16	2384.20	476.79	3032.15	736.62
Silver Premium	2506.41	465.80	2673.98	475.94	2904.37	528.23	3546.79	842.92
Gold Premium	2993.06	614.27	3214.66	636.48	3595.10	698.50	4578.80	1103.98
Platinum Premium	3309.47	665.79	3792.78	735.42	4737.77	976.43	5987.43	1158.51

Note: All premiums are in dollars paid for a 21-year old non-smoking enrollee for a year of insurance coverage. Calculations are weighted by approximate enrollment on the plan-rating area level.

in a market, specifically by issuer, on either a state or rating area level. Secondary analyses on coverage and cost-sharing use true enrollment numbers, as these are observed on a state-plan level. For a more detailed explanation of the construction of frequency weights and controls, please see Appendix section 3.A.6.

3.2.2 Establishing EHB Changes

Documenting Essential Health Benefit changes is an area rife with difficulties. As such, one of the main contributions of this work is simply documenting these changes. For starters, lists of EHBs are extensive, especially in earlier years. The number of EHBs by state ranges from 34 to 53 in 2014. The EHB lists are also non-uniform. However, by 2017, each essential benefits designated by states comes from a list of 45 EHB categories. As a starting point, I restrict attention to this list for all years, as these will be the relevant EHBs moving forward. I will call these *common essential health benefits*. Furthermore, each of these 45 categories is addressed by every plan in every state and year in the cost and benefit PUFs. This makes changes trackable from year to year, whereas other benefit categories may not be expressed in every year or in all states.

Another problem with establishing EHBs and their evolution over time is the non-uniformity in how EHBs are both established and interpreted. For many essential health benefits, being classified as an EHB by the CMS is somewhat arbitrary. Between states, benchmark plans may have the same verbiage in two states but be classified differently. Take routine foot care for example, one of the 45 common EHBs. In nearly all states, the detailed base-benchmark plan specifies routine foot care for treatment of diabetes or another medically necessary purpose only. Still, states with virtually identical verbiage in their benchmark plan have different EHB classifications by the CMS. This also creates inconsistencies between years within a state, as often EHB classification will change while the verbiage of the benchmark plan remains the same. So, routine foot care is not considered in the analysis. Other benefits apply EHBs somewhat arbitrarily between states but make adjustment of these benefits possible. For example, infertility treatment is considered an EHB in many states where only diagnostic services related to infertility are covered. This differs significantly from the states that offer Artificial Reproductive Technology (ART) such as Invitro Fertilization (IVT). Accordingly, states that only require coverage of diagnostic services seem to allow ”substantially equal” coverage that does *not* cover infertility treatment in any manner. Because of this observation, infertility treatments were examined carefully and recoded to reflect reality more closely.[21]

An additional consideration when looking at EHBs is overlap between benefit categories' coverage. A clear example of this is for Cosmetic Surgery and Reconstructive Surgery. In many states, both Cosmetic Surgery and Reconstructive Surgery are coded as EHBs, though the Cosmetic Surgery EHB specifies that it is only for reconstructive, medically necessary purposes. As a result (along with the fact that Cosmetic Surgery suffers from classification issues mentioned above), these two benefits are combined into one Reconstructive Surgery benefit and analyzed. Nutritional Counseling, Diabetes Education, and Weight Loss Programs are three separate benefit categories, and a combination of any two may represent the same coverage. For example, Georgia's 2017 Weight Loss Program EHB and Nutritional Counseling EHB refer to the same benefit intended to be used to treat morbid obesity, limited at 4 sessions per year. Another form of overlap that occurs is in coverage limitations, where two plans have combined limits. For example, Speech Therapy, Occupational Therapy and Physical Therapy (the latter two of which are grouped together as a single EHB) often have limits on both benefits together. Additionally, these benefits often fall under Outpatient Rehabilitation, a more general EHB category. As a result, I consider these three benefits as one. A state's official EHB package may also cover some "uncommon" benefit that actually reflects common EHB provision. For example, in New Jersey, Private Duty Nursing appears to be an EHB in 2014 and 2017 but not in 2015 and 2016 based upon PUFs. In reality, the 2015 and 2016 plans code "Home Health Care

[21]For the purposes of this paper, Infertility Treatment is henceforth defined as either offering some form of Assisted Reproductive Technology or offering artificial insemination services. Though these are different services with different price points, only one state, Pennsylvania, sees an EHB change involving infertility treatment. Since Pennsylvania's EHB package in 2017 requires coverage of artificial insemination, this is how this benefit can be thought of.

Services" as an EHB, which represents the same coverage[22].

Other overlaps that exist between benefits, though less systematic, need to also be considered. For this iteration of this project, I do not consider an EHB upheaval to have occured if prior EHB summaries included such a benefit in their covered benefits. Often times services such as chemotherapy, radiation, and hemodialysis are covered under outpatient services or primary care visits in early year documents, but not classified as EHB. Even more common is prosthetic devices; only nine states classified this as EHB in 2014, but 34 states did so by 2017. Still, prosthetic devices was covered by many states explicitly under Durable Medical Equipment, which has been an EHB in all states and years.

Besides various inconsistencies and peculiarities in the establishment of EHB, it is also important to consider state mandated benefits in tandem with them. To demonstrate this, consider Diabetes Care Management mandates which exist in 32 of the 35 states studied here. Though these mandates vary by state, each covers some combination of education, nutritional counseling, diabetic equipment and supplies, and routine foot care. Thus, new classification of EHB in these categories may not in fact be a requirement increase for plans. This relationship between EHB and mandates also can be seen between EHB requirements for cosmetic surgery and state mandates requiring coverage for cleft palate and other congenital anomalies.

Another situation that arises is new classification of EHB that simply represent coverage that is required under federal law. The most extreme example of this is coverage of Well Baby Visits and Care. In 2014, this benefit was classified as EHB by zero states (though some have it mandated in state law). By 2017, all 35 states classify this benefit as an EHB. Still, this is a reflection of requirements under that ACA that apply to all plans, namely that preventive services must be covered by all plans with no cost sharing requirements on behalf of the policyholder. These include over 30 different services for children and babies. This requirement pre-dates the timeframe of this study and were one of the first pieces of the ACA that were implemented in late 2010. These preventive services also cover adults, and include intensive behavioral counseling

[22]Most states' Private-Duty Nursing EHBs *only* cover this benefit when provided at home.

for obese individuals and those at risk for diabetes and cardiovascular disease. As a result, states with Nutritional Counseling EHB that only cover these services do not have requirements beyond what all plans must cover. Another example of this which pre-dates the ACA is coverage of breast reconstructive surgery, which is required by the Women's Health and Cancer Rights Act of 1998, requiring all individual and group health plans to cover all stages of breast reconstruction, prosthetics, and treatment for any complications arising as a result of a mastectomy. Thus, some Reconstructive Surgery EHB upheavals do not present requirements above this. For a more detailed discussion of the work done to define EHB changes, see the Data Appendix.

A final project-relevant consideration is that not all EHB changes will affect coverage: sometimes, all offered plans in a market already offer some benefit, even before it is an EHB. I define a *binding change* to be one that can affect coverage. In other words, a binding benefit increase is one in which a plan begins with imperfect adherence and results in perfect adherence, as a direct result of the policy change. Binding decreases, however, apply for all declassifications in EHB, as plans have an option to change. This provides an opportunity to examine the assymetry in these changes, which will be discussed further. In an ideal situation, to see the average effect of requiring benefit coverage, a state would transition from zero plans to all plans offering a benefit. Unfortunately, this only occurs in one case[23]

A description of 2017 EHB Changes

From 2016 to 2017 there were 31 EHB changes which I consider for this study. This includes ten EHB declassifications (decreases) and 21 *binding* new EHB classifications (increases). This includes a set of 17 unique benefits across 14 of the 35 states in this study. Pennsylvania, who chose a new benchmark plan for the 2017 plan year, had the highest quantity of new EHB classifications with nine. A summary of these EHB changes changes are provided in Table 3.2.

[23] From 2016-2017, an EHB in Pennsylvania is established to cover Infertility Treatment (artificial insemination) where before 2017 no plans covered infertility treatment.

Table 3.2. 2017 Effective Essential Health Benefit Changes: ACA Individual Market

State	# of Changes	EHB Change
Pennsylvania	9	Accidental Dental, Allergy Testing, Chemotherapy, Dialysis, **Infertility Treatment**, Nutritional Counseling, Prosthetic Devices, Radiation Therapy, Transplant Services
Missouri	3	Nutritional Counseling, Temporomandibular Joint Disorder, Routine Foot Care
Wisconsin	3	Chemotherapy, Infusion Therapy, Radiation Therapy
South Carolina	3	-Allergy Testing, -Infusion Therapy, Nutritional Counseling
Georgia	2	Cosmetic Surgery, Nutritional Counseling
Wyoming	2	-Allergy Testing, -Infusion Therapy
Arkansas	1	-Dialysis
Iowa	1	-Nutritional Counseling
Illinois	1	Infusion Therapy
Indiana	1	Nutritional Counseling
Mississippi	1	-Urgent Care Facilities
Montana	1	-Weight Loss Programs
New Jersey	1	**Allergy Testing**
New Mexico	1	-Weight Loss Programs
Oklahoma	1	-Bariatric Surgery

Note: Bold text indicates that an EHB innovation caused all plans in a market to enhance coverage. Benefits with a - are EHB declassifications (decreases).

3.3 A Brief Theoretical Treatment of EHB

To examine the possible incidence of EHB changes on plans within a market, consider a single plan offered in a regulated market with perfect competition such that there are no profits; premiums are priced such that the total expected premium payments received is equal to total expected claims plus some constant administrative cost. Supposing that the set of plans cover a set of benefits $\mathscr{B}$, which can be partitioned into mandated ($\mathscr{B}^m$) and voluntarily provided ($\mathscr{B}^v$) benefits. Mandated benefits are common to plans provided by all issuers. We can express expected claims as

$$E(\text{claims}) = \sum_{b^m \in \mathscr{B}^m} ((1-c_{b^m})p_{b^m} - i_{b^m})E(Q_{b^m}) + \sum_{b^v \in \mathscr{B}^v} ((1-c_{b^v})p_{b^v} - i_{b^v})E(Q_{b^v}) - E(D(Q|p))$$

,

where p_b is the price of receiving some medical good or service, c_b is the proportion of the payment that the member is responsible for paying (coinsurance), and i_b is a flat fee that a member must pay to receive the service (copay). The expected quantity demanded of some service $E(Q_b)$ depends on the pool of enrollees[24]. Enrollees may also be subject to a deductible for certain services, $D(Q|p)$, which depends on the quantity of services performed given the price of certain services[25].

After providing benefits for a year, $\mathscr{B}^m$ expands to include newly mandated benefit b^n. Suppose first that the above plan does not already cover this benefit voluntarily. *Ceteris paribus*,

[24]More formally, we can write this as $E(Q_b) = \int Q_b(t)dF(t)$, where $Q_b(t)$ is the quantity of service b demanded by type t, and $F(t)$ is the probability distribution of types in the enrollment pool.

[25]The total deductible paid depends on the quantity of all services that are subject to the deductible, as well as the price of those services. Deductible payments are capped at the dollar amount specified in the plan. Two intricacies that are not explicitly captured in the model are worth noting. Firstly, copayment and coinsurance are often functions of whether the deductible has been met yet, depending on the service. Secondly, another element of cost-sharing is the maximum out-of-pocket (MOOP) cost that an enrollee can be liable for. This caps the sum of coinsurance, copay and deductible payments made. These two elements imply that order of service utilization matters, specifically when a deductible has been met but the MOOP threshold has not. Including these in the model should not affect predictions.

this change would increase the total number of claims that the issuer must process, which would increase the premium charged for the plan to ensure that the no profit condition continues to hold. Still, the issuer may adjust on other margins as to partially or wholly mitigate the effect on premiums. One option is to adjust cost-sharing that the beneficiary is responsible for with respect to existing benefits, whether that be coinsurance or copayment rates, or characteristics of the deductible, such as its limit and applicability to various benefits. Issuers could instead "skimp" on voluntarily-provided benefits by reducing the set $\mathscr{B}^v$.

Suppose alternatively that a firm already provides $b^n \in \mathscr{B}^v$ prior to the mandate passage. If there are other issuers in the market that do not do the same, then the pool of enrollees in that plan may be adversely selected. Requiring coverage by all plans may, then, augment the distribution of enrollees and decrease premiums in these plans. On the other side of this, plans that are newly bound to the mandate may receive more high-risk individuals. Thus, the differential effect between these two plan types is of interest.

There are a few other possible predictions that come from this model. For one, mandating benefit coverage may affect health insurer's ability to negotiate low prices with providers. This upward pressure on prices would exacerbate the above marginal adjustments by non-covering issuers, and also would affect issuers that already provide the coverage for the benefit. Provision of these benefits may also affect quantity demanded of certain goods and services. This benefit may experience excessive demand due to introduction of coverage (moral hazard); alternatively, positive externalities may be created, causing individuals to have less demand for other benefits in the near or distant future. This, of course, depends on the elasticity of demand of the good's marginal user. These demand-based margins are more difficult to test empirically without utilization data.

3.4 Empirical Methodology:

Premiums

Due to modified community rating in the ACA markets, the insurance premium of each plan within a state may only vary by the age of the enrollee and the ratings area within which it is offered. Because all ages' premiums are a pre-determined factor multiplied by a 21 year old's premium, I use this measure, logged, as my outcome variable[26]. Thus, each observation is at a plan-ratings area level. Consider the following regression:

$$Y_{j,r,s,t} = \alpha_t + \gamma_s + \beta T_{s,t} + \lambda X_{j,s,t} + \varepsilon_{j,r,s,t}, \tag{3.1}$$

where $Y_{j,r,s,t}$ is the logged monthly premium for a 21 year old policy holder with plan j in rating area r, state s,and year t. Year fixed effects, α_t, control for premium-determining factors across time that are common across states. State fixed effects, γ_s, control for time-invariant premium-determining factors within states. An alternative specification will use ratings area fixed effects instead. Our control vector, $X_{j,s,t}$ includes indicators for metal level (Platinum, Gold, Silver, Bronze, or Catastrophic), plan type (HMO, PPO, EPO, POS), and Medicaid Expansion status of the state. In estimating the model, I use estimated frequency weights, which are defined for each observation.

Our policy variable of interest, $T_{s,t}$, is a measure of state-mandated benefits in state s and year t. For the base analysis, we consider two policy measures. Because EHB changes that affect coverage are of interest, both measures reflect the intensity of binding changes. The first treatment that I use is simply the cumulative net number of binding EHB changes that has occurred. EHB adjustments are reflected in this number for (1) any EHB increase that did not have 100% coverage prior to the policy change and (2) any EHB decrease. The second policy measure reflects the intensity of treatment: specifically, it is the gross proportion of plans in the state that adjusted coverage as a result of the policy change[27]. This helps account for mandate

[26]Since I use logged premiums as my outcome variable, my coefficients can be interpreted in terms of percent increase in premiums. Thus, using 21 year old premiums vs. any other age should not affect the analysis. When interpreting coefficients using premium as the outcome variable, it is necessary to specify that this is for 21 year olds, otherwise a multiplicative factor should be applied.

[27]For example, if a state sees two binding EHB increases, one with prior coverage of 70% of enrollees and the other with prior coverage of 50% of enrollees, then the policy variable will be $T_{s,t} = (1-0.5)+(1-0.7) = 0.8$ in

adjustments that affect a greater or lesser number of enrollees or plans. Results from regressions using both of these policy measures reflect the effect of benefits on market premiums as a whole rather than those plans or issuers which were directly affected. Treatment can also be split into three types: Ambulatory benefits, preventive benefits, and other benefits, to consider whether net changes in EHBs of different types have differential or opposing effects. As with our second policy measure, treatment is defined as the proportion of plans that change due coverage as a direct result of the mandate change. As such, both of these coefficients are interpreted as the market-wide increase in premiums given that all plans were to see such a change in one benefit due to a mandate change. Identification of these results as having causal interpretations relies on the assumption that, on average, plan premiums would evolve similarly from state-to-state regardless of treatment status. The validity of this assumption will be explored in further detail below.

3.4.1 Result of Initial Empirical Model

Table 3.3 shows that net changes in mandated benefits have little effect on the individual health insurance market's premiums. Point estimates of the effect of these mandates on premiums are small (less than 1%) but positive. This may be partially driven by heterogeneity across mandate types, as a one unit increase in preventive services is associated with a decrease in premiums of nearly 13%, while other services are associated with an 11% increase in premiums.

3.4.2 Caveats of the Current Specification

Subject to identification assumptions described above, we can interpret our coefficients as the effect of adding or removing each EHB (which may affect coverage) on average monthly premium paid by a consumer in the individual market. This provides a general idea of the result of changing EHBs on prices in the individual insurance market. However, there are a few properties of the policy environment that create problems with these approaches. Firstly,

the year 2017.

Table 3.3. Effect of Mandating Benefits on Plan Premiums; Basic Specification, 2016 to 2017

	(1) Log(Yearly Premium)	(2) Log(Yearly Premium)	(3) Log(Yearly Premium)
EHB Change	0.00516	0.00792	
	(0.0077)	(0.0360)	
Ambulatory			0.00903
			(0.0239)
Preventive			-0.127***
			(0.0432)
Other			0.110**
			(0.0458)
Observations	30,174	30,174	30,174
R-Squared	0.621	0.621	0.632
Fixed Effects	State & Year	State & Year	State & Year
Year	2016-2017	2016-2017	2016-2017

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the state level. Control variables for these regressions include dummies for metal tier(platinum, gold, silver, bronze, or catastrophic), plan type (HMO, PPO, EPO, or POS), and medicaid expansion status. Regressions absorb state and year fixed effects. Column (1) measures the effect of any binding EHB change on plans premiums within an affected market. Column (2) does the same, using an intensity measure (cumulative proportion of plans that changed) rather than a count. Column (3) uses number of changes categorized as ambulatory services, preventive services, and other services.

it is desirable to understand the effects of these changes on plans that were actually required to adjust their coverage. Though the unconditional effect of mandates is of interest, there are some other ways to handle this. Since unaffected individuals' plans are still considered newly treated, and since the proportion of unaffected individuals' plans varies by plan and benefit, the effect of some of these mandates are biased toward zero. It is desirable to exploit the variation in coverage, which drives the ability to consider the "bindingness" of these changes, more directly in my empirical specification.

Secondly, there is an inherent asymmetry between an EHB increase and an EHB decrease. When we consider an EHB increase, we are either in a situation where no plans are required to adjust (because coverage is already provided by all plans in the previous period) or some (or all) plans are required to adjust coverage upwards. The latter is considered a binding EHB increase. When we consider an EHB decrease, though, issuers are not required to adjust coverage. Instead, a requirement that was previously in place is eased. When looking at binding EHB changes, then, declassification of some EHB where issuers do not reduce coverage may cause results to be even more biased toward zero. Using the intensity measure takes care of some of this, and issuers select into non-coverage in similar ways. Still, reducing one's plan benefits after providing it is an inherently different decision than not providing it prior to a mandate passage. Disentangling upward and downward EHB movements is thus necessary for fully capturing these EHB changes, especially if they have differential effects.

An additional problem with the above specification is the usual "parallel trends" assumption, that each states' prices will evolve similarly, conditional on the covariates in the regression, in the absence of the policy change. Although I control for Medicaid Expansion status above, other time-varying characteristics likely affect the trajectory of prices in these states. Even if including time-varying controls, I cannot ensure that these differences are fully accounted for. Furthermore, by measuring premiums across the entire market, the model allows for measurements of premiums of insurance issuers that have both entered and exited the markets between 2016 and 2017. Entrance/exits among issuers whose characteristics differ from those who remain in both periods may bias results in either direction. Thus, a panel structure is desirable to mitigate this possibility.

3.4.3 Alternate Specification

According to the analysis PUFs, issuers in the ACA marketplace generally do not vary benefit coverage across plans within a state, especially those which may be classified as an EHB. Instead, either all of the plans or none of the plans that they offer tend to cover some benefit category. Because of this, we can exploit within-state variation between issuers who are forced to change coverage by treatment, and those who are not. Though one potential approach is to look specifically at how plans adjust their coverage, there is a great deal of new and discontinued plans in each year, even among issuers that do not enter or exit the market. As issuers may significantly adjust their offered benefits (by both adding and removing plans), a reasonable outcome to track over time is the average premium paid by enrollees to hold a plan from an issuer within a specific metal tier. Thus, I employ a longitudinal regression by restricting analysis to issuers that offer some metal tier in both periods of analysis. Define treatment variable $T^{b,1}_{i,s,t}$ as equaling one when a benefit is newly mandated in state s and time t such that issuer i must now cover the benefit. Similarly, define treatment variable $T^{b,2}_{i,s,t}$ as equaling one when issuer i in state s and time t reduce their coverage of a benefit whose EHB provision has been rolled back. Consider, then, the following panel regression:

$$Y_{i,m,s,t} = \alpha_t + \theta_{s,t} + \gamma_{i,m,s} + \sum_{b \in B} [\beta_1 T^{b,1}_{i,s,t} + \beta_2 T^{b,2}_{i,s,t}] + \varepsilon_{i,m,s,t} \tag{3.2}$$

Here, I again include time fixed effects α_t. Instead of state fixed effects, I instead us issuer-metal level fixed effects ($\gamma_{i,m,s}$), which account for non-time varying factors that affect prices of an issuers' metal-specific plan offerings. This pinpoints variation in specific plan offering types while still allowing for the introduction of additional plans (or removal of plans) within a metal tier by an insurance issuer. I also include $\theta_{s,t}$, which is either an indicator for

Medicaid expansion status or a time-by-state fixed effect. Including a time-by-state fixed effect controls for time varying shocks to state healthcare markets that were not accounted for in the previous specification; comparing this with only the use of state Medicaid expansion status provides a reference for possible biases in our initial model related to state specific shocks that could not be adequately captured.

Our first coefficients of interest, β_1, gives us the effect of being compelled by law to cover a new benefit on an insurance issuer's plan premiums. Our second coefficient of interest β_2, provides the effect of selectively not providing a newly declassified previous mandate. Note that treatment variables can only be zero or one, and that the sum of these over all benefits provides for the number of benefits they are newly required to provide (and the number of benefits that they selectively no longer provide).

This empirical strategy provides a few advantages to my initial approach. The first problem above is addressed, as premiums of plans that are not forced to change are now treated as counterfactual premiums rather than treated ones. Additionally, EHB decreases and increases are differentiated and can be interpreted separately. Finally, by restricting the analysis to issuer-metal tiers that are offered in both periods, and adding both state-time and issuer-metal tier fixed effects, I pinpoint changes in premiums of plan offerings while relying on a more realistic assumption that plans within a state (rather than across states) will vary similarly over time in the absence of the policy change[28].

The adjustments made to our model also change the interpretation of results. These results are conditional upon being enrolled in a plan sold by an issuer who remains in the market in both periods around the policy change. Furthermore, the measured effect is the average differential percent premium increase between issuers who are required to change a benefit and those who are not. Previous results were not measuring the effect of adjusting coverage, but simply being in a state where some plans had to adjust coverage. If adverse selection into plans that previously

[28]One disadvantage to this approach results from the fact that I employ state-by-time fixed effects but many states do not see a policy change for any issuers. Accordingly, they do not provide variation that can be used in the model, and thus are not included in the analysis.

provided coverage is tempered by the policy change, the initial specification would see effects not only dampened by issuers that provide prior coverage, but counteracted (their effect may be negative rather than zero). An additional adjustment to the interpretation is that instead of looking at "net change in EHB provision", we interpret efects of new classifications and declassifications separately.

3.4.4 Results

The results of this model, which is in the spirit of a triple difference approach, indicate that within-state variation provides for more statistically significant estimates. Specifically, binding EHB increases are associated with differential premium increases among plans that newly mandated benefits. While an approximately 2% premium increase occurs across the board for most metal tiers, platinum plans increase at least twice as much, proportionally speaking. EHB decreases, on the other hand, are also associated with premium hikes. However, when time-by-state fixed effects are included, this result disappears. This non-result may indicate that only issuers who expected rising costs for other reasons decided to roll back benefits (in order to curb large increases). This supports the large positive coefficient in columns (1) and (3), as state-time shocks may have induced certain issuers to stop offering certain benefits. By soaking up the variation across states over time with fixed effects, comparisons between plans within a single state show no premium change differential between plans that chose to and chose not to adjust.

3.5 Other Response Margins

Using both specifications above, I repeat the analysis for other possible margins that issuers may adjust with respect to their plan offerings. In this section I examine plan attributes related to cost-sharing, namely deductibles, maximum out-of-pocket payments, and actuarial value. While certain states (e.g. California) require all plans to have fall within a set of pre-

Table 3.4. Effect of Mandating Benefits on Plan Premiums; Panel Specification by Issuer-Metal Level, 2016 to 2017

	(1) Log(Yr Prem)	(2) Log(Yr Prem)	(3) Log(Yr Prem)	(4) Log(Yr Prem)
EHB Increase	0.0271***	0.0159***		
	(0.0073)	(0.0060)		
EHB Increase X Silver			0.0273***	0.0164**
			(0.0074)	(0.0069)
EHB Increase X Bronze			0.0244	0.0184
			(0.0161)	(0.0128)
EHB Increase X Gold			0.0293***	0.0185**
			(0.0074)	(0.0073)
EHB Increase X Plat.			0.104***	0.0421*
			(0.0133)	(0.0217)
EHB Increase X Cat.			0.0207***	0.0133***
			(0.0056)	(0.0049)
EHB Decrease	0.0586***	0.00757		
	(0.0184)	(0.0394)		
EHB Decrease X Silver			0.0420*	-0.00989
			(0.0226)	(0.0394)
EHB Decrease X Bronze			0.0535**	0.00159
			(0.0219)	(0.0390)
EHB Decrease X Gold			0.0809***	0.0290
			(0.0225)	(0.0399)
EHB Decrease X Cat.			0.0612*	0.0111
			(0.0339)	(0.0634)
Observations	960	960	960	960
R-Squared	0.905	0.948	0.904	0.947
Panel Level	Metal-Issuer	Metal-Issuer	Metal-Issuer	Metal-Issuer
Controls	Medicaid	Time X State FE	Medicaid	Time X State FE

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the issuer level. Regressions include fixed effects for year and issuer-metal tier. Columns (1) and (3) use Medicaid Expansion status as a time-varying control, while columns (2) and (4) use time-by-state fixed effects. Columns (1) and (2) shows the differential effect of a binding EHB increase (or decrease) on plan premiums of affected plans compared to non-affected plans. Columns (3) and (4) do the same, but using separate treatment variables for different metal tiers. Units are issuer-metal tiers determined choices for these attributes, most states allow plans to vary plans at their own discretion[29]. Because these plan attributes are consistent across ratings areas, observations for this analysis are on a plan level, rather than a plan-rating area level. This allows us to use true enrollment numbers for weights rather than estimated ones. Positive coefficients from the deductible and MOOP regressions would indicate more cost sharing responsibility on the behalf of the consumer, while the opposite is true for the actuarial value regression. Because catastrophic plans have the maximum allowable deductible and MOOP, as well as no certified actuarial value, they are excluded from this analysis. The other response margin that I would hope to investigate in this section is plan coverage. Based upon my knowledge of the dataset, using a count of coverage among non-mandated benefits (or something similar) as a dependent variable would not be a reliable measure of coverage. This is due to inconsistencies in how non-EHBs are often categorized, and the lack of inclusion of benefits that fall outside of the standardized list of 68. Instead, I leave this as an open question future research.

Results of cost-sharing regressions vary. Our basic specification shows that a binding benefit mandate increase is associated with general decreases in plan deductibles and an increase in actuarial value –both signifying richer plan designs. Effect of net EHB change on maximum out-of-pocket cost has positive yet economically small, insignificant coefficients. There is similarly no consistent result across outcomes when sub-dividing mandate types, though point estimates indicate that "other" benefits are associated with less rich plan designs. When using the panel design, results indicate that binding EHB increases are associated with economically meaningful but statistically marginal deductible increases of $100. Conversely, we see statistically significant maximum out-of-pocket decreases of $78 associated with binding EHB increases. These opposing changes are consistent with no significant change in actuarial value captured. EHB declassifications, on the other hand, are associated large but nonsignificant increases in maximum out-of-pocket costs.

[29]Still, these plans must be in accordance with metal-tier requirements; for example, gold plans must fall between 78% and 82% actuarial value. This allows for the possibility of wiggle room without major changes.

Having mixed results on different cost-sharing margins makes sense in the context of health insurance markets. Having a robust result across three would mean that issuers are consistently adjusting on the same margins; though this is possible, it is just as likely that certain issuers may adjust their deductible while another adjusts their MOOP of plans. This may explain why, for example, point estimates on some treatment variables are relatively large but are not significant at any level due to large standard errors. It is also not unreasonable that different metal tiers of plans have opposite signs: issuers may adjust their plan offerings so that certain tiers of plans become more favorable for consumers with regard to cost sharing (or premiums). What is also possible is that issuers increase deductibles while decreasing maximum out-of-pocket because the deductible affects a large portion of enrollees, while MOOP only affects a small handful, namely those who have very high utilization. Thus, without compromising measured actuarial value, it may be the case that issuers are decreasing their costs of providing plans by shifting the point of medical utilization when cost-sharing begins. Given that plans must remain within a certain range of actuarial values, decreasing marginal issuer costs for early utilization while increasing them for high levels of utilization will decrease overall costs while still partially offsetting actuarial value increases.

3.6 Discussion

I present a few additional caveats that call for future research on Essential Health Benefits. Firstly, there are frequent discrepancies between EHB summaries provided by the CMS and base-benchmark plans. This follows from the fact that EHB classification changed in 2015 despite base-benchmark plans remaining steady. However, the issue is more serious than this: often times, EHB changes move in opposite directions from how the base-benchmark plan moves. For example, the base-benchmark plan for DE's 2014-2016 plans explicitly covers nutritional

Table 3.5A. Effect of Mandating Benefits on Deductibles: Basic Specification, 2016 to 2017

	(1) Deductible	(2) Deductible	(3) Deductible
EHB Change	-55.25**	-196.4	
	(24.4653)	(133.2416)	
Ambulatory			55.23
			(60.3101)
Preventive			-22.18
			(196.2863)
Other			-249.6
			(206.3493)
Observations	6,231	6,231	6,231
R-Squared	0.574	0.574	0.575
Fixed Effects	State & Year	State & Year	State & Year
Year	2016-2017	2016-2017	2016-2017

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the state level. Control variables for these regressions include dummies for metal tier(platinum, gold, silver, or bronze; catastrophic is disincluded), plan type (HMO, PPO, EPO, or POS), and medicaid expansion status. Regressions absorb state and year fixed effects. Column (1) measures the effect of any binding EHB change on plans' deductibles within an affected market. Column (2) does the same, using an intensity measure (cumulative proportion of plans that changed) rather than a count. Column (3) uses number of changes categorized as ambulatory services, preventive services, and other services.

Table 3.5B. Effect of Mandating Benefits on Plan Deductibles: Panel Specification by Issuer-Metal Level, 2016 to 2017

	(1) Deductible	(2) Deductible	(3) Deductible	(4) Deductible
EHB Increase	49.01	106.2*		
	(64.0799)	(62.7418)		
EHB Increase X Silver			61.04	99.49*
			(59.3713)	(53.2383)
EHB Increase X Bronze			16.49	112.3
			(56.1058)	(82.0568)
EHB Increase X Gold			58.90	97.36
			(84.9029)	(81.5980)
EHB Increase X Platinum			-184.0***	-197.6
			(45.6896)	(135.3737)
EHB Decrease	163.5	8.021		
	(178.6875)	(166.1863)		
EHB Decrease X Silver			29.43	-122.9
			(291.1039)	(287.1861)
EHB Decrease X Bronze			554.7**	402.4
			(279.1711)	(283.9141)
EHB Decrease X Gold			-103.0	-255.4
			(225.8016)	(219.9312)
Observations	816	816	816	816
R-Squared	0.962	0.960	0.962	0.960
Panel Level	Metal-Issuer	Metal-Issuer	Metal-Issuer	Metal-Issuer
Controls	Medicaid	Time X State FE	Medicaid	Time X State FE

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the issuer-state level. Regressions include fixed effects for year and issuer-metal tier. Columns (1) and (3) use Medicaid Expansion status as a time-varying control, while columns (2) and (4) use time-by-state fixed effects. Columns (1) and (2) shows the differential effect of a binding EHB increase (or decrease) on plan deductibles of affected plans compared to non-affected plans. Columns (3) and (4) do the same, but using separate treatment variables for different metal tiers.

Table 3.6A. Effect of Mandating Benefits on Maximum Out-of-Pocket Costs: Basic Specification, 2016 to 2017

	(1) MOOP	(2) MOOP	(3) MOOP
EHB Change	5.993 (7.0985)	10.83 (37.2298)	
Ambulatory			41.25*** (14.8471)
Preventive			-39.48 (87.6787)
Other			-3.971 (82.3951)
Observations	6,231	6,231	6,231
R-Squared	0.415	0.415	0.415
Fixed Effects	State & Year	State & Year	State & Year
Year	2016-2017	2016-2017	2016-2017

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the state level. Control variables for these regressions include dummies for metal tier(platinum, gold, silver, bronze, or catastrophic), plan type (HMO, PPO, EPO, or POS), and medicaid expansion status. Regressions absorb state and year fixed effects. Column (1) measures the effect of any binding EHB change on plans' maximum out-of-pocket costs within an affected market. Column (2) does the same, using an intensity measure (cumulative proportion of plans that changed) rather than a count. Column (3) uses number of changes categorized as ambulatory services, preventive services, and other services.

Table 3.6B. Effect of Mandating Benefits on Plan Maximum Out-of-Pocket Costs: Panel Specification by Issuer-Metal Level, 2016 to 2017

	(1) MOOP	(2) MOOP	(3) MOOP	(4) MOOP
EHB Increase	-27.93	-78.22***		
	(18.4186)	(29.8340)		
EHB Increase X Silver			39.47*	-10.70
			(23.1465)	(47.3909)
EHB Increase X Bronze			-118.0***	-206.9***
			(25.4641)	(64.9591)
EHB Increase X Gold			-64.82	-115.0***
			(55.7932)	(40.3756)
EHB Increase X Platinum			62.41	-53.05
			(179.6736)	(223.2628)
EHB Decrease	50.07	314.4		
	(224.9267)	(231.1654)		
EHB Decrease X Silver			88.98	355.4
			(233.6787)	(257.0131)
EHB Decrease X Bronze			-211.3***	55.06
			(58.6428)	(144.1876)
EHB Decrease X Gold			266.5	532.8
			(487.1915)	(479.6369)
Observations	816	816	816	816
R-Squared	0.887	0.877	0.887	0.877
Panel Level	Metal-Issuer	Metal-Issuer	Metal-Issuer	Metal-Issuer
Controls	Medicaid	Time X State FE	Medicaid	Time X State FE

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the issuer-state level. Regressions include fixed effects for year and issuer-metal tier. Columns (1) and (3) use Medicaid Expansion status as a time-varying control, while columns (2) and (4) use time-by-state fixed effects. Columns (1) and (2) shows the differential effect of a binding EHB increase (or decrease) on plan maximum out-of-pocket costs of affected plans compared to non-affected plans. Columns (3) and (4) do the same, but using separate treatment variables for different metal tiers.

Table 3.7A. Effect of Mandating Benefits on Actuarial Value: Basic Specification, 2016 to 2017

	(1) Act. Value	(2) Act. Value	(3) Act. Value
EHB Change	0.000587***	0.00129	
	(0.0002)	(0.0013)	
Ambulatory			0.000341
			(0.0008)
Preventive			-0.000471
			(0.0018)
Other			0.00178
			(0.0019)
Observations	6,231	6,231	6,231
R-Squared	0.942	0.942	0.942
Fixed Effects	State & Year	State & Year	State & Year
Year	2016-2017	2016-2017	2016-2017

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the state level. Control variables for these regressions include dummies for metal tier(platinum, gold, silver, bronze, or catastrophic), plan type (HMO, PPO, EPO, or POS), and medicaid expansion status. Regressions absorb state and year fixed effects. Column (1) measures the effect of any binding EHB change on plans' actuarial value within an affected market. Column (2) does the same, using an intensity measure (cumulative proportion of plans that changed) rather than a count. Column (3) uses number of changes categorized as ambulatory services, preventive services, and other services.

Table 3.7B. Effect of Mandating Benefits on Plan Actuarial Value: Panel Specification by Issuer-Metal Level, 2016 to 2017

	(1) Act. Value	(2) Act. Value	(3) Act. Value	(4) Act. Value
EHB Increase	-0.000519	-0.000405		
	(0.0004)	(0.0004)		
EHB Increase X Silver			-0.000261	-0.0000529
			(0.0004)	(0.0004)
EHB Increase X Bronze			0.00105	0.00109
			(0.0007)	(0.0008)
EHB Increase X Gold			-0.00130**	-0.00109**
			(0.0006)	(0.0005)
EHB Increase X Platinum			-0.00226	-0.000181
			(0.0020)	(0.0031)
EHB Decrease	0.00128	-0.00378		
	(0.0019)	(0.0031)		
EHB Decrease X Silver			0.00372	-0.00137
			(0.0056)	(0.0062)
EHB Decrease X Bronze			0.00359**	-0.00151
			(0.0016)	(0.0030)
EHB Decrease X Gold			-0.00336	-0.00845**
			(0.0027)	(0.0036)
Observations	816	816	816	816
R-Squared	0.994	0.994	0.994	0.994
Panel Level	Metal-Issuer	Metal-Issuer	Metal-Issuer	Metal-Issuer
Controls	Medicaid	Time X State FE	Medicaid	Time X State FE

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors are clustered at the issuer-state level. Regressions include fixed effects for year and issuer-metal tier. Columns (1) and (3) use Medicaid Expansion status as a time-varying control, while columns (2) and (4) use time-by-state fixed effects. Columns (1) and (2) shows the differential effect of a binding EHB increase (or decrease) on plan actuarial value of affected plans compared to non-affected plans. Columns (3) and (4) do the same, but using separate treatment variables for different metal tiers.

counseling for illnesses including diabetes, malnutrition, eating disorders and cardiovascular disease. The base-benchmark plan that applies to the 2017 plan year, which is from the same issuer (and thus in the same format) removes this provision. Still, CMS EHB classification of nutritional counseling becomes newly classified as an EHB in 2017.

Because of the restrictive nature of the standardized list of possible EHB benefits, it is also possible that innovations to EHB that some states enforce are not at all reflected in CMS documents. A prime example of this is in the state of Alabama. Between 2014 and 2017, Alabama kept the same base-benchmark plan. When looking over these documents, the only change to the base benchmark plan is the addition of coverage of Occupational Therapy for children ages two to nine. Though this adjustment is nowhere to be found in CMS summaries, Blue Cross Blue Shield provides this benefit for the first time in the individual market beginning in 2017. Measured changes to CMS documents, then, may miss high-cost or otherwise substantial EHB increases that are not necessarily discussed in summaries.

These sorts of issues will likely require official documentation requests from states. Based upon early conversations with the Life & Health Oversight Manager of the Arizona Department of Insurance and Financial Institutions (DIFI), I would have concluded that Arizona's handful of EHB shifts between 2014 and 2015 were not true changes in policy or enforcement. Specifically, I was informed that "the Arizona Department of Insurance and Financial Institutions... enforces compliance with the state benchmark, not the state summary, so our review of plans for compliance with the benchmark would not have changed based on the change to the CMS summary." However, when browsing through Arizona's SERFF public filing system, I came across official EHB checklists created and used by the state of Arizona. These checklists change from 2014 to 2015, specifically mirroring the changes made to the EHB summaries. This indicates that it is possible that some states use CMS summaries at least in some capacity to decide EHB requirement enforcement, which means that 2014 to 2015 could in fact be a policy change year. Further, it nudges me toward filing for official documents, as discussion with state employees may result in inaccurate information.

These three examples illustrate discrepancies between state and CMS classification, and clearly necessitate a state-by-state understanding of procedure regarding EHB enforcement in future works. While documents for states like Arizona may be available publicly, this will require further digging and potentially FOIA requests in other states. Still, regardless of the state-by-state variation in interpretation of EHB changes, the results on the 2017 EHB changes is noteworthy, as significant changes are well-identified.

3.7 Conclusion

In closing, this paper provides a needed investigation into the effects of benefit mandates in the individual markets in the landscape of the Patient Protection and Affordable Care Act. Firstly, in response to binding EHB increases, issuers appear to adjust on various margins, including both increasing premiums[30] and shifting consumer cost sharing toward early utilization. On the other hand, issuers do not appear to adjust financial characteristics of plans as a result of rolling back newly rolled-back mandates. Given the inconclusive results on the analysis of the markets as a whole, it is clear that coverage data enhances the ability of econometricians to evaluate the effect of these premium increases on plans that are newly bound to these mandate upheavals.

The clear path forward for future work on Essential Health Benefits involves finding official sources in order to confirm state-by-state variation in EHB requirements. Once true enforcement of EHB statutes is established, this analysis can be conducted more confidently. Using public SERFF filings, one may also be able to confirm coverage of various benefits and continue to exploit both between state and within state variation in benefit requirements and benefit coverage, respectively. Still, based upon my work, I've found that summaries of coverage are not necessarily all-encompassing, and are not always fully informative. Given that all

[30]Based upon the dataset at hand, it is unclear to what extent this premium shift is due to an increase in costs associated purely with benefit additions and how much can be attributed to differential changes in adverse selection. Given that plans that previously provided these newly mandated benefits may have disproportionately contained enrollees who needed this coverage, the coverage shift may have reduced this disparity. I leave this analysis of decomposing the premium shift to future works on the topic.

newly mandated benefits under the ACA are to be govern installed as Essential Health Benefits, including recent updates by Illinois (2020), South Dakota (2021), Michigan (2022), New Mexico (2022), Oregon (2022), and Colorado (2023), as well as planned changes in Vermont (2024), North Dakota (2025), and Virginia (2025), state insurance departments who make this decision may be interested in possible outcomes associated with these changes.

Still, future work to solidify our understanding of the impacts and bite of EHB changes is necessary. A few other pieces will be crucial to the success of future work on this topic. Three years ago, I submitted a FOIA request to the CMS regarding the selection of EHB benchmarks for the 2017 plan year. In 2014, many states defaulted in their benchmark plan selection; this information is available online through the National Conference of State Legislatures (NCSL). However, this information is *not* available for 2017 (though I know through communication with states that Alaska, for example, defaulted for their 2017 benchmark). Information on this selection can reflect the nature of this variation: if a state chose a certain benefits package, it may have done so with the intention of providing specific benefits or innovating plan designs. If the state instead defaulted, this change may be more plausibly exogenous.

Chapter 3, in full is currently being prepared for submission for publication of the material. Hall, Zachary. The dissertation author was the primary investigator and author of this material.

3.A Chapter 3 Appendix

3.A.1 Description of Rating Areas

As mentioned in the text, states are partitioned into rating areas within which the price of a plan must be the same. Some states opted to have their whole state be a single rating area, while Florida created one rating area per county for a total of 67. Most other states in this analysis, besides Alaska, use combinations of full counties to form its rating areas. Alaska, on the other hand, uses 3 digit zip code groupings, meaning that individuals who live in zip codes that share the first three digits (e.g. ”995” in zip code 99503) are in the same rating area. This means that some counties are split between rating areas.

In order to have these rating areas in usable form, it was necessary to have each FIPS five-digit county code classified by rating area. I first went through the CMS website to obtain the makeup of each rating area by county name for each state. I then cross-referenced these names with a FIPS county code file. In dealing with Alaska, a zip code-county file is matched with a zip-code population file in order to establish the proportion of individuals in each county that live in each rating area. These proportions are then used when calculating both plan-area frequencies and market controls for Alaska.

3.A.2 Essential Health Benefits and Other State Mandated Benefits

Essential Health Benefits are medical benefit categories that are required by law to be covered by all non-grandfathered plans offered in the small group (fewer than 50 employees) and individual insurance markets under the Affordable Care Act. While state mandated benefits pre-date the ACA, the introduction of EHBs created a considerable upheaval in the quantity thereof. Any analysis of the effects of changes to Essential Health Benefits requires careful documentation of state mandated benefits for a handful of reasons. This portion of the data appendix documents the decisions made with the raw data at hand in order to standardize information and accurately measure EHB levels in an attempt to accurately capture policy variation over time. Establishing what is required by law requires attention to detail and an analysis of the EHB package as a whole, along with the mandates that precede these EHBs. Editing raw plan benefit data for inconsistencies is also necessary, especially if one wants to discuss non-EHB benefit coverage. The purpose of this appendix is to explain work that was done to create understanding of benefit requirement changes. Researchers on the topic should use this as a starting point for any improvements on the research community's understanding of EHB benefits.

The Center for Medicare and Medicaid Services (CMS) provides information on state Essential Health Benefit packages on their website, including each state's EHB summary. These summaries list benefits with their EHB status and, given that they are an EHB, any quantitative limits on service, exclusions, and explanations about the extent of the coverage. The provision of EHB is dependent upon these limitations on coverage, "including coverage of benefit amount, duration, and scope." (45 CFR § 156.115) In the time period that this paper covers, there were three separate EHB packages that applied at each time: the first in 2014, the second in 2015 and 2016, and the third in 2017 and 2018. I traced these changes by accessing archived CMS webpages, each with EHB summaries for the package that was required to be covered at the time by Human Health Services (HHS). These changes can also be found by looking at Benefits and Cost Sharing Public Use Files (PUFs) from 2014 to 2018, also provided by the CMS. In each year, this file lists benefits as either "covered" or "not covered" and lists the benefit's EHB classification. These two resources can be cross-referenced in order to confirm EHB packages for each state.

2014 EHB packages

The EHB packages that held for the first calendar year of the U.S. health insurance market under the ACA were first available from the CMS in November of 2012, in tandem with an official proposed ruling for EHB. The base-benchmark plans upon which EHB packages are based was either submitted by states from the list of candidates by October 1, 2012, or, if the state failed to do so, was defaulted to the largest plan by enrollment in the largest product in the state's small group market (77 Federal Register 70644). Twenty four states, including 22 involved in this study, did not submit plans. Of the states that submitted plans, three chose the state's largest HMO plan, three chose state employee plans, and the remaining 21 states (including DC) chose small group plans, with all but Arkansas, Delaware and Oregon opting for the largest in the state.

Each of the 2014 EHB summaries compiled by the CMS address a list of 45 standard benefits, each of which is listed as either "Covered" or "Not Covered". I call these *core benefits*. Many of these can be classified under the 10 statutory EHB categories (i.e. the categories which *must* be covered by all plans). Also listed within these are benefits which are prohibited from being an EHB, which may in fact be listed as covered. Benefits that were outside of the set of core categories were listed separately under "Other". These other benefits may still fall under the statutory categories. Furthermore, these documents state the base-benchmark plan information, including product and plan name, plan type, and supplemented categories (often pediatric oral and vision). They also describe whether Habilitative Services is included in the benchmark plan and, if not, whether the state established their own definition for Habilitative Services.

The 2014 PUF mostly reflects the same set of benefits listed as EHBs. All core benefits are addressed by all plans in all states and continue to be in all subsequent years[31]. An additional set of benefits are also addressed by all plans in all states and all years. These non-core and core benefits together make up what I call the *standardized set of common benefits*. In 2014, only common benefits are listed as EHBs in the PUF. Non-core common benefits intersect with many, but not all, of the "other" benefits from the 2014 EHB summaries. As a result, some benefits listed as EHBs in 2014 summaries are not in the PUFs. In addition, benefits are also classified as being state-mandated or not. As a rule, state-mandated benefits are not automatically listed as EHBs in 2014, unless they have been classified as such in the EHB package. This means that many non-core and non-common benefits are classified as state-mandated benefits but not EHBs – *all* non-common benefits will be classified in this manner if mandated by the state prior to the

[31]The exception to this is Non-Emergency Care When Traveling Outside the U.S., which was removed as an EHB by all states in 2015 and addressed by no plans starting in 2017.

ACA's passage. These mandated benefits, most of which are cited in law in specific documents (discussed later), along with EHBs, define benefits that must be covered by all plans.

2015-2016 EHB packages

A revision to the listed Essential Health Benefits for each state was posted to the CMS website on June 19, 2014. Sent out to issuers in May of that year, these documents list "corrections" to EHB packages, which may have been identified by the state, the CMS, or both. As opposed to previous packages which only listed the 45 core benefits, *all* EHB summaries list all common benefits, regardless of whether or not they are covered. Additionally, state-mandated benefits are now listed as EHB. This differs from the previous practice, which only listed common benefits as EHBs. As a result, the list of EHBs in the 2015 and 2016 plan years are more expansive than those from 2014, and all state-mandated benefits, regardless of their origin, are listed as EHB. Essential Health Benefit information from PUFs match these summaries, although EHBs in the 2015 file reflect 2014 EHB requirements.

2017-2018 EHB packages

A further change in mandated benefits occurred beginning in the 2017 plan year. For this, states were asked to submit another EHB package so that they could adjust from their previous choice if necessary. The choices were the same, but were to be chosen from a set of candidate plans from 2014 rather than 2012. Unfortunately, unlike with 2014-2016 base-benchmark plans, I have been unable to obtain whether each state chose a new plan, kept their old one, or specifically whether they defaulted in their plan choice[32]. Still, we can obtain the plan type and plan name from product documents, which may inform whether a change was made[33]. Unfortunately,

[32]During the course of my research I have contacted several states to ask about the nature of their EHB changes. The state of Alaska informed me that they defaulted to the largest small group plan in the state in both decision periods. No other states have responded to this question. I also have found from a document released from Michigan that they chose the same plan as before (largest HMO/largest small group plan), and that it differed slightly from the previous plan in 5 categories. Still, these are all clarifications of coverage in certain categories.

[33]One inconsistency that I have been unable to reconcile is in the CMS' listing of the states that submitted changes to their base-benchmark plans for the 2017 plan year before the deadline of September 30, 2015. This says that 19 states, including 15 from this study, submitted changes to their EHB-benchmark plan summary documents. Still, some of these states' corresponding EHB summaries do not show changes, and other states that have clear changes (including Pennsylvania) are not listed.

knowing whether any change was made to the underlying plan is more difficult, and some of these plan changes are not conclusive by looking at plan name alone. As a result, the nature of observed EHB changes (e.g. whether or not the EHBs were changed as a result of a state's choice) are not necessarily fully known.

Benchmark plan summaries are again more expansive than 2014, listing all common benefits. However, these are the only listed benefits; state-mandated benefits that are not reflected in the common benefits are no longer listed as EHB. In fact, they are also not listed as mandated in the PUFs, as a "state mandate" column is not included in PUFs for years 2017 and on. Thus, EHB packages are seemingly less rich, as they include a set of fewer benefits. Moreover, we cannot use a combination of PUFs and EHB benchmark summaries to determine mandated benefits, and must refer back to previous years for these mandates.

3.A.3 State Mandated Benefits

While Essential Health Benefits are newly mandated benefits under the ACA which vary by state, states have been legislating benefit mandates for years. Gruber (1994) notes that the total number of state mandates – which also include provider and coverage mandates – grew from two in 1965 to nearly 1000 in 1991. This and other papers on state mandates, including Kowalski et al. (2008) and Bailey (2014), use a document of mandated benefits compiled by Blue Cross Blue Shield Association of America (BCBS) from various years. While I was unable to obtain this document from BCBS, I did receive a copy from Legislative Library within the Connecticut Office of Legislative Research, which was released in December 2018. Since 1991, the total number of state mandates, including mandated offerings, has risen to 2,069, about 1,200 of which are benefit mandates. This compilation is particularly helpful as it provides the year that the law was enacted and notes whether a law requires mandated *coverage* or mandated *offering*; only the former is considered in this research project. This document also mentions federal mandates which have been passed, including maternity stay (1996), breast reconstruction (1998), mental health parity (2008), contraceptives (2012) and clinical trials (2014), which are not made clear by other documents[34].

One shortcoming of this source is that it does not specify which plans each mandate applies to. Unlike EHB requirements, which cover all individual and small group plans, some mandates only apply to a select market (individual, small group or large group), managed care type (HMO, PPO, EPO, or POS) or funding arrangement (self-funded or fully insured). Fortunately, mandates for each state are also summarized by the CMS, and are available alongside EHB summaries; this includes a past version from archived web pages. These documents only include benefit mandates. While these documents are in a less standardized form than the BCBS compilation and do not provide year of passage, they provide valuable information, including market applicability (individual vs. group, HMO vs. PPO, etc.) and slightly more detailed explanation of the benefit requirement. Most importantly, they state a citation to the specific law from which the coverage requirement is drawn. These citations are crucial for confirming the true nature of state mandates in law. This can be especially helpful when there is a mismatch between sources[35] or a need for further scrutiny.

For the purposes of this research, state-mandated benefits that are investigated are those listed as required in PUFs. Since we are looking at changes in state mandates over time, and most of these are static, it is not necessary to examine every mandate in extreme detail. Instead, it is crucial to analyze those mandates which may overlap with EHB mandates, as to have a more full and accurate view of the policy environment. It is necessary, then, to deal with the mandates deemed appropriate to be classified as such by the CMS in their PUFs from 2014 to 2016. As noted previously, these non-common benefit categories were classified as EHB in 2015 and 2016, and then removed from EHB requirements starting in 2017. Additionally, PUFs from 2017 and on do not include state mandate status.

The following refers to classification of state mandates in PUFs, which serves as my

[34]Though this summary by BCBS is the most complete compilation of mandates by state, it is by no means exhaustive. As an example, Maine has provider mandates requiring coverage of services provided by dental hygienists and dental therapists. These categories are not mentioned in the BCBS document.

[35]One drawback of these documents is that some states include mandated offerings without noting them as such. Other states either do not include mandated offerings, or note them in the market applicability section.

starting point for establishing state-mandated benefits. For the purposes of this data appendix, I will discuss mandated benefits that apply to all individual health insurance plans, unless otherwise mentioned. In 2014, most common benefits that were mandated by a state were automatically classified as an EHB. Excluding misclassifications and Habilitation Services, all remaining 22 exceptions were in non-core benefits, 19 of which were Reconstructive Surgery mandates. Each of these benefits is classified as an EHB in 2015 and on, and covered by all plans in all periods. Thus, they are treated simply as EHBs in all periods.

Once we have established what I consider our “baseline” measure for each EHB and mandated benefit requirements above, we can record the number and types of mandates within each state, and track changes to Essential Health Benefits packages over time . This understanding of state mandated benefits is what an individual may obtain if they have no further information from EHB benefit packages, state laws, or the interaction thereof than what is described in the PUFs and main information in CMS EHB summaries. However, when one begins to examine benefits as they relate to each other, including how these benefits evolve over time, it becomes clear that more careful examination is necessary to understand the true requirements for healthcare coverage in the state. Then, as a result of careful scrutiny and documentation, actual *requirement changes* to insurance issuers can be used as a treatment variable in research. Without this, estimates will be biased, as many more benefit changes will be documented than are actually creating changes to coverage requirements.

Additional support for further scrutiny comes from seeing how EHBs change over time in various states. For example, all changes that took place for the 2015 plan year that involved “state and CMS-identified corrections to EHB packages” do not reflect a shift in the underlying benchmark plan, but rather either an updated understanding of the benefits covered or a change in interpretation by governing bodies. This may also be the case for many EHB changes in 2017, as many states, including Alaska, Michigan, and Utah, did not submit new plans. This would indicate that the underlying plans did not change, and EHB upheavals may be due to some systematic change in how requirements are documented or something related to a state required benefit.

We can also see a number of peculiarities and trends in both EHB classification status and coverage of certain benefits. Many non-core common benefits, such as well-child care and prosthetic devices, experience large EHB classification boosts, moving from covered by few to covered by (nearly) all states. Meanwhile, other benefits have coverage issues that necessitate further scrutiny. As a summary of what is seen below, eliminating and changing categories is done due to a combination of coverage issues, benefit mandate overlaps, and recognition of systematic changes that do not reflect actual coverage requirement adjustments.

3.A.4 Eliminated Benefit Categories

Dental Benefits

Changes to most dental benefit mandates are not considered in this analysis. This is for a couple of reasons. Firstly, all four common adult dental care benefits, Routine Dental Services (Adult), Basic Dental Care - Adult, Major Dental Care - Adult and Orthodontia - Adult, cannot be classified as EHB pursuant to 45 CFR 156.115. Although orthodontia and routine care are classified by some state as EHB and state mandate, respectively, in 2014, these state's plans did not abide by these mandates by covering these benefits, instead citing "Other Law/Regulation" and often citing the above CFR statute explicitly. By design, these benefits cannot be required to be covered by QHP.

Dental benefits that cover children are dis-included in the study of benefits for entirely separate reasons. These benefits *must* be covered, as pediatric oral services are explicitly required as a statutory EHB, meaning that all EHB packages must include some sort of children's dental. As a result, all states include Dental Check-Up for Children in their EHB packages in all years. Still, of the 175 state-years in the sample, full coverage is provided for this benefit by all plans in only 15 state-years, and covered by no QHPs in 20 state-years. Basic and major dental care for children[36] have similar coverage peculiarities: as EHB classification from 2014 to 2017 grew

[36]Upon examining EHB packages and coverage PUFs, two facts presented themselves: 1) A state has a Basic

from 26 to 34 states, only seven states ever provide full coverage, and generally do so somewhat consistently. Generally, plans cite that a ”Dental Plan Available” as the reason for non-coverage of these EHB – presumably meaning that coverage can be obtained through an add-on dental plans. This same problem occurs for EHB classification and coverage of children’s orthodontia. This lack of bite on medical plans – the plans of interest in relation to the effects of EHB – makes these eight dental benefits uncharacteristic of typical EHB in their effectiveness of mandating direct coverage. As a result, these benefit mandates are not considered.

Non-Emergency Care When Traveling Outside the United States

In 2014, all states’ EHB packages addressed a benefit called Non-Emergency Care When Traveling Outside the United States, and 25 classified it as an EHB. This common core benefit was addressed by all plans in this year. However, in 2015, all states declassified this benefit as an EHB. Starting in 2017, only plans from five states address this benefit, and two states do so from 2018 on. This is the only benefit that began as a common benefit, let alone a core benefit, that is not addressed by all plans in all periods. Even in 2014, when coverage was mandated, only eight states provide coverage in all QHP. This lack of bite and automatic declassification of this benefit preclude it from inclusion in my analysis.

Well Baby Visits and Care

One of the earliest effective provisions of the ACA, coverage of preventive services without cost sharing became required of all non-grandfathered health insurance plans on September 23, 2010. Unlike Essential Health Benefits, this mandate applied to all states and all plans (45 CFR § 147.130), not just those offered in the small group and individual markets. These requirements, including mandates for immunizations and preventive care and screenings, are based upon recommendations from various government entities[37]. Over 30 services for children

children’s dental care mandate if and only if it has one for Major Dental coverage for children, and 2) a plan (in all years) covers basic children’s dental care if and only if it covers major dental care for children. Thus, these can be treated as one benefit and one mandate.

[37]Requirements for “evidence-based items and services”, such as tobacco smoking cessation and obesity screening, are based upon recommendations from the United States Preventive Services Task Force. Requirements for immunizations are based upon recommendations from the Advisory Committee on Immunization Practices of the Centers for Disease Control and Prevention. Preventive care and screenings for infants, children, and adolescents is

and infants are specifically covered[38]; these are known as Well Child Care services.

The most sweeping EHB increase that occurred from 2014 to 2017 occurred in the non-core common benefit Well Baby Visits and Care. In 2014, only one state classified this as an EHB; after 2015, when 14 more states added the benefit, all states had Well Baby Visits and Care as an essential benefit by 2017. Three states, Arkansas, Georgia and Montana, documented that they required "Well Child Care", which is also covered by the preventive services mandate. Thus, paired with information about coverage of preventive services, it is clear that this sweeping EHB upheaval does not reflect a change in requirements that could cause plans to change coverage, but rather a change in the documentation of existing requirements[39]. It is thus unnecessary to consider changes to this EHB among states.

Routine Foot Care

Routine Foot Care is an EHB that must be investigated for entirely different reasons. One of the main problems with this core benefit is the lack of consistency with regard to its classification as an Essential Health Benefit. Detailed summary of benefits (SOB) documents for 2017 EHB base-benchmark plans are available from the same resource as the less detailed EHB summaries. Though we have been unable to obtain prior EHB documents, these SOBs can be instructive in understanding EHB requirements. Most base-benchmark plans include some discussion of "Routine Foot Care", "foot care", or other foot treatment. This is often paired with discussion of some underlying disease, mainly diabetes. If not associated with some specific set of underlying diseases, plans require that the foot care is medically necessary.

A few observations about SOB's discussion of routine foot care is necessary. Firstly, we should note that 19 states in this study have Routine Foot Care as an EHB at some point, but only six do so from 2017 on, and only two states maintain their EHB requirement in all years. As a result, there is a great deal of variation over time with this requirement. Secondly, irregularities

based upon guidelines supported by the Health Resources and Services Administration.

[38]Required services can be found here at https://www.healthcare.gov/preventive-care-children/

[39]It is also not possible that these benchmark plans did not cover Well Child/Baby Care; since these base-benchmark plans come from plan year 2012, they were already required to cover these preventive services.

in EHB summaries make this benefit difficult to understand. For example, many states list the benefit as ”covered” but not an EHB in early years. Other states will list it as not an EHB but still include an explanation mentioning that coverage is provided for individuals with diabetes or for whom it is medically necessary. Finally, nearly all[40] of the 19 states still include some explicit provision of routine foot care in their current 2017 SOBs. This wording often matches previous EHB summaries from when the EHB had been covered. Furthermore, four of the remaining 16 states have verbiage in their SOBs that include medically necessary foot coverage, but this is not reflected in 2017 EHBs, or any other year. There is no discernible difference between the wording of plans in states that do and do not classify Routine Foot Care as an EHB.

This confusion, while apparent to a researcher, may be something that simply implies that EHBs are decided on a state by state basis by those states, and some may interpret a benefit in different ways than others. However, a greater degree of difficulty is added when one discovers that, even in states where Routine Foot Care is required to be covered, it is often not covered by all plans. It appears that issuers may have interpreted these EHBs as not requiring Routine Foot Care coverage. To make things even more difficult, many plans also list Routine Foot Care as “not covered”, but still note that it is covered for individuals with diabetes. As a result of this confusion and inconsistency, I do not consider this benefit in my analysis. While it may be a piece of sometimes expensive diabetes treatment, Routine Foot Care is a relatively low-cost benefit, and hopefully this will not affect results.

Clinical Trials

Clinical Trials are listed as a mandated benefit in the individual market by 16 states in the PUF and SRB documents. This classification misses Texas and Montana, who also mandate coverage in the individual market[41]. Still, this distinction is unimportant in the context of the

[40]The only two exceptions are Oklahoma which only mentions excluding routine foot care for comfort and cosmetic purposes (which could be construed as covering medically-necessary foot care); and South Carolina, whose state guideleines for diabetes care include foot examinations. See https://scdhec.gov/sites/default/files/docs/Health/docs/Guidelines%20for%20Care%20V2%203-23-12.pdf

[41]Texas passed Senate Bill no. 39 in their 81st legistlative session in 2009 to mandate coverage of Phase I - IV clinical trials; Montana did the same, but Montana’s law was likely done in conjunction with the ACA, as a provision that was written into state law in case that the ACA was repealed. This was passed in 2013. Illinois and

ACA, as one provision of the ACA is that QHP must cover Phase I-IV clinical trials related to cancer and other life-threatening diseases if they are approved or funded by a handful of agencies (NIH, CMS, CDC, etc.). Further, issuers may not discriminate based off of clinical trial participation and may not deny routine patient costs[42]. As coverage of clinical trials must be provided by all QHP in all states, the state clinical trials mandates need not be considered. Additionally, only a small portion of plans (in 2017 only) that address Clinical Trials do not cover them. Thus, this is further proof that coverage data on many non-core plans may be inaccurate or at the very least incomplete; those who do not address a benefit may still be covering it.

3.A.5 Overlapping Benefits

Another phenomenon that necessitates deeper examination of benefits is overlap of benefit categories, which are listed below:

Education, Nutritional Counseling and Other Diabetes-related Benefits

A set of benefits which require a great deal of joint attention are those related to the treatment of diabetes. The two common, non-core EHB which relate to this are Diabetes Education and Nutritional Counseling[43]. Diabetes Care Management mandates of some sort exist in 46 states, including 32 of the 35 used in this study[44]. These mandates often cover supplies and equipment, such as insulin and testing strips, as well as prescription drugs to treat diabetes. Furthermore, they may also stipulate coverage of outpatient diabetes self-management programs; this refers to health management or health education programs designed specifically to aid diabetics in navigating their illness. This may also be paired with medical nutrition therapy, provided by a Registered Dietician, for these individuals. These latter benefits respectively coincide with Diabetes Education and Nutritional Counseling, two common, non-core EHBs.

New Hampshire both mandate Clinical Trial coverage in the group market only. Ohio requires Phase II and III coverage, but only for state employees. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3626735/.

[42]This can be found in Section 2709 of the Public Health Service Act.

[43]Core benefits Weight Loss Programs and Bariatric Surgery also may also tie directly to diabetes; however, these two benefits will be discussed in a separate section

[44]AL,ND and OH lack diabetes mandates

These two benefits grew from EHB in five and four states in 2014 to 33 and 26 states in 2017, respectively. A large part of this upheaval is likely due to the overlap of these benefits with the aforementioned mandates. This warrants further investigation.

While neither of these two benefits were classified as mandates in 2014, this was corrected for the following year. Many states reclassified Diabetes Education as a mandate (and thus an EHB); this accounts for a large portion of the EHB increases in this area from 2014 to 2017. Only two states, Arkansas and Texas, classified Nutritional Counseling as mandates for 2015. The standard for mandate classification of Nutritional Counseling was not applied equally across all states. While Texas' diabetes mandate is the most thorough with regards to nutritional therapy for diabetes, Arkansas' is similar to many other states that did not classify Nutritional Counseling as a mandated benefit.

As an EHB, Nutritional Counseling, while narrow as a benefit, may refer to coverage of any assortment of chronic illnesses. These include asthma, COPD, morbid obesity, and gastrointestinal disorders[45]. Nutritional Counseling may also loosely refer to nutritional guidance provided to individuals undergoing home health care or hospice care. Thus, while the extent of a Diabetes Education is more or less subsumed by a Diabetes Care Management mandate[46], the scope of Nutritional Counseling is much greater.

One key in establishing changes in the Nutritional Counseling EHBs is ensuring that a change in requirements has occurred. Yet, USPSTF guidelines (which govern preventive services that must be provided by all health insurance plans in the United States) include "intensive behavioral counseling interventions" in various circumstances[47] As an example of some issues related to this: In 2017, some states newly classified Nutritional Counseling as an EHB, when its only coverage was that which was already mandated. This does not constitute a change in

[45]Other diseases covered under 2017 benchmark plans include, but are not limited to: cardiovascular disease, hypertension, kidney disease, eating disorders, food allergies, hyperlipidemia and cleft palate.

[46]This has a few exceptions, as some Diabetes Education EHBs mention education programs for other diseases, including those described as covered by nutrition programs above.

[47]The United States Preventive Services Task Force recommends counseling for obese individuals ($\geq$ 30 BMI), as well as preventive counseling for those who are at risk for type 2 diabetes and cardiovascular disease. These are thus mandated as covered in all states.

required coverage. This could also hold true for an EHB that only covers nutritional guidance in a home health care setting.

As such, it is necessary to examine these benefits jointly, with specific attention to the content of Diabetes Care Management mandates and Nutritional Counseling EHBs. Since the overlap of these three benefits will generally affect the classification of Nutritional Counseling, it is also worth documenting the content of the mandate, as nutritional counseling in some areas may represent already-covered benefits.

Prosthetic Devices

Between 2014 and 2017, Prosthetic Devices went from classified as an EHB in nine states to an EHB in 34 of the 35 states in this study[48]. In general, the emergence of this core benefit can be attributed to its relationship with another benefit, Durable Medical Equipment (DME). In many benchmark plan SOBs, DME, which usually includes things like walkers and oxygen tanks, is listed alongside, or in conjunction with, prosthetic devices such as prosthetic legs. In fact, many states in early years classified prosthetic device coverage in base-benchmark plans as DME EHBs, possibly since this was a core (default) benefit. This is often listed explicitly in the base-benchmark summary in these early years under *explanation*. This overlap also occurred in classification of mandated benefits, as many prosthetic and orthotic mandates are classified under DME in years 2014 - 2016. Since DME coverage is *always* more expansive than just prosthetic devices (and it is an EHB in all periods in all states), I code the prosthetic device mandate as "yes" if it is explicitly required either by law or an EHB explanation.

Reconstructive Surgery, Cosmetic Surgery, and Breast Reconstruction

The Women's Health and Cancer Rights Act (WHCRA) of 1998 mandated that all health plans that provide "medical and surgical benefits with respect to a mastectomy" must also

[48]The only state that does not classify Prosthetic Devices as an EHB, Utah, has a mandated offering requirement, so this option is available to all consumers. Information both from the CMS and BCBS fail to mention that this is a mandated offering rather than mandated coverage, which the former classifies under DME. Still, other equipment is covered under this EHB as well. While this mandated offering covers limb prosthetics, the Utah DME EHB covers eye and breast prosthetics only, along with other DME. In fact, this benchmark plan, available on the CMS EHB webpage, has the most comprehensive list of possible DME, addressing coverage of over 200 types of DME.

cover breast reconstruction, including reconstruction of both breasts for symmetry, necessary prostheses and treatment of physical complications. This federal law continues to apply to all individual and group insurance policies issued in the United States, including on the ACA marketplaces. Though this law does not require coverage of mastectomies, it increased coverage requirements for many plans. [49]. The bite of this law was strengthened by the implementation of the Affordable Care Act. Statutory EHB requirements Ambulatory Patient Services and Hospitalization include outpatient and inpatient surgical services, respectively. These benefits are universal EHBs, and never explicitly exclude mastectomy coverage. I assume, then, that all plans in all states are required to cover medically necessary mastectomy and thus breast reconstruction[50].

Besides mandated breast reconstruction, the Reconstructive Surgery EHB can refer to a handful of other types of surgery. These include surgeries to repair congenital deformities such as a cleft lip/palate, as well as deformities caused by accidental injuries. These surgeries may also be covered under the Cosmetic Surgery EHB. Unfortunately, states' classification of these benefits into these categories were not consistent across states or years. One of these inconsistencies is in which benefit is classified as an EHB in order to reflect certain coverage. The other more troubling inconsistency is that often times inclusion of these surgeries in a benchmark plan translate to non-EHB classification of Cosmetic Surgery with an explanation that the "exclusion does not include congenital anomalies or accidental injuries." This causes coverage requirements to be a bit more ambiguous.[51] As such, similar to coverage of Routine Foot Care, the bite of Cosmetic/Reconstructive Surgery EHB classifications are not always clear.

[49] Albournez et al. (2012) find that in 2008, about 46% of individuals who received a mastectomy received some sort of breast reconstruction. These reconstruction types include implants (60.5%), pedicled flaps (34%) and microsurgical flaps (5.5%). A fraction of the proportion of women who do not receive reconstruction each year may instead us breast prostheses, which is also covered under the WHCRA.

[50] There are a few plans that do not indicate coverage of at least breast reconstruction in the PUF data. Using plan documents I was able to verify coverage of reconstructive surgery in some of these plans but not all. This leaves a total of three issuers in two states (GA & NM) in 2015 and 2016 that do not signal coverage of these benefits. However, these are not confirmed non-coverages; only plans that do not indicate coverage of at least breast reconstruction include plans that have near 0 enrollment (issuer 58594) or

[51] Routine Foot Care also has this property; often times, EHB classification is "no" but reflects coverage of foot care for diabetics.

Infertility Treatment

A combination of factors make Infertility Treatment difficult to quantify. This mostly stems from the variety of coverage that may be part of an infertility benefit mandate. Consider four possible covered services for infertility: diagnosis, treatment of underlying conditions, artificial insemination services, and in vitro fertilization. In early years, diagnosis of infertility alone constituted an EHB, but this was generally rolled back in later years. The following three states exemplify three possible extents of a mandate to treat infertility. Illinois' EHB package, for example, requires multiple attempts at *In Vitro Fertilization* (IVF)[52], including coverage of at least 4 and up to 6 oocyte retrievals, a key step in the IVF process, in certain circumstances. This mandate also covers all previously mentioned infertility-related benefits as well as others such as treatments such as zygote intrafallopian tube transfer and low tubal ovum transfer.

Some problems remain unresolved, and may be up to state-by-state interpretation of and use of EHB. This main concern is in the degree to which plans within a state must follow the coverage of the base-benchmark EHB plan. This is specifically in reference to sub-categories within benefits, and certain goods or services that may be covered under a benchmark plan that do not have their own categories for EHB classification. For example, consider cochlear implants. This is a benefit that is not common, and never considered an EHB nor a state required benefit in PUFs as its own category. However, coverage of cochlear implants is required in Wisconsin due to a state mandate; as such, it required to be covered explicitly under the "Durable Medical Equipment" benefit in all years. Meanwhile, the mandate for hearing aids (which is in the same statute in Wisconsin law), is classified separately as its own mandated benefit. Though the mandate applies to dependents under 18, the EHB expands this to all covered individuals. It is difficult to know whether quantifying cochlear implants as a separate mandated benefit would be necessary: firstly, it acts as a substitute for traditional hearing aids rather than a complement,

[52]Illinois has a state mandate that requires all group contract that employ over 25 individuals to provide this coverage. As Illinois chose a small group product as their base-benchmark plan in all years, it makes sense that the "most enrolled" small group (under 50 employees) in the state would cover many companies with between 25 and 50 employees rather than smaller ones. The ACA thus extended this mandate to individual contracts and small group contracts with under 25 employees.

so an individual would not be using both. Thus this mandate, and separate EHB coverage, of two benefits has the effect of a single mandate. This, paired with the fact that cochlear implants is covered with other DME, makes cochlear implants' lack of its own category make more sense.

It should be noted that EHB changes do not reflect minor changes that may have affected mandates, such as changes in limits. For example, beginning in 2017 states were no longer allowed to have combined limits for habilitation services and rehabilitation services. As a result, some states, such as Texas, updated their EHB package, which initially included a combined limit on outpatient rehabilitation, habilitation, and chiropractic care. This is because the underlying plan lists ”physical services”, which includes but is not limited to physical, occupational, and manipulative therapy.

3.A.6 Methodology for Constructing Plan-Area Frequencies and Market Controls

For the years 2014 to 2018, the Center for Medicare & Medicaid Services (CMS) provides excel files under the name "Issuer Level Enrollment Data." These consist of two separate datasets, described below:

1. **Plan Data:** For each insurance plan, this tab provides state totals for:
   - Total number of individuals **enrolled** at any point in the given file year
   - Total number of individuals who **disenrolled** at any point in the given file year
2. **Issuer-County Data:** Within each *county*, enrollment for each issuer is provided, including:
   - Total number of individuals **enrolled** at any point in the given file year
   - Total number of **females** and **males** enrolled at any point in the given file year
   - Total number of enrollments for those in the following four age categories: **0-17**, **18-34**, **35-54**, and **55+**

- Total number of enrollments for those in the following income categories: **less than 138%** of the Federal Poverty Level (FPL), **138% to 250%** of FPL, **250% to 400%** of FPL, **over 400%** of FPL, and unknown income category
- Total number of enrollees who are tobacco **smokers**

Approximate Plan-Area Frequencies were constructed using both data tabs above in each year. The frequencies of interest are $f_{i,j,a}$, the number of individuals who purchased plan $j = 1, 2, ..., J$ from issuer i in each ratings area $a \in \mathscr{A}$. Since all work is done within an issuer-state, I will omit the i subscript for the following formulation. These will be used as frequency weights for premium observations, each of which are measured on a plan-ratings area level (and each plan is from one issuer). The two properties that are desirable in order to minimize distortions of the data are:

1. The total number of policies sold by each issuer in each ratings area matches the data; and
2. The total number of policies sold of each plan in the state matches the data

These two properties are the benchmark that I require my weights to meet.

Suppose for example that all plans offered by an issuer are offered in all ratings areas. A basic way to estimate frequencies is to use the number of individuals enrolled within an issuer-state that purchased each plan,$f_{j\cdot} = \sum_{a \in \mathscr{A}} f_{j,a}$, the issuer's number of enrollees in each ratings area,$f_{\cdot a} = \sum_{j=1}^{J} f_{j,a}$, and the total number of enrollees for the issuer, $f_{\cdot\cdot} = \sum_{a \in \mathscr{A}} f_{\cdot a} = \sum_{j=1}^{J} f_{j\cdot}$. If we assume that

$$\frac{f_{j,a}}{f_{j\cdot}} = \frac{f_{\cdot a}}{f_{\cdot\cdot}},$$

frequency weights can be calculated by simply re-arranging the formula to achieve

$$\tilde{f}_{j,a} = \frac{f_{\cdot a}}{f_{\cdot\cdot}} f_{j\cdot}$$

This formulation assumes that the distribution of plan enrollment is the same within issuers on a state and ratings area level. Though this is not entirely realistic, it is necessary to make some assumption in order to obtain weights. Using this formula ensures that both benchmarks are met.

However, issuers are often less uniform in their plan offerings. In some instances, certain plans are only offered in a subset of the ratings areas. This may be some or all plans, and there is often no apparent groupings of plans in ratings areas. One adjustment to the above formula is to use:

$$\tilde{f}_{j,a} = \frac{f_{\cdot a}}{f^{\mathscr{A}_j}} f_{j\cdot} 1(a \in \mathscr{A}_j),$$

where $f^{\mathscr{A}_j} = \sum_{a \in \mathscr{A}_j} f_{\cdot a}$, and $\mathscr{A}_j$ is the set of all ratings areas that plan j is offered in. This is just an adjustment to the original formula that accounts for the fact that some plans are not offered in all areas. Consider an instance where, WLOG, $\mathscr{A}_1 \subseteq \mathscr{A}_2 \subseteq ... \subseteq \mathscr{A}_J$, and $\mathscr{A}_k \subset \mathscr{A}_{k+1}$ for exactly one k. Consider summed totals within ratings areas across plans:

$$\sum_{j=1}^{J} \tilde{f}_{j,a} = \sum_{j=1}^{J} \frac{f_{\cdot a}}{f^{\mathscr{A}_j}} f_{j\cdot} 1(a \in \mathscr{A}_j)$$

.

If $a \in \mathscr{A}_k$, meaning it is only served by some plans, then

$$\sum_{j=1}^{J} \frac{f_{\cdot a}}{f^{\mathscr{A}_j}} f_{j\cdot} 1(a \in \mathscr{A}_j) = f_{\cdot a} \frac{f_{k+1\cdot} + ... + f_{J\cdot}}{f^{\mathscr{A}_{k+1\cdot}}} < f_a \frac{f_{1\cdot} + ... + f_{J\cdot}}{f^{\mathscr{A}_{k+1}}} < f_a$$

This method underestimates coverage in ratings areas that do not include all plans, and overestimates coverage in ratings areas that do, even in a simple case of plans not being in all ratings areas. More generally, when $\mathscr{A}_1 \subseteq \mathscr{A}_2 \subseteq ... \subseteq \mathscr{A}_J$, and $\mathscr{A}_{k_l} \subset \mathscr{A}_{k_l+1}$ for all k_l, where l indexes the sets in order of cardinality and $l = 1, ..., L-1$, property 1 above is violated.

In order to fix this, I use the following process. First, consider all plans covered only in ratings areas $\mathscr{A}_{k_1}$. Here, the cardinality of the set of areas covered by these plans is weakly less than the cardinality of all other sets covered by the issuer ($\#(\mathscr{A}_{k_1}) \leq \#(\mathscr{A}_j)\ \forall j$). Considering only these plans, calculate $\tilde{f}_{j,a}$ as above. Then, subtract these totals from observed ratings area totals for all $a \in \mathscr{A}_{k_1}$, and do the same for the overall number of observations.

$$\hat{f}^1_{\cdot a} = f_{\cdot a} - \sum_{j=1}^{k_1} \tilde{f}_{j,a}\ ,\ \hat{f}^1_{\cdot\cdot} = f - \sum_{a \in \mathscr{A}} \sum_{j=1}^{k_1} \tilde{f}_{j,a} = f_{\cdot\cdot} - \sum_{j=1}^{k_1} f_{j\cdot}$$

The second equality in the second equation holds because property 2 holds. This is trivial, as things are done by plan. These running enrollment totals for areas will be used for the next step of the process. Note that these running totals will be unaffected for areas that are not covered by these plans. More generally this total is iteratively defined as $\hat{f}^l_{\cdot a} = \hat{f}^{l-1}_{\cdot a} - \sum_{j=k_{l-1}+1}^{k_l} \tilde{f}_{j,a}$. We also define a running total tally, which is equal to the number of plans which have not yet been dealt with after step l of the process.:

$$\sum_{a \in \mathscr{A}} \hat{f}^l_{\cdot a} = \hat{f}^l_{\cdot\cdot} = \hat{f}^{l-1}_{\cdot\cdot} - \sum_{a \in \mathscr{A}} \sum_{j=k_{l-1}+1}^{k_l} \tilde{f}_{j,a} = \hat{f}^{l-1} - \sum_{j=k_{l-1}+1}^{k_l} f_{j\cdot} = \sum_{j=k_l+1}^{J} f_{j\cdot}$$

We further define $\hat{f}^{\mathscr{A}^l_{k_{l+1}}} = \sum_{a \in \mathscr{A}_{k_{l+1}}} \hat{f}^l_{\cdot a}$ as the total remaining running enrollment in all areas that plan k_{l+1} is offered in after iterative step l. We then move to all plans covered only in ratings areas $\mathscr{A}_{k_2}$, and so on, until all frequencies have been calculated. In order to show that this process satisfies property 1, we see that

$$\sum_{j=1}^{J} \tilde{f}_{j,a} = \sum_{j=1}^{k_1} \tilde{f}_{j,a} + \sum_{j=k_1+1}^{k_2} \tilde{f}_{j,a} + \ldots + \sum_{j=k_{L-1}+1}^{J} \tilde{f}_{j,a}$$

$$= \sum_{j=1}^{k_1} \frac{f_{\cdot a}}{f^{\mathscr{A}_{k_1}}} f_{j\cdot} 1(a \in \mathscr{A}_{k_1}) + \sum_{j=k_1+1}^{k_2} \frac{\hat{f}^1_{\cdot a}}{\hat{f}^{\mathscr{A}^1_{k_2}}} f_{j\cdot} 1(a \in \mathscr{A}_{k_2}) + \ldots + \sum_{j=k_{L-1}+1}^{J} \frac{\hat{f}^{L-1}_{\cdot a}}{\hat{f}^{\mathscr{A}^{L-1}_{k_L}}} f_{j\cdot} 1(a \in \mathscr{A}_{k_L})$$

I now prove by induction that property 1 holds. First, consider rating area a_1, where $a_1 \in \mathscr{A}_{k_L}$. Consider the final term in the above sum:

$$\sum_{j=k_{L-1}+1}^{J} \frac{\hat{f}^{L-1}_{\cdot a_1}}{\hat{f}^{\mathscr{A}^{L-1}_{k_L}}} f_{j\cdot} = \sum_{j=k_{L-1}+1}^{J} \frac{\hat{f}^{L-1}_{\cdot a_1}}{\sum_{b \in \mathscr{A}_{k_L}} \hat{f}^{L-1}_{\cdot b}} f_{j\cdot} = \hat{f}^{L-1}_{\cdot a_1} \sum_{j=k_{L-1}+1}^{J} \frac{f_{j\cdot}}{\sum_{y=k_{L-1}+1}^{J} f_{y\cdot}} = \hat{f}^{L-1}_{\cdot a_1}$$

The second equality holds follows from the fact that $\sum_{a \in \mathscr{A}_{k_L}} \hat{f}^{L-1}_{\cdot a} = \hat{f}^{L-1}_{\cdot\cdot}$, along with equation (?) above. If $a_1 \notin \mathscr{A}_{k_1}, ..., \mathscr{A}_{k_{L-1}}$, then this is the only non-zero term in the sum, $\hat{f}^{L-1}_{\cdot a_1} = f_{\cdot a_1}$, and property 1 holds for this area. If instead $a_1 \in \mathscr{A}_{k_l}, ..., \mathscr{A}_{k_L}$ for some $l < L$, we have $\hat{f}^{L-1}_{\cdot a_1} = \hat{f}^{L-2}_{\cdot a_1} - \sum_{j=k_{L-2}+1}^{k_{L-1}} \tilde{f}_{j,a_1}$. Our entire sum now becomes:

$$\sum_{j=1}^{J} \tilde{f}_{j,a_1} = \sum_{j=1}^{k_1} \frac{f_{\cdot a_1}}{f^{\mathscr{A}_{k_1}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_1}) + \sum_{j=k_1+1}^{k_2} \frac{\hat{f}^{1}_{\cdot a_1}}{\hat{f}^{\mathscr{A}^{1}_{k_2}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_2}) + ...$$

$$+ \sum_{j=k_{L-2}+1}^{k_{L-1}} \tilde{f}_{j,a_1} + \hat{f}^{L-2}_{\cdot a_1} - \sum_{j=k_{L-2}+1}^{k_{L-1}} \tilde{f}_{j,a_1}$$

$$= \sum_{j=1}^{J} \tilde{f}_{j,a_1} = \sum_{j=1}^{k_1} \frac{f_{\cdot a_1}}{f^{\mathscr{A}_{k_1}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_1}) + \sum_{j=k_1+1}^{k_2} \frac{\hat{f}^{1}_{\cdot a_1}}{\hat{f}^{\mathscr{A}^{1}_{k_2}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_2}) + ... + \sum_{j=k_{L-3}+1}^{k_{L-2}} \tilde{f}_{j,a_1} + \hat{f}^{L-2}_{\cdot a_1}$$

Again, if $a_1 \notin \mathscr{A}_{k_1}, ..., \mathscr{A}_{k_{L-2}}$, then $\hat{f}^{L-2}_{\cdot a_1} = f_{\cdot a_1}$ and the other terms in the sum are 0 and we are done. If not, we move on to the next step.

Suppose that after a number of steps, the equation is reduced to:

$$\sum_{j=1}^{J} \tilde{f}_{j,a_1} = \sum_{j=1}^{k_1} \frac{f_{\cdot a_1}}{f^{\mathscr{A}_{k_1}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_1}) + \sum_{j=k_1+1}^{k_2} \frac{\hat{f}^{1}_{\cdot a_1}}{\hat{f}^{\mathscr{A}^{1}_{k_2}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_2}) + ... + \sum_{j=k_l+1}^{k_{l+1}} \tilde{f}_{j,a_1} + \hat{f}^{l+1}_{\cdot a_1}$$

$$= \sum_{j=1}^{k_1} \frac{f_{\cdot a_1}}{f^{\mathscr{A}_{k_1}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_1}) + \sum_{j=k_1+1}^{k_2} \frac{\hat{f}^1_{\cdot a_1}}{\hat{f}^{\mathscr{A}^1_{k_2}}} f_{j\cdot} 1(a_1 \in \mathscr{A}_{k_2}) + ... + \sum_{j=k_{l-1}+1}^{k_l} \tilde{f}_{j,a_1} + \hat{f}^l_{\cdot a_1}$$

If $a_1 \notin \mathscr{A}_{k_1}, ..., \mathscr{A}_{k_{l-1}}$, then $\hat{f}^l_{\cdot a_1} = f_{\cdot a_1}$ and property 1 holds. Property 1 thus holds for all $a \in A$ by induction. This also ensures that all estimates are non-negative

Unfortunately, there are a handful of issuers that are less uniform than this. Instead of plans being "nested" in ratings areas, they are often spread out sporadically, across ratings areas. Adjust the previous setting, where instead I group plans by the number of ratings areas that they exist in, $\#(\mathscr{A}_j)$. Those in group $l = 1$ are in the fewest number of ratings areas, while $l = L$ are in the greatest number of ratings areas. When we use our previous approach, but do so in order of these new groups, our sum of interest is now:

$$\sum_{j=1}^{J} \tilde{f}_{j,a} = \sum_{j=1}^{k_1} \tilde{f}_{j,a} + \sum_{j=k_1+1}^{k_2} \tilde{f}_{j,a} + ... + \sum_{j=k_{L-1}+1}^{J} \tilde{f}_{j,a}$$

$$\sum_{j=1}^{J} \tilde{f}_{j,a} = \sum_{j=1}^{J} \frac{f_{\cdot a}}{f^{\mathscr{A}_j}} f_{j\cdot} 1(a \in \mathscr{A}_j)$$

The following example shows distortions. Suppose an issuer offers two plans; plan 1 is offered in ratings areas a and b, while plan 2 in ratings areas b, c and d. The following is known from the data: $f_{1\cdot} = 100$, $f_{2\cdot} = 200$, $f_{\cdot a} = 60$, $f_{\cdot b} = 140$, and $f_{\cdot c} = f_{\cdot d} = 50$. Approximate frequencies for plan 1 would be found first, with $\tilde{f}_{1,a} = f_1 \frac{f_{\cdot a}}{f_{\cdot a} + f_{\cdot b}} = 100 \frac{60}{60+140} = 30$. Since plan 1 is the only plan in rating area a, this approximated sum $\sum_{j=1}^{2} \tilde{f}_{j,a} = 30 \neq f_{\cdot a}$. Thus property 1 is again violated in this simple example.

This example provides intuition for how to deal with the issues presented by this rating irregularity. The reason that enrollment in rating area a was underestimated is that ratios based upon the running remaining totals (in this case the total number) assume that these ratios are held true even when more information is available to use. Specifically, we know that this is the last plan that addresses ratings area a. This means that more enrollment should be assigned to that ratings area-plan in order to exhaust all enrollments in ratings area a. It is very clear, then that in the above example, it should be that $\tilde{f}_{1,a} = 60$, with the remaining 40 plans going to plan 1 in ratings area b. Realizing this not only helps us create estimates with better properties, but in this case, allows us to find exact numbers for ratings area-plan cells.

Consider the following final process for calculating approximate frequency weights. Define set $\mathscr{J}_l = \{j = 1, 2..., J | \#(\mathscr{A}_j) = l\}$. Begin with plans in group $l = 1$, if there are any. Allot all plan counts to this ratings area, and calculate $\hat{f}^1_{\cdot a}$ for all a. Do the following for plans in groups $l = 2, 3, ..., L$:

1. Examine first if there are any ratings areas a s.t. $a \cup \mathscr{J}_m = \emptyset$ for $m = l+1, ..., L$, meaning that it is being addressed for the last time. If this is the case, assign the remaining enrollment to the appropriate plans in the appropriate ratio. Here, though, instead of using the ratio we have used in the past, we instead use the relative ratio of enrollment between plans, rather than ratings areas.

$$\tilde{f}_{j,a} = \frac{f_{j\cdot}}{\hat{f}^{\mathscr{J}_l^{l-1} \cap a}_{\cdot\cdot}} \hat{f}^{l-1}_{\cdot a}$$

where

$$\hat{f}^{\mathscr{J}_l^{l-1} \cap a}_{\cdot\cdot} = \sum_{y \in \mathscr{J}_l \& a \in \mathscr{A}_y} f_{y\cdot}$$

Notice that this formulation is different from before. Now, we use the ratio of We then define $\hat{f}_{j\cdot} = f$ Though this is not always the case, using this final method gives us the exact

This again creates distortions using our updated approach. Again, property 1 is often violated. To show this, consider

I use the following process to move this.

Note that each approach above nests the previous one, so the final version is just the most generalized form of the others.

Issuer enrollment by rating area was found by simply summing county level issuer enrollment by ratings areas. For Alaska, the aforementioned proportions are used to estimate the approximate number of individuals enrolled in each ratings area by county. This means that in Alaska the following assumption is used: the distribution of individuals who purchased insurance plans is independent of zip code. This allows me to use the proportion of individuals who live in each ratings area in a county to find approximate enrollment (by multiplying it by enrollment in that county). These approximations are then summed by ratings areas as well. The proportion of individuals enrolled in a plan conditional on being sold by an issuer in a state was then calculated from the Plan Data.

Market Controls were constructed for issuer-states and issuer-ratings areas. One or the other was used in analyses, depending on the level of the fixed effects. These controls include the proportion of enrollment that is male, the proportion of enrollment that is under the 138% of the poverty level, the proportion of enrollment that are over the age of 55, and the proportion of enrollment that are under the age of 18. These were constructed by summing total and demographic level enrollment by issuer and ratings area (or state) and dividing totals. For income groups, since a portion of those who enroll to not report their income, a separate total for proportion was created, so that poverty numbers reflect the proportion in poverty out of those known. I chose to do this on an issuer level because the pool of individuals covered by an issuer are theoretically those who directly affect premiums through their utilization of medical goods and services.

Editing Enrollment Data

Some observations in the raw data tabs are missing in order to ensure privacy of respondents. As a general rule, if total enrollment, or any other category, has a value of 10 or less, it is replaced with a star (*). If the value is 0, it is coded as a 0. Further, in the Issuer Tab, if including a value greater than 10 would allow one to deduce another missing value, it is coded as a star (*). For example, suppose that 30 people enroll with a certain issuer within a county, 8 of which are female and 22 of which are male. The number of female enrollees would be coded as a star (*)

since it is less than 10, and the number of male enrollees would be coded as a star because if its value of 22 was included, one could conclude that there were 8 female enrollees.

Since the Plan Data only includes two categories, none of which are subcategories of the other, missing data values are simply replaced with 5, the approximate arithmetic average of the 10 possible numbers (1-10) that a missing value represents. I use the following flow chart to recode the Issuer-County Data:

1. If total enrollment is missing, and all subcategories have values of 0 or *, the observations are replaced with 5.

2. If total enrollment is missing, but *any* subcategory has values other than 0 or *, the observations were investigated by hand, as this is a mistake. This happens for fewer than 15 issuer-counties in each year. These all seemed to be mistakes, and occurred systematically in issuer-states with few missing value lines in total, indicating that these were heavily enrolled issuers. By cross-referencing issuer-state enrollment totals from the Plan Data with issuer-state enrollment totals from Issuer-County Data, I was able to approximate these totals. Any missing sub-categories (usually gender), were adjusted afterward as well.

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