Commitment, Competition, and Preventive Care Provision*

Anran Li†

November 20, 2023

The most recent draft is available here or on my website

Abstract

Preventive care, such as vaccines, cancer screenings, and chronic disease management, affects long-term population health. Insurer competition and limited consumer commitment could disincentivize insurers' preventive investment because insurers cannot internalize all investment cost savings as consumers leave the insurer in the future. Competition thereby creates a tradeoff between investment externalities and market power: lessening competition increases both preventive investment and premiums. Exploiting a shift-share instrument for consumer turnover, I find turnover reduces insurers' preventive investment. I develop and estimate a dynamic equilibrium model where insurers compete on premiums and preventive investment, and affect consumers' health status. Counterfactual analyses reveal that when transitioning to a single private insurer, insurers' preventive investment rises, and consumers' medical expenses fall. The distortion to consumer surplus from forgone investment savings is on par with that from pricing power. An investment mandate could relieve free-riding across insurers and achieve Pareto improvements. These results demonstrate efficiency losses of fragmented insurer markets due to investment externalities.

*I am indebted to my advisors, David Dranove, Igal Hendel, Gaston Illanes, and Molly Schnell, for their invaluable mentorship and advice. For helpful comments, I thank Vivek Bhattacharya, Zarek Brot-Goldberg, Shengmao Cao, Hyein Cho, Emily Cuddy, Jose Ignacio Cuesta, Michael Dickstein, Benjamin Friedrich, Eilidh Geddes, Ben Handel, Nicole Holz, Elisa Jacome, Kirabo Jackson, Paul Kim, Jennifer Kwok, Riley League, Gaston Lopez, Anthony LoSasso, Casey Mulligan, Francisco Pareschi, Tomas Philipson, Rob Porter, Conor Ryan, Michael Powell, Elena Prager, Hannes Schwandt, Mark Shepard, Amanda Starc, Pietro Tebaldi, Nicholas Tillpman, Silvia Vannutelli, Benjamin Vatter, Jingyuan Wang, as well as seminar participants at Northwestern IO, Northwestern Applied Micro, Northwestern Kellogg Strategy, the University of Chicago CCSRG, Lake Forest College, the 2022 NBER Health Economics Research Boot Camp, the 2023 Becker Friedman Institute Health Economics Initiative Annual Conference, the 2023 American Society of Health Economists Annual Conference, the 2023 Stanford Institute for Theoretical Economics Conference, and the 2023 Annual Midwest Health Economics Conference. I thank Ryan Christenson, Mary Fields, Carl Letamendi, Mike Martin, Sterling Peterson, and Brantley Scott for their assistance with data access. I thank Irving Birkner, Ambreen Chaudhri, Frank Limbrock, Richard Williams, and the Kellogg Research Support team for their assistance with data management. I thank Zihan Tan and Xiaoming Zhao for helpful discussions on computational methods. I gratefully acknowledge financial support from the Center of Industrial Organization at Northwestern University, the Susan Schmidt Bies Fellowship from Northwestern University, and the Predoctoral Fellowships in Health Economics Research from the University of Chicago.

†Li: Department of Economics, Northwestern University, anranli@u.northwestern.edu.

1 Introduction

Seven out of ten deaths in the US are caused by preventable diseases, such as heart attack, cancer, and diabetes (CDC, 2021b). Preventive care can intervene before diseases occur, detect and treat diseases early, and manage the disease to slow or stop its progression (Kenkel, 2000). Vast medical research finds preventive care increases life expectancy and reduces future medical expenses (CDC, 2021a). However, preventive care is underutilized compared to levels recommended by major professional organizations such as the US Preventive Services Task Force (USPSTF, 2021). Conventional wisdom suggests consumers' behavioral biases, including myopia, procrastination, or low valuation of prevention, explain under-utilization. Less attention is paid to how supply-side factors drive underinvestment in equilibrium.

I study how commitment and competition affect preventive care provision. Limited consumer commitment reduces insurers' preventive care investment, because insurers cannot internalize all investment cost savings as consumers may leave the insurer in the future. Insurer competition increases consumer turnover and creates investment externalities, exacerbating underinvestment. A possible solution would be to allow a single insurer to monopolize the market and internalize the maximum attainable investment returns. However, such lessened competition involves a tradeoff between greater market power and higher preventive investment, i.e., a tradeoff between higher prices and lower medical expenses. This paper aims to explore this tradeoff, quantify the impacts of insurer competition on preventive investment and consumer welfare, and evaluate policy solutions.

My analysis proceeds in four steps. First, I show empirically that consumer turnover reduces insurers' preventive investment, exploiting a shift-share instrument for turnover. Second, I develop and estimate a dynamic model of insurance demand and supply. Insurers compete on premiums and preventive investment, which affects consumers' health levels in equilibrium. Third, I use the model to examine the welfare effects of insurer competition. Upon transitioning from duopolists to a monopolist, reduced turnover incentivizes preventive investment, which in turn improves population health. The welfare distortion to consumer surplus from forgone investment savings, or extra health expenses, is on par with that from pricing power. This highlights the efficiency losses of competition due to investment externalities. Finally, I evaluate policies to promote preventive investment. I find automatic re-enrollment raises inertia and strengthens consumer commitment, but harms welfare: premium increases outweigh gains from elevated investment. Conversely, investment mandates solve insurers' coordination problems, relieve free-riding, and achieve Pareto improvements. These contrasting policy impacts suggest that regulations to promote preventive care must consider the investment-price tradeoff, and direct quality regulation is effective in addressing investment externalities.

I study preventive care provision in the individual health insurance exchange (hereafter, the exchange). It serves consumers without government-provided or employer-sponsored insurance. Consumers choose insurance products every year without committing to staying with a specific insurer. Their turnover includes changing across insurers within the market or across market segments into and out of the exchange. The government mandates coverage and zero-cost sharing of preventive procedures but has no further preventive care requirements. Insurers invest in preventive care by educating and reminding consumers of eligible procedures and rewarding providers for prescribing preventive services.

I begin with three motivating facts that illustrate the incentive structure of insurers' preventive investment. First, I show that my selected preventive care reduces future medical costs (CDC, 2021a; USPSTF, 2021), which creates intertemporal cost-saving incentives. Second, I show insurers have control over the utilization of preventive care. I compare the utilization patterns of consumers forced to switch insurers and those who stay with insurers that receive switchers, exploiting a quasi-experimental variation of insurer exits (Abaluck et al., 2021). I find the supply side is essential in determining prevention utilization.

Third, I show that consumer turnover reduces insurers' prevention provision. I construct a shift-share instrument to address potential endogeneity in consumer retention on the exchange. The instrument employs variations in national job hiring trends across industries ("shift") and industry-employment structure across states ("share"). Higher job hiring rates lead to lower consumer retention on the exchange, as insurance is often tied to employment status. I find a 1 percentage point increase in consumer turnover lowers insurers' preventive investment by $5.31 per enrollee and prevention utilization by 0.78 percentage points. These results indicate that insurers respond to variations in future investment returns created by limited consumer commitment.

Motivated by these stylized facts, I develop an equilibrium framework to quantify the welfare effects of insurer competition and to evaluate policies that promote prevention. Consumers' demand for insurance follows a standard static discrete choice model. Consumers' key primitives are their level of inertia, which governs their retention probabilities, and preferences for premium, prevention, and out-of-pocket medical expenses. Insurers choose price and preventive care investment in an infinite period dynamic game. They trade off extra investment costs with increased future profits and better enrollee health, considering consumer turnover. Insurers' key primitives are investment cost functions, i.e., the map from expenses in preventive care to utilization, and the returns to prevention function, i.e., the map from current health and preventive care utilization to future health levels. The novelty is that the model incorporates insurers' intertemporal quality incentives and endogenizes consumers' health levels as a function of preventive investment in equilibrium.

I estimate the model in three steps for the Utah exchange, using Utah All Payer Claims Data (APCD) and several public datasets on the uninsured and product characteristics. The APCD is an individual-year panel of enrollment and claims records for all commercially insured consumers. I first calibrate returns to prevention from medical and epidemiological studies. I estimate how state variables evolve with insurers' policies using standard regression methods in the dynamic games literature (Aguirregabiria et al., 2021). Next, I estimate consumer preferences using the two-step MLE-BLP estimator of Goolsbee and Petrin (2004). Finally, I back out primitives of insurers' investment cost functions from first-order conditions of prevention provision.

Model estimates reveal four key market features related to preventive investment. First, consumers' willingness to pay for preventive care is not economically meaningful. This implies relying only on consumer choices cannot result in sufficient preventive care provision or optimal population health in equilibrium. Second, insurers' dynamic cost-saving motives dominate static strategic market share motives for preventive investment—83.6% of the benefits from a marginal unit of prevention accrue to increases in expected future profits. Third, prevention provision is costly for insurers. To achieve the government's utilization targets, insurers' per-member preventive investment needs to rise 3 to 4 times from the current level. Fourth, consumer turnover impacts expected investment returns. The presence of an extra competitor, or a 10 percentage point increase in consumer inflows and outflows, lowers expected investment cost savings by 28.1% or 14.7%, respectively.

I use the model and estimates to quantify the welfare impacts of insurer competition. I compare the stationary equilibrium between the status quo duopoly and a scenario in which a monopoly operates on the exchange. Removing competitors reduces consumer turnover, which raises internalization of investment returns and eliminates free-riding across insurers. Preventive investment per member thereby triples from \$106 to more than \$300. Meanwhile, enhanced pricing power raises markups by 11 to 17 percentage points across simulations with different monopolist characteristics. The health impacts of increased investment per insured dominate that of decreased share of insured consumers who receive prevention: Average medical expenses fall by \$167 to \$406 per consumer, 2.7% to 6.5% of the baseline.

Changes in premiums and consumer surplus hinge on primitives that govern investment savings or market power. For example, if the monopolist has flat cost functions of prevention utilization, decreased claims costs could offset increased markups so premiums drop. Reduced medical expenses could compensate for enhanced pricing power, so consumer surplus increases. Instead, if the monopolist has steep investment cost functions, claims cost reductions are likely to be of smaller magnitudes, so markup upsurges dominate, and premiums rise. Elevated prevention provisions might not overturn the exploitation of pricing power, resulting in falls in consumer surplus. Similarly, high or low brand-specific elasticities could inflate or restrict losses from market power, leading to consumer surplus gains or losses.

Across simulations with different monopolist characteristics, premiums vary from a 2.9% decrease to a 26.5% increase. This delivers a new insight that by discouraging investment in consumers' health, insurer competition without consumer commitment might raise medical expenses and premiums in plausible scenarios, creating a worst-of-both-world. Changes in consumer surplus range from -$70 to $48 per member. This suggests the welfare distortion to consumer surplus from underinvestment is about the same size as that from high pricing power. These results reiterate the ambiguous welfare impacts of insurer competition and highlight its efficiency losses due to investment externalities.

Finally, I assess policies to promote prevention provision. On demand-side policies, I examine automatic re-enrollment, which defaults the consumer into his previous period insurer choice if the consumer does not actively make a plan choice. This enrollment policy strengthens consumer commitment but reduces demand elasticities, granting insurers larger investment incentives and pricing power. In the stationary equilibrium, premium increases push consumers to drop coverage and forgo preventive care. This adverse health impact outweighs the gains from enhanced investment per insured: average medical expenses increase following automatic re-enrollment; consumer surplus decreases.

I further explore a supply-side policy: preventive investment mandates. Insurers' investment manifests a prisoner's dilemma: insurers could underinvest and steal healthy enrollees from competitors, rather than invest in preventive care efficiently to achieve mutual benefits of better population health. Imposing a minimum investment floor could solve insurers' coordination problem and relieve investment externalities. A moderate mandate of up to $190 minimum investment per member achieves Pareto improvements: medical expenses and premiums fall, while insurers' profits rise. A $500 per member investment mandate maximizes consumer surplus, as it balances investment savings and premium increases that compensate for extra investment costs.

Policy simulations provide two recommendations for regulators. First, the investment-price tradeoff should guide policy designs. The contrasting effects of supply-side and demand-side policies highlight that effective regulations must simultaneously address investment externalities and pricing power distortions. Second, the most promising solution to underinvestment is managed competition with investment mandates. This is because even a monopolist of the exchange will never fully recoup all investment cost savings, as consumers eventually age into Medicare. Hence, direct quality regulation resolves investment externalities more effectively than altering competitive structures or retention probabilities, which further sheds light on the recent policy debate of preventive care coverage mandates.[1]

[1]The Affordable Care Act mandates private health insurers to fully cover certain preventive care services

Overall, my analysis illustrates potential efficiency losses of competition and highlights the critical but often neglected role of long-term quality incentives. A key premise of the managed competition paradigm is that private insurers compete on prices and product characteristics to create value. However, the lack of long-run internalization of investment benefits, induced by insurer competition and consumer turnover, could disincentivize value-creation efforts in preventive investment. I provide new evidence that such inefficiencies exist, develop a new framework to examine its welfare impacts, and evaluate policy solutions.

This paper relates to several threads of literature. First, it contributes to the literature on preventive care provision and utilization (Einav et al., 2020; Jones et al., 2019; Kremer and Snyder, 2015; Kotb, 2023; Kowalski, 2023; Newhouse, 2021). Existing studies focus on demand-side frictions that cause underinvestment: consumers' ex-ante moral hazard (Ellis and Manning, 2007; Kenkel, 2000; Phelps, 1978), behavioral hazard (Baicker et al., 2015), self-control problems (Bai et al., 2021), or undervaluing prevention (Bauer et al., 2022). I offer an equilibrium analysis of how supply-side interactions drive prevention underprovision.

Second, this paper expands the literature on partial commitment in insurance (Atal et al., 2022; Crocker and Moran, 2003; Diamond et al., 2018; Finkelstein et al., 2005; Ghili et al., 2022; Herring, 2010). Hendel and Lizzeri (2003) shows limited consumer commitment results in insurers' front-loaded pricing strategies. The closest papers are Fang and Gavazza (2011); Cebul et al. (2011). The former shows that job turnover reduces workers' and employers' joint decisions on health expenses. The latter conjectures in a theoretical model that turnover induced by search frictions undermines investment in future health. I build on the literature by showing how insurers respond to limited consumer commitment by adjusting preventive quality. I also develop a novel framework to quantify relevant welfare effects.

Third, this paper adds to the literature on competition and market design in healthcare. More broadly, it fits into the literature on endogenous product design (Crawford, 2012; Fan, 2013). Existing papers focus on static insurer competition (Curto et al., 2021; Dafny, 2010; Dickstein et al., 2023; Decarolis et al., 2020; Einav et al., 2019; Ho and Lee, 2017; Polyakova and Ryan, 2019; Saltzman, 2019; Shepard, 2022; Starc and Town, 2020; Tebaldi, 2017). This paper studies an underexplored dynamic quality provision incentive. I uncover a novel mechanism that insurer competition could have perverse effects on population health by discouraging preventive investment. I also offer a novel conceptual insight into the tradeoff between investment externalities and market power, induced by insurer competition.

This paper proceeds as follows. Section 2 describes market institutions and background on preventive care. Section 3 presents motivating facts that consumer commitment is relevant for insurers' preventive investment. Section 4 develops an equilibrium model of insurance

at no cost to patients. But this requirement was struck down in March 2023 and is under an appeal process.

demand and insurers' pricing and prevention provision. Section 5 outlines estimation methods and reports model estimates. Section 6 presents welfare analyses and policy simulations. Section 7 provides a discussion and concludes.

2 Setting

2.1 The Exchange

I study the individual health insurance exchange ("the exchange"), a marketplace established in 2014 by the Affordable Care Act (ACA). I examine the exchange nationwide for motivating facts in Section 3 and the Utah exchange for structural exercises in Sections 5, 6.

The exchange is a valuable setting for studying preventive care investment because consumers interact with insurers directly on the market. There are no other players on the supply side, such as employers, confounding insurers' incentives. Furthermore, the exchange has good data availability on product characteristics, enrollment, and claims records, which facilitates careful examination of consumers' and insurers' behaviors in equilibrium.

Private insurers offer various coverage options on the exchange. 3% of the US population who are not eligible for Medicaid or Medicare and without employer-sponsored insurance purchase exchange products. Products are offered at the county level and follow standardized cost-shares. Appendix C2 describes additional institutional details.

The exchange has two features that are relevant for all health insurance markets: high consumer turnover and low preventive care provision. I describe the former below and the latter in the next subsection. Consumer turnover consists of turnover across insurers within the exchange and turnover across market segments into and out of the exchange. Either job or income changes could alter consumers' eligibility for different insurance programs, resulting in across-market turnover. Table A2 panel (c) and Table A3 show that only 73% of current enrollees remain insured in the exchange the following year; 27% stay 5 years later. The market segment that has the largest consumer swaps with the exchange is employer-sponsored insurance. This motivates using job hiring trends as an instrument for consumer retention in Section 3.3. The mean retention rate for a single insurer is 53% because of both across-market and within-market across-insurer turnover.

2.2 Underinvestment in Preventive Care

There are two major ways that insurers could invest in preventive care. One option is to educate and remind consumers. Many insurers hire patient outreach coordinators, who identify the gap in preventive care utilization and remind consumers of eligible procedures (Sweeney, 2016). Insurers also offer various wellness programs to promote preventive services (see Figure A1a, A1b). The other option of preventive investment is to incentivize providers' prescriptions via value-based payment models (see Figure A1c, A1d). These contracts reward physicians with incentive payments per completion of preventive procedures.[2] Most insurers on the exchange have existed for decades and likely already had wellness promotion and provider incentive programs in place. Hence, insurers change annual preventive investment by varying the quantity or intensity of those programs. Preventive investment is viewed as marginal costs, but not fixed costs in this paper.

The Healthcare Effectiveness Data and Information Set (HEDIS) provides guidelines on recommended clinical routines, frequency, and eligible population for preventive procedures. For example, women aged 50 to 74 should receive mammography every two years. Following HEDIS guidelines, I identify preventive procedures and eligible consumers from claims records and compute prevention utilization that is comparable across insurers. The Centers for Medicare and Medicaid Services (CMS) uses HEDIS utilization measures as plan quality measures in Medicare Advantage star rating programs.

I focus on eight common preventive procedures that are widely considered cost-effective and life-saving. The first two, immunizations for children and adolescents, avoid disease onset. Another three procedures prevent the disease from developing beyond its early stages, including breast, cervical, and colorectal cancer screenings. The remaining three minimize the progression of established disease, including statin therapy for cardiovascular disease, comprehensive diabetes care, and asthma medication. These preventive procedures target diseases that are leading causes of death and are recommended by the US Preventive Services Task Force (USPSTF). Moreover, these procedures have HEDIS guidelines available, are feasible to measure using claims records, and have sufficiently large sample sizes. Table A1 reports clinical services, recommended frequency, eligible population, and medical benefits of these procedures.

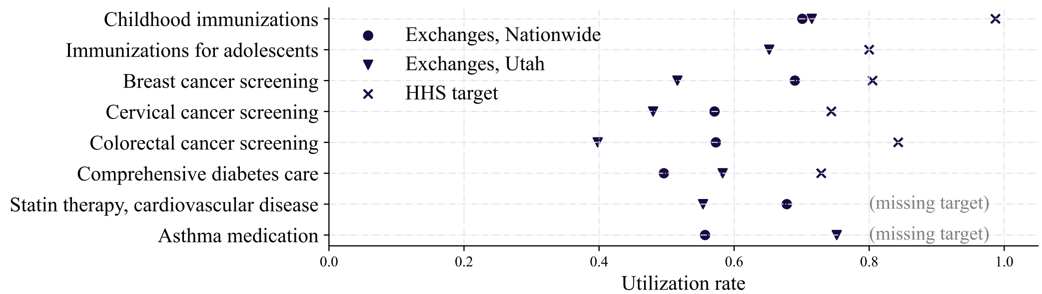
During my sample period, ACA mandates coverage for all preventive services I studied and requires the first six procedures to be free to consumers. Consumers' out-of-pocket expenses for the remaining two, diabetes care and asthma medication, do not differ significantly across insurers because of standardized cost-sharing schemes. However, these rules do not imply that insurers will make every effort to ensure consumers receive preventive services.

Figure 1 displays prevention utilization rates in the nationwide and Utah exchange and utilization targets of the Department of Health and Human Services (HHS). There exists an average utilization gap of 20 percentage points between the status quo and HHS targets.

Consumer turnover and related investment externalities could hinder insurers' preven-

[2] I abstract away from the contracting process between insurers and providers, and model the two parties together as one united agent who incurs effort costs to provide prevention.

Figure 1. Preventive care utilization, observed equilibrium in the exchange and government targets



Notes: The national utilization rate is calculated by an enrollment-weighted average for all insurers on the exchange using CMS Marketplace Quality Rating System Public Use Files in 2018-2019. The utilization rate of the Utah exchange is the mean of 2018-2019, calculated with Utah All Payer Claims Data. Colorectal cancer screening utilization in the Utah exchange is underestimated because I use colonoscopy within the last five years instead of the last ten years (for lack of data).

tive investment. Practitioners have expressed concerns that insurers are "less willing to invest in longer-term strategies in disease prevention and wellness when the economic benefits are likely to be achieved by a different payer as patients join new health plans" (Pistollato et al., 2020; Attia, 2023). Several cross-sectional variations are also consistent with this hypothesis. Appendix B1 shows that the US has worse chronic disease management, more preventable hospital admissions, and preventable deaths than other single-payer countries, which presumably have less consumer turnover. In the US, market segments with lower turnover, such as employer-sponsored or Medicare Advantage markets, have higher preventive care prevalence than the exchange. Although these stylized facts are indicative of turnover disincentivizing investment, they may reflect systematic institutional differences. Hence, I will employ a shift-share design to examine whether consumer turnover reduces insurers' investment.

3 Motivating Evidence

To establish that limited consumer commitment reduces insurers' prevention provision, there are two prerequisites to be satisfied: First, preventive care increases future profits, creating dynamic incentives; Second, insurers could control prevention utilization. I begin by showing these two conditions hold in Sections 3.1 and 3.2. I proceed to demonstrate consumer turnover reduces insurers' preventive investment in Section 3.3. Key datasets used to characterize these motivating facts are introduced below; data sources used for model estimation are presented in Section 5.2.

3.1 Selected Preventive Care Increases Future Profits

Not all preventive care saves money and lives (Kowalski, 2021; Newhouse, 2021). I focus on preventive care that is well-known to reduce future costs and on associated eligibles who are perceived to receive net benefits from prevention. These preventive procedures (in Figure 1) improve health, hence lowering future expenses by reducing adverse health events compared to the no prevention scenario (CDC, 2021a; USPSTF, 2021).

I offer three pieces of evidence that preventive care studied in this paper increases future profits. The first is insurers' revealed preferences. Insurers in my sample choose to spend money on preventive care without being mandated to, suggesting these preventive procedures bring net returns from insurers' perspective. As consumers are not responsive to preventive care (shown both in the existing literature and in Section 5), expectations of future cost savings are the main drivers of this expenditure. Second, I summarize epidemiological and medical studies on health benefits and cost savings of preventive procedures in Appendix B2. Preventive procedures yield future cost savings due to reduced procedure costs to treat adverse health events.[3] Third, I present two examples from my sample in Appendix B3 to show preventive care generates future savings: Colorectal cancer screening reduces future costs through intervening before disease occurs and detecting and treating diseases at an early stage; Diabetes care reduces future costs through managing disease to slow or stop its progression. In addition to these evidence, Appendix B4 clarifies some more subtle concerns with returns to prevention.

3.2 Insurers Have Control Over Prevention Utilization

To show insurers control preventive care utilization, I exploit a quasi-experimental variation of insurer exits (Abaluck et al., 2021). Insurer C dropped out of Utah's and other states' exchange in 2018 as a part of a restructuring plan, which does not correlate with its enrollee's preventive utilization patterns (Recht, 2017; Small, 2017). This exit forces consumers who initially stayed with Insurer C to switch to other insurers. I examine utilization patterns of consumers who switch from Insurer C to insurers that remain operating, Insurers A, B, and consumers who stay with Insurer A or B throughout in 2016-2019. Using the Utah All Payer Claims Data (described in detail in Section 5.1), I identify eligible consumers and preventive procedures with HCPCS and ICD codes in claims records, following HEDIS guidelines.

Figure A2 reports utilization rates separately for each preventive procedure before and after insurer switches. Two patterns are outlined. First, there are significant differences in procedure utilization for switchers pre- and post-switches. This utilization difference is not caused by consumers' moral hazard because financial characteristics, especially cost-sharing structures, are standardized across exchange insurers. If consumers' unobserved propensity to utilize medical care is assumed to be constant during the analysis period, this significant difference between pre- and post-switch reflects insurer effects in procedure utilization. Sec-

[3] Starc and Town (2020) shows expenses on prescription drugs to manage chronic diseases reduce medical expenses, and insurance plan designs respond to cost-reduction effects.

ond, the utilization rates for switchers and stayers are not significantly different post-switch. Given that switchers and stayers could have different unobservable characteristics, suggested by their first choice of insurance product, the no difference result post-switch suggests that insurer effects, but not enrollees' characteristics, is a major determinant of utilization.

In addition, I employ an event study design (Finkelstein et al., 2016) in Appendix B5 that exploits consumers' switching across insurers. I find consumers who move to insurers with a 1 percentage point higher prevention utilization rate increase their likelihood of using prevention by 0.9 percentage points after insurer changes. This exercise further reveals the supply side is essential in determining prevention utilization.

The stylized fact that insurers control prevention utilization is not surprising. The lack of knowledge on recommended preventive services hinders patients from seeking preventive care (Tam et al., 2018). Statistics from the National Health Interview Survey show 57.4% and 71.4% of eligible women do not have up-to-date mammography or cervical cytology because they don't know they need these tests or doctors don't say they need them. Two-thirds of consumers don't know that insurers are required by law to pay the full expenses for preventive services recommended by USPSTF (Lantz et al., 2016), thereby forgoing preventive visits. Given that consumers cannot make informed choices, we would expect insurers' efforts play a key role in preventive care utilization.

3.3 Consumer Turnover Reduces Insurers' Prevention Provisions

Previous analysis reveals that prevention creates dynamic incentives, and insurers could control prevention utilization. This implies profit-maximizing insurers would respond to market conditions that change the expected investment returns. For example, insurers would lower preventive investment when consumer turnover heightens. Seminal work by Crocker and Moran (2003); Fang and Gavazza (2011) confirms such dynamic forces exist in employers' health investment. To ensure health insurers in my sample respond to dynamic incentives created by consumer turnover, this section employs a shift-share design and shows turnover reduces insurers' prevention provision by lowering expected future returns.

Data Sources. The key measures for this exercise are prevention provision and turnover. I use the CMS Marketplace Quality Rating System (QRS) Public Use Files (PUF) to extract information on the procedure-insurer-state-year level HEDIS prevention utilization rates and eligibles for exchange insurers nationwide in 2018-2019. I construct aggregate utilization rates using a weighted average of all available preventive procedures (listed in Figure A7b). Table 1 shows the mean aggregate utilization is 64.8%.

I extract preventive investment from the CMS Medical Loss Ratio (MLR) reports. The MLR data contains quality improvement expenses at the insurer-state-year level, separately

Table 1. Regression sample statistics

	Mean	Std.		Mean	Std.
Premiums per member ($)	6408	(1456)	Preventive investment per member ($)	107	(111)
Medical claims per member ($)	5080	(1084)	-, medical incentive expenses ($)	44	(90)
Member-months (in millions)	3.36	(4.86)	-, improve health outcomes ($)	30	(27)
Share of consumers retained	74.2	(4.61)	-, promote wellness activities ($)	12	(17)
Aggregate prevention utilization	64.8	(7.38)	-, other investment categories ($)	21	(21)

Notes: State-year means and standard deviations (in parentheses) are reported for the exchange nationwide. The utilization and retention rates are measured in 0-100 percentage points.

for individual, small group, and large group markets. The quality improvement expense is used as a proxy for preventive investment, including expenses to improve health outcomes, promote wellness activities, and medical incentive payments, etc.[4] Table 1 reports the mean per-member annual quality expenses are \$107 for the exchange insurers, 1.7% of premium revenues, or 2.1% of medical claims.

Finally, I construct state-year level consumer retention, i.e., the share of consumers who remain in exchanges the following year, with the CMS Marketplace Open Enrollment Period PUF in 2017-2019, using new consumers and re-enrollees counts.[5] Mean retention rate is 73.7%. I obtain industry-state-year level hires and employment counts from the US Census Bureau's Longitudinal Employer-Household Dynamics Job-to-Job Flows PUF and Current Population Survey. I use labor market statistics to construct instruments for retention.

Empirical Specification. To analyze how consumer turnover affects insurers' preventive investments, I start with the following regression, where s denotes state; t denotes year:

$$y_{st} = \beta_0 r_{st} + \alpha_s + \alpha_t + \varepsilon_{st}. \tag{1}$$

y_{st} is preventive care investments or utilization rates; r_{st} is the percentage of current enrollees who will stay in the exchange in the next year; α_s, α_t are state, year fixed effects.

Estimating equation (1) has two potential problems: reverse causality that consumers leave the exchange to get insurance elsewhere due to the low quality of exchange plans; omitted variable bias of unobserved health shocks. To address these challenges, I construct a shift-share instrument z_{st} (Bartik, 1991; Autor et al., 2013) for retention rate r_{st}:

$$z_{st} = \sum_m h_{mt} w_{smt_0}, \quad t_0 < \min t. \tag{2}$$

h_{mt} is industry-specific national job hiring trends, i.e., the number of new hires over the

[4] One concern with the quality investment measure is that insurers may manipulate quality improvement expenses to satisfy MLR requirements (Cicala et al., 2019). If that is the case, companies with smaller claims to premium ratios would have larger quality expenses to premium ratios. Figure A3a shows such a negative correlation does not exist for exchange insurers. Figure A3b additionally shows the MLR ratio distribution for exchange insurers does not bunch at the regulatory minimum threshold.

[5] It is ideal to construct insurer-state-year level retention but such data is unfortunately not available.

number of employed individuals of industry m in year t ("shift"). w_{smt_0} is state-specific employment structure, i.e., industry m's employment over total employment in state s in year t_0 before the analysis period ("share"). Figure A4 displays job hiring trends by industry. Figure A5 depicts the geography of the instrument.

Exploiting the shift-share instrument, I estimate the following equations:

$$r_{st} = \beta_2 z_{st} + \alpha_s + \alpha_t + \upsilon_{st}, \tag{3}$$

$$y_{st} = \beta_1 \hat{r}_{st} + \alpha_s + \alpha_t + \upsilon_{st}, \tag{4}$$

where standard errors are clustered at the state level, and each observation is weighted by the exchange's market size.[6] The coefficient of interest is β_1.

Identifying Assumptions and Validity Checks. Recent literature on shift-share instruments highlights two paths to identification: quasi-randomness of shifts (Borusyak et al., 2022), or quasi-randomness of shares (Goldsmith-Pinkham et al., 2020). The identification assumption underlying my shift-share design is that "shifts", i.e., national job hiring trends, are as good as random and not correlated with factors that would affect preventive investments and utilization other than consumer turnover.

Although the quasi-randomness of shifts assumption cannot be directly tested, I provide suggestive evidence that the exclusion restriction is not violated: I do not find statistically significant relationships between the instrument and proxies for unobserved health shocks, previous period demographics, and prevention utilization in Medicare, a market not supposed to affected by labor turnover shocks. Appendix B6 reports these validity checks in detail.

First-Stage. The first-stage correlation exploits the institutional feature that employment status and insurance status are correlated, and that the exchange serves individuals without employer-sponsored insurance. As labor markets boom, individuals become more likely to change jobs. An individual can, for example, change his employment from a firm that does not offer insurance to a firm that provides employer-sponsored insurance. This is equivalent to an outflow of the exchange's consumer pool because the individual now drops out of the exchange and gets insurance from his employer. Likewise, the individual can change his employment from a firm that offers insurance to one that does not, equivalent to an inflow into the exchange. As more job hiring happens, more inflows and outflows occur; thus, the retention rate of the current cohort of exchange enrollees falls.

Point estimates of the first-stage correlation are reported in Table 2 column (1)-(2): as 43 more individuals change to new jobs from old jobs or unemployment, 1 more current enrollee

[6] I apply the exchange's eligibility criteria based on age and income to American Community Survey and calculate the number of eligibles as the market size. Appendix B6 shows the estimates are robust to weighting by realized exchange enrollment or total state population and running regressions at insurer-state-year level.

leaves the exchange. This is consistent with statistics from the Medical Expenditure Panel Survey: 3.7% labor market transitioners (job-to-job, unemployed-to-employed transitions, and vice versa) change from the exchange to other insurance.

Table 2. Effect of consumer retention on preventive care utilization and investments

	Exchanges retention		Aggregate utilization rate		Per member investment	
	2018–19	2017–19	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shift-share IV	–0.352**	–0.507***				
	(0.141)	(0.109)				
Exchanges retention			0.333**	0.786*	3.10**	5.31**
			(0.148)	(0.409)	(1.18)	(2.37)
Outcome mean	74.2	70.0	64.8	64.8	107	107
N	88	141	88	88	141	141
F-stats	13.658	23.328				

Notes: This table reports coefficients and standard errors (in parentheses, clustered at state level) from the estimation of equation (3) in columns (1), (2); equation (1) in columns (3), (5); equation (4) in columns (4), (6). The utilization and retention rates are measured in 0-100 percentage points; quality investment is measured in dollars. The regression includes state and year fixed effects and is weighted by state-year-level exchange market size. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

2SLS Results. Figure A6 provides an initial look at the impacts of consumer retention on prevention utilization. There exists a positive relationship between retention and prevention utilization. Table 2 columns (3)-(4) report corresponding OLS and 2SLS estimates. Their relative magnitudes are analyzed in Appendix B6. A 1 percentage point increase in retention increases prevention utilization by 0.78 percentage points, 1.2% out of baseline means.

Table 2 columns (5)-(6) examines the effect of consumer retention on insurers' preventive investment. 1 percentage point increase in consumer retention raises per member preventive investment by $5.3, 4.9% out of baseline means. Table A4 further estimates the effect for each sub-category of quality investment. Investment increases mostly come from expenses on promoting wellness activities and medical incentive payments. This is consistent with the facts in Section 2.2, that insurers' preventive investment mainly works through *varying quantities or intensities* of *existing* consumer wellness or provider incentive programs.[7]

Robustness. My findings are robust to alternative empirical specifications. First, I show the precision of the estimates is unchanged following alternative inference procedures of Adao et al. (2019), Borusyak et al. (2022). Second, I show estimates are robust to alternative in-

[7] Two possible timing scenarios explain insurers' responses to consumer turnover. The first is that insurers form correct and rational beliefs of consumer turnover based on market analysis or job hiring forecast, then make investment decisions accordingly at the beginning of each plan year. The second is that as job hiring happens throughout the year, insurers observe consumer turnover, forecast retention rates based on current consumer flows, and adjust preventive investments for the rest of the plan year accordingly.

strument construction, such as jackknifed (Autor and Duggan, 2003) or recentered (Borusyak and Hull, 2023) instruments. Finally, I conduct a permutation test that constructs a placebo instrument. The test suggests the estimated impacts of turnover on preventive measures are unlikely to be driven by noise. Appendix B6 reports robustness exercises in detail.

The Mechanism of Dynamic Investment Returns. I conduct three additional tests to probe whether insurers' intertemporal investment considerations drive the estimated effects.

First, I examine whether the effects are more muted for states where insurers in the exchange have a bigger presence in employer-sponsored markets. I estimate an augmented version of equations (3), (4), where I interact the exchange retention rate and the instrument with an indicator denoting whether the market share of exchange insurers in the employer-sponsored insurance market is in the top quartile. The negative coefficient on the interaction terms in Table 3 column (1) is sensible, as the likelihood of capturing the returns of preventive investment increases when an insurer is a bigger player in the employer market. Furthermore, when the percentile cutoff for market share in the employer-sponsored market increases, the difference in investment returns and incentives between the two groups grows. The coefficient on the interaction term expands, as shown in Figure A7a.

Table 3. Effect of consumer retention on procedure utilization

	Utilization (preventive care)						Utilization (placebo)			
	Aggregate (1)	*cdc* (2)	*mma* (3)	*bcs* (4)	*ccs* (5)	*msc* (6)	*uri* (7)	*cwp* (8)	*lbp* (9)	*aab* (10)
Exch. retention	0.816*	0.728*	0.583*	0.377	1.671*	-0.148	–0.028	0.148	–0.072	–0.358
	(0.418)	(0.430)	(0.297)	(0.311)	(0.930)	(0.284)	(0.120)	(0.237)	(0.204)	(0.223)
Exch. retention × first quartile mks.	–0.290 (0.950)									
Outcome mean	64.8	47.0	56.2	68.1	55.2	50.4	88.5	84.0	74.1	28.8
N	88	88	88	88	88	88	88	88	88	88

Notes: This table reports coefficients and standard errors (in parentheses, clustered at state level) from the estimation of equation (4). Utilization of breast, cervical cancer screenings (*bcs*, *ccs*), diabetes care (*cdc*), asthma medication (*mma*) are defined in Table A1. Utilization of smoking cessation (*msc*), treatment for upper respiratory infection (*uri*), antibiotics treatment (*aab*), testing for pharyngitis (*cwp*), diagnosis of low back pain (*lbp*) are defined in Table B8. The utilization and retention rates are measured in 0-100 percentage points. The regression includes state and year fixed effects and is weighted by state-year-level exchange enrollment. *,**,*** denote statistical significance at the 10%, 5%, and 1% level.

Second, I examine whether the effects differ across clinical procedures with differential future cost savings. I examine placebo procedures, which focus on best practices of diagnosis and treatment, rather than managing patients' health or detecting preventable diseases to yield future returns. The estimated effects of retention on placebo's utilization are close to zero and not statistically significant, as shown in Table 3 columns (7)-(10). In contrast, utilization of procedures with future health benefits in columns (2)-(5) increases as retention rises. Procedures with shorter return spans, like chronic disease management, are also more affected than those with longer return horizons, such as smoking cessation. Figure A7b shows similar patterns hold for all available preventive procedures in QRS files.

Third, I examine whether the effects are driven by selection in utilization propensity. Table A5 shows that consumer flows do not change the distribution of income, age, or metal level choices on the exchange. Hence, it is not the case that outflow consumers are healthier and value prevention provision less than inflows. Table A6, A7 show that health conditions, cost levels, and utilization propensity of preventive procedures are not statistically different between inflows, outflows, and those staying in the exchange. These tests do not support the hypothesis that turnover impacts prevention utilization through differential utilization propensity, for example, consumers are busy changing jobs so they do not have time to visit doctors or use prevention.

Implications for Market Designs. Previous analysis demonstrates that insurers respond to changes in future investment returns created by consumer turnover. Competition could amplify across-insurer turnover and create investment externalities, thereby shifting expected investment returns and intensifying underinvestment. Figure A8 affirms this hypothesis in the exchange nationwide: there is a positive correlation between competition and turnover[8], and a negative correlation between competition and prevention provisions.

The interplay between limited consumer commitment and insurer competition makes its welfare impacts ambiguous. Competition could reduce insurers' preventive investment and intensify disease burdens by lowering expected investment returns. Conversely, competition restricts insurers' pricing power, which could increase the share of insured consumers who receive prevention and improve population health. Likewise, consumer surplus is affected by the competing forces of lower investment (thus higher out-of-pocket medical expenses) and lower premiums. To disentangle these equilibrium impacts and explore policies that better incentivize prevention provision, I design a model of insurance demand and insurer competition on premium and preventive investment.

4 Model

I now develop a model of consumers' insurance demand and insurers' investment and pricing decisions. Key forces of the model are: Consumers make repeated choices without commit-

[8]The positive correlation between the number of insurers and the probability of switching insurance plans or insurers could be explained by both increased choice varieties, and that competition for market share may induce insurers to price aggressively, which raises consumer turnover. Theoretically, the effect of competition on consumer turnover is ambiguous and depends on the model setup, for example, whether including logit taste shocks in the flow utility or whether firms compete as those in a linear city model or Salop model, etc.

ting to an insurer; Insurers trade off extra investment costs with increased future profits and better enrollee health, considering consumer turnover; Insurers' preventive investment and price strategies vary with market structure and involve a tradeoff between investment externalities and market power.

Players and Timing. The equilibrium model is an infinite horizon dynamic game, focusing on players in the exchange. Let i denote individual, f denote insurer, j denote product, t denote year, m denote county. Let F denote the full set of insurers on the market; U denote uninsurance; J denote the full set of products; J_f denote the set of products of insurer f.

In each period's stage game, the following steps happen in order: Insurers first simultaneously choose premium $\vec{p}_{fmt} = \{p_{jmt}\}_{j \in J_f}$ and per enrollee preventive investment x_{fmt}. Individuals then choose products, observing all attributes. Next, state transition happens. The effect of insurers' investment realizes, and enrollees' health risks evolve from $\vec{\mu}_{mt-1}$ to $\vec{\mu}_{mt}$. Market shares evolve from $\vec{s}_{mt-1}$ to $\vec{s}_{mt}$, and consumers flow into and out of the exchange market. In what follows, I present the details of each step in reverse order.

I define health risks as consumers' non-preventive medical expenses in a standardized plan. The model separately considers claims costs of non-preventive medical services, i.e., health risks, and costs of preventive procedures, which belong to preventive investments.

State Transitions. I describe the market share and health risk transitions separately.

End-of-period market shares are affected by insurers' strategies and resulting consumer choices within the period, and consumer flows into and out of the exchange. The former is standard. The latter captures both consumer swaps between the exchange and other market segments, such as employer-sponsored or Medicaid markets, and the overlapping generation component of consumers aging into Medicare and newborns coming into the exchange.

I assume market size and shares of consumer flows are constant across time for a given market.[9] Every insurer loses the same share of their current enrollees $1 - \kappa_m$ to other market segments. $1 - \kappa_m$ share of new consumers (denoted by I) flow into the exchange. I assume share of consumer flows, κ_m, is not affected by insurers' premiums or investment strategies.[10]

Market share of product j at the end of period t is a weighted sum of choice probabilities

[9]The alternative assumption that reconciles best with the reduced form is to assume the share of consumer flows is drawn from a given distribution so that ex-post realizations could differ across time. However, this alternative increases computation complexity. The simplified "constant across time but vary by market" assumption delivers the same intuition that expected retention rates impact insurers' investment strategies.

[10]Although earlier literature finds job-lock, i.e., the reduction in job mobility, induced by non-portability of employer-sponsored insurance (Madrian, 1994; Currie and Madrian, 1999; Gruber, 2000), recent literature that revisits this question using different ACA provisions finds no or little effects of insurance on employment or job mobility (Bailey and Chorniy, 2016; Gooptu et al., 2016; Leung and Mas, 2018; Bae et al., 2020). I thus assume away the impact of insurance quality on consumer flows, which primarily reflects job transitions.

of consumers with different previous insurer choices:[11]

$$s_{jmt} = \sum_{k \in J \cup U} \left[\kappa_m s_{kmt-1} \left(\sum_{\{i: d_{it-1}=k\}} s_{ijmt} \right) \right] + (1-\kappa_m) \left(\sum_{\{i: d_{it-1}=I\}} s_{ijmt} \right), \tag{5}$$

where the first term is the share of consumers who choose insurance option (or uninsured) k in the previous period and remain in the exchange in the current period, times their choice probability of product j in the current period; the second term is the share of inflows in the current period, times their choice probability of product j in the current period.

Turning to health risks transitions, I assume insurers' preventive investment in period t does not affect their enrollees' non-prevention medical expenses in period t but affects their enrollees' health risks at the end of period t (i.e., non-prevention medical expenses in period $t+1$). This timing assumption could be violated, for example, when not receiving flu shots immediately results in influenza infections and increases non-prevention expenses during the current insurance coverage period. Conversely, the assumption holds when a lack of blood glucose monitoring harms kidney health gradually, and the patient starts to require additional treatment for diabetic complications a year later.

Mean health risk of insurer f's enrollees at the end of period t, μ_{fmt}, depend on enrollees' past health, $\tilde{\mu}_{fmt}(\vec{s}_{mt-1}, \vec{\mu}_{mt-1})$, current period prevention $q_1 e_{fmt}$, random health shock ν_{fmt}.

$$\underbrace{\mu_{fmt}}_{\substack{\text{health risks} \\ \text{(non-prevention expenses)}}} = \underbrace{\tilde{\mu}_{fmt}(\vec{s}_{mt-1}, \vec{\mu}_{mt-1})}_{\substack{\text{effect of} \\ \text{past health}}} + \underbrace{\overbrace{q_1}^{\substack{\text{returns to} \\ \text{prevention}}} \times \overbrace{e_{fmt}}^{\substack{\text{percent enrollees} \\ \text{utilizing prevention}}}}_{\substack{\text{effect of} \\ \text{current period prevention}}} + \underbrace{\nu_{fmt}}_{\substack{\text{random} \\ \text{shock}}} . \tag{6}$$

Past health $\tilde{\mu}_{fmt}$ measures mean health risks in period t after consumers choose insurers but before preventive investment takes effect, $\tilde{\mu}_{fmt} = \sum_i \sum_{j \in J_f} \left(\mu_{imt-1} s_{ijmt}\right) / \sum_i \sum_{j \in J_f} \left(s_{ijmt}\right)$. Effects of current prevention $q_1 e_{fmt}$ is defined by returns to prevention q_1 times prevention utilization rate e_{fmt}. e_{fmt} is determined by insurers' preventive investments x_{fmt} (described later). Returns to prevention, q_1, measure how much cost savings full prevention utilization could yield, compared to the no prevention scenario, due to the reduction of future adverse health events. $q_1 e_{fmt}$ measures the average cost savings (health improvement) across the insurer's enrollees. Idiosyncratic health shocks ν_{fmt} is drawn from $N(q_0, \sigma_\nu^2)$, where q_0 captures health risks evolution as enrollees age, absent any prevention usage.

For simplicity, I assume returns to prevention are constant across health risk levels and prevention utilization levels. I assume inflows and outflows have the same health risks, μ_{Imt},

[11]The model does not separately keep track of market shares and their transitions by whether consumers utilize prevention because utilization rates for stayers and non-forced switchers are not statistically different prior to switches. Non-forced switchers refer to consumers who change insurers, not due to insurer exits.

which is reasonable given the stylized facts in Table A6.

Consumer Choices. Let μ_{imt-1} denote consumer i's health risk at the end of period $t-1$ (i.e., the beginning of period t), d_{imt-1} denote previous insurer choice, p_{ijmt} denote premiums that consumer pays out-of-pocket, co_ins_{jmt} denote coinsurance, X_{jmt} denote other product attributes, such as deductibles or out-of-pocket maximums. Consumer i's flow utility from choosing product j is

$$u_{ijmt} = \underbrace{\delta_{jmt}}_{\substack{\text{common utility}\\ \text{component}}} + \underbrace{\alpha_1 \mu_{imt-1} p_{ijmt}}_{\substack{\text{price sensitivity}\\ \text{by health status}}} + \underbrace{\gamma \mu_{imt-1} \text{co\_ins}_{jmt}}_{\substack{\text{out-of-pocket}\\ \text{medical expenses}}} + \underbrace{\eta \mathbf{1}[d_{imt-1} \neq j]}_{\text{inertia}} + \underbrace{\epsilon_{ijmt}}_{\text{T1EV}}, \tag{7}$$

$$\delta_{jmt} = \underbrace{\alpha_0 p_{ijmt}}_{\text{premium}} + \underbrace{\rho e_{jmt}}_{\text{prevention}} + \underbrace{\theta X_{jmt}}_{\text{other char.}} + \underbrace{\xi_{mt} + \xi_{jm} + \xi_{jt}}_{\text{fixed effects}} + \underbrace{\xi_{jmt}}_{\text{unobserved preferences}}. \tag{8}$$

α_1 captures the selection that healthy consumers are more price sensitive than sick consumers. γ captures the selection that sick consumers value products with lower cost shares more as it brings lower out-of-pocket medical expenses. ϵ_{ijmt} is independent and identically distributed from extreme-value type-I distribution. The outside option $j = 0$ is uninsurance (U), where consumers pay zero premiums, pay some cost share of total medical expenses, and receive some prevention due to charity care. I normalize $\delta_{0mt} = 0$.

I assume consumers are myopic and choose products that maximize flow utility:[12]

$$d_{imt} = \arg\max_j u_{ijmt}. \tag{9}$$

This choice framework is compatible with different micro-foundations of why consumers like prevention. For example, consumers might prefer preventive services per se or because they like future cost savings brought by prevention. The reduced form way of letting prevention enter consumers' flow utility does not impose any assumptions on whether consumers know the returns to prevention or to what extent consumers are forward-looking.

I embed inertia into the choice framework because it is an important form of consumer commitment that could affect insurers' investment decisions. I assume inertia exists for all consumers except the uninsured (U) and inflows (I), who are forced to make active choices.[13]

Insurers' Premium and Preventive Investment Strategies. Each period, insurers make dynamic pricing and preventive investment decisions while holding fixed other product characteristics. The per enrollee flow profit from product j, revpm_{ijmt}, equals premium p_{jmt},

[12] There exists a large literature on consumer myopia in health insurance (Einav et al., 2015; Brot-Goldberg et al., 2017; Dalton et al., 2020). Moreover, the non-dynamic consumer assumption facilitates computation.

[13] The uninsured tend to have fewer interactions with the medical system, so they do not have the high hassle costs of changing from one provider network to another. Estimating a specification that allows inertia to differ by insurance status, the point estimate for uninsured consumers is close to zero and insignificant.

minus insurers' cost share of enrollees' non-prevention claims expenses $(1 - \text{co\_ins}_{jmt})\mu_{imt-1}$, minus preventive investment per enrollee x_{fmt}. Preventive investment x_{fmt} includes both claims costs paid to providers for performing preventive procedures, and promotion expenses on consumer wellness or provider incentives programs to increase prevention utilization.

$$\underbrace{\text{revpm}_{ijmt}}_{\text{per enrollee profit}} = \underbrace{p_{jmt}}_{\text{premium}} - \underbrace{(1 - \text{co\_ins}_{jmt})\mu_{imt-1}}_{\text{claims costs paid by insurers}} - \underbrace{x_{fmt}}_{\text{preventive investment}} . \tag{10}$$

The per-period profit of insurer f is

$$\pi_{fmt}(\vec{s}_{mt-1}, \vec{\mu}_{mt-1}, \vec{x}_{mt}, \vec{p}_{mt}) = \sum_{i}\sum_{j \in J_f}\left(s_{ijmt} \times (p_{jmt} - (1 - \text{co\_ins}_{jmt})\mu_{imt-1} - x_{fmt})\right). \tag{11}$$

Each insurer maximizes its expected total discounted profits. I assume insurers' strategies on different market segments are independent, such that the exchange insurers in the model only maximize profits from the exchange market segment. I assume insurers solve stationary optimization problems, i.e., the period t does not directly enter state transitions and flow profits. This is a common assumption in the dynamic games literature (Ericson and Pakes, 1995). Insurer f's policy choices satisfy the Bellman equation,

$$\begin{aligned} V_{fm}(\vec{s}_{mt-1}, \vec{\mu}_{mt-1}) = \max_{x_{fmt}, \vec{p}_{fmt}} \Big\{ &\pi_{fmt}(\vec{s}_{mt-1}, \vec{\mu}_{mt-1}, \vec{x}_{mt}, \vec{p}_{mt}) \\ &+ \beta \int V_{fm}(\vec{s}_{mt}, \vec{\mu}_{mt}) g_f(\vec{s}_{mt}, \vec{\mu}_{mt} | \vec{s}_{mt-1}, \vec{\mu}_{mt-1}, \vec{x}_{mt}, \vec{p}_{mt}) dF_{\vec{\mu}_{mt}} \Big\}. \end{aligned} \tag{12}$$

$g_f(\vec{s}_{mt}, \vec{\mu}_{mt} | \vec{s}_{mt-1}, \vec{\mu}_{mt-1}, \vec{x}_{mt}, \vec{p}_{mt})$ is insurer f's beliefs about future market share and health risks of all players, conditional on current state variables and own and rivals' policies.

Insurers differ in preventive investment cost functions, namely, how efficiently they can transform preventive investment expenses into actual prevention utilization, which affects future health risks and profits. Differential management practices across insurers or provider networks across markets explain variations in investment cost functions. I restrict the relation between preventive investment per enrollee x_{fmt} and prevention utilization e_{fmt} to a convex structure following Pakes and McGuire (1994).

$$\underbrace{x_{fmt}}_{\text{investment expenses (dollars)}} = \underbrace{a_{fm}}_{\text{investment cost curvature}} \times \frac{e_{fmt}}{1 - \underbrace{e_{fmt}}_{\text{prevention utilization}}}, \tag{13}$$

where a_{fm} measures the curvature of the investment cost functions.

The monotonic mapping between preventive investment and utilization in equation (13) is equivalent to assuming insurers could directly choose prevention utilization, which is reasonable given the stylized facts in Section 3.2.[14] Equations (6) and (13) link insurers' invest-

[14] This setup implicitly assumes insurers' investment does not change consumer preference and rules out

ment expenses to health risk transitions through utilization. Given some fixed investment expenses, insurers with smaller investment cost curvatures a_{fm} could achieve higher prevention utilization, thus lowering enrollees' future health risks more and capturing larger future profits.

Insurers' first order condition (FOC) on preventive investment per enrollee x_{fmt} is

$$[x_{fmt}] \qquad \underbrace{s_{fmt}}_{\text{marginal investment cost}} = \underbrace{\sum_{j\in J_f}\sum_i \left(\frac{\partial s_{ijmt}}{\partial x_{fmt}}\text{revpm}_{ijmt}\right)}_{\text{marginal static revenue}} + \underbrace{\beta\frac{\partial V_{fm}(\vec{s}_{mt},\vec{\mu}_{mt})}{\partial x_{fmt}}}_{\text{marginal future revenue}}. \tag{14}$$

The left-hand side measures static investment costs. The first term on the right-hand side captures static strategic incentives: market share and static profit increase with enhanced investment if consumers value prevention. The second term, the option value of preventive investment, measures dynamic incentives: expected future profits rise with enhanced investment because of reduced enrollee health risks and higher market share due to increases in current market share and choice inertia. The associated dynamic tradeoff is: higher preventive investment costs more in the current period but lowers future health expenses. Higher preventive investment also attracts more current market share and thus increases market share and profit in the future.

Insurers' first order condition on premium p_{jmt} is

$$[p_{jmt}] \quad 0 = \sum_{j\in J_f}\sum_i \left(\frac{\partial s_{jmt}}{\partial p_{jmt}}\text{revpm}_{ijmt}\right) + s_{jmt} + \beta\frac{\partial V_{fm}(\vec{s}_{mt},\vec{\mu}_{mt})}{\partial p_{jmt}}. \tag{15}$$

The first two terms measure static strategic incentives. The former measures the decrease in profit due to market share decrease when premiums rise. The latter denotes the increase in profit due to the per-enrollee revenue increase. The third term, the option value of prices, captures dynamic incentives: higher prices reduce the insured rate, so fewer individuals receive preventive services for cost savings, raising future health expenses. Higher prices also attract less current market share and decrease market share in the future.

Oblivious Assumptions and Discussions. I make several oblivious assumptions to reduce state space. While the usual oblivious concept keeps track of own states and market averages (Weintraub et al., 2008) or dominant firms (Benkard et al., 2015), I let insurers keep track of representative enrollees of all insurers on the market.

First, I assume insurers only keep track of the health status of a representative consumer based on his previous enrollment pattern. That is, $\mu_{imt} = \mu_{fmt-1}$ if $d_{imt-1} = f$, in equation (7). This setup abstracts from selection *within* an insurer based on each individual's health

the possibility of habit formation. Appendix B5 formally tests and finds a limited extent of habit formation.

risk but preserves selection *across* insurers based on their enrollees' mean health status. Insurers do not need to keep track of the *full distribution* of health risks. Instead, the *vector* of each insurer's mean health risks is sufficient for predicting consumer choices or calculating profit.

Second, I assume inertia exists at the insurer level: consumers do not incur disutilities when they change products within an insurer; they incur disutilities when they change across insurers. This setup preserves the force that inertia helps insurers retain consumers and recover investment gains. It also reduces state space dimensions so that multi-product insurers only need to keep track of market shares and enrollee health risks at the firm level, not the product level.

Third, I assume insurers' strategies on different market segments are independent. This setup does not require insurers to keep track of a high-dimensional vector of continuous state variables on *all* market segments. However, it excludes the recapture of enrollees on other markets from the model and understates returns to preventive investment. Extending the model to allow for cross-market interactions is an exciting avenue for future research.

Finally, I do not model non-linear returns to prevention trajectories over time. Practically, certain preventive procedures, such as cancer screenings, may only realize substantial cost savings in the long term and have little cost savings in the short term, creating a convex returns curve. In contrast, a Markov transition rule with a linear returns trajectory as in equation (6), facilitates computation by cutting out time or investment histories from the state space. This simplification would bias simulated strategies if the targeted model output is a time path of preventive investment. Nonetheless, it is less of a concern if I focus on a snapshot of investment strategies in stationary distributions where consumers behave like in an overlapping generation model.

With these assumptions, state variables relevant to insurers' decisions in market m period t reduce to two simple vectors: market shares of every insurer and uninsurance $\vec{s}_{mt-1} = \{s_{fmt-1}\}_{f \in F \cup U}$ and mean enrollee health risks of each insurer and uninsurance $\vec{\mu}_{mt-1} = \{\mu_{fmt-1}\}_{f \in F \cup U}$, at the end of the previous period, $t-1$.

Equilibrium. I consider pure-strategy Markov perfect Nash equilibrium (MPNE)(Maskin and Tirole, 1988a,b) of this dynamic oligopoly game. The equilibrium specifies that players' equilibrium strategies depend solely on the current state, which comprises all payoff-relevant variables. Each player has rational expectations about competitors' policy functions of price and preventive investment and the evolution of state variables.

Formally, an MPNE of this model consists of policies $\{d^*_{im}\}_{i \in N}$, $\{p^*_{fm}\}_{f \in F}$, $\{x^*_{fm}\}_{f \in F}$, value functions $\{V^*_{fm}\}_{f \in F}$ such that: individual's choice function satisfies equation (9); insurer's value function satisfies equation (12); preventive investment policy satisfies equation (14); insurance premium policy satisfies equation (15); insurance market clear each period so that aggregate insurance demand equals aggregate supply. Moreover, state variables transit according to equations (5), (6), and insurers employ the above policies to form expectations. MPNE exists following Escobar (2013), conditional on the existence of stage game equilibria.

5 Estimation

The model outlined in the previous section has three sets of primitives to be estimated. The first primitive is state transition parameters, including shares of consumer flows κ_m, returns to prevention q_1, health risk growth without prevention q_0, variations of health shocks σ_ν. The second primitive is consumer preferences, including inertia η, mean preferences for price and its correlation with health risks α_0, α_1, mean preferences for prevention, out-of-pocket health expenses, other financial characteristics ρ, γ, θ, product-specific preferences δ_{jmt}. The third primitive is curvatures of preventive investment cost functions by insurer-market, a_{fm}.

I present estimation methods and identification of each primitive in Section 5.1. Section 5.2 describes the estimation sample and additional data sources. In Section 5.3, I report estimation results and discuss key market features implied by model estimates.

5.1 Estimation Method and Identification

I estimate the model in three steps. I begin with estimating state transitions and consumer preferences offline. I then plug these estimates into the dynamic game to back out insurers' investment cost primitives. Below, I describe each estimation step in order.

State Transitions. I estimate state transition parameters by minimizing the sum of the squared distance between observed and predicted values of state variables. Rearranging the market share transition equation (5), I estimate the share of consumer flows κ_m by solving

$$\hat{\kappa}_m = \arg\min_{\kappa_m} \sum_{j \in J \cup U, t} \left(s_{jmt} - \left[\sum_{k \in J \cup U} \big(\kappa_m s_{kmt-1} \big(\sum_{\{i: d_{it-1}=k\}} s_{ijmt} \big) \big) + (1-\kappa_m) \big(\sum_{\{i: d_{it-1}=I\}} s_{ijmt} \big) \right] \right)^2, \tag{16}$$

where the term in brackets denotes market share in year t predicted with parameter κ_m and observed choices in t by previous enrollment; s_{jmt} denotes observed market shares in year t.

Turning to health risk transitions, I rewrite equation (6) to get a linear function between health risk growth across years and prevention,

$$\Delta\mu_{fmt} = \mu_{fmt+1} - \tilde{\mu}_{fmt} = q_0 + q_1 e_{fmt} + \tilde{\nu}_{fmt}. \tag{17}$$

$\tilde{\nu}_{fmt}$ is normalized to a mean zero random variable. It is tempting to estimate state transition parameters q_0, q_1, σ^2_ν with an OLS regression of equation (17), similar to the common practice in the dynamic games literature (Aguirregabiria et al., 2021). However, such regression may suffer from selection biases: The unobserved health status $\tilde{\nu}_{fmt}$, may correlate with health risk growth $\Delta\mu_{fmt}$, the insurance plan that a consumer chooses d_{imt} and the associated prevention characteristics $e_{fmt} = \sum_{k \in F} \mathbf{1}[d_{imt} = k] e_{kmt}$.

To get around the selection problem, I calibrate the returns to prevention parameter q_1 from epidemiological and medical studies. I focus on studies in the US that report total discounted *gross* cost savings due to reduced procedure costs to treat adverse health events. These savings do not net out claims costs of preventive procedures. I convert the reported total discounted cost savings to annualized per person returns estimates using discount rates and year spans in those studies and disease incidence from the CDC. I then aggregate returns across preventive services listed in Figure 1 to get the *annualized average gross* cost savings of full prevention usage, compared to the no utilization scenario. Appendix B2 reports my calculation in detail.

With calibrated $\hat{q}_1$, I estimate health risk growth without prevention q_0 by finding the parameter that minimizes the sum of the squared distance between predicted and observed health risk growth. The remaining variations not explained by the linear relation are attributed to the uncertainty in preventive returns σ_ν.

$$\hat{q}_0 = \arg\min_{q_0} \sum_{f,m,t} \left(\Delta\mu_{fmt} - q_0 - \hat{q}_1 e_{fmt}\right)^2, \quad \hat{\sigma_\nu^2} = \mathrm{Var}(\Delta\mu_{fmt} - \hat{q}_0 - \hat{q}_1 e_{fmt}). \tag{18}$$

Consumer Preferences. I estimate consumer preferences using the two-step MLE-BLP estimator of Goolsbee and Petrin (2004). The first step uses individual-level panels of enrollment records to recover preference heterogeneity and uses aggregate market shares to pin down common utility components. It is a constrained maximum likelihood estimation with four parameters outlined in equation (7): heterogeneity in price preference α_1, preference for out-of-pocket medical expenses γ, inertia η, and a series of product-market-year common utility δ_{jmt}. The constraints impose observed and predicted market shares match.

Identification of inertia η comes from comparing choice patterns of consumers who are new inflows and consumers who stay in exchanges, in a similar spirit of Handel (2013). Inflow consumers do not have previous insurers involved. Hence, the differences in choice patterns between stayers and inflow consumers identify inertia. The differential correlations between premiums and choice patterns by consumers with different health risks identify differences in price sensitivity α_1. The correlation between choice patterns and health risks, holding cost-shares fixed; and the correlation between choice patterns and cost-shares, holding health risks fixed, identify preferences for out-of-pocket medical expenses γ. Common utilities δ_{jmt} are solved using the Berry (1994) inversion and contraction mapping in Berry et al. (1995).

The second step is 2SLS estimation of equation (8), projecting the estimated common utility δ_{jmt} onto its components. This step recovers mean preferences for premium α_0, prevention ρ, and other financial attributes θ. The correlations between product characteristics and choice patterns identify these mean preferences. Insurers' knowledge of consumers' unobserved preferences when making pricing and preventive investment decisions creates a correlation among the second-stage residual, premiums, and prevention characteristics. I address this endogeneity concern using Hausman instruments and controlling for county-year, product-county, and product-year fixed effects (Hausman, 1996; Nevo, 2001). The identifying assumption is that variations in prices and prevention utilization in other markets m' can signal an insurer's cost changes in all markets, which also shifts the equilibrium policy choices in market m. It is plausible that prices and prevention utilization in market m' are mean independent of residual demand shocks ξ_{jmt} in market m, after conditional on county-year, product-county, and product-year fixed effects, $\xi_{mt}, \xi_{jm}, \xi_{jt}$.

Preventive Investment Cost Functions. I parameterize the investment cost functions as equation (13). I back out investment cost curvatures using FOCs on prevention provisions, after estimating state transitions and consumer preferences.

In practice, preventive investment expenses are only observed at the insurer-state-year level, which aggregates across counties. However, with the monotonic parametric relation in equation (13)[15], I can rewrite insurers' FOCs as if they are choosing prevention utilization, e_{fmt}, which is observed at the insurer-county-year level.

$$[e_{fmt}] \qquad \underbrace{\frac{\partial x_{fmt}}{\partial e_{fmt}} s_{fmt}}_{\text{marginal investment cost}} = \underbrace{\sum_{j \in J_f} \sum_i \left(\frac{\partial s_{ijmt}}{\partial e_{fmt}} \text{revpm}_{ijmt} \right)}_{\text{marginal static revenue}} + \underbrace{\beta \frac{\partial V_{fm}(\vec{s}_{mt}, \vec{\mu}_{mt})}{\partial e_{fmt}}}_{\text{marginal future revenue}}. \tag{19}$$

At an observed equilibrium, both the marginal revenue curve (the right-hand side of equation (19)) and the marginal cost curve (the left-hand side of equation (19)) are functions of investment cost curvatures. Their intersection pins down a utilization level, depicted in Figure A9b. When cost curvatures decrease, a marginal unit of prevention requires fewer expenses, mirrored by an outward shift of the marginal cost curve. Insurers with lower cost curvatures also extract higher marginal revenue from a marginal unit of prevention, reflected by an outward shift of the marginal revenue curve. The intersection of curves associated with lower cost curvatures thus maps to higher prevention utilization. Given this monotone mapping between prevention utilization (observed policies) and investment cost curvatures (underlying primitives), the estimation essentially backs out a set of cost curvatures that

[15] The particular functional form chosen for the preventive investment cost function is not critical for the identification argument of model parameters. Other families of monotone convex functions, such as quadratic functions, deliver the same intuitions and qualitative predictions for the counterfactuals.

rationalize observed utilization policies using all insurers' FOCs of prevention provision. This is in a similar spirit to backing out marginal costs that rationalize prices using static pricing FOCs (Berry, 1994; Berry et al., 1995).

Formally, investment cost curvatures are identified by levels of policy choices. Conditional on rival's policies and specific market conditions, flatter investment cost functions, or lower marginal investment costs imply larger intertemporal cost savings, which in turn map to higher observed prevention utilization. Experimentation with simulations, reported in Figure A9c, confirms this monotonic mapping. Furthermore, Figure A9c reveals insurers' investment policies are mostly affected by their own, not rivals', investment cost curvatures. This is because the willingness to pay for prevention is tiny in my setting, and the insurer's investment is determined mainly by its intertemporal cost-saving motives to manage its enrollees' health rather than strategic considerations to compete for static market share with rivals (relevant estimates in Section 5.3). This property helps rule out multiple solutions to the system of equations of all insurers' FOCs in a given market. Provided that the monotonic mapping from investment cost curvatures to prevention utilization exists, and only one set of investment cost curvatures satisfies the system of FOCs, the investment cost curvature parameters are identified.

Implementation-wise, FOCs in this model have extra dynamic terms compared to those in standard static inversions: the option value of prevention term, $\beta \frac{\partial V_{fm}}{\partial e_{fmt}}$. My estimation algorithm deals with these dynamic terms using an inner and outer loop structure. In the inner loop, for each guess of investment cost function parameters in market m, I solve for value functions V_{fm} that satisfy equation (12) for every insurer using the full solution approach and interpolate the option value terms evaluated at the observed equilibrium. In the outer loop, I plug in the derived option values and evaluate equation (19) for each guess of investment cost function parameters. Furthermore, the high dimensional state space, the continuous rather than discrete feature of both state variables and policy choices, and the multi-agent game rather than single-agent optimization setup bring computational challenges. I employ several techniques to reduce computation burdens, for example, polynomial approximations, trilinear interpolation. Appendix C3 describes the algorithm and computation techniques in detail. The discounting parameter β is set to 0.9 (Ryan, 2012; Collard-Wexler, 2013).

To reduce the multiplicity of equilibria, I focus on equilibria that are limits to finitely repeated games following Goettler and Gordon (2011). I use backward induction to solve for an equilibrium of the T-period game and then let $T \to \infty$. For each T and each state, I solve the stage game equilibrium using the best response iterations. My numerical algorithm for computing the equilibrium to the infinite-horizon game corresponds to the value function iterations with initial values zero for V_{fm}, and equilibrium strategies being played within each state for each iteration, rather than merely playing best responses to strategies from the previous iteration. Besides employing this equilibrium refinement, I inspect multiplicity with several tests in Appendix C4. Although I cannot prove the uniqueness of the stationary equilibrium, I find the Markov process of the dynamic game converges to a unique stationary distribution from different starting values of the iterations.

5.2 Estimation Sample

The primary data source for structural estimation is the Utah All Payer Claims Data (APCD) in 2014-2019. The APCD has information on realized insurer-metal level choices and medical and pharmaceutical claims for every commercially insured Utah resident and their age, gender, zip code. Table A2 reports summary statistics of consumers in the Utah exchange. Using Utah APCD, I construct individual-year-level health risks, i.e., consumers' expected medical expenses in a standardized plan, with the Johns Hopkins Adjusted Clinical Groups System. I construct univariate county-insurer-year level preventive utilization using a weighted average of utilization rates across preventive procedures in Figure 1. I use various public datasets to construct medical expenses, prevention utilization, counts of the uninsured, and product characteristics. Appendix C1 describes data sources and variable construction in detail.

Since identifying eligible consumers for certain preventive procedures requires up to 5 prior years' claims records (see Table A1), the 2014-2019 Utah APCD allows me to construct prevention utilization for the years 2018-2019. Hence, I estimate the first two primitives, state transitions and consumer preferences, with the 2018-2019 data. My estimation sample for the third primitive, preventive investment cost curvatures, uses the year 2019. I exclude early periods of my sample because the market was volatile in the early years right after its establishment following ACA. This is reflected by the extensive changes in consumer retention, market structure, or premiums in Table A2 panels (d)-(f). It is reasonable to assume rational insurer beliefs and stationary market conditions five years after establishing the exchange (Saltzman and Lucarelli, 2021). Two insurers (Insurer A, B) operated on the Utah exchange in 2019, each offering three vertically differentiated products.

The top panel in Table 4 reports statistics for the consumer preference estimation sample. The Utah exchange has 363,161 consumers, with an insured rate of 55%. The mean annual premium is $6,623, with a $1,618 standard deviation showing price variations across counties. The mean ACG-adjusted medical expenses are $6,040 per enrollee. I assume consumers pay a fixed proportion of total premiums and medical expenses. Appendix C2 describes reconciling exchange regulations in detail, such as premium subsidies, etc.

The bottom panel in Table 4 reports prevention utilization statistics for the estimation sample of investment cost functions. Mean claims costs per enrollee paid to providers for

Table 4. Estimation sample statistics

	Mean	Std.
Number of consumers	363,161	
Uninsured rate in the exchange	0.454	(0.069)
Total premium	6,623	(1,618)
Total medical expenses (ACG-adjusted)	6,040	(1,898)
Prevention utilization, Insurer A	0.422	(0.071)
Prevention utilization, Insurer B	0.460	(0.140)
Preventive procedure expenses per member, A	78	(249)
Preventive procedure expenses per member, B	77	(296)

Notes: This table reports the mean and standard deviation (in parenthesis) of equilibrium objects across markets (county-year pairs), in the estimation sample. Preventive procedure expenses per member average across all enrollees, i.e., include zeros.

preventive procedures are \$78 and \$77 for Insurers A and B, 1.3% of total claims expenses. Insurers A, B's mean prevention utilization is 42.2% and 46.0%, with variations across counties due to differential provider networks, consumer flows, market shares, or enrollee health.

5.3 Estimation Results

State Transition Estimates. Table 5 reports state transition estimates. Figure A10 plots the distribution of the share of retained consumers across all counties. Across counties, the mean share of consumers who remain in the exchange in the next year is 65.6%.

Table 5. State transition estimates

Mean share of retained consumers, κ_m	0.656	(0.071)
Returns of prevention, q_1 (calibrated, \$)	851	
Health risk growths without prevention, q_0 (\$)	563	(14)
Standard deviation, randomness of preventive returns, σ_ν (\$)	1035	(31)

Notes: This table reports state transition estimates from estimating equations (16), (18). Standard errors (in parentheses) are derived with delta methods. Returns to prevention are calibrated from medical studies.

The calibration exercise shows a 10 percentage point increase in prevention utilization slows insurer-level mean health risk growth by \$85 per member per year. In addition, Table A8 reports OLS estimates of returns to prevention using equation (17). Despite the endogeneity concerns outlined in Section 5.1, the OLS estimator is about the same magnitude as the calibrated estimator: A 10 percentage point increase in prevention utilization slows down health risk growth by \$66 per member per year. Minimum distance estimators reveal that insurer-level mean health risks would increase by \$563 annually if there were zero preventive care utilization. The standard deviation of returns to prevention shocks is \$1035.

Consumer Preference Estimates. Table 6 reports demand estimates. Implied enrollment-weighted average own-premium elasticity is -5.47, similar to -3.2 to -4.5 (Geddes, 2022), -5.2 (Drake, 2019), -7.2 (Saltzman, 2019) for the Oregon, California, and Washington exchange.

Increasing all products' posted annual premiums by \$100 decreases the insured rate by 2.0%, consistent with 1.5% to 4% (Tebaldi, 2017) of the California exchange. Raising all products' out-of-pocket annual premiums by \$100 lowers the insured rate by 9.1%.

Table 6. Consumer preference estimates

(a). First step MLE estimation		
Inertia (disutility of changing insurer), η	-2.505	(0.014)
Increase in premium coefficients as health risks increase by \$1,000, α_1	0.312	(0.001)
Coefficient on out-of-pocket medical expenses (in \$1,000), γ	-0.454	(0.007)
(b). Second step 2SLS estimation		
Coefficient on premium (in \$1,000), α_0	-6.984	(1.594)
Coefficient on prevention, ρ	0.113	(0.587)
F-statistics, first stage with Hausman instruments	14582, 931328	

Notes: This table reports consumer preference estimates using the two-step estimator of Goolsbee and Petrin (2004). Standard errors (in parentheses) are derived using the delta method.

Estimates of α_1 confirm adverse selection: healthy (low-health-risk) consumers are more price elastic than sick (high-health-risk) consumers. For example, own-premium elasticities in Salt Lake County would be -6.4 or -4.9 if consumers' health risks were \$3,000 or \$7,000.

Comparison of γ and α_0 shows, on average, one dollar expense on premiums brings 11.7 times negative utility as a dollar expense on out-of-pocket medical expenses. This aligns with existing studies: consumers place 5.4 (Abaluck and Gruber, 2011) to 13.7 (Brown and Jeon, 2023) times more weight on premiums than expected OOP medical expenses.

The average own-elasticity of prevention is 0.05. Willingness to pay for the observed levels of prevention provisions is \$9, one-tenth of monthly out-of-pocket premiums.[16] The small willingness to pay is not surprising given the stylized facts in Section 3.2 that consumers lack knowledge of recommended preventive services. It is also consistent with existing studies that consumers undervalue prevention (Kenkel, 2000). My revealed preference framework cannot tell whether the little willingness to pay for preventive care is due to consumers not having correct beliefs of the preventive services offered or not valuing prevention enough.[17]

Inertia, or average disutilities from changing insurers, is \$460, equivalent to 5.1 monthly out-of-pocket premiums. This estimated inertia level of the Utah exchange is lower than that of consumers in the employer-sponsored insurance market, which is around \$2,000, or 11.8 times monthly out-of-pocket premiums (Handel, 2013).

Table A9 shows demand estimates under alternative specifications, including a random

[16] The second stage regression would lead to underestimation of consumers' willingness to pay for prevention if product fixed effects capture preferences for brand quality that includes product-specific time-invariant preventive quality. I find a correlation of 0.011 between the product fixed effects term and the prevention attributes terms, suggesting the abovementioned underestimation channel is not at work.

[17] In a parsimonious model where consumers observe a noisy signal of the prevention characteristics, the estimated parameter is preference for prevention scaled by a measure of how precise the beliefs on prevention characteristics are. The estimated parameter is a lower bound for true preference for prevention.

coefficient specification with health risks drawn from the empirical distribution, and allowing heterogeneity in willingness to pay for prevention by health risks. The implied premium and prevention elasticities are not meaningfully different.

Estimates of Preventive Investment Cost Functions. Table 7 reports mean investment cost curvature estimates and derived investment expenses across all counties. Figure A10 depicts their distributions. I also report estimates of Salt Lake County, the largest Utah county, which is used in counterfactual simulations in Section 6. The point estimate of investment cost curvature is slightly smaller for Insurer B than Insurer A, meaning Insurer B is more efficient in converting investment expenses to prevention utilization. This is consistent with Insurer B having a higher share of integrated providers and thus lower costs to motivate its providers.

Table 7. Estimations of Curvatures of Preventive Investment Cost Functions

	State Mean		Salt Lake Cty.	
Insurer	A	B	A	B
Investment cost curvature estimates	0.15	0.11	0.19	0.14
	(0.04)	(0.03)	(0.06)	(0.06)
Per member preventive investment at observed equilibrium ($)	178	130	228	147
	(61)	(41)	(78)	(62)
Per member preventive investment of HHS utilization targets ($)	604	438	760	560
	(209)	(144)	(259)	(235)

Notes: This table reports investment cost curvatures estimates using insurers' FOCs (equation (19)). Preventive investment is derived by evaluating equation (13) at model estimates and observed or targeted utilization. Standard errors (in parenthesis) are based on 50 bootstrap samples with resampling of markets and consumers.

Figure A11 plots model-implied cumulative and marginal returns to prevention expenses. Returns to preventive investment are concave. At the observed equilibrium where the prevention utilization rate is around 50% and consumer retention is 65%, the marginal future returns of a dollar's preventive investment is 84 cents. I further benchmark my estimated returns to prevention curves to the existing literature. For the Medicare population whose prevention utilization is around 75% and consumer retention is around 95%, a marginal dollar expense on prescription drugs to manage chronic diseases reduces medical expenses by 20 to 30 cents (Chandra et al., 2010; CBO, 2012; Starc and Town, 2020). My estimates predict a marginal dollar of preventive care generates 31 cents of cost savings in the next year, at the same prevention utilization and consumer retention, consistent with existing studies.

The derived mean preventive investment per member at observed equilibrium across all counties is $178 and $130 for Insurers A and B. Assuming total preventive investment is a sum of claims costs paid to medical providers, plus expenses to promote prevention utilization, I deduct observed per member claims costs of preventive procedures, $78 and $77 for insurers

A and B (reported in Table 4), from the derived total investment expenses. The remainder is insurers' expenses to incentivize consumer utilization and provider prescription, \$100 and \$53 for Insurers A and B. These estimates are similar in magnitudes to those reported in MLR (in Table 1), where insurers operating on the exchange spend an average of \$107 per member annually on quality improvements, with a standard deviation of \$111.

I calculate counterfactual investment costs if insurers were to achieve the 80% prevention utilization rate, the HHS target. Average per member preventive investment across all counties becomes \$604 and \$438 for Insurers A and B.[18] Suppose claims costs paid to medical providers for performing preventive procedures are a linear function of the prevention utilization rate. In that case, cost increases compared to the status quo can be decomposed into a \$70 increase in claims costs and a \$356 increase in expenses to promote prevention utilization for Insurer A, or \$35 and \$273 for Insurer B. The significant increase in promotion expenses reflects that it gets harder to incentivize a marginal consumer to utilize or incentivize a marginal provider to prescribe preventive care from the insurers' standpoint.

Key Market Features Implied by Model Estimates. Model estimates shed light on four market features that are key to understanding incentives in prevention provision.

First, consumers' revealed willingness to pay for prevention is low. As consumers do not value prevention and are myopic about future medical expenses, their choice probabilities for insurers offering few preventions are higher than the social planner. This choice pattern is suboptimal for consumers' health in the long run.

Second, preventive investment is costly for insurers. To achieve the government's utilization targets, insurers' per-member preventive investment needs to rise 3 to 4 times from the status quo. To compensate for that, insurers need to capture a substantially higher share of investment cost savings than the current level.

Third, dynamic cost-saving motives dominate static strategic market share motives in preventive investment. Under the same market share and health risk conditions, prevention utilization of Insurers A and B are nearly 100% lower in the static competition equilibrium than in the dynamic competition equilibrium: Insurers would barely provide any preventive services in static oligopoly competition. I also simulate the case where consumers do not value prevention in dynamic competition. Insurers still invest in preventive care even without static revenue benefits. Prevention utilization rates of Insurers A and B are, on average, 6.0 and 5.2 percentage points lower than the equilibrium with estimated prevention preferences.

[18]The derived preventive investment per member when prevention utilization reaches the targets is equivalent to about 10% of premiums on the exchange. To benchmark this derived investment statistic, I consider Medicare Advantage, where prevention utilization is closest to government targets (about 5 percentage points lower). Preventive investment per member in Medicare Advantage is 17% of benchmark premiums.

I further decompose the FOC of prevention provisions (equation (19)) for each county-insurer pair at the observed policies and state variables. On average, 83.6% of the benefits from a marginal unit of prevention utilization accrue to increases in expected future profits; 16.4% to static profits. The increase in static profit is small because consumers are not very responsive to preventive attributes; there is little market share growth following additional prevention provisions. The significant gains in expected future profits capture two forces: preventive investment in the current period decreases claims costs for future periods; current investment also attracts market share and hence increases consumer base and profit for future periods due to inertia. The former dynamic force dominates the latter because of the small elasticity of prevention.

Fourth, limited consumer commitment impacts insurers' expected investment returns. Simulations reveal the presence of an extra competitor, i.e., increasing across-insurer turnover from monopoly to duopoly markets, lowers expected investment cost savings by 28.1%. A 10 percentage point drop in the share of consumers who remain in the exchange in the next year, or increases in across-market turnover, brings a 14.7% decrease in expected cost savings.

Robustness and Model Fit. The estimation procedure in Section 5.1 uses state transition estimates and consumer preferences estimates as inputs to the dynamic game, and finds insurers' investment cost primitives to rationalize observed prevention utilization levels. I implement an alternative estimation procedure for robustness: First, I estimate consumer preferences the same as outlined in Section 5.1. Second, I estimate insurers' investment cost functions using insurer-state-year-level prevention utilization rates in QRS PUF and preventive investment expenses in MLR data (introduced in Section 3.3). Finally, I input consumer preferences and investment cost function estimates into the dynamic games, and back out state transition parameters, including the returns to prevention parameter, using the FOC of preventive utilization (equation (19)). The resulting estimates are reassuringly similar in magnitude to those reported in this section. See Appendix C5 for details.

Appendix C6 reports model fit. In-sample tests reveal that the model and its estimates predict consumer choices and insurers' strategies with reasonable precision. I further use an out-of-sample test to compare the simulated effects of consumer retention with reduced form estimates in Section 3.3, which are similar in magnitude.

6 Counterfactuals

Using the equilibrium framework and model estimates from the previous section, I first analyze the welfare effects of insurer competition in Section 6.1. This exercise sheds light on the relative distortions of investment externalities and market power. I then explore policy instruments that aim to promote prevention in Section 6.2, including investment mandates and automatic re-enrollment policies that vary choice inertia.

I consider two categories of welfare metrics in counterfactual simulations. The first category compares the mean of equilibrium objects in the stationary distribution under different policy regimes, which is informative of welfare outcomes of mature markets.[19] The second category compares welfare outcomes along equilibrium transition paths upon implementing counterfactual policies as unexpected persistent shocks. Since we are eventually interested in the stationary states of policy instruments, I report the first metrics in the main text; the second metrics are reported in the appendix. Economic intuitions and qualitative predictions are the same, regardless of the welfare metrics used.

I account for misjudged preferences for out-of-pocket medical expenses relative to premium expenses by allowing a wedge between consumers' anticipated and experienced utility (Train, 2015). The former determines insurance product choices, while the latter determines consumer surplus. Formally, I define consumer surplus in market m year t as

$$\mathrm{CS}_{mt} = \int_i \frac{1}{\alpha_i}\left(\max_j \mathrm{E}[u_{ijmt}] + \sum_{j\in J\cup U} \left(s_{ijmt}(\alpha_i-\gamma)\mu_{imt-1}\mathrm{co\_ins}_{jmt}\right)\right) dF_i. \tag{20}$$

u_{ijmt} is defined in equation (7). Consumer-specific price preference $\alpha_i = \alpha_0 + \alpha_1 \mu_{imt-1}$.[20,21]

Besides consumer surplus, I consider health risks, i.e., non-prevention medical expenses, as relevant welfare measures. Consumer surplus in equation (20) only considers *consumers' cost share* of medical expenses. A paternalistic planner cares about population health and *total* medical expenses, which indicates societal well-being and human capital (Grossman, 2000), and relates to productivity and economic growth (Well, 2007; Ashraf et al., 2008).

Since state transitions and investment cost curvatures are county(-insurer)-specific, all simulations reported in this section use estimates in Salt Lake County, the largest Utah county. The takeaways of counterfactuals are very similar if using other counties' estimates.

[19]The model in Section 4 generates a Markov process $\omega_{mt} = \{\vec{p}_{mt}, \vec{x}_{mt}, \vec{s}_{mt}, \vec{\mu}_{mt}\}$, a vector of policy choices $(\vec{p}_{mt}, \vec{x}_{mt})$ and state variables $(\vec{s}_{mt}, \vec{\mu}_{mt})$. I assume the Markov process has a unique stationary distribution following Goettler and Gordon (2011). The stationary distribution of a Markov process is a probability distribution that remains unchanged in the Markov chain as time progresses.

[20]I report both ex-ante and ex-post consumer surplus, in main text and appendix separately. The former accounts for idiosyncratic match value between consumers and insurance products, while the latter measures utility from pure product characteristics. Welfare predictions are robust. Ex-post consumer surplus is defined by

$$\mathrm{CS}_{mt} = \int_i \frac{1}{\alpha_i}\left(\sum_j \left(s_{ijmt}(u_{ijmt}-\epsilon_{ijmt})\right) + \sum_{j\in J\cup U} \left(s_{ijmt}(\alpha_i-\gamma)\mathrm{co\_ins}_{jmt}\mu_{imt-1}\right)\right) dF_i. \tag{21}$$

[21]Certain sources of inertia may be excluded from the welfare calculation, while others imply a tangible social cost that should be included when consumers switch insurers. See Handel and Schwartzstein (2018) for discussions on various micro-foundations of choice inertia. Since my model does not distinguish sources of inertia, I report consumer surplus that does (in main text) and does not fully incorporate inertia (appendix).

6.1 The Welfare Effects of Insurer Competition

I examine the interplay between commitment and competition. Competition raises turnover, intensifying underinvestment and disease burdens. Conversely, competition constrains market power in setting premiums, which could increase the share of insured consumers who receive prevention, benefiting population health. Likewise, competition impacts consumer surplus via the competing forces of lower medical expenses and higher premiums. Therefore, the welfare effects of insurer competition are theoretically ambiguous due to the tension between incentivizing investment and suppressing pricing power.

Tradeoff Investment Externalities and Market Power. I compare the simulated equilibrium of the status quo asymmetric duopolist to that of a monopolist. The monopoly market is a good benchmark for understanding the effects of commitment and competition because it allows the insurer to internalize as much investment returns as possible and eliminates strategic interactions that induce free-riding. Furthermore, it facilitates comparing the relative welfare impacts of investment externalities and market power.

Since the characteristics of the monopolist are welfare relevant, I report two scenarios to bound welfare predictions: keep Insurer B, the insurer with flatter investment cost functions and lower brand preferences on the market; keep Insurer A, the insurer with steeper investment cost functions and higher brand preferences on the market. Any scenario that lets the new insurer take a weighted average of Insurer A and B's characteristics falls between the extremes. To avoid the mechanical variety effects caused by the dimension of logit draws, I let the monopolist offer the same product twice. Table 8 and report key equilibrium objects. Table A10 panel (II) reports all relevant statistics.

Table 8 panel (a) reports equilibrium objects related to cost savings. Removing competitors from the market eliminates consumer turnover across insurers, which impacts insurers' investment strategies through two channels. First, it allows the insurer to internalize more investment returns as its enrollees can no longer switch to competitors. The net present value of expected investment cost savings doubles resultantly. Second, it inhibits the insurer from free-riding competitors' investments since the insurer can no longer steal healthy consumers from competitors. To further disentangle the roles of internalization of investment returns and removal of free-riding, I run an interim scenario where the monopolist plays against a non-strategic opponent that offers prevention at the same level as the outside option. The former and latter channels account for 84% and 16% of the investment increase, respectively.

Preventive investment triples from \$106 to more than \$300 per enrollee in both scenarios.[22] This closes 63% of the prevention utilization gap between the duopoly equilibrium and

[22] I validate the magnitude of simulated investment growth with out-of-sample fit. I use the exchange

Table 8. Equilibrium strategies and welfare, asymmetric duopoly and monopoly equilibrium

	(1) Duopoly	(2) Monopoly B	(3) Changes	(4) Monopoly A	(5) Changes
(a). Cost savings channel					
NPV, cost savings per member, Insurer A	516	-	-	1538	1023
NPV, cost savings per member, Insurer B	954	1830	877	-	-
Investment per member, Insurer A	76	-	-	306	230
Investment per member, Insurer B	138	342	204	-	-
Investment per member, market mean	106	342	236	306	200
(b). Market power channel					
Markup, Insurer A	0.255	-	-	0.422	0.167
Markup, Insurer B	0.147	0.258	0.112	-	-
Markup, market mean	0.204	0.258	0.054	0.422	0.219
Premium, Insurer A	7,429	-	-	8,427	998
Premium, Insurer B	5,860	6,464	604	-	-
Premium, market mean	6,661	6,464	-197	8,427	1,766
(c). Consumer welfare					
Insured rate	0.647	0.503	-0.144	0.483	-0.164
Health risks per consumer	6,255	5,849	-406	6,088	-167
Consumer surplus per consumer	-1,005	-957	48	-1,075	-70

Notes: This table reports simulated policies and welfare in the baseline asymmetric duopoly equilibrium and monopoly equilibrium. To avoid the mechanical variety effects caused by the dimension of logit draws, I let the monopolist offer the same product twice. The statistics in columns (3) and (5) represent those in the monopoly equilibrium in columns (2) and (4) minus the duopoly equilibrium in column (1). All statistics are the mean of each equilibrium object in the stationary distribution. Consumer surplus numbers can be negative because they account for the disutilities of changing insurers and correct for misjudged preferences of out-of-pocket health expenses. NPV means net present value.

government targets. Monopolist B's investment growth is larger than that of monopolist A. This is because Insurer B faces relatively low marginal costs, and captures relatively high marginal returns from a unit of prevention care. Returns on investment (ROI) decrease from around 6.8 to 5 due to the convex cost structure. These simulated ROIs are similar in magnitudes to those in literature: 5.6 (CDC, 2022), 6.2 (Masters et al., 2017).

Table 8 panel (b) depicts equilibrium objects relevant to market power. Upon lessening competition, the monopolist exerts pricing power and increases markup by 11 to 17 percentage points. The direction of changes in premiums is ambiguous and depends on the relative magnitudes of health risk reductions and markup increases. If Insurer B, the insurer with flat investment cost functions and low brand-specific elasticities, is kept on the market, decreases in claims costs counteract markup increases so that market-level mean premiums decline by \$197. In contrast, if Insurer A, the insurer with steep investment cost functions and high

nationwide to estimate the correlation between state-year-level preventive investment per member and HHI, controlling for state and year fixed effects—an HHI increase of 1000 correlates with \$60.6 increase in preventive investment per member. In my simulation, transitioning from asymmetric duopolists to monopolists A (B) increases HHI in the stationary equilibrium by 2167 (3188). The out-of-sample correlation would predict an increase in preventive investment per member of \$131 (\$193), similar in magnitude to model simulations.

brand-specific elasticities, remains operating, markup upsurge dominates; market-level mean premiums rise by $1766.

The result that premiums might not increase stems from endogenizing consumers' health levels in equilibrium as a function of insurers' investment. Allowing preventive investment to create surplus and lower marginal costs provides a countervailing force to increased markup. In plausible scenarios when investment savings are large enough to dominate enhanced pricing power, i.e., when monopolist B operates, premiums do not rise. This analysis thus delivers a new insight that, when preventive investment is effective in lowering future health expenses and brand-specific elasticities are high, insurer competition without consumer commitment might raise medical expenses and premiums, creating a worst-of-both-world.

Table 8 panel (c) reports changes in consumer welfare. Because of enhanced preventive investment, average health risks across all consumers drop by $167 to $406 per consumer, 2.7% to 6.5% from the baseline. Two factors explain why health risks decrease more in the equilibrium with monopolist B than with monopolist A. First, monopolist B invests more per member. Second, the share of consumers who receive preventive services is lower when monopolist A operates than when monopolist B operates: premium increases crowd out consumers to uninsurance where they receive little prevention. As consumers are myopic about future medical expenses and do not fully value prevention, removing the insurer with inadequate prevention provision moves consumers to choices that are better for their health in the long run.

Decomposing health improvements further, average health risks per insured and uninsured consumer drop by $305 to $645, or $79 to $267, separately. Both insured and uninsured consumers become healthier because consumers choose among and flow across all options in the new stationary equilibrium. They benefit from enhanced investment of any supply-side players. Changes in market-level total medical expenses depend on how much the uninsured utilize medical services to meet their health needs. Assuming both the insured and uninsured utilize healthcare fully to the level of their health risks, changes in market-level medical expenses would be almost equivalent to changes in health risks. Market-level medical expenses would otherwise drop if the uninsured forgo healthcare. I report changes in health risks but not changes in medical expenses hereinafter since the former is a direct model output and does not require further assumptions on consumer behaviors.

Changes in consumer surplus range from $-70 to $48 across simulations, reflecting the combined welfare effects of investment externalities and market power. To further disentangle the roles of pricing power and investment cost savings, I run an interim scenario allowing the monopolist to optimally choose preventive investment policies while keeping pricing policies the same in the baseline duopoly equilibrium. Compared to the baseline, consumer surplus raise by \$264 and \$136 in the only investment response scenario with monopolists A and B, respectively. This is because enhanced investment improves population health, which lowers both out-of-pocket medical expenses and premiums.

Allowing the insurer to change the pricing strategy and charge a higher markup shrinks consumer surplus gains. If the insurer with low investment costs operates as the monopolist, investment gains dominate losses from market power; reduced out-of-pocket health expenses compensate for increased premiums. The monopolist creates more surplus and reduces population disease burden more than duopolists so consumers are almost indifferent. Consumer surplus increases by \$48 per person in the monopolist B equilibrium. Conversely, if the insurer with high investment costs remains operating, enhanced prevention provision cannot overturn the exploitation of pricing power. Consumer surplus falls by \$70 per person in the monopolist A equilibrium. This reiterates the ambiguous welfare effect of competition. Furthermore, this decomposition exercise suggests that the welfare distortions due to limited commitment are about the same size as those due to market power.

There are several caveats in interpreting the consumer surplus estimates. First, the revealed preference framework does not tell apart preferences and information. If consumers value preventive care but lack information on plans' preventive quality, choice patterns are correctly predicted, but consumer surplus is underestimated. Second, I do not model insurer-provider price negotiation. Considering that reduced competition strengthens insurers' bargaining leverages and reduces negotiated procedures prices and thus premiums (Ho and Lee, 2017), my estimates understate consumer welfare gains. Third, my model does not capture the fact that, despite charity care, uninsured consumers may delay not only prevention but also medical treatment. In that case, my estimates overstate consumer welfare gains because moving to a single insurer increases the uninsured rate. Fourth, my model only captures monetary gains from better health through reduced health expenses and premiums. It omits welfare gains such as improved well-being and productivity.

I report welfare outcomes for insurers, medical providers, and the government in Table A10. Changes in insurer profits range from -20 to 123 million, hinging on the opposite forces of growth in per-member profit versus drops in insured rates. Medical providers' losses from uncompensated charity care grow by around 280 million as uninsured rates rise. Government expenses in premium subsidies decrease by 132 to 429 million because decreases in insured rates dominate increases in premiums. The welfare numbers for players other than consumers should be interpreted cautiously, as they closely relate to how uncompensated care or costs of public funds are calculated, which my model abstracts from. In addition, social welfare shall include productivity spillovers from better population health, which is omitted in my model.

Robustness and Sensitivity. I examine robustness under alternative simulation specifications. Table A10 panel (I) reports simulations that start from hypothetical symmetric duopolists instead of asymmetric duopolists. Table A11 panel (I) displays equilibrium statistics along transition paths, depicting welfare changes in response to an unexpected persistent policy shock in the first simulation period. Table A11 panel (II) reports equilibrium statistics in a case where the monopolist does not duplicate product offerings, and ex-post consumer surplus is used to correct for the dimension of logit draws. The tradeoff between investment externalities and market power remains unchanged. Changes in consumer surplus are ambiguous, while average health risks decrease in all specifications due to elevated investment.

Appendix D1 reports sensitivity to the calibrated parameter q_1, returns to prevention. As returns to prevention decrease, the relative importance of dynamic cost savings incentives diminishes compared to static market share incentives, and the investment gap closes between the monopoly and duopoly equilibrium. Cost savings gains shrink and eventually fall behind losses from pricing power, which lowers the share of insured consumers who receive preventive services. Returns to prevention need to be at least 0.25 or 0.65 times the baseline for the monopoly market to have better population health or higher consumer surplus than the duopoly market, respectively. This exercise reiterates the competing forces of market power losses and investment cost savings in shaping welfare.

Generalizability. The estimates from the Utah exchange likely provide an upper bound of gains of a monopoly payer in other insurance markets. First, consumers in the exchange are more price elastic than consumers in other markets, for example, employer-sponsored markets. This expands losses from the monopolist's pricing power. Second, consumer turnover in other markets is of smaller magnitudes. Consumers have a higher inertia level, which reduces turnover across insurers, and the market-wide retention rate is higher. This indicates that investment cost savings from transitioning to a monopoly are less pronounced in other markets than in the exchange. Nonetheless, the forces analyzed in this paper are portable to other healthcare settings. My equilibrium framework highlights potential efficiency losses due to investment externalities, which are prevalent in all fragmented payer markets.

Additional Results. I benchmark the best-case scenario monopoly to a planner in Appendix D2. The planner offers the same products as the private insurer but sets premium and preventive investments to maximize consumer surplus, subject to break-even constraints every period. The planner invests 12.5% more per member than the monopolist due to the elimination of consumer free-riding and Spencian distortion, and prices are 33.9% lower. Employing markup regulations moves the monopolist equilibrium 72% and 36% closer to the planner frontier regarding health risks and consumer surplus.

I further compare the monopoly case analyzed previously, which is subject to consumer flows into and out of the exchange and highlights the effects of competition, to a monopoly case where consumer flows across market segments are also removed. The monopolist invests 7.5% more per member in the latter case than in the former case, demonstrating the effects of investment leakage from market segmentation.

6.2 Policy Simulations to Promote Prevention Provision

The previous section has disentangled the tradeoff between underinvestment and high markup. In this section, I further evaluate policies to promote prevention provisions given this tradeoff.

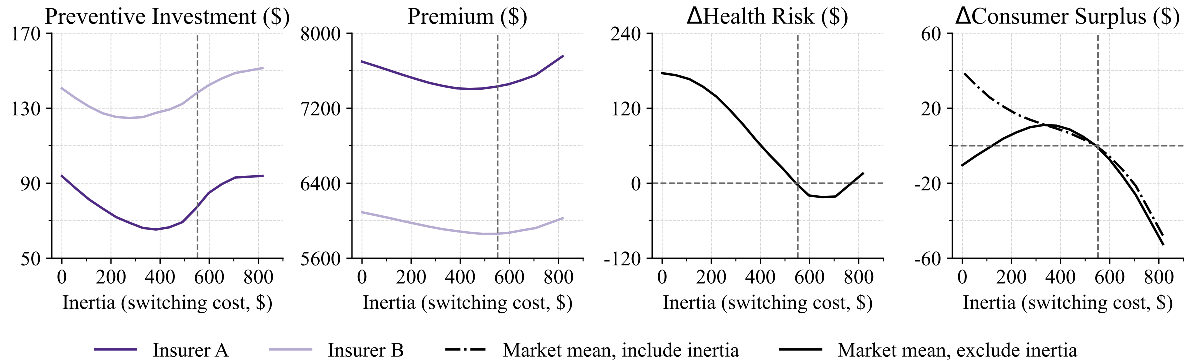
Regarding policies that regulate consumers, I explore the effects of raising consumers' retention probabilities, such as automatic re-enrollment. As for policies that regulate insurers, I study preventive investment mandates. I then briefly discuss additional policies, such as preventive investment subsidies, risk adjustment, varying churn across markets, or informational campaigns that raise consumers' preferences for prevention. Finally, I summarize the features of policies that could incentivize investment and improve welfare.

Raising Consumers' Retention Probabilities. I first investigate the welfare impacts of raising consumers' retention probability: varying inertia by automatic re-enrollment[23] (Drake and Anderson, 2019; Shepard and Wagner, 2022) or default designs (Handel and Kolstad, 2015; Brot-Goldberg et al., 2023). Inertia is an essential source of consumer commitment. Increasing inertia raises consumer retention and allows insurers to capture a more significant portion of their investment returns, thereby alleviating underinvestment from limited commitment. Yet it reduces demand elasticities, granting insurers larger market power.

Figure 2 exhibits how equilibrium statistics change with various levels of inertia. Preventive investment and premiums both display U shapes when inertia rises. In regions with considerable inertia, inertia blocks turnover across insurers, which raises expected investment returns and reduces demand elasticity simultaneously. Premiums and preventive investment increase compared to the status quo when inertia becomes more prevalent. In contrast, inertia lowers premiums and preventive investment in regions with small degrees of inertia. The prediction of premiums is consistent with existing studies (Dubé et al., 2009; Cabral, 2012): insurers' incentive to lower prices and invest in customer acquisition outweighs the incentive to raise prices and harvest the existing customer base. Furthermore, the strategic effect of heightened price competition dominates the direct impact of increased inertia, which boosts consumer turnover, dampens expected investment returns, and reduces prevention efforts.

[23] The current exchange regulation (link) is that, if consumers are enrolled in coverage during the open enrollment period and don't select a plan for the next year by 12/15, they will be automatically re-enrolled into their current plan. The automatic re-enrollment rates can be varied, for example, with the length of the open enrollment period to alter the number of eligibles and decision time (Goodell, 2014).

Figure 2. Equilibrium strategies and welfare, by choice inertia



Notes: Statistics plotted are the mean of each equilibrium object in the stationary distribution. The vertical dashed line denotes choice inertia (converted into dollar amount of switching costs) in the status quo equilibrium. The horizontal dashed line denotes the value of the statistic in the status quo equilibrium.

Average health risks first decrease then increase with inertia. The impact of enhanced per-member investment first dominates then falls behind the effect of increased premiums and receded shares of the insured consumers who receive prevention. The impacts of inertia on consumer surplus hinge on whether it is a tangible cost to be included in welfare calculation.

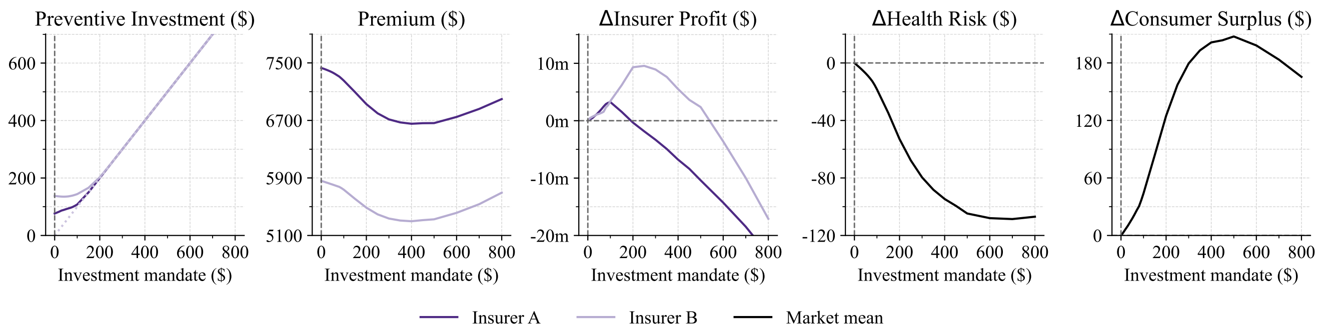
This exercise of varying inertia sheds light on the potential of using long-term insurance contracts to promote prevention. Extending contract length reduces consumer turnover and encourages preventive investment, but has its own tradeoff, such as intertemporal consumption smoothing (Ghili et al., 2022; Atal et al., 2022). The long-term contract is a too-far extrapolation from the myopic consumer repeated choices set-up, such that my current model cannot convincingly speak to its welfare effects. Understanding the welfare implications of long-term contracts while considering preventive care is an exciting future research direction.

I further simulate a hypothetical case, where I decrease the share of consumer inflows and outflows by 20 percentage points. The resulting retention rate of the exchange is comparable to that of the employer-sponsored insurance market or Medicare Advantage. Reducing the churn across market segments reduces the portion of consumers who can choose freely and are not subject to inertia, thereby having similar welfare predictions as increasing aggregate inertia level. Gains from enhanced investment per insured are overturned by adverse health impacts of increased premiums, which pushes consumers to drop coverage and forgo preventive care. Losses from pricing power dominate investment gains: consumer surplus drops by \$167 per consumer when churn decreases by 20 percentage points; average health risks rise by \$395, 6.3% from the baseline. This exercise reveals the investment and welfare effects of market segmentation, which causes investment leakage but also raises demand elasticities.

Preventive Investment Mandates. I next examine the design of preventive investment mandates, which require insurers to invest in prevention above certain thresholds per enrollee under all market conditions. Preventive investment mandates have been enforced in some states' Medicaid programs, for example, South Carolina requires managed care insurers to reach a minimum utilization level of several preventive care measures.

Figure 3 depicts equilibrium statistics with rising mandates. Preventive investment is always higher in with-mandate than in no-mandate scenarios; it binds in scenarios with large mandates. Premiums are U-shaped functions of mandates: reductions in claims expenses from enhanced investment first exceed then fall behind growth in investment costs.

Figure 3. Equilibrium strategies and welfare, by investment mandates



Notes: Statistics plotted are the mean of each equilibrium object in the stationary distribution. The vertical dashed line denotes the baseline without investment mandates. The horizontal dashed line denotes the value of the statistic in the status quo equilibrium. Changes in insurer profits are measured in millions.

Notably, Pareto improvements could be achieved with preventive investment mandates of up to $190 per enrolled member. Insurers' preventive investments are strategic substitutes. Their investment game manifests a prisoner's dilemma: insurers could either invest for mutual benefits of better population health (cooperate) or not invest and steal competitors' healthy enrollees (defect). By imposing a minimum investment floor, the planner could remove some non-cooperative strategies so that free-riding is relieved and every insurer contributes to the public good of population health. As mandates increase, investment expands, population health improves, and both insurers' profits as well as consumer surplus increase. Yet at larger mandate levels, insurers' profits decrease compared to the status quo due to costly prevention provisions, making Pareto improvement not attainable. At all levels of mandates, insurers are still earning positive profits, so this policy will not induce exits.

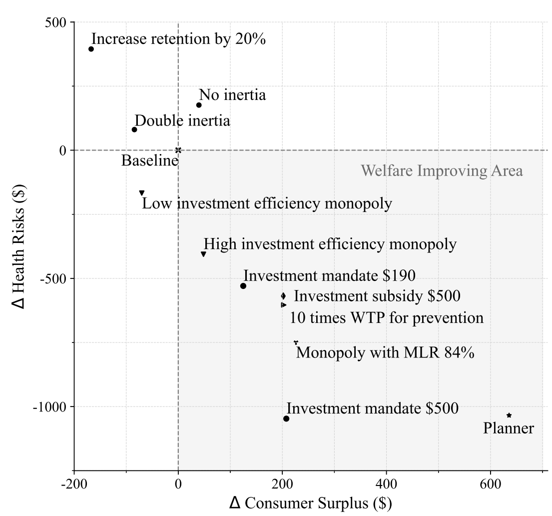
Average health risks exhibit a U shape, whereas consumer surplus displays an inverse U shape. This mirrors the tradeoff between investment gains and losses from price increases. Investment mandates boost preventive provisions and lower consumer health risks. However, insurers may raise prices to compensate for extra investment expenses. If mandates are too high, price increases could crowd out the share of insured enrollees who receive prevention, eventually harming population health.

The optimal mandate that maximizes consumer surplus is a minimum of $500 preventive investment per enrollee, 3 to 4 times the status quo investment level. It lowers average health risks by $1,047 per consumer and improves consumer surplus by $208. The mandate best for population health is a minimum of $700 investment per enrollee, reducing average health risks by $1,086, and raising consumer surplus by $183. Alternatively, a prevention utilization mandate that maximizes consumer surplus is 75%, 5% lower than the HHS targets, and 30% higher than the status quo. A prevention utilization mandate at 85%, 5% higher than the HHS targets, reduces average health risks the most.

Additional Policies. Appendix D2 reports additional policy simulations, including preventive investment subsidies, increasing consumers' valuation of prevention via informational campaigns, and risk adjustment. Subsidizing insurers certain amounts per enrollee for their preventive investment reduces marginal investment costs, which in turn boosts prevention provisions and lowers premiums. When information campaigns raise consumers' willingness to pay for prevention, insurers do not necessarily rely on future cost savings for preventive investment; they do so also to compete for market share and static profits, which strengthens investment incentives. Risk adjustment equalizes insurers' claims expenses, exaggerating free-riding incentives and penalizing preventive efforts.

Summary and Policy Implications. Figure 4 compares the effectiveness of policy instruments. For each policy, I plot changes in average health risks against changes in consumer surplus, compared to the status quo. Any policies in the bottom right quadrant are preferred over the status quo on these welfare metrics. There are two takeaways.

Figure 4. Summary of policy simulations



Notes: Statistics plotted are the mean of each equilibrium object in the stationary distribution, and averaged across all consumers. The grey vertical and horizontal lines indicate the status quo.

First, the investment-price tradeoff outlined in Section 6.1 shall guide policy designs. This is most directly reflected by the contrasting effects of demand and supply side policies. Demand-side policies, such as alternating inertia levels, change the demand elasticity, which insurers strategically take advantage of. Although inelastic demand increases expected investment returns and encourages preventive investment, the welfare losses from market power dominate: gains from boosted investment are overturned by inflated premiums and declined insured rates. On the contrary, supply-side policies maintain the competitive market structure under a given demand curvature while promoting investment incentives. Hence, effective policies ideally would both address investment externalities and constrain market power.

Second, the most promising method for dealing with under-investment in preventive care is not eliminating competition so that the monopolist can internalize more of the returns from investment, but rather direct quality regulation. The duopoly competition with minimum preventive investment mandates outperforms the monopoly, even with markup regulation. This is because even a monopolist will never fully recoup all the cost savings from investment, as consumers eventually age into Medicare. Investment externalities can not be fully resolved with varying market structures but could be addressed by directly setting quality standards. This result reflects the consequences of the fragmentation of the current health system.

7 Discussion and Conclusion

Although preventive care is widely acknowledged as an essential but under-provided health service, market frictions resulting in under-provision in equilibrium are not well understood. This paper contributes to our understanding of the mechanisms and tradeoffs behind prevention under-provision by analyzing consumers' and insurers' behaviors and their interactions in equilibrium. My main contributions are three-fold. First, I offer a novel conceptual insight into the tradeoff between investment externalities and market power of insurer competition. Second, I provide new evidence for a classic idea that consumer turnover could reduce insurers' health investment. Third, I develop a framework of dynamic insurer competition with endogenous product characteristics to study welfare effects and regulatory solutions.

The investment and welfare effects of limited consumer commitment shed light on the potential efficiency costs of fragmented payer markets. The intuition applies broadly that the lack of long-run internalization of investment benefits impedes value creation in insurance. Besides preventive care, private insurers may hesitate to cover high-cost curative drugs, such as Hepatitis C drugs or gene therapy, that deliver substantial value over time but require high upfront payments. Private insurers may also lack sufficient incentives to manage enrollees' health because consumers switch from private payers to Medicare at age 65, and insurers do not own enrollees' lifetime risks. These dynamic externalities and inefficiencies crucially shape incentives to invest in health capital, impacting societal health expenditures.

This paper also provides specific lessons for market designs in healthcare. While competition restricts insurers' pricing power, existing studies show that competition in insurance markets could harm consumer welfare because competition lowers insurers' bargaining leverage (Ho and Lee, 2017) or induces cream skimming (Cutler and Reber, 1998; Kong et al., 2023; Ryan, 2023). This paper further uncovers a novel mechanism in which increased insurer competition has perverse effects by reducing dynamic investment in enrollees' health. It outlines the critical balance between constraining static market power distortions and preserving intertemporal investment incentives in healthcare market designs.

While this paper's primary focus is preventive investment in healthcare, my framework provides general takeaways that can be applied to settings where commitment, competition, and investment interact. For example, employers are more likely to provide skill training the longer workers' job tenure (Royalty, 1996; Acemoglu and Pischke, 1999). Non-competes restrict worker mobility, incentivize employers' human capital investment, but grant employers monopsony power in wages (FTC, 2023; Shi, 2023). Likewise, manufacturers are more likely to make contract-specific investments the longer duration of contracts (Joskow, 1987; Hart, 1995). But long-term contracts make buyers forgo lower-cost manufacturers on spot markets. My model highlights that competition could amplify underinvestment through limited commitment, thereby underscoring the investment-market power tradeoff for regulators.

In addition to investment externalities caused by limited consumer commitment, other market frictions can also reduce preventive investment in equilibrium. One example is the common agency problem, where multiple insurers (principals) seek to motivate one medical provider (agent) to invest in improved care, and all insurers have incentives to free-ride on others (Frandsen et al., 2019). I see the extension of my model to capture other frictions that impede preventive investment and find solutions to incentivize investment as fruitful directions for future research.

References

Abaluck, Jason and Jonathan Gruber, "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program," *American Economic Review*, 2011, *101* (4), 1180–1210.

_ **, Mauricio Caceres Bravo, Peter Hull, and Amanda Starc**, "Mortality Effects and Choice Across Private Health Insurance Plans," *Quarterly Journal of Economics*, 2021, *136* (3), 1557–1610.

Acemoglu, Daron and Jörn-Steffen Pischke, "The Structure of Wages and Investment in General Training," *Journal of Political Economy*, 1999, *107* (3), 539–572.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales, "Shift-Share Designs: Theory and Inference," *Quarterly Journal of Economics*, 2019, *134* (4), 1949–2010.

Aguirregabiria, Victor, Allan Collard-Wexler, and Stephen Ryan, "Dynamic Games in Empirical Industrial Organization," in "Handbook of Industrial Organization," Vol. 4, Elsevier, 2021, pp. 225–343.

Ashraf, Quamrul, Ashley Lester, and David Weil, "When Does Improving Health Raise GDP?," *NBER Macroeconomics Annual*, 2008, *23* (1), 157–204.

Atal, Juan Pablo, Hanming Fang, Martin Karlsson, and Nicolas Ziebarth, "German Long-Term Health Insurance: Theory Meets Evidence," 2022.

Attia, Peter, *Outlive: The Science and Art of Longevity*, Harmony, 2023.

Autor, David and Mark Duggan, "The Rise in the Disability Rolls and the Decline in Unemployment," *Quarterly Journal of Economics*, 2003, *118* (1), 157–206.

_ , David Dorn, and Gordon Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–68.

Bae, Hannah, Katherine Meckel, and Maggie Shi, "Dependent Insurance Coverage and Parental Job Mobility: Evidence from the Affordable Care Act," 2020.

Bai, Liang, Benjamin Handel, Edward Miguel, and Gautam Rao, "Self-Control and Demand for Preventive Health: Evidence from Hypertension in India," *Review of Economics and Statistics*, 2021, *103* (5), 835–856.

Baicker, Katherine, Sendhil Mullainathan, and Joshua Schwartzstein, "Behavioral Hazard in Health Insurance," *Quarterly Journal of Economics*, 2015, *130* (4), 1623–1667.

Bailey, James and Anna Chorniy, "Employer-Provided Health Insurance and Job Mobility: Did the Affordable Care Act Reduce Job Lock?," *Contemporary Economic Policy*, 2016, *34* (1), 173–183.

Bartik, Timothy, "Who Benefits from State and Local Economic Development Policies?," 1991.

Bauer, Daniel, Darius Lakdawalla, and Julian Reif, "Health Risk and the Value of Life," 2022.

Benkard, Lanier, Przemyslaw Jeziorski, and Gabriel Weintraub, "Oblivious equilibrium for concentrated industries," *The RAND Journal of Economics*, 2015, *46* (4), 671–708.

Berry, Steven, "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 1994, pp. 242–262.

_ , James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, pp. 841–890.

Borusyak, Kirill and Peter Hull, "Non-random Exposure to Exogenous Shocks," *Econometrica*, 2023.

— , — , **and Xavier Jaravel**, "Quasi-Experimental Shift-Share Research Designs," *Review of Economic Studies*, 2022, *89* (1), 181–213.

Brot-Goldberg, Zarek, Amitabh Chandra, Benjamin Handel, and Jonathan Kolstad, "What Does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics," *Quarterly Journal of Economics*, 2017, *132* (3), 1261–1318.

— , **Timothy Layton, Boris Vabson, and Adelina Yanyue Wang**, "The Behavioral Foundations of Default Effects: Theory and Evidence From Medicare Part D," *American Economic Review*, 2023, *113* (10), 2718–2758.

Brown, Zach and Jihye Jeon, "Endogenous Information and Simplifying Insurance Choice," 2023.

Cabral, Luis, "Switching Costs and Equilibrium Prices," 2012.

CBO, "Offsetting Effects of Prescription Drug Use on Medicare's Spending for Medical Services," 2012. link, Accessed: 2023/05/12.

CDC, "Are You Up to Date on Your Preventive Care?," 2021. link, Accessed: 2021/10/21.

— , "National Center for Chronic Disease Prevention and Health Promotion," 2021. link, Accessed: 2021/10/21.

— , "Return on Investment, Prevention for a Healthier America: Investments in Disease Prevention Yield Significant Savings, Stronger Communities," 2022. link, Accessed: 2023/02/07.

Cebul, Randall, James Rebitzer, Lowell Taylor, and Mark Votruba, "Unhealthy Insurance Markets: Search frictions and the Cost and Quality of Health Insurance," *American Economic Review*, 2011, *101* (5), 1842–1871.

Chandra, Amitabh, Jonathan Gruber, and Robin McKnight, "Patient Cost-sharing and Hospitalization Offsets in the Elderly," *American Economic Review*, 2010, *100* (1), 193–213.

Cicala, Steve, Ethan Lieber, and Victoria Marone, "Regulating Markups in US Health Insurance," *American Economic Journal: Applied Economics*, 2019, *11* (4), 71–104.

Collard-Wexler, Allan, "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica*, 2013, *81* (3), 1003–1037.

Crawford, Gregory, "Endogenous Product Choice: A Progress Report," *International Journal of Industrial Organization*, 2012, *30* (3), 315–320.

Crocker, Keith and John Moran, "Contracting with Limited Commitment: Evidence from Employment-Based Health Insurance Contracts," *RAND Journal of Economics*, 2003, pp. 694–718.

Currie, Janet and Brigitte Madrian, "Health, Health Insurance and the Labor Market," *Handbook of Labor Economics*, 1999, *3*, 3309–3416.

Curto, Vilsa, Liran Einav, Jonathan Levin, and Jay Bhattacharya, "Can Health Insurance Competition Work? Evidence from Medicare Advantage," *Journal of Political Economy*, 2021, *129* (2), 570–606.

Cutler, David and Sarah Reber, "Paying for Health Insurance: The Trade-off between Competition and Adverse Selection," *Quarterly Journal of Economics*, 1998, *113* (2), 433–466.

Dafny, Leemore, "Are Health Insurance Markets Competitive?," *American Economic Review*, 2010, *100* (4), 1399–1431.

Dalton, Christina, Gautam Gowrisankaran, and Robert Town, "Salience, Myopia, and Complex Dynamic Incentives: Evidence from Medicare Part D," *Review of Economic Studies*, 2020, *87* (2), 822–869.

Decarolis, Francesco, Maria Polyakova, and Stephen Ryan, "Subsidy Design in Privately Provided Social Insurance: Lessons from Medicare Part D," *Journal of Political Economy*, 2020, *128* (5), 1712–1752.

Derenoncourt, Ellora, "Can You Move to Opportunity? Evidence from the Great Migration," *American Economic Review*, 2022, *112* (2), 369–408.

Diamond, Rebecca, Michael Dickstein, Timothy McQuade, and Petra Persson, "Insurance without Commitment: Evidence from the ACA Marketplaces," 2018.

Dickstein, Michael, Kate Ho, and Nathaniel Mark, "Market Segmentation and Competition in Health Insurance," *Journal of Political Economy*, 2023.

Drake, Coleman, "What Are Consumers Willing to Pay for a Broad Network Health Plan?: Evidence from Covered California," *Journal of Health Economics*, 2019, *65*, 63–77.

_ and David Anderson, "Association Between Having an Automatic Reenrollment Option and Reenrollment in the Health Insurance Marketplaces," *JAMA Internal Medicine*, 2019, *179* (12), 1725–1726.

Dubé, Jean-Pierre, Günter Hitsch, and Peter Rossi, "Do Switching Costs Make Markets Less Competitive?," *Journal of Marketing Research*, 2009, *46* (4), 435–445.

Einav, Liran, Amy Finkelstein, and Paul Schrimpf, "The Response of Drug Expenditure to Nonlinear Contract design: Evidence from Medicare Part D," *Quarterly Journal of Economics*, 2015, *130* (2), 841–899.

_ , _ , and Pietro Tebaldi, "Market Design in Regulated Health Insurance markets: Risk Adjustment vs. Subsidies," 2019.

_ , _ , Tamar Oostrom, Abigail Ostriker, and Heidi Williams, "Screening and Selection: The Case of Mammograms," *American Economic Review*, 2020, *110* (12), 3836–70.

Ellis, Randall and Willard Manning, "Optimal Health Insurance for Prevention and Treatment," *Journal of Health Economics*, 2007, *26* (6), 1128–1150.

Ericson, Richard and Ariel Pakes, "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 1995, *62* (1), 53–82.

Escobar, Juan, "Equilibrium Analysis of Dynamic Models of Imperfect Competition," *International Journal of Industrial Organization*, 2013, *31* (1), 92–101.

Fan, Ying, "Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market," *American Economic Review*, 2013, *103* (5), 1598–1628.

Fang, Hanming and Alessandro Gavazza, "Dynamic Inefficiencies in an Employment-Based Health Insurance System: Theory and Evidence," *American Economic Review*, 2011, *101* (7), 3047–77.

Finkelstein, Amy, Kathleen McGarry, and Amir Sufi, "Dynamic Inefficiencies in Insurance Markets: Evidence from Long-term Care Insurance," *American Economic Review*, 2005, *95* (2), 224–228.

_ , Matthew Gentzkow, and Heidi Williams, "Sources of Geographic Variation in Health Care: Evidence from Patient Migration," *Quarterly Journal of Economics*, 2016, *131* (4), 1681–1726.

Frandsen, Brigham, Michael Powell, and James Rebitzer, "Sticking Points: Common-Agency Problems and Contracting in the US Healthcare System," *RAND Journal of Economics*, 2019, *50* (2), 251–285.

FTC, "FTC Proposes Rule to Ban Noncompete Clauses, Which Hurt Workers and Harm Competition," 2023. link, Accessed: 2023/07/04.

Geddes, Eilidh, "The Effects of Price Regulation in Markets with Strategic Entry: Evidence from Health Insurance Markets," 2022.

Ghili, Soheil, Benjamin Handel, Igal Hendel, and Michael Whinston, "Optimal Long-term Health Insurance Contracts: Characterization, Computation, and Welfare Effects," *Review of Economic Studies*, 2022, *forthcoming.*

Goettler, Ronald and Brett Gordon, "Does AMD Spur Intel to Innovate More?," *Journal of Political Economy*, 2011, *119* (6), 1141–1200.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 2020, *110* (8), 2586–2624.

Goodell, Sarah, "Reenrollment," *Health Affairs*, 2014.

Goolsbee, Austan and Amil Petrin, "The Consumer Gains from Direct Broadcast Satellites and the Competition with Cable TV," *Econometrica*, 2004, *72* (2), 351–381.

Gooptu, Angshuman, Asako Moriya, Kosali Simon, and Benjamin Sommers, "Medicaid Expansion Did Not Result in Significant Employment Changes or Job Reductions in 2014," *Health Affairs*, 2016, *35* (1), 111–118.

Grossman, Michael, "The Human Capital Model," in "Handbook of Health Economics," Vol. 1A, Elsevier, 2000, pp. 347–408.

Gruber, Jonathan, "Health Insurance and the Labor Market," *Handbook of Health Economics*, 2000, *1*, 645–706.

Handel, Ben and Jonathan Kolstad, *Getting the Most from Marketplaces: Smart Policies on Health Insurance Choices*, Brookings Institution Washington (DC), 2015.

Handel, Benjamin, "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts," *American Economic Review*, 2013, *103* (7), 2643–82.

— **and Joshua Schwartzstein**, "Frictions or Mental Gaps: What's Behind the Information We (Don't) Use and When Do We Care?," *Journal of Economic Perspectives*, 2018, *32* (1), 155–78.

Hart, Oliver, *Firms, Contracts, and Financial Structure*, Clarendon press, 1995.

Hausman, Jerry, "Valuation of New Goods Under Perfect and Imperfect Competition," in "The Economics of New Goods," University of Chicago Press, 1996, pp. 207–248.

Hendel, Igal and Alessandro Lizzeri, "The Role of Commitment in Dynamic Contracts: Evidence from Life Insurance," *Quarterly Journal of Economics*, 2003, *118* (1), 299–328.

Herring, Bradley, "Suboptimal Provision of Preventive Healthcare due to Expected Enrollee Turnover Among Private Insurers," *Health Economics*, 2010, *19* (4), 438–448.

Ho, Kate and Robin Lee, "Insurer Competition in Health Care Markets," *Econometrica*, 2017, *85* (2), 379–417.

Jones, Damon, David Molitor, and Julian Reif, "What Do Workplace Wellness Programs Do? Evidence From the Illinois Workplace Wellness Study," *Quarterly Journal of Economics*, 2019, *134* (4), 1747–1791.

Joskow, Paul, "Contract Duration and Relationship-Specific Investments: Empirical Evidence from Coal Markets," *American Economic Review*, 1987, pp. 168–185.

Kenkel, Donald, "Prevention," in "Handbook of Health Economics," Vol. 1A, Elsevier, 2000, pp. 1675–1720.

KFF, "Spending on Medicare Advantage Quality Bonus Payments Will Reach at Least 12.8 Billion in 2023," 2023. link, Accessed: 2023/08/16.

Kong, Edward, Timothy Layton, and Mark Shepard, "Adverse Selection and (un) Natural Monopoly in Insurance Markets," 2023.

Kotb, Sarah, "When Cure is Better than Prevention: The Fragmentation of Health Insurance and Underinvestment in Preventative Care," 2023.

Kowalski, Amanda, "Mammograms and Mortality: How Has the Evidence Evolved?," *Journal of Economic Perspectives*, 2021, *35* (2), 119–140.

— , "Behaviour within a Clinical Trial and Implications for Mammography Guidelines," *Review of Economic Studies*, 2023, *90* (1), 432–462.

Kremer, Michael and Christopher Snyder, "Preventives Versus Treatments," *Quarterly Journal of Economics*, 2015, *130* (3), 1167–1239.

Lantz, Paula, Douglas Evans, Holly Mead, Carmen Alvarez, and Lisa Stewart, "Knowledge Of and Attitudes Toward Evidence-Based Guidelines For and Against Clinical Preventive Services: Results from a National Survey," *The Milbank Quarterly*, 2016, *94* (1), 51–76.

Leung, Pauline and Alexandre Mas, "Employment Effects of the Affordable Care Act Medicaid Expansions," *Industrial Relations: A Journal of Economy and Society*, 2018, *57* (2), 206–234.

Madrian, Brigitte, "Employment-Based Health Insurance and Job Mobility: Is There Evidence of Job-Lock?," *Quarterly Journal of Economics*, 1994, *109* (1), 27–54.

Maskin, Eric and Jean Tirole, "A Theory of Dynamic Oligopoly, I: Overview and Quantity Competition with Large Fixed Costs," *Econometrica*, 1988, pp. 549–569.

_ **and** _ , "A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles," *Econometrica*, 1988, pp. 571–599.

Masters, Rebecca, Elspeth Anwar, Brendan Collins, Richard Cookson, and Simon Capewell, "Return on Investment of Public Health Interventions: A Systematic Review," *J Epidemiol Community Health*, 2017, *71* (8), 827–834.

Nevo, Aviv, "Measuring Market Power in the Ready-to-Eat Cereal Industry," *Econometrica*, 2001, *69* (2), 307–342.

Newhouse, Joseph, "An Ounce of Prevention," *Journal of Economic Perspectives*, 2021, *35* (2), 101–118.

Pakes, Ariel and Paul McGuire, "Computing Markov-Perfect Nash Equilibria: Numerical Implications of a Dynamic Differentiated Product Model," *RAND Journal of Economics*, 1994, *25* (4), 555–589.

Phelps, Charles, "Illness Prevention and Medical Insurance," *Journal of Human Resources*, 1978, pp. 183–207.

Pistollato, Michele, Rajini Jayasuriya, and Elaine Damato, "Will Payers Fund More Services in Preventive Care?," 2020. link, Accessed: 2022/08/23.

Polyakova, Maria and Stephen Ryan, "Subsidy Targeting with Market Power," 2019.

Recht, Hannah, "Here's How Affordable Care Act Marketplaces Are Shaping Up Under Trump's Watch," 2017. link, Accessed: 2022/08/31.

Royalty, Anne Beeson, "The Effects of Job Turnover on the Training of Men and Women," *ILR Review*, 1996, *49* (3), 506–521.

Ryan, Conor, "Mergers in the Presence of Adverse Selection," 2023.

Ryan, Stephen, "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 2012, *80* (3), 1019–1061.

Saltzman, Evan, "Demand for Health Insurance: Evidence from the California and Washington ACA Exchanges," *Journal of Health Economics*, 2019, *63*, 197–222.

_ **and Claudio Lucarelli**, "Learning in a New Market: The Case of the ACA Exchanges," 2021.

Shepard, Mark, "Hospital Network Competition and Adverse Selection: Evidence from the Massachusetts Health Insurance Exchange," *American Economic Review*, 2022, *112* (2), 578–615.

— **and Myles Wagner**, "Reducing Ordeals Through Automatic Enrollment: Evidence from a Health Insurance Exchange," 2022.

Shi, Liyan, "Optimal Regulation of Noncompete Contracts," *Econometrica*, 2023, *91* (2), 425–463.

Small, Leslie, "Molina Posts $230M Loss in Second Quarter, Will Pull Out of Two States' ACA Exchanges," 2017. link, Accessed: 2022/08/31.

Starc, Amanda and Robert Town, "Externalities and Benefit Design in Health Insurance," *Review of Economic Studies*, 2020, *87* (6), 2827–2858.

Sweeney, Evan, "BCBS of Tennessee Uses Data, Outreach to Close Preventive Care Gaps," 2016. link, Accessed: 2022/08/23.

Tam, Denise, Yvonne Lo, and Wendy Tsui, "Knowledge, Practices and Expectations of Preventive Care: a Qualitative Study of Patients Attending Government General Outpatient Clinics in Hong Kong," *BMC Family Practice*, 2018, *19* (1), 1–8.

Tebaldi, Pietro, "Estimating Equilibrium in Health Insurance Exchanges: Price Competition and Subsidy Design under the ACA," 2017.

Train, Kenneth, "Welfare Calculations in Discrete Choice Models When Anticipated and Experienced Attributes Differ: A Guide with Examples," *Journal of Choice Modelling*, 2015, *16*, 15–22.

USPSTF, "US Preventive Services Task Forces Published Recommendations," 2021. link, Accessed: 2021/10/21.

Weintraub, Gabriel, Lanier Benkard, and Benjamin Van Roy, "Markov Perfect Industry Dynamics with Many Firms," *Econometrica*, 2008, *76* (6), 1375–1411.

Well, David, "Accounting for the Effect of Health on Economic Growth," *Quarterly Journal of Economics*, 2007, *122* (3), 1265–1306.

Online Appendix for "Commitment, Competition, and Preventive Care Provision"

Contents

A Additional Tables and Figures

Table A1. Preventive procedures of interest

Procedure: Childhood Immunizations (*cis*) *Clinical Routines, Frequency, Eligibles*: Four diphtheria, tetanus, and acellular pertussis vaccines; three polio; one measles, mumps, and rubella vaccines; three Haemophilus influenza type B vaccines; three hepatitis B vaccines, one chicken pox vaccine by age 2 *Medical Benefits*: Prevent early death and diseases
Procedure: Immunizations for Adolescents (*ima*) *Clinical Routines, Frequency, Eligibles*: One meningococcal conjugate vaccine for adolescents aged 11-13; one tetanus, diphtheria toxoids and acellular pertussis vaccine for adolescents aged 10-13 *Medical Benefits*: Prevent early death and diseases
Procedure: Breast Cancer Screening (*bcs*) *Clinical Routines, Frequency, Eligibles*: Mammogram every two years for women aged 50-74 *Medical Benefits*: Detect diseases in early-stage
Procedure: Cervical Cancer Screening (*ccs*) *Clinical Routines, Frequency, Eligibles*: Cervical cytology performed every 3 years for women aged 20-64, or cervical cytology and human papillomavirus co-testing every 5 years for women aged 30-64 *Medical Benefits*: Find precancerous noncancerous tumors before they become invasive cancers; detect disease in early stage
Procedure: Colorectal Cancer Screening (*col*) *Clinical Routines, Frequency, Eligibles*: Fecal occult blood test every year, or flexible sigmoidoscopy every five years, or colonoscopy every ten years for individuals aged 50-75 *Medical Benefits*: Find precancerous noncancerous tumors before they become invasive cancers; detect disease in early stage
Procedure: Comprehensive Diabetes Care (*cdc*) *Clinical Routines, Frequency, Eligibles*: Eye exams, Hemoglobin A1c (HbA1c) testing, and nephropathy exams every year for patients aged 18-75 with Type 1 or 2 diabetes *Medical Benefits*: Reduce the probability of diabetes complications, e.g., vascular diseases, end-stage renal disease
Procedure: Statin Therapy for Cardiovascular Disease (*spc*) *Clinical Routines, Frequency, Eligibles*: Have at least one high or moderate-intensity statin medication every year for male patients aged 21-75 and female patients aged 40-75 with clinical atherosclerotic cardiovascular disease *Medical Benefits*: Prevent adverse events, e.g., myocardial infractions
Procedure: Asthma Medication (*amr*) *Clinical Routines, Frequency, Eligibles*: Have a ratio of controller medications to total asthma medications of 0.50 or greater every year for patients aged 5-85 with persistent asthma *Medical Benefits*: Prevent asthma exacerbation related ED visits and hospitalizations

Notes: The information is extracted from HEDIS Technical Specifications for Health Plans 2017.

Table A2. Summary statistics, the Utah exchange

	(1) 2014	(2) 2015	(3) 2016	(4) 2017	(5) 2018	(6) 2019
Total insured	75,017	175,366	192,926	209,490	192,231	198,740
Market size	262,884	335,540	334,981	359,188	352,670	363,161
(a). Demographics (%)						
Age below 18	23.40	24.33	25.12	25.22	25.75	26.87
Age 18-34	28.98	30.96	30.72	30.50	30.27	29.93
Age 35-55	31.29	29.93	29.20	29.46	29.23	28.90
Age above 55	16.33	14.78	14.97	14.82	14.75	14.30
(b). Choice pattern (%)						
Bronze plans	11.93	17.18	13.18	25.26	38.67	41.16
Silver plans	54.98	61.24	68.97	69.89	58.57	57.42
Gold plans	33.10	21.58	17.80	4.51	2.29	1.11
(c). Share remain insured in the exchange years later (%)						
Remain insured in the exchange in 2014	100	-	-	-	-	-
Remain insured in the exchange in 2015	77.33	100	-	-	-	-
Remain insured in the exchange in 2016	52.57	63.67	100	-	-	-
Remain insured in the exchange in 2017	38.56	44.68	60.92	100	-	-
Remain insured in the exchange in 2018	30.94	33.88	43.46	61.62	100	-
Remain insured in the exchange in 2019	27.44	29.54	36.73	48.92	72.92	100
(d). Inflows, Outflows, and Switching (%)						
Retained in the exchange from the previous year	-	33.08	58.13	57.29	69.05	72.71
_, stay with the previous insurer	-	29.13	39.83	48.65	41.98	69.58
_, switch insurer	-	3.95	18.31	8.64	27.08	3.13
(e). Market share (%)						
Insurer A	17.84	22.42	35.48	32.94	48.99	50.07
Insurer B	-	-	0.62	1.71	5.52	4.49
Insurer C	1.35	9.99	19.73	23.67	-	-
Insurer D	3.53	3.51	1.72	-	-	-
Insurer E	-	2.60	-	-	-	-
Insurer F	-	2.01	-	-	-	-
Insurer G	5.81	11.74	-	-	-	-
Uninsured	71.46	47.74	42.41	41.68	45.49	45.27
(f). Annual premiums ($)						
Full premium	3,132	3,144	3,528	4,248	6,420	6,084
	(548)	(546)	(670)	(1,482)	(1,633)	(1,594)
Out-of-pocket premium	1,064	1,068	1,008	1,427	1,177	981
	(169)	(170)	(202)	(364)	(548)	(370)
(g). Annual medical expenses ($)						
Total expenses	5,184	4,820	4,947	4,881	5,616	5,441
	(31,324)	(21,807)	(22,680)	(28,067)	(25,123)	(25,270)
Out-of-pocket expenses	702	724	703	699	952	916
	(1,476)	(1,743)	(1,629)	(3,197)	(2,970)	(2,845)
Total expenses (ACG-adjusted risk)	4,890	4,825	5,123	4,150	6,134	5,948
	(14,928)	(15,897)	(17,198)	(14,562)	(19,329)	(18,418)

Notes: This table reports mean and standard deviations (in parenthesis, at the individual level) for key statistics of exchange enrollees from Utah APCD. Insurer C exited the Utah exchange in 2018. It returned in 2019 but did not actively enroll consumers or engage in marketing activities (link, last accessed 2022/10/31). The market share of Insurer C is less than 0.1% in 2019.

Table A3. Consumer turnover across and within insurance market segments

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Across market, for consumers enrolled in Col (1) in $t-1$, share that enroll in Col (2)-(7) in t (%)						Within, share
	Medicare	Medicaid	Exchanges	Employer sponsored	Other private	Uninsured	not switch plans (%)
Medicare	96.5	0.0	0.0	0.0	0.0	3.5	90
Medicaid	0.3	87.8	0.6	2.2	0.1	9.0	
Exchanges	2.0	3.0	73.7	7.0	1.9	12.4	53.5
Employer sponsored	0.3	0.5	0.4	95.7	0.2	2.9	92.5
Other private	2.3	2.6	8.4	6.5	70.7	9.5	
Uninsured	1.2	13.0	3.0	17.4	1.4	63.9	

Notes: Turnover statistics across market segments in Columns (2)-(7) are national means and are derived from the 2014-2019 Medical Expenditure Panel Survey. Column (8) reports the share of consumers who do not switch plans conditional on staying within the same market segment. These share statistics are taken from Koma et al. (2019) for Medicare, Cunningham (2013) for employer-sponsored insurance, and derived from CMS Marketplace Open Enrollment Period Public Use File 2017-2019 for the exchange. Missing cells indicate that the turnover statistics are not available.

Table A4. Effect of consumer turnover on sub-categories of per member quality investments

	Medical incentive payments (1)	Improve health outcomes (2)	Prevent hospital readmissions (3)	Support health info. IT (4)	Improve patient safety (5)	Promote wellness activities (6)
Exchanges retention	2.53*	0.22	0.13	1.48	–0.08	1.03**
	(1.26)	(0.64)	(0.16)	(1.28)	(0.18)	(0.40)
Outcome mean	44	30	6	9	7	12
N	141	141	141	141	141	141

Notes: This table reports output from estimation of equation (4). The retention rate is measured in 0-100 percentage points; quality investment is measured in dollars. The regression specification and sample are the same as in Table 2. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level, separately.

Table A5. Effect of the shift-share instrument on the exchange's composition

Share below 200 FPL (1)	Share aged 0–25 (2)	Share aged 26–54 (3)	Share choosing Gold plans (4)	Share choosing Silver plans (5)	Share choosing Bronze plans (6)
0.030	0.007	0.013	–0.147	0.088	0.059
(0.069)	(0.024)	(0.027)	(0.183)	(0.159)	(0.120)

Notes: This table reports the coefficients of the shift-share instrument in the regression of outcome variables in each column on the instrument. The share in each column is measured among all enrollees in the exchange. Gold, Silver, and Bronze plans have standardized 80%, 70%, and 60% cost-shares. The regression is at the state-year level in 2017-2019. The regression specification includes state, year fixed effects, and weights each observation by the exchange's market size. Standard errors are reported in parentheses and clustered at the state level. Outcome data comes from CMS Marketplace Open Enrollment Period PUF. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A6. Differences in medical expenses and health, by inflows and outflows of the exchange

Cost and health conditions	Outflows		Cost and health conditions	Outflows	
Total expenses	216.87	(1043.50)	Probability, heart attack	0.001	(0.007)
Insurer expenses	169.26	(1013.86)	Probability, stroke	0.004	(0.007)
Consumer expenses	47.62	(82.11)	Probability, cancer	0.016	(0.014)
Probability, high blood pressure	-0.019	(0.024)	Probability, diabetes	-0.011	(0.015)
Probability, coronary heart disease	-0.009	(0.007)	Probability, arthritis	0.015	(0.016)
Probability, angina	-0.005	(0.006)	Probability, asthma	0.015	(0.022)

Notes: This table reports the coefficients and standard errors (in parentheses) of the outflow indicator in the regression of health conditions and medical costs on those indicators, controlling for year, geographic market fixed effects. The sample includes inflows and outflows of the exchange in 2015-2019 nationwide from the Medical Panel Expenditure Survey. Outflows are individuals enrolled in the exchange in the current year and not enrolled in the exchange in the next year. Inflows are individuals not enrolled in the exchange in the current year and enrolled in the exchange in the next year. The medical expenses in the analysis are only when individuals are enrolled in the exchange to eliminate cost differences inherent in each market segment. *,**,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A7. Differences in prevention utilization between inflows, outflows, stayers of the exchange

Procedure utilization	Inflows		Outflows	
Diabetes kidney exams	0.0097	(0.015)	-0.0095	(0.016)
Diabetes HbA1c tests	-0.0070	(0.016)	-0.0099	(0.011)
Diabetes eye exams	-0.0037	(0.002)	-0.0016	(0.002)
Chlamydia screening	0.0211	(0.019)	-0.0144	(0.018)
Well-child visits	0.0090	(0.010)	-0.0138	(0.011)
Prenatal, postpartum care	0.0095	(0.010)	-0.0135	(0.018)

Notes: This table reports the coefficients and standard errors (in parentheses) of the outflow and inflow indicators, in the regression of utilization of medical procedures for eligible individuals on those indicators, controlling for year, insurer, geographic market fixed effects. The sample includes inflows (or outflows) and stayers of the exchange in 2017-2019 Utah APCD. Stayers are individuals enrolled in the exchange in the current year and the next year. Inflows and outflows are defined the same as in Table A6. To eliminate systematic differences between market segments, utilization is measured only when the individuals are enrolled in the exchange. *,**,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A8. Alternative estimates of health risk transitions

	(1)	(2)	(3)	(4)	(5)	(6)
Prevention utilization, q_1	–1,619	–2,629	–2,633	–1,337	–768	–659
	(8)	(14)	(14)	(16)	(15)	(72)
Number of observations	7,420,956	6,804,903	6,804,903	6,804,903	6,804,903	439,274
Number of individuals	3,176,548	1,985,453	1,985,453	1,985,453	1,985,453	151,563
Individual, year fixed effects		✓	✓	✓	✓	✓
Demographics: 5-yr age bin, county FEs			✓	✓	✓	✓
Time-varying health conditions: ACG cells				✓	✓	✓
Forwarded prevention utilization					✓	✓
Health risks growth without prevention, q_0	897	1,345	1,347	773	521	471
Randomness in preventive returns, σ_ν	476	477	477	477	476	120

Notes: This table reports coefficients (q_1), standard errors (in parentheses, clustered at individual level) from estimating a specification equivalent to equation (17) but at the individual-year level: $\Delta\mu_{it} = \mu_{it+1} - \mu_{it} = q_0 + q_1 e_{it} + \beta X_{it} + \nu_{it}$. q_0, σ_ν are derived following equation (18). The regression sample is individuals in the UT commercial market columns (1)-(5), or in the UT exchange for column (6). Prevention utilization and health risks are generated by the ACG system. Columns (5)-(6) include forwarded prevention utilization in year $t+1$ to address a timing hypothesis that investment in year t $(t+1)$ affects health risks in both year t and $t+1$ $(t+1$ and $t+2)$.

Table A9. Alternative estimates of consumer preferences

	(1)	(2)	(3)
(a). Estimates			
Inertia (disutility of changing insurer), η	-2.505	-3.301	-2.486
	(0.014)	(0.014)	(0.014)
Increase in premium coefficients as health risks increase by \$1k, α_1	0.312	0.009	0.376
	(0.001)	(0.001)	(0.010)
Increase in prevention coefficients as health risks increase by \$1k, ρ_1			0.080
			(0.058)
Coefficient on out-of-pocket medical expenses (in \$1,000), γ	-0.454	-1.779	-0.454
	(0.007)	(0.010)	(0.010)
Coefficient on premium (in \$1,000), α_0	-6.984	-6.008	-6.965
	(1.594)	(1.126)	1.587
Coefficient on prevention (in \$1,000), ρ	0.113	0.163	-0.001
	(0.587)	(0.415)	(0.584)
(b). Derived statistics			
Average own premium elasticity	-5.47	-6.50	-5.48
↓ in insured rate if all products' OOP annual premiums ↑ by \$100	9.1%	10.3%	12.1%
↓ in insured rate if all products' posted annual premiums ↑ by \$100	2.0%	2.1%	2.8%
Average own prevention elasticity	0.05	0.07	0.05
Average willingness to pay for observed prevention characteristics	9	12	9

Notes: This table reports alternative consumer preference estimates using the two-step estimator of Goolsbee and Petrin (2004). Column (1) corresponds to the baseline (preferred) specification. Column (2) uses random coefficients in equation (7), i.e., μ_{imt-1} is drawn from the observed health risk distribution, instead of setting $\mu_{imt-1} = \mu_{fmt-1}$ if $d_{imt-1} = f$ as demographic coefficients. I do not use this specification as my primary specification because solving the dynamic game with random coefficients embedded in stage games' payoff functions is not computationally feasible. Column (3) allows preferences for prevention to differ by health risks, i.e., adding $\rho_1\mu_{imt-1}e_{jmt}$ in equation (7), and sets μ_{imt-1} the same as in the baseline. Standard errors (in parentheses) are derived using the delta method.

Table A10. Equilibrium statistics, (a)symmetric duopoly and monopoly equilibrium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	(I) Symmetric Duopoly to Monopoly						(II) Asymmetric Duopoly to Monopoly						
Monopoly characteristics	(a) Insurer A			(b) Insurer B				(c) Insurer B		(d) Insurer A		(e) Mean Char.	
Specification	Duo.	Mon.	Diff.	Duo.	Mon.	Diff.	Duo.	Mon.	Diff.	Mon.	Diff.	Mon.	Diff.
Investment per member (PM.), Insurer A	-	-	-	-	-	-	76	-	-	306	230	313	237
Investment PM., Insurer B	-	-	-	-	-	-	138	342	204	-	-	-	-
Investment PM., Market mean	114	306	192	133	342	209	106	342	236	306	200	313	207
NPV, cost savings PM., Insurer A	-	-	-	-	-	-	516	-	-	1538	1023	1466	950
NPV, cost savings PM., Insurer B	-	-	-	-	-	-	954	1830	877	-	-	-	-
NPV, cost savings PM., Market mean	662	1538	876	955	1830	875	-	-	-	-	-	-	-
Premium, Insurer A	-	-	-	-	-	-	7429	-	-	8427	998	7503	74
Premium, Insurer B	-	-	-	-	-	-	5860	6464	604	-	-	-	-
Premium, Market mean	7615	8427	812	5674	6464	790	6661	6464	-197	8427	1766	7503	842
Markup, Insurer A	-	-	-	-	-	-	0.255	-	-	0.422	0.167	0.308	0.053
Markup, Insurer B	-	-	-	-	-	-	0.147	0.258	0.112	-	-	-	-
Markup, Market mean	0.262	0.422	0.161	0.155	0.258	0.103	0.204	0.258	0.054	0.422	0.219	0.308	0.104
Insured rate	0.638	0.483	-0.155	0.649	0.503	-0.146	0.647	0.503	-0.144	0.483	-0.164	0.438	-0.210
Health risk per consumer	6374	6088	-286	6004	5849	-155	6255	5849	-406	6088	-167	6044	-211
Consumer surplus PM., include inertia, ex-ante	-1088	-1075	13	-889	-957	-68	-1005	-957	48	-1075	-70	-1054	-49
Consumer surplus PM., exclude inertia, ex-ante	-1038	-1046	-8	-842	-929	-88	-955	-929	25	-1046	-91	-1024	-69
Consumer surplus PM., include inertia, ex-post	-1387	-1337	50	-1169	-1215	-46	-1302	-1215	87	-1337	-35	-1303	-2
Consumer surplus PM., exclude inertia, ex-post	-1336	-1308	29	-1122	-1188	-66	-1252	-1188	64	-1308	-56	-1274	-22
Total consumer surplus, include inertia, ex-ante	-395.3	-390.5	4.8	-322.9	-347.4	-24.5	-365.0	-347.4	17.6	-390.5	-25.5	-382.7	-17.7
Total consumer surplus, exclude inertia, ex-ante	-377.0	-379.9	-2.9	-305.8	-337.6	-31.8	-346.8	-337.6	9.3	-379.9	-33.1	-371.9	-25.1
Total consumer surplus, include inertia, ex-post	-503.7	-485.4	18.3	-424.6	-441.2	-16.6	-472.7	-441.2	31.5	-485.4	-12.7	-473.3	-0.5
Total consumer surplus, exclude inertia, ex-post	-485.3	-474.8	10.5	-407.4	-431.4	-23.9	-454.5	-431.4	23.2	-474.8	-20.3	-462.5	-8.0
Total insurer profit	311.6	364.7	53.1	182.8	221.4	38.6	241.5	221.4	-20.2	364.7	123.1	229.2	-12.3
Total uncompensated care	687.4	958.8	271.4	651.9	940.8	289.0	668.7	940.8	272.2	958.8	290.2	1065.6	396.9
Total govt. expenses on premium subsidies	1538.9	1258.2	-280.7	1222.8	961.3	-261.5	1390.6	961.3	-429.3	1258.2	-132.5	952.4	-438.2

Notes: Panel (I) reports simulated policies and welfare in the symmetric duopoly and monopoly equilibrium. Subpanels (a) and (b) report the scenarios where investment cost curvatures and product offerings take parameter estimates of Insurer A or Insurer B, separately. The statistics in columns (3) and (6) represent those in the monopoly equilibrium (columns (2), (5)) minus the duopoly equilibrium (columns (1), (4)). Since the simulations use symmetric duopolists, I only report the market means, and omit the reporting of each separate insurer's strategies. Panel (II) reports simulated policies and welfare in the baseline asymmetric duopoly equilibrium and monopoly equilibrium. Subpanels (c) and (d) report the monopoly scenario where Insurer B or Insurer A is kept on the market, separately. Subpanel (e) reports a scenario, where Insurer A and B merge and the new insurer takes their mean investment cost curvatures and brand preferences. The statistics in columns (9), (11), (13) represent those in the monopoly equilibrium (columns (8), (10), (12)) minus the duopoly equilibrium (column (7)). In all simulations, to avoid the mechanical variety effects caused by the dimension of logit draws, I let the monopolist offers the same product twice. All statistics are the mean of each equilibrium object in the stationary distribution. Ex-ante and ex-post consumer surplus are calculated following equation (20) and (21), separately. Consumer surplus numbers can be negative because they account for the disutilities of changing insurers and correct misjudged preferences for out-of-pocket expenses. Total welfare metrics of consumer surplus, insurer profit, medical providers' uncompensated care, and government expenses are measured in millions and aggregate over 363,161 consumers in the Utah exchange. The cost of public funds is assumed to be 30 cents for 1 dollar public spending (Polyakova and Ryan, 2019) when calculating government subsidies. I assume the profit margins of medical services is 13% (Macrotrends, link, last accessed on 2023/01/16).

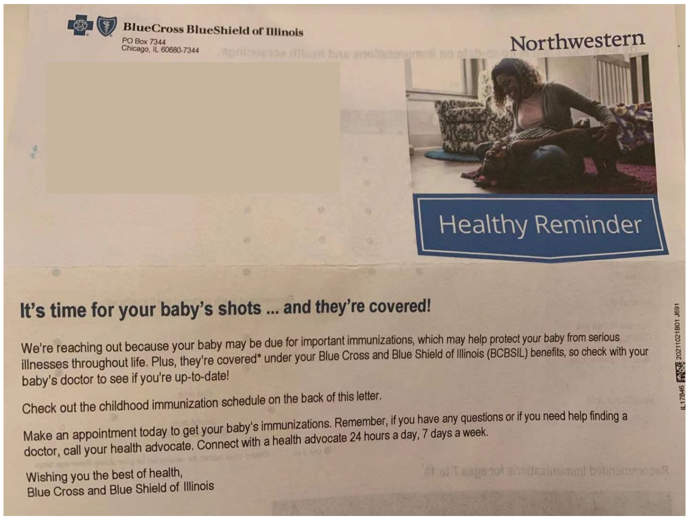
Table A11. Equilibrium statistics, asymmetric duopoly and monopoly, robusness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(I) Simulation Forward					(II) Alternative Product Offerings						
Monopoly characteristics		(a) Insurer A		(b) Insurer B			(c) Insurer B		(d) Insurer A		(e) Mean Char.	
Specification	Duo.	Mon.	Diff.	Mon.	Diff.	Duo.	Mon.	Diff.	Mon.	Diff.	Mon.	Diff.
Investment per member (PM.), Insurer A						76	-	-	303	227	356	279
Investment PM., Insurer B						138	2191	2053	-	-	-	-
Investment PM., Market mean						106	2191	2085	303	197	356	250
NPV, cost savings PM., Insurer A						516	-	-	1275	760	1249	733
NPV, cost savings PM., Insurer B						954	1529	575	-	-	-	-
Premium, Insurer A						7429	-	-	8000	571	7200	-229
Premium, Insurer B						5860	7349	1489	-	-	-	-
Premium, Market mean						6661	7349	688	8000	1339	7200	540
Markup, Insurer A						0.255	-	-	0.345	0.089	0.255	0.000
Markup, Insurer B						0.147	0.154	0.008	-	-	-	-
Markup, Market mean						0.204	0.154	-0.050	0.345	0.141	0.255	0.052
Insured rate						0.647	0.429	-0.218	0.408	-0.239	0.373	-0.274
Health risk per consumer	6349	6106	-244	6199	-150	6255	5885	-369	6116	-138	6044	-211
Consumer surplus PM., include inertia, ex-ante	-1032	-1010	22	-1095	-64	-1005	-978	27	-1097	-92	-1058	-53
Consumer surplus PM., exclude inertia, ex-ante	-982	-984	-1	-1066	-84	-955	-954	1	-1067	-112	-1030	-75
Consumer surplus PM., include inertia, ex-post	-1335	-1268	67	-1358	-23	-1302	-1130	171	-1274	28	-1222	79
Consumer surplus PM., exclude inertia, ex-post	-1285	-1241	44	-1329	-43	-1252	-1106	145	-1244	7	-1195	57
Total consumer surplus, include inertia, ex-ante	-374.8	-366.9	7.8	-397.8	-23.1	-365.0	-355.1	9.9	-398.3	-33.3	-384.2	-19.2
Total consumer surplus, exclude inertia, ex-ante	-356.8	-357.3	-0.5	-387.3	-30.5	-346.8	-346.3	0.5	-387.6	-40.8	-374.1	-27.3
Total consumer surplus, include inertia, ex-post	-484.8	-460.5	24.4	-493.1	-8.3	-472.7	-410.5	62.2	-462.7	10.1	-443.9	28.8
Total consumer surplus, exclude inertia, ex-post	-466.8	-450.8	16.0	-482.6	-15.7	-454.5	-401.7	52.8	-451.9	2.6	-433.8	20.7
Total insurer profit	239.0	185.9	-53.0	352.8	113.9	241.5	160.4	-81.2	246.1	4.5	155.8	-85.8
Total uncompensated care	699.7	1062.3	362.6	1017.2	317.5	668.7	1082.4	413.7	1106.3	437.7	1191.4	522.7
Total govt. expenses on premium subsidies	1083.6	708.1	-375.5	966.1	-117.5	1390.6	755.1	-635.6	970.1	-420.5	728.6	-662.1

Notes: Panel (I) reports simulated policies and welfare in the baseline asymmetric duopoly equilibrium and monopoly equilibrium. All statistics reported are measured along the transition path. I solve for insurers' optimal strategy profiles under the corresponding market structure and parameters, and then simulate forward for 40 periods, 10000 times, starting from the observed condition of each county. I calculate the averages of total discounted welfare metrics across simulation paths, then transform the total discounted values to equivalent annualized welfare metrics to make them comparable to other tables. The initial state variables for the simulation forward process take the observed values of those in Salt Lake County. To avoid the mechanical variety effects caused by the dimension of logit draws, I let the monopolist offers the same product twice. Panels (a) and (b) report the monopoly scenario where Insurer B or Insurer A is kept on the market, separately. The statistics in columns (3), (5) represent those in the monopoly equilibrium (in columns (2), (4)) minus the duopoly equilibrium (in column (1)). Panel (II) reports simulated welfare in the baseline asymmetric duopoly equilibrium and monopoly equilibrium, where the monopoly offers three products. Statistics reported are the mean of each equilibrium object in the stationary distribution. Subpanels (c) and (d) report the monopoly scenario where Insurer B or Insurer A is kept on the market, separately. Subpanel (e) reports a scenario, where Insurer A and B merge and the new insurer takes their mean investment cost curvatures and brand preferences. The statistics in columns (8), (10), (12) represent those in the monopoly equilibrium (in columns (7), (9), (11)) minus the duopoly equilibrium (in column (6)). Ex-ante and ex-post consumer surplus are calculated following equation (20) and (21), separately. Consumer surplus numbers can be negative because they account for the disutilities of changing insurers and correct misjudged preferences for out-of-pocket expenses. Total welfare metrics of consumer surplus, insurer profit, medical providers' uncompensated care, and government expenses are measured in millions and aggregate over 363,161 consumers in the Utah exchange. The cost of public funds is assumed to be 30 cents for 1 dollar public spending (Polyakova and Ryan, 2019) when calculating government subsidies. I assume the profit margins of medical services is 13% (Macrotrends, link, last accessed on 2023/01/16).

Figure A1. Examples of insurers' investment in preventive care

(a) Remind consumers



From: **Blue Cross and Blue Shield of Illinois** <BCBSIL_noreply@bcbsil.com>
Date: Tue, Feb 14, 2017 at 8:15 PM
Subject: Your LifeTimes - February 2017
To:

Take control and be the boss of your health

If you have a chronic condition, managing your health better can pay off later on. So take the first step to a healthier tomorrow and join the Condition Management program.

Condition Management is available to you and your covered family members through your Blue Cross and Blue Shield of Illinois (BCBSIL) benefits at no additional cost. It's easy to join; just call 866-412-8795 and select "Blue Care Connection" to enroll.

A Blue Care Advisor℠ will call you

A Blue Care Advisor is a licensed clinician with special training to help you manage your health condition. Your Advisor will schedule regular phone calls with you to try to help you set and reach health goals.

You will work together to figure out if there are any obstacles to taking better care of yourself and how to overcome them. Your Advisor will also work with your doctors to make sure you are getting the care you need.

(b) Provide wellness programs

Aetna's approach to preventive care*

We realize how important all aspects of preventive care are, both to our members' health and our customers' bottom lines. That's why we provide coverage for recommended clinical screenings, vaccinations and preventive care doctor visits. In fact, many of our plans cover most preventive care services at 100 percent, with no copays or deductibles.

We also provide an extensive array of wellness programs designed to promote healthy lifestyles and improve members' overall health. For those members who already have chronic conditions, our disease management programs help them manage their conditions and minimize complications.

But making the benefits available isn't enough – we also actively encourage members to take advantage of their preventive care benefits through targeted mailings and programs. For example, our ActiveHealth® Management CareEngine® system compares member health data with over 1,000 current evidence-based guidelines of care to identify opportunities for better care, including preventive care and increased patient safety.

Aetna also offers a wide variety of tools to help plan sponsors and members get the most out of their health benefits, including communications programs and online health information, such as:

- Programs for Women – including our Beginning Right℠ maternity program and an extensive women's health website.
- Health Education Reminders – encouraging members to get the care today that will help prevent, detect or monitor conditions early on, when they are most treatable.
- 24-Hour Nurse Line – members can have their health questions answered by a registered nurse anytime, night or day.
- Personalized support – experienced wellness counselors available to help members understand health issues, reduce risk and set meaningful goals.
- The Member Wellness Message Program – a series of single-topic educational pieces addressing general wellness topics and Aetna's information tools for members that plan sponsors can distribute to Aetna members by e-mail, in their company newsletters or on their intranet sites.

*Not all program services are available to Small Group customers. Refer to plan documents for a complete description of benefits, exclusions, limitations and conditions of coverage available. Plan features and availability may vary by location and are subject to change.

(c) Incentivize providers, pay for performance contracts

Comprehensive Diabetes				
Service	Procedure	Bonus	Performance Criteria	Plans†
Comprehensive Diabetes Care - 18-75 year olds with diabetes (Types 1 & 2)	*HbA1c Screen	$25	At least one screen annually	Medicaid, ICP, SNP, Prime, Complete
	HbA1c Good Control (<7%)	$50	One paid per member per calendar year	
	*Fundoscopic Eye Exam	$25	At least one annually, completed by an Optometrist or Ophthalmologist	
	*Microalbuminuria Screen	$25	At least one screen annually	

Comprehensive Women's Care					
Breast Cancer Screening	Females Ages 50-74	Mammogram	$50	One paid per calendar year	Medicaid, ICP, SNP, Prime, Complete
Cervical Cancer Screening	Females Ages 21-64	Cervical Cytology	$25	One paid per calendar year	Medicaid, ICP, SNP, Prime, Complete
Chlamydia Screening	Females Ages 16-24	Chlamydia screen	$25	One paid per calendar year	Medicaid

ILLINOIS Meridian Health Plan

FLYPS04 Effective 7/1/2015

(d) Value-based payment programs

Supplemental Material

Molina Medicare Options Plus Quality Partner Program[1]

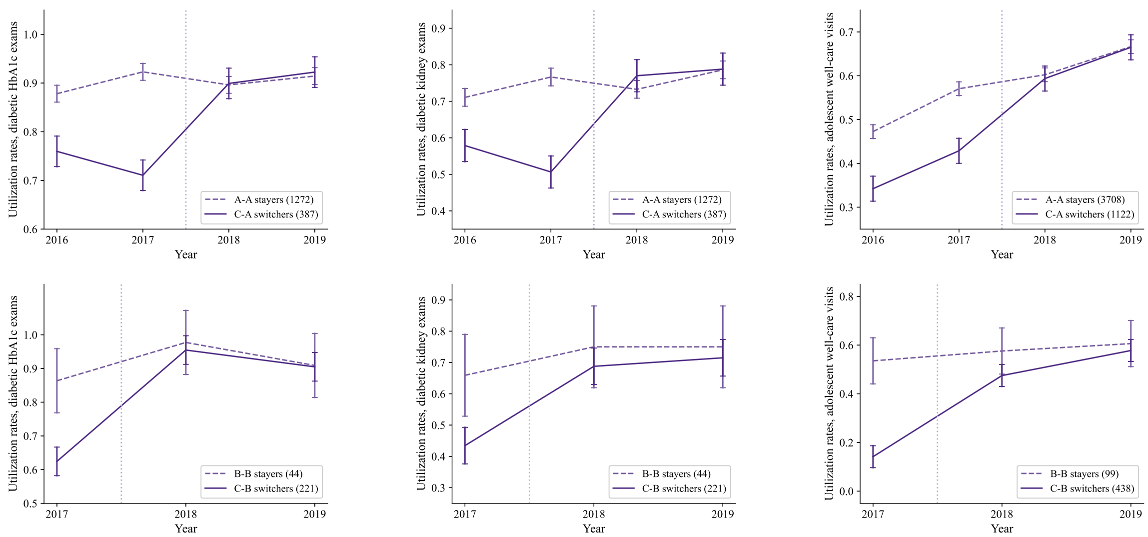
Molina Healthcare of Florida, Illinois, Michigan, New Mexico, Ohio, Texas, Utah, Washington and Wisconsin, Inc.'s (Molina Healthcare) Medicare Options Plus Quality Partner Program is a bonus payment program that recognizes Participating Providers who consistently demonstrate the best quality of care on behalf of Molina Medicare Options Plus Members.

B. Compensation for the HEDIS® Performance Metrics Bonus is as follows:
   1. Provider is eligible to receive a one-time twenty-five dollar ($25) bonus for each Needed HEDIS® Metric it completes during the Measurement Year for Medicare Options Plus Members assigned to Provider, if the Member remains a Molina Healthcare Member at the time of payment for the HEDIS® Performance Metric Bonus and the following requirements are met:
      a. Provider is involved with the Member receiving the Needed HEDIS® Metric; and

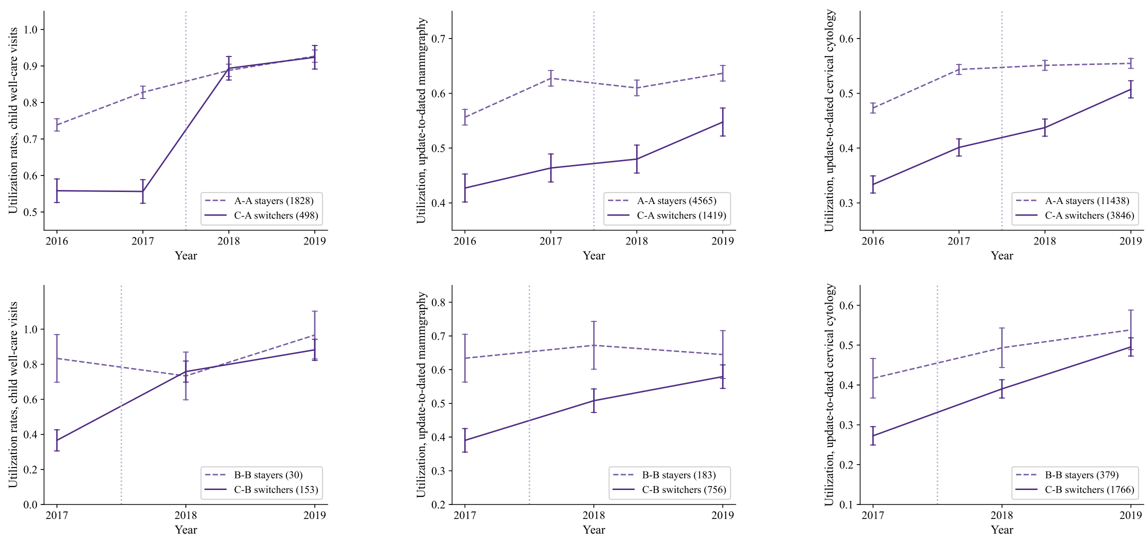
Notes: Panel (a) is mail and email reminders that Blue Cross Blue Shield sends to Northwestern enrollees. Panel (b) is a screenshot of preventive care promotion programs offered by Aetna. The original webpage is available here (last accessed 08/23/2022). Panel (c) is a screenshot of the incentive contract from Meridian. The original document is available online (last accessed 08/02/2022). Panel (d) is a screenshot of the value-based payment programs from Molina. The original document is available online (last accessed 08/24/2022).

Figure A2. Preventive care utilization rate, pre- and post- insurer switch

(a) Diabetic HbA1c exams (b) Diabetic kidney exams (c) Child well-care visits



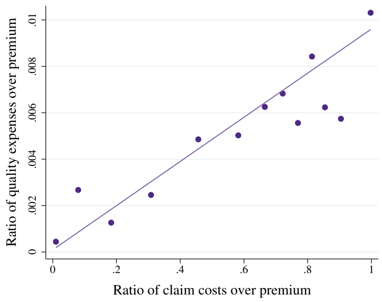
(d) Adolescents well-care visits (e) Breast cancer screening (f) Cervical cancer screening



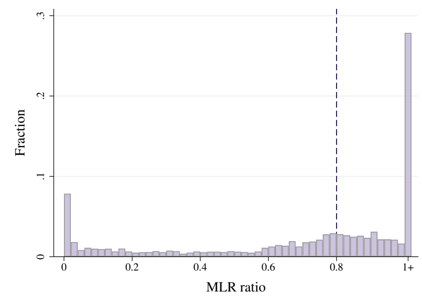
Notes: This figure plots the utilization rate and 95% confidence interval of several preventive procedures among consumers with particular insurance enrollment patterns. The dotted vertical line denotes the event of switching insurers. C-to-A (C-to-B) switchers were enrolled with Insurer C in 2016-2017 and Insurer A (B) in 2018-2019. A-to-A (B-to-B) stayers are enrolled with Insurer A (B) throughout 2016-2019. The sizes of each group are reported in parentheses. Outcome data comes from UT APCD. Outcomes in panels (a) and (b) are diabetic HbA1c exams and kidney exams, respectively, and the samples are further restricted to consumers with diabetes. Outcomes in panels (c) and (d) are child and adolescents well-care visits separately, and the samples are further restricted to consumers aged 3-6 and 12-21. Outcomes in panels (e) and (f) are breast and cervical cancer screenings, and the samples are further restricted to female consumers aged 50-74 and 40-64. In order to extend the outcome measure to the year 2016, I use cervical cytology performed within the past three years as the only clinical routine to define cervical cancer screenings and do not consider cervical cytology and human papillomavirus co-testing within the past 5 years. This is reasonable because the number of patients with cervical cytology and human papillomavirus co-testing is small. I do not report utilization for other preventive services in Table A1 because they do not require repeated clinical procedures over the years, or the sample size for stayers and switchers is not large enough. The cell sizes of C-to-B switchers and B-to-B stayers who stay with Insurer B are small, so I require only one year of enrollment before the switching event to satisfy cell size reporting requirements. The utilization gap closes more quickly for procedures that require yearly services, such as diabetes care, than for procedures that require services once every year, such as cancer screenings.

Figure A3. Validating the Medical Loss Ratio (MLR) data

(a) Correlation, claims and quality expenses

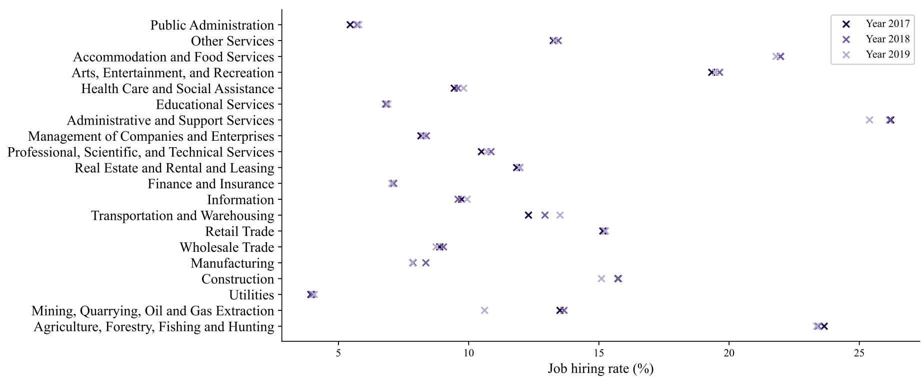


(b) Distribution of MLR ratio



Notes: Panel (a) is a binned scatter plot of the correlation between the ratio of medical claims over premium income and the ratio of quality improvement expenses over premium. The sample includes all insurers with positive premium income in the individual market. Panel (b) plots the distribution of MLR ratio for all insurers with positive premium income in the individual market. The dashed line is the regulatory threshold, which requires insurers that cover individuals and small businesses to spend at least 80% of their premium income on healthcare claims and quality improvement. Insurers with an MLR ratio greater than 1 are all classified into the "1+" bins. Data comes from the 2017-2019 Medical Loss Ratio.

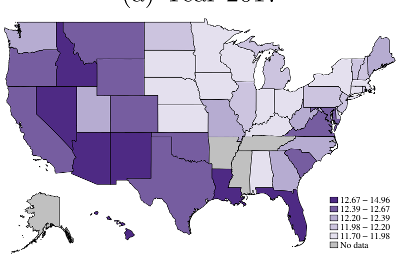
Figure A4. Job hiring rate by industry



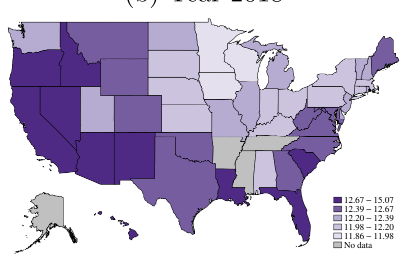
Notes: National job hiring rate by industry is defined by the number of new hires over the number of employed individuals of a certain industry. Data comes from the Longitudinal Employer-Household Dynamics Survey Job-to-Job Flows PUF in 2017-2019.

Figure A5. Geography of shift-share instrument

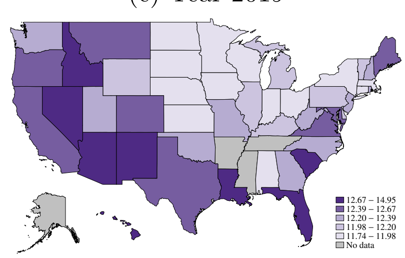
(a) Year 2017



(b) Year 2018



(c) Year 2019

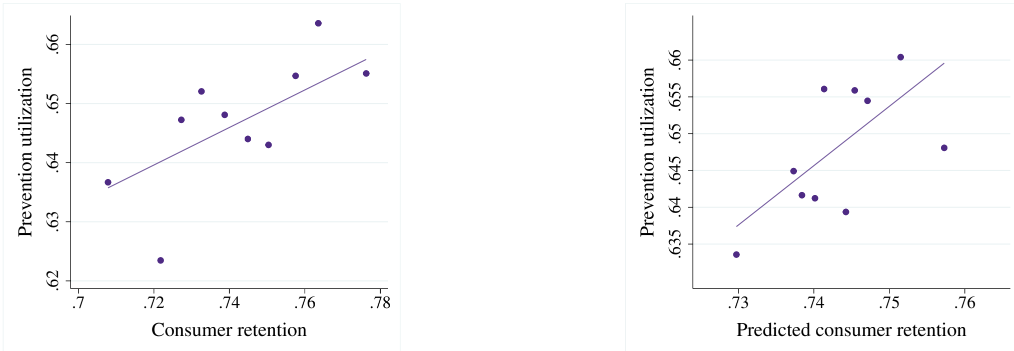


Notes: Color blocks correspond to five quintiles of the instrument value across the state-year pairs. Data sources are the same as in Figure A4. AK, AR, MS, and TN do not report job hiring statistics during the sample period. The industry employment share is measured in the year 2014.

Figure A6. Correlation between consumer retention and preventive care utilization

(a) OLS: retention and utilization

(b) 2SLS: predicted retention and utilization

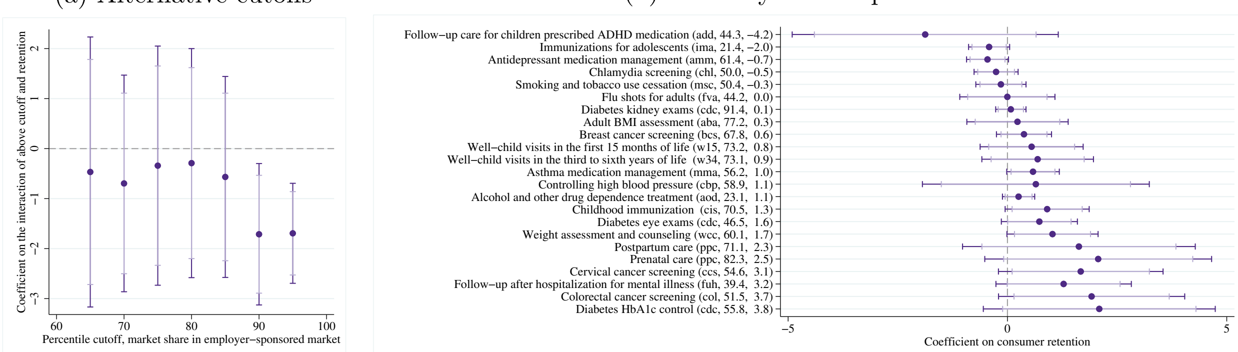


Notes: These figures are state-year level binned scatter plots of the correlation between consumer retention and prevention utilization of the exchange nationwide. The dots are residualized from state and year fixed effects, and weighted by the exchange's market size. The left figure uses the raw retention rate, while the right figure uses predicted consumer retention from the estimation of first-stage correlation (equation (3)).

Figure A7. Effect of consumer turnover on procedure utilization

(a) Alternative cutoffs

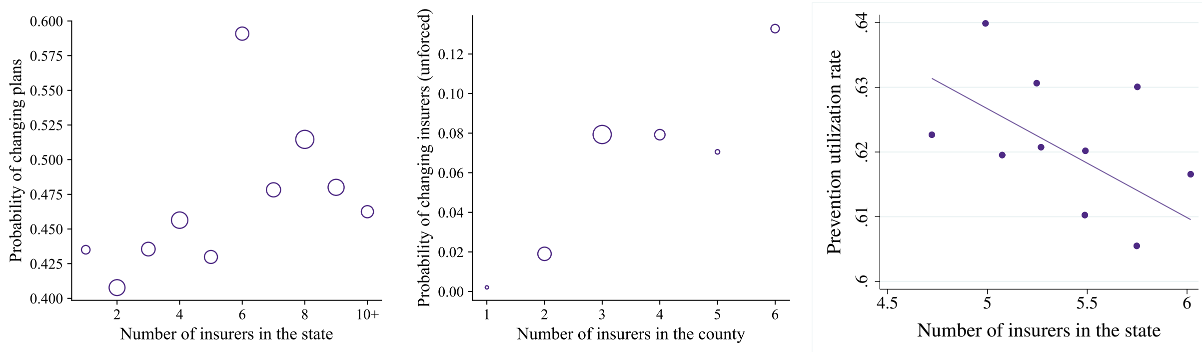
(b) Effect by clinical procedures



Notes: This figure reports the robustness of mechanisms tests in shift-share regressions. Panel (a) reports the estimation of an augmented version of equations (3) and (4), in which I interact the exchange retention rate and the shift-share instrument with an indicator denoting whether the market share of exchange insurers in the employer-sponsored insurance market is above certain percentiles. The x-axis varies percentile cutoffs and the y-axis plots the coefficient on the interaction terms of retention rate and the above cutoff indicators. Panel (b) reports the estimation of equations (3) and (4) separately for each clinical procedure. In parentheses, the abbreviations are the names of corresponding HEDIS measures; the first number is the baseline mean utilization rates for each procedure; the second number is the percent effect, measured by the regression coefficients divided by mean utilization rates. The procedures are sorted by the percent effects. Light bars plot 90% confidence intervals, and dark bars plot 95% confidence intervals. The regression specification and sample are the same as in Table 2.

Figure A8. Correlation between competition, turnover and prevention utilization on the exchange

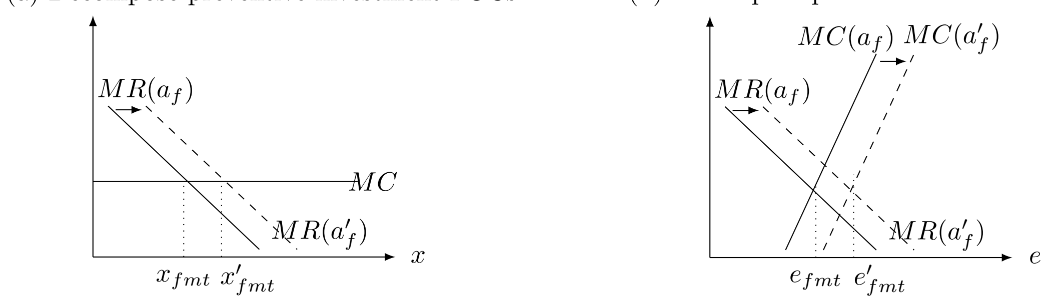
(a) Turnover, nationwide (b) Turnover, UT (c) Utilization, nationwide



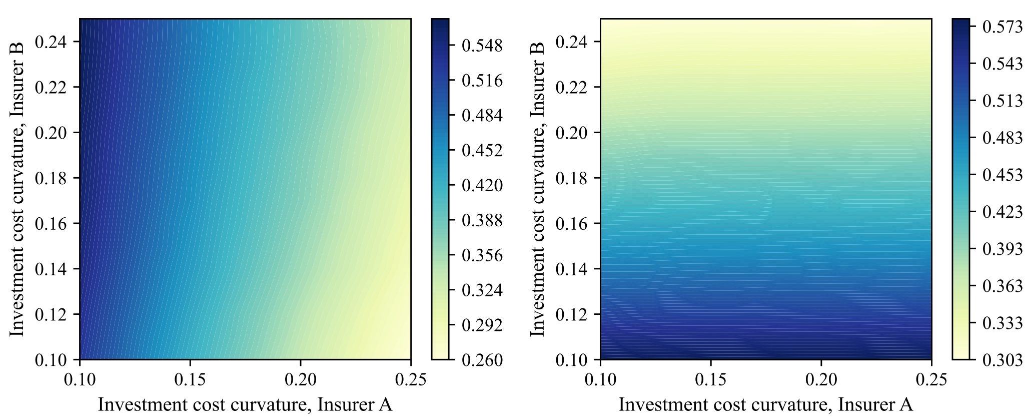
Notes: Panel (a) plots the correlation between the number of insurers and the probability of switching plans at the state-year level in the exchange nationwide in 2017-2019. Panel (b) plots the probability of unforced switching insurers at the county-year level in the Utah exchange in 2014-2019. Unforced switching refers to the change of insurers not due to insurer exits. The size of the dot is proportional to the number of enrollees in the given market structure bin in panels (a), (b). Panel (c) is binned scatter plots of state-year level correlation between the number of insurers and prevention utilization for the exchange nationwide. The dots are residualized from state and year fixed effects, and weighted by the exchange's market size.

Figure A9. Illustration of investment cost curvature identification

(a) Decompose preventive investment FOCs (b) Decompose prevention utilization FOCs

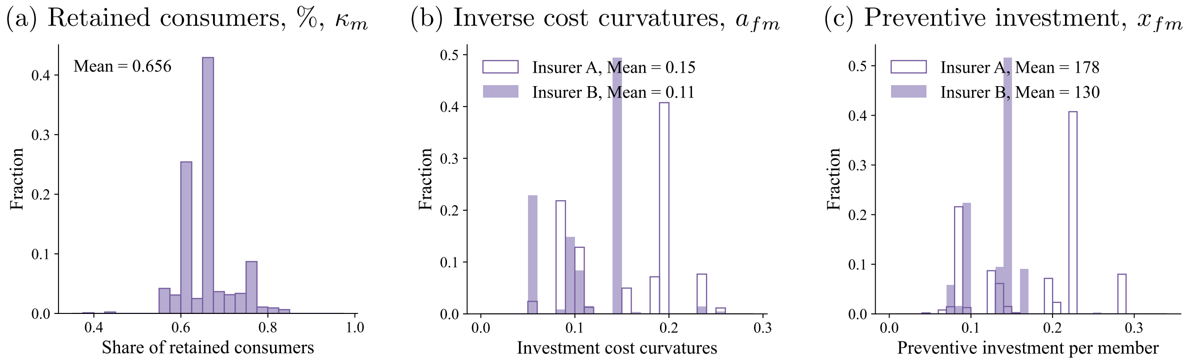


(c) Simulated prevention utilization strategies under alternative investment cost curvatures



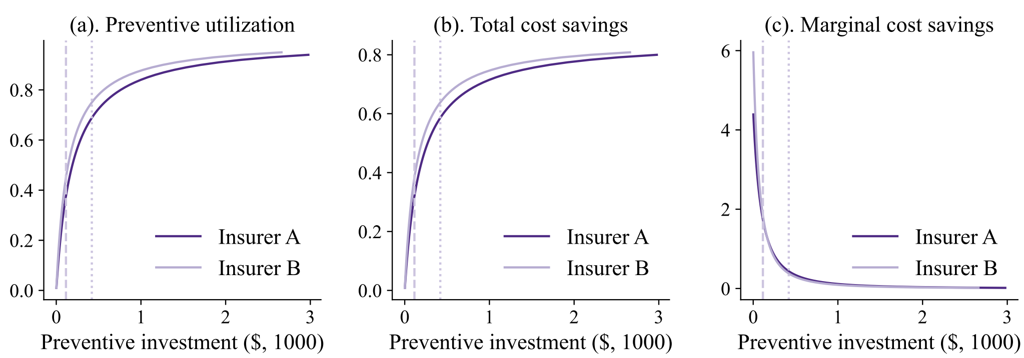
Notes: Panel (a), (b) correspond to decomposing the left-hand side (marginal cost curves) and right-hand side (marginal revenue curves) of equation (14), (19) separately. The solid lines are marginal revenue and costs under parameter a_f, and the dashed lines are under a'_f, where $a'_f < a_f$. Panel (c) plots simulated preventive utilization choices under different investment cost curvatures (on both axes), taking the market conditions of Salt Lake County in 2019. A darker color indicates higher simulated utilization.

Figure A10. Distribution of market-specific estimates and derived statistics



Notes: These figures plot the distribution of county(-insurer)-specific statistics, including estimates of the share of retained consumers in panel (a), estimates of investment cost curvature in panel (b), derived statistics of preventive investment per enrollee at observed equilibrium in panel (c). All plots are enrollment-weighted.

Figure A11. Model-implied cumulative, average, and marginal returns to prevention



Notes: Panel (a) plots the relationship between preventive investment and utilization evaluated at model estimates in Salt Lake County using equation (13). Panel (b), (c) plot the relationship between preventive investment and its total or marginal returns in the next year separately, evaluated at model estimates in Salt Lake County using equations (6) and/or (13). The returns calculation assumes full consumer retention. The dashed (dotted) line denotes utilization/investment levels at the status quo (Medicare market).

B Additional Motivating Evidence

B1 Preventive Care Utilization Across Markets and Countries

Table B1. Prevention utilization, US and other countries with single-payer health systems

		Countries with single-payer health systems					
	US	Average	Canada	Denmark	Norway	Sweden	UK
(a). Cancer screening utilization rate (in %)							
Breast cancer screening	72.8	81.3	78.5	82.0	76.4	95.2	74.6
Cervical cancer screening	73.5	72.1	74.0	62.3	76.3	75.9	72.2
Colorectal cancer screening	66.8	60.1	40.6	76.0	†	†	63.8
(b). Potentially preventable hospital admissions caused by specific diseases (per 100,000 population)							
Asthma	37.1	36.2	14.6	53.7	22.2	15.6	74.9
Chronic obstructive pulmonary disease	194.1	218.5	224.5	286.7	215.8	141.5	224.1
Congestive heart failure	411.7	164.2	172.8	156.6	164	225.3	102.2
Diabetes	226	91.5	97.9	130.1	72.5	78.8	78.5
(c). Other prevention measures (per 100,000 population)							
Number of primary care physicians	30	89	132		85	64	75
Number of preventable death	112	70	72		60	65	84
Life expectancy at birth	78.6	82.4	82.0	82.5	83.2	83.2	81.3

Notes: The clinical routines, frequency, and eligible population for cancer screenings are reported in Table A1, except that the eligible population for colorectal cancer screening is adults aged 60 to 74 in the UK. The cancer screening utilization rates are in 2018, except for Canada in 2017; and are taken from National Cancer Institute Cancer Trends Progress Report for the US, Statistics Canada Cancer Screening Health Fact Sheets for Canada, Eurostats for Denmark, Norway, and Sweden's breast cancer screening and colorectal cancer screening, OECD statistics for Denmark, Norway, Sweden's cervical cancer screening, NHS Digital for the UK. The number of age-sex standardized hospital admission and primary care physicians per capita, and life expectancy are taken from OECD statistics in 2018. Preventable death per capita is from European Observatory on Health Systems and Policies in 2019. †: Norway and Sweden are excluded in the average computation of colorectal cancer screenings because they do not have a national program for this preventive procedure. All other country-cancer screening procedure pairs have national programs, similar to the National Breast and Cervical Cancer Early Detection Program offered by CDC in the US, to promote cancer screenings utilization.

Table B2. Prevention utilization in different insurance market segments

Preventive procedure utilization rate (%, in 2018)	(1) Exchange	(2) Medicare (MCR) FFS	(3) Medicaid HMO	(4) Commercial HMO/PPO	(5) MCR Advantage HMO/PPO
Breast cancer screening	67.0	65.7†	58.4	73.5 / 70.7	73.2 / 73.7
Cervical cancer screening	56.4		59.3	75.2 / 73.5	
Colorectal cancer screening	52.8			64.1 / 60.3	71.1 / 75.2
Childhood immunization	66.2		70.4	69.5 / 70.4	
Antidepressant medication management	62.5		53.5	69.2 / 69.2	72.3 / 74.6
Asthma medication compliance	53.9		39.1	53.4 / 56.7	
Diabetes eye exam	48.7	68.0	57.4	55.9 / 49.6	74.2 / 72.7
Diabetes blood sugar control	55.6		48.7	58.2 / 51.1	66.1 / 68.4
Statin therapy for cardiovascular disease	69.5		76.3	80.7 / 80.4	81.1 / 80.4

Notes: The commercial insurance market in Column (5) includes the exchange as in Column (1) and small group and large group employer-sponsored insurance markets. Column (1) reports the mean across every insurer on the exchange from CMS QRS data. Column (2) is derived from Dartmouth Atlas Selected Primary Care Access and Quality Measures Longitudinal data. Columns (3) to (5) are taken from National Committee for Quality Assurance HEDIS Measures and Technical Resources data. Missing cells indicate that the utilization statistics are not available or applicable to a certain population. †: The breast cancer screening measure reports the percentage of women aged 50 to 74 years in the insurance market segment who had a mammogram within the past two years for all columns, except Column (2), where the sample is restricted to female Medicare fee-for-service enrollees aged 67 to 69.

B2 Returns to Preventive Care in Epidemiological and Medical Studies

Table B3. Cost savings of disease prevention, from epidemiological and medical literature

Preventive procedure	Clinical health benefits	Decrease in disease incidence	Decrease in mortality rates	Annual cost savings per eligible	Share of eligibles	Annual cost savings per person
Childhood immunizations	Prevent early death and diseases (Zhou et al., 2014)	4.6 times per vaccinated child (Zhou et al., 2014; Whitney et al., 2014)	10 per 1000 vaccinated (Zhou et al., 2014; Whitney et al., 2014)	$136 (Zhou et al., 2014; Whitney et al., 2014)	2.6%	$4
Influenza vaccines	Prevent influenza-related illness, hospitalizations, deaths (Lee et al., 2012)	2 per 10000 vaccinated (Reed et al., 2012)	-	$20 (Nichol, 2001)	100%	$20

Notes: The cost savings estimate corresponds to savings from reduced procedure costs from more adverse health events, as listed in the "benefits" column, and does not net out the preventive procedures' costs. I report the mean cost savings per patient estimates for procedures with multiple medical study sites. Childhood immunizations refer to vaccines in the HEDIS guidelines, including diphtheria and tetanus toxoids and acellular pertussis (DTaP), Haemophilus type b conjugate (Hib), inactivated poliovirus (IPV), measles/mumps/rubella (MMR), hepatitis B (HepB), varicella (VAR), 7-valent pneumococcal conjugate (PCV7), hepatitis A (HepA), and rotavirus (Rota) vaccines.

Table B4. Cost savings of cancer screenings, from epidemiological and medical literature

Preventive procedure	Clinical health benefits	Decrease in cancer incidence	Decrease in mortality rates	Cancer screening utilization rates	National cancer care costs	Annual cost savings per person
Breast Cancer Screenings	Detect diseases in early stage, which costs relatively less to treat (Salzmann et al., 1997)	-	6 per 1000 screened (Eddy, 1989; Humphrey et al., 2002)	76.4% (National Cancer Institute, 2021a)	$29.8 (National Cancer Institute, 2021c)	$60 (Greenwood and Henritze, 1996)
Colorectal Cancer Screenings	Find precancerous noncancerous tumors before they become invasive cancers (Eddy, 1990b); Detect disease in early stage	43 per 1000 screened (Eddy, 1990b; Knudsen et al., 2021)	26 per 1000 screened (Knudsen et al., 2021)	68.8% (Klabunde et al., 2013)	$24.3 (National Cancer Institute, 2021c)	$205 (Loeve et al., 2000; Lansdorp-Vogelaar et al., 2009)
Cervical Cancer Screenings	Find precancerous noncancerous tumors before they become invasive cancers (Eddy, 1990a); Detect disease in early stage, which has a higher survival rate and is much less expensive to treat (Subramanian et al., 2010)	22 per 1000 screened (Eddy, 1990a)	10 per 1000 screened (Eddy, 1990a; Shaukat et al., 2013)	73.5% (National Cancer Institute, 2021b)	$2.3 (National Cancer Institute, 2021c)	$24

Notes: The cost savings estimate corresponds to savings from reduced procedure costs from more adverse health events, as listed in the "benefits" column, and does not net out the preventive procedures' costs. I report the mean cost savings per patient estimates for procedures with multiple medical study sites. I report the cancer screening rates and total national cancer care costs (in billions) in 2019. The sample of individuals eligible for cancer screening procedures, i.e., the denominator in the cancer screening rate, is calculated following US Preventive Services Task Force guidelines. The decrease in cancer probability is calculated by comparing the no-screening scenario to the screening scenario recommended by the US Preventive Services Task Force. If not reported in the paper, I calculate cost savings per enrollee by dividing the nationwide decrease in cancer care costs by the US population. The decrease in costs of cancer care is calculated by multiplying current national cancer care costs with a decrease in cancer probability, which is a lower bound estimate of cost savings and does not factor in the fact that early-stage diseases cost less to treat.

Table B5. Cost savings of disease management, from epidemiological and medical literature

Preventive procedure	Clinical health benefits	Annual cost savings per patient	Disease incidence for non-elderly individuals	Annual cost savings per person
Diabetes nephropathy care	Reduce the probability of end-stage renal disease, kidney transplantation, dialysis (Klonoff and Schwartz, 2000)	$4618 for type 1 diabetes patients, $1880 for type 2 diabetes patients (Klonoff and Schwartz, 2000)	0.45% for type 1 diabetes, 8.45% for type 2 diabetes (CDC, 2020b)	$180
Diabetes glycemic control	Reduce the probability of vascular diseases (Wagner et al., 2001)	$1747 (Wagner et al., 2001; Nundy et al., 2014)		$155
Diabetes retinopathy care	Prevent blindness (Javitt et al., 1994; Klonoff and Schwartz, 2000)	$2166 (Javitt et al., 1994)		$193
Statin therapy for cardiovascular disease	Prevent adverse events, e.g., myocardial infractions (McConnachie et al., 2014)	$75 (Lazar et al., 2011; Kazi et al., 2016)	8% for atherosclerotic cardiovascular disease (Klimchak et al., 2020), 26.5% for cardiovascular disease (Roger et al., 2011)	$6
Asthma medication	Prevent asthma exacerbation related ED visits and hospitalizations (Rust et al., 2015; De Keyser et al., 2020)	$186 (Herndon et al., 2012; Rust et al., 2015)	13.4% (CDC, 2020a)	$25

Notes: The cost savings estimate corresponds to savings from reduced procedure costs from more adverse health events, as listed in the "benefits" column, and does not net out the preventive procedures' costs. I report the mean cost savings per patient estimates for procedures with multiple medical study sites. I calculate the disease incidence rate for the non-elderly population by taking the weighted average of the age-specific disease incidence rate using the population share of each age group if the age-specific disease incidence rate is available.

B3 Empirical Examples That Preventive Care Reduces Future Costs

Future Cost Savings by Detecting Diseases Early. I examine the statement that preventive care detects diseases early, which costs less to treat (Blumen et al., 2016; Subramanian et al., 2010, 2011). The corresponding example is colorectal cancer screenings. The share of early-stage cancer cases over all detected cases and cancer screening utilization are expected to be positively correlated, while cost growth and cancer screening utilization are expected to be negatively correlated.

I begin by constructing the share of colorectal cancer in each stage at diagnosis at the state-year level. All medical claims data do not contain information on a cancer diagnosis beyond its detection. To overcome this limitation, I collect cancer case listings data from the National Cancer Institute's Surveillance, Epidemiology, and End Results Programs (SEER) in 2012-2019. SEER is an administrative, patient-level cancer registry of all cancer diagnoses in thirteen states.[1] For each diagnosed cancer, SEER contains information on the diagnosis year, the size and stage of each tumor at diagnosis, and the basic demographics of the patient. SEER classifies diagnosis into four stages: in situ, localized, regional, and distant. I define

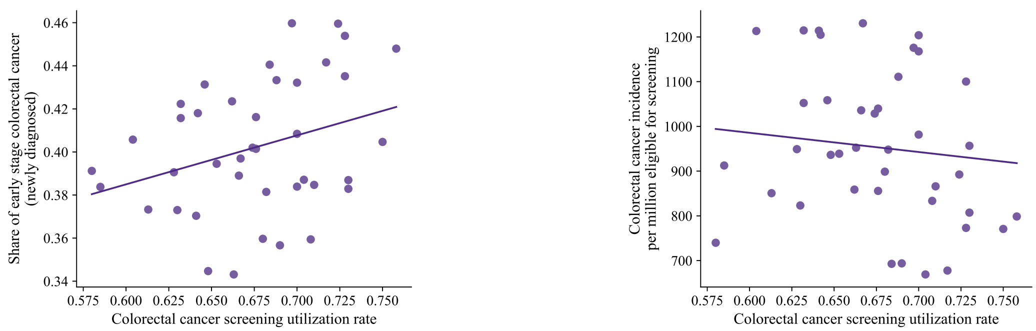
[1]These states are AK, CA, GA, HI, IA, KY, LA, MI, NJ, NM, UT, VT, and WI. AK, MI, and WI do not have complete listings for the entire state, so I exclude them from my analysis.

early-stage cancer as a diagnosis in the “in situ” or “localized” stage.

I calculate the state-year level cancer screenings utilization rate from CDC’s Behavioral Risk Factor Surveillance System (BRFSS) database in 2012-2019. I extract the self-reported usage of blood stool tests, sigmoidoscopy, or colonoscopy within the past ten years of the survey. I define the eligible population and up-to-date screenings following the HEDIS guidelines. I validate my calculation using the bi-annual colorectal cancer screening utilization reports in 2012-2018 from CDC (here; last accessed on 2021/09/28).

Figure B1. Correlation between cancer screening utilization and share of early-stage newly diagnosed cancer cases

(a) Share of early-stage disease (b) Cancer incidence



Notes: Panel (a) plots the correlation between cancer screening utilization rates and the share of newly diagnosed cancer that is in the early stage among all newly diagnosed cancer cases. Panel (b) plots the correlation between cancer screening utilization rate and cancer incidence, i.e., the number of new cancer cases per million eligibles. The eligible population for utilization rate and cancer cases calculation are all individuals aged 50-74. Each dot is a state-year pair. The fitted line controls for state and year fixed effects. Utilization data comes from BRFSS. Cancer listings and population data come from SEER.

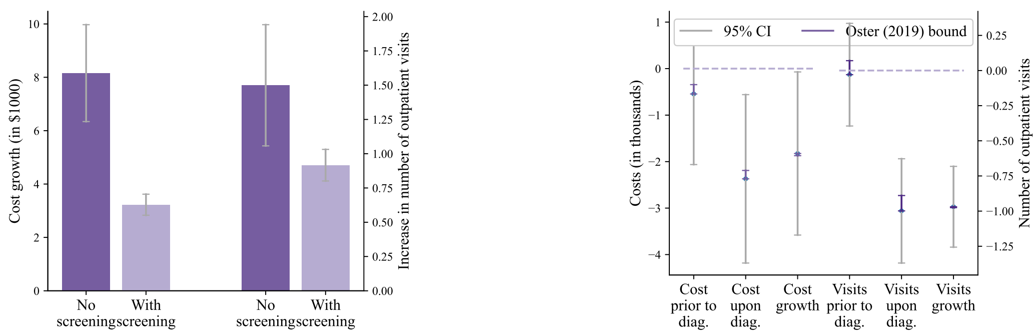
I first examine the statement that cancer screenings detect diseases in early stage. Figure B1 panel (a) plots the state-year level cancer screening utilization rate against the percentage of newly diagnosed early-stage colorectal cancer cases over all newly diagnosed colorectal cancer cases. I restrict the sample to individuals recommended to have preventive colorectal cancer screenings according to HEDIS guidelines, i.e., individuals between 50 and 74, when I calculate utilization rates and the share of early-stage diseases. After controlling for state and year fixed effects, more screening utilization correlates with a higher share of early-stage cancers in newly diagnosed cases.

I then investigate the statement that colorectal cancer screenings could find precancerous noncancerous tumors before they become invasive cancer. If so, a higher utilization rate in cancer screening would correlate with a lower rate of cancer incidence because the diseases are prevented early. Figure B1 panel (b) plots the correlation between colorectal cancer screening utilization and colorectal cancer incidence, which is derived by dividing the number of new cancer cases of individuals aged between 50 and 74 over the total population aged between 50 and 74 in a given state-year. After controlling for state and year fixed effects, a negative correlation exists between screening tests and cancer cases, as expected.

I next examine the statement that early-stage diseases cost less to treat than late-stage diseases. Using Utah APCD, I compare increases in outpatient visits and cost growth for patients newly diagnosed with colorectal cancer by whether they have taken colorectal cancer screening tests within a year of diagnosis. I use a first-difference estimator rather than an absolute measure to control for the patient's time-invariant medical resource utilization habits and health conditions. The underlying hypothesis is that patients with recent cancer screenings are more likely to have early-stage diseases. Differences in costs or visits growth between patients who have and have not taken screening tests thus reflect the costs of treating diseases in different stages.

Figure B2. Cost and number of outpatient visits by whether the patient with colorectal cancer had recently utilized screening tests

(a) Raw data (b) Regression estimates



Notes: Panel (a) plots differences in the number of outpatient visits and costs for patients who are newly diagnosed with colorectal cancer between the year of diagnosis and the year before diagnosis. The gray bars are 95% confidence intervals. Panel (b) plots the coefficient of the indicator of having taken screening tests in the regression of outcome variables listed on the indicator. Costs and the number of visits before and upon diagnosis are measured annually. The regression controls for gender, age, year, and county fixed effects. The purple bar plots the bounds of the coefficient following the procedures in Oster (2019). Data comes from UT APCD.

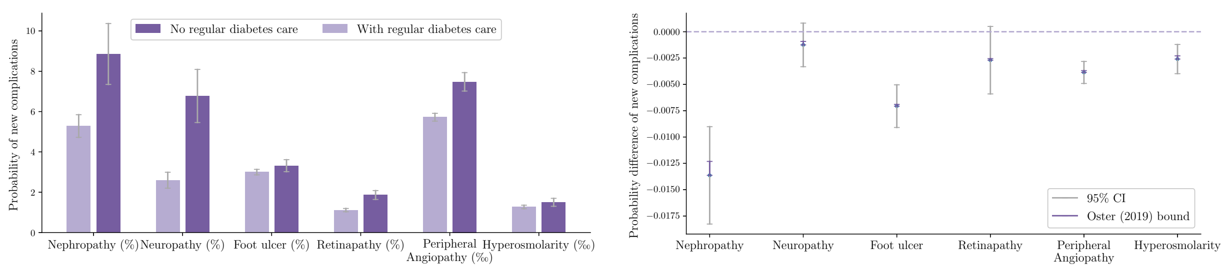
Figure B2 panel (a) plots mean increases in cost growth and the number of outpatient visits by cancer screening utilization status. Patients with recent usage of cancer screenings have smaller cost growth and fewer times of outpatient visits for either chemo or radiology therapy in the year of diagnosis than patients without preventive screenings. To address the potential selection bias that individuals who have and have not utilized preventive screenings have systematic differences in unobservable characteristics, I control for demographics and follow Oster (2019) to bound regression coefficients in case of unobservable selection. Figure B2 panel (b) exhibits no statistically significant differences in costs or the number of visits before diagnosis between the with and without screenings groups. The differences in costs and the number of visits after diagnosis still hold after econometric corrections.

The abovementioned stylized facts that more screening correlates with a lower incidence of disease and a higher share of early-stage disease, and that individuals who utilize screening tests have smaller cost growth upon diagnosis, are consistent with medical research findings that screening tests bring cost savings via early detection of diseases.

Future Cost Savings by Slowing Dieases Progression. I examine the statement that preventive care saves future medical costs by slowing disease progression. The corresponding example is routine care for patients with diabetes, including glycemic control, nephropathy care, and retinopathy care. We would expect diabetic patients without regular care to have their health conditions deteriorate more quickly and incur higher medical expenses in the long term than diabetic patients with regular care.

Figure B3. Probability of developing diabetic complications by whether the patient with diabetes had recently utilized screening tests

(a) Raw data　　　　(b) Regression estimates



Notes: Panel (a) plots differences in probability of diabetic complications in the next year for diabetes patients who do not have these complications in the current year, by whether they have taken regular diabetes care in the current year. The gray bars are 95% confidence intervals. Panel (b) plots the coefficient of the indicator of having taken routine diabetes care in the regression of outcome variables listed on the indicator. The regression controls for gender, age, year, and county fixed effects. The purple bar plots the bounds of the coefficient following the procedures in Oster (2019). Data comes from UT APCD.

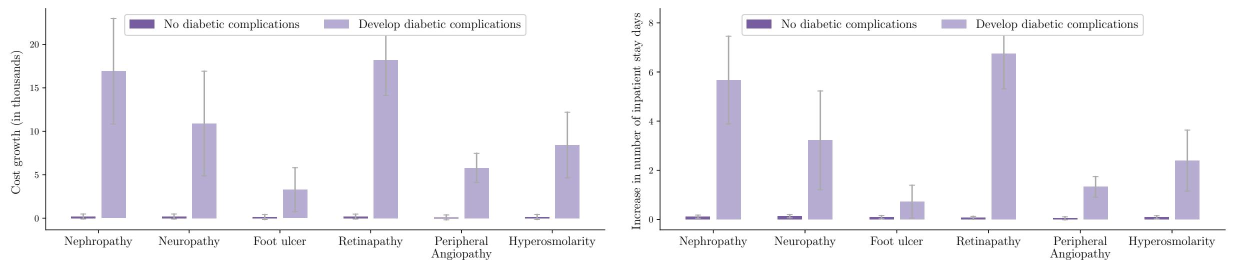
I begin by examining whether diabetic patients who utilize routine preventive care are less likely to develop diabetic complications than patients who do not. Figure B3 panel (a) plots the probability of developing the most common diabetic complications in the next year for diabetic patients who do not have these complications in the current year by whether they have taken regular diabetes care in the current year. Routine diabetes care correlates with a lower probability of developing all types of diabetic complications. The pattern still holds after I control for demographics or implement Oster (2019)'s bounding technique to address potential selection biases in unobservable health, as reported in Figure B3 panel (b).

I then investigate whether patients who utilize routine diabetes care experience smaller cost growth than patients who do not. I use a first-difference estimator rather than an absolute measure to control for the patient's time-invariant medical resource utilization habits and health conditions. The underlying hypothesis is that patients without regular diabetes care experience considerable cost growth because they are more likely to develop diabetic complications, which are severe and expensive to treat. For example, hyperosmolarity, a con-

Figure B4. Increase in costs and inpatient stays by whether the patient has developed diabetic complications

(a) Cost growth

(b) Increase in number of inpatient stay days



Notes: This figure plots cost growth and increase in the number of inpatient-stay days between the current year and the next year for diabetes patients who do not have these complications in the current year by whether they have developed diabetic complications in the next year. Gray bars are 95% confidence intervals. Data comes from the UT APCD.

dition where the patient's blood is more concentrated than normal due to high blood sugar levels and can cause coma, often results in emergency room visits and requires intensive inpatient care. The hypothesis that diabetic complications are expensive to treat is confirmed empirically in Figure B4. Patients with newly developed diabetic complications have much more significant cost growth and number of inpatient-stay days growth than patients who have not developed diabetic complications.

I next examine whether the slowdown of disease progression concentrates on a subset of patients likely to develop all types of complications or whether the slowdown in disease progression impacts all patients, where patients tend to develop different complications. Among patients with diabetic complications, 16% have more than one complication. Patients with severe complications, such as hyperosmolarity and peripheral angiopathy, do not overlap. This suggests the gains from routine care are universal for all diabetic patients.

The abovementioned empirical patterns that diabetes care correlates with a lower probability of developing diabetic complications and that diabetic complications are expensive to treat are consistent with the medical research findings that diabetes care brings cost-savings via slowing down disease progression.

B4 Discussions: Selected Preventive Care Increases Future Profits

A sufficient condition for turnover to affect insurers' preventive investment is preventive care brings future returns. Consider a stylized framework where insurers' utility consists of static investment costs, static returns, future returns times consumers' retention probabilities, and intrinsic values of providing prevention. Shocks to consumer retention probabilities will affect optimal investment as long as future returns are nonzero. Therefore, I present evidence that *selected* preventive care *reduces future costs*, and, *raises future profits* in the main text.

I further discuss a few subtle caveats. One is that preventive care makes enrollees healthy but does not increase future profits because healthy consumers value insurance less and are more likely to drop coverage. I address this concern by allowing consumers of different health statuses to have differential preferences for insurance in the structural model in Section 4. Model estimates and simulations reveal adverse selection is not severe: preventive investment increases insurers' future returns in the estimated parameter space.

Another caveat relates to the counterfactual scenario without prevention offerings. For example, current cancer screenings avoid high right-tail expenses of treating end-stage cancer compared to the no-prevention scenario when patients remain with the insurer in the future and catch diseases late. However, the cost-savings prediction can be reversed if, in the no-prevention scenario, patients switch to other insurers in future periods, catch late-stage cancer, and incur intensive future treatment with other insurers. In this case, insurers would reduce prevention provisions to raise future returns. This alternative scenario is consistent with my framework that expected future returns impact investment strategies. Furthermore, insurers' revealed preferences indicate that cost-reducing effects dominate cost-increasing effects for preventive care studied.

Note that I take as given insurers invest in selected preventive care in this paper. The focus of my analysis is whether a single private insurer invests more than insurers facing oligopoly competition. Examining whether preventive care generates net returns is outside the scope and not the focus of this paper, but it is an exciting path for future research.

B5 Quantifying Insurer Effects in Prevention Utilization

Empirical Specification. I test how a consumer's likelihood of utilizing preventive procedures changes when moving to an insurer with a different utilization rate. I estimate an event-study specification (Finkelstein et al., 2016):,

$$y_{it} = \alpha_i + \tau_t + \sum_{s=-8}^{7} \mathbf{1}[s = r(i,t)](\rho_s + \theta_s \delta_i) + x_{it}\beta + \epsilon_{it}, \tag{B1}$$

where y_{it} is an indicator for consumer i utilizing any preventive procedures of interest in the year t. δ_i is defined as $\bar{y}_{d(i)} - \bar{y}_{o(i)}$, representing the difference in preventive procedure utilization rate between the destination insurer $d(i)$ and the origin insurer $o(i)$. The utilization rates are calculated using consumers who change insurers (referred to as "movers" hereafter) and consumers who do not change insurers (referred to as "non-movers" hereafter). δ_s is a set of coefficients for each year relative to the event year of changing insurers $r(i,t)$, where relative year -1 is set as the baseline year. ρ_s is a set of indicators for each relative year, which controls for any changes in preventive procedure utilization related to insurer changes that do not differ across insurer change directions. The regression also includes individual fixed effects α_i to control for all time-invariant consumer characteristics, such as baseline health stats, race, ethnicity, and sex, calendar year fixed effects τ_t to control for time trends, and five-year age groups fixed effects x_{it}.

The key parameter of interest θ_s can be interpreted as the response to changes in insurer-specific utilization rate[2], if the underlying assumption is satisfied that there are no differential trends in prevention utilization of movers that vary systematically with their origin or destination. This assumption can be violated if, for example, consumers who have increased the use of preventive care choose to move to insurers with higher utilization rates. This can be directly tested by looking at the series of θ_s in the years before moving. If the assumption holds, the set of coefficients before insurer changes should be flat and close to zero.

Data Sources and Regression Samples. The sample period of UT APCD is not long enough to analyze the utilization pattern, especially for preventive procedures that happen once every few years. To overcome this challenge, I use the 2011-2019 New Hampshire (NH) Comprehensive Health Care Information System limited use health care claims dataset (CHIS). NH CHIS is similar to UT APCD, containing information on realized insurer-metal level choices, medical and pharmaceutical claims, and demographics for every commercially insured NH resident.[3] The extended sample period of NH CHIS provides me with longer pre-periods to examine potential violations of the no "pre-trend" assumption and more cohorts of insurer change variations to precisely identify the effects of insurer changes.

The regression exercise includes all commercially insured consumers in NH CHIS, instead of restricting to the exchange enrollees, to ensure a sufficiently large sample size. I keep consumers who stay with the same insurer ("movers") and consumers who change insurers once during 2011-2019 ("non-movers"), and exclude insured-to-uninsured moves or uninsured-to-insured moves. I further restrict the sample to consumers eligible for different preventive procedures following the HEDIS guidelines, for example, using only consumers with diabetes when the preventive procedure of interest is comprehensive diabetes care; and using women aged between 50-74 when the preventive procedure is mammography.

Event Study Estimates. Figure B5 plots coefficients θ_s estimated from equation (B1), representing a consumer's response to changes in insurer-specific care utilization in each year relative to the event of insurer changes.

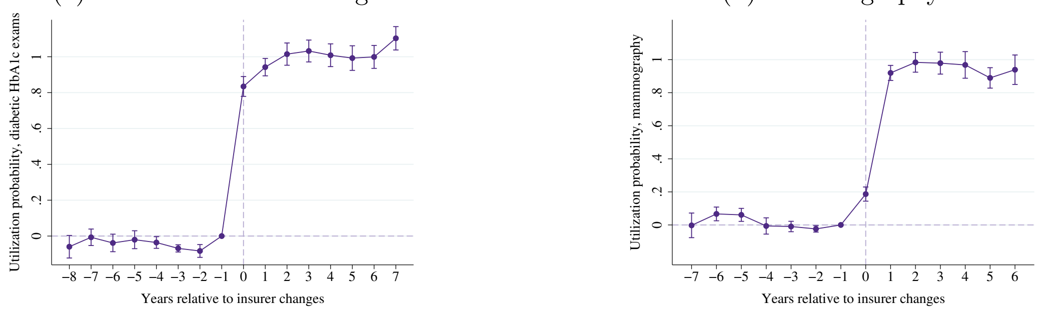
[2]The insurer-specific utilization in this event study exercise is averaged across years and can be mapped to the investment cost curvatures a_{fm} in the structural model in Section 4. The year-to-year utilization fluctuations within an insurer can be caused by differential consumer flows, market share, or enrollee health.

[3]I do not use NH CHIS for my main analysis for two reasons. First, the number of exchange enrollees is relatively small, which may cause bias in constructing prevention utilization rates at the insurer-county-year-market segment level. Second, the small number of geographic markets does not provide enough variations for structural estimation. NH only has one rating area, leaving no price variations across geographic markets.

The coefficients during the years before insurer changes are close to zero and stay flat in Figure B5. This suggests there are no differences in preventive care usage among movers, either in levels or trends, that are systematically correlated with the direction of insurer changes. In other words, there is no evidence of selective moves based on consumers' trajectory of prevention utilization. This result is not surprising given the consumer preferences estimates in Section 5.3: although consumers prefer high-quality preventive care, the relative weight that consumers put on preventive quality when making product choices, compared to other product characteristics, is low. It is thus highly implausible that consumers change insurers specifically to receive high-quality prevention.

Figure B5. Effect of insurer-specific prevention utilization on consumers' prevention usage

(a) Diabetic HbA1c testing (b) Mammography



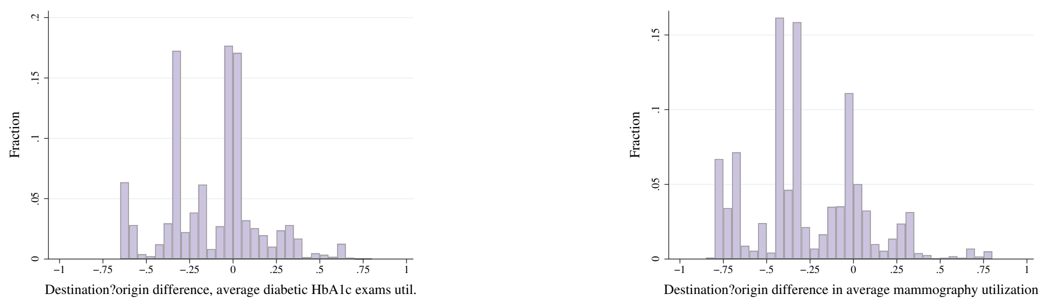
Notes: This figure shows point estimates of θ_s and 95% confidence interval from estimation of equation (B1). Standard errors are clustered at the county level. The regression sample includes consumers who stayed with the same insurer or changed insurers once during 2011-2019. Panel (a) further restricts the analysis sample to consumers with diabetes. Panel (b) further restricts to female consumers aged 51-68 in 2011. The sample sizes for panels (a) and (b) are 28,281 and 25,707. Outcome data comes from NH CHIS.

The change in the insurer-specific preventive care utilization affects a consumer's prevention utilization immediately after insurer changes. Consumers with diabetes who move to insurers with a 1 percentage point higher diabetes care utilization rate increase their likelihood of using HbA1c exams by 0.83 percentage points in the year of insurer changes. After the year of insurer changes, a consumer's likelihood of monitoring their blood sugar level with HbA1c exams increases by 0.94 percentage points in response to a one percentage point increase in the insurer-specific care utilization rate. A similar utilization pattern holds for mammography, except that the increase in the likelihood of utilization is less pronounced in the year of insurer changes. This is because the recommended clinical frequency for breast cancer screening is once every two years. The estimated effects in the moving year could still capture the influence of the origin insurer. In the years after insurer changes, when the destination insurer completely takes over, a consumer's likelihood of having update-to-dated mammography increases by around 0.96 percentage points in response to a one percentage point increase in the insurer-specific utilization rate. In other words, over 90% of the differences in prevention utilization rates between destination and origin insures are absorbed after insurer changes for diabetes care and cancer screening.

Heterogeneity by Direction of Moves. I examine whether event study estimates are sensitive to the direction of moves. Figure B6 plots distributions of δ_i, the average prevention utilization of a mover's destination insurer minus the average utilization of her origin insurer. The distribution is not perfectly symmetric, potentially due to a small sample size.

Figure B6. Distribution of destination-origin differences in prevention utilization

(a) Diabetic HbA1c exams (b) Mammography



Notes: This figure plots the distribution of δ_i, the difference in average utilization between the origin and destination insurers, across consumers who change insurers once. Panel (a) further restricts the analysis sample to consumers with diabetes. Panel (b) further restricts the analysis sample to female consumers aged 51-68 in 2011. The number of consumers in panels (a) and (b) are 12,101 and 12,121, separately. Outcome data comes from NH CHIS.

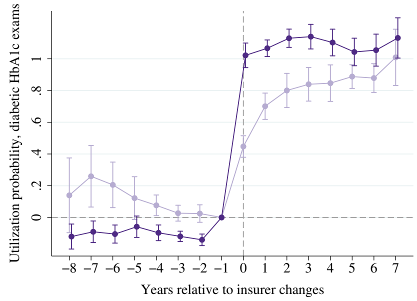
To ensure that my estimates are not driven by one particular direction of moves, I estimate an augmented event study regression with sequences of coefficients specific to upward and downward moves,

$$y_{it} = \alpha_i + \tau_t + \sum_{s=-8}^{7} \left(\mathbf{1}[s = r(i,t)] \sum_{d=\mathbf{1}[\delta_i>0]} (\rho_s^d + \theta_s^d \delta_i) \right) + x_{it}\beta + \epsilon_{it}, \tag{B2}$$

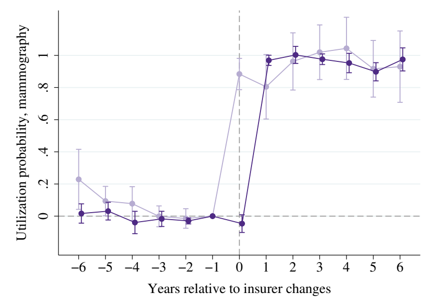
where δ_s^1 represents changes in response to moving to higher utilization insurers ($\delta_i \geq 0$), as shown in Figure B7 by the dark line, while δ_s^0 represents changes in response to moving to lower utilization insurers ($\delta_i < 0$), as shown in the figure by the light line. Consumers in both directions respond to changes to the insurer-specific utilization rate by adjusting their likelihood of using preventive procedures closer to the care use rate in the destination insurer. The responses post moves between the high- to low-utilization (downward) moves group and the low- to high-utilization (upward) moves are not statistically different for breast cancer screenings. In contrast, the upward moves group has larger responses than the downward moves group for diabetic HbA1c testing. This asymmetric response can be explained by habit formation: patients who build a habit of getting regular checkups or preventive procedures may continue to do so regardless of the insurers that they enroll with. The downward move group thus provides a lower bound of insurer effects in prevention utilization, which is still sizable after several years of insurer changes.

Figure B7. Event study estimates of insurer-specific prevention utilization on individual's prevention use, by moving directions

(a) Diabetic HbA1c testing



(b) Mammography



Notes: This figure shows point estimates of θ_s and 95% confidence interval from the estimation of equation (B2). The dark line plots δ_s^1, i.e., changes in response to moving to higher utilization insurers ($\delta_i \geq 0$); the light line plots δ_s^0, i.e., changes in response to moving to lower utilization insurers ($\delta_i < 0$). Standard errors are clustered at the county level. The regression sample includes consumers who stayed with the same insurer or changed insurers once during 2011-2019. Panel (a) further restricts the analysis sample to consumers with diabetes. Panel (b) further restricts the analysis sample to female consumers aged 51-68 in 2011. The sample sizes for panels (a) and (b) are 28,281 and 25,707. Outcome data comes from NH CHIS.

B6 Additional Results of the Shift-Share Design

Validity Checks of the Identifying Assumption. The identification assumption underlying my shift-share design is that "shifts", i.e., national job hiring trends, are as good as random, and not correlated with factors that would affect preventive investments and utilization other than consumer turnover. Although the quasi-randomness of shifts assumption cannot be directly tested, I provide three pieces of suggestive evidence that the exclusion restriction is not violated.

First, I regress potential confounders on the instrument, including proxies for unobserved health shocks and the initiation of health policies. I do not find statistically significant relationships between the instrument and potential confounders, as is reported in Table B6 columns (1)-(5).

Second, I regress demographics and preventive investments in the previous period on the instrument. If job hiring shocks are as good as randomly assigned to industries within the analysis period, the instruments constructed with these shocks would not predict predetermined variables. I fail to reject imbalance at conventional levels of statistical significance, as is shown in Table B6 columns (6)-(15).

Third, I regress utilization rates of preventive procedures in Medicare on the instruments as a placebo test. Procedure utilization rates in Medicare are hypothesized not to be affected by instruments constructed with job hiring shocks because Medicare's enrollee pool is fixed and out of the labor force. Table B6 columns (16)-(18) find no statistically significant relationships between utilization rates in Medicare and the instrument.

Table B6. Falsification tests of the shift-share instrument identification assumptions

Medicaid expansion	Number of exchange insurers	Share premature death	Share adults w. obesity	Per capita diabetes patients	Lagged share female
(1)	(2)	(3)	(4)	(5)	(6)
0.114	–1.367	0.013	–0.005	–0.005	–0.001
(0.318)	(2.851)	(0.010)	(0.013)	(0.006)	(0.001)
Lagged share White	Lagged share Black	Lagged share Hispanic	Lagged share age above 65	Lagged share uninsured	Lagged share high school grad.
(7)	(8)	(9)	(10)	(11)	(12)
0.006	–0.003	–0.003	0.008	–0.027	–0.018
(0.007)	(0.003)	(0.004)	(0.008)	(0.020)	(0.010)
Lagged share some college	Lagged share college graduates	Lagged PM preventive investments	Medicare mammography screening	Medicare diabetes monitoring	Medicare preventable readmissions
(13)	(14)	(15)	(16)	(17)	(18)
–0.014	0.013	–1.123	–0.076	–0.002	0.000
(0.016)	(0.010)	(2.291)	(0.055)	(0.005)	(0.000)

Notes: This table reports the coefficients of the shift-share instrument in the regression of outcome variables in each column on the instrument. The utilization and retention rates are measured in 0-100 percentage points; quality investment is measured in dollars. The regression sample is at the state-year level in 2017-2019. The regression specification includes state, year fixed effects, and weights each observation by the state-year-level population. Standard errors are reported in parentheses and clustered at the state level. The outcome data of column (1) comes from Kaiser Family Foundation. The outcome data of column (2) comes from CMS Marketplace plan attributes PUF. Outcome data of columns (3)-(9) and (16)-(18) comes from county health rankings. The outcome data of columns (10)-(14) comes from American Community Survey. Column (15) outcome data comes from Medical Loss Ratio reports. *,**,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Comparison of OLS and 2SLS estimates. It is sensible that 2SLS estimates are larger than OLS estimates. For example, adverse health shocks, as omitted variables, prevent unemployed individuals from starting to work or receiving employer-sponsored insurance, thus increasing the portion of enrollees retained in the exchange. This implies $Cov(r_{st}, \varepsilon_{st}) < 0$. If sick consumers prefer prevention more than healthy consumers, insurers would respond to adverse health shocks by intentionally lowering prevention provisions to screen out unhealthy and unprofitable individuals. This implies $Cov(y_{st}, \varepsilon_{st}) < 0$. These two correlations together indicate OLS estimates underestimate the effects of consumer retention on preventive care utilization.

Robustness of Primary Estimates. I examine whether the baseline estimates of the effects of consumer retention on preventive investment and prevention utilization are robust.

I first augment my baseline specification with multiple inference methods. Adao et al. (2019) notes that standard inference procedures, such as geographic clustering, may result in standard errors that are too small for shift-share instruments because observations with similar exposure shares are likely to have correlated residuals. I implement the inference

Table B7. Effect of consumer turnover on prevention utilization and investments, robustness

	Alternative inference		Alternative instrument				Alternative weighting		Alternative
Baseline	AKM	BHJ	Jackknife	Recentered	Share	Two IVs	Population	Enrollment	level
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(a). Aggregate utilization rate									
0.786*	0.786***	0.786***	0.587*	0.785*	0.839**	0.674*	0.648*	0.933*	0.773***
(0.409)	(0.000)	(0.059)	(0.349)	(.409)	(0.416)	(0.400)	(0.386)	(0.472)	(0.184)
(b). Per member quality improvement expenses									
5.31**	5.31***	5.31*	5.67**	5.31**	5.33**	5.75**	5.96**	4.57**	4.20**
(2.37)	(0.00)	(0.74)	(2.56)	(2.37)	(2.50)	(2.45)	(2.40)	(2.22)	(1.62)

Notes: This table reports the coefficient of exchange retention variable from the estimation of equation (4). Column (1) reports baseline estimates from the same specification as Table 2. Columns (2)-(10) tweak the specification and perform sensitivity analysis, which is described in Section B6. The regression sample, outcome variables, and data sources are the same as in Table 2. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

procedures of Adao et al. (2019). I also apply the equivalence results of Borusyak et al. (2022) to transform the regression to the shift level to conduct inference, which yields asymptotically valid standard errors. Table B7 columns (2)-(3) confirm these alternative inference methods leave the precision of the estimates unchanged.

Next, I test the sensitivity of my results to the construction of the shift-share instrument. I construct a jackknife instrument with $h_{mt,-s}$ that leaves out a state's job hiring from the shock following Autor and Duggan (2003) to correct for the potential bias that national job hiring trends aggregate regional health shocks that directly enter the residual ε_{st}.[4] I build a recentered instrument with residualized shocks $\tilde{h}_{mt}$ that subtracting the expected shock from realized shocks following Borusyak and Hull (2023) to address potential non-randomness in shock exposure. I build another instrument where the share w_{smt_0} is measured as an industry m's employment over the total population in state s year t_0. I additionally instrument for retention rates with job hiring instruments in both the current and the previous years to account for the fact that enrollment for current exchange plans starts in November of the previous year. Resulting estimates in Table B7 columns (4)-(7) are similar to the baseline.

I also rerun the analysis at the insurer-state-year level or change the regression weights. The resulting estimates in Table B7 columns (8)-(10) are similar to the baseline.

I finally conduct a permutation test that builds a placebo instrument using simulated job hiring shifters drawn from a standard normal distribution and true employment shares in data following Adao et al. (2019); Derenoncourt (2022). I repeat the 2SLS estimation 1000 times using the true preventive investments or utilization as the dependent variable and the

[4] Borusyak et al. (2022) establishes that not-leave-one-out shift-share instrument is valid if the typical industry locates in a much larger number of states than the number of industry a typical state specializes in. Their empirical application confirms this condition is satisfied in the setting of US employment structures.

placebo instrument. Only 0.5% and 3.8% of the resulting coefficients are significant at the 5% level for investment and utilization, separately.[5] This suggests the estimated impacts of turnover on preventive measures are unlikely to be driven by noise.

Measuring More Prevention and Placebo Procedures. Table B8 reports the definition of utilization rates of more preventive care procedures, as well as all available appropriate treatment and testing procedures in CMS QRS files, which are used as placebos. These placebos focus on best practices of diagnosis and treatment, rather than managing patients' health or detecting preventable diseases to yield future returns.

Table B8. Eligibles and clinical procedures of other procedures

(a). Placebos
Procedure: Appropriate Treatment for Upper Respiratory Infection (*uri*)
Clinical Routines, Frequency, Eligibles: the share of children who are not dispensed antibiotics among those who are diagnosed with upper respiratory infections
Procedure: Avoidance of Antibiotic Treatment for Acute Bronchitis/Bronchiolitis (*aab*)
Clinical Routines, Frequency, Eligibles: the share of adults who are not dispensed antibiotics among those who are diagnosed with acute bronchitis
Procedure: Appropriate Testing for Pharyngitis (*cwp*)
Clinical Routines, Frequency, Eligibles: the share of patients who receive a group A streptococcus test among those who are diagnosed with pharyngitis and dispensed antibiotics
Procedure: Use of Imaging Studies for Low Back Pain (*lbp*)
Clinical Routines, Frequency, Eligibles: the share of patients who do not receive X-ray, MRI, or CT scans within 28 days of diagnosis among those who are diagnosed with lower back pain
(b). Preventive care with returns in longer time spans
Procedure: Medical Assistance With Smoking and Tobacco Use Cessation (*msc*)
Clinical Routines, Frequency, Eligibles: Adults 18 years of age and older who are current smokers or tobacco users and who discussed or were recommended cessation medications during the measurement year.

Notes: The information is extracted from HEDIS Technical Specifications for Health Plans 2017.

C Additional Details on Estimation

C1 Constructing Variables

Market Shares. I extract uninsured counts from the US Census Bureau's 2014-2019 Small Area Health Insurance Estimates (SAHIE) to construct market share. SAHIE provides model-based estimates of annual health insurance coverage for counties and states by race, ethnicity, sex, age, and income levels. I apply the exchange's eligibility criteria based on age and income to the uninsured counts to calculate the market share of the outside option.

[5]For comparison, the statistics of percent significant at the 5% level from the permutation test is 16.1% in Derenoncourt (2022), and 55% in the application of Adao et al. (2019).

Product Characteristics. Product characteristics, such as premiums, deductibles, out-of-pocket limits, and coinsurance, come from CMS Marketplace Product Attributes Public Use Files in 2014-2019. I group insurance plans into metal levels so that every insurer only offers three products: Gold, Silver, Bronze. This is because UT APCD only has information on metal-level choices but not plan-level product choices. The grouping is reasonable because plans in the same metal level have similar financial characteristics and share the same provider network. I exclude catastrophic plans due to small market shares (less than 0.35%) and special enrollment requirements (only individuals below 30 or with approved financial hardship status are eligible).

I assume proportional prices between metal levels for tractability so that insurers only choose one price instead of three prices in the simulation. I back out the fixed price ratio between metal levels using the mean across all insurer-metal pricing pairs from CMS Health Insurance Exchanges Products Attributes PUF in 2014-2019. I further assume out-of-pocket premiums are a fixed proportion of posted premiums; see Appendix C2 for details.

I extract cost shares of each metal level by taking the mean of observed out-of-pocket expenses over total medical expenses for consumers in the exchange from UT APCD. I obtain cost shares of the uninsured from the Medical Expenditure Panel Survey (MEPS). MEPS is a nationally representative dataset on insurance coverage, medical spending, health status. I define the uninsured as individuals without insurance for at least nine months in the calendar year. The uninsured pay 18% of total medical expenses out of pocket due to charity care.

I assume demand shocks of all products are constant ex-ante over time, $E[\xi_{jmt}] = \xi_j$. In the current version of estimation, ξ_j is seen as a constant, and insurers do not integrate over the distribution of ξ_{jmt} when making pricing and preventive investment decisions. An ideal version of the model would treat ξ_{jmt} as a normal random variable with mean ξ_j and standard deviations $Std(\xi_{jmt})$, which unfortunately is not computationally feasible.

Health Risks. I use the Johns Hopkins ACG® System Version 13.0 to construct individual-year-level health risks. The ACG system is one of the most widely used risk adjustment and predictive modeling packages in the healthcare sector, specifically designed to use diagnostic claims data to predict medical expenditures. The concurrent risk model in the ACG system transforms diagnostic codes (e.g., ICD-9/10CM) and demographics (age and sex) into individual-level measures of predicted expected medical expenses in the same year. The output is an index representing each individual's health status relative to a reference population. Scaling the ACG risk index by the costs of the reference population gives a standardized and monetized health risk measure, which nets out medical expense variations due to procedure prices and is comparable across individual-year pairs.

I collect medical expenses of the uninsured from the Medical Expenditure Panel Survey

(MEPS) Household Component in 2015-2019.

I assume health risks of inflow consumers μ_{Imt} are equal to the beginning of the period market-level mean health risks. The model's qualitative predictions still hold if I set μ_{Imt} to a specific fixed value or a random variable.

I set the upper and lower bar of insurer-year level annual mean health risks to be \$7,500 and \$3,000 per member. I validate these bounds using the CMS annual Rate Review Filings data in 2014-2019. Insurers declare average experienced claims per member month in the rate review. The 99th and 1st percentiles of the state-year level mean enrollee cost distribution, measured across all exchange insurers nationwide, are \$7,440 and \$3,278.

Prevention Utilization. I construct county-insurer-year level univariate prevention utilization by aggregating across preventive procedures in Figure 1 and dividing the number of consumers utilizing those procedures over the number of eligibles. I assume preventive utilization, e_{fmt}, differs at the insurer f level but not the product j level for two reasons. First, the provider network, an essential determinant of preventive services, is the same across all metal levels within an insurer in the Utah exchange. Second, aggregating at the insurer level, not the product level, makes denominators and numerators larger and statistics more precise.

I construct prevention utilization rates for the uninsured, exploiting three public datasets from the CDC: the 2015-2019 Behavioral Risk Factor Surveillance System (BRFSS), the 2014 Medical Expenditure Panel Survey Preventive Services Self-Administered Questionnaire, and the 2015-2018 National Health Interview Survey (NHIS). I follow HEDIS guidelines to construct utilization rates of each available preventive service by insurance status in Table C1. Columns (1)-(3) suggest a utilization gap of about twenty percentage points between uninsured and insured consumers for every survey-reported preventive procedure, including routine checkups, flu shots, blood pressure and cholesterol screenings, diabetic blood sugar, foot, and eye exams, asthma medications, pap smear or mammogram, and colorectal cancer screenings. Column (4) calculates utilization rates for individuals who are uninsured for three consecutive years to account for the potential impact that recommended frequencies of certain preventive procedures are once every few years, and the newly uninsured consumers could have gotten preventive services during previous insured periods. The prevalence of preventive care for the continuously uninsured is thirty percent lower than for the insured.

I construct prevention utilization for the uninsured option, analogous to that for the insured consumers, taking a weighted average of utilization rates of the uninsured derived from BRFSS, MEPS, and NHIS. The weights are the number of eligibles for each preventive procedure. I assume utilization gaps between the insured and uninsured are constant between public data sources and my sample. For preventive services reported in more than one

Table C1. Preventive care utilization by insurance status

	Insured (1)	Insured with Exchanges (2)	Uninsured (3)	Uninsured three cont. yrs (4)
(I). Utilization rate, BRFSS				
(a). Update-to-dated diabetes care (%)				
HbA1c exams	86.53	-	63.26	57.97
Foot exams	74.06	-	55.29	42.81
Eye exams	69.85	-	45.07	39.44
(b). Update-to-dated cancer screenings (%)				
Breast cancer screenings	78.85	-	53.37	38.27
Cervical cancer screenings	75.98	-	61.35	52.06
Colorectal cancer screenings	68.28	-	33.28	24.24
(c). Update-to-dated routine primary care (%)				
Routine physical exams	76.17	-	44.66	39.42
Flu shots	41.47	-	17.89	14.15
Cholesterol screenings	67.26	-	59.67	54.63
(II). Utilization rate, MEPS				
(a). Update-to-dated cancer screenings (%)				
Breast cancer screenings	77.03	79.90	47.20	-
Cervical cancer screenings	79.73	84.77	57.30	-
Colorectal cancer screenings	63.15	51.69	39.76	-
(b). Update-to-dated routine primary care (%)				
Flu shots	59.79	39.73	17.75	-
Cholesterol screenings	90.37	84.16	67.09	-
Blood pressure screenings	93.21	84.95	75.64	-
(III). Utilization rate, NHIS				
(a). Update-to-dated diabetes care (%)				
HbA1c exams	85.25	81.35	63.54	60.53
(b). Update-to-dated asthma care (%)				
Asthma controller medications	17.22	18.61	15.28	13.17
(c). Update-to-dated cancer screenings (%)				
Breast cancer screenings	30.48	33.44	11.71	8.60
Cervical cancer screenings	44.71	34.26	33.63	28.74
Colorectal cancer screenings	32.77	27.83	14.27	11.21
(d). Update-to-dated routine primary care (%)				
Flu shots	47.24	32.02	16.42	12.99
Cholesterol screenings	70.88	62.61	32.95	27.41
Blood pressure screenings	87.18	81.39	55.06	46.47

Notes: This table reports preventive care utilization rate by insurance status. Update-to-dated diabetes care, asthma care, and cancer screenings are defined following the HEDIS guidelines (see Table A1 for eligible population, recommended clinical procedures, and frequency), except that in Panel (II) up-to-dated cervical cancer screenings are reported as pap smear in past five years instead of three years. Update-to-dated routine primary care refers to routine physical exams or flu shots within a year; cholesterol checks for individuals aged above 20 within five years in panels (I) and (II) or within a year in panel (III); blood pressure checks for individuals aged above 20 within two years in panel (I) and (II), or within a year in panel (III). Columns (1)-(3) in panel (I) and (III) reports utilization rates for individuals who are insured or uninsured at the time of the survey. Column (4) in panels (I) and (III) reports utilization rates for individuals who are uninsured for three consecutive years before the survey. Columns (1)-(3) in panel (II) report utilization rates for individuals who are insured, insured with the exchange, or uninsured for at least nine months during the survey year. Data comes from BRFSS 2015-2019 for panel (I), MEPS Preventive Services Self-Administered Questionnaire in 2014 for panel (II), and NHIS in 2015-2018 for panel (III).

dataset, I use the average across data sources. Table C2 reports the calculation details.

Compared to the set of preventive procedures used in calculating the preventive utilization for the insured option in Table A1, the group of preventive procedures for the uninsured utilization in Table C2 excludes the statin therapy for cardiovascular disease and includes flu shots instead of immunizations for children and adolescents due to data availability. The

Table C2. Prevention utilization for the uninsured option

Preventive procedures	Utilization gaps from surveys	Derived utilization rates	Data sources	Share eligible among uninsured (%)
Breast cancer screenings	24.75	26.85	BRFSS, MEPS, NHIS	4.14
Cervical cancer screenings	16.05	31.95	BRFSS, MEPS, NHIS	15.80
Colorectal cancer screenings	25.63	14.17	BRFSS, MEPS, NHIS	9.09
Comprehensive diabetes care	28.89	29.41	BRFSS	6.92
Asthma medication	1.94	73.26	NHIS	1.09
Immunizations for children	32.15	39.35	BRFSS, MEPS, NHIS	1.78
Immunizations for adolescents	32.15	33.05	BRFSS, MEPS, NHIS	1.82
Prevention utilization for uninsured options		28.50		

Notes: The asthma medication and immunizations shares are taken from corresponding samples in UT APCD in 2019. The utilization gaps are the means across data sources in Table C1. Derived utilization rates are calculated by subtracting the mean utilization gap from utilization rates in Table A1. The univariate utilization rate for uninsured options is a weighted average across preventive procedures.

difference in the set of preventive procedures should not cause significant bias because the number of eligible consumers for statin therapy or immunizations is markedly small compared to the number of eligible consumers for other preventive procedures. In other words, statin therapy and immunizations have small weights, thus a relatively small contribution to the overall utilization index. Another simplification in the calculation is using national utilization rates from all insurance markets instead of those in the Utah exchange to ensure a sufficiently large sample size. Moreover, the uninsured prevention utilization is assumed to be constant across geographic markets in structural estimation and counterfactual simulations.

The uninsured preventive utilization is derived to be 0.285. The low but positive prevention utilization of uninsured consumers may be explained by charitable care from physician offices and federally qualified health centers. Statistics from the National Ambulatory Medical Care Survey show out of all office visits paid by charity care, 28.97% provide preventive care, and 21.45% provide routine chronic care. In addition, CDC runs two free cancer screening programs for the uninsured with incomes up to 250 FPL: the National Breast and Cervical Cancer Early Detection Program, the Colorectal Cancer Control Program.

C2 Reconciling the Exchange Regulations

Pricing Regulations. Insurers on the exchange set premiums subject to several regulatory constraints. First, Insurers are not allowed to reject enrollees based on pre-existing health conditions or price-discriminate based on individual health risk. Second, insurers can collect different premiums from consumers based on age, but the age gradient in premiums has to follow a pre-specified regulatory age curve. Since I only model a representative enrollee and do not differentiate on enrollee ages, I take the average premium across all ages in the estimation model. Third, insurers are required to charge the same premium for a specific product in all counties belonging to the same "rating area", a collection of counties pre-specified by each state. However, since insurers do not have to serve all counties in a rating area, I consider a county to be the exchange market boundary following Fang and Ko (2018). I calculate mean premiums across plans within the same metal level and county since the Utah APCD only has information on metal-level choices but not plan-level choices.

Premium Subsidies. The Affordable Care Act offers premium subsidies to low-income participants whose income is between 100 and 400 FPL to defray the cost of the insurance premium, formally known as Advanced Premium Tax Credits (APTC). The APTC is calculated in several steps. First, the Modified Adjusted Gross Income is converted to the percent of the Federal Poverty Level (FPL). The IRS specifies a mapping between FPL levels and the maximum dollar the household should pay for insurance premiums. Households with annual income between 100 and 400 FPL are eligible for APTC. Second, calculate the maximum subsidy a household can receive by subtracting the maximum allowed premiums from the previous step from the benchmark premium, i.e., the second-lowest-cost silver plan in the household's county of residence. If the premium of the household's chosen plan is less than the maximum subsidy they can receive, the household pays zero premium; otherwise, they pay for the premium differences between the selected plan and the maximum subsidy.

My empirical exercise abstracts from the premium subsidies regulations in two ways. First, I do not have income or household information in UT APCD. I take the income distribution from the American Community Survey for individuals eligible for the Utah exchange and calculate the expected premium that a single applicant whose income is drawn from the abovementioned distribution would face. Second, in counterfactual exercises, I do not model the non-linear subsidy determination process but assume that the subsidy is paid in a fixed proportion to premiums that insurers set. This fixed proportion is the mean of observed subsidy-listed premium ratios for all exchange markets in 2017-2019, extracted from CMS Marketplace Open Enrollment Period PUF.

Cost-Sharing Subsidies. The ACA offers cost-sharing subsidies for households purchasing a Silver plan if their income is below 250 FPL. The cost-sharing subsidies reduce households' out-of-pocket liability from deductibles, co-pays, and co-insurance. Due to implementation issues, insurers rather than the federal government paid cost-sharing subsidies, especially in later years during my sample periods (Keith, 2019). Therefore, in counterfactual exercises, I set the cost-sharing parameter for Silver products to the expected cost shares given the income distribution from ACS for the Utah exchange eligibles and assume that insurers pay for the cost-sharing subsidies.

Individual Mandates. The ACA used to have an individual mandate that required consumers nationwide to have health insurance coverage or pay a penalty, which was repealed by the Tax Cuts and Jobs Act of 2017 and became ineffective in 2019. I do not model individual mandate, i.e., impose a penalty for the outside option of uninsured for two reasons. First, the regulation is not binding in reality, and many uninsured people do not pay for the penalty (Lurie et al., 2021). Second, Fiedler (2018) and Lurie et al. (2021) show the responses to the individual mandate are relatively small, especially in the exchange.

Risk Adjustments. Risk adjustment on the exchange transfers funds from insurers with ex-ante relatively less risky enrollees to those with ex-ante relatively more risky enrollees. Risk adjustment is a budget-neutral program, and the government calculates these transfers through a risk-adjustment formula developed by the Department of Health and Human Services (Kautter et al., 2014). I do not model risk adjustment in my empirical model for two reasons. First, risk adjustment is imperfect (Layton, 2017), and insurers could select healthy enrollees in multiple ways, for example, network designs (Shepard, 2022) or formulary designs (Geruso et al., 2019). Second, I focus on policies that change the market's overall risk composition rather than the risk distribution across insurers.

Medical Loss Ratio Regulations. All insurers on the fully insured commercial market are subject to the Medical Loss Ratio (MLR) regulation. MLR regulations require insurance companies that cover individuals and small businesses to spend at least 80% of their premium income on healthcare claims and quality improvement (see Cicala et al. (2019) for more descriptions). The MLR ratio on the exchange is calculated by dividing the sum of healthcare claims and quality improvement expenses over premiums net of taxes, licensing, and regulatory fees. I do not impose MLR constraints when solving for insurers' pricing and preventive investment decisions in the stage game for two reasons. First, the MLR constraint is set at the state-year level rather than the county-year level, the level of insurers' policy choices. Second, my model does not contain measures of fee adjustment terms required in the MLR formula. Ex-post checks show that the MLR constraint does not bind at the equilibrium solutions in most cases if I drop the fee adjustment term in the denominator and impose a relaxed constraint of 0.7 following Tebaldi (2017).

C3 Algorithms for Estimating and Simulating Industry Equilibrium

I describe the algorithm to estimate the curvatures of investment cost functions. Intuitively, I search for investment curvature parameters that satisfy the first order conditions of preventive investment. The complexity is to deal with the extra dynamic incentive terms, as is described in Section 5.1. The estimation algorithm has an inner and outer loop structure.

In the inner loop, for each guess of investment curvature parameters in the market m, an industry equilibrium defined in Section 4 is solved. I solve for the value functions V_{fm} that satisfy equation (12) for every insurer using the full solution approach and calculate the dynamic option value terms with interpolation. The implementation is as follows.

1. Choose a grid of state variables $\{\hat{s_f}, \hat{s}_l, \hat{\mu_f}, \hat{\mu}_l, \hat{\mu_u}\} \in \hat{G}$. I use the hat notation to denote grids for what follows. The vector of state variable has five dimensions: at the end of the previous period, the market share of insurer A $\hat{s_f}$, the market share of insurer B $\hat{s}_l$, health risks of enrollees of insurer A $\hat{\mu_f}$, health risks of enrollees of insurer A $\hat{\mu}_l$, health risks of uninsured enrollees $\hat{\mu_u}$. The grid includes four or five equally spaced points for each dimension, with a further restriction that the sum of the first two dimensions, i.e., the sum of the market shares for both insurers, cannot exceed one.

2. Initialize the value functions $V_{fm}^{k=0}$ and $V_{lm}^{k=0}$ to zeros for all states, where k denotes the iteration rounds in the full solution approach.

3. Solve insurers' first-order conditions in equations (15) and (19) for $\{p^*_{fm}, e^*_{fm}, p^*_{lm}, e^*_{lm}\}$ at each point in the state variable grids given continuation values V_{fm}^{k-1} and V_{lm}^{k-1}, using the method of the best response iterations. I use a series of third-degree polynomials, constructed with the full vector of state variables, to interpolate between grid points and approximate the value function when solving for insurers' strategies.

4. Calculate the new values of value functions V_{fm}^k and V_{lm}^k as the total discounted payoffs given insurers' current policies $\{p^*_{fm}, e^*_{fm}, p^*_{lm}, e^*_{lm}\}$ and continuation values based on V_{fm}^{k-1} and V_{lm}^{k-1}.

5. Check for value function convergence. If the sum of norms $\left\|V_{fm}^k - V_{fm}^{k-1}\right\| + \left\|V_{lm}^k - V_{lm}^{k-1}\right\|$ is greater than ϵ and the iteration round is less than $K = 80$, repeat steps 2-5. Otherwise, set $V_{fm}^k = V_{fm}$ and $V_{lm}^k = V_{lm}$.

6. Interpolate the value functions V_{fm} and V_{lm} at arbitrary states, using the values of V_{fm} and V_{lm} evaluated at the grid of state variables $\hat{G}$. The interpolation method is an extension of trilinear interpolation into higher dimensions, which is fast and easy to compute. Let $\hat{x}^0$ denote the nearest grid point smaller than x, and $\hat{x}^1$ denote the nearest grid point larger than x. Define

$$x^{d0} = \frac{x - \hat{x}^0}{\hat{x}^1 - \hat{x}^0}, \quad x^{d1} = \frac{\hat{x}^1 - x}{\hat{x}^1 - \hat{x}^0}, \quad x \in \{s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um}\}$$

the value functions evaluated at an arbitrary state are computed as

$$
\begin{aligned}
&V_{fm}(s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um}) \\
&= \sum_{i_1 \in \{0,1\}} \sum_{i_2 \in \{0,1\}} \sum_{i_3 \in \{0,1\}} \sum_{i_4 \in \{0,1\}} \sum_{i_5 \in \{0,1\}} s_{fm}^{d,i_1} s_{lm}^{d,i_2} \mu_{fm}^{d,i_3} \mu_{lm}^{d,i_4} \mu_{um}^{d,i_5} V_{fm}(\hat{s}_{fm}^{i_1}, \hat{s}_{lm}^{i_2}, \hat{\mu}_{fm}^{i_3}, \mu_{lm}^{i_4}, \mu_{um}^{i_5}).
\end{aligned}
$$

7. Calculate the partial derivatives of value functions with respect to state variables, $\frac{\partial V_{fm}}{\partial x}$, $\frac{\partial V_{lm}}{\partial x}$, where $x \in \{s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um}\}$ at the observed state, using the interpolated value function from step 6. For example, for $x = s_{fm}$,

$$
\frac{\partial V_{fm}}{\partial s_{fm}} = \frac{V_{fm}(s_{fm} + \Delta s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um}) - V_{fm}(s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um})}{\Delta s_{fm}}.
$$

The derivatives on other dimensions are calculated similarly.

8. Calculate the option value terms at the observed state variables and policy choices using the chain rule. For example, the option values of preventive care quality for a firm f is

$$
\frac{\partial V_{fm}}{\partial e_{fm}} = \frac{\partial V_{fm}}{\partial s_{fm}} \frac{\partial s_{fm}}{\partial e_{fm}} + \frac{\partial V_{fm}}{\partial s_{lm}} \frac{\partial s_{lm}}{\partial e_{fm}} + \frac{\partial V_{fm}}{\partial \mu_{fm}} \frac{\partial \mu_{fm}}{\partial e_{fm}} + \frac{\partial V_{fm}}{\partial \mu_{lm}} \frac{\partial \mu_{lm}}{\partial e_{fm}} + \frac{\partial V_{fm}}{\partial \mu_{um}} \frac{\partial \mu_{um}}{\partial e_{fm}},
$$

where $\frac{\partial x_{fm}}{\partial e_{fm}}, x \in \{s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um}\}$ are calculated using the state transition equations (5) and (6), and $\frac{\partial V_{fm}}{\partial x_{fm}}, x \in \{s_{fm}, s_{lm}, \mu_{fm}, \mu_{lm}, \mu_{um}\}$ are derived from step 7. The option values of prices are calculated similarly.

In the outer loop, I plug in the derived option value terms from the inner loop for each guess of investment curvature parameters and evaluate the objective function, which is the sum of squares of the investment first order conditions. I search for parameters that achieve the minimum objective functions.

To shorten computation time, I search over a fixed set of grids $\{\hat{a}_f, \hat{a}_l\} \in \hat{A}$ for every market m with different κ_m. This is because the consumer preferences parameters and state transitions rules are the same across markets. For a given consumer flow κ_m parameter, the only other primitive that differs across markets is the investment curvature parameter. I first compute and store the V_{fm} and V_{lm} values for every possible realization of state variables in the grid $\hat{G}$, and for every possible realization of investment curvature parameters in the grids of $\hat{A}$. I then search over $\hat{A}$ to find the parameter that minimizes the objective function evaluated at observed state variables and policy choices for every market. This computational design is faster than executing the inner-outer loop structure separately for every market one by one, because the latter design may compute V_{fm} at a certain state variable and a certain parameter guess multiple times in the sequential process of executing the algorithm market by market, while the former design saves the output of the time-consuming value function iterations so that V_{fm} evaluated at a certain state variable and a certain parameter guess will only be computed once.

C4 Multiplicity of Equilibria

In addition to following the equilibrium refinement in Goettler and Gordon (2011), I perform three sets of inspections to restrict the multiplicity of equilibria. Although I cannot prove the uniqueness, I find convergence to the same stationary distribution.

First, given a value function, I solve the stage game with different starting values in the best response iterations to check that the sub-game within each state has a unique equilibrium. Statewise uniqueness is necessary for the dynamic game to have a unique equilibrium. The potential reason for stage games to have multiple equilibria is that consumers with inertia are segmented by their previous period choices (Aksoy-Pierson et al., 2013). Insurers choose between a high price to monopolize the segment of their previous period enrollees or a low price to attract consumers from all segments. Simulations reveal that when inertia rises to more than two times the baseline, multiple equilibria arise in some simulations, where monopolizing the segment can also dominate.

Second, I check that value function iterations converge to the same approximated value functions from different starting values. Statewise uniqueness from the previous step alone is not enough for a unique equilibrium of the dynamic game: multiple equilibria could arise if there is more than one set of value functions that is consistent with rational expectations about equilibrium behavior and industry dynamics (Besanko et al., 2014). I begin the value function iteration with initial values being a vector of zero. This iteration gives me a baseline value function after convergence. I repeat value function iterations with the baseline value function, or values between zero and the baseline value function, as initial values. Value and policy functions after convergence are reassuringly the same as those using zeros as initial values.

Third, given value functions and policy functions from the previous steps, I check that starting from different distributions of initial states, the Markov chain converges to the same stationary distribution.

C5 Alternative Estimation Procedure

The estimation procedure in Section 5.1 uses state transition estimates and consumer preferences estimates as inputs to the dynamic game and finds insurers' investment cost primitives to rationalize the observed prevention utilization levels. One concern with this approach is that the returns to prevention parameter calibrated from medical studies is inaccurate. In addition to the sensitivity test around this parameter reported in Appendix D1, I implement an alternative estimation procedure in this section to address this concern.

The alternative estimation procedure proceeds in three steps. First, I estimate consumer preferences the same as outlined in Section 5.1. Second, I estimate insurers' investment cost functions, i.e., the relationship between prevention utilization and preventive investment expenses, using insurer-state-year-level prevention utilization rates from the QRS PUF and preventive investment expenses from MLR data from the exchange nationwide (introduced in Section 3.3). I parameterize preventive investment cost functions as equation (13) and use a nonlinear least square estimator to estimate investment cost curvatures, a, which is a constant across insurer-state-year pairs in this estimation routine. To address the endogeneity concern that unobserved cost shocks affect both prevention utilization rates and total preventive investment expenses, I use the shift-share instrument of labor market shocks (introduced in Section 3.3). The intuition of first-stage correlation is that consumer turnover predicted by labor market shocks would affect insurers' expected investment returns and, thus, insurers' investment expenses through differential prevention provision (utilization). The exclusion restriction is likely satisfied since state-year-level local cost shocks are uncorrelated with national-level aggregate labor market shocks.

Finally, I input consumer preferences and investment cost function estimates into the dynamic games and estimate state transition parameters. For a given parameter of returns to prevention, the remaining state transition parameters, including standard deviations of health risk shocks σ_ν, and health risks growth without prevention q_0 and consumer flows κ_m, are estimated using the min-distance estimator by minimizing the sum of squared distance between predicted and observed state variables (see equation (16), (17) in Section 5.1). The returns to prevention parameter is backed out using the FOC of preventive utilization (equation (19)). The marginal investment costs associated with observed preventive utilization choices would imply expected investment returns by FOCs. The estimation procedure thus finds returns to prevention primitives that generate these implied expected investment returns. In other words, it finds returns to prevention primitives that could rationalize the observed prevention utilization levels.

Table C3 displays estimation results. Panel (a) exhibits investment cost estimates. Per-member preventive investment at the observed equilibrium for Insurer A and B would be \$156 and \$137, slightly smaller than \$228 and \$147 as in the main text. Panel (b) reports state transition estimates. A 10 percentage point increase in prevention utilization rate slows insurer-level mean health risk growth by \$98 per member per year, similar to the calibrated value of \$85. Insurer-level mean health risks would increase by \$656 annually if there was no preventive care utilization. The standard deviation of returns to prevention shocks is \$1027. I do not report consumer preference estimates as they are the same as in Section 5.3.

I do not use the procedure described in this section as the primary estimation method for two reasons. First, estimating investment cost function would pull together all insurers on the exchange nationwide and use data at the state level. It does not allow heterogeneous cost

Table C3. State transitions and investment cost estimates

	Alternative Method	Primary Method
(a). Investment cost functions		
Investment cost curvature a_f, Insurer A	0.13	0.19
Investment cost curvature a_f, Insurer B	0.13	0.14
Per member preventive investment at observed equilibrium ($), Insurer A	156	228
Per member preventive investment at observed equilibrium ($), Insurer B	137	147
(b). State transition		
Returns of prevention, q_1 ($)	979	851
Health risk growths without prevention, q_0 ($)	656	563
Standard deviation, randomness of preventive returns, σ_ν ($)	1027	1035

Notes: Preventive investment is derived by evaluating equation (13) at model estimates and specified utilization levels (for the Salt Lake County). Primary and alternative estimation methods are described in Section 5 and Appendix C5, separately.

functions by insurer identity or more granular geographic markets (i.e., counties). Second, estimating investment cost function uses accounting costs from insurers, which could introduce measurement errors. Nevertheless, it is reassuring that estimates from this alternative method are similar in magnitudes to those derived from the primary method in Section 5.

C6 Model Fit

I evaluate model fit with three tests. First, to evaluate the performance of the demand model, I compare predicted and observed choice patterns for consumers with different previous period insurer choices. The estimation procedure only matches the aggregate market share that combines all consumer types in a given market. Figure C1a reveals that the demand model predicts choice probabilities for each consumer type relatively well.

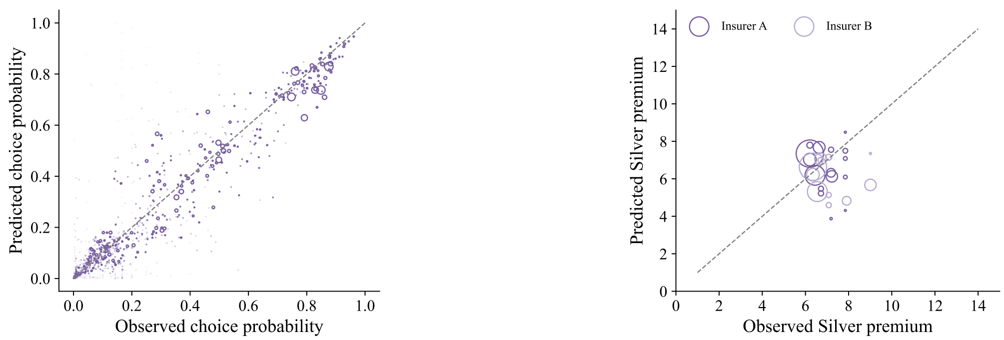
Second, I assess the supply model exploiting FOCs of premiums. I compare simulated premiums, which make premium FOCs hold under model estimates and observed state variables, with observed premiums. Figure C1b shows simulated policies reproduce observed policies with reasonable precision.

Finally, I simulate the equilibrium effect of consumer retention. Simulations show a 1 percentage point increase in the share of consumers retained in the exchange raises preventive investment per enrollee by $2.1, and prevention utilization rates by 0.44 percentage points. These model predictions are quantitatively similar to the reduced form estimates in Section 3.3, which estimates a 1 percentage point increase in consumer retention raises preventive investment per enrollee by $5.3, and prevention utilization rates by 0.78 percentage points.

There are several reasons why model simulations do not match reduced form estimates exactly. First, the structural exercises focus on the UT exchange, while the regression exercises use the universe of exchange markets nationwide. Second, I impose stationary assump-

Figure C1. Comparison of simulated and observed strategies

(a) Choice patterns (b) Silver premiums



Notes: These figures plot simulated and observed data moments, including market shares of each insurer among consumers grouped by county-year-previous period insurer choices in 2018-2019 in panel (a), Silver premiums by county-insurer in 2019 in panel (b). The size of the dot is proportional to the number of consumers in each specific group, defined by county-year-previous period insurer choices in panel (a), or county in panel (b). The gray dashed line is the 45-degree line.

tion in the structural exercise, while not necessarily all markets in the regression exercises are mature. However, it is reassuring to see that model simulations and reduced form estimates are similar in magnitudes.

D Additional Counterfactual Results

D1 Sensitivity to Returns to Prevention

I explore how model estimates and welfare predictions of competition change with the calibrated parameter q_1, returns to prevention. Table D1 displays the results of this sensitivity exercise. The returns to prevention parameters increase gradually from column (1) to (10), with column (10) replicating the baseline returns to prevention parameter in the main text.

I begin by re-estimating the model using alternative returns to prevention of each column in Table D1 panel (a). The investment cost estimates decrease along with decreases in returns to prevention. This is because the returns to prevention parameter governs expected future profit gains from preventive investment, which reveals marginal costs by first-order conditions. To rationalize observed prevention utilization levels, under fixed demand parameters and implied marginal returns in static profits, small marginal gains in future profits must map to low marginal investment costs.

Table D1 panel (b) then presents derived statistics of investment expenses using these alternative returns to prevention and their corresponding model estimates. The mean preventive investment per member at the observed equilibrium decreases when the returns to prevention drop, consistent with the prediction of declining investment costs analyzed above. However, these derived per-member investment expenses in columns (1)-(4) are considerably smaller than the observed per-member claims costs of preventive procedures, \$78 and \$77 for

Table D1. Sensitivity to returns to prevention

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Returns to prevention, q_1 (\$)	85	170	255	340	426	511	596	681	766	851
Relative to baseline calibrated value	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
(a). Model estimates										
Health risk growths without prevention, q_0 (\$)	155	203	250	298	346	394	437	479	521	563
Std., randomness of preventive returns, σ_ν (\$)	1092	1085	1079	1072	1065	1059	1053	1047	1041	1035
Investment cost curvature, a_f, Insurer A	0.05	0.06	0.07	0.08	0.10	0.12	0.13	0.15	0.17	0.19
Investment cost curvature, a_f, Insurer B	0.02	0.03	0.04	0.05	0.07	0.08	0.09	0.11	0.12	0.14
(b). Derived statistics										
Per member preventive investment, Insurer A (\$)	60	73	85	97	121	146	158	182	207	228
Per member preventive investment, Insurer B (\$)	22	33	44	55	78	89	100	122	133	147
Future profits from \$1 marginal investment, A (\$)	0.48	0.55	0.61	0.65	0.69	0.72	0.74	0.76	0.78	0.80
Future profits from \$1 marginal investment, B (\$)	0.55	0.68	0.75	0.80	0.84	0.86	0.88	0.90	0.91	0.92
(c). Willingness to pay for prevention, if using baseline investment cost curvature estimates										
Willingness to pay for maximum prevention (\$)	306	288	269	249	229	209	188	166	144	24
Relative to baseline willingness to pay	12.48	11.73	10.95	10.15	9.34	8.52	7.66	6.77	5.87	1.00
Relative to monthly out-of-pocket premiums	3.76	3.53	3.29	3.05	2.81	2.56	2.30	2.04	1.77	0.30
(d). Welfare changes, stationary distribution, monopoly equilibrium minus duopoly equilibrium										
Changes, health risks, lower bound (\$)	43	2	-42	-99	-170	-233	-273	-324	-369	-405
Changes, health risks, upper bound (\$)	206	182	153	113	38	-7	-40	-93	-123	-167
Changes, consumer surplus, lower bound (\$)	-276	-251	-229	-202	-167	-143	-126	-103	-88	-70
Changes, consumer surplus, upper bound (\$)	-129	-106	-87	-61	-34	-12	2	20	35	48

Notes: I re-estimate the model under different values of returns to prevention (in each column), and report those estimates in panel (a). The first two rows in panel (b) report derived preventive investment per member at the observed equilibrium, using alternative returns to prevention and their corresponding investment cost curvatures estimates. The last two rows in panel (b) and panel (d) display statistics in the simulated stationary equilibrium, simulated with alternative returns to prevention and their corresponding model estimates. Panel (c) reports the willingness to pay for prevention that rationalizes the observed prevention utilization, using investment cost curvature estimates at the baseline and the alternative returns to prevention in each column. The upper and lower bounds of welfare in panel (d) correspond to keeping the insurer with high or low investment cost curvature, i.e., Insurer B or Insurer A, in the monopoly equilibrium.

Insurers A and B separately (reported in Table 4). Since per-member investment consists of claims costs of preventive procedures plus expenses to promote utilization, this contradiction suggests these small returns to prevention in columns (1)-(4) are likely to be misspecified.

To resolve the investment expenses contradiction, I further report in Table D1 panel (c) counterfactual willingness to pay for prevention that could rationalize the observed prevention utilization, if using the baseline investment cost curvature estimates and alternative returns to prevention parameters. Suppose the expected future cost reductions from preventive investments are small, but insurers still invest in prevention. In that case, insurers must invest in preventive care to increase static profit. If so, consumer choices must be relatively elastic to preventive provisions. Simulations displayed in panel (c) confirm this hypothesis. Suppose returns to prevention are one-tenth of the baseline, and investment cost curvatures are at baseline levels. In that case, consumers' willingness to pay for prevention needs to be 12.48 times the status quo, or 3.76 times monthly out-of-pocket premiums. As consumers may lack knowledge of recommended preventive procedures or undervalue prevention due to behavior biases (analyzed in Section 3.2), these large willingness-to-pay estimates in columns (1)-(5) indicate that their corresponding small returns to prevention are likely to deviate from true returns parameters.

I finally examine the welfare predictions of lessened competition in Table D1 panel (d), using alternative returns to prevention parameters and their corresponding model estimates. The upper and lower bounds of welfare correspond to keeping the insurer with high or low investment costs, i.e., Insurer B or Insurer A, in the monopoly equilibrium, the same as in the main text. As is displayed in columns (1)-(2), average health risks across all consumers could be higher in the monopoly equilibrium than in the duopoly equilibrium when returns to prevention are small. This is because the relative importance of dynamic cost savings incentives diminishes (exhibited in the last two rows of panel (b)) with decreasing returns to prevention. Investment gaps between the monopoly and duopoly equilibrium close, and gains from investment cost savings shrink. Furthermore, market power is restricted in the duopoly market, so more consumers are insured and receive preventive services, bringing down consumer health risks. Returns to prevention need to be at least 0.25 times the baseline for the investment cost savings to be substantially large so that the monopoly market has better population health than the duopoly market.

As for consumer surplus, the duopoly equilibrium brings higher consumer surplus than the monopoly equilibrium unambiguously when returns to prevention are small, as is shown in panel (d) columns (1)-(5). This is because changes in consumer surplus depend on the relative magnitude of two opposite forces: market power losses and investment cost savings. If returns to prevention are extensively small, the extra surplus from investment cost savings that a monopoly creates is not enough to offset losses from market power; consumers are thus worse off in the monopoly market than in the duopoly market. Returns to prevention need to be at least 0.65 times the baseline to make it possible that the monopoly market has a higher consumer surplus than the duopoly market.

In light of these sensitivity exercises, markets with high returns to prevention are more likely to benefit from lessened competition, which allows the monopoly to create more surplus from enhanced preventive investment.

D2 Additional Simulations

Benchmark the Monopolist to a Planner. I benchmark the best-case scenario monopoly equilibrium to a planner equilibrium. The planner for the exchange offers the same products as the private insurer but sets premium and preventive investments to maximize consumer surplus, subject to break-even constraints every period. Note that the planner for the exchange in this exercise differs from a social planner, who considers investment externalities and interactions across market segments.

The planner invests \$49 (12.5%) more per member than the monopolist due to the elimination of consumer free-riding and Spencian distortion. First, the planner fully internalizes investment cost savings, whereas the insurer's returns are capped by its cost shares. Second, the planner equates the marginal investment costs to the marginal value of prevention averaged across all consumers, while the monopolist equates that to the marginal consumer. Meanwhile, the planner charges competitive prices with zero markups, \$2,191 (33.9%) lower than the monopolist. Consumer surplus is \$636 higher in the planner equilibrium, and average health risks are \$1,034 (16.5%) lower. The contrasting comparison between investment and pricing strategies reveals that market power, rather than deficit investment, accounts for the majority of welfare losses from the Pareto frontier.

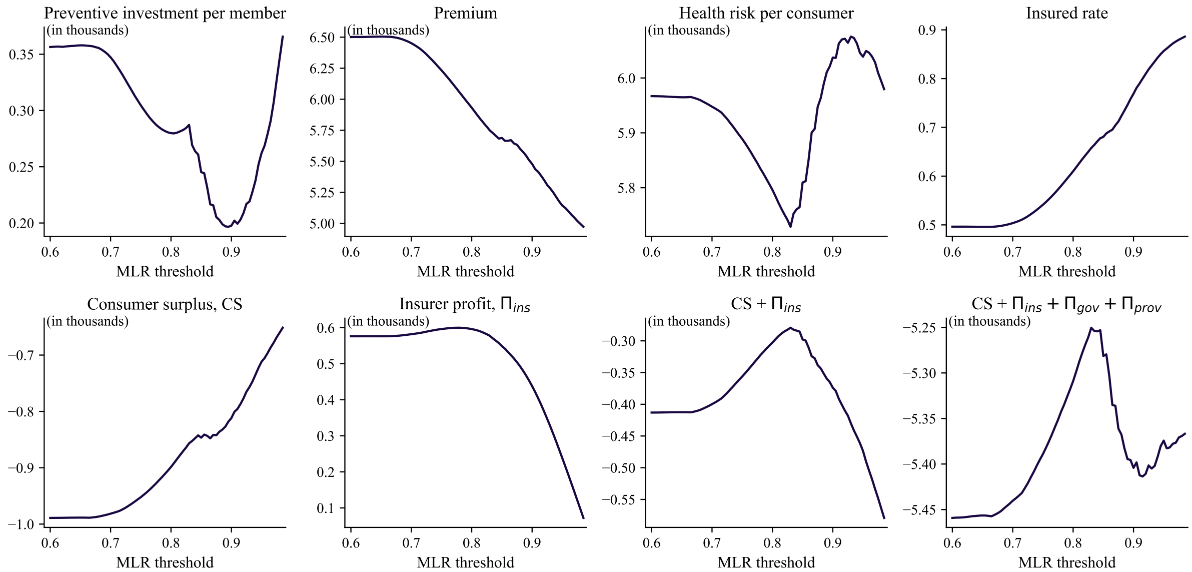
Monopoly with Markup Regulations. I investigate the effects of markup regulations, which map to the Medical Loss Ratio (MLR) regulations in reality. The MLR regulations specify that insurers must spend at least a certain share of premiums on medical claims and quality improvement, which includes preventive investments, under all market conditions. See Appendix C2 for relevant regulatory details.

Note that duopolists' simulated investment and markup stay almost the same regardless of whether we impose a greater than 70% MLR regulation because competition constrains their markup to a relatively low level. In the absence of competition, monopolists' markup is substantially affected by markup regulations.

Figure D1 depicts equilibrium objects under different MLR thresholds. The MLR regulation constrains premiums but has ambiguous effects on preventive investment per enrollee. Preventive investments could fall in the presence of an MLR constraint because it constrains profit margins and lowers expected future investment returns. Conversely, when the markup constraint binds, raising preventive investment could inflate costs, enabling insurers to charge higher prices and extract higher static profits. Despite this, population health improves with raising MLR thresholds, because the insured rates rise due to price reductions and cost savings gains that more consumers receive prevention services dominate the Furthermore, the monopolist under markup regulations still invests more per enrollee in prevention than duopolists without markup regulations, because the insurer could internalize more investment cost savings when turnover is restricted.

Consumer surplus increases monotonically with MLR thresholds since both limited commitment and market power distortions are relieved. Average health risks depend on changes

Figure D1. Equilibrium strategies and welfare by MLR thresholds



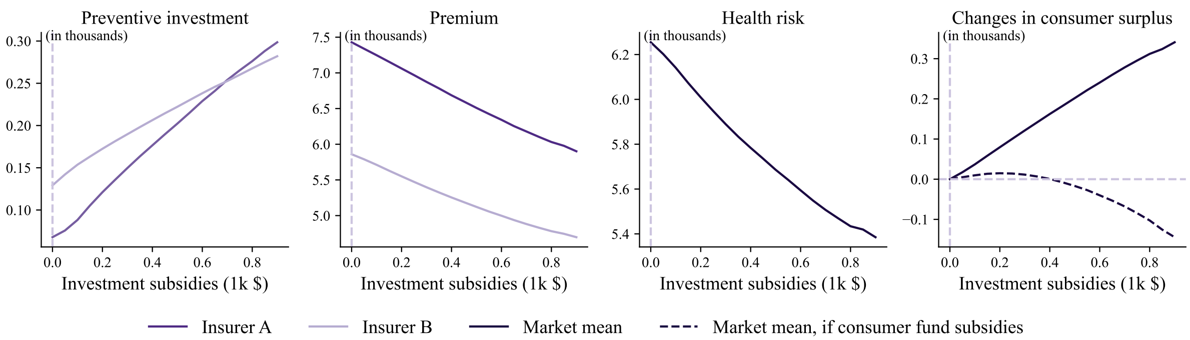
Notes: These figures compare simulated equilibrium strategies of Insurer B and average welfare across all consumers on the market, by MLR threshold. The MLR threshold refers to a regulated share, where insurers must spend at least the regulated share of premiums on medical claims and preventive investments under all market conditions. Statistics plotted are the mean of each equilibrium object in the stationary distribution. Consumer surplus can be negative because it accounts for switching costs, and corrects for misjudged preferences for out-of-pocket expenses.

in investment per member and insured rates, where the former is indefinite and the latter increases with MLR. Insurer profits fall mechanically. An 84.5% MLR minimizes average health risks and maximizes the sum of consumer surplus and insurer profits, moving the monopolist \$178 and \$343 closer to the planner frontier regarding consumer surplus and health risks. Nevertheless, insurers might game MLR regulations by inflating or misreporting costs (Cicala et al., 2019; Kim, 2022), which downplays its effectiveness.

Preventive Investment Subsidies. I explore the effectiveness of subsidizing insurers for preventive investment, similar to the Quality Bonus Program in Medicare Advantage that rewards insurers for high utilization of preventive and other services. Instead of nonlinear bonus schemes as in Medicare Advantage, I simulate uniform investment subsidies that reimburse insurers certain amounts per enrollee for their prevention provisions, equivalent to a reduction in marginal investment costs.

Figure D2 displays equilibrium statistics with rising subsidies. Insurers expand prevention provisions in response to lowered investment costs, leading to reductions in consumer health risks. Premiums drop as both investment and claims expenses decline. An investment subsidy of \$500 per enrollee, similar in magnitudes to that in Medicare Advantage (KFF, 2023), reduces average health risks by \$569 per consumer and boosts consumer surplus by \$202. However, if consumers as tax-payers fund preventive investment subsidies, consumer surplus is affected by two opposite forces: losses from subsidy funds versus gains from lower out-of-pocket medical expenses and premiums. In this case, a \$200 per enrollee investment subsidy maximizes gains in consumer surplus by \$15. A \$400 per enrollee investment subsidy keeps consumers indifferent while reducing average health risks by \$471.

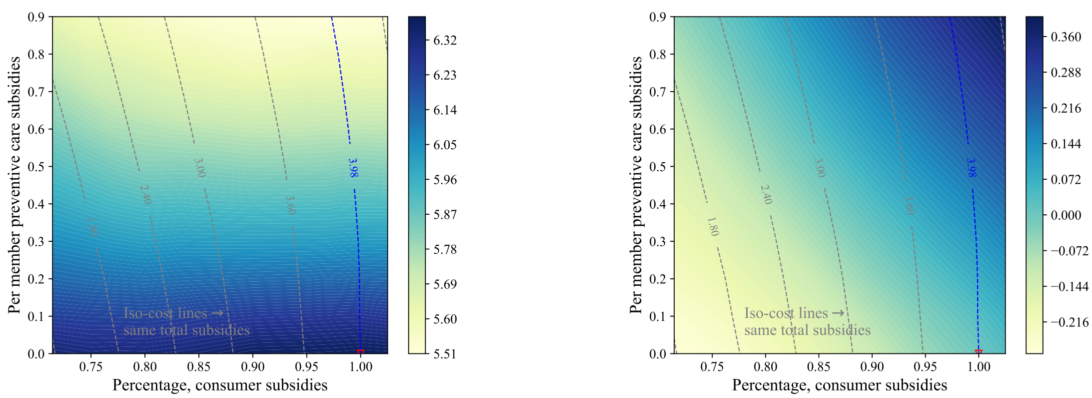
Figure D2. Equilibrium objects and welfare, by preventive investment subsidies to insurers



Notes: This figure compares simulated equilibrium strategies and welfare, in scenarios with varying preventive investment subsidies to insurers. Statistics plotted are the mean of each equilibrium object in the stationary distribution. The vertical dashed line denotes preventive investment subsidies in the status quo equilibrium. All statistics, including the per-member subsidy amount, are measured in thousands.

Figure D3. Consumer welfare by subsidy allocation policies

(a) Health risks (b) Consumer surplus changes



Notes: This figure plots simulated average health risks across all consumers on the market in panel (a) and changes in consumer surplus relative to the status quo in panel (b) under different subsidy allocation schemes. Statistics plotted are the mean of each equilibrium object in the stationary distribution. The baseline scenario, denoted by the red triangle in the figure, is the current market condition, where consumer subsidies are in the full scheme, and preventive investment subsidies are zero. The horizontal axis varies the percentage of consumer subsidies compared to the current market condition. The vertical axis varies per member preventive investment subsidies. The colors in the panel correspond to outcome values; dark (light) color corresponds to large (small) values. The gray dashed lines are iso-cost lines of government expenditures per consumer, where the sum of preventive investment and consumer subsidies are fixed. Statistics in both panels are measured in thousands.

I additionally analyze an alternative subsidy scheme, which allocates premium subsidies for consumers and preventive investment subsidies for insurers under fixed government budgets. Whether demand- or supply-side subsidies are more efficient is theoretically ambiguous.

Premium subsidies to consumers encourage insurance takeup so that more consumers receive preventive services, whereas preventive investment subsidies to insurers induce prevention provisions to the insured and also attract consumers to sign up for insurance and receive health management. Optimal allocation thus balances welfare losses from high premiums and losses from underinvestment.

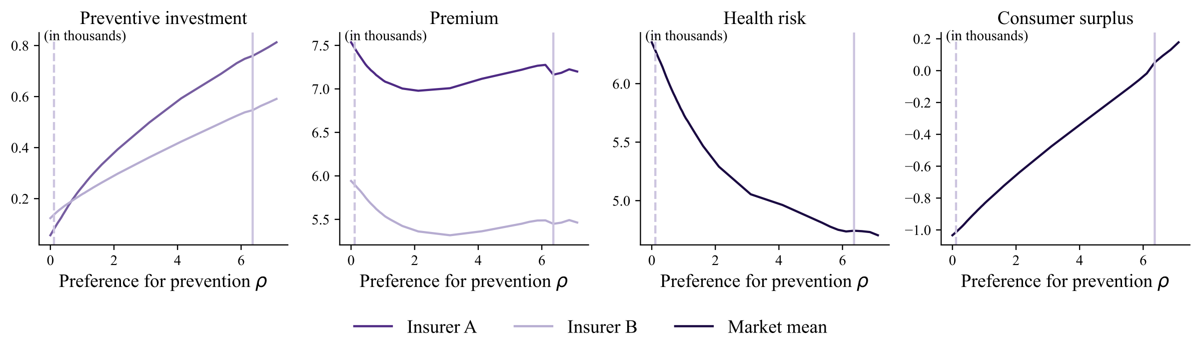
Figure D3 panel (a) depicts average health risks per consumer under alternative subsidy allocations. Average health risks decrease along with rises in consumer subsidies because consumer subsidies encourage insurance takeup so that more consumers receive prevention services. Consumers' health also improves when investment subsidies increase, as expected. Insurers increase preventive investment per enrollee in response to decreases in investment costs, and more consumers are attracted to the insured option and receive health management when more prevention is provided. Although subsidies to either side of the market benefit population health, a marginal investment subsidy is more effective than a marginal demand subsidy evaluated at the status quo: converting 1.8% of current consumer subsidies to a $600 per member preventive investment subsidy reduces average medical expenditures by $450.

Figure D3 panel (b) displays changes in consumer surplus relative to the status quo subsidy policy, where premium subsidies to consumers are in the full scheme, and preventive investment subsidies to insurers are zero. Price-sensitive consumers benefit from demand-side subsidies, whereas supply-side subsidies encourage investment, so consumers' out-of-pocket expenditures drop. Starting from the baseline subsidy scheme, marginal gains from correcting intertemporal limited commitment distortions outweigh marginal gains from correcting static market power frictions. Converting 1.8% of current consumer subsidies to a $500 per member preventive investment subsidy improves consumer welfare by $136 per member.

Raise Consumers' Willingness to Pay for Prevention. I simulate a scenario where consumers' willingness to pay for preventive care is raised, for example, through government informational campaigns about the importance of prevention (e.g., CDC's National Center for Chronic Disease Prevention and Health Promotion Program, National Breast and Cervical Cancer Early Detection Program, and National Colorectal Cancer Control Program). As consumers put more decision weights on prevention attributes, insurers do not necessarily rely on future cost savings to make preventive investments; they do so also to compete for static market share, which strengthens investment incentives.

Since my revealed preference framework cannot distinguish the roles of preferences or information, it is possible to use star rating programs like the Medicare Advantage markets to reduce informational frictions about plan quality and improve consumers' responsiveness to preventive attributes. Both raising valuation for preventive care and raising the precision level of plan quality work through increasing the coefficient of prevention preference, ρ, in the flow utility (equation (8)). The predicted investment and welfare outcomes of a hypothetical star rating program are thus the same as a hypothetical program targeting the valuation of prevention.

Figure D4. Equilibrium strategies and welfare by prevention preferences



Notes: These figures compare simulated equilibrium strategies and average welfare across all consumers on the market by the prevention preferences parameter, ρ. Statistics plotted are the mean of each equilibrium object in the stationary distribution. The vertical dashed line denotes the prevention preference at the observed equilibrium, while the vertical solid line denotes the prevention preference of the Medicare Advantage consumers, calibrated using Vatter (2021). Consumer welfare numbers can be negative because they account for switching costs and correct for misjudged preferences for out-of-pocket expenses.

Figure D4 reports equilibrium objects under various willingness to pay for prevention. The competitive market provides 4 to 13 times, or \$400 to \$700 more preventive expenses per member, if the willingness to pay for prevention of the exchange consumers raises to that of Medicare Advantage consumers (calibrated using Vatter (2021)), 51 times status quo.

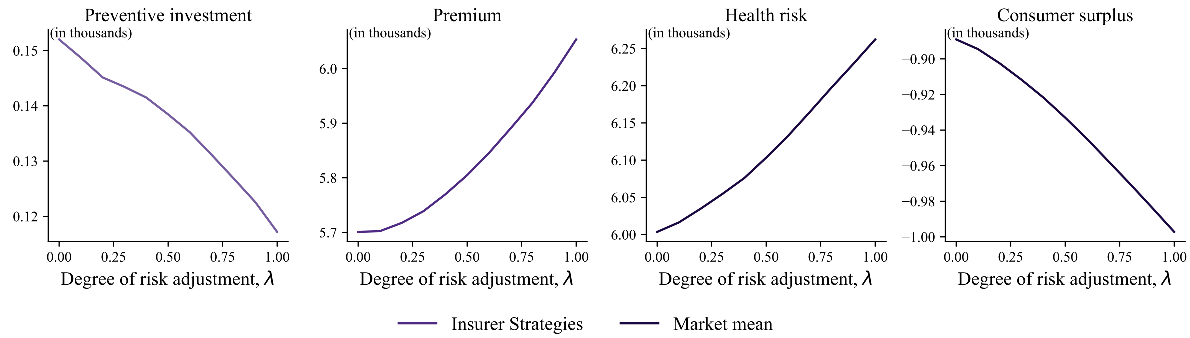
Risk Adjustment. I examine the effects of risk adjustment. I set claims cost per enrollee as a weighted average of the insurer's own enrollees' health risks and market-level mean health risks. Under perfect risk adjustment, insurers pay market-level mean costs, whereas insurers pay their own enrollees' health costs without risk adjustment. By equalizing claims expenses across insurers, risk adjustment allows insurers to free-ride rivals' preventive investments.

Figure D5 depicts equilibrium objects under various degrees of risk adjustment. Changing the degree of risk adjustment from none to perfect exaggerates insurers' free-riding incentives and penalizes preventive efforts, consistent with theoretical predictions in Eggleston et al. (2012). Despite this, risk adjustment brings benefits not modeled: it corrects for adverse selection, reduces insurers' cream-skimming, and stabilizes insurance markets (Geruso and Layton, 2017).

References

Aksoy-Pierson, Margaret, Gad Allon, and Awi Federgruen, "Price Competition Under Mixed Multinomial Logit Demand Functions," *Management Science*, 2013, *59* (8), 1817–1835.

Figure D5. Equilibrium strategies and welfare, by the degree of risk adjustment



Notes: These figures compare simulated equilibrium strategies and average welfare across all consumers on the market by the degree of risk adjustment, λ. I simulate symmetric duopolists that take the estimates of Insurer B for simplicity. Statistics plotted are the mean of each equilibrium object in the stationary distribution. In each simulation scenario, insurers pay a weighted average of its costs and market level mean costs, $\mu = (1-\lambda)\mu_{jmt} + \lambda\bar{\mu}_{mt}$. $\lambda = 0$ corresponds to no risk adjustment, whereas $\lambda = 0$ corresponds to perfect risk adjustment. Consumer welfare numbers can be negative because they account for switching costs and correct misjudged preferences for out-of-pocket expenses.

Besanko, David, Ulrich Doraszelski, and Yaroslav Kryukov, "The Economics of Predation: What Drives Pricing When There Is Learning-by-Doing?," *American Economic Review*, 2014, *104* (3), 868–897.

Blumen, Helen, Kathryn Fitch, and Vincent Polkus, "Comparison of Treatment Costs for Breast Cancer, by Tumor Stage and Type of Service," *American Health & Drug Benefits*, 2016, *9* (1), 23.

CDC, "2019 National Health Interview Survey Data.," 2020. link, Accessed: 2022/07/14.

_ , "National Diabetes Statistics Report," 2020. link, Accessed: 2022/08/25.

Cicala, Steve, Ethan Lieber, and Victoria Marone, "Regulating Markups in US Health Insurance," *American Economic Journal: Applied Economics*, 2019, *11* (4), 71–104.

Cunningham, Peter, "Few Americans Switch Employer Health Plans for Better Quality, Lower Costs," 2013. link, Accessed: 2022/07/21.

Eddy, David, "Screening for Breast Cancer," *Annals of Internal Medicine*, 1989, *111* (5), 389–399.

_ , "Screening for Cervical Cancer," *Annals of Internal Medicine*, 1990, *113* (3), 214–226.

_ , "Screening for Colorectal Cancer," *Annals of Internal Medicine*, 1990, *113* (5), 373–384.

Eggleston, Karen, Randall Ellis, and Mingshan Lu, "Risk Adjustment and Prevention," *Canadian Journal of Economics*, 2012, *45* (4), 1586–1607.

Fang, Hanming and Ami Ko, "Partial Rating Area Offering in the ACA Marketplaces: Facts, Theory and Evidence," 2018.

Fiedler, Matthew, "How did the ACA's Individual Mandate Affect Insurance Coverage? Evidence from Coverage Decisions by Higher Income People," *USC-Brookings Schaeffer Initiative on Health Policy*, 2018.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Sources of Geographic Variation in Health Care: Evidence from Patient Migration," *The Quarterly Journal of Economics*, 2016, *131* (4), 1681–1726.

Geruso, Michael and Timothy Layton, "Selection in Health Insurance Markets and Its Policy Remedies," *Journal of Economic Perspectives*, 2017, *31* (4), 23–50.

_ , _ , and Daniel Prinz, "Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges," *American Economic Journal: Economic Policy*, 2019, *11* (2), 64–107.

Greenwood, Mary and Joanne Henritze, "Coorscreen: A Low-Cost, On-Site Mammography Screening Program," *American Journal of Health Promotion*, 1996, *10* (5), 364–370.

Herndon, Jill Boylston, Soeren Mattke, Alison Evans Cuellar, Seo Yeon Hong, and Elizabeth Shenkman, "Anti-Inflammatory Medication Adherence, Healthcare Utilization and Expenditures among Medicaid and Children's Health Insurance Program Enrollees with Asthma," *Pharmacoeconomics*, 2012, *30* (5), 397–412.

Humphrey, Linda, Mark Helfand, Benjamin Chan, and Steven Woolf, "Breast Cancer Screening: a Summary of the Evidence for the US Preventive Services Task Force," *Annals of Internal Medicine*, 2002, *137* (5_Part_1), 347–360.

Javitt, Jonathan, Lloyd Paul Aiello, Yenpin Chiang, Frederick Ferris, Joseph Canner, and Sheldon Greenfield, "Preventive Eye Care in People with Diabetes is Cost-Saving to the Federal Government: Implications for Health-Care Reform," *Diabetes Care*, 1994, *17* (8), 909–917.

Kautter, John, Gregory Pope, Melvin Ingber, Sara Freeman, Lindsey Patterson, Michael Cohen, and Patricia Keenan, "The HHS-HCC Risk Adjustment Model for Individual and Small Group Markets under the Affordable Care Act," *Medicare & Medicaid Research Review*, 2014, *4* (3).

Kazi, Dhruv, Andrew Moran, Pamela Coxson, Joanne Penko, Daniel Ollendorf, Steven Pearson, Jeffrey Tice, David Guzman, and Kirsten Bibbins-Domingo, "Cost-Effectiveness of PCSK9 Inhibitor Therapy in Patients with Heterozygous Familial Hypercholesterolemia or Atherosclerotic Cardiovascular Disease," *Journal of the American Medical Association*, 2016, *316* (7), 743–753.

Keith, Katie, "More Insurers Win Lawsuits Seeking Cost-Sharing Reduction Payments," *Health Affairs*, 2019, *10.*

Keyser, Heather Hoch De, Rachelle Ramsey, and Monica Federico, "They Just Don't Take Their Medicines: Reframing Medication Adherence in Asthma from Frustration to Opportunity," *Pediatric Pulmonology*, 2020, *55* (3), 818–825.

Kim, Paul, "Risk-Corridors in Medicare Part D: Financial Risk-Sharing or Profit-Limiting Mechanism?," 2022.

Klabunde, Carrie, Djenaba Joseph, Jessica King, Arica White, and Marcus Plescia, "Vital Signs: Colorectal Cancer Screening Test Use — United States, 2012," *Morbidity and Mortality Weekly Report*, 2013, *62* (44), 881.

Klimchak, Alexa, Miraj Patel, Şerban Iorga, Natasha Kulkarni, and Nathan Wong, "Lipid Treatment and Goal Attainment Characteristics among Persons with Atherosclerotic Cardiovascular Disease in the United States," *American Journal of Preventive Cardiology*, 2020, *1*, 100010.

Klonoff, David and Daniel Schwartz, "An Economic Analysis of Interventions for Diabetes.," *Diabetes Care*, 2000, *23* (3), 390–404.

Knudsen, Amy, Carolyn Rutter, Elisabeth Peterse, Anna Lietz, Claudia Seguin, Reinier Meester, Leslie Perdue, Jennifer Lin, Rebecca Siegel, Paul Doria-Rose et al., "Colorectal Cancer Screening: an Updated Modeling Study for the US Preventive Services Task Force," *Journal of the American Medical Association*, 2021, *325* (19), 1998–2011.

Koma, Wyatt, Juliette Cubanski, Gretchen Jacobson, Anthony Damico, and Tricia Neuman, "No Itch to Switch: Few Medicare Beneficiaries Switch Plans During the Open Enrollment Period," 2019. link, Accessed: 2022/07/21.

Lansdorp-Vogelaar, Iris, Marjolein Van Ballegooijen, Ann Zauber, Dik Habbema, and Ernst Kuipers, "Effect of Rising Chemotherapy Costs on the Cost Savings of Colorectal Cancer Screening," *Journal of the National Cancer Institute*, 2009, *101* (20), 1412–1422.

Layton, Timothy, "Imperfect Risk Adjustment, Risk Preferences, and Sorting in Competitive Health Insurance Markets," *Journal of Health Economics*, 2017, *56*, 259–280.

Lazar, Lawrence, Mark Pletcher, Pamela Coxson, Kirsten Bibbins-Domingo, and Lee Goldman, "Cost-Effectiveness of Statin Therapy for Primary Prevention in a Low-cost Statin Era," *Circulation*, 2011, *124* (2), 146–153.

Lee, Bruce, Sarah Bartsch, and Alyssa Willig, "The Economic Value of a Quadrivalent Versus Trivalent Influenza Vaccine," *Vaccine*, 2012, *30* (52), 7443–7446.

Loeve, Franka, Martin Brown, Rob Boer, Marjolein van Ballegooijen, Gerritt van Oortmarssen, and Dik Habbema, "Endoscopic Colorectal Cancer Screening: a Cost-Saving Analysis," *Journal of the National Cancer Institute*, 2000, *92* (7), 557–563.

Lurie, Ithai, Daniel Sacks, and Bradley Heim, "Does the Individual Mandate Affect Insurance Coverage? Evidence from Tax Returns," *American Economic Journal: Economic Policy*, 2021, *13* (2), 378–407.

McConnachie, Alex, Andrew Walker, Michele Robertson, Laura Marchbank, Julie Peacock, Christopher Packard, Stuart Cobbe, and Ian Ford, "Long-term Impact on Healthcare Resource Utilization of Statin Treatment, and its Cost Effectiveness in the Primary Prevention of Cardiovascular Disease: a Record Linkage Study," *European Heart Journal*, 2014, *35* (5), 290–298.

National Cancer Institute, "Cancer Trends Progress Report Breast Cancer Screening," 2021. link, Accessed: 2022/07/13.

_ , "Cancer Trends Progress Report Cervical Cancer Screening," 2021. link, Accessed: 2022/07/13.

_ , "Cancer Trends Progress Report Financial Burden of Cancer Care," 2021. link, Accessed: 2022/07/13.

Nichol, Kristin, "Cost-Benefit Analysis of a Strategy to Vaccinate Healthy Working Adults Against Influenza," *Archives of Internal Medicine*, 2001, *161* (5), 749–759.

Nundy, Shantanu, Jonathan Dick, Chia-Hung Chou, Robert Nocon, Marshall Chin, and Monica Peek, "Mobile Phone Diabetes Project Led to Improved Glycemic Control and Net Savings for Chicago Plan Participants," *Health Affairs*, 2014, *33* (2), 265–272.

Oster, Emily, "Unobservable Selection and Coefficient Stability: Theory and Evidence," *Journal of Business & Economic Statistics*, 2019, *37* (2), 187–204.

Polyakova, Maria and Stephen Ryan, "Subsidy Targeting with Market Power," 2019.

Reed, Carrie, Martin Meltzer, Lyn Finelli, and Anthony Fiore, "Public Health Impact of Including Two Lineages of Influenza B in a Quadrivalent Seasonal Influenza Vaccine," *Vaccine*, 2012, *30* (11), 1993–1998.

Roger, Véronique, Alan Go, Donald Lloyd-Jones, Robert Adams, Jarett Berry, Todd Brown, Mercedes Carnethon, Shifan Dai, Giovanni De Simone, Earl Ford et al., "Heart Disease and Stroke Statistics—2011 update: a Report from the American Heart Association," *Circulation*, 2011, *123* (4), e18–e209.

Rust, George, Shun Zhang, Luceta McRoy, and Maria Pisu, "Potential Savings from Increasing Adherence to Inhaled Corticosteroid Therapy in Medicaid-Enrolled Children," *The American Journal of Managed Care*, 2015, *21* (3), 173.

Salzmann, Peter, Karla Kerlikowske, and Kathryn Phillips, "Cost-Effectiveness of Extending Screening Mammography Guidelines to Include Women 40 to 49 Years of Age," *Annals of Internal Medicine*, 1997, *127* (11), 955–965.

Shaukat, Aasma, Steven Mongin, Mindy Geisser, Frank Lederle, John Bond, Jack Mandel, and Timothy Church, "Long-Term Mortality After Screening for Colorectal Cancer," *New England Journal of Medicine*, 2013, *369* (12), 1106–1114.

Shepard, Mark, "Hospital Network Competition and Adverse Selection: Evidence from the Massachusetts Health Insurance Exchange," *American Economic Review*, 2022, *112* (2), 578–615.

Subramanian, Sujha, Justin Trogdon, Donatus Ekwueme, James G Gardner, Timothy Whitmire, and Chandrika Rao, "Cost of Breast Cancer Treatment in Medicaid: Implications for State Programs Providing Coverage for Low-Income Women," *Medical Care*, 2011, pp. 89–95.

_ , _ , _ , James Gardner, Timothy Whitmire, and Chandrika Rao, "Cost of Cervical Cancer Treatment: Implications for Providing Coverage to Low-Income Women Under the Medicaid Expansion for Cancer Care," *Women's Health Issues*, 2010, *20* (6), 400–405.

Tebaldi, Pietro, "Estimating Equilibrium in Health Insurance Exchanges: Price Competition and Subsidy Design under the ACA," 2017.

Vatter, Benjamin, "Quality Disclosure and Regulation: Scoring Design in Medicare Advantage," 2021.

Wagner, Edward, Nirmala Sandhu, Katherine Newton, David McCulloch, Scott Ramsey, and Louis Grothaus, "Effect of Improved Glycemic Control on Health Care Costs and Utilization," *Journal of the American Medical Association*, 2001, *285* (2), 182–189.

Whitney, Cynthia, Fangjun Zhou, James Singleton, and Anne Schuchat, "Benefits from Immunization During the Vaccines for Children Program Era—United States, 1994–2013," *Morbidity and Mortality Weekly Report*, 2014, *63* (16), 352.

Zhou, Fangjun, Abigail Shefer, Jay Wenger, Mark Messonnier, Li Yan Wang, Adriana Lopez, Matthew Moore, Trudy Murphy, Margaret Cortese, and Lance Rodewald, "Economic Evaluation of the Routine Childhood Immunization Program in the United States, 2009," *Pediatrics*, 2014, *133* (4), 577–585.