Commitment, Competition, and Preventive Care Provision

Anran Li*

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Abstract

Preventive care affects long-term population health. Insurer competition and limited consumer commitment disincentivize insurers' preventive investment because insurers cannot internalize all investment savings as consumers leave in the future. Lessening competition creates a tradeoff by increasing both preventive investment and premiums. I develop and estimate a dynamic equilibrium model where insurers compete on premiums and preventive investment, and insurers' investment affects consumers' health. 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. These results demonstrate efficiency losses of fragmented insurer markets due to investment externalities.

*Li: Cornell University, anran.li@cornell.edu. First version: 2023/01.

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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 can increase life expectancy and reduce 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 that 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, i.e., consumer turnover, 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., between higher prices and lower medical expenses. This paper aims to explore this tradeoff, quantify the impacts of insurer competition on investment, health, and welfare, and evaluate policy options.

I make three conceptual and empirical contributions. First, I offer new insights into the tradeoff between investment externalities and market power induced by competition. My analysis reveals efficiency losses of fragmented insurer markets and the role of government interventions to address underinvestment in prevention. Second, I provide new evidence that the supply side is essential for preventive care provision and that insurers respond to consumer turnover in preventive investment with novel empirical strategies. Third, I develop a new framework of dynamic oligopoly competition with endogenous price, quality, and population health. The framework is generalizable to quantifying the effects of investment externalities and evaluating regulatory solutions.

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 yearly 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. I focus on prevention procedures that are well-known to save future costs (CDC, 2021a; USPSTF, 2021), which creates intertemporal cost-saving incentives for insurers. Insurers invest in preventive care by educating and reminding consumers of eligible procedures and rewarding providers for prescribing preventive services.

I begin with two motivating facts that illustrate the incentive structure of prevention provision. First, I show that insurers play a major role in the utilization of preventive care. Exploiting a quasi-experimental variation of insurer exits (Abaluck et al., 2021), I compare prevention utilization between consumers forced to switch insurers and those who stay with insurers that receive switchers, before and after insurer switches.

I find the utilization pattern of switchers quickly converges to stayers, with insurer effects explaining about 90% variations in prevention utilization. Second, I show insurers' preventive investment respond to variations in expected future returns created by consumer turnover. 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 consumer turnover lowers insurers' preventive investment and prevention utilization. These facts highlight the importance of the supply side and dynamic incentives in prevention provision.

Motivated by these facts, I develop an equilibrium model to quantify the welfare effects of insurer competition given investment externalities, and to evaluate policies that promote prevention. Consumers make repeated insurance choices following 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 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 several key market features related to preventive investment. First, consumers' willingness to pay for preventive care is not economically meaningful and does not differ much by health status. This implies relying only on consumer choices cannot result in sufficient preventive care provision or optimal population health in equilibrium. Moreover, preventive attributes are ineffective for insurers to select healthy consumers. 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. Finally, 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 its estimates to quantify the welfare impacts of insurer competition, incorporating investment externalities. I compare the stationary distribution between the status quo duopoly equilibrium and

a low-cost monopoly equilibrium. Transitioning to the monopoly, average medical expenses drop by \$406 per consumer per year, 6.5% from the baseline. This positive gross return relies on two channels: investment and price. First, reduced turnover increases internalization of investment cost savings and eliminates free-riding across insurers, so investment per insured rises by \$235. Second, as reduced health expenses from investment could offset increased markup, and consumers are relatively price elastic, premiums do not rise much. Changes in the share of the insured, i.e., those who receive prevention, do not counteract gains from increased investment per insured. The combined effects at the intensive and extensive margins imply that lessening competition could improve population health.

Consumers are almost indifferent between the duopoly and monopoly scenarios, with a \$48 per person-year surplus change. Consumer surplus is determined by two competing forces, the savings in medical expenses from investment and the losses from pricing power. Crucially, allowing preventive investment to make consumers healthy lowers the marginal claims costs of insurance. This provides a countervailing force to inflated markup, so premiums do not rise as much as in a standard model where consumers' health and costs are constant. Losses from pricing power are thus restricted, and gains from investment are expanded. The distortion of underinvestment and high medical expenses is on par with that of high pricing power. These results reiterate the ambiguous welfare impacts of competition and highlight potential efficiency losses of competition due to investment externalities.

Finally, I assess policies to promote prevention provision. The investment mandate is the most effective among many policy instruments. 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. An investment mandate of \$500 per member maximizes consumer surplus, as it balances investment savings and premium increases that compensate for the extra investment costs.

Policy comparisons further provide two recommendations for regulators. First, the investment-price tradeoff should guide policy designs. Demand-side policies, such as automatic re-enrollment, raise inertia and strengthen consumer commitment but harm welfare: premium increases outweigh gains from elevated investment. In contrast, supply-side policies, such as mandates or subsidies, improve welfare as they address underinvestment while maintaining competitive market structures. These opposing effects 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. This sheds light on the role of government policies and the recent debate on preventive care coverage mandates.[1]

My analysis illustrates the potential efficiency losses of competition and highlights the critical but often

[1]The Affordable Care Act mandates private health insurers to fully cover certain preventive care services at no cost to patients. But this requirement was struck down in March 2023 and is under an appeal process.

neglected role of long-term investment incentives. The lack of long-run internalization of investment benefits could distort other types of health investment in addition to prevention provisions. For example, private insurers may not cover high-cost curative drugs, such as Hepatitis C drugs or gene therapy, that deliver significant value in the long run but require high upfront payments. Likewise, the price-investment tradeoff associated with competition generalizes to other markets with long-term relationships. For example, non-compete contracts in labor markets restrict worker mobility, which grants employers monopsony power to suppress wages but encourages investment in workers' human capital. I design a generalizable framework to evaluate welfare impacts of such investment inefficiencies, price-investment tradeoffs, and policy options.

This paper contributes to several threads of literature. The first is 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; Polyakova and Ryan, 2019; Saltzman, 2019; Shepard, 2022; Starc and Town, 2020; Tebaldi, 2017). To the best of my knowledge, this paper is the first to develop a model of dynamic competition on price and quality, with endogenous health, in this literature. I offer a novel insight into the tradeoff between investment externalities and market power induced by competition. I uncover the new insight that competition could have perverse effects on population health by discouraging preventive investment.[2]

Second, this paper expands the literature on partial commitment and investment leakage (Atal et al., 2022; Cebul et al., 2011; Crocker and Moran, 2003; Diamond et al., 2018; Finkelstein et al., 2005; Ghili et al., 2022; Hendel and Lizzeri, 2003; Herring, 2010; Joskow, 1987). Existing studies show worker turnover reduces employers' provision of skill training (Royalty, 1996; Acemoglu and Pischke, 1999), workers' and employers' joint decisions on health expenses (Fang and Gavazza, 2011). Similarly, the inability to recoup long-term returns distorts drug innovation directions (Budish et al., 2015). I provide new evidence that insurers respond to consumer turnover by adjusting quality with a novel shift-share design.

Third, this paper adds to a small literature on preventive care provision and utilization (Einav et al., 2020; Frakes and Gruber, 2022; Jones et al., 2019; Kowalski, 2023; Kotb, 2023; Kremer and Snyder, 2015; Newhouse, 2021; Ryan, 2021). Existing studies focus on demand-side frictions that cause underinvestment: consumers' ex-ante moral hazard (Ehrlich and Becker, 1972; Ellis and Manning, 2007; Phelps, 1978), behavioral hazard (Baicker et al., 2015), self-control problems (Bai et al., 2021), undervaluing prevention (Bauer et al., 2022). I offer a first equilibrium analysis of how supply-side interactions drive underprovision.[3]

2. Empirical Setting

2.1. The Exchange and Consumer Turnover

I study the individual health insurance 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

[2] Existing studies show that while constraining pricing power, insurer competition could harm consumer welfare by lowering insurers' bargaining leverage (Ho and Lee, 2017) or inducing cream skimming (Cutler and Reber, 1998; Chade et al., 2022; Kong et al., 2023; Ryan, 2023). Similarly, competition among medical providers may lead to unnecessary or harmful care (Kessler and McClellan, 2000; Currie et al., 2023). Handel and Ho (2021) offers a review.

[3] Appendix B provides a stylized framework to illustrate frictions discussed in the literature and this paper.

structural exercises in Sections 5-7.

The exchange is a valuable setting for studying preventive 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 and age-rating schedules. Insurers are not allowed to reject enrollees or price-discriminate based on health status. Appendix C1 describes additional institutional details.

One prominent feature of the exchange is consumer turnover, which 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 1, Table A13 report consumer retention for Utah and nationwide exchange separately. 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 3.2. The mean retention rate for a single insurer is 53%.

Table 1. Consumer retention, Utah exchange

Consumer cohort: those enrolled in exchange in year	2014	2015	2016	2017	2018	2019
Total insured	75,017	175,366	192,926	209,490	192,231	198,740
Share retained in exchange from the previous year (%)	-	33.08	58.13	57.29	69.05	72.71
Share retained in exchange in 2019 (%)	27.44	29.54	36.73	48.92	72.92	100
Share remain insured with previous-year insurers (%)	-	29.13	39.83	48.65	41.98	69.58

Notes: This table reports consumer retention for each consumer cohort (in each column). Data is from Utah All Payer Claims data.

2.2. Preventive Care and Intertemporal Incentives

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 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 medical guidelines on usage 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.

I offer several pieces of evidence that preventive care in this paper increases insurers' future profits. The most important one 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 6.1), expectations of future cost savings are the main drivers of insurers' expenditure. Second, I summarize medical studies on health benefits and cost savings of preventive procedures in Appendix C2.[4] Preventive procedures yield future cost savings due to reduced procedure costs to treat adverse health events.[5] Third, Appendix C3 presents stylized patterns in my sample on cost savings: cancer screenings correlate with low future costs as it intervenes before diseases occur and treats diseases at early stages; diabetes care correlates with low future costs as it manages disease to slow or stop its progression. Appendix D4 uses a cross-insurer movers design to estimate the cost effect of moving to insurers with higher prevention utilization, and finds suggestive evidence of future cost savings of prevention. Finally, I present various exercises throughout the paper to check positive returns to prevention and gauge the robustness of my main conclusion.[6]

2.3. Underinvestment in Preventive Care

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

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 is to incentivize providers' prescriptions via value-based payment models (Figure A1c, A1d). These contracts reward physicians with incentive payments per completion of preventive procedures. 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. 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 thus 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

[4] In economics literature, 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.

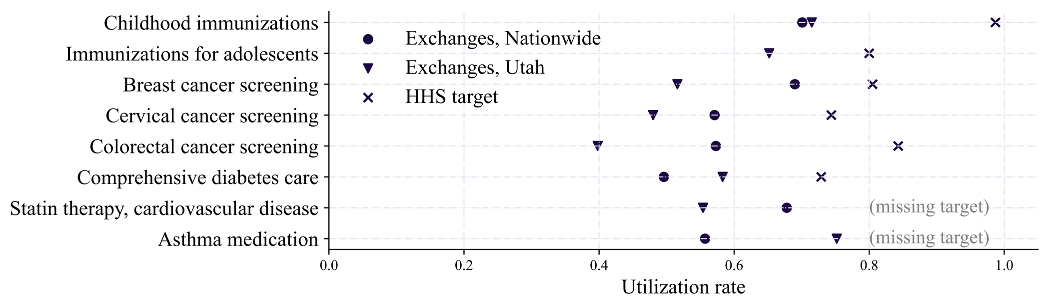
[5] Appendix C4 reconciles with Newhouse (2021): though many preventive procedures are not cost-effective, those selected in Figure 1 are shown cost-effective in literature. I also discuss gross versus net cost savings and clarify some subtle concerns with returns to prevention in Appendix C4.

[6] The exercises include the following. First, using the reduced form estimates in Section 3.2, I back out insurers perceived returns to prevention that rationalizes their investment responses to consumer turnover in Section 3.2.5 and Appendix E3. These inferred returns are similar to those calibrated from medical studies reassuringly. Second, in the structural estimation, I back out insurers' perceived returns to prevention that rationalize their observed investment strategies as an alternative estimation strategy in Section 6.4 and Appendix F4. These estimated returns are similar to those calibrated from medical studies reassuringly. Third, in the counterfactuals, Section 7 and Appendix G1 perform a careful sensitivity analysis where I reestimate the structural model under alternative returns-to-prevention parameters and re-simulate main counterfactuals with new return parameters and estimates. Model predictions are robust under a reasonable range of returns to prevention.

50 to 74 should receive mammography every two years. Following HEDIS guidelines, I first identify preventive procedures and eligible consumers with HCPCS and ICD codes from claims records. I then compute prevention utilization that is comparable across insurers. The Centers for Medicare and Medicaid Services (CMS) uses HEDIS utilization as a quality measure in star rating programs for insurance plans.

Figure 1 displays prevention utilization rates in the exchange and the 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 targets, confirming the underinvestment problem. Procedures with shorter return spans, such as chronic disease management, have higher utilization rates than those recouping returns in longer periods, such as cancer screenings, which is unsurprising given consumer turnover.

Figure 1. Preventive care utilization, observed equilibrium 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 calculated similarly using Utah APCD. Table A1 reports clinical services, frequency, and eligible population for each preventive care.

Consumer turnover and related investment externalities could hinder insurers' preventive 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, as shown in Appendix A2. First, 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. Second, 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 regression design to examine whether consumer turnover reduces insurers' investment in the motivating evidence.

3. Motivating Evidence

I provide two motivating facts to illustrate the incentive structure of prevention provision. Section 3.1 shows insurers play a major role in the utilization of prevention using a novel cross-plan movers design. Section 3.2 shows insurers reduce preventive investment in response to consumer turnover with a novel shift-share regression design. These analyses highlight the importance of supply-side strategies and dynamic incentives.

3.1. Insurers Play Major Roles in Prevention Utilization

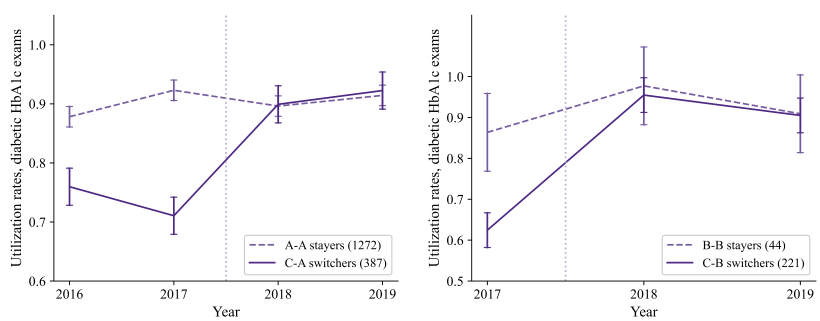
3.1.1. Data Sources. The key measures in this exercise are insurance enrollment and prevention utilization. I use the 2014-2019 Utah All Payer Claims Data (APCD). The APCD is an individual-year panel of enrollment and claims records for commercially insured residents. It also contains demographics (age, gender, zip code). I identify realized insurer-metal choices from enrollment records. I construct prevention utilization for eligible consumers using medical and pharmaceutical claims following HEDIS guidelines, reported in Figure 1. Table A2 reports summary statistics of consumers in Utah exchange.

To enlarge analysis samples, I supplement UT APCD with the 2010-2019 New Hampshire (NH) APCD. Table A3 reports summary statistics of consumers in the NH commercial insurance market.

3.1.2. Stylized Patterns. 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 that remain operating on the Utah exchange, Insurers A and B. I examine utilization patterns before and after the insurer exit for switchers (i.e., consumers who switch from Insurer C to Insurer A or B) and stayers (i.e., consumers who stay with Insurer A or B throughout).

Figure 2 reports utilization rates for an example procedure, diabetic HbA1c exams, before and after insurer switches for a balanced panel of stayers and switchers. Two patterns are outlined.

Figure 2. Preventive care utilization, pre- and post- insurer switch



Notes: This figure plots the utilization rate and 95% confidence interval for diabetic HbA1c exams among a balanced panel of consumers with specific enrollment patterns in UT APCD. The solid and dashed lines denote the utilization of switchers and stayers separately. The dotted vertical line denotes the event of switching insurers. Sample sizes for each group of a specific enrollment pattern are in parentheses.

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 products. If consumers' unobserved propensity to utilize care is assumed to be constant during the analysis period, this significant difference between pre- and post-switch reflects insurer effects in utilization.

Second, 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.

Taken together, these stylized patterns suggest that the supply side is essential for prevention utilization. Appendix D1 shows these patterns are robust across clinical procedures and analyzes differences across procedures. Appendix D2 discusses possible reasons for differences in insurer effects on prevention utilization, including investment amount and provider networks.

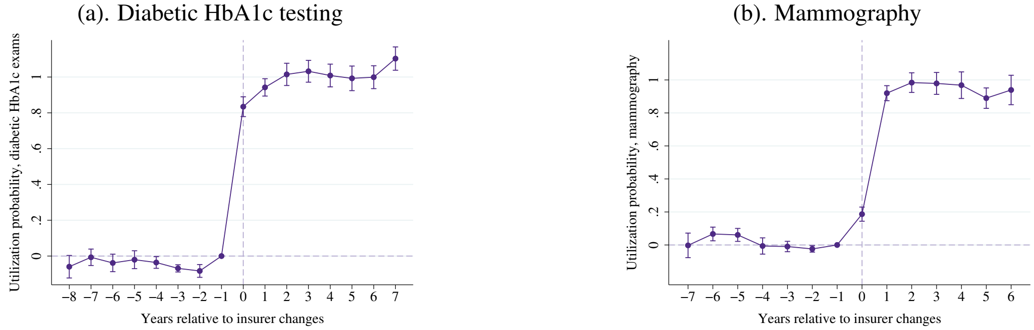
3.1.3. Regression Analysis. To quantify insurer effects in utilization, I further employ an event study (Finkelstein et al., 2016) that exploits consumers' switching across insurers. As Utah APCD is underpowered, I use New Hampshire APCD for this exercise, which provides longer time spans to examine trends and more cohorts of insurer changes.[7] I estimate the following specification:

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

where y_{it} denotes consumer i utilizing preventive procedures in year t. δ_i is defined as $\bar{y}_{d(i)} - \bar{y}_{o(i)}$, the difference in prevention utilization between the destination and origin insurer, $d(i)$ and $o(i)$. ρ_s controls for changes in utilization related to insurer changes that do not differ across insurer change directions. The regression includes individual fixed effects α_i to control for time-invariant consumer characteristics, e.g., baseline health status, calendar year fixed effects τ_t to control for time trends, age groups fixed effects x_{it}. Figure 3 plots the coefficient of interest, θ_s, representing consumers' responses to changes in insurer-specific care utilization.[8]

Figure 3. Effect of insurer-specific prevention utilization on consumers' prevention usage

(a). Diabetic HbA1c testing (b). Mammography



Notes: This figure shows point estimates and 95% confidence interval of θ_s from estimating equation (1). Standard errors are clustered at the county level. The regression sample includes consumers who stayed with the same insurer or changed insurers once during 2010-2019, and are eligible for diabetes care or mammography in NH APCD. The number of individuals in the analysis sample is 28,281 and 25,707 for panels (a) and (b).

The identifying assumption is that there is no selective moves based on consumers' trajectory of prevention utilization. This is plausible given the flat and close-to-zero pre-trends in Figure 3. The change in the insurer-specific utilization affects a consumer's prevention utilization immediately after the insurer changes and persists over time. Consumers who move to insurers with a 1 percentage point (pp) higher prevention utilization rate increase their likelihood of using prevention by 0.9pp after insurer changes.[9]

[7] I do not use the NH APCD for the main structural analysis because NH only has one rating area, leaving no price variations across markets for structural estimation.

[8] I pick the two procedures in Figure 3 because they have large enough sample sizes; and are representative of prevention types, early detection (mammography), and disease management (diabetes care). The pattern is robust across other preventive procedures.

[9] The recommended clinical frequency for mammography is once every two years, so the estimated effects in the moving year

Appendix D3 shows my findings of insurer effects in utilization are robust to alternative specifications and the direction of moves. Appendix D4 uses the same design to estimate the cost effect of moving to insurers with higher prevention utilization, and finds suggestive evidence of future cost savings of prevention.

The stylized fact that insurers control prevention utilization is unsurprising. 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 their zero cost-shares for prevention, thereby forgoing preventive visits (Lantz et al., 2016). As consumers cannot make informed choices, we would expect insurers' efforts to be key in prevention utilization. This is consistent with the existing studies that insurance plans are crucial for the use of high-value care (Garthwaite and Notowidigdo, 2019; Geruso et al., 2020; Handel et al., 2024).

3.1.4. Implications. This exercise reveals that insurers play a major role in prevention utilization. Thus, I use insurer choice as a proxy for prevention utilization in the empirical model; I do not separately model consumers' utilization decisions conditional on insurer choice. Furthermore, it is important to incorporate supply-side strategies when analyzing prevention underutilization.

3.2. Consumer Turnover Reduces Insurers' Prevention Provisions

3.2.1. 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 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 A4b). Table 2 shows the mean aggregate utilization is 64.8%.

Table 2. 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.

I extract preventive investment from the CMS Medical Loss Ratio (MLR) reports. It would be ideal to have direct measures of insurers' preventive investment, but such proprietary data do not exist. I use quality improvement expenses in MLR as proxies for preventive investment, including expenses to improve health outcomes, promote wellness activities, medical incentive payments, etc. Although MLR does not specify the exact clinical procedures, investment in preventive care by incentivizing consumers or providers belongs to quality expenses. The quality expenses are also consistent with a broad prevention concept, aiming to improve health and generate future savings. Appendix E1 gives detailed examples of quality improvement expenses, discusses possible measurement errors, and provides plausible evidence that this measure in MLR

still capture the influence of the origin insurer and are less pronounced. In years after insurer changes, when the destination insurer completely takes over, estimated effects for mammography and diabetic care are similar.

is not manipulated. This data is at the insurer-state-year-market segment (individual, small-group, or large-group) level. Table 2 shows 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. The mean retention rate is 74%.

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

$$y_{st} = \beta_0 r_{st} + \alpha_s + \alpha_t + \varepsilon_{st}. \tag{2}$$

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 (2) may suffer from reverse causality that consumers leave the exchange to get insurance elsewhere due to the low quality of exchange plans. To address this challenge, I construct a shift-share instrument (IV) z_{st} (Bartik, 1991) for retention rate r_{st}:

$$z_{st} = \sum_m h_{mt} w_{smt_0}, \quad t_0 < \min t. \tag{3}$$

h_{mt} is national-level industry-specific job hiring trends, i.e., the number of new hires over the 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"). h_{mt} comes from the Longitudinal Employer-Household Dynamics Job-to-Job Flows PUF, and w_{smt_0} is from Current Population Survey. Figure A2 displays job hiring trends by industry. Figure A3 depicts the IV's geography.

I estimate the following 2SLS equations, with the coefficient of interest being β_1:

$$\text{First stage: } r_{st} = \beta_2 z_{st} + \alpha_s + \alpha_t + \upsilon_{st}, \tag{4}$$

$$\text{Second stage: } y_{st} = \beta_1 \hat{r}_{st} + \alpha_s + \alpha_t + \upsilon_{st}. \tag{5}$$

3.2.3. First-Stage. The first-stage exploits the institutional feature that insurance and employment status are correlated. As more job hiring occurs, 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 individuals change insurance status; 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 4 columns (1)-(2): as 43 more individuals change to new jobs from old jobs or unemployment, 1 more current enrollee leaves the exchange. This is consistent with statistics from Medical Expenditure Panel Survey: 3.7% labor market transitioners change from the exchange to other insurance.

3.2.4. 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.

Table 3. Validity checks of the shift-share instrument identification assumptions

(a). Previous period demographics and investments					
Lagged share female	–0.002	(0.001)	Lagged share white	0.007	(0.007)
Lagged share Black	0.000	(0.002)	Lagged share Hispanic	–0.002	(0.005)
Lagged share age above 65	–0.002	(0.004)	Lagged share uninsured	0.008	(0.018)
Lagged share high school degree	0.007	(0.007)	Lagged share college degree	–0.002	(0.004)
Lagged preventive investments	–0.736	(0.590)			
(b). Medicare outcomes (placebo)					
Utilization, diabetes management	0.004	(0.010)	Utilization, annual physical exam	–0.023	(0.023)
Utilization, mammography	0.003	(0.014)	Utilization, flu vaccines	–0.005	(0.012)
Preventable hospital stay per 1000	0.000	(0.000)			
(c). Healthcare supply					
Medicaid expansion	0.169	(0.327)	Number of exchange insurers	–1.713	(2.763)
Primary care providers per 1000	0.003	(0.009)			
(d). Exchange composition					
Share below 200 FPL	0.029	(0.071)	Share aged 0–25	0.001	(0.023)
Share aged 26–54	0.018	(0.029)	Share choosing Gold plans	–0.144	(0.186)
Share choosing Silver plans	0.091	(0.160)	Share choosing Bronze plans	0.053	(0.127)
(e). Unemployment rate	0.001	(0.003)			
(f). Health and health behaviors					
Share doing physical exercise	0.005	(0.030)	Share obesity	–0.006	(0.013)
Share smokers	–0.011	(0.008)	Share heavy drinkers	0.005	(0.005)
Share days, poor physical health	–0.003	(0.007)	Share days, poor mental health	0.004	(0.008)
Premature death per 1000	0.000	(0.000)	Opioids overdose death per 1000	–0.022	(0.056)

Notes: This table reports the coefficients and standard errors (in parenthesis, clustered at state level) of the shift-share instrument in the regression of outcome variables in each column on the instrument. The regression sample is extended to 2014-2019 whenever outcomes are available to address the concern that the estimates might be noisy due to the short sample period. The regression includes state and year fixed effects and is weighted by state-year-level exchange market size. The outcome data in panel (a) is from American Community Survey and Medical Loss Ratio reports; panel (b) is from Dartmouth Atlas, CMS mapping Medicare disparities website and Robert Wood Johnson Foundation county health rankings dataset; panel (c) is from Kaiser Family Foundation and Area Health Resource Files; panel (d) is from CMS Open Enrollment Period PUF; panel (e) is from American Community Survey; panel (f) is Behavioral Risk Factor Surveillance System, Robert Wood Johnson Foundation county health rankings dataset and National Vital Statistics System. Gold, Silver, and Bronze plans have standardized 80%, 70%, and 60% cost-shares. *,**,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

First, 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 in the analysis period, the instrument constructed with these shocks would not predict predetermined variables. I fail to reject imbalance at conventional levels of statistical significance, as in Table 3 panel (a).

Second, I regress utilization rates of preventive procedures in Medicare on the instrument as a placebo test. Procedure utilization in Medicare is 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 3 panel (b) finds no statistically significant relationships between utilization rates in Medicare and the instrument.

Third, I find no statistically significant relationships between the instrument and healthcare supply other than insurers' investment, such as initiation of health policies, insurance market structure, and per capita primary care physicians. To further address the concern that labor market churn may lead insurers, especially those with high prevention provisions, to exit, I rerun the analysis at the insurer-state-year level as robustness tests in Table A20. Results in Table 3 panel (c) suggest labor churn does not affect outcomes of interest through the supply of care providers.

Fourth, I inspect a concern that the instrument changes the composition of exchange enrollees, which might, in turn, affect equilibrium utilization. Table 3 panel (d) shows consumer flows do not change the distribution of income, age, or metal-tier level choices on the exchange. Table A4 further shows health conditions and cost levels are not statistically different between inflows and outflows using Medical Expenditure Panel Survey. I fail to find evidence that the instrument changes the composition of exchange enrollees.

Fifth, I investigate a reverse causality concern that labor market churn might lead to less prevention usage. Consumers' limited time or broken provider relationships during job changes may impede doctor visits and prevention usage. Table A5 compares the propensity of using preventive care between inflows, outflows, and stayers of the exchange and finds no statistical difference. This does not support the instrument itself changing outcomes via utilization propensity.

Sixth, I examine the concern that the instrument picks up local economic shocks that may affect equilibrium behaviors.[10] Table 3 panels (e) fail to find statistically significant relationships between the instrument and unemployment rates. The instrument is a reallocation shock that changes the flow of individuals across different employment and insurance sectors but not the stock of the employed. To further compare outcomes in states with the same economic conditions but different predicted consumer turnover, I rerun the analysis controlling for local employment conditions (Chodorow-Reich and Wieland, 2020). Table A20 reports this robustness exercise.

Finally, I examine the concern that the instrument itself may affect enrollees' health or health behaviors and, thus, equilibrium outcomes. Table 3 panels (f) fail to find statistically significant relationships between the instrument and local health or health behaviors. A possible caveat is that measures for health behaviors in Table 3 are imperfect, such that prevention usage falls when labor markets boom. In that case, 2SLS estimates will capture the combined effect of insurers' reducing investment in response to turnover and individuals' reducing healthy behaviors in response to labor market shocks, providing an upper bound on the effect of turnover on utilization. However, the measure of insurers' investment does not factor in individuals' behavior changes, nor do insurers respond to health shocks with investment strategies[11]. The estimated effect of turnover on insurers' investment strategies is intact reassuringly.[12]

[10] Existing literature is inconclusive on how economic conditions affect health behaviors. Ruhm (2000) finds when the economy strengthens, smoking and obesity increase, physical activity reduces, and diet becomes less healthy. In contrast, Finkelstein et al. (2024) finds no quantitatively important effect of economic conditions on health behaviors.

[11] This is because there is little heterogeneity in willingness to pay for prevention by health or demographics (shown in Section 6.1), and preventive investment is not a meaningful selection margin to cream-skim healthy enrollees.

[12] Even if the threat to identification is at work that local economic shocks affect equilibrium utilization, key structural estimates in Sections 4-7 remain unaffected. The reduced form estimates of the effect of turnover on utilization or investment are not

3.2.5. Primary 2SLS Estimates. Figure A5 provides an initial look at the impacts of consumer retention on prevention utilization: The binned scatter plot reveals a positive relationship between retention and utilization. Table 4 columns (3)-(4) report corresponding OLS and 2SLS estimates. Their relative magnitudes are analyzed in Appendix E2. A 1 percentage point increase in retention increases prevention utilization by 0.78 percentage points, 1.2% out of baseline means.

Table 4. 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 (F-stats)	88 (13.7)	141 (23.3)	88	88	141	141

Notes: This table reports coefficients and standard errors (in parentheses, clustered at state level) from the estimation of equation (4) in columns (1), (2); equation (2) in columns (3), (5); equation (5) in columns (4), (6). The utilization and retention rates are measured in 0-100 percentage points; 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.

Table 4 columns (5)-(6) examine 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. They adjust preventive investment mainly by *varying quantities or intensities* of *existing* consumer wellness or provider incentive programs.[13]

The prevention measures in Table 4 aggregate across clinical procedures with differential returns spans. While some procedures, such as cancer screenings, may have convex return trajectories over time, other procedures, such as disease management, could realize returns quickly. For example, if diabetes or asthma are not managed well, patients could end up in the emergency room in the next year and increase medical spending significantly. Investment in procedures with shorter return spans responds more to turnover than those with longer spans, shown later in Section 3.2.8.

These results indicate that insurers respond to consumer turnover in investment strategies.

3.2.6. Robustness. Appendix E4 shows the 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 instrument construction, such as jackknifed (Autor and Duggan, 2003) or recentered (Borusyak and Hull, 2023) instruments. Third, I show estimates are robust to running regressions at the insurer-state-year level, alternative weighting and controls. Finally, I conduct a permutation test that constructs a placebo instrument. The test suggests

extrapolated or used as moments in estimation. Instead, they are used in the out-of-sample test, where the model-predicted effect of turnover is compared to and found to be similar. See Section 6.3 for details.

[13]Two possible timing scenarios may explain insurers' responses to the yearly (transitory) variations in turnover. The first is that insurers form correct and rational beliefs of consumer turnover, 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.

the estimated impacts are unlikely to be driven by noise.

3.2.7. Back-of-envelope Calculation of Insurers' Perceived Returns. With the 2SLS estimates, I conduct a back-of-envelope exercise to determine insurers' perceived returns to prevention. I back out the perceived returns that rationalize the estimated investment and utilization responses to consumer retention perturbations. Specifically, the 2SLS strategy gives insurers' responses in investment expenses to increased retention. The expected returns for this extra investment can be derived by the 2SLS estimates of utilization responses, scaled by insurers' perceived returns to prevention utilization. I search for the return parameter that equates the marginal investment expenses and the marginal expected returns. Appendix E3 describes the details. Depending on the assumption of returns to prevention trajectory over time, the annualized returns to preventive care are bounded between $443 and $4137 per person-year. This reassuringly aligns with those reported in the medical studies in Appendix C2. This highlights the importance of dynamic incentives when analyzing insurers' strategies.

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

First, I examine the estimated effect by sub-categories of investment in Table A6. Investment increases mostly come from expenses on promoting wellness activities and medical incentive payments, which is consistent with the facts on how insurers invest in Section 2.3.

Table 5. 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

Notes: This table reports coefficients and standard errors (in parentheses, clustered at state level) from the estimation of equation (5). 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 A7. 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. The number of observations is 88. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level.

Second, 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 regression 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 5 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 A4a.

Third, 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 5 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 A4b shows similar patterns hold for all available preventive procedures in QRS files.

Finally, the estimated effects are not driven by selection. The validity checks presented in Section 3.2.4 do not support the hypothesis that turnover affects investments or utilization through changing consumers' health status, utilization propensity, or exchange composition.

3.2.9. Implications and the Need for a Model. Previous analysis confirms that insurers respond to changes in future investment returns created by consumer turnover. Hence, it is important to incoporate insurers' intertemporal strategies for policy analysis.

Competition could amplify across-insurer turnover and intensify underinvestment. Figure A6 affirms this hypothesis in the exchange nationwide: there is a positive correlation between competition and turnover[14], and a negative correlation between competition and prevention provisions.

This interplay between consumer commitment and insurer competition makes the welfare impacts ambiguous. Competition 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 price and preventive investment.

4. Model

Previous analyses have shown the importance of incorporating the supply side, especially insurers' dynamic incentives and investment externalities, into the analysis of prevention underprovision. I now develop a model of consumers' insurance demand and insurers' investment and pricing decisions.

In the equilibrium framework, consumers make repeated insurance choices without committing 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. The model's novelty is that it incorporates insurers' intertemporal quality incentives, and it endogenizes population health as a function of insurers' strategies in equilibrium.

[14]The positive correlation between number of insurers and the probability of switching insurance plans or insurers could be explained by increased choice varieties, or that competition for market share may induce insurers to price aggressively, which raises consumer turnover. Theoretically, the effect of competition on consumer turnover 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.

4.1. 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.

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

End-of-period market shares are affected by two factors. The first is insurer strategies and resulting consumer choices within the market. This captures consumers switching across insurers, and between insurers and the outside option (uninsurance). The second is consumer flows into and out of the exchange. This 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 consumers flowing into and out of the exchange are constant across time for a given market.[15] Every insurer and the outside option 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 this share of consumer flows, κ_m, is not affected by insurers' premiums or investment strategies.[16]

Market share of product j at the end of period t is a weighted sum of choice probabilities of consumers with different previous insurer choices:[17]

$$s_{jmt} = \sum_{k \in J \cup U} \left[\kappa_m s_{kmt-1} \left(\sum_{\{i: d_{it-1}=k\}} s_{ijmt} \right) \right] + (1 - \kappa_m) \left(\sum_{\{i: d_{it-1}=I\}} s_{ijmt} \right), \tag{6}$$

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.

[15] 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.

[16] Although earlier literature finds job immobility induced by non-portability of employer-sponsored insurance (Madrian, 1994; Currie and Madrian, 1999; Gruber, 2000), recent literature that revisits this question 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 (product characteristics) on consumer flows, which primarily reflects job transitions.

[17] The model does not separately keep track of market shares and their transitions by whether consumers utilize prevention because utilization rates for stayers and switchers are not statistically different prior to switches.

Turning to the production of health, mean health risk (non-prevention medical expenses) 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}. Past health $\tilde{\mu}_{fmt}$ measures mean health risks in period t after consumers choose insurers but before preventive investment takes effect, $\tilde{\mu}_{fmt} = \sum_{i,j \in J_f} \left(\mu_{imt-1} s_{ijmt}\right) / \sum_{i,j \in J_f} \left(s_{ijmt}\right)$. 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 in Section 4.4). 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. I assume inflows and outflows have the same health risks, μ_{Imt}, which is reasonable given the stylized facts in Table A4.[18]

$$\underbrace{\mu_{fmt}}_{\text{health risk}} = \underbrace{\tilde{\mu}_{fmt}(\vec{s}_{mt-1}, \vec{\mu}_{mt-1})}_{\text{past health}} + \underbrace{\overbrace{q_1}^{\substack{\text{returns to}\\ \text{prevention}}} \times \overbrace{e_{fmt}}^{\substack{\text{percent enrollees}\\ \text{utilizing prevention}}}}_{\text{current period prevention}} + \underbrace{\nu_{fmt}}_{\text{random shock}} . \tag{7}$$

The health risk transition (equation (7)) embeds three assumptions. First, 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, 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. Equation (7) also abstracts away from the possibility that using prevention may involve extra doctor visits or extra non-prevention expenses. I perform sensitivity analysis by adjusting cost terms in Section 7.1.2 to address these caveats.

Second, equation (7) does not capture non-linear returns to prevention trajectories over time. Practically, certain preventive procedures, such as cancer screenings, may realize substantial cost savings in the long term and have little cost savings in the short term, creating a convex returns curve; other procedures, such as disease management, may materialize the same returns every period. A Markov transition rule with a linear returns trajectory facilitates computation by cutting out time or investment histories from the state space. This simplification will 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.

Third, I assume constant returns to prevention across health risk levels and prevention utilization levels. Detailed estimates of returns by health risks or utilization are unfortunately unavailable in existing medical studies. In Section 7.1.2, I use alternative functional forms for health transitions to probe the sensitivity of main results, accounting for diminishing returns to extra utilization or heterogeneous returns to prevention

[18] Model estimates and predictions are robust to the alternative specification where inflows are healthier or sicker than outflows, with their health risks set to be a fixed proportion.

by health status.

4.3. 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

$$u_{ijmt} = \underbrace{(\alpha_0 + \alpha_1\mu_{imt-1})p_{jmt}}_{\substack{\text{price preference}\\ \text{by health status}}} + \underbrace{(\rho_0 + \rho_1\mu_{imt-1})e_{jmt}}_{\substack{\text{prevention preference}\\ \text{by health status}}} + \underbrace{\gamma\mu_{imt-1}\text{co\_ins}_{jmt}}_{\substack{\text{out-of-pocket}\\ \text{medical expenses}}} + \underbrace{\eta\mathbf{1}[d_{imt-1} \neq j]}_{\text{inertia}}$$
$$+ \underbrace{\theta X_{jmt}}_{\text{other char.}} + \xi_{jm} + \xi_{jt} + \xi_{mt} + \epsilon_{ijmt}. \tag{8}$$

α_1 captures the selection that healthy consumers are more price sensitive than sick consumers. ρ_1 captures the selection that sick consumers may prefer preventive care more than healthy 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 choose products that maximize flow utility:[19]

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

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 and inflows, who are forced to make active choices.[20]

There are two canonical ways to model health insurance choices: one where consumers choose insurance plans and medical care utilization in two steps (Einav et al., 2013; Marone and Sabety, 2022), the other where consumers choose insurance plans based on product characteristics (Curto et al., 2021; Decarolis et al., 2020). I follow the latter, and do not incorporate consumers' optimal utilization decision, ex-post moral hazard, or selection on moral hazard for three reasons.[21] First, the government mandates most preventive

[19] 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.

[20] 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.

[21] This choice framework also assumes away from consumers' ex-ante moral hazard that the insured demand less prevention than the uninsured. Existing research finds no (Card et al., 2008) or limited extent (Spenkuch, 2012; Zweifel and Manning, 2000) of ex-ante moral hazard.

care to be free to consumers, and cost-shares for other medical care are standardized on the exchange. These cost-sharing rules and, thus, consumers' utilization response to plans' financial characteristics are held constant throughout estimation and counterfactuals. Second, consumers have a limited role in determining prevention utilization, while insurers play a major role, as revealed in Section 3.1. Plan choices are, hence, a reasonable and sufficient proxy for prevention utilization: the mechanism that consumers use prevention for better future health is captured by their strategies of choosing an insurer that offers better prevention. Appendix F5 analyzes how model estimates are affected if insurer choices are not a sufficient proxy for prevention utilization, i.e., when consumers choose insurance plans and medical care utilization sequentially. Third, as the model focuses on capturing how insurers' intertemporal price and investment strategies vary with turnover, simplifying demand-side strategies but keeping the no-commitment feature is innocuous and makes computing dynamic games feasible.

4.4. 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}, 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}.[22] 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

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

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 their cost functions of preventive investment, namely, how efficiently they can trans-

[22] We do not model insurers differentiating investment to each consumer, i.e., we use x_{fmt} instead of x_{ifmt}. This is because empirically, within the same insurer, we do not observe statistically significant differences in utilization among eligible consumers of different characteristics.

form 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 cost functions. The convex structure 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.

The monotonic mapping between preventive investment and utilization in equation (13) is equivalent to assuming insurers could directly choose prevention utilization. This abstracts from the selection that those more health conscious endogenously choose plans with high preventive care coverage and use more prevention. While making computing dynamic games feasible, this modeling choice is reasonable given the stylized facts that insurer effects play a major role in determining prevention utilization. Appendix F5 analyzes how model estimates are affected if equilibrium utilization is determined by both insurers' investment and consumers' characteristics.

Equations (7) and (13) link insurers' investment 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.[23]

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: static profit change with enhanced investment; the direction depends on profit and cost of the marginal consumer given selection. 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

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

[23]This setup implicitly assumes insurers' investment does not change consumer preference and rules out the possibility of habit formation. Appendix D3 formally tests and finds a limited extent of habit formation.

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.

4.5. Oblivious Assumptions and Equilibrium. 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 (19). This setup abstracts from selection *within* an insurer based on each individual's health risk but preserves selection *across* insurers based on their enrollees' average health. 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 market shares or calculating profit. As each insurer can have different mean health risks, thus different price and prevention sensitivity for their representative consumer, this simplified setup still preserves selection that insurers can attract healthier marginal enrollees by lowering prices or quality.

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. This setup is likely reasonable because for the employer-sponsored market, with which the Exchanges market has the largest consumer swaps, provisions of preventive care could be fringe benefits that employers offer and not result from insurers' profit maximization decisions. Thus, it is plausible that insurers are not facing joint profit maximization across market segments, but are instead designing strategies separately for each market. Extending the model to allow for cross-market interactions is an exciting avenue for future research.

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 period $t-1$.

I consider pure-strategy Markov perfect Nash equilibrium (MPNE)(Maskin and Tirole, 1988a,b) of this dynamic oligopoly game, with oblivious assumptions stated above. 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 (6), (7), and insurers employ the above policies to form expectations.

5. Estimation and Identification

The model outlined in Section 4 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 prevention and its correlation with health risks $\alpha_0, \alpha_1, \rho_0, \rho_1$, mean preferences for out-of-pocket health expenses and other financial characteristics γ, θ, product-specific preferences δ_{jmt}. The third primitive is curvatures of preventive investment cost functions, a_{fm}.

These three primitives are estimated in the stated order: 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 present estimation methods and the identification of each primitive in order. I then describe the estimation sample and additional data sources.

5.1. 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 (6), I estimate the share of consumer flows κ_m by solving

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

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 t.

Turning to health risk transitions, I rewrite equation (7) 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 C2 reports my calculation in detail.[24]

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.

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

5.2. Consumer Preferences. I estimate consumer preferences using the two-step MLE-BLP estimator of Goolsbee and Petrin (2004). I rewrite consumers' flow utility (equation (8)) as the sum of common utility terms δ_{jmt} and idiosyncratic terms:

$$u_{ijmt} = \delta_{jmt} + \alpha_1 \mu_{imt-1} p_{ijmt} + \rho_1 \mu_{imt-1} e_{jmt} + \gamma \mu_{imt-1} \text{co}_{jmt} + \eta \mathbf{1}[d_{imt-1} \neq j] + \epsilon_{ijmt}. \tag{19}$$

$$\delta_{jmt} = \alpha_0 p_{ijmt} + \rho e_{jmt} + \theta X_{jmt} + \xi_{mt} + \xi_{jm} + \xi_{jt} + \xi_{jmt}. \tag{20}$$

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 parameters outlined in equation (19): heterogeneity in price preference α_1, prevention preference ρ_1, 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 inflows identify inertia. The differential correlations between premiums and choice patterns by consumers with different health risks identify differences in price sensitivity α_1. Similar logics apply to identifying ρ_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 MPEC algorithm (Su and Judd, 2012; Dube et al., 2012).

The second step is 2SLS estimation of equation (20), 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

[24]To address the concern that returns to prevention in medical studies may not generalize well to the full population, I examine the sensitivity to the returns to prevention parameter in Section 7.1.2. I also use an alternative estimation strategy to back out insurers' perceived returns to prevention that rationalize their observed investment strategies. Appendix F4 shows these estimated returns are reassuringly similar to those calibrated from medical studies.

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, $\xi_{mt}, \xi_{jm}, \xi_{jt}$.

5.3. Cost Functions of Preventive Investment. I parameterize the investment cost functions as equation (13).[25] 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 (markets). However, with the parametric relation in equation (13), I can rewrite insurers' FOCs as if they are choosing prevention utilization, e_{fmt}, which is observed at the insurer-county-year level.

$$[e_{fmt}] \qquad \underbrace{\frac{\partial x_{fmt}}{\partial e_{fmt}} s_{fmt}}_{\text{marginal investment cost}} = \underbrace{\sum_{j \in J_f} \sum_i \left(\frac{\partial s_{ijmt}}{\partial e_{fmt}} \text{revpm}_{ijmt} \right)}_{\text{marginal static revenue}} + \underbrace{\beta \frac{\partial V_{fm}(\vec{s}_{mt}, \vec{\mu}_{mt})}{\partial e_{fmt}}}_{\text{marginal future revenue}}. \tag{21}$$

Cost primitives are identified by levels of policy choices. Intuitively, given state transitions, consumer demand, and rivals' strategies, we know the marginal returns of an observed utilization policy. Using FOC, we find parameters that satisfy the implied marginal costs, in other words, rationalize observed utilization.

Formally, identification of a_{fm} comes from the monotone mapping between observed policy and cost primitives. At an observed equilibrium, both the marginal revenue curve (the right-hand side of equation (21)) and the marginal cost curve (the left-hand side of equation (21)) are functions of investment cost curvatures. Their intersection pins down a utilization level (depicted in Figure A7a). 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 primitives that rationalize observed utilization policies using all insurers' FOCs of prevention provision.[26] This is in a similar spirit to backing out marginal costs that rationalize prices using static pricing FOCs (Berry, 1994; Berry et al., 1995).

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 a three-layer loop structure. In the inner loop, for each guess of cost parameters in market m and an arbitrary value function V_{fm}, I solve stage games' equilibria by searching for a fixed point in insures' best response functions for prices and preventive investment.[27] In the interim loop, given

[25] 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.

[26] Simulations, reported in Figure A7b, confirms this monotonic mapping observed policies and primitives for all insurers.

[27] Pure-strategy equilibria may not exist in Nash-Bertrend games in markets with severe adverse selection (Dickstein et al., 2023;

insurers' best response mappings, I use the full solution approach to find value functions V_{fm} that satisfy Bellman equations (equation (12)) for every insurer. In the outer loop, given value functions, I interpolate option value terms evaluated at the observed equilibrium and evaluate the investment FOC (equation (21)) for the guessed cost parameter. I repeat the process until finding the cost parameters that make FOC holds. Appendix F2 details the algorithm. The discounting parameter β is set to 0.9 (Ryan, 2012; Collard-Wexler, 2013).

Computationally, 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 present challenges. I employ several techniques to reduce computation burdens, for example, polynomial approximations and extending trilinear interpolation for value functions. See Appendix F2 for details.

To reduce the multiplicity of equilibria, I focus on equilibria that are limits to finitely repeated games following Goettler and Gordon (2011). Namely, in the interim loop, I use backward induction to solve for an equilibrium of the T–period game and then let T go to infinity. 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.

Appendix F3 further inspects multiplicity in stage games, value function iterations, and stationary distributions separately. 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.

5.4. Estimation Sample. The primary data for structural estimation is the Utah APCD. Using claims records and Johns Hopkins Adjusted Clinical Groups System (ACG), I construct individual-year-level health risks, i.e., consumers' expected medical expenses in a standardized plan.[28] I construct univariate county-insurer-year level preventive utilization using a weighted average of utilization rates across preventive procedures in Figure 1. I further use various public datasets to construct counts, medical expenses, prevention utilization of the uninsured, and product characteristics. See Appendix F1 for details.

Table 6. Estimation sample statistics

	Mean	Std.		Mean	Std.
Number of consumers	363,161		Prevention utilization, Insurer A	0.422	(0.071)
Uninsured rate in the exchange	0.454	(0.069)	Prevention utilization, Insurer B	0.460	(0.140)
Total premium	6,623	(1,618)	Preventive procedure expenses, A	78	(249)
Total medical expenses (ACG-adj.)	6,040	(1,898)	Preventive procedure expenses, B	74	(296)

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

The left panel in Table 6 reports statistics in the estimation sample of consumer preferences and state

Kong et al., 2023). Simulations reveal the market does not unravel at the estimated degree of selection. The fixed point algorithm for the stage game is in a similar spirit to Goettler and Gordon (2011); Fan (2013).

[28]When calculating the FOCs, insurers' marginal claims costs are set as consumers' health risks times cost-shares times an insurer-specific price index. The price index is constructed by comparing costs that different insurers pay for the same procedures, weighted by the frequency of the procedures. This index is held fixed for the structural exercises as the model abstracts away from the insurer-provider bargaining process.

transitions. 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 C1 describes reconciling exchange regulations in detail, such as premium subsidies, etc.

The right panel in Table 6 reports prevention utilization in the estimation sample of investment cost functions. My estimation sample for this primitive only 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. Mean claims costs per enrollee paid to providers for 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%.

6. Results

6.1. Parameter Estimates

6.1.1. State Transitions. Table 7 panel (a) reports state transition estimates. Across counties, the mean share of consumers who remain in the exchange in the next year is 65.6%. Figure A8 plots the distribution of retention across all counties. Turning to health risk transitions, the calibration exercise shows a 1 percentage point increase in prevention utilization slows insurer-level mean health risk growth by $8.51 per member per year.[29] Minimum distance estimators reveal 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.

6.1.2. Consumer Preferences. Table 7 panels (b)-(c) report demand estimates. The enrollment-weighted average own-premium elasticity is -5.47 in the Utah exchange, 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%.

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

[29] As discussed in Section 2.2, this paper offers three exercises throughout to probe positive returns to prevention: the returns parameter from medical studies is reassuringly similar to those backed out with reduced form estimates or structurally estimated from the dynamic games. I also examine the sensitivity to the returns to prevention to address the concern that returns to prevention in medical studies may not generalize well to the full population. See Section 2.2 for an overview; E3, F4, 7.1.2 for details.

Table 7. State transition and consumer preference estimates

(a). 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)
(b). Demand estimation, first step MLE estimates		
Inertia (disutility of changing insurer), η	-2.486	(0.014)
Increase in premium coefficients as health risks increase by \$1,000, α_1	0.376	(0.001)
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	(0.007)
(c). Demand estimation, second step 2SLS estimates		
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: Panel (a) reports state transition estimates from estimating equations (16), (18). Returns to prevention are calibrated from medical studies. Panels (b) and (c) report consumer preference estimates using the two-step estimator of Goolsbee and Petrin (2004). All standard errors (in parentheses) are derived using the delta method.

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.[30] Estimates of ρ_1 further imply that there do not exist meaningful differences in willingness to pay for prevention by consumers' health risks. The small willingness to pay is not surprising given the stylized facts in Section 3.1 that consumers lack knowledge of recommended preventive services. It is also consistent with existing studies that consumers undervalue prevention (Kenkel, 2000). Note that my revealed preference framework cannot tell whether the little willingness to pay is due to consumers not having correct beliefs of preventive services offered or not valuing prevention sufficiently.[31]

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 A8 shows demand estimates under alternative specifications, including a random coefficient specification with health risks drawn from the empirical distribution, not including heterogeneity in willingness to pay for prevention by health risks. The implied elasticities are not meaningfully different.

6.1.3. Cost Functions of Preventive Investment. Table 8 reports mean cost curvature estimates and derived investment expenses across all counties. Figure A8 depicts their distributions. I also report estimates

[30] 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 residual product fixed effects term and the prevention attributes terms, suggesting the abovementioned underestimation channel is not at work.

[31] 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.

of Salt Lake County, the largest Utah county, which is used in counterfactual simulations in Section 7. The point estimate of 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 8. Estimations of curvatures of 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 (21)). 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 A9 plots model-implied cumulative and marginal returns to prevention expenses. Returns to preventive investment are concave. At the observed equilibrium, 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 at the Medicare utilization and retention level, 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. Suppose total preventive investment is a sum of claims costs paid to medical providers, plus expenses to promote prevention utilization. I thus deduct observed per member claims costs of preventive procedures, $78 and $77 for insurers A and B, 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, where insurers operating on the exchange spend an average of $107 per member annually on quality improvements, with a standard deviation of $111.

6.2. Key Market Features Implied by Model Estimates

Model estimates shed light on several market features that are key to understanding incentives in prevention provision.

On the demand side, the first feature is that consumers are price-sensitive, and their degree of inertia is low. This implies that price competition and consumer turnover are especially relevant for the market.

Second, 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. This also implies only relying on the demand side cannot give rise to an efficient level of prevention provision on the market.

Third, the willingness to pay for prevention does not differ much by consumers' health status, as it is not economically meaningful regardless. This implies that offering preventive attributes is not an effective selection tool for insurers to cream-skim healthy consumers. When insurers provide great prevention, increases in marginal static revenue won't be offset by the costs of attracting sicker consumers. To ensure the uniqueness of the state game equilibrium where insurers simultaneously choose prices and preventive investments, I use estimates that abstract from differential preferences for prevention by health in the counterfactual exercises.

Turning to the supply side, the first feature is that preventive investment is costly for insurers. As shown in Table 8, to achieve the government's utilization targets, the average per member preventive investment becomes \$604 and \$438 for Insurers A and B, a 3-to-4 times rise from the status quo. To compensate for that, insurers need to capture a substantially higher share of investment cost savings than the current level.

Second, 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: average prevention utilization rates of Insurers A and B are only 6.0 and 5.2 percentage points lower than the status quo equilibrium.

I further decompose the FOC of prevention provisions (equation (21)) 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.

Third, 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 brings a 14.7% decrease in expected cost savings.

6.3. Model Fit

First, I use in-sample tests to compare model-predicted and observed moments that are not used in the estimation procedure. I compare predicted and observed choice patterns for consumers with different previous-period insurer choices. The estimation matches aggregate market shares that combine all consumers, not detailing their previous choices. I also compare observed and simulated premiums, which make premium FOCs hold under model estimates and observed state variables. The estimation uses investment but not premium FOCs. Figure A10 reveals simulated policies reproduce observed policies with reasonable precision.

Second, I use an out-of-sample test to compare model simulations and reduced form estimates in Section 3.2. The model predicts 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 (pp) at status quo equilibrium. Encouragingly, these model predictions are quantitatively similar to the reduced form estimates, where a 1 pp increase in consumer retention raises preventive investment per enrollee by \$5.3, and prevention utilization rates by 0.78pp.[32] This indicates that the model, estimates, and equilibrium assumptions are a good approximation of economic forces in the data.

6.4. Alternative Estimation Method and Robustness

Appendix F4 reports estimates from an alternative estimation procedure. The estimation method in Section 5 uses state transition 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. 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. Finally, I input consumer preferences and cost curvature estimates into the dynamic game. I back out state transition parameters, including insurers' perceived returns to prevention, using the FOC of prevention provisions. The resulting estimates are reassuringly similar in magnitude to those reported in Section 6.1.

7. Counterfactuals

Using the equilibrium framework and model estimates from previous sections, I first analyze the welfare effects of insurer competition in Section 7.1. 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 7.2, such as 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.[33] 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.

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

[32] Two reasons explain why model simulations do not match reduced form estimates exactly. First, the structural exercises focus on the UT exchange, while the regression uses exchange markets nationwide. Second, I impose stationary assumption in the structural exercise, while not necessarily all markets in the regression exercises are mature.

[33] 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.

consumer surplus in market m year t as

$$\text{CS}_{mt} = \int_i \frac{1}{\alpha_i}\left(\max_j \text{E}[u_{ijmt}] + \sum_{j\in J\cup U}\left(s_{ijmt}(\alpha_i-\gamma)\mu_{imt-1}\text{co\_ins}_{jmt}\right)\right)dF_i. \tag{22}$$

u_{ijmt} is defined in equation (19). Consumer-specific price preference $\alpha_i = \alpha_0 + \alpha_1\mu_{imt-1}$.[34,35]

Besides consumer surplus, I consider health risks, i.e., non-prevention medical expenses, as relevant welfare measures. Consumer surplus in equation (22) 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).

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.

7.1. The Welfare Effects of Insurer Competition

7.1.1. Primary Estimates. I examine the interplay between commitment and competition. To benchmark the efficiency losses of investment externalities against market power, I compare the simulated equilibrium of the status quo duopolist to that of a low-cost monopolist, where Insurer B operates on the exchange.[36] To avoid the mechanical variety effects caused by the dimension of logit draws, I let the monopolist offer the same product twice. Figure 4 reports key equilibrium objects that showcase key welfare mechanisms–the price-investment tradeoff. Table A9 panel (II) reports all relevant statistics, including welfare outcomes for consumers, insurers, medical providers, and the government.

Figure 4 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 it can no longer steal healthy consumers from competitors. The former and latter channels account for 84% and 16% of the investment increase, respectively. Preventive investment triples from \$106 to \$342 per insured.[37] This closes 63% of the

[34] 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

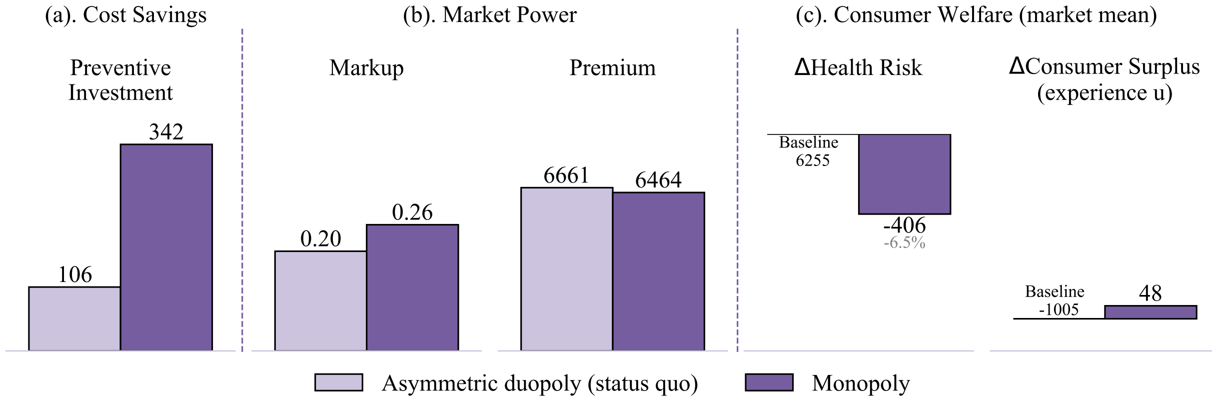
$$\text{CS}_{mt} = \int_i \frac{1}{\alpha_i}\left(\sum_{j\in J\cup U}\left(s_{ijmt}(u_{ijmt}-\epsilon_{ijmt})\right) + \sum_{j\in J\cup U}\left(s_{ijmt}(\alpha_i-\gamma)\text{co\_ins}_{jmt}\mu_{imt-1}\right)\right)dF_i. \tag{23}$$

[35] 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 (Table A9, A10) fully incorporate inertia .

[36] I report the low-cost monopoly (keeping Insurer B) scenario, as it will be the firm that wins the market if the government runs an auction to let the firms compete for the market. The high-cost monopoly scenario (keeping Insurer A), and scenarios with alternative monopoly characteristis are reported as robustness in Table A9, A10.

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

Figure 4. Equilibrium strategies and welfare, duopoly equilibrium and monopoly equilibrium



Notes: This figure reports simulated policies and welfare in the baseline asymmetric duopoly equilibrium (dark bars) and monopoly equilibrium (light bars). 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.

prevention utilization gap between the duopoly equilibrium and government targets. 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).

Figure 4 panel (b) depicts equilibrium objects relevant to market power. Upon lessening competition, the monopolist exerts pricing power, and markup increases by 6 percentage points. However, market-level mean premiums decline by $197. This result 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. These two competing forces make premium changes theoretically ambiguous. In plausible scenarios, for example, with high returns to prevention, low investment costs, or high price elasticity, investment savings are large enough to dominate enhanced pricing power; premiums do not rise. This analysis therefore delivers a new insight that insurer competition without consumer commitment might raise medical expenses and premiums, creating a worst-of-both-world.

Figure 4 panel (c) reports changes in consumer welfare. Average health risks across all consumers drop by $406 per person per year, 6.5% from the baseline. This result of positive gross return relies on two forces: investment savings and market power. First, reduced turnover increases preventive investment per insured. Second, as consumers are relatively price elastic, and reduced health expenses from investment could offset increased markup, changes in the share of insured consumers who receive prevention do not offset gains from increased investment per insured. The combined effects at the intensive and extensive margins imply that lessening competition can improve population health.

Changes in consumer surplus are $48 per consumer per year. To further disentangle the roles of investment externalities and market power, I run an interim scenario allowing the monopolist to optimally choose preventive investment policies while keeping pricing policies the same as in the baseline duopoly equilibrium. Compared to the baseline, consumer surplus raise by $264 in the only investment response

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.

scenario. This is because enhanced investment improves population health, lowering out-of-pocket medical expenses and premiums. Allowing the insurer to change pricing policies and charge a higher markup shrinks consumer surplus gains. Since the distortions of underinvestment, i.e., high health expenses, are on par with losses from high pricing power, consumers are almost indifferent. This analysis, therefore, highlights potential efficiency losses of competition from investment externalities.

A crucial force for the consumer surplus result is that preventive investment makes consumers healthy and lowers the marginal cost of insurance. This force counteracts increased markup, so premiums do not rise as much as in a standard model where consumers' health and costs are held constant. Thus, losses from pricing power are restricted compared to the canonical model, and gains from investment are expanded. This analysis highlights the role of surplus-creating investment and investment-price tradeoffs. It reiterates the ambiguous welfare impacts of competition when long-term quality incentives are considered.

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 could increase uninsured rates. Fourth, if promoting prevention exaggerates moral hazard and increases the prevalence of both high-value and low-value care, model estimates overstate welfare gains. Finally, 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.

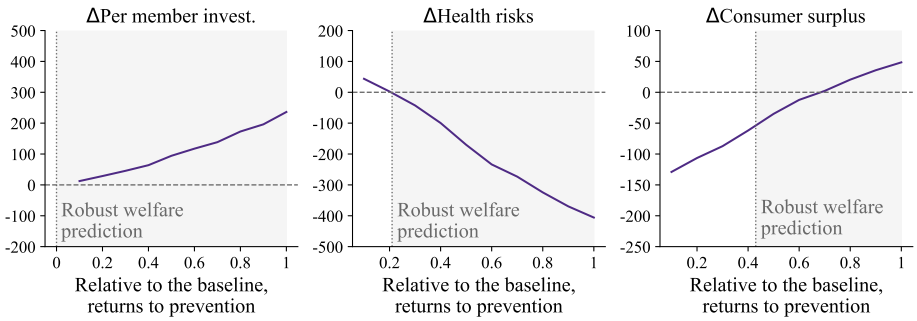
7.1.2. Sensitivity. Previous analysis highlights two forces that drive model predictions: cost savings and market power. I test the sensitivity of main results to the former force, by using alternative values of returns to prevention and health transition functions. I also show robustness to simulation specifications.

First, I examine the sensitivity to the returns to prevention parameter to address the concern that returns to prevention in medical studies may not generalize well to the full population. I re-estimate the model under alternative return parameters. The return parameter governs expected future profit gains from preventive investment, which, in turn, reveals marginal investment costs by first-order conditions. When returns to prevention are less than 0.3 times the baseline, new investment cost estimates are considerably smaller than the observed expenses in preventive care. This implies that these small insurers' perceived returns are likely misspecified, as they cannot rationalize the observed insurers' strategies. Appendix G1 describes the exercise in detail.

Figure 5 reports the sensitivity of main results to returns to prevention. I re-simulate equilibrium using new estimates under each return parameter. As returns to prevention fall, the relative importance of dynamic cost savings incentives diminishes compared to static market share incentives, so 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. Markets

with high returns to prevention are more likely to benefit from lessened competition, because the high returns allow the monopoly to create more surplus from enhanced preventive investment. The welfare prediction is robust under a reasonable range of returns to prevention: the returns need to be less than 0, 0.2, or 0.4 times the baseline, respectively, to flip the main result that lessening competition could boost investment, improve population health, or leave consumers almost indifferent.

Figure 5. Equilibrium strategies and welfare, sensitivity to returns to prevention



Notes: This figure reports simulated changes in preventive investment per member (left column), health risk (middle column), and consumer surplus (right column) from the baseline asymmetric duopoly equilibrium to monopoly equilibrium. All statistics are the mean of each equilibrium object in the stationary distribution. I re-estimate the model using alternative returns to prevention parameters and re-simulate equilibrium with new parameter estimates. The welfare prediction at the baseline is that removing a competitor could increase preventive investment, improve health, and leave consumers almost indifferent. The shaded area is a parameter space with robust welfare prediction.

Second, I inspect the sensitivity of model predictions to health transition functions (equation (7)). I begin by setting health transition as a quadratic function to account for possible non-linear returns of prevention utilization. As marginal returns to extra utilization diminish, cost savings gains from the monopoly-duopoly investment gap shrink. Figure A11a reveals the welfare prediction is robust under a reasonable range of concavity: removing a competitor could enhance investment and improve health and surplus, but the magnitude of consumer gains becomes smaller.

I then allow for heterogenous returns to prevention by health status. Sick consumers may benefit more from preventive investment, either because they receive larger health gains from an extra unit of utilization, or they are more responsive such that the investment translates to more usage of prevention. In that case, cost savings gains from the monopoly-duopoly investment gap shrink compared to the baseline, as consumers in the monopoly equilibrium are healthier than those in the duopoly equilibrium. The welfare prediction holds if returns to prevention for the sickest are no more than 5.2 times that for the healthiest. Figure A11b depicts the results.

I also consider cost adjustments to allow for the possibility that using prevention may involve extra non-prevention expenses like doctor visits. These extra expenses make investment in preventive care even more costly, so dynamic incentives become more important to induce investment. The welfare gaps between the monopoly and the duopoly widen along with rising investment expenses, leaving welfare predictions robust. Figure A11c confirms this.

Third, I show my main results are robust to alternative simulation specifications. Table A9 panel (II) reports scenarios where a high-cost monopoly instead of a low-cost monopoly operates on the market. Table

A9 panel (I) reports simulations that start from hypothetical symmetric duopolists instead of asymmetric duopolists. Table A10 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 A10 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. In all specifications, consumers are close to indifferent, with ambiguous changes in consumer surplus; while average health risks decrease due to elevated investment.

7.1.3. Generalizability. The estimates from the Utah exchange likely provide an upper bound of gains of a single private 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 markets. My equilibrium framework highlights potential efficiency losses due to investment externalities, which are prevalent in all fragmented payer markets.

7.1.4. Benchmark to a Planner. I benchmark the best-case scenario monopoly to a planner. 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.[38] 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. Appendix G2 details this exercise.

7.2. Policy Simulations to Promote Prevention Provision

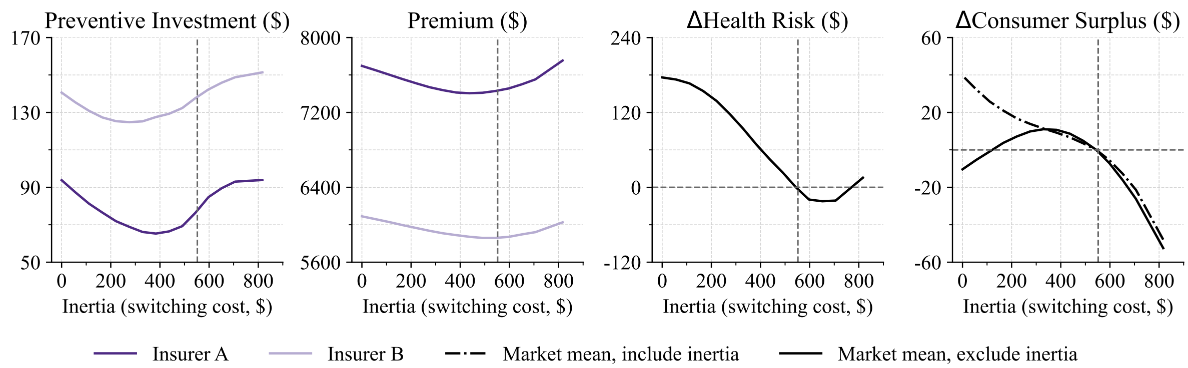
The previous section has disentangled the tradeoff between underinvestment and high markup. In this section, I further evaluate policies to promote prevention provisions given this tradeoff. Regarding policies that regulate consumers, I explore the effects of raising consumers' retention probabilities, such as automatic re-enrollment. As for policies that regulate insurers, I study preventive investment mandates. I then discuss additional policies, such as preventive investment subsidies, risk adjustment, varying churn across markets, varying contract length, or informational campaigns that raise consumers' preferences for prevention. Finally, I summarize the features of policies that could improve investment and welfare.

7.2.1. Raising Consumers' Retention Probabilities. I first investigate the welfare impacts of raising consumers' retention probability: varying inertia with automatic re-enrollment designs (Drake and Anderson, 2019; Shepard and Wagner, 2022), default designs (Handel and Kolstad, 2015; Brot-Goldberg et al., 2023), or charging a penalty when switching occurs similar to life insurance. Inertia is an essential source of

[38] This setup is equivalent to the planner maintaining duopoly competition, shutting down across-insurers turnover, and mandating competitive pricing.

consumer commitment. Increasing inertia raises consumer retention and allows insurers to capture a more significant portion of their investment returns, thereby alleviating underinvestment. Yet it reduces demand elasticities, granting insurers larger market power.

Figure 6. 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.

Figure 6 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.

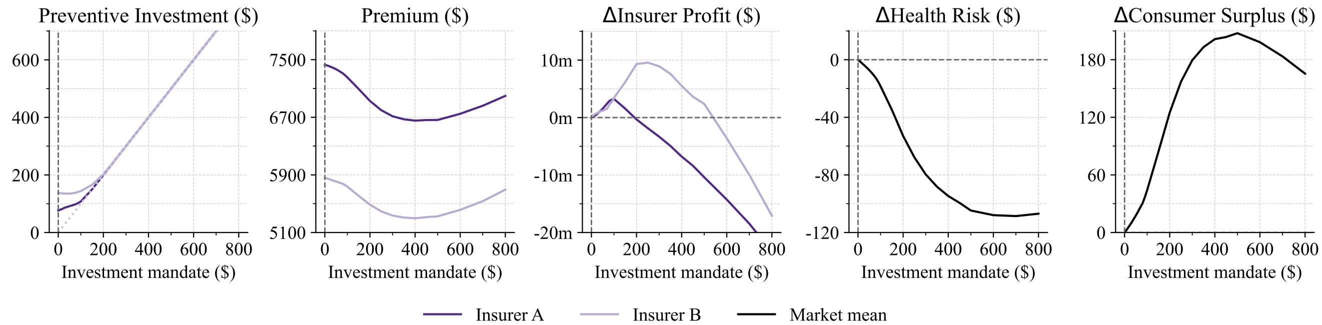
Average health risks first decrease then increase with inertia. The impact of enhanced per-member investment first dominates then falls behind the effect of increased premiums and receded shares of insured consumers who receive prevention.[39] The impacts of inertia on consumer surplus hinge on whether it is a tangible cost to be included in the calculation.

7.2.2. 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 7 depicts equilibrium statistics with rising mandates. Preventive investment is always higher in

[39] Note that inflow consumers without previous insurer choices are not subject to inertia. Increasing inertia raises insured rates for stayers, but lowers those for inflows due to high premiums. The latter dominates the former as the inertia level increases, reducing the aggregate insured rate and, thus, the shares of insured consumers who receive prevention.

Figure 7. 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.

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.

Notably, Pareto improvements could be achieved with preventive investment mandates of up to $190 per enrolled member, about 2.7% of per member premiums. 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 an 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 still earn positive profits, so this policy will not induce exits.

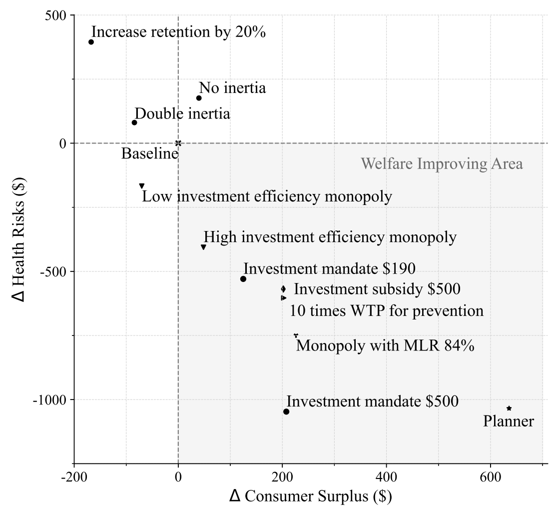
Average health risks exhibit a U shape, whereas consumer surplus displays an inverse U shape. This mirrors the tradeoff between investment gains and losses from price increases. Investment mandates boost preventive provisions and lower consumer health risks. However, insurers may raise prices to compensate 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, or about 7% of per member premiums.

7.2.3. Additional Policies. Appendix G2 reports additional policy simulations. First, subsidizing insurers certain amounts per enrollee for their preventive investment reduces marginal investment costs, which in turn boosts prevention provisions and lowers premiums. Second, 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. Third, extending contracts to two years, or decreasing the share of consumer flows across market segments raises consumer retention and encourages investment while also reducing demand elasticities; it

turns out to be not welfare-enhancing due to the price-investment tradeoff. Finally, risk adjustment equalizes insurers' claims expenses, exaggerating free-riding incentives and penalizing preventive efforts.

7.2.4. Summary and Policy Implications. Figure 8 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 three takeaways.

Figure 8. 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 7.1 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 sheds light on the recent policy debate on the ACA preventive care coverage mandates (KFF, 2024). It outlines the critical role of government policies in improving prevention utilization.

Third, the welfare gap between the first-best planner and each policy instrument reflects the efficiency costs of investment externalities in a fragmented payer market. This friction applies to the broader healthcare

setting: Private insurers may 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. Private insurers may hesitate to cover high-cost curative drugs, e.g., Hepatitis C drugs or gene therapy, that deliver substantial value over time but require high upfront payments. These intertemporal externalities could intensify disease burdens and raise public expenditures on Medicare. My analysis highlights the crucial long-run investment consideration for a wide range of healthcare policies, such as the current policy debate on insurance coverage for expensive drugs that could produce dramatic long-term health effects (KFF, 2023).

8. 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 expands our understanding of the mechanisms and tradeoffs behind prevention under-provision by analyzing consumers' and insurers' behaviors in equilibrium. My main contributions are three-fold. First, I offer novel conceptual insights into the tradeoff between investment externalities and market power of competition. My analysis reveals efficiency losses of fragmented insurer markets and highlights the critical but often neglected role of long-term investment incentives. Second, I provide new evidence that the supply side is important for preventive care and that consumer turnover could reduce insurers' health investment. Third, I develop a new framework of dynamic competition with endogenous product characteristics to study welfare effects of competition given investment externalities and evaluate regulatory solutions.

In addition to investment externalities caused by competition and consumer commitment, other market frictions can also reduce preventive investment in equilibrium. One example is the common agency problem (Frandsen et al., 2019), 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. 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.

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

Anran Li (anran.li@cornell.edu) – October 9, 2024

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Contents

A. Additional Tables and Figures

A1. 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 19-34	28.98	30.96	30.72	30.50	30.27	29.93
Age 35-54	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. Summary statistics, the New Hampshire commercial market

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			By market segment		By insurer switching status		
Sample	All consumers	All consumers	Exchange	Employer sponsored	Non-movers	Move once	Others
Sample year	2010-19	2019	2019	2019	2019	2019	2019
Number of individuals	3,003,723	1,156,154	36,131	1,120,023	116,304	473,314	566,536
Number of payers	67	29	2	29	22	29	28
(a). Demographics (%)							
Age below 18	19.05	17.88	9.91	18.13	12.13	20.56	16.82
Age 18-34	21.97	21.98	22.75	21.96	12.35	22.63	23.42
Age 35-55	29.31	27.96	31.73	27.83	24.69	25.86	30.38
Age above 55	29.48	32.01	35.50	31.89	50.83	30.52	29.38
(b). Annual medical expenses ($)							
Total expenses	2,970	2,941	4,348	2,896	5,863	2,442	2,759
	(14,677)	(15,753)	(20,014)	(15,595)	(22,152)	(14,620)	(15,005)
Payer expenses	2,586	2,563	3,336	2,538	5,391	2,126	2,348
	(14,296)	(15,363)	(19,364)	(15,215)	(21,803)	(14,271)	(14,562)
Out-of-pocket expenses	383	378	1,012	357	471	316	410
	(1,039)	(1,027)	(1,710)	(990)	(1,006)	(935)	(1,099)

Notes: This table reports mean and standard deviations (in parenthesis, at the individual level) for key statistics of commercial market enrollees from New Hampshire APCD. Column (1) reports the sample statistics for all consumers/payers ever appeared during 2010-2019, while the remaining columns report sample statistics for relevant consumer groups in 2019. Consumers can move into and out of the commercial market due to swaps with Medicaid or aging into Medicare. The non-mover group refers to consumers who did not change insurers in 2010-2019; the move-once group refers to consumers who changed insurers once during 2010-2019.

Table A4. 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. The number of individuals in the regression is 2886. 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 A5. 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 A4. 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 A6. 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

Notes: This table reports output from estimation of equation (5). 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 4. Number of observations is 141. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level, separately.

Table A7. Eligibles and clinical procedures of procedures in Table 5

(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.

Table A8. 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
$\downarrow$ in insured rate if all products' OOP annual premiums $\uparrow$ by \$100	9.1%	10.3%	12.1%
$\downarrow$ in insured rate if all products' posted annual premiums $\uparrow$ 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 in Section 5. Column (1) corresponds to the baseline (preferred) specification that is used in counterfactuals. Column (2) uses random coefficients in equation (19), 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 and sets μ_{imt-1} the same as in the baseline. Standard errors (in parentheses) are derived using the delta method.

Table A9. Equilibrium statistics, duopoly and monopoly equilibrium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	(I) Symmetric Duopoly to Monopoly						(II) Asymmetric Duopoly to Monopoly				
Monopoly characteristics	(a) Insurer A			(b) Insurer B				(c) Insurer B		(d) Insurer A	
Specification	Duo.	Mon.	Diff.	Duo.	Mon.	Diff.	Duo.	Mon.	Diff.	Mon.	Diff.
Investment per member (PM.), Insurer A	-	-	-	-	-	-	76	-	-	306	230
Investment PM., Insurer B	-	-	-	-	-	-	138	342	204	-	-
Investment PM., Market mean	114	306	192	133	342	209	106	342	236	306	200
NPV, cost savings PM., Insurer A	-	-	-	-	-	-	516	-	-	1538	1023
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
Premium, Insurer B	-	-	-	-	-	-	5860	6464	604	-	-
Premium, Market mean	7615	8427	812	5674	6464	790	6661	6464	-197	8427	1766
Markup, Insurer A	-	-	-	-	-	-	0.255	-	-	0.422	0.167
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
Insured rate	0.638	0.483	-0.155	0.649	0.503	-0.146	0.647	0.503	-0.144	0.483	-0.164
Health risk per consumer	6374	6088	-286	6004	5849	-155	6255	5849	-406	6088	-167
Consumer surplus PM., include inertia, ex-ante	-1088	-1075	13	-889	-957	-68	-1005	-957	48	-1075	-70
Consumer surplus PM., exclude inertia, ex-ante	-1038	-1046	-8	-842	-929	-88	-955	-929	25	-1046	-91
Consumer surplus PM., include inertia, ex-post	-1387	-1337	50	-1169	-1215	-46	-1302	-1215	87	-1337	-35
Consumer surplus PM., exclude inertia, ex-post	-1336	-1308	29	-1122	-1188	-66	-1252	-1188	64	-1308	-56
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
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
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
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
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
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
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

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. The statistics in columns (9), (11) represent those in the monopoly equilibrium (columns (8), (10)) 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 (22) and (23), 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).

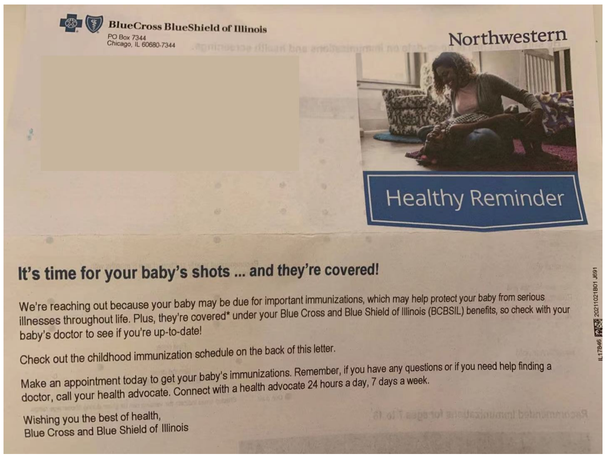
Table A10. Equilibrium statistics, asymmetric duopoly and monopoly, robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	(I) Simulation Forward					(II) Alternative Product Offerings				
Monopoly characteristics		(a) Insurer A		(b) Insurer B			(c) Insurer B		(d) Insurer A	
Specification	Duo.	Mon.	Diff.	Mon.	Diff.	Duo.	Mon.	Diff.	Mon.	Diff.
Investment per member (PM.), Insurer A						76	-	-	303	227
Investment PM., Insurer B						138	2191	2053	-	-
Investment PM., Market mean						106	2191	2085	303	197
NPV, cost savings PM., Insurer A						516	-	-	1275	760
NPV, cost savings PM., Insurer B						954	1529	575	-	-
Premium, Insurer A						7429	-	-	8000	571
Premium, Insurer B						5860	7349	1489	-	-
Premium, Market mean						6661	7349	688	8000	1339
Markup, Insurer A						0.255	-	-	0.345	0.089
Markup, Insurer B						0.147	0.154	0.008	-	-
Markup, Market mean						0.204	0.154	-0.050	0.345	0.141
Insured rate						0.647	0.429	-0.218	0.408	-0.239
Health risk per consumer	6349	6106	-244	6199	-150	6255	5885	-369	6116	-138
Consumer surplus PM., include inertia, ex-ante	-1032	-1010	22	-1095	-64	-1005	-978	27	-1097	-92
Consumer surplus PM., exclude inertia, ex-ante	-982	-984	-1	-1066	-84	-955	-954	1	-1067	-112
Consumer surplus PM., include inertia, ex-post	-1335	-1268	67	-1358	-23	-1302	-1130	171	-1274	28
Consumer surplus PM., exclude inertia, ex-post	-1285	-1241	44	-1329	-43	-1252	-1106	145	-1244	7
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
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
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
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
Total insurer profit	239.0	185.9	-53.0	352.8	113.9	241.5	160.4	-81.2	246.1	4.5
Total uncompensated care	699.7	1062.3	362.6	1017.2	317.5	668.7	1082.4	413.7	1106.3	437.7
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

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. The statistics in columns (8), (10) represent those in the monopoly equilibrium (in columns (7), (9)) minus the duopoly equilibrium (in column (6)). Ex-ante and ex-post consumer surplus are calculated following equation (22) and (23), 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

Service	Procedure	Bonus	Performance Criteria	Plans†
Comprehensive Diabetes				
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

Meridian Health Plan
ILLINOIS
FLYPS04
Effective 7/1/2015

(d). Value-based payment programs

Supplemental Material

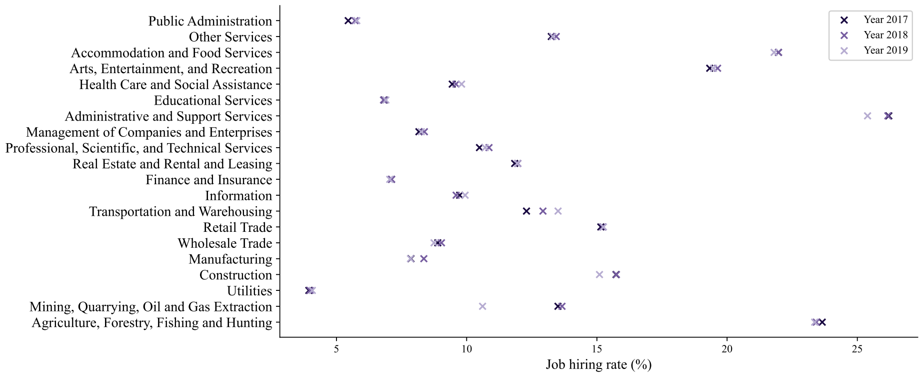
Molina Medicare Options Plus Quality Partner Program[1]

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).

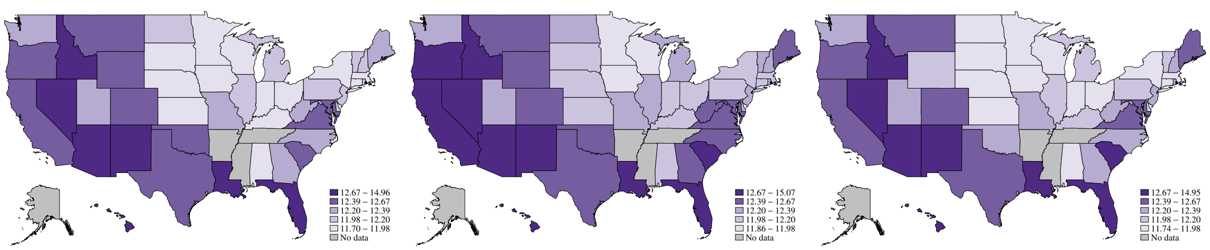
Figure A2. Job hiring rate by industry



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 A3. Geography of shift-share instrument

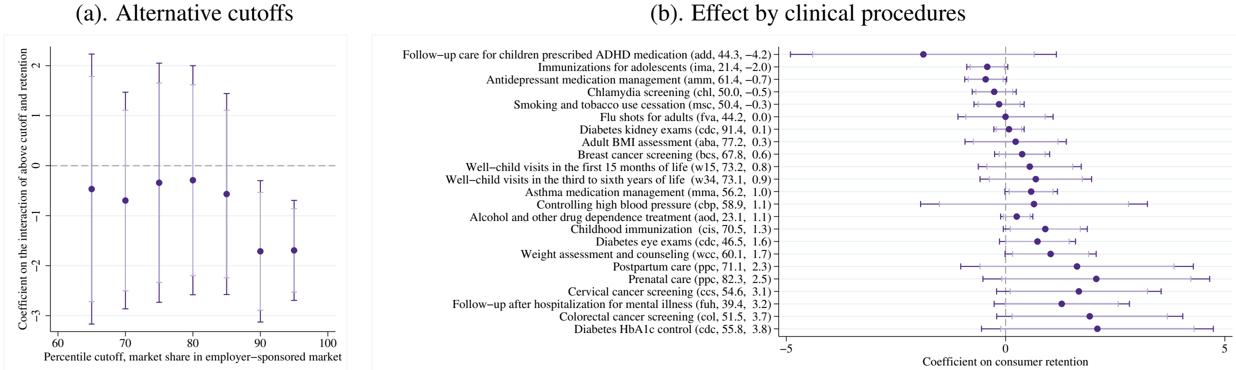
(a). Year 2017 (b). Year 2018 (c). Year 2019



Notes: Color blocks correspond to five quintiles of the instrument value across the state-year pairs. Data sources are the same as in Figure A2. AK, AR, MS, and TN do not report job hiring statistics during the sample period. The industry employment share is measured in 2014.

Figure A4. Effect of consumer turnover on procedure utilization, robustness

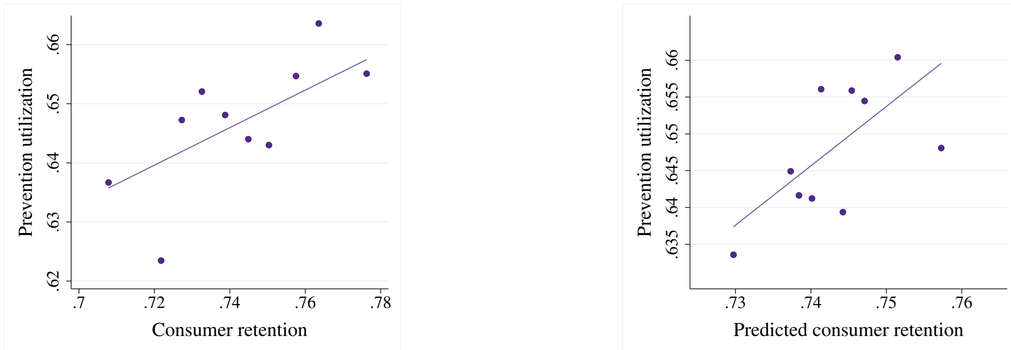
(a). Alternative cutoffs (b). Effect by clinical procedures



Notes: This figure reports the robustness of mechanisms tests in shift-share regressions. Panel (a) reports the estimation of an augmented version of equations (4) and (5), 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 (4) and (5) 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 (dark) bars plot 90% (95%) confidence intervals The regression specification and sample are the same as in Table 4.

Figure A5. Correlation between consumer retention and preventive care utilization

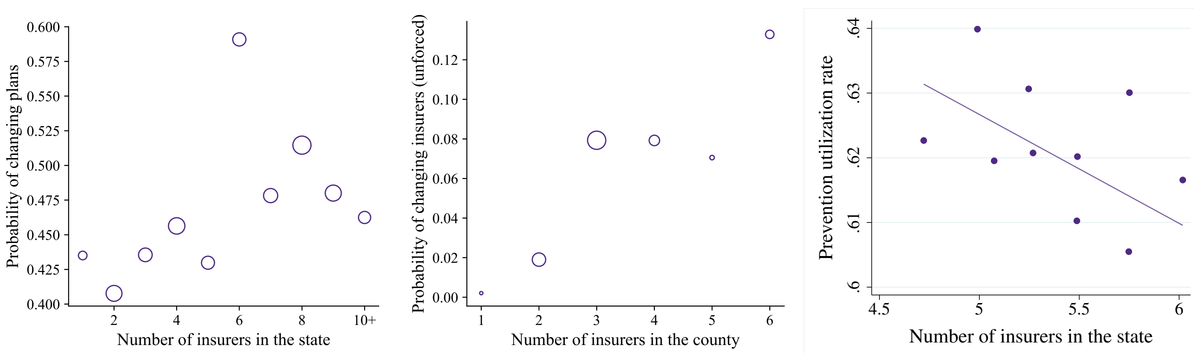
(a). OLS: retention and utilization (b). 2SLS: predicted retention and utilization



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 (4)).

Figure A6. Correlation between competition, turnover and prevention utilization on the exchange

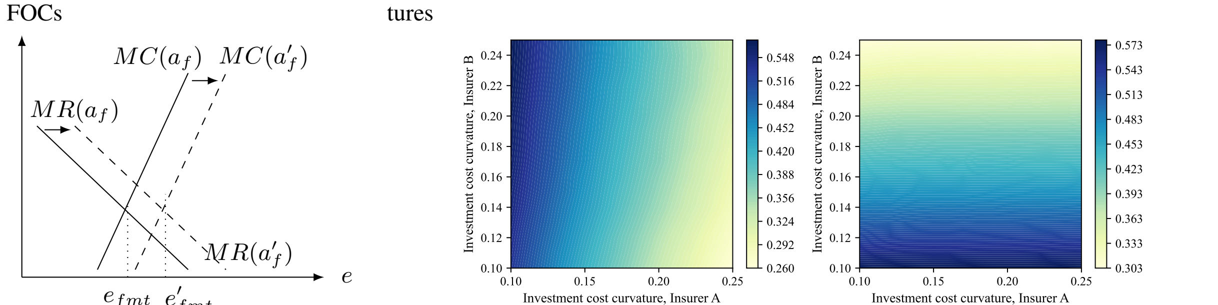
(a). Turnover, nationwide (b). Turnover, UT (c). Utilization, nationwide



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.

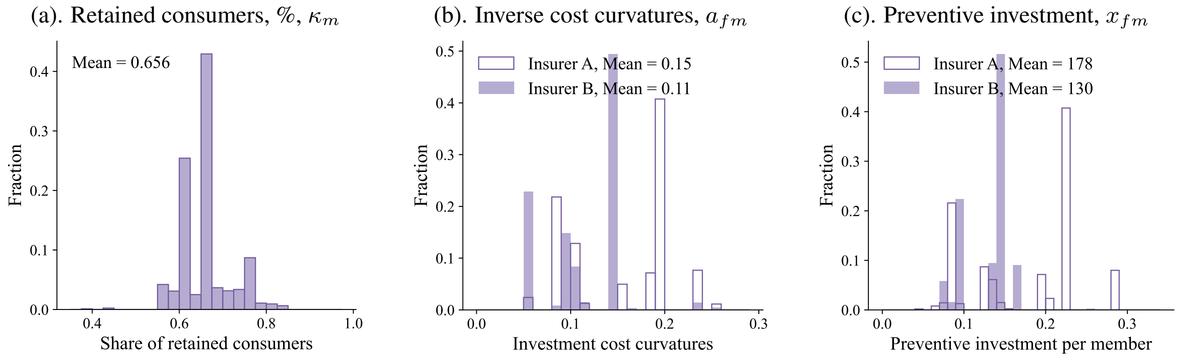
Figure A7. Illustration of investment cost curvature identification

(a). Decompose prevention utilization FOCs (b). Simulated prevention utilization strategies under alternative investment cost curvatures



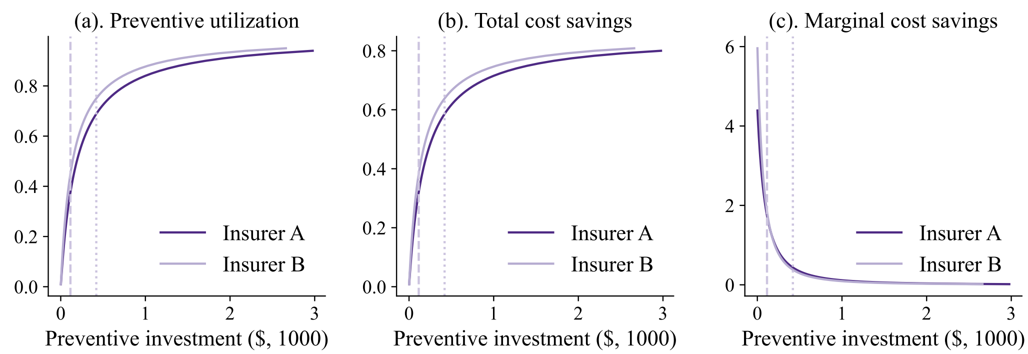
Notes: Panel (a) corresponds to decomposing the left-hand side (marginal cost curves) and right-hand side (marginal revenue curves) of equation (21). The solid lines are marginal revenue and costs under parameter a_f, and the dashed lines are under a'_f, where $a'_f < a_f$. Panel (b) plots simulated 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 A8. Distribution of market-specific estimates and derived statistics



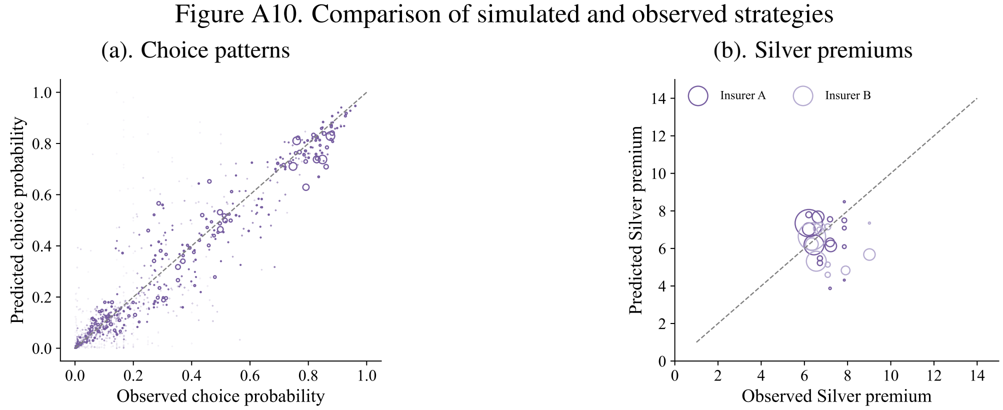
Notes: These figures plot the distribution of county(-insurer)-specific statistics, including estimates of the share of retained consumers in panel (a), estimates of investment cost curvature in panel (b), derived statistics of preventive investment per enrollee at observed equilibrium in panel (c).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

Figure A9. 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 (7) and/or (13). The returns calculation assumes full consumer retention. The dashed (dotted) line denotes utilization/investment levels at the status quo (Medicare market).

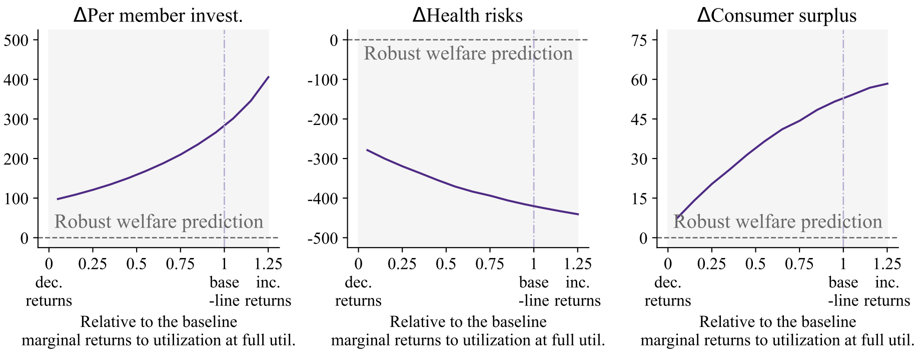
Figure A10. Comparison of simulated and observed strategies



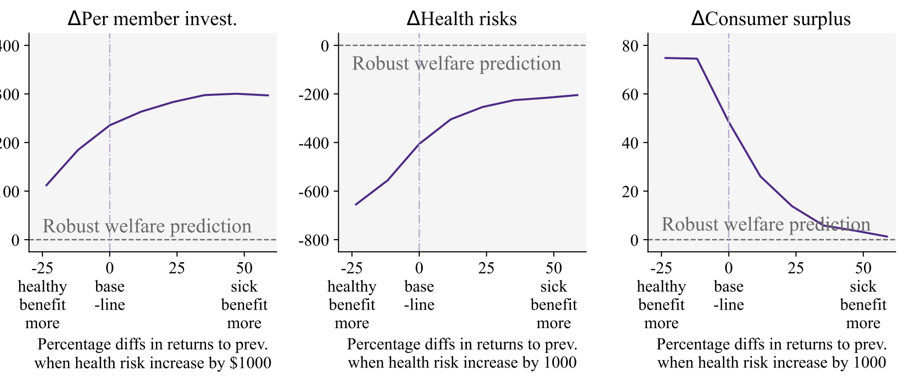
Notes: Panel (a) compares observed and predicted choice patterns for consumers with different previous period insurer choices. The estimation procedure only matches the aggregate market share that combines all consumer types in a given market. Panel (b) compares observed and simulated Silver premiums, which make premium FOCs hold under model estimates and observed state variables. 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.

Figure A11. Equilibrium strategies and welfare, sensitivity to health transitions

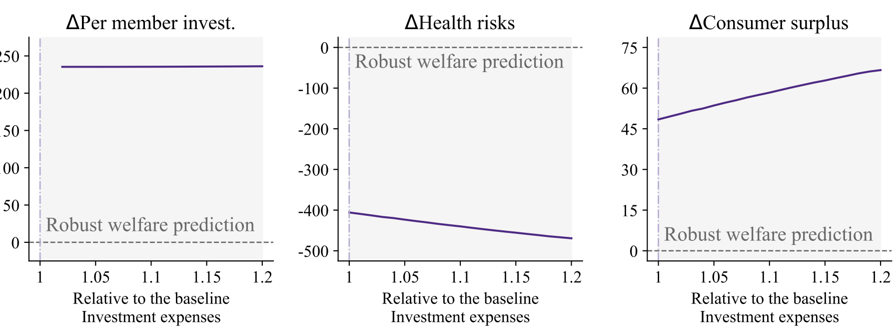
(a). Increasing or decreasing returns to utilization



(b). Differential returns by health status



(c). Magnitude of investment expenses



Notes: This figure reports simulated changes in preventive investment per member (left column), health risk (middle column), and consumer surplus (right column) from the baseline asymmetric duopoly equilibrium to monopoly equilibrium. All statistics are the mean of each equilibrium object in the stationary distribution. The vertical dash-dot line denotes the baseline specification. Panel (a) reports sensitivity to increasing or decreasing returns to utilization. I add $q_2 e_{fmt}^2$ term to equation (7). I set arbitrary values of q_1, q_2 such that the modified health transition has the same returns to prevention at zero and full utilization, but differential returns and marginal returns in between. The baseline scenario has linear health transition and constant returns to utilization ($q_2 = 0$). Concave (convex) health transitions have diminishing (increasing) returns to utilization, such that at full utilization, the marginal returns are close to zero (more than the baseline). Panel (b) reports sensitivity to differential returns by health. I add the $q_2 e_{fmt} \tilde{\mu}_{fmt-1}$ term to equation (7). I set arbitrary values of q_2 such that the modified health transition has the same returns to prevention at the maximum of the health risk grid. The baseline scenario has homogenous returns by health ($q_2 = 0$). When sick (healthy) consumers benefit more from prevention investment, the percentage difference between returns to prevention when health risk increases is positive (negative). Panel (c) reports sensitivity to investment expenses by inflating the investment cost functions with a cost adjustment scalar. The welfare prediction at the baseline is that removing a competitor could increase preventive investment, improve health, and leave consumers almost indifferent. The shaded area denotes the parameter space with robust welfare prediction.

A2. Preventive Care Utilization Across Markets and Countries

This section uses two correlational tests to provide some proof of concept evidence that if consumer turnover for insurers is eliminated, the prevalence of preventive care may increase.

First, I compare prevention utilization between the US and other countries with single-payer health systems in Table A11. The US has similar cancer prevention utilization but worse chronic disease management than other single-payer countries. Second, I compare preventive care utilization and consumer turnover in the U.S. across different insurance market segments in Table A12, A13. Market segments with lower consumer turnover have higher preventive care prevalence. Although these cross-sectional comparisons may reflect other institutional differences, the differences in preventive care prevalence and its correlation with consumer turnover do not reject the hypothesis that consumer turnover discourages prevention provision.

Table A11. 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. Utilization rates are measured in 0-100 percentage points. The cancer screening utilization rates are in 2018, except for Canada in 2017; and are taken from the 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 the 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 the CDC in the US, to promote cancer screening utilization.

Table A12. 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	86.7	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: Utilization rates are measured in 0-100 percentage points. 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. Consumer turnover across market segments is reported in Table A13.

Table A13. 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: Consumer retention rates are measured in 0-100 percentage points. 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.

B. A Stylized Framework to Illustrate Frictions

This section offers a stylized framework to illustrate frictions that drive prevention underutilization. I start from a neoclassical case of rational consumers choosing prevention without insurance in Section B1. I show how classical demand-side frictions, such as ex-ante moral hazard and behavioral biases, lead consumers to invest less in prevention compared to the neoclassical scenario. Next, taking demand-side behaviors as given, I add the supply side and highlight innovations of this paper in contrast to existing studies in Section B2. I show how insurers' investment strategies affect consumers and how a single competitively priced insurer compares to a social planner on investment. This analysis underscores the insight that when the

demand side cannot make optimal choices for their health, providing dynamic incentives to the supply side to maintain population health can be effective. Finally, I discuss the supply-side friction shown in this paper, i.e., investment externalities lower insurers' investment in Section B3.

B1. Classical Demand-side Frictions.

Consider a consumer with concave utility function $u(.)$ and discounting parameter β_c in a two-period model. In the second period, the consumer faces a lottery between two health states, being healthy H with probability μ, or falling ill L with probability $1-\mu$. Without loss of generosity, assume the consumer is in a certainty state W in the first period. All states H, L, W are measured in monetary terms as consumption available to the consumer; $H > L$. The consumer can invest in prevention x_c, which reduces both the consumption available to him in the first period and the probability that he falls ill in the next period. The return to consumers' prevention investment is concave: $\mu'(x_c) > 0, \mu''(x_c) < 0$.

The consumer maximizes his expected utility as follows

$$\max_{x_c} \Big\{ u(W - x_c) + \beta_c \big(\mu(x_c) u(H) + (1 - \mu(x_c)) u(L) \big) \Big\}.$$

The first-order condition (FOC) is

$$[x_c] \quad \underbrace{u'(W - x_c)}_{\text{marginal cost}} = \underbrace{\beta_c \mu'(x_c)(u(H) - u(L))}_{\text{marginal benefit}}.$$

The consumer chooses the amount of prevention such that the first-period utility losses from less consumption (marginal cost of prevention) are equivalent to the second-period utility gains of not falling ill (marginal benefit of prevention).

Ex-ante Moral Hazard. We consider a scenario where the consumer can purchase insurance with coverage I_t at a price p_t ($p_t \leq I_t$), where t denotes the period. I_t is set exogenously, similar to the standardized cost-sharing schemes as in the exchange market, and does not depend on the consumer's health status.

With insurance, the healthy state is $\tilde{H} = H - p_2$, and the sick state is $\tilde{L} = L + I_2 - p_2$. To make the consumer willing to purchase insurance, p_2 is set such that the expected utility with insurance is higher than without insurance: $\mu(x_c)u(\tilde{H}) + (1 - \mu(x_c))u(\tilde{L}) > \mu(x_c)u(H) + (1 - \mu(x_c))u(L)$. In the first period, due to the certainty state, $I_1 = 0$, $p_1 = 0$. We assume the consumer purchases insurance when he is indifferent between purchasing or not.

The consumer's maximization problem and FOCs of preventive investment are:

$$\max_{x_c} \Big\{ u(W - x_c) + \beta_c \big(\mu(x_c) u(\tilde{H}) + (1 - \mu(x_c)) u(\tilde{L}) \big) \Big\}. \tag{A1}$$

$$[x_c] \quad \underbrace{u'(W - x_c)}_{\text{marginal cost}} = \underbrace{\beta_c \mu'(x_c)(u(\tilde{H}) - u(\tilde{L}))}_{\text{marginal benefit}}. \tag{A2}$$

We now analyze how insurance coverage I_2 affects consumers' prevention choices. Taking the derivative of equation (A2) with respect to I_2, we get

$$-u''(W - x_c)\frac{dx_c}{dI_2} = \beta_c \mu''(x_c)\frac{dx_c}{dI}(u(\tilde{H}) - u(\tilde{L})) - \beta_c \mu'(x_c) u'(\tilde{L})$$

Rearranging the equation,

$$\frac{dx_c}{dI_2} = \frac{\beta_c \mu'(x_c) u'(\tilde{L})}{u''(W - x_c) + \beta_c \mu''(x_c)(u(\tilde{H}) - u(\tilde{L}))} < 0. \tag{A3}$$

Gaining access to insurance to deal with a possible sick state reduces the consumers' investment in prevention. This is the ex-ante moral hazard channel discussed in Ehrlich and Becker (1972).

The intuition can be directly seen from equation (A2). Access to insurance decreases the utility difference between the healthy state and the unhealthy state, i.e., $u(\tilde{H}) - u(\tilde{L}) < u(H) - u(L)$. Compared to the without insurance scenario, access to insurance reduces the returns of consumers' preventive investment. Consequently, consumers invest in prevention less when having insurance.

Behavioral Biases. We analyze how the consumer's behavioral biases affect his preventive investment. Existing papers have shown that consumers' self-control problems (Bai et al., 2021), behavioral hazard (Baicker et al., 2015) or undervaluing prevention (Bauer et al., 2022) make them behave myopic, i.e., discount future utility to a large extent. Without loss of generosity, we analyze how β_c affects x_c.

We study the case where consumers have access to insurance, as the neoclassical no insurance scenario is a special case with $I = 0$ and $p(I) = 0$. Totally differentiate equation (A1), we get

$$\frac{dx_c}{d\beta_c} = \frac{\mu'(x_c)(u(\tilde{H}) - u(\tilde{L}))}{\beta_c \mu''(x_c)(u(\tilde{H}) - u(\tilde{L})) + u''(W - x_c)} > 0. \tag{A4}$$

This is as expected: The more weight the consumer puts on future utility, the higher utility gains from a marginal unit of investment will be, and the more the consumer will invest in the current period.

We can also analyze how the extent of ex-ante moral hazard varies with consumer myopia. Differentiate equation A3 with respect to β_c, it is easy to see that

$$\frac{d^2 x_c}{dI_2 d\beta_c} = \frac{\mu'(x_c) u'(\tilde{L}) u''(W - x_c)}{(u''(W - x_c) + \beta_c \mu''(x_c)(u(\tilde{H}) - u(\tilde{L})))^2} < 0. \tag{A5}$$

As the consumer discounts future utility more, he receives less utility gains of smoothing across healthy and unhealthy states. Thus, the generosity of insurance coverage affects the consumers' optimal investment decisions less when the consumers become more myopic.

In the extreme case of complete myopic $\beta_c = 0$, the consumer will not make any preventive investment; the friction of ex-ante moral hazard goes away.

$$\beta_c = 0, \Rightarrow \; x_c = 0, \quad \frac{dx_c}{dI_2} = 0. \tag{A6}$$

B2. Adding the Supply Side.

One contribution of this paper is to recognize the role of insurers (the supply side) in determining prevention utilization. Section 2.3 shows that insurers could improve prevention utilization by reminding and educating the consumer or incentivizing providers to prescribe preventive care. Section 3.1 shows that consumers who move to insurers with a 1 percentage point (pp) higher prevention utilization rate increase their likelihood of using prevention by 0.9pp after insurer changes.

Mapping this to the stylized framework, the probability of consumers falling sick is a function of *both* insurer investment x_i and consumer investment x_c in the first period, $\mu(.) = \mu(x_i, x_c)$. The return to

prevention investment is concave: $\partial\mu/\partial x_i > 0$, $\partial\mu/\partial x_c > 0$, $\partial^2\mu/\partial x_i^2 < 0$, $\partial^2\mu/\partial x_c^2 < 0$, $\partial^2\mu/\partial x_i\partial x_c < 0$. Without loss of generosity, we consider the case where the insurer only makes preventive investment in the first period, the same as the consumer.

We start from the simple case where insurance coverage I_t and price p_t are exogenously determined. Due to the certainty state, $I_1 = 0, p_1 \geq 0$. In the first period, the insurer chooses preventive investment x_i as a product characteristic. The consumer chooses whether to buy the insurance contract (I_1, x_i, p_1) and then decide on their own preventive investment x_c. In the second period, consumers decide whether to buy the insurance contract (I_2, p_2), $p_2 \leq I_2$. The consumer's optimization decision is set up the same as in equation (A1), except that μ is a function of both x_i, x_c.

To make consumers willing to purchase insurance, p_t is set such that the expected utility with insurance is higher than without. Let $\tilde{H} = H - p_2$ and $\tilde{L} = L + I_2 - p_2$ denote healthy and sick state after insurance. p_2 satisfies:

$$\mu(x_i, x_c)u(\tilde{H}) + (1 - \mu(x_i, x_c))u(\tilde{L}) > \mu(x_i, x_c)u(H) + (1 - \mu(x_i, x_c))u(L).$$

Let $EU(x_i, x_c) = \mu(x_i, x_c)u(\tilde{H}) + (1 - \mu(x_i, x_c))u(\tilde{L})$ denote expected utility in the second period, p_1 satisfies

$$u(W - p_1 - x_c^*) + \beta_c EU(x_i, x_c^*) > u(W - x_c') + \beta_c EU(x_i, x_c').$$

where x_c^*, x_c' are consumers' optimal investment when with and without insurance in the first period. x_c^*, x_c' satisfy the following FOC:

$$u'(W - p_1 - x_c^*) = \beta_c \frac{\partial\mu}{\partial x_c^*}(u(\tilde{H}) - u(\tilde{L})). \tag{A7}$$

$$u'(W - x_c') = \beta_c \frac{\partial\mu}{\partial x_c'}(u(\tilde{H}) - u(\tilde{L})). \tag{A8}$$

How Insurance Affects the Consumer's Strategies. We analyze how insurance affects consumers' behaviors in three aspects. First, how access to insurance in the *second* period affects first-period investment x_c. Second, how access to insurance in the *first* period affects first-period investment x_c. Third, how the insurer's investment x_i in the first period affects the consumer's first-period investment x_c.

To answer the first question, we use the tricks in Section B1. Differentiate the first order conditions with respect to I_2, it is easy to see that

$$\frac{dx_c^*}{dI_2} = \frac{\beta_c \frac{\partial\mu}{\partial x_c^*} u'(\tilde{L})}{u''(W - p_1 - x_c^*) + \beta_c \frac{\partial^2\mu}{\partial(x_c^*)^2}(u(\tilde{H}) - u(\tilde{L}))} < 0, \tag{A9}$$

$$\frac{dx_c'}{dI_2} = \frac{\beta_c \frac{\partial\mu}{\partial x_c'} u'(\tilde{L})}{u''(W - x_c') + \beta_c \frac{\partial^2\mu}{\partial(x_c')^2}(u(\tilde{H}) - u(\tilde{L}))} < 0. \tag{A10}$$

The intuition is the same as in the previous case: access to insurance decreases the utility difference between the healthy state and the unhealthy state, thus lowering the returns of consumers' preventive investment. Consumers invest in prevention less when being able to insure against the sick state, consistent with ex-ante moral hazard.

Second, to see how x_c^*, x_c' compare with each other, we take the derivative of equation (A7) with respect to p_1:

$$\frac{dx_c^*}{dp_1} = -1 - \beta_c \frac{\partial^2 \mu / \partial (x_c^*)^2}{u''(W - x_c^* - p_1)} (u(\tilde{H}) - u(\tilde{L})) < 0. \tag{A11}$$

Intuitively, when the insurance product becomes more expensive, less consumption is available to the consumer in the first period. The reduction in marginal utility from making preventive investments becomes higher, and the consumer invests less in prevention.

Note that equation (A8) is a special case of equation (A7) when $p_1 = 0$. This implies

$$x_c' > x_c^*,$$

the consumer invests more in prevention when he does not have access to insurance in the *first* period. This is caused by the consumers' intertemporal consumption-smoothing considerations.

Finally, to analyze how the insurer's investment x_i interacts with the consumer's investment x_c, we differentiate the first-order conditions with respect to x_i:

$$\frac{dx_c^*}{dx_i} = -\beta_c \frac{\partial^2 \mu / \partial x_c^* \partial x_i}{u''(W - p_1 - x_c^*)} (u(\tilde{H}) - u(\tilde{L})). \tag{A12}$$

The sign of $\frac{dx_c^*}{dx_i}$ is the same as the cross derivative $\frac{\partial^2 \mu}{\partial x_c \partial x_i}$, i.e., the subsitutablity between x_c and x_i. If the insurer's and the consumers' investments are substitutes, $\frac{\partial^2 \mu}{\partial x_c' \partial x_i} < 0$, $\frac{dx_c^*}{dx_i} < 0$: the consumer invests less as the insurer invests more. When the insurer's and the consumers' investments are complements, $\frac{\partial^2 \mu}{\partial x_c \partial x_i} > 0$, $\frac{dx_c^*}{dx_i} > 0$: the consumer invests more as the insurer invests more.

Taking together the effect of I_2, p_1, x_i, it is likely that the consumers' self-directed investment x_c in the presence of an investing insurer is less than that of a neoclassical consumer in Section B1, due to ex-ante moral hazard, consumption smoothing, and the substitutability between the insurer's and the consumer's prevention effort. The consumption smoothing channel dominates when the consumer is very myopic: as $\beta_c \to 0$, equations (A9), (A10), (A11) and (A12) becomes:

$$\frac{dx_c^*}{dI_2} \to 0, \quad \frac{dx_c'}{dI_2} \to 0, \quad \frac{dx_c^*}{dp_1} \to -1, \quad \frac{dx_c^*}{dx_i} \to 0.$$

A Single Insurer's Strategies. Let β_i denote the insurers' discounting parameter. Let $\tilde{\mu}(x_i) = \mu(x_i, x_c(x_i))$.

$$\tilde{\mu}'(x_i) = \frac{\partial \mu}{\partial x_i} + \frac{\partial \mu}{\partial x_c}\frac{dx_c}{dx_i} > 0, \quad \tilde{\mu}''(x_i) = \frac{\partial^2 \mu}{\partial x_i^2} + \frac{\partial^2 \mu}{\partial x_c^2}(\frac{dx_c}{dx_i})^2 + \frac{\partial \mu}{\partial x_c}\frac{d^2 x_c}{d^2 x_i} < 0,$$

after internalizing the equilibrium response $\frac{dx_c}{dx_i}$ that product characteristics x_i affect the consumers' investment decision, insurers' investment still increases the probability of the healthy state, and there is decreasing returns to scale in the returns to insurers' investment.

The insurer's maximization problem and FOCs of preventive investment are:

$$\max_{x_i} \left\{ p_1 - x_i + \beta_i \big(\tilde{\mu}(x_i) p_2 + (1 - \tilde{\mu}(x_i))(p_2 - I_2) \big) \right\}.$$

$$[x_i] \qquad \underbrace{1}_{\text{marginal cost}} = \underbrace{\beta_i \tilde{\mu}'(x_i) I_2}_{\text{marginal benefit}} \tag{A13}$$

Equation (A13) captures the intertemporal tradeoff: The insurer equalizes the static marginal cost of investment with the marginal benefit of making consumers healthy in the future to reduce claims expenses.

We compare the equilibrium effects of prevention with an investing insurer $\mu(x_i, x_c^*)$ to that of the neoclassical case without insurance $\mu(0, x_c)$ in Section B1. Depending on the curvature of the returns to prevention function $\mu(,)$, the direction is ambiguous as $x_i > 0, x_c^* < x_c$: adding the insurance contract with supply-side investment can either increase or decrease the probability of the healthy state, thus either benefit or harm population health.

However, if consumers suffer from a significant degree of behavioral biases, i.e., $\beta_c \to 0$, the demand-side preventive investment will be similar, $x_c^* \sim x_c \to 0$. The effect of supply-side investment dominates, and we have $\mu(x_i, x_c^*) > \mu(0, x_c)$: offering an insurance contract with the supply-side investment will improve the probability of the healthy state compared to the without insurance case, thus improve the population health. In other words, when the demand side cannot make optimal choices for their health, providing dynamic incentives to the supply side to maintain population health can be effective – this is exactly one of the insights this paper aims to deliver.

Compare the Single Insurer with a Planner. We now compare the insurers' investment decisions with the planner. The planner invests x_p to maximize the total social welfare

$$\max_{x_p} \left\{ \underbrace{p_1 - x_p + \beta_i\big(p_2 + (1-\tilde{\mu}(x_i))I_2\big)}_{\text{insurer profit}} + \underbrace{u(W - p_1 - x_c(x_p)) + \beta_c\big(\tilde{\mu}(x_i)u(\tilde{H}) + (1-\tilde{\mu}(x_i))u(\tilde{L})\big)}_{\text{consumer utility}} \right\}.$$

$$\begin{aligned} [x_p] \qquad & \underbrace{1}_{\text{static investment costs}} \quad \underbrace{-u'(W - p_1 - x_c)x_c'(x_p)}_{\text{static utility cost, less consumption}} \\ = \qquad & \underbrace{\beta_i\tilde{\mu}'(x_p)I_2}_{\text{future gains, reduced claims}} \quad + \quad \underbrace{\beta_c\tilde{\mu}'(x_p)(u(\tilde{H}) - u(\tilde{L}))}_{\text{future utility gains, being healthy}} \quad . \end{aligned} \tag{A14}$$

Comparing equations (A13), (A14), it is ambiguous how the single insurer's investment compares to the social planner; the direction depends on the curvature of returns to prevention $\mu(.)$ and the utility function $u(.)$.

Suppose the consumer is very myopic, such that his discounting parameter is tiny, $\beta_c \to 0$. In this case, the behavioral biases dominate the consumer's investment decision, and its response to insurer strategies is very small. From equation (A12), we see that $dx_c^*/dx_i \to 0$. The planners' FOC, equation (A14) becomes

$$[x_p] \qquad \underbrace{1}_{\text{static investment costs}} \quad = \quad \underbrace{\beta_i\tilde{\mu}'(x_p)I_2}_{\text{future gains, reduced claims}} \quad + \quad \underbrace{\beta_c\tilde{\mu}'(x_p)(u(\tilde{H}) - u(\tilde{L}))}_{\text{future utility gains, being healthy}} \quad . \tag{A15}$$

Comparing equations (A13) and (A15), we see that the planer invests more than the single insurer

$$x_p^* > x_i^*.$$

This is because the planner internalizes the utility gains of consumers being healthy, while the only investment benefit to the single insurer is reduced claims. In some sense, consumers are free-riding on insurers' costly investments.

B3. Adding Supply-side Frictions.

Another contribution of this paper is to quantify how the supply-side friction, investment externalities, affects insurers' dynamic strategies. As shown in Section 3.2, insurers reduce preventive investment when consumer turnover lowers the expected future returns of investment.

Mapping this to the stylized framework, we add another symmetric insurer k to the model. In the first period, only insurer j offers a contract and makes preventive investment x_i^j; while in the second period, both insurers offer a contract. To keep the analysis simple, we stick with the case of exogenously determined coverage I_t at price p_t for both insurers. p_t are set such that the consumer's expected utility with insurance is higher than without.

When choosing an insurer in the second period, the consumer draws independent and identically distributed random taste shocks, ϵ_j, ϵ_k, which follows a standard normal distribution. The consumer experiences a disutility η if he changes the insurer choice (Handel, 2013); $\eta > 0$. He chooses insurer j if

$$EU(x_i^j, x_c) + \epsilon_j > EU(x_i^j, x_c) - \eta + \epsilon_k.$$

The Consumer's Strategies. Given the insurer choice, the consumer's optimization decision is set up the same as in equation (A1), except that μ as a function of both x_i, x_c, and the expected utility is a weighted average between the scenarios of choosing j and k. The analysis in Section B2 on how insurance affects the consumer's investment still applies: the consumers' self-directed investment x_c in the presence of an investing insurer is less than that of a neoclassical consumer in Section B1, due to ex-ante moral hazard, consumption smoothing, and the substitutability between insurers' and consumers' prevention effort. The consumption smoothing channel dominates when the consumer is very myopic.

The Insurer's Strategies. Let ϕ denote the density function of the standard normal distribution. The probability that the consumer stays with the insurer j is

$$\Pr(\epsilon_j - \epsilon_k + \eta > 0) = \phi(\eta) < 1.$$

The insurer's maximization problem and FOCs of preventive investment are:

$$\max_{x_i^j} \left\{ p_1 - x_i^j + \beta_i \phi(\eta) \big(\tilde{\mu}(x_i^j) p_2 + (1 - \tilde{\mu}(x_i^j))(p_2 - I_2) \big) \right\}.$$

$$[x_i^j] \qquad \underbrace{1}_{\text{marginal cost}} = \underbrace{\beta_i \phi(\eta) \tilde{\mu}'(x_i^j) I_2}_{\text{marginal benefit}} \tag{A16}$$

Equation (A16) captures the intertemporal tradeoff: The insurer equalizes the static marginal cost of investment with the marginal benefit of making consumers healthy in the future to reduce claims expenses.

Comparing equations (A13) and (A16), we see that the marginal benefit term is now scaled by the consumers' retention probability $\phi(\eta)$. For the same amount of preventive investment, there now exists a possible investment leakage that insurer j's investment could help insurer k lower its second-period claims expenses. Given this externality, insurer j further lowers its optimal investment,

$$x_i^{j*} < x_i^* < x_p^*.$$

In other words, investment externalities amplify the underinvestment problem of preventive care.

We consider how consumer inertia η affects insurer j's investment. Taking the derivative of equation (A16) with respect to η, we get

$$\frac{dx_i^j}{d\eta} = \frac{\phi'(\eta)\tilde{\mu}'(x_i^j)}{\phi(\eta)\tilde{\mu}''(x_i^j)} > 0.$$

The intuition is simple: raising inertia increases the consumers' retention probability, thereby boosting the expected investment returns and preventive investment.

C. Additional Details on Setting

C1. 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).

C2. Returns to Preventive Care in Epidemiological and Medical Studies

This section reports the calibration of the returns to prevention parameters from epidemiological and medical studies.

Sample Restriction. I start the initial search by going through all articles from the search result of "[specific procedure] cost savings" in Google Scholar, where I input the name of each preventive care procedure in the bracket. Then, I restrict the sample to all studies that focus on the US population to address the concern that the returns to prevention may not generalize well across different populations.

I further restrict to studies that report returns to preventive care regarding the *gross* cost savings due to reduced procedure costs to treat adverse health events. These savings do not net out claims costs of preventive procedures and are consistent with the returns concept used in the structural model in Section 4.

I do not report articles that measure the prevention returns using quality-adjusted life years, which is commonly used in the public health literature but does not measure returns to prevention on a monetary basis. Researchers could convert the gains in quality-adjusted life-years into monetary values by multiplying that with estimates of the value of a statistical life. However, the resulting values capture the individuals' valuation of being alive from using preventive care, e.g., the gains in utility from living longer by monitoring chronic diseases early or detecting diseases early to treat them in early but not late stages. It does not capture the savings in medical costs of treating adverse health events, i.e., the cost savings modeled in Section 4. I thus do not use these articles in the calibration exercise.

As fewer medical studies report returns to prevention due to reduced procedure costs than those reporting returns to prevention in quality-adjusted life years, the total number of studies in the calibration exercise is relatively small. I report all studies that I could find for the calibration exercise. To address the concern that these medical estimates may not be precise or generalize well to the full population, I also benchmark these medical estimates using the economic estimates from my sample. These benchmarking exercises are discussed later in this section.

Calculation Method and Assumptions. Cost savings reported in the medical articles are usually total discounted cost savings throughout a patient's life span. The cost savings are generated by comparing the total projected medical expenses in the scenario of using and not using preventive care. I take this difference as the return to prevention between full preventive usage and no prevention usage.

There are two caveats to recovering this parameter of cost savings from preventive care utilization. First, the medical studies and epidemiological modeling do not report the projected expenses at partial (i.e., between zero and one) utilization within a population, so I can not recover returns to prevention at partial usage. Second, although the medical articles report their study population, they do not provide detailed demographics or health conditions, so I cannot recover returns to prevention by different population characteristics. I thus impose parametric assumptions about the returns to preventive care as a function of utilization percentage point utilization of preventive care and health conditions of the relevant population in the baseline model. I perform sensitivity analysis around that parametric function, i.e., allowing differential returns by utilization level or health risks, in Section 7.1.2.

With this interpretation, my targeted calibration output is the *annualized average gross cost savings at full prevention usage*. I calculate this statistic in the following steps. First, I convert all cost savings estimates to 2019 dollars to standardize this estimate across studies. Second, I convert total discounted cost savings estimates to annualized cost savings using the discount rates and year spans reported in each study. If the study reports the annualized cost-saving estimates per patient, I take those statistics directly. For articles that

report a range of possible cost-savings, I calculate the mean point for that range but also report that range in the calibration process. Third, I aggregate the estimates across different medical articles on the same preventive procedure by reporting the weighted average cost savings estimates per patient. As not all studies report the cost savings range and sample size, I cannot use the usual inverse-variance meta-analysis method to aggregate estimates from each study or impute a confidence interval for the calibrated estimates. I instead take a simple mean across studies but report the confidence interval and sample size whenever they are available. Recognizing that the lack of variance weighting may cause measurement error in the calibrated return parameter, I perform sensitivity analysis around the returns to prevention parameter in Section 7.1.2 to gauge whether the main welfare prediction is robust under alternative calibrated returns to prevention.

The previous three steps result in an estimate of cost savings per eligible patient for each preventive procedure. To convert it to a per-person measure, I calculate cost savings per person by multiplying cost savings per eligible patient and the share of eligible patients in the population. This calculation step implicitly assumes that the disease incidence in the general population is the same as the targeted enrollee population in my sample. This assumption could be violated with adverse selection; for example, consumers with certain chronic diseases prefer insurers that manage that particular disease well so that the disease incidence among relevant enrollees is higher than the general population, making my calibrated cost savings per person a lower bound of the true returns. To address this issue, I perform sensitivity analysis around the returns per person parameter in Section 7.1.2.

Finally, I aggregate returns across preventive procedures listed in Figure 1 to get the *annualized average gross* cost savings of full prevention usage, compared to the no utilization scenario.

Table A14 reports the returns to tertiary prevention, i.e., chronic disease management. I describe diabetic nephropathy and glycemic control as examples of how I calibrate the targeted cost savings output. As shown in the first row, Klonoff and Schwartz (2000) is a meta-analysis reporting the future cost savings on reduced adverse health events or intensive treatment for end-stage renal disease for the usage of diabetes nephropathy care in the current year. For type 1 diabetes patients, over a time span of 31 years, the net present value of total savings, in 1994 dollars, is \$126,800 using a discount factor of 0.95. For type 2 diabetes patients, over a time span of 12 years, the net present value of total savings, in 1994 dollars, is \$57,520 using a discount factor of 0.95. I first convert these two numbers into the annual cost savings per patient in 2019 dollars. I amortize the total savings each year, which gives an annualized cost savings of $42,500/(\frac{1-0.95^{31}}{1-0.95})$. Converting this to the 2019 dollars gives an annualized cost savings per type 1 diabetes patient of $\left(42,500/(\frac{1-0.95^{31}}{1-0.95})\right) \times 1.97 = \$5,258$. Similarly, the annualized cost savings for type 2 diabetes patients is $\left(\$9,900/(\frac{1-0.95^{12}}{1-0.95})\right) \times 1.97 = \$2,140$. I convert this per-patient measure to the per-person measure using the disease incidence reported by CDC: the average cost savings per person is $\$5,258 \times 0.0045 + \$2,140 \times 0.0845 = \$205$.

Turning to diabetes glycemic control, Wagner et al. (2001); Nundy et al. (2014) are two case studies that report the annualized cost savings per diabetic patient due to reduced probability of diabetic complications and reduced medical treatments. Since the statistics reported are already annualized, I only need to convert them into 2019 dollars. This gives an estimated savings of \$1,247 to \$1,729 (Wagner et al., 2001), and \$2,947 (Nundy et al., 2014). As these studies do not differentiate between type 1 and type 2 diabetes, I

assume the returns reported are the same for diabetes patients in each type. Multiplying these numbers with the disease incidence, I get an estimate of $\$2,947 \times 0.089 = \$263$ cost savings per person from Nundy et al. (2014), and the range of $\$1,247 \times 0.089 = \$112$ to $\$1,726 \times 0.089 = \$173$ cost savings per person from (Wagner et al., 2001). I take the mean of the range reported in Wagner et al. (2001) and take the average of cost savings reported across these two studies. This gives an estimated annualized cost savings of $((112 + 117)/2 + 173)/2 = \$202$. The remainder rows in Table A14 are calculated similarly.

I calibrate the cost savings of cancer screenings and disease prevention following a similar procedure in Table A15, A16. However, as the returns may be realized longer for cancer screenings than chronic disease management, the studies on the returns to cancer screenings are more sparse. I employ an additional method to supplement medical studies, exploiting the statistics on cancer incidence decreases. Cervical and colorectal cancer screenings can find precancerous noncancerous tumors before they become invasive cancers (American Cancer Society, 2024; Eddy, 1990a,b), which lowers the disease incidence and treats the disease at an early stage with less intensive and less expensive treatment. I calculate the cost savings as the costs avoided from treating late-stage diseases.

This calculation method, which uses reductions in disease incidence, provides a lower bound of cost savings from cancer screenings. This is because screening can find precancerous and noncancerous tumors before they become invasive and detect and treat cancer in the early stages. Reductions in disease incidence only capture the former mechanism and do not account for the latter mechanism, where cost savings come from early-stage diseases costing less to treat than late-stage diseases. The latter cost savings from reduced adverse health events and intensive treatments are captured with the original calculation method using the total net present value from medical studies. I thus add up cost estimates from avoided diseases and cost estimates from avoided intensive treatment when they are both available.

I describe cervical cancer screenings as an example to illustrate this supplementary calibration method. As shown in the first row of the cervical cancer screenings panel, Table A15, Eddy (1990a) conducts a meta-analysis on decreases in invasive cervical cancer incidence from screening and also uses disease modeling to derive the same statistics. It finds that compared to the no-screening scenario, full utilization of cervical cancer screening could decrease the incidence of invasive cervical cancer by 22 per 1000 screened. The current national cancer care cost for cervical cancer is \$2.3 million (NCI, 2021c), and the estimated number of cervical cancer cases (in all cancer stages) is 295 thousand (NCI, 2021a). The annual average cost per cervical cancer patient is $\$2.3 \times 10^9/(295 \times 10^3) = \$7797$. The cost per screened woman saved from preventing precancerous noncancerous tumors from developing into cervical cancer is the reduction in disease incidence times the cost of treating the diseases, which is $\$7797 \times 22/1000 = \$172$. I then multiply the cost savings per screening by the percentage of women eligible for cervical cancer screening within the population, derived from demographic statistics in the ACS. This converts the estimates to cost savings per person, which is $\$172 \times 0.29 = \$50$. The calculation for colorectal cancer screenings is conducted similarly.

Comparing Calibrated Estimates to Model Estimates. I compare the magnitude of the calibrated estimates to those estimated in my sample with different reduced-form or structural techniques.

First, I compare the calibrated cost savings per patient to the reduced form estimates in Appendix D4, which uses a cross-insurer movers design to estimate the cost effect of moving to insurers with higher

prevention utilization. Table A18 reports the future cost savings effects of diabetes patients using glycemic control, which turns out to be around $1,961 per patient annually. This is encouragingly in line with the calibrated medical estimates reported in Table A14, with annual savings per patient ranging within $1,247 to $2,957. In addition, Table A18 displays that future cost savings of mammography for eligible women are more muted and not statistically significant. This is consistent with the calibrated estimates of Table A15, where the returns to mammography are close to zero.

Second, I aggregate the cost savings per person across preventive procedures of interest. I compare the calibrated total returns to two in-sample returns-to-prevention estimates. One is the insurer's perceived returns to prevention that rationalizes their investment responses to consumer turnover estimated in the shift-share exercise (see Section 3.2.5 and Appendix E3 for details). The calibrated returns to prevention are around a thousand dollars annually, which encouragingly falls into the range of back-of-envelope estimates, $443 to $4237, as shown in Table A19. Another is insurers' perceived returns to prevention that rationalize their observed investment strategies in the structural model (see Section 6.4 and Appendix F4 for details). Table A23 displays that the structural estimate of annual average cost savings is $979, which is reassuringly similar in magnitudes to the calibrated returns.

Table A14. Cost savings of disease management, from epidemiological and medical literature

Preventive procedure	Clinical health benefits	Citation	Study population and sample size	Study period	Total discounted savings, years span, discounted factor reported	Annual cost savings per patient reported	Annual cost savings per patient imputed, in 2019 dollars	Disease incidence for non-elderly individuals	Annual cost savings per person	Mean cost savings across studies
Diabetes nephropathy care	Reduce the probability of end-stage renal disease, kidney transplantation, dialysis (Klonoff and Schwartz, 2000)	Klonoff and Schwartz (2000)	Meta-analysis across 17 studies, N unavailable	1994	$42,500 for type 1 diabetes over 31 years; $9,990 for type 2 diabetes over 12 years; discount at 0.95	-	$5,258 for type 1 diabetes; $2,140 for type 2 diabetes	0.45%, 8.45% for type 1/2 diabetes (CDC, 2020b)	$205	$205
Diabetes glycemic control	Reduce the probability of vascular diseases (Wagner et al., 2001), thus reducing outpatient, emergency department, inpatient visits (Nundy et al., 2014)	Wagner et al. (2001)	Case study: diabetic patients aged 18 years or older, consistently enrolled in an HMO in western Washington State (N=4744)	1992-1997	-	$685-$950	$1,247-$1,729	8.9%(CDC, 2020b)	$112-$173	$202
		Nundy et al. (2014)	Case study, employees with diabetics in an academic medical center's employee health plan in Chicago (N=348)	2012-2023	-	$2,664	$2,957	8.9%(CDC, 2020b)	$263	$202
Diabetes retinopathy care	Prevent blindness (Javitt et al., 1994; Klonoff and Schwartz, 2000)	Javitt et al. (1994)	Disease modeling based on epidemiological studies and clinical trials, N unavailable	1994	-	$2,166	$4,105	8.9%(CDC, 2020b)	$349	$349
Statin therapy for cardio-vascular disease	Prevent adverse events, e.g., myocardial infractions (McConnachie et al., 2014)	Lazar et al. (2011)	Disease modelling for people over 35, N not available	2011	-	$82	$94	8% (Klimchak et al., 2020)	$8	$38
		Kazi et al. (2016)	Disease modelling for people over 35, N not available	2016	$3607 over 5 years, discount at 0.95	-	$853		$68	$38
Asthma medication	Prevent asthma exacerbation related ED visits and hospitalizations (Rust et al., 2015; De Keyser et al., 2020)	Herndon et al. (2012)	Case study, children aged 2–18 years diagnosed with asthma in Florida and Texas Medicaid (N=18,456)	2004-2007	-	$71	$96	13.4% (CDC, 2020a)	$13	$31
		Rust et al. (2015)	Case study, children aged 5-12 years diagnosed with asthma in 14 southern states (N=239,167)	2007	-	$300	$369	13.4% (CDC, 2020a)	$49	$31

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.

Table A15. Cost savings of cancer screenings, from epidemiological and medical literature

Preventive procedure	Clinical health benefits	Citation	Study population and sample size	Study period	Total discounted savings, years span, discounted factor reported	Annual cost savings per screened reported	Decrease in cancer incidence	National cancer care costs	Total cancer cases	Annual cost savings per screened, imputed, in 2019 dollars	Annual cost savings per person, imputed, in 2019 dollars	Mean cost savings across studies
Colorectal Cancer Screenings	Find precancerous noncancerous tumors before they become invasive cancers (Eddy, 1990b); Detect disease in early stage	Eddy (1990b)	Meta-analysis and disease modelling, N not applicable	-			37 per 1000 screened	$24.3 billions (NCI, 2021c)	1,932 thousands (NCI, 2021a)	$465	$135	$151
		Knudsen et al. (2021)	Meta-analysis and disease modelling, N not applicable	-			47 per 1000 screened	$24.3 billions (NCI, 2021c)	1,932 thousands (NCI, 2021b)	$591	$171	$151
		Loeve et al. (2000)	Disease modeling, N not applicable	1993	$3685 in 25 years, discount at 0.97	-				$367	$106	$102
		Lansdorp-Vogelaar et al. (2009)	Disease modeling, N not applicable	2009	$4821 to $6659 in 30 years, discount at 0.97	-				$287 to $396	$98	$102
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)	Eddy (1990a)	Meta-analysis and disease modelling, N not applicable	-			22 per 1000 screened	$2.3 billions (NCI, 2021c)	259 thousands (NCI, 2021a)	$172	$50	$50
Breast Cancer Screenings	Detect diseases in early stage, which costs relatively less to treat (Salzmann et al., 1997)	Greenwood and Henritze (1996)	Case study, a company in Colorado (N=10,600)	1985-1993	-	$37				$60	$9	$9

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 estimate 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 A16. Cost savings of disease prevention, from epidemiological and medical literature

Preventive procedure	Clinical health benefits	Citation	Study population and sample size	Study period	Total discounted savings, years span, discounted factor reported	Annual cost savings per eligible reported	Annual cost savings per eligible imputed, in 2019 dollars	Disease incidence for non-elderly individuals	Annual cost savings per person	Mean cost savings across studies
Childhood immunizations	Prevent early death and diseases (Zhou et al., 2014)	Zhou et al. (2014)	Disease modelling, N not applicable	2009	$3168 in 80 years, discount at 0.97	-	$124	2.7%	$3.3	$3.8
Childhood immunizations	Prevent early death and diseases (Zhou et al., 2014)	Whitney et al. (2014)	Disease modelling, N not applicable	1994-2013	$4086 in 80 years, discount at 0.97	-	$160	2.7%	$4.3	$3.8
Influenza vaccines	Prevent influenza-related illness, hospitalizations, deaths (Lee et al., 2012)	Nichol (2001)	Disease modelling, N not applicable	2001	-	$13.36	$20	100%	$20	$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.

C3. Stylized Patterns on Cost Savings from Prevention

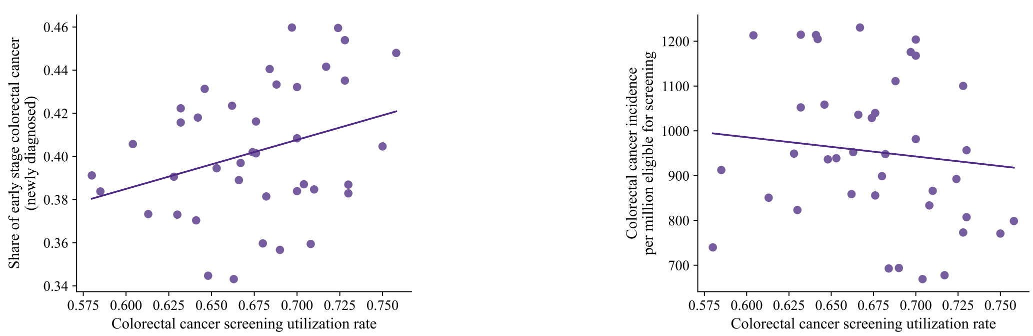
Future Cost Savings by Detecting Diseases Early. I show evidence consistent with the statement that preventive care detects diseases early, which costs less to treat (Blumen et al., 2016; Subramanian et al., 2010, 2011). The corresponding example is colorectal cancer screenings. The share of early-stage 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. 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 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 A12. 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. SEER reports data for 13 states: AK, CA, GA, HI, IA, KY, LA, MI, NJ, NM, UT, VT, WI. I exclude AK, MI, and WI from my analysis because they do not have complete listings for the entire state.

I first show suggestive patterns that cancer screenings detect diseases in early stage. Figure A12 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.

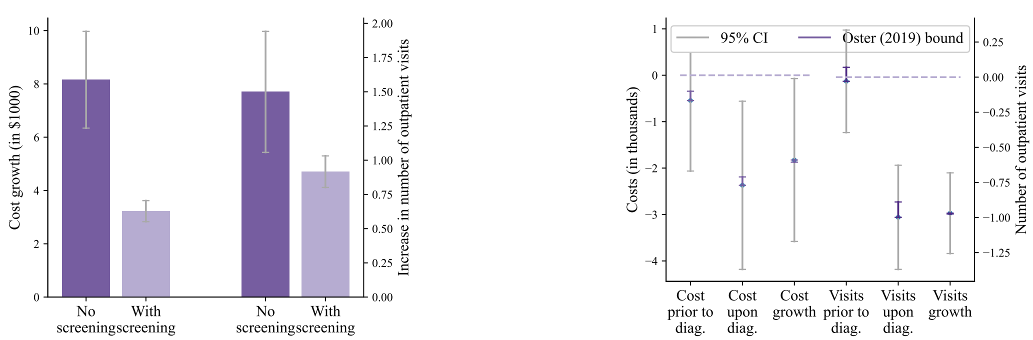
After controlling for state and year fixed effects, more screening utilization correlates with a higher share of early-stage cancers in newly diagnosed cases.

I then present suggestive patterns 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 A12 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 show suggestive evidence 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 A13. 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 A13 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 A13 panel (b) exhibits no statistically significant differences in costs or the number of visits before

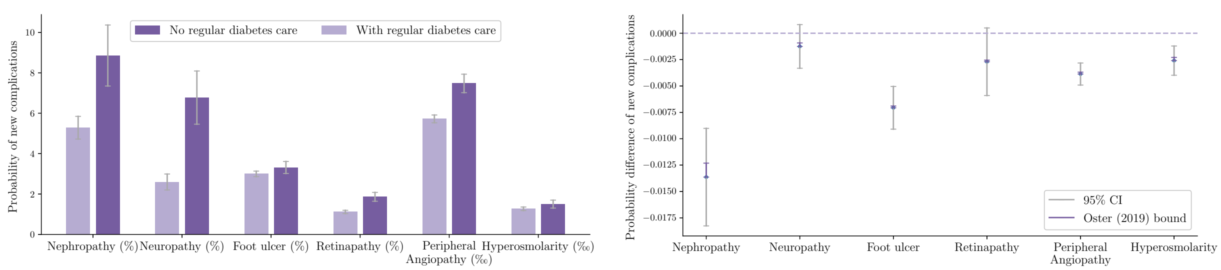
diagnosis between the with and without screenings groups. The differences in costs and the number of visits after diagnosis still hold after econometric corrections.

The abovementioned stylized facts are consistent with the statement 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. These findings indicate that screening tests bring cost savings via early detection of diseases.

Future Cost Savings by Slowing Dieases Progression. I show evidence consistent with 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 A14. Probability of developing diabetic complications by whether the patient with diabetes had recently utilized screening tests

(a). Raw data (b). Regression estimates

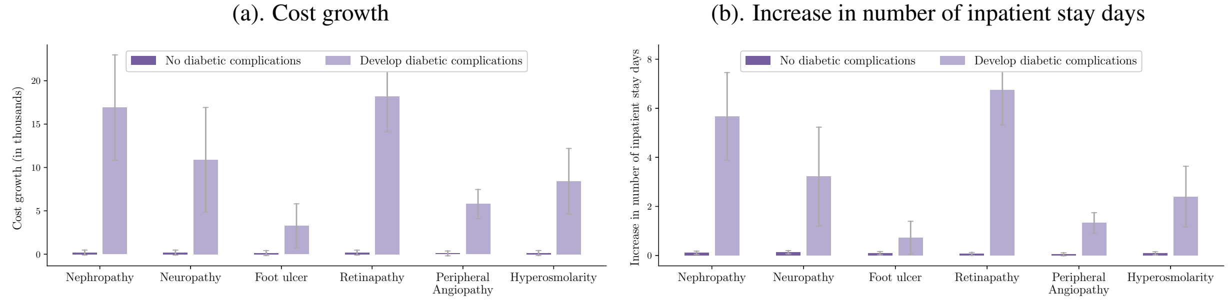


Notes: Panel (a) plots differences in probability of diabetic complications in the next year for diabetes patients who do not have these complications in the current year, by whether they have taken regular diabetes care in the current year. The gray bars are 95% confidence intervals. Panel (b) plots 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 showing stylized patterns where diabetic patients who utilize routine preventive care are less likely to develop diabetic complications than patients who do not. Figure A14 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 A14 panel (b).

I then present stylized patterns where 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 condition 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

Figure A15. Increase in costs and inpatient stays by whether the patient has developed diabetic complications



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.

A15. 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 present stylized patterns where 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 are consistent with the statement that diabetes care correlates with a lower probability of developing diabetic complications and that diabetic complications are expensive to treat. These findings indicate that diabetes care brings cost-savings via slowing down disease progression.

C4. Discussions: Selected Preventive Care Increases Future Profits

Reconciling Existing Literature. Not all preventive care saves money and lives. For example, mammograms for women aged 40-49 may be harmful due to overdiagnosis, while mammograms for women aged 50-74 could reduce mortality and bring net benefits (Kowalski, 2021, 2023). I thus focus on preventive care (in Figure 1) that is well-known to improve health and lower future expenses by reducing adverse health events compared to the no prevention scenario (CDC, 2021a; USPSTF, 2021).

A recent review article by (Newhouse, 2021) uses cancer screenings as an example to show the limited cost-effectiveness of some preventive procedures. He focuses on primary and secondary prevention, i.e., those avoiding disease onset or preventing the disease from developing beyond its early stages (as stated on Page 102), but not territory prevention, i.e., minimizing the progression of established diseases like chronic disease management. This aligns with the cost savings estimates in Section C2, that breast and cervical cancer screenings have smaller returns than diabetes management. Preventive procedures studied in this paper include all three categories of preventive care services: primary, secondary, and tertiary prevention.[1]

[1]As is defined by Kenkel (2000): primary preventive procedures, such as childhood vaccines, smoking cessation counseling, and weight loss programs, avoid disease onset. Secondary prevention prevents the disease from developing beyond its early stages and often depends on screening. For example, colorectal cancer screenings aim to detect precancerous tumors or the disease when it is more likely to be amenable to treatment. Tertiary prevention minimizes the progression and symptoms associated with established

Newhouse (2021) references Cohen et al. (2008). It summarizes the public health literature on the cost-effectiveness of preventive measures and finds that a modest amount (20% out of 1500 procedures) are cost-saving. Many cost-effective procedures are tertiary prevention, i.e., treatments for existing conditions, like treating/preventing heart diseases. Notably, vaccines and colorectal cancer screenings (selected in Figure 1) is cost-saving in primary and secondary prevention.

Newhouse (2021) also notes the difference between clinical and non-clinical preventive interventions: some preventive clinical procedures are cost-saving, while non-clinical interventions like workplace wellness programs usually do not (Jones et al., 2019; Song and Baicker, 2019). This paper studies increasing the usage of the former, clinical preventive care; not the latter, non-clinical interventions that emphasize nutrition, physical activity, stress reduction, and primary prevention.

Gross versus Net Savings. 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. In other words, the *gross* savings are non-zero; while there are no such requirement for *net* savings. Therefore, I present evidence that *selected* preventive care *reduces future costs*, and, *raises future profits* in the main text and in Section C2.

More Discussions. 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.

disease. Examples include the control of blood sugar levels in patients with diabetes to prevent damage to blood vessels and organs.

D. Robustness of Insurer Effects in Prevention Utilization

D1. Utilization Patterns Upon Insurer Switches Across Procedures.

Figure A16 plots mean utilization rates for each preventive procedure before and after insurer switches, for a balanced panel of stayers and switchers. I report in Figure A16 all procedures whose cell size is large enough to satisfy the reporting requirement, so not every procedure listed in Table A1 is plotted. The balanced panel nets out the effect of enrollee composition, which might contaminate the estimation of insurer effects. Notably, utilization rates for the balanced panel (in Figure A16) are in line with those calculated for all enrollees in an unbalanced panel (in Figure 1), reassuringly.

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. Two possible reasons explain these differences across clinical procedures. First, diabetes care has a relatively shorter return period than cancer screenings. For example, if diabetic conditions are not managed well, patients could end up in the emergency room in the next year and increase medical spending significantly. In comparison, the returns to cancer screenings can take place in a relatively longer time span. The returns to invest in chronic disease management can be larger than the returns to screenings in the short run. Thus, given consumer turnover, we might expect more considerable insurer investment and more significant insurer effects in those categories.

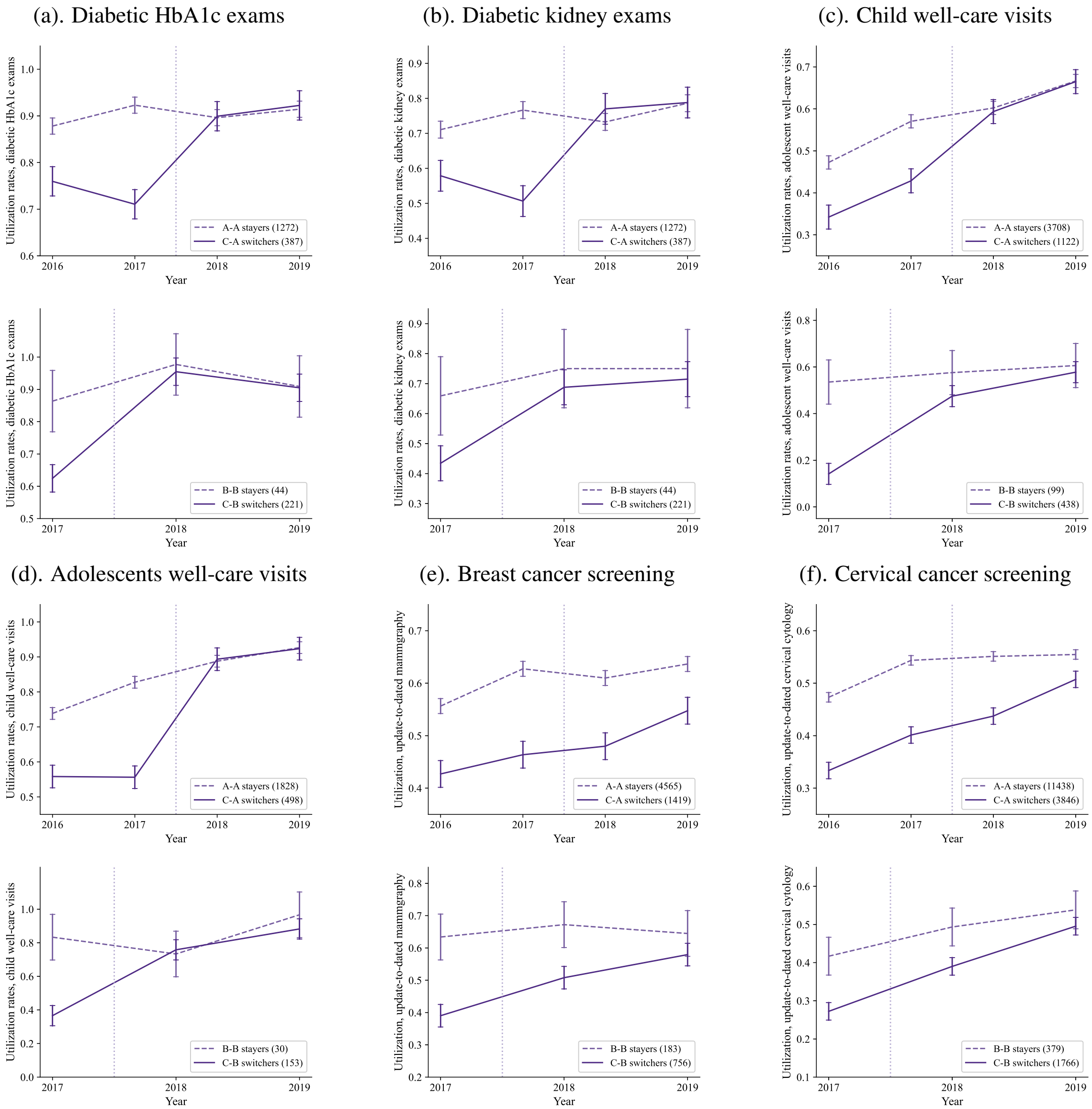
Second, mechanically, the utilization rates for cancer screenings are defined as up-to-date screening tests in the past several years. The utilization rate in the first year of the insurer switch reflects the combined effects of the destination insurer (in the first year of the switch) and origin insurer (in the years before the switch). In contrast, utilization rates for disease management are defined for a one-year window; thus, the post-period reflects only the effect of the destination insurer. We would expect the utilization rate for cancer screenings to converge over time between stayers and switchers post-insurer switch, reflecting the destination insurer gradually phasing in to increase consumers' screening utilization. This is indeed depicted in Figure A16 panels (e)-(f). Due to this measurement issue, results of chronic disease management, i.e., Figure A16 panels (a)-(b), better capture insurers' effect for prevention utilization.

D2. Potential Mechanisms of Insurer Effects.

Several pieces of suggestive evidence explain why Insurers A and B have higher prevention utilization than Insurer C. First, Insurers A and B spend 40% more on preventive investments than Insurer C, according to MLR reports. Second, Insurers A and B contract with a set of physicians who are more likely to prescribe preventive care than Insurer C. I calculate each physician's propensity to prescribe prevention using the averages across their eligible patients of all insurers in all market segments. Physicians in Insurer C's exchange network are, on average, about 15% less likely to prescribe preventive care than those in Insurer A and B's exchange networks. Notably, we do not observe Insurer A and B change their network much after Insurer C exits.

If all insurers have the same technology for translating dollar investments in preventive care into actual utilization, Insurers A and B will have higher utilization than Insurer C due to higher investments. It is also possible that Insurers A and B have better prevention incentivizing technology because of provider networks, such that for the same amount of dollar investment, they can obtain higher utilization rates. This paper

Figure A16. Preventive care utilization rate, pre- and post- insurer switch



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. Outcome data comes from UT APCD. Outcomes in panels (a)-(f) are diabetic HbA1c exams, diabetic kidney exams, child and adolescent well-care visits, and breast and cervical cancer screenings, separately. Procedures and eligible population (i.e., regression sample) are reported in Table A1. 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.

models insurers and physicians together as one united agent who incurs effort costs to provide prevention. Disentangling their separate effects for prevention utilization is an exciting avenue for future research.

D3. Robustness of Primary Estimates.

Analogous DID Estimates of Insurer Effects. Table A17 reports analogous point estimates in differences-in-differences estimation for equation (1).

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 0.87 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 one-to-one 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.

Table A17. Effect of insurer-specific preventive care utilization rate on consumers' preventive care usage

	Utilization Probability	
	HbA1c monitoring (1)	Mammography (2)
(a) Post insurer switches		
$\delta_i \times Post$	0.986***	0.725***
	(0.022)	(0.025)
(b) Post insurer switches: Year 0, 1-2, 3+		
$\delta_i \times Post_0$	0.874***	0.190***
	(0.023)	(0.016)
$\delta_i \times Post_{1-2}$	1.015***	0.955***
	(0.022)	(0.024)
$\delta_i \times Post_{3+}$	1.058***	0.967***
	(0.022)	(0.031)
Observations	231,363	226,248

Notes: This table reports the effect of insurer-specific preventive care utilization rate on consumers' preventive care usage. The regression controls for relative year fixed effects, individual fixed effects, calendar year fixed effects, and five-year age groups fixed effects. The regression sample includes consumers who stayed with the same insurer or changed insurers once during 2011-2019. Column (1) further restricts the analysis sample to consumers with diabetes. Column (2) further restricts the analysis sample to female consumers aged 51-68 in 2011. Standard errors are clustered at the county level. *,** ,*** denote statistical significance at the 10%, 5%, and 1% level, respectively. Outcome data comes from NH APCD.

Balanced Event Window. I show that event studies look similar when estimated using balanced event windows. To resolve the problem that insurer changes cohorts used to identify θ_s are not the same in equation

(1), I estimate an augmented event study regression,

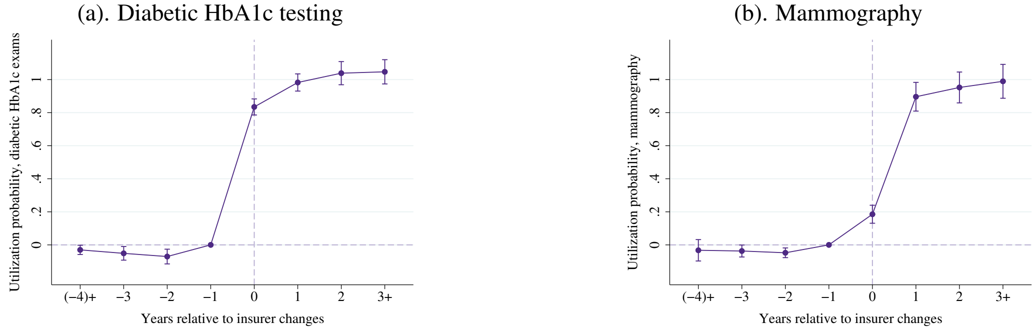
$$y_{it} = \alpha_i + \tau_t + \sum_{s=\{-4(+),-3,\ldots,2,3+\}} B_i \mathbf{1}[s = r(i,t)](\rho_s + \theta_s \delta_i) + x_{it}\beta + \epsilon_{it}, \tag{A17}$$

where B_i is an indicator denoting whether the consumer i is part of the balanced window around the event of insurer changes. I define $B_i = 1$ when the consumer moves between 2014-2017 and report the coefficients of θ_s, where $\theta_s, s \in \{-3, -2, .., 1, 2\}$ are identified within a balanced event window. This design ensures that θ_s are identified of the same set of insurer switch cohorts, but comes at the cost that fewer numbers of insurer switch cohorts are used for identification.

Figure A17 shows the balanced panel restrictions do not alter baseline predictions. Note that the recommended clinical frequency for mammography is once every two years, so the estimated effects in the moving year still capture the influence of the origin insurer and are less pronounced. In years after insurer changes, when the destination insurer completely takes over, estimated effects for mammography and diabetic care are similar.

Figure A17. Effect of insurer-specific prevention utilization on consumers' prevention usage, balanced event window

(a). Diabetic HbA1c testing (b). Mammography



Notes: This figure shows point estimates of θ_s and 95% confidence interval from estimation of equation (A17). 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 number of individuals in the analysis sample is 28,281 and 25,707 for panels (a) and (b). Data comes from NH APCD.

Heterogeneity by Direction of Moves. I examine whether event study estimates are sensitive to the direction of moves. Figure A18 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.

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,

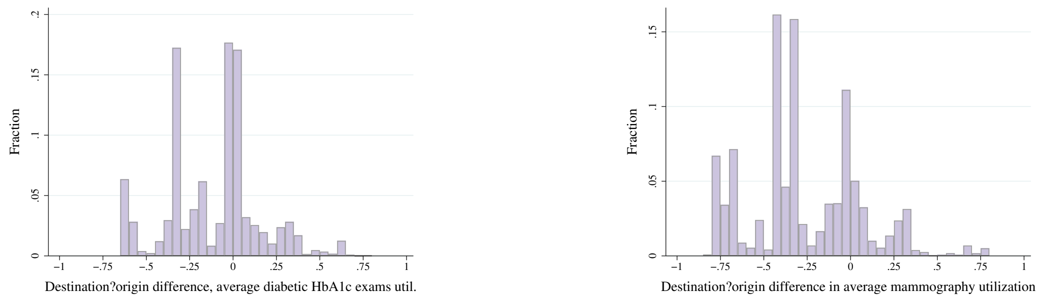
$$y_{it} = \alpha_i + \tau_t + \sum_{s=\{-4(+),-3,\ldots,2,3+\}} \left(\mathbf{1}[s = r(i,t)] \sum_{d=\mathbf{1}[\delta_i > 0]} (\rho_s^d + \theta_s^d \delta_i) \right) + x_{it}\beta + \epsilon_{it}, \tag{A18}$$

where δ_s^1 represents changes in response to moving to higher utilization insurers ($\delta_i \geq 0$), as shown in Figure A19 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 A18. Distribution of destination-origin differences in prevention utilization

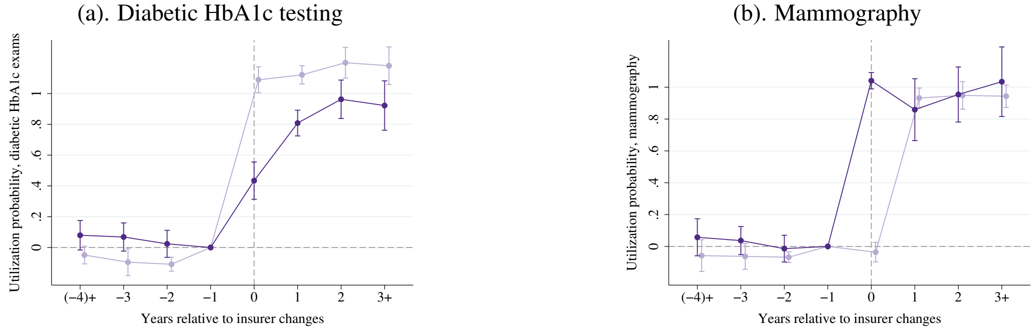
(a). Diabetic HbA1c exams (b). Mammography



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. Data comes from NH APCD.

Figure A19. 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 (A18). 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 number of individuals in the analysis sample is 28,281 and 25,707 for panels (a) and (b). Data comes from NH APCD.

D4. Additional Results on Insurer Effects in Costs.

I further employ the movers design to examine the effects of insurer-specific prevention utilization on cost outcomes. I estimate equation (A17), but substitute y_{it} as consumer i's medical expenses in year t:

$$y_{it} = \alpha_i + \tau_t + \sum_{s=\{-4(+),-3,\ldots,2,3+\}} B_i \mathbf{1}[s = r(i,t)](\rho_s + \theta_s \delta_i) + x_{it}\beta + \epsilon_{it}.$$

To get rid of the effect of insurer-specific time-invariant bargaining power on total costs, I residualize y_{it} on insurer fixed effects before estimating equation (A17). This allows me to capture the effects of changing to insurers with higher prevention utilization on consumer's future health risks. I use a balanced time window specification so that all switchers used to identify θ_s are observed for the entirety of the post-period.

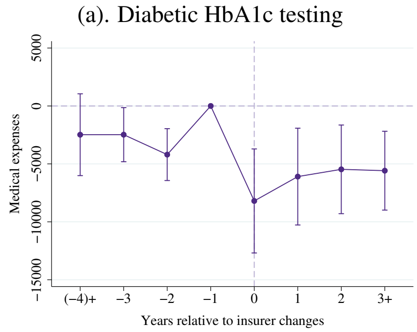
Figure A20 shows event study results. Table A18 reports analogous differences-in-differences estimates. Column (1) indicates that moving to an insurer with 1 percentage point higher HbA1c care utilization reduces future health risks of diabetic patients by around \$1,900. This is consistent with the positive medical estimates of returns to diabetic glycemic control in Table A14. As indicated by the stylized patterns in Section C3, blood sugar monitoring reduces the probability of diabetic complications, such as vascular diseases, thus lowering future medical expenses. This exercise affirms the cost savings of chronic disease management and reiterates the intertemporal cost savings incentives created by prevention.

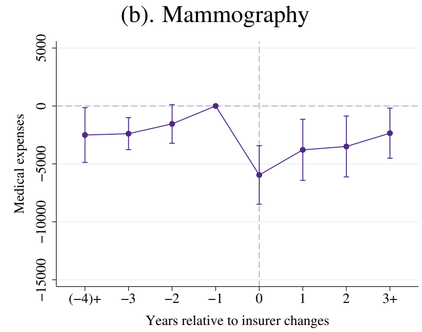
Table A18 column (3) shows that changing to an insurer with 1 percentage point higher mammography utilization reduces future health risks of women eligible for mammography by about \$1000. The point estimates have the direction of cost savings as expected, which is consistent with medical estimates reported in Table A15. As suggested by the stylized patterns in Section C3, cancer screenings could save future medical expenses by detecting and treating the disease in the early stage. However, the point estimates are not statistically significant. This aligns with the findings in Kowalski (2021) that breast cancer screenings have less pronounced cost effects. This could be due to the ambiguity of cost-savings for the procedure or because the returns to cancer screenings may only be recouped in the long term and thus not reflected in the short analysis panel.

It is worth noting that these results are generated using only a couple of insurer switch cohorts in New Hampshire. The sample size is relatively small, and the sample period is not sufficiently long. This could explain the wide confidence intervals in Figure A20. The magnitude of estimates in this section may not generalize well to the average population or capture the cost effects of prevention usage in distant years. Employing larger and longer samples to estimate causal returns to prevention is an exciting direction for future research.

Nevertheless, this exercise provides suggestive evidence of the positive returns to prevention. It reiterates the intertemporal cost-savings motives created by preventive care.

Figure A20. Effect of insurer-specific prevention utilization on future health risks





Notes: This figure shows point estimates of θ_s and 95% confidence interval from estimation of equation (A17). 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 number of individuals in the analysis sample is 28,281 and 25,707 for panels (a) and (b). Data comes from NH APCD.

Table A18. Effect of insurer-specific preventive care utilization rate on future health risks

	HbA1c monitoring	HbA1c monitoring	Mammography	Mammography
	(1)	(2)	(3)	(4)
$\delta_i \times B_i \times$ Post 0-2 years	-1961**		-1150	
	(821)		(680)	
$\delta_i \times B_i \times$ Post		-1882*		-684
		(935)		(694)
Observations	231,362	231,362	226,245	226,245

Notes: This table reports the effect of insurer-specific preventive care utilization rate on consumers' future health risks. The regression controls for relative year fixed effects, individual fixed effects, calendar year fixed effects, and age groups fixed effects. The regression sample includes consumers who stayed with the same insurer or changed insurers once during 2011-2019. Columns (1)-(2) further restrict the analysis sample to consumers with diabetes. Columns (3)-(4) further restrict the analysis sample to female consumers aged 51-68 in 2011. Standard errors are clustered at the county level. $^{*},^{**},^{***}$ denote statistical significance at the 10%, 5%, and 1% level, respectively. Data comes from NH APCD.

E. Robustness of Insurers' Responses to Consumer Turnover

E1. Validating MLR Measures.

It would be ideal to have direct measures of insurers' preventive investment, e.g., expenses on reminder messages to consumers or performance bonuses to providers. However, such proprietary data, unfortunately, do not exist systematically. I use quality improvement expense is used as a proxy for preventive investment from MLR data. Below, I discuss why this best measure that researchers are able to get is reasonable.

Activities in each quality expense category can be found in the CMS MLR Annual Reporting Form Filling Instructions (2019). Examples include expenses for effective case management, care coordination, chronic disease management, expenses associated with identified best clinical practices and evidence-based medicine, coaching programs designed to educate individuals on clinically effective methods for dealing with specific chronic conditions or designed to achieve specific and measurable improvements, etc. Although the MLR does not specify the exact clinical procedures or care categories, investment in preventive care by reminding consumers or incentivizing providers is part of these quality expenses. These quality expenses are also consistent with the broad prevention concept and aim to improve health and generate future savings.

Notably, medical incentive payments in MLR reports include shared savings and performance bonuses. However, shared savings programs (e.g., accountable care organizations) are not prevalent in the commercial insurance market, and only 2.5% of payments are capitated (Werner et al., 2023), so shared savings or capitation payments do not account for the majority of medical incentive payments.

One concern with the quality investment measure is that insurers may manipulate their reporting in quality improvement expenses to satisfy MLR requirements. If that is the case, companies with smaller claims to premium ratios would have larger quality expenses to premium ratios. Figure A21a shows such a negative correlation does not exist for exchange insurers. Figure A21b additionally shows the MLR ratio distribution for exchange insurers does not bunch at the regulatory minimum threshold. These evidence are not consistent with the prediction that insurers manipulate quality improvement expenses to satisfy MLR requirements.

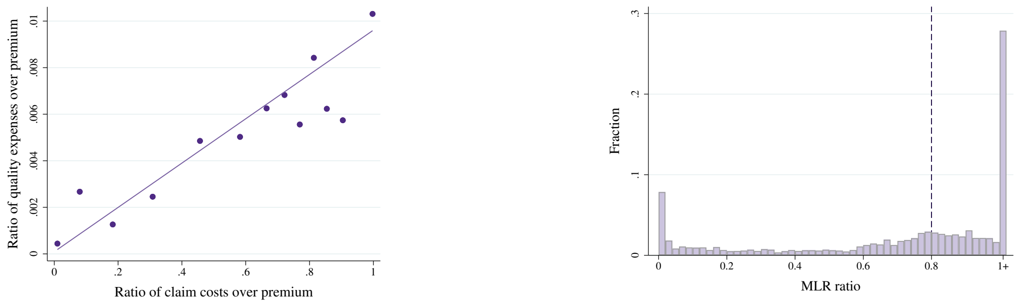
Furthermore, existing evidence of manipulating MLR reporting lies in medical claim costs (Cicala et al., 2019), but not in quality expenses. This could be because quality expenses usually account for only 1-2% of the premium income, while claims costs account for over 80% of the premium income. The percentage of quality expenses is very small such that the reporting needs to increase considerably to satisfy the MLR requirements. This makes manipulation of preventive investment easily detected and not common in practice.

Finally, even if investment expenses in MLR reporting are contaminated by manipulation, it affects only the regression exercises in Section 3.2 by introducing a measurement error to the dependent variable. There are no clear mechanisms that insurers with differential turnover shocks manipulate differentially quality expenses. Thus, the measurement error of the dependent variable is innocuous for the motivating evidence. The main conclusion of Section 3.2, that insurers' investment strategies respond to consumer turnover, is unaffected. Moreover, the manipulation of quality improvement expenses does not affect any of the structural exercises, as these expenses are not used as moments in the estimation. (They are only used as

Figure A21. 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.

aggregate statistics of industry reporting, to which model estimates are compared and found to be in similar magnitudes.)

E2. 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.

E3. Back-of-Envelope Calculation of Insurers' Investment Returns.

I back out insurers' perceived returns to investment to cover the investment expenses under different scenarios, using the estimates in Section 3.2. The idea is to exploit insurers' first-order condition of investment (equation (14)), that the marginal investment expenses equal the marginal investment returns. More specifically, my calculations differ along two dimensions.

First, I vary statistics inputs. One option is to use baseline means. I back out insurers' perceived returns parameter that equates expected investment returns with investment expenses at the observed equilibrium. Another option is to use 2SLS estimates. I calculate insurers' perceived returns that rationalize their investment and utilization responses to the consumer retention shock.

Second, I use different assumptions of returns to prevention over time. I use two scenarios: constant returns over time or convex returns over time, such that a large fraction of returns are recouped in a couple of years after the investment. The former assumption applies to preventive care procedures involving short-term returns procedures like disease management, while the latter assumption applies to long-term returns procedures like screenings. In reality, insurers' perceived returns will be bounded between these scenarios.

Table A19. Back-of-envelope calculation of insurers' perceived returns to prevention

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Returns over		Per-person yearly statistics			NPV	Inferred returns (q_1)
Scenario	time	Measure	Retention	Utilization	Inv. Cost	NPV, Returns	($, at full utilization)
(a). Use baseline means as inputs							
1	Constant	Level, baseline mean	0.500	0.640	226	$0.4045q_1$	559
(b). Use 2SLS estimates as inputs							
2	Constant	Level, before shock	0.500	0.640	226	$0.4045q_1$	
		Level, after shock	0.507	0.648	232.78	$0.4198q_1$	
		Changes	0.007	0.008	6.78	$0.0153q_1$	443
3	Convex	Level, before shock	0.500	0.640	226	$0.01658q_1$	
		Level, after shock	0.507	0.648	232.78	$0.0182\ q_1$	
		Changes	0.007	0.008	6.78	$0.0016q_1$	4237

Notes: This table summarizes the back-of-envelop calculation of insurers' perceived returns to prevention (q_1). q_1 measures annualized average returns when the insurers' enrollees fully utilize their eligible preventive care. Panel (a) infers the returns by equating the insurers' preventive investment with expected returns at the observed equilibrium using baseline means. Panel (b) infers the returns by equating the changes in insurers' preventive investment to the changes in expected returns, using the 2SLS estimates of the effect of consumer retention shocks. Column (2) states the timing assumption of returns to prevention, while columns (3)-(7) report key statistics in the calculation process. Column (3) indicates whether the statistics reported in columns (4)-(7) are in levels or changes. The shock refers to a one percentage point increase in consumer retention rate on the exchange market. Before-shock levels are the same as the baseline mean. After-shock levels are calculated using the 2SLS estimates from Section 3.2.

The targeted output is insurers' perceived annualized returns if all eligible consumers utilize prevention, q_1. Table A19 summarizes the back-of-envelop calculation. Below, I describe the calculation in detail.

Scenario 1 - Constant Returns Over Time, Baseline Means. I calculate insurers' perceived returns when the investment returns are constant over time, and the first-order condition is evaluated at the baseline means.

At the observed equilibrium, the mean utilization rate of preventive care is $e = 64\%$ (extracted from Table 2). The share of consumers who remain with the insurer in the next year is about $r = 50\%$ (extracted from Table A2 panel (d)). These two statistics are reported in Table A19 columns (4) and (5).

Using the above statistics, I calculate the statistics in Table A19 column (7): the net present value of cost savings, i.e., the reduction in medical expenses when consumers are healthy in future periods. Assuming linear returns to prevention, cost savings recouped in year $t+1$ of investment made in year t is

$$\underbrace{r}_{\text{consumer retention}} \times \underbrace{e}_{\text{prevention utilization}} \times \underbrace{q_1}_{\substack{\text{annualized returns to prevention} \\ \text{at full utilization}}} = 0.5 \times 0.64 \times q_1.$$

Cost savings recouped in year $t+2$ of investment made in year t is

$$\underbrace{r^2}_{\text{consumer retention}} \times \underbrace{e}_{\text{prevention utilization}} \times \underbrace{q_1}_{\substack{\text{annualized returns to prevention} \\ \text{at full utilization}}} = 0.5^2 \times 0.64 \times q_1.$$

Summing across all future periods with a discounting parameter $\beta = 0.9$, the net present value of investment

observed at the status quo equilibrium is

$$NPV = \underbrace{\beta r q_1 e}_{\text{returns in } t+1} + \underbrace{\beta^2 r^2 q_1 e}_{\text{returns in } t+2} + ... + \underbrace{\beta^n r^n e q_1}_{\text{returns in } t+n} + ...$$
$$= 0.9 \times 0.5 \times 0.64 q_1 ... + 0.9^n \times 0.5^n \times 0.64 q_1 + ... = 0.4045 q_1.$$

I proceed to calculate the statistics in Table A19 column (6): expenses of preventive investment, which includes the claims costs paid to providers for performing preventive procedures, and promotion expenses on consumer wellness or provider incentives programs to increase prevention utilization. The expense to promote prevention at status quo equilibrium is \$107 per member-year (extracted from Table 2). The medical claims to pay for prevention at a 42% prevention utilization rate is \$78 per person-year (extracted from Table 6). Assuming a linear cost structure, the medical claims at a 64% prevention utilization rate is $0.64/0.42 \times \$78 = \$119$. Summing up the promotion and claims expenses, the preventive investment at the status quo is $x = \$226$ per person-year.

Equating the static marginal expenses to the expected future marginal returns, I derive insurers' perceived investment returns in Table A19 column (8):

$$NPV = x, \quad 0.4045 q_1 = \$226, \quad q_1 = \$559.$$

Scenario 2 - Constant Returns Over Time, 2SLS Estimates. I calculate insurers' perceived returns when the investment returns are constant over time, and the first-order condition is evaluated with the perturbation of consumer turnover. The idea is to back out the perceived returns that will rationalize insurers' responses to shocks in consumer retention, as indicated by the 2SLS estimates.

As shown in Scenario 1, the expected future marginal return at the status quo equilibrium is $0.4045 q_1$, and the marginal investment expense at the status quo is \$226.

Suppose consumer retention on the exchange market increases by 1 percentage point (pp). This increases the retention rate of the insurer by about $0.01 * (0.7 - 0.2)/0.7 = 0.007$ percentage points, since within the exchange, about 20% switch insurers (extracted from Table A2 panel (d)). The change in retention rate is reported in Table A19 column (4). The new share of consumers remaining with the insurer after the turnover perturbation is $r' = 0.5 + (0.7 - 0.2)/0.7 * 0.01 = 0.507$.

The 2SLS estimates indicate that equilibrium utilization increases by 0.79 percentage points in response to a 1 percentage point increase of consumer retention on the exchange (extracted from Table 4). The new utilization rate after the turnover perturbation is

$$e' = e + \underbrace{r \times \frac{de}{dr}}_{\text{responses to retention shock in utilization}} = 0.64 + 0.01 * 0.79 = 0.648.$$

The change in utilization rate is $dr \times \frac{de}{dr} = 0.008$, as reported in Table A19 column (5).

I now calculate the expected investment returns at the new retention and utilization rate. Summing across

future periods using a similar logic as in Scenario 1, we get

$$\underbrace{\beta r q_1 e}_{\text{returns in } t+1} + \underbrace{\beta^2 r^2 q_1 e}_{\text{returns in } t+2} + ... + \underbrace{\beta^n r^n q_1 e}_{\text{returns in } t+n} + ...$$
$$= 0.9 \times 0.507 \times 0.648 q_1 + ... + 0.9^n \times 0.507^n \times 0.648 q_1 + ... = 0.4198 q_1.$$

Thus, the increase in expected future returns when consumer retention on the exchange rises by 1 percentage point is

$$\Delta NPV = 0.4198 q_1 - 0.4045 q_1 = 0.0153 q_1.$$

This is reported in Table A19 column (7), the change in expected returns from increased retention and increased utilization.

The 2SLS estimates also indicate that the promotion expenses increase by $\frac{dx}{dr} = 5.31$ (extracted from Table 4). Assuming a linear cost structure of prevention claims, full prevention utilization would involve a cost of $c(e) = \$78/0.42 = \$186$ per person-year (extracted from Table 6). Elevation in medical claims expenses for the increased utilization is $(0.01{*}0.79) \times (\$78/0.42) = \$1.47$. The total increases in investment expenses in response to the consumer retention shock is

$$\Delta x = \underbrace{dr \times \frac{dc}{dr}}_{\text{responses in promotion expenses}} + \underbrace{dr \times \frac{de}{dr}}_{\text{responses in utilization}} \times \underbrace{c(e)}_{\text{claims cost of utilization}}$$
$$= \$5.31 + \$1.47 = \$6.78.$$

This is reported in Table A19 column (6), the change in investment expenses from increased utilization and increased promotion.

To rationalize insurers' response to a 1 percentage point increase in consumer retention, we equate the increase in expected future returns with the increases in investment expenses,

$$\underbrace{\Delta NPV}_{\text{marginal investment returns}} = \underbrace{\Delta x}_{\text{marginal investment expenses}}, \quad 0.0153 q_1 = 6.78, \quad q_1 = \$443.$$

Table A19 column (8) reports this perceived return. Reassuringly, the inferred return in this scenario, which rationalizes the 2SLS estimates of insurers' responses to turnover shocks, is similar to the return calculated in Scenario 1, which rationalizes insurers' strategies at the baseline means under the same timing of returns assumption.

Scenario 3 - Convex Returns Over Time, 2SLS Estimates. I calculate insurers' perceived returns when the investment returns are convex over time, and the first-order condition is evaluated with the perturbation of consumer turnover. Without a loss of generosity, I assume that the returns to prevention start to recoup five years after the investment occurs. I back out the perceived returns that will rationalize insurers' responses to shocks in consumer retention.

The insurer's retention rate at the baseline is 0.5, and the prevention utilization rate is 0.64 (derived in Scenario 1). Under the new timing assumption, the expected future return without the consumer retention

shock is

$$\underbrace{\beta r q_1 e}_{\text{returns in } t+1} + ... + \underbrace{\beta^4 r^4 q_1 e}_{\text{returns in } t+4} + \underbrace{\beta^5 r^5 q_1 e}_{\text{returns in } t+5} + ... + \underbrace{\beta^n r^n q_1 e}_{\text{returns in } t+n} + ...$$
$$= 0 + ... + 0 + .. + 0.9^5 \times 0.5^5 \times 0.64 q_1 + ... + 0.9^n \times 0.5^n \times 0.64 q_1 + ... = 0.01658 q_1.$$

When consumer retention on the exchange increases by 1 percentage point, the insurer's new retention rate is 0.507, and the new utilization rate is 0.648 (derived in Scenario 2). Under the new timing assumption, the expected future returns when consumer retention on the exchange rises by 1 percentage point is

$$\underbrace{\beta r' q_1 e'}_{\text{returns in } t+1} + ... + \underbrace{\beta^4 r'^4 q_1 e'}_{\text{returns in } t+4} + \underbrace{\beta^5 r'^5 q_1 e'}_{\text{returns in } t+5} + ... + \underbrace{\beta^n r'^n q_1 e}_{\text{returns in } t+n} + ...$$
$$= 0 + ... + 0 + .. + 0.9^5 \times 0.507^5 \times 0.648 q_1 + ... + 0.9^n \times 0.507^n \times 0.648 q_1 + ... = 0.0182 q_1.$$

We thus calculate the change in expected future returns when consumer retention on the exchange rises by 1 percentage point, the statistics in

$$\Delta NPV = 0.0182 q_1 - 0.0166 q_1 = 0.0016 q_1.$$

Insurers' preventive investment raises by $6.78 in response to the consumer retention shock (derived in Scenario 2). To rationalize insurers' response to a 1 percentage point increase in consumer retention, we equate the increase in future returns with the increases in investment expenses,

$$\underbrace{\Delta NPV}_{\text{marginal investment returns}} = \underbrace{\Delta x}_{\text{marginal investment expenses}}, \quad 0.0016 q_1 = 6.78, \quad q_1 = \$4237.$$

Practically, preventive care procedures involve short-term returns procedures (Scenario 2) and long-term returns procedures (Scenario 3). Hence, insurers' perceived returns will be bounded between the second and third scenarios, namely, between $443 and $4237. Note that the calibrated returns to prevention estimates (from medical studies) in Section C2 falls in this range, reassuringly.

E4. Robustness of Primary Estimates.

I examine whether the baseline estimates of the effects of consumer retention on preventive investment and prevention utilization are robust in Table A20.

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 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 A20 rows (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

Table A20. Effect of consumer turnover on prevention utilization and investments, robustness

	Aggregate utilization		Per member quality expenses	
(1) Baseline	0.786*	(0.409)	5.31**	(2.37)
(a). Alternative inference				
(2) Adao et al. (2019)	0.786***	(0.000)	5.31***	(0.00)
(3) Borusyak and Hull (2023)	0.786***	(0.059)	5.31*	(0.74)
(b). Alternative instrument construction				
(4) Jackknife	0.587*	(0.349)	5.67**	(2.56)
(5) Recentered	0.785*	(0.409)	5.31**	(2.37)
(6) Alternative share	0.839**	(0.416)	5.33**	(2.50)
(7) Two IVs	0.674*	(0.400)	5.75**	(2.45)
(c). Alternative specification				
(8) Population weighted	0.648*	(0.386)	5.96**	(2.40)
(9) Enrollment weighted	0.933*	(0.472)	4.57**	(2.22)
(10) Insurer-state-year level	0.773***	(0.184)	4.20**	(1.62)
(11) Control for unempl. rate	0.784*	(0.425)	5.35**	(2.37)
(12) Control for predicted unempl. growth	1.317**	(0.528)	5.29**	(2.30)

Notes: This table reports the coefficient and standard errors (in parentheses, clustered at state level) of exchange retention variable from the estimation of equations (2) and (5). Row (1) reports baseline estimates from the same specification as Table 4: the regression includes state and year-fixed effects and is weighted by state-year-level exchange market size. Rows (2)-(11) tweak the specification, described in Section E4. The regression sample, outcome variables, and data sources are the same as in Table 4. *,**,*** denote statistical significance at the 10%, 5%, and 1% level, respectively.

shocks that directly enter the residual ε_{st}.[2] 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 A20 rows (4)-(7) are similar to the baseline.

Third, I rerun the analysis at the insurer-state-year level or change the regression weights. In the baseline specification, I apply the exchange's eligibility criteria based on age and income to the American Community Survey and calculate the number of eligibles as the market size. Alternative weights are by realized exchange enrollment or state population. Resulting estimates in Table A20 rows (8)-(10) are similar to the baseline.

To further address the concern that the instrument may affect outcomes by changing local economic conditions, I rerun the analysis, controlling for local unemployment rates or predicted local unemployment growth following Chodorow-Reich and Wieland (2020). The predicted local unemployment growth is a bartik-style measure, which allocates national-industry-level unemployment growth to each state using the state-specific employment structure. This design compares outcomes in states with the same local economic conditions but different predicted consumer turnover. The resulting estimates in Table A20 rows (11)-(12) are similar to the baseline.

I finally conduct a permutation test that builds a placebo instrument using simulated job hiring shifters

[2] 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.

drawn from a standard normal distribution and true employment shares in data following Adao et al. (2019). I repeat the 2SLS estimation 1000 times using the true preventive investments or utilization as outcome variables and the placebo instrument. Only 0.5% and 3.8% of the resulting coefficients are significant at the 5% level for investment and utilization, separately. This suggests the estimated impacts of turnover on preventive measures are unlikely to be driven by noise.

F. Additional Details on Estimation

F1. 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.

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 C1 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 A21. 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

Table A21. Preventive care utilization by insurance status

	Insured (1)	Insured with Exchanges (2)	Uninsured (3)	Uninsured three cont. yrs (4)
(a). Update-to-dated diabetes care (%), BRFSS				
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 (%), BRFSS				
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 (%), BRFSS				
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
(d). Update-to-dated cancer screenings (%), MEPS				
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	-
(e). Update-to-dated routine primary care (%), MEPS				
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	-
(f). Update-to-dated diabetes care (%), NHIS				
HbA1c exams	85.25	81.35	63.54	60.53
(g). Update-to-dated asthma care (%), NHIS				
Asthma controller medications	17.22	18.61	15.28	13.17
(h). Update-to-dated cancer screenings (%), NHIS				
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
(i). Update-to-dated routine primary care (%), NHIS				
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. Data comes from Behavioral Risk Factor Surveillance System (BRFSS) 2015-2019 for panels (a)-(c), Medical Expenditure Panel Survey (MEPS) Preventive Services Self-Administered Questionnaire in 2014 for panels (d)-(e), and National Health Interview Survey (NHIS in 2015-2018 for panels (f)-(i). Update-to-dated diabetes care, asthma care, and cancer screenings are defined following the HEDIS guidelines (see Table A1), except that in MEPS 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 BRFSS and MEPS or within a year in NHIS; blood pressure checks for individuals aged above 20 within two years in panel in BRFSS and MEPS, or within a year in panel in NHIS. BRFSS and NHIS measures insurance status in Columns (1)-(3) at the time of the survey; MEPS defines status if an individual is in that status for at least nine months during the survey year. Column (4) reports utilization rates for individuals who are uninsured for three consecutive years before the survey.

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 dataset, I use the average across data sources. Table A22 reports the calculation details.

Table A22. 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 A21. 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.

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 A22 excludes the statin therapy for cardiovascular disease and includes flu shots instead of immunizations for children and adolescents due to data availability. The 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.

F2. 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. The estimation algorithm has a three-layer loop structure.

In the inner loop, for each guess of investment curvature parameters in the market m and an arbitrary value function V_{fm}, I solve stage games' equilibria by searching for a fixed point in insurers' prices and preventive investment.

In the interim 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 B $\hat{\mu_l}$, 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 (21) 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 (6) and (7), 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.

F3. 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.

F4. Alternative Estimation Procedure

The estimation procedure in Section 5 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 G1, 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. 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 3.2). 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 3.2). 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). The returns to prevention parameter is backed out using the FOC of preventive utilization (equation (21)). 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 A23 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

Table A23. 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 F4, separately.

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 6.1.

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 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.

F5. Model Extension: Incorporating Consumers' Utilization Decisions.

The empirical model in Section 4 abstracts from modeling individuals' medical care utilization decisions and uses insurers' identity as a proxy. This section analyzes the case when prevention utilization in equilibrium is affected by both insurers' identities and consumers' optimal utilization decisions. I first derive the direction of bias of model estimates. I then present a corrected estimand that gives unbiased estimators of the consumer preference and health risks transitions, and derive conditions such that the bias in the estimator for investment cost functions is small.

Formally, let λ denote the forecast parameter (Abaluck et al., 2021), defined by the projection of the causal insurer effects in utilization e^*_{fmt} on the observational insurer effect e_{fmt}. I refer to e^*_{fmt} as the causal quality index and e_{fmt} the observational quality index. Normalizing the means of both parameters to zero, this projection can be written as

$$e^*_{fmt} = \lambda e_{fmt} + \zeta_{fmt}, \tag{A19}$$

where ζ_{fmt} is mean-zero and uncorrelated with e_{fmt} by definition. The observational quality index e_{fmt} is an average unbiased predictor of causal quality effects when $\lambda = 1$, whereas observational effects have little association with true causal effects when the value of λ is small. As insurer effects explain a larger share of

variations in prevention utilization, the observational index is more likely to predict the true insurer effects in promoting prevention utilization one-for-one.

Consumer Preference Estimates. The observational quality index appears in the second step of estimating consumer preference. The projection seeks to back out consumers' value of the insurers' causal quality effects in managing enrollees' health through promoting preventive care utilization. Plugging equation (A19) into the projection equation,

$$\delta_{jmt} = \alpha_0 p_{jmt} + \rho e^*_{fmt} + \theta X_{jmt} + \xi_{jmt} = \alpha_0 p_{jmt} + \rho\lambda e_{fmt} + \theta X_{jmt} + \xi_{jmt} + \rho\zeta_{fmt},$$

where $\rho\zeta_{fmt}$ is mean-zero and uncorrelated with any of the regressors in $\{p_{jmt}, e_{fmt}, X_{jmt}, \xi_{jmt}\}$, by definition.

The estimated parameter of the observational quality index $\rho\lambda$ is the preference for preventive care quality ρ scaled by a measure of how precise the observational quality index predicts true insurer quality λ. If the observational quality index is an unbiased predictor of true insurer quality, i.e., $\lambda = 1$, the demand estimates of consumer preferences for preventive care quality are unbiased. Otherwise, if the observational quality index does not predict the true insurer quality one-for-one, rescaling the second step estimates by $\frac{1}{\lambda}$ gives an unbiased estimate for consumer preference.

If the selection is that more health-conscious consumers endogenously choose plans with high preventive care coverage and use more prevention, the observational quality index overstates the true insurer effects, $\lambda < 1$. In that case, the estimated sensitivity to prevention will underestimate the true preference for prevention.

State Transition Estimates. I apply the same trick and plug equation (A19) into equation (7),

$$\mu_{fmt+1} = \tilde{\mu}_{fmt} + q_0 + q_1 e^*_{fmt} + \nu_{fmt} = \tilde{\mu}_{fmt} + q_0 + q_1\lambda e_{fmt} + \nu_{fmt} + \zeta_{fmt}.$$

The estimates of q_1 are not affected because they are calibrated from the medical studies.

The estimated cost growth q_0 is affected. The estimation procedure produces

$$\sum_{f,m,t} w_{fmt}(\Delta\mu_{fmt} - \hat{q}_1 e^*_{fmt} + \hat{q}_1(e^*_{fmt} - e_{fmt})) = q_0 + \hat{q}_1 \sum_{f,m,t} w_{fmt}((\lambda - 1)e_{fmt} + \zeta_{fmt}),$$

where the direction of $\hat{q}_1 \sum_{f,m,t} w_{fmt}((\lambda-1)e_{fmt} + \zeta_{fmt})$ is not determined. I adjust the estimand by calculating

$$\sum_{f,m,t} w_{fmt}(\Delta\mu_{fmt} - \lambda e_{fmt})) = \sum_{f,m,t} w_{fmt}(\Delta\mu_{fmt} - \hat{q}_1 e^*_{fmt} + \hat{q}_1(e^*_{fmt} - \lambda e_{fmt})) = q_0 + \hat{q}_1 \sum_{f,m,t} w_{fmt}\zeta_{fmt} \approx q_0,$$

where the last approximation holds under the conditions that there are sufficient variations in ζ_{fmt} such that $\sum_{f,m,t} w_{fmt}\zeta_{fmt} \approx 0$.

The estimated variance of idiosyncratic returns to prevention, ν_{fmt}, is affected. The estimation procedure calculates

$$\begin{aligned} &\text{Var}[\mu_{fmt+1} - \tilde{\mu}_{fmt} - q_0 - q_1 e_{fmt}] = \text{Var}[\mu_{fmt+1} - \tilde{\mu}_{fmt} - q_0 - q_1 e^*_{fmt} + q_1(e^*_{fmt} - e_{fmt})] \\ =&\text{Var}[\nu_{fmt} + q_1(\lambda-1)e_{fmt} + q_1\zeta_{fmt}] = \sigma^2_\nu + q_1^2(\lambda-1)^2\sigma^2_e + q_1^2\sigma^2_\zeta \geq \sigma^2_\nu, \end{aligned}$$

where the last equivalence holds when $\text{Cov}(e_{fmt}, \nu_{fmt}) = 0$, and also by the definition of ζ_{fmt}. The estimation procedure thus overestimates the variance of idiosyncratic health shocks σ_ν^2, regardless of the selection direction.

To derive an unbiased estimator of σ_ν^2, I adjust the estimand by multiplying the observational quality index by the forecast parameter,

$$\text{Var}[\mu_{fmt+1} - \tilde{\mu}_{fmt} - q_0 - q_1 \lambda e_{fmt}] = \text{Var}[\nu_{fmt} + \rho \zeta_{fmt}] = \sigma_\nu^2 + \rho^2 \sigma_\zeta^2.$$

Further subtracting the variance of the forecast residual multiplied by the forecast parameter, $\rho^2 \sigma_\zeta^2$, from the estimand gives an unbiased estimator of σ_ν^2.

Investment Cost Curvature Estimates. Plugging equation (13) into equations (21) and (15), and rewrite the first order conditions gives

$$[e^*_{fmt}] \quad 0 = \sum_{j \in J_f} \sum_{l \in F} \left(\frac{\partial s_{jmt}}{\partial e_{fmt}} (p_{jmt} - \mathbf{1}[d_{imt-1} = l] \mu_{lmt-1} - \frac{1}{a^*_{fm}} \frac{e^*_{fmt}}{1 - e^*_{fmt}}) \right) - \sum_{j \in f} \left(s_{jmt} \frac{1}{a^*_{fm}} \frac{1}{(1 - e^*_{fmt})^2} \right) + \beta \frac{\partial V_{fm}}{\partial e_{fmt}}.$$

$$[p_{fmt}] \quad 0 = \sum_{j \in J_f} \sum_{l \in F} \left(\frac{\partial s_{jmt}}{\partial p_{fmt}} (p_{jmt} - \mathbf{1}[d_{imt-1} = l] \mu_{lmt-1} - \frac{1}{a^*_{fm}} \frac{e^*_{fmt}}{1 - e^*_{fmt}}) \right) + \sum_{j \in f} \left(s_{jmt} \right) + \beta \frac{\partial V_{fm}}{\partial p_{jmt}}.$$

Suppose the previous two steps of correction for estimating consumer preference and health risks transitions so that the estimators for $\frac{\partial s_{jmt}}{\partial e_{fmt}}$, and $\frac{\partial V_{fm}}{\partial e_{fmt}}$ are unbiased. The potential bias for the investment efficiency estimates a_{fm} comes from using e_{fmt} as a proxy for e^*_{fmt}. The estimator $\hat{a}_{fm}$ solves

$$[e_{fmt}] \quad 0 = \sum_{j \in J_f} \sum_{l \in F} \left(\frac{\partial s_{jmt}}{\partial e_{fmt}} (p_{jmt} - \mathbf{1}[d_{imt-1} = l] \mu_{lmt-1} - \frac{1}{\hat{a}_{fm}} \frac{e_{fmt}}{1 - e_{fmt}}) \right) - \sum_{j \in f} \left(s_{jmt} \frac{1}{\hat{a}_{fm}} \frac{1}{(1 - e_{fmt})^2} \right) + \beta \frac{\partial V_{fm}}{\partial e_{fmt}}.$$

$$[p_{fmt}] \quad 0 = \sum_{j \in J_f} \sum_{l \in F} \left(\frac{\partial s_{jmt}}{\partial p_{fmt}} (p_{jmt} - \mathbf{1}[d_{imt-1} = l] \mu_{lmt-1} - \frac{1}{\hat{a}_{fm}} \frac{e_{fmt}}{1 - e_{fmt}}) \right) + \sum_{j \in f} \left(s_{jmt} \right) + \beta \frac{\partial V_{fm}}{\partial p_{jmt}}.$$

Only when both $\lambda = 1$ and $\zeta_{fmt} = 0, \forall f, m, t$ is the estimator $\hat{a}_{fm}$ derived with e_{fmt} unbiased.

The direction of bias is ambiguous, and there is no a quick ex-post fix to derive an unbiased estimator. This is because a_{fm} is derived from a nonlinear system of equations: although the first order condition of p_{fmt} choice is a linear equation of a_{fmt}, the first order condition of e_{fmt} choices is a nonlinear equation of a_{fmt} and the GMM objective function is also nonlinear. Simulations show that as long as the forecast parameter λ is close to 1, and the variance of projection residual σ_ζ^2 is small, the bias of investment efficiency estimator $\hat{a}_{fmt}$ is small.

G. Additional Counterfactuals

G1. Sensitivity to the Returns to Prevention Parameter

I explore how model estimates and welfare predictions of competition change with the calibrated parameter q_1, returns to prevention. Table A24 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 parameter in the main text.

Table A24. 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.

I begin by re-estimating the model using alternative returns to prevention of each column in Table A24 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 A24 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 Insurers A and B separately (reported in Table 6). 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 A24 panel (c) counterfac-

tual 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 3.1), 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 A24 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.

G2. Additional Simulations

G2.1. 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 con-

straints 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.

G2.2. Monopoly with Markup Regulations. I investigate the effects of markup regulations, which map to the Medical Loss Ratio 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 C1 for details.

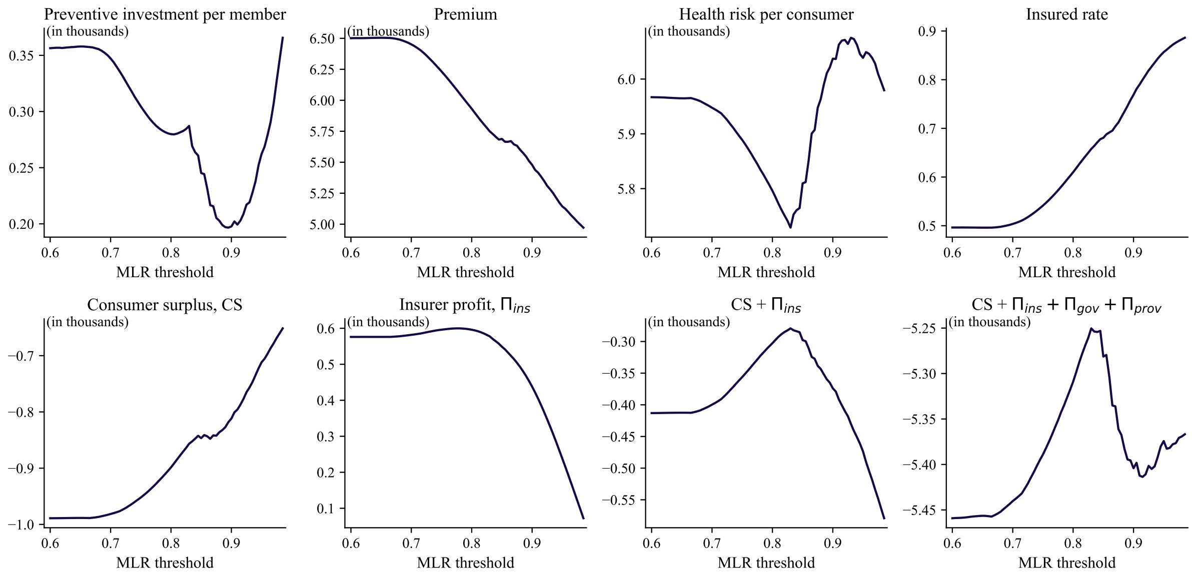
Note that duopolists' simulated investment and markup stay almost the same regardless of whether we impose a greater than 70% MLR regulation because competition constrains their markup to a relatively low level. In the absence of competition, monopolists' markup is substantially affected by markup regulations.

Figure A22 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 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.

G2.3. Preventive Investment Subsidies. I explore the effectiveness of subsidizing insurers for preventive investment, similar to the Quality Bonus Program in Medicare Advantage (MA) that rewards insurers for high utilization of preventive and other services. Instead of nonlinear bonus schemes as in MA, I simulate uniform investment subsidies that reimburse insurers certain amounts per enrollee for their prevention

Figure A22. 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.

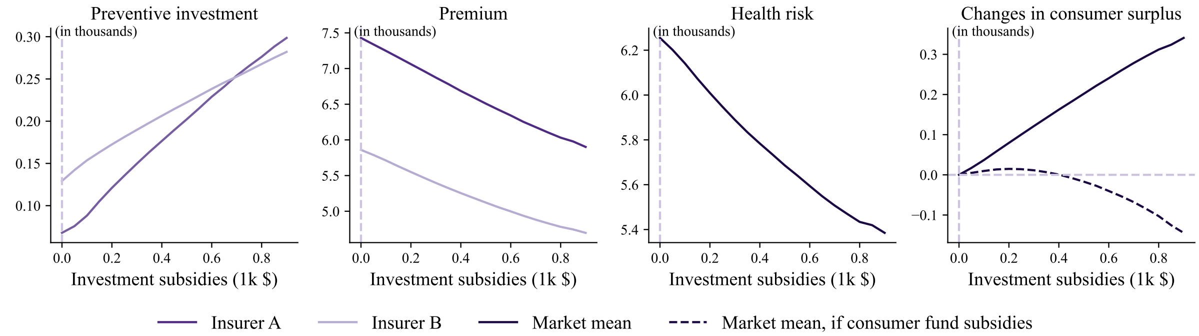
provisions, equivalent to a reduction in marginal investment costs.

Figure A23 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.

G2.4. 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). 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 (20)). The predicted investment and welfare outcomes

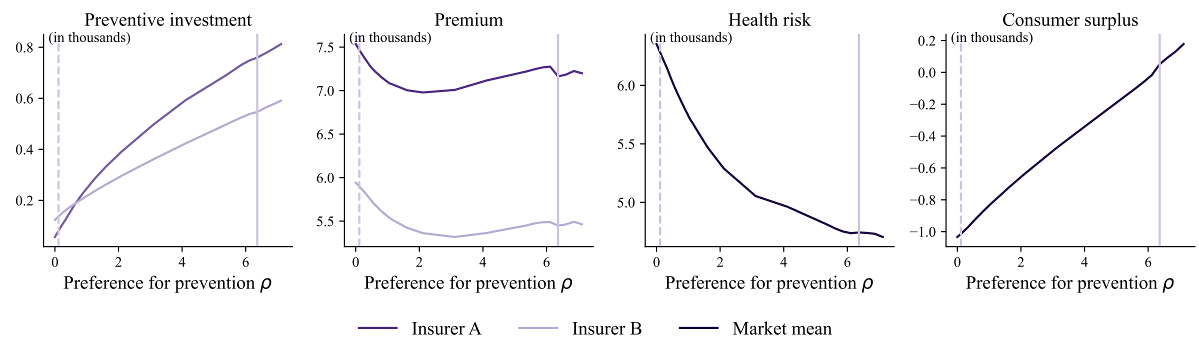
Figure A23. Equilibrium objects and welfare, by preventive investment subsidies to insurers



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.

of a hypothetical star rating program are thus the same as a hypothetical program targeting the valuation of prevention.

Figure A24. 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).

Figure A24 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 rises to that of MA consumers.

G2.5. Varying Shares of Consumer Flows Across Market Segments. 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 and average health risks rise when churn across markets decreases. This exercise reveals the investment and welfare effects of market segmentation, which causes

investment leakage but also raises demand elasticities.

G2.6. Extending the Contract Length to Two Years. I examine the effects of extending the insurance contract length to two years. I assume that consumers incur a lump-sum payment for the insurance policy at the beginning of the two-year coverage period to avoid the potential consumer lapse issue associated with per-period payments. I assume consumers value the average annual premium in equation (8) when making insurance choices, and insurers' investment policies stay the same during the coverage period. I only simulate the scenario of a two-year contract, as contracts with longer time spans may be an over-extrapolation using myopic consumers in the model.

Compared to the stationary distribution of a one-year contract, insurers invest one time more, i.e., \$ 126 more per consumer per year, in the two-year contract scenario, as expected. However, increasing consumers' retention probabilities implicitly reduces demand elasticities, so that insurers charge higher premiums, 14% more than the status quo. On average, losses from price increases dominate gains from investment increases, so consumers' average health status deteriorates, while consumer surplus falls. This exercise reiterates the importance of the investment-price tradeoff for healthcare policy designs.

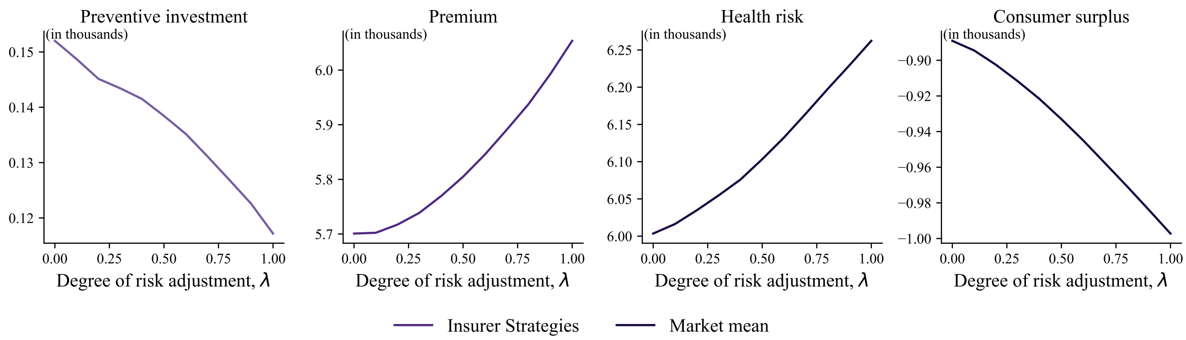
There are two caveats to interpreting this welfare prediction. First, the result is drawn under the status quo choice patterns. If consumers are of a higher degree of forward-looking when purchasing long-run insurance policies, it could be that consumers place a higher valuation on reductions in future medical expenses or could be more price sensitive. In that case, losses from market power may be constrained, and gains from investment savings could be expanded, so that long-term insurance contracts may be welfare-improving. Second, the result is drawn under the assumption of no liquidity constraints. If consumers face liquidity constraints or have intertemporal borrowing constraints so that they can not smooth consumption in the face of lump-sum payments, my estimates will overstate the gains of long-term contracts.

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 prevention is an exciting future research direction.

G2.7. 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.

Figure A25 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).

Figure A25. 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 $\lambda = 1$ corresponds to perfect risk adjustment.

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