NBER WORKING PAPER SERIES

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Working Paper 30719
http://www.nber.org/papers/w30719

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2022

We are grateful to Amanda Starc, Joel Segel, Emilie Jackson, and participants at the Conference of the American Society of Health Economists and the National Tax Association conference for their helpful comments and suggestions. We gratefully acknowledge funding from the Laura and John Arnold Foundation, the Agency for Healthcare Research and Quality (K01-HS25786-01), the National Institute of Mental Health (T32-MH019733), and the National Institute on Aging (T32-AG000186, P01AG032952). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or any other organization. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w30719.ack

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NBER Working Paper No. 30719
December 2022
JEL No. H51,I11,I13

ABSTRACT

Health plans for the poor increasingly limit access to specialty hospitals. We investigate the role of adverse selection in generating this equilibrium among private plans in Medicaid. Studying a network change, we find that covering a top cancer hospital causes severe adverse selection, increasing demand for a plan by 50% among enrollees with cancer versus no impact for others. Medicaid's fixed insurer payments make offsetting this selection, and the contract distortions it induces, challenging, requiring either infeasibly high payment rates or near-perfect risk adjustment. By contrast, a small explicit bonus for covering the hospital is sufficient to make coverage profitable.

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1 Introduction

Adverse selection, the tendency of high-cost consumers to demand more generous insurance, is a common concern in insurance markets. It is well-established that selection can, and does, distort prices and cause consumers to sort inefficiently between insured and uninsured states or between more or less generous coverage (Einav, Finkelstein, and Cullen 2010; Handel, Hendel, and Whinston 2015). In the extreme, selection can completely unravel markets (Akerlof 1970; Hendren 2013). However, selection can affect more than prices and market stability. It can also incentivize insurers to distort contracts to "cream-skim" low-risk consumers and avoid high-risk consumers (Rothschild and Stiglitz 1976; Veiga and Weyl 2016). While price distortions affect who enrolls in insurance, contract distortions can reduce the quality of insurance contracts for all who enroll, including restricting access to the benefits most needed by the sickest consumers. Hence, such contract distortions may be a first-order concern for consumer welfare.

In this paper, we provide new evidence on the role of adverse selection in shaping the design of hospital networks by health insurers. We study these incentives in Medicaid managed care, the largest individual health insurance market in the U.S., covering over 55 million people and accounting for over $300 billion in annual payments to private health plans (Kaiser Family Foundation 2022). Because Medicaid covers some of the nation's most vulnerable populations, understanding the incentives that shape access to specialty hospitals—a longstanding concern in this market (Marks et al. 2022)—is potentially important for understanding the drivers of widely-documented health and healthcare disparities. Despite the importance of Medicaid, there is little work on the role of selection in this market.[1]

The Medicaid program represents a novel and interesting context in which to study the consequences of adverse selection, as Medicaid markets differ in two key ways from more oft-studied markets. First, Medicaid *fully subsidizes* premiums, so enrollees pay $0 for all plans. Second, insurer payments in Medicaid are typically set administratively, not through competition (Layton, Ndikumana, and Shepard 2017). Price competition is a core aspect of selection models going back to Rothschild and Stiglitz (1976), with cream-skimming incentives arising from insurers' ability to

1. One notable exception is evidence from Texas Medicaid that selection incentives widened health disparities under Medicaid managed care (Kuziemko, Meckel, and Rossin-Slater 2018).

enter with low-quality *and low-price* plans. Whether and to what extent cream-skimming arises in markets like Medicaid, with administered prices and fully-subsidized consumer premiums, is not known. In simple models of vertical competition, 100% premium subsidies eliminate problems associated with selection, since consumers have no reason to choose lower-quality plans (e.g., Cutler and Reber (1998); Einav, Finkelstein, and Cullen (2010)). However, insurers' inability to adjust prices in response to selection may limit their ability to increase plan generosity, potentially *worsening* selection-related contract distortions.

Using data from New York's Medicaid program, we present visually transparent evidence of adverse selection in response to a health plan's coverage of a top specialty cancer hospital. In 2005, a large, private Medicaid plan added this cancer hospital to its provider network, becoming the only private plan in Medicaid to cover the hospital. Consistent with adverse selection, demand among enrollees with cancer responded differentially to this change in coverage: the plan's market share rose by 50% among enrollees with cancer, while remaining constant among non-cancer enrollees. One year after adding the cancer hospital, the plan reversed course and dropped the hospital from its network, leading to a symmetric outflow of enrollees with cancer.

We explore heterogeneity in, and pathways for, these demand responses to coverage of the specialty cancer hospital. We find that people with more severe and costly cancers (e.g., metastatic cancers) were more likely to shift to the plan. This exacerbates adverse selection and is consistent with a model where demand for specialty hospital coverage rises with disease severity. Both the initial 2005 inflow and subsequent 2006 outflow of cancer enrollees were driven mainly by enrollees switching plans, rather than shifts in new Medicaid enrollee choices, indicating that demand for this hospital was strong enough to overcome the high levels of inertia in plan choice typically observed in this market (Geruso, Layton, and Wallace 2020). Finally, there was little change in use of the cancer hospital by the plan's existing enrollees, suggesting that adverse selection, rather than a change in utilization among inframarginal enrollees, was the driving factor behind the insurer's decision to subsequently drop the cancer hospital from its network.

While there is clear evidence of adverse selection, the enrollees driving this selection constitute a small group. Only 2% of Medicaid enrollees in our setting have cancer. Hence, the prevalence of cancer among the plan's enrollees only rose from 2.2% to 3.2% following its decision to cover the hospital, leading to small changes in the plan's average cost. Despite this, the plan responded by immediately dropping the specialty hospital. In the subsequent 8 years, no other Medicaid plan covered that hospital. This presents a puzzle: Why did a small shift in plan cost lead to a substantial change in network design?

In the paper's final section, we address this puzzle by analyzing a simple model of insurer incentives to cover a specialty hospital in markets with fixed (administered) plan prices. We show that the overall incentive depends on changes in costs/revenues for the plan's existing (inframarginal) enrollees, plus a "selection incentive" determined by the profitability of marginal enrollees who select the plan because of its specialty cancer hospital coverage. Importantly, given Medicaid's fixed plan prices, the insurer *cannot* earn additional revenue on existing enrollees. Therefore, unless specialty hospital coverage is *cost-reducing* for inframarginals, the insurer will lose money by covering it unless the selection incentive is strictly positive—that is if the marginal enrollees are profitable. For a specialty hospital whose coverage is differentially appealing (and salient) to the sickest enrollees with cancer, we show that this is unlikely to hold absent strong corrective policies.

To explore the level of corrective policy necessary to overcome this problem, we use our estimates in a set of simple simulations. We demonstrate that this requires either *perfect* risk adjustment, or *near-perfect* risk adjustment combined with high plan base payments (giving insurers average margins exceeding 15%). This is true even if, as in our empirical setting, the marginal group is small. It is not the *size* of the marginal group that is essential, but rather its *profitability*.

A key reason for the challenging economics of specialty hospital coverage is that Medicaid plan payments are fixed (i.e., set by states) regardless of health plan network breadth, giving plans little incentive to implement quality improvements that are costly or lead to adverse selection. This differs from a standard insurance market where insurers can raise prices to offset a modest cost increase or selection disincentive.[2] Motivated by this observation, we consider a simple policy counterfactual that pays insurers an explicit price bonus if they cover the cancer hospital (while keeping enrollee premiums at zero). Even with weak or moderate risk adjustment, a small bonus of $5-10 per member-month (1-2% of average costs) restores profitable coverage, and the bonus can be smaller with stronger risk adjustment. This "pay-for-quality" policy is a way to incentivize

2. Whether coverage of an adversely selected benefit will be profitable with flexible prices depends on insurer market power and the covariance among marginal consumers of cost and willingness to pay for the benefit. Veiga and Weyl (2016) work out the theoretical conditions for this product design problem in a standard insurance market.

specific plan quality improvements while mitigating potentially problematic effects of a full mandate to cover the hospital. However, it forces policymakers to decide which contract dimensions deserve explicit subsidization.

Our paper makes several contributions to the literature on adverse selection and benefit design in health insurance. First, we add to a nascent literature about the effects of adverse selection on contract design (Geruso, Layton, and Prinz 2019; Carey 2017; Lavetti and Simon 2016) and network design in particular (Shepard 2022). We extend that literature to the zero-premium Medicaid setting, presenting results in a set of transparent figures that highlight the vulnerability of specialty hospital coverage to adverse selection. Second, we provide new evidence on the benefits (and limitations) of policies designed to correct selection-induced inefficiencies, such as risk adjustment and quality bonuses (Geruso and Layton 2017). Finally, we add to a literature highlighting inadequate specialty care access in Medicaid (Bisgaier and Rhodes 2011; Timbie et al. 2019), providing a new explanation for this old phenomenon.

2 Setting and Data

2.1 Medicaid Managed Care

Medicaid managed care (MMC) differs from other individual health insurance markets in several key ways relevant to selection and provider network design. First, MMC plans are typically the residual claimants on (nearly) all spending incurred by their enrollees. The package of covered services is standardized across plans, and cost-sharing, where it exists, is minimal (Brooks et al. 2020). Therefore, the primary dimension on which MMC plans differ is their provider networks (Wallace, forthcoming). Second, Medicaid enrollees almost never pay premiums to enroll. Instead, states generally pay insurers a fixed amount per enrollee based on past spending at the plan- or market-level, and often risk-adjusted to account for differences in the clinical conditions of enrollees across plans. Because plan payment is set by the state with no role for endogenous premium-setting by insurers, an adversely selected plan cannot adjust revenues in response to an influx of higher cost enrollees on its own, though states may adjust plan payments via risk adjustment or other parts of the payment system. New York phased in risk adjustment between 2008 and 2011. Prior to that, New York negotiated payments with MMC plans and adjusted rates according to age, sex, geography, and Medicaid eligibility category (Courtot, Coughlin, and Lawton 2012). Third, states often operate publicly-managed fee-for-service (FFS) programs alongside managed care, with some enrollees being allowed to choose between FFS and MMC and other enrollees being mandated into one program or the other.

2.2 Description of the Natural Experiment

In order to investigate the role of adverse selection in provider network formation, we leverage a natural experiment in which a large MMC plan (hereafter, the "focal plan") in New York City added a world-renowned specialty cancer hospital to its provider network at the start of 2005. Prior to being added to the focal plan's network, this hospital was not covered in any of the 18 plans available in New York City (Table A1). Hence, MMC enrollees went from having no access to this specialty cancer hospital to having access through the focal plan. The plan covered the hospital for only one year, dropping it in early 2006. Following program regulations, the plan allowed patients who had started care at the hospital to complete their care episodes (New York State Department of Health 2015), but limited access to the hospital for other enrollees.

These network changes let us observe enrollee selection responses to both the focal plan's addition and exclusion of the cancer hospital. During our study period (2004-08), coverage among other MMC plans was stable. All other MMC plans excluded the cancer hospital, and utilization in those plans was extremely limited, a point we verify empirically. Enrollees in the FFS program retained access to the hospital—to the extent that the hospital was willing to accept them—throughout the study period.

2.3 Data and Outcomes

To evaluate this natural experiment, we merge administrative health records from the New York State Department of Health with managed care provider directories. We obtained de-identified administrative data on enrollment, plan choice, and healthcare claims for the entire New York Medicaid population from 2004 to 2008 and a unique dataset on the provider networks of MMC plans in New York from 2004 to 2017.

The enrollment data allow us to construct monthly market shares for each MMC plan. Claims data allow us to construct measures of MMC and FFS spending for each enrollee, including "carved-out" FFS spending for enrollees in MMC plans. To assess the extent to which sicker enrollees select into the focal plan due to the inclusion of the specialty cancer hospital in its network, we construct market shares separately for enrollees with and without cancer, as described below. In addition to market shares, the available data allow us to construct a range of enrollee-level healthcare use and spending measures. The provider network data allow us to observe that the specialty cancer hospital was added to the network of the focal plan in the first quarter of 2005 and removed in the first quarter of 2006.

2.4 Sample Definition

We restrict our sample in three ways. First, we focus on enrollees living in the geographic market around the specialty cancer hospital, New York City. Second, we restrict the sample to non-elderly adults age 18-64, since Medicare-eligible enrollees were not covered by MMC. Third, we remove enrollees eligible for Medicaid on the basis of eligibility for SSI as they are subject to different rules related to MMC enrollment.

We identify Medicaid enrollees with cancer using the Agency for Healthcare Research and Quality's Clinical Classifications Software (CCS). An enrollee is categorized as having cancer if at any time during 2004-08 the individual has at least: (1) two outpatient claims on different days with a diagnosis that maps to one of the CCS cancer categories (11-43), or (2) one inpatient claim with a diagnosis that maps to a CCS cancer category. We use this simple algorithm, rather than trying to define time spans corresponding to cancer episodes, because Medicaid enrollment spells tend to be short, and the first observed claim with a diagnosis may correspond to cancer that was present well beforehand. To examine heterogeneity in the selection effect, we disaggregate by cancer severity. Appendix Section B provides additional details on the construction of cancer diagnosis and severity measures.

Table 1 presents summary statistics separately for enrollees with and without cancer. The cancer cohort includes roughly 15,000 enrollees in each month (2.3% of adult Medicaid enrollees in our sample). Enrollees with cancer are on average 9 years older than enrollees without cancer and are disproportionately female. Unsurprisingly, the cancer cohort has much higher monthly spending (\$1,422) than the cohort without cancer (\$392).[3]

3 Empirical Analysis

We leverage the addition and removal of the specialty cancer hospital to the network of the focal plan to show the impact of covering the hospital on risk selection and utilization of the hospital. Section 3.1 presents basic evidence of selection, Section 3.2 analyzes utilization responses, and Section 3.3 estimates the impact on the focal plan's profits.

3.1 Evidence of Adverse Selection

Figure 1a presents the focal plan's overall market share among enrollees with and without cancer during the 2004-2008 period. The vertical red lines mark the dates the specialty cancer hospital was added (left line) and removed (right line) from the plan's network. There is a clear divergence in the plan's cancer and non-cancer market shares aligned with the network changes. While the plan's non-cancer market share stays relatively flat around 3.5-3.8%, its cancer market share increases rapidly in late 2004 (just before the addition) and throughout 2005, before declining sharply in 2006 after the cancer center is dropped. The slightly "early" gains in market share likely reflect either: (1) patients' switching in response to the announced change or (2) the fact that our network data are updated quarterly, meaning that the cancer center's addition (first listed at the start of 2005) may have actually occurred during the last quarter of 2004. The increase in market share, from 3.6% to a peak of 5.4%, represents a 50 percent increase, followed by a similar decline over the 18 months from 2006 to mid-2007. These changes can also be seen in the share of the plan's enrollees with cancer (Figure A1), which was similar to other plans and to FFS Medicaid in early 2004 before rising well above them during 2005.

To formally test for differences in the plan's cancer market share over time, we estimate a regression version of Figure 1a that takes the following form:

$$EnrollMCO_{it} = \sum_t \beta_t \left[Cancer_i \times Time_t\right] + \gamma Cancer_i + \alpha_t + \varepsilon_{it} \tag{1}$$

3. Since 28% of the sample is enrolled in FFS, and some benefits are 'carved out' from MMC, *MMC plan* spending differs from *total Medicaid* spending, but mean MMC plan spending is also much higher for cancer (\$571) than for non-cancer enrollees (\$154).

where $EnrollMCO_{it}$ is a dummy for person i's enrollment in the focal plan in month t, $Cancer_i$ is a dummy indicating whether i is in the cancer cohort, and α_t are dummies for each month in the series (excluding June 2004, the reference month). This regression functions as a difference-in-differences specification, with the coefficients of interest, β_t, capturing differential selection into the focal plan among the cancer cohort relative to the non-cancer cohort.

Figure 1b shows OLS estimates of the β_t coefficients in equation (1), with shading representing 95% confidence intervals. The conclusions parallel the findings in Figure 1a. The timing and sharp contrast of the changes in the plan's cancer and non-cancer market shares suggest that the plan experienced adverse selection due to covering the cancer center. Figure A2 in the Appendix presents evidence that the 2005 inflow and subsequent 2006 outflow of cancer enrollees are driven mainly by enrollees *switching* plans, rather than by shifts in new Medicaid enrollee choices.

We next demonstrate that adverse selection was driven by the *sickest* cancer patients. We use our event study specification in equation (1) but pool the time dummies into broader periods to increase power. We focus on estimates of β_t for the "peak selection" period, July 2005-June 2006. Figure 2 plots estimates of the peak selection coefficient by cancer type (y-axis) against the estimated profitability of the group to MMC plans (x-axis) based on revenues and costs in the Medicaid data. The figure shows that selection into the focal plan was larger for less profitable (higher-cost) cancer types. The clearest example is metastatic cancer, the highest-cost cancer type, which has one of the largest selection coefficients.

In Figure A3 we investigate heterogeneity in selection among cancer enrollees by other attributes: age, sex, race, location, and prior use of the cancer hospital. Many of these patterns are intuitive (e.g., weaker selection by younger enrollees), but overall there is less heterogeneity on these attributes. The exception is prior use of the hospital, with the enrollees who previously visited the cancer hospital being much more likely to select into the plan (>20x more likely than the full sample). Selection driven by existing care relationships is consistent with prior work (Shepard 2022; Tilipman 2022). Nonetheless, there is still positive and significant selection for cancer patients without prior use of the hospital.

3.2 Impacts on Utilization of the Cancer Center

In this section, we study the effect of the focal plan's inclusion of the cancer hospital on use of the hospital, both inside the plan and overall in Medicaid. This analysis provides evidence as to whether network coverage expanded overall access to the cancer hospital in Medicaid, leading to a causal increase in utilization, or merely shifted users of the cancer hospital across plans (a sorting/selection effect).

As a benchmark for the estimates, we note that utilization per 100 enrollees spiked dramatically within the focal plan during 2005, rising from 0.07 enrollee-days in mid-2004 to 2.08 in late-2005, before falling back to near-zero by late-2006 (Figure A4a). Similarly, the portion of the focal plan's cancer patients who used the cancer hospital rose from near-zero in mid-2004 to almost 15% in late-2005 (Figure A4b). This dramatic 40-fold increase could reflect a utilization response, re-sorting of patients into the focal plan, or both.

We use two strategies to disentangle causal utilization responses from sorting. First, we examine total utilization of the cancer hospital across *all Medicaid enrollees*. Assuming that the focal plan's coverage does not affect whether people enroll in Medicaid, an overall utilization increase would suggest a causal utilization-response, while no change in overall Medicaid utilization would suggest that the increased utilization of the cancer hospital in the focal plan was driven by re-sorting. Second, we examine utilization patterns for people who joined the focal plan at different times relative to its addition of the cancer hospital. A utilization increase in early 2005 among the plan's *pre-existing* enrollees, who joined prior to the network change, would be consistent with a causal increase in overall utilization. Greater utilization only among enrollees who joined while the focal plan covered the cancer hospital (late 2004 to 2005), with little change among pre-existing enrollees, would reflect a sorting effect.

Figure 3a implements the first strategy by plotting overall Medicaid utilization of the cancer hospital and utilization separated out by plan type.[4] The evidence is mixed but overall suggests at most a modest causal utilization-response. There was little change in total use in early 2005 around the cancer hospital's addition—as a large increase among focal plan enrollees was mirrored by a decline for FFS and other MMC plans (consistent with re-sorting). There is a decline in total use

4. While this graph shows total utilization, patterns are similar if we normalize by Medicaid enrollment, which is stable during this period.

after the plan's exclusion in 2006, but it partly rebounds by early-2007 as cancer hospital users shift into FFS Medicaid. If we approximate the upper bound of any causal effect as the fall in total use from the 2005 peak (1,226 enrollee-days) to the mean from early-2007-onward (1,005 enrollee-days), that yields 22%. This is non-zero but explains only a small share of the increase in enrollee-days within the focal plan, suggesting the sorting effect dominates.

In Figure 3b, we show that evidence from the second strategy is consistent with this conclusion. Among the focal plan's enrollees who joined prior to Q3 2004, utilization of the cancer hospital is consistently low from 2004-2008. By contrast, utilization rates are much higher for people joining the plan in late-2004 to 2005, peaking at over 6.0 enrollee-days per 100 enrollees for the group joining in late-2005. This rate falls for subsequent cohorts joining in 2006, consistent with the cancer hospital's patients sorting into other plans (largely FFS). These two pieces of evidence lead us to conclude that most of the effect of the specialty hospital inclusion on the plan's costs and profits was driven by selection, not a causal effect of inclusion on use of the hospital.

3.3 Impact on Focal Plan's Profit Margins

We now estimate the effects of hospital inclusion on the plan's profits. As we formalize in Section 4, the selection impact on plan profits equals the change in demand times the average profits (or losses) for marginal enrollees. For the change in demand, we use the 1.8% market share increase among cancer enrollees (Figure 1a) and continue to assume zero demand response among non-cancer enrollees. For the cost of these marginal enrollees, we use the estimated share of marginal enrollees by cancer type (derived from estimates in Figure 2) and multiply each by the average cost for that cancer type in the focal plan during 2005. This yields a monthly average plan-paid cost of \$800 for marginal enrollees. This is substantially higher than the overall average of \$571 for Medicaid enrollees with cancer, reflecting the importance of differential selection by cancer severity. This \$800 per month is well above the average price paid for these enrollees (\$203 per month) given Medicaid's weak risk adjustment at this time.

Using these estimates, we find that adverse selection led to a total loss of $\approx$ \$172,000 per month by the selection peak, or \$2 million annually if the cancer hospital remained in-network. Although small relative to total plan revenues for the study sample (\$62 million annually), this loss represents about a 15% reduction in the plan's estimated profit margins.[5] Moreover, given its continually rising cancer market share throughout 2005, these losses may have continued to accelerate had the plan not dropped the cancer hospital. The plan's exclusion decision in 2006, therefore, is consistent with a rational response to the financial incentives created by adverse selection.

4 Model

We now develop a model of an insurer's incentives to cover a hospital to understand how a small amount of adverse selection could lead an insurer to exclude a top specialty hospital. A key goal of this section is to contrast the insurer's incentives in a setting where it endogenously sets premiums (as in most individual insurance markets) to the Medicaid setting, where insurers cannot charge premiums and per-enrollee revenues are determined administratively. We then use the model to evaluate potential policy responses.

4.1 Model Setup

Consider a market in which enrollees (i) choose among available insurance plans $j \in \{1, ..., J\}$. Insurers each offer a single plan. The Medicaid program pays each insurer a baseline per-member fee (or subsidy) of R, which we initially assume is invariant to specialty hospital coverage. Additionally, insurers may be able to set an add-on premium P_j that is passed on to enrollee premiums. We consider two policy cases:

1. **Standard markets:** Insurers can set P_j flexibly.

2. **Medicaid case:** No add-on premiums are allowed ($P_j = 0$).

Insurer revenues are further risk-adjusted based on enrollee risk scores, φ_i, so the plan receives $\varphi_i \cdot (R + P_j)$ for covering i.

We model the decision of a single insurer j whether to cover a specialty hospital, holding fixed all other benefits (of j and other insurers). Let $x_j \in \{0, 1\}$ indicate j's coverage decision.

5. We assume the plan had administrative costs of \$25.16 PMPM, consistent with the statewide average during the sample period (Newell and Baumgarten 2009).

The decision affects its enrollee-specific expected costs, $C_{ij}\left(x_j\right)$. We focus on the case where the hospital is weakly cost-increasing, $\Delta C_{ij} \equiv C_{ij}(1) - C_{ij}(0) \geq 0$, which seems natural for a top cancer hospital. Coverage may also affect enrollee demand, $D_{ij}(x, P)$, which indicates whether individual i chooses j, as a function of all plans' benefits, x, and premiums P. Insurer profits equal:

$$\begin{aligned}\pi_j(x,P) &= \sum_i \left[\varphi_i(R+P_j) - C_{ij}\left(x_j\right)\right] \cdot D_{ij}(x,P) \\ &= \sum_i \left[(R+P_j) - C_{ij}^{RA}\left(x_j\right)\right] \cdot \widetilde{D}_{ij}(x,P) \qquad (2)\end{aligned}$$

where $C_{ij}^{RA}\left(x_j\right) \equiv C_{ij}\left(x_j\right)/\varphi_i$ is risk-adjusted costs and $\widetilde{D}_{ij}(x,P) \equiv \varphi_i D_{ij}(x,P)$ is risk-weighted demand. In a setting without risk adjustment, these collapse to standard costs and demand.

4.2 Profitability of Specialty Hospital Coverage

Now consider how profits change when insurer j shifts from excluding to covering the specialty hospital, holding fixed all other insurers' benefits at x_{-j}. In standard markets, the insurer can reset premium P_j flexibly to maximize profits, with $P_j^*(1)$ and $P_j^*(0)$ representing these premiums, and with $\Delta P_j^* \equiv P_j^*(1) - P_j^*(0)$. For notational ease, we treat premiums and other insurers' benefits as implicit, writing simply $\pi_j\left(x_j\right)$ for profits (and likewise for other variables) and use "Δ" to denote changes from $x_j = 0$ to $x_j = 1$. The profit change, $\Delta\pi_j \equiv \pi_j(1) - \pi_j(0)$, equals:

$$\Delta\pi_j^{Flexible} = \underbrace{\sum_i \left[(R+P_j^*(1)) - C_{ij}^{RA}(1)\right] \cdot \Delta\widetilde{D}_{ij}}_{\text{(1) Selection: Profitability of marginals}} + \underbrace{\left(\Delta P_j^* - \overline{\Delta C}_{0j}^{RA}\right) \cdot \widetilde{D}_j(0)}_{\text{(2) }\Delta\text{Revenue - Costs on inframarginals}} \qquad (3)$$

Term (1) is the selection incentive: the profitability of "marginal" enrollees attracted by the plan's covering the specialty hospital. This term will be negative (an *adverse* selection incentive) if marginal consumers' risk-adjusted costs are high relative to total payments ($= R + P_j$). Term (2) captures the change in profits on inframarginal enrollees, which equals the number of inframarginals ($\widetilde{D}_j(0)$) times the increase in premiums (ΔP_j^*) minus the mean change in costs for inframarginals, $\overline{\Delta C}_{0j}^{RA}$.

Now, consider how $\Delta\pi_j$ differs in the "Medicaid case" with zero add-on premiums:

$$\Delta\pi_j^{Medicaid} = \underbrace{\sum_i \left[R - C_{ij}^{RA}(1)\right] \cdot \Delta\widetilde{D}_{ij}}_{\text{(1) Selection: Profitability of marginals}} - \underbrace{\overline{\Delta C}_{0j}^{RA} \cdot \widetilde{D}_j(0)}_{\text{(2) }\Delta\text{Costs on inframarginals}} \quad (4)$$

It is straightforward to see why selection incentives may matter so much in the Medicaid case. With flexible pricing, the plan can offset a small adverse selection incentive or inframarginal cost increase by raising premiums, thereby increasing revenues. With fixed prices, it cannot. Therefore, covering the specialty hospital will only be profitable if marginal enrollees are profitable (*advantageous* selection)—and sufficiently so to outweigh any extra expenses on inframarginals.

This expression shows how challenging it is for profit-maximizing insurers to offer benefits that primarily appeal to sicker enrollees, absent intervention. Note that it is not critical how *large* the marginal group is; if that group is *unprofitable*, the plan will lose money by covering the extra provider/service. This helps explains why even a small increase in the focal plan's average costs due to the inclusion of the cancer hospital ultimately led the plan to reverse course and exclude the hospital from its network.

4.3 Policy Responses

How can policymakers encourage specialty hospital coverage within the constraints of the Medicaid system where enrollee premiums are fixed at $0? In this section, we use our empirical evidence to simulate two types of corrective policies to understand the tradeoffs involved. First, we consider stronger risk adjustment and higher Medicaid fees (R), which seek to offset adverse selection directly by making marginal enrollees profitable. Second, we consider an explicit fee bonus, ΔR, if plans cover the specialty hospital. This bonus allows plans to earn extra revenue from coverage—as in the standard-market case—but does so via subsidies, keeping enrollee premiums zero. It can be seen as a "pay-for-quality" incentive to help overcome adverse selection or other market failures leading to undesirably low quality on an observable dimension.

Throughout, we focus on estimating the profitability of marginal enrollees (term (1) of equation (4)), since this selection incentive is what our evidence identifies most cleanly. As discussed above, a positive selection incentive is a *necessary* condition for the plan to earn profits if the specialty hospital is a higher-cost facility. Further, the evidence in Figure 3 suggests that specialty hospital utilization impacts for inframarginal enrollees may be small, implying that selection incentives comprise the main effect of the coverage decision on profits. To estimate the quantities in term (1) of equation (4), we define i as cancer diagnosis groups, following the classification in Figure 2. We identify demand changes (ΔD_{ij}) using the DD estimates underlying the figure. To estimate $C_{ij}(1)$, we (conservatively) use average costs for group i in the focal plan during 2005. If specialty hospital coverage led to selection on unobserved sickness within diagnosis group, this may underestimate the selection incentive.

Risk Adjustment and Medicaid Fees We start by simulating changes to risk adjustment and fees within the existing system. For fees, R, we consider a range of values resulting in average profit margins across all Medicaid enrollees (with and without cancer) from 0% to 30%, a range consistent with reasonable lower and upper bounds in Medicaid. For risk adjustment, we simulate a range from zero to perfect risk adjustment. To do so, we set risk scores for group i to be a power-scaling of actual average costs: $\varphi_i = (C_{ij}/\overline{C})^{\gamma}$. Here, $\gamma = 0$ corresponds to no risk adjustment ($\varphi_i = 1 \rightarrow C_{ij}^{RA} = C_{ij}$ for all i), $\gamma = 1$ implies perfect risk adjustment ($C_{ij}^{RA} = \overline{C}$ for all i), and increasing γ between 0 and 1 involves stronger risk adjustment.

Figure 4 shows the result of this exercise in a heatmap, where the x-axis is the strength of risk adjustment (γ), the y-axis is the average margin implied by the fee, and the outcome (shown by the color shading) is the selection incentive (term (1) of equation (4)). Without risk adjustment and with a zero average margin, marginal enrollees cost over \$220,000 per month and generate about \$45,000 in revenue, implying losses of more than \$175,000 per month. Without stronger risk adjustment, even Medicaid fees that generate average margins of 30% are insufficient to make coverage profitable; the marginal enrollees are simply too costly. Only with either perfect risk adjustment, or near-perfect risk adjustment ($\gamma > 0.90$) plus high fees (margins > 15%), is the policy strong enough to make the selection incentive positive.

Bonus for Specialty Hospital Coverage What if policymakers instead give insurers an explicit fee bonus, ΔR, for cancer hospital coverage that relaxes the fixed-pricing constraint? The bonus does not affect the selection incentive term—which is still captured by the numbers in Figure 4.

Instead, it gives the plan extra revenue of ΔR times its initial enrollment, about 25,000 per month, if it covers the hospital. Thus, a \$10/month bonus (a $\approx 2\%$ increase relative to average per-enrollee costs) gives the plan \$250,000; a \$5 bonus gives it \$125,000. Thus, a \$10 bonus is enough to fully compensate for adverse selection even without *any* risk adjustment and 0% baseline margins; a \$5 bonus is enough with moderate risk adjustment ($\gamma = 0.5$) and a 5% baseline margin. In general, the stronger risk adjustment is and the higher baseline margins are, the smaller the bonus can be.

Why does a small bonus offset adverse selection so easily, whereas this required near-perfect risk adjustment? The key insight is that cancer hospital coverage attracts a very sick but also *small* group of marginal enrollees (≈1% of the plan's initial enrollment). A small bonus applied to *all* enrollees is enough to offset even severe risk adjustment shortfalls. By contrast, risk adjustment works by trying to match revenues to costs *for the marginal enrollees*, which is often challenging in practice. For observable quality measures, therefore, an explicit pay-for-quality program is simpler and may be easier to adjust—e.g., by flexibly changing ΔR based on observed outcomes. However, unlike risk adjustment, such a program would require the policymaker to decide which benefits to subsidize.

Clearly, these simulations only capture part of the broader network-setting problem. We have not simulated supply-side responses, including other insurers' actions and hospital-insurer bargaining. For both risk adjustment and explicit bonuses, one potential concern is that the specialty hospital exploits its bargaining leverage to raise prices.[6] Despite these limitations, the simulations provide important insights regarding: (1) how difficult it is to achieve equilibria where top specialty hospitals are covered by for-profit plans when those plans cannot charge premiums; and (2) the relative effectiveness of explicit subsidies versus standard policies such as risk adjustment.

5 Conclusion

In this paper, we provide new evidence on the role of adverse selection in insurers' decisions to cover top specialty hospitals in Medicaid. Using a natural experiment in which a single MMC

6. Both policies provide less leverage than a full *mandate* to cover the cancer hospital, a common policy response to distortionary adverse selection. A bonus, unlike a mandate, preserves flexibility to exclude the hospital when there is a compelling reason—e.g., if a plan wished to steer patients towards another cancer hospital better integrated into its network.

plan added a well-known cancer hospital to its provider network and dropped it a year later, we find evidence of extreme adverse selection on cancer hospital coverage. Given the capitated plan payment systems in place in the Medicaid program, the analysis suggests that MMC plans have a strong disincentive to cover the cancer hospital absent strong corrective policies. This disincentive comes primarily from adverse selection, with at most small causal utilization impacts among inframarginal enrollees.

Our analysis suggests that these incentives are a natural consequence of Medicaid's fixed-price system, which does not allow insurers to boost per-enrollee revenue when they implement a costly quality improvement such as inclusion of a specialty cancer hospital. Medicaid insurers only have a profit incentive to cover costly benefits if the marginal enrollees attracted are strictly profitable (that is, a positive selection incentive). Our results indicate that for specialty services and other types of care differentially demanded by sick enrollees, this condition is challenging to meet, requiring near-perfect risk adjustment and/or high Medicaid plan payments that are costly to the government. On the other hand, directly subsidizing the coverage of such services can make coverage economically feasible despite selection incentives, with necessary subsidies shrinking as risk adjustment strengthens.

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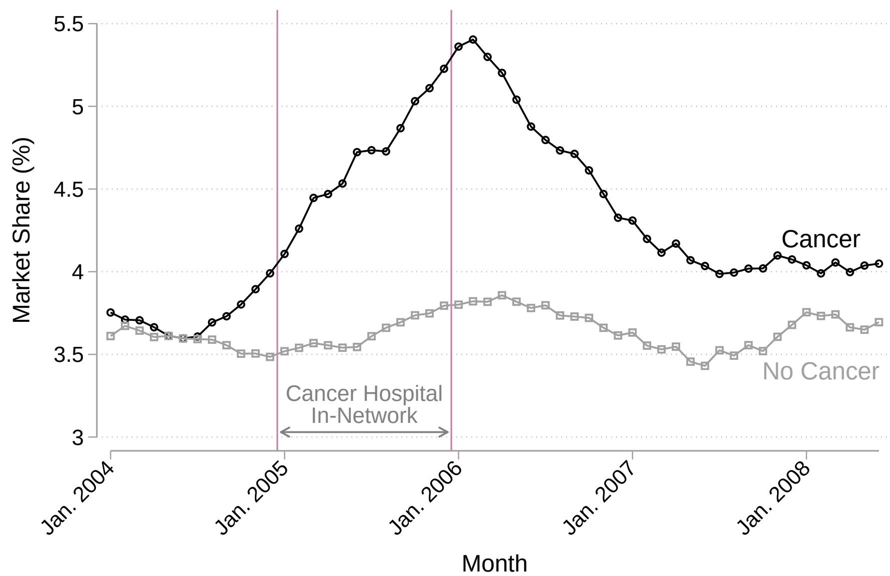
6 Exhibits

(a) The Focal Plan's Market Share Among Medicaid Enrollees With and Without Cancer



(b) Event Study Regression Estimates: Selection into the Focal Plan

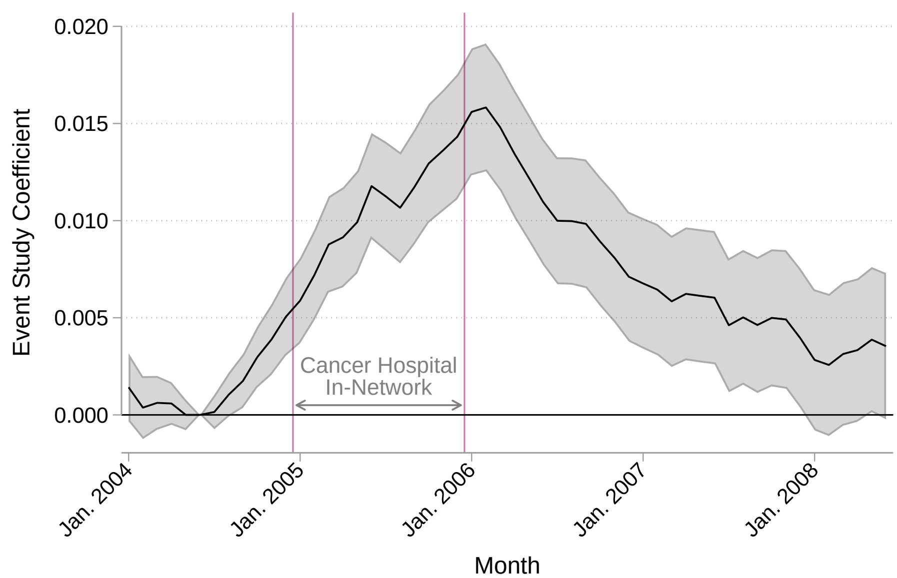


Figure 1: Selection into the Focal Plan by Enrollees with Cancer

Note: Figure 1a plots the focal plan's Medicaid market share among enrollees with and without cancer from January 2004-June 2008. Consistent with adverse selection, the plan's market share among enrollees with cancer rose quickly around its inclusion of the cancer hospital in early 2005, while its non-cancer market share remained relatively flat. The reverse occurred after the plan dropped the cancer hospital in early 2006. Figure 1b shows the event study version of Figure 1a; specifically, it presents the event study coefficients (β_t) recovered from estimating equation (1), with the shading representing 95% confidence intervals (standard errors clustered at the enrollee level). See Section 2 for additional details on the outcomes and sample.

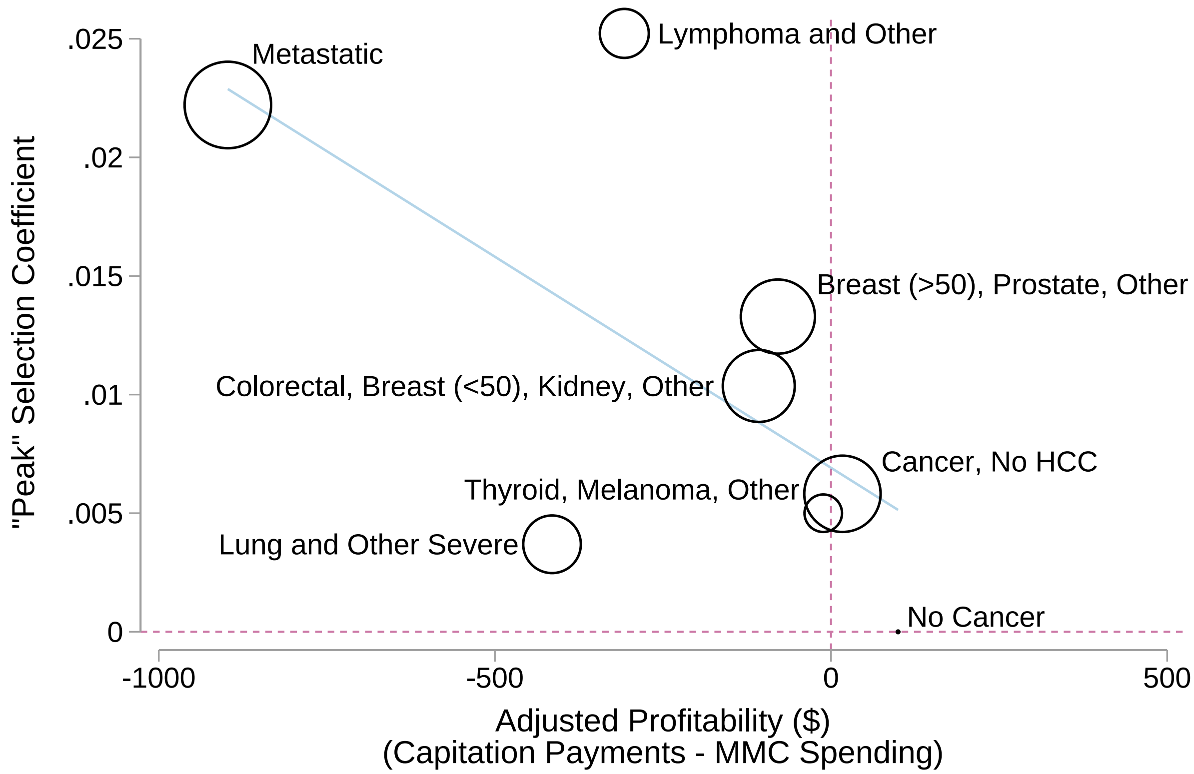
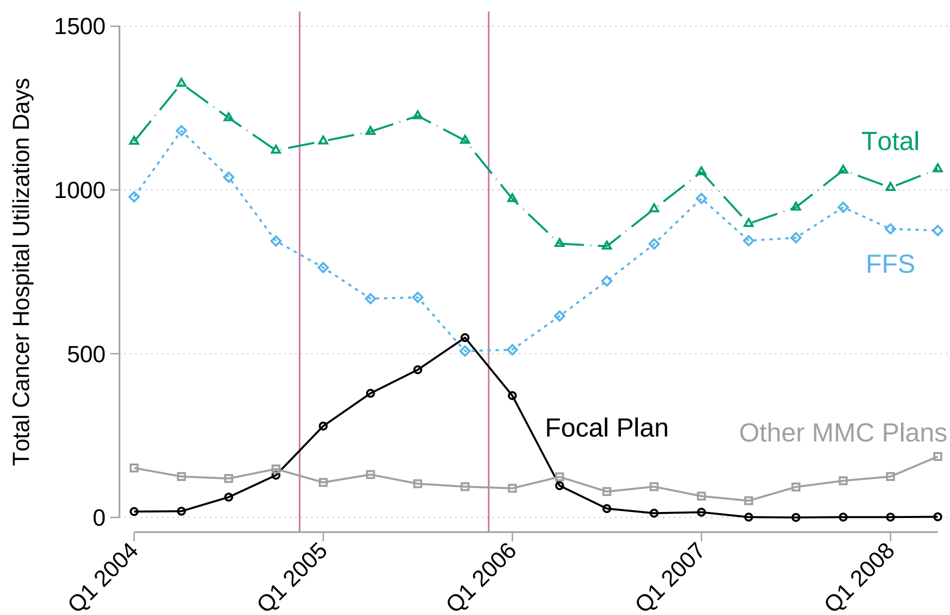


Figure 2: Heterogeneity in Selection into Focal Plan, by Cancer Type

Note: The figure shows heterogeneity in adverse selection into the focal plan by cancer severity. Each point is a cancer type, defined as Hierarchical Condition Categories (HCCs) used by the U.S. Department of Health and Human Services for risk adjustment (see Appendix B.2 for details), with bubble sizes indicating prevalence in our data. The x-axis is cancer type profitability, calculated as average managed care revenue minus costs for that cancer type in 2005-06 across all managed care plans (after adjusting for plan, year, and month fixed effects in a regression). Profitability is mainly driven by cost, but it accounts for the limited risk adjustment used in pratice. The y-axis is the "peak" selection coefficient for the cancer type, based on estimates of event study estimates of β_t in regression (1), with time dummies ($Time_t$) pooled into five periods to increase power. The estimates shown are for the "peak selection" period of July 2005-June 2006. (For a full list of time periods and coefficient estimates, see Appendix Table A2.) All estimates are based on separate regressions for each cancer type, using enrollees without cancer as the control group.

(a) Quarterly Utilization of Cancer Hospital: Overall and by Type of Medicaid Plan



(b) Utilization Rate of Cancer Hospital, by Time of Joining the Focal Plan

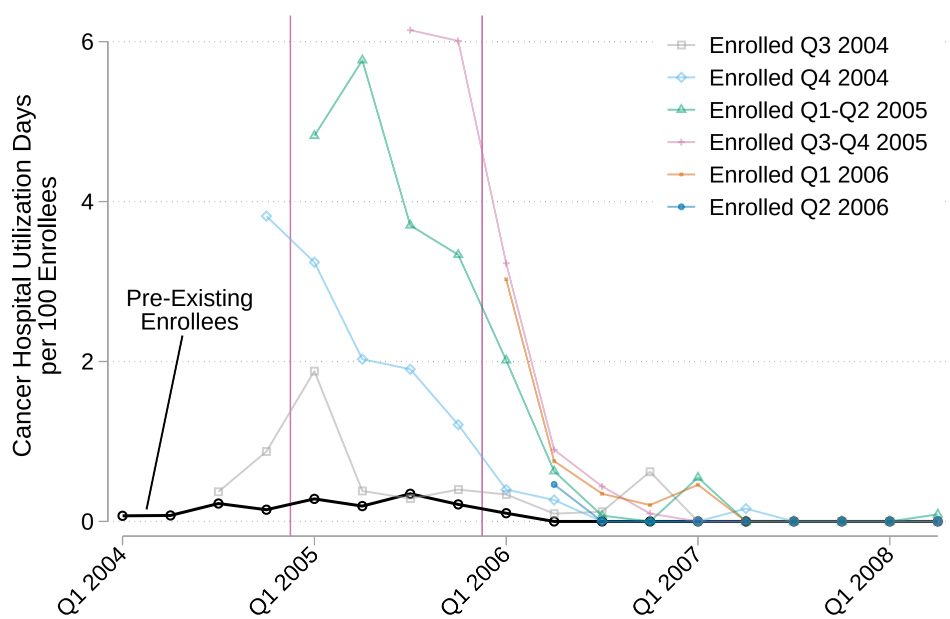


Figure 3: Utilization of the Specialty Cancer Hospital

Note: Figure 3a displays total quarterly utilization of the specialty cancer hospital (enrollee-days with a claim incurred at it), both overall in Medicaid ("Total") and disaggregated by market segment (Focal Plan, Other Medicaid managed care (MMC) plans, and FFS Medicaid). Figure 3b shows quarterly utilization of the specialty cancer hospital (enrollee-days per 100 enrollees) among enrollees in the focal plan, disaggregated by the time period the enrollee first joined the focal plan (Q3 2004, Q4 2004, etc.). The "pre-existing enrollees" group includes all of the focal plan's enrollees who joined prior to Q3 2004.

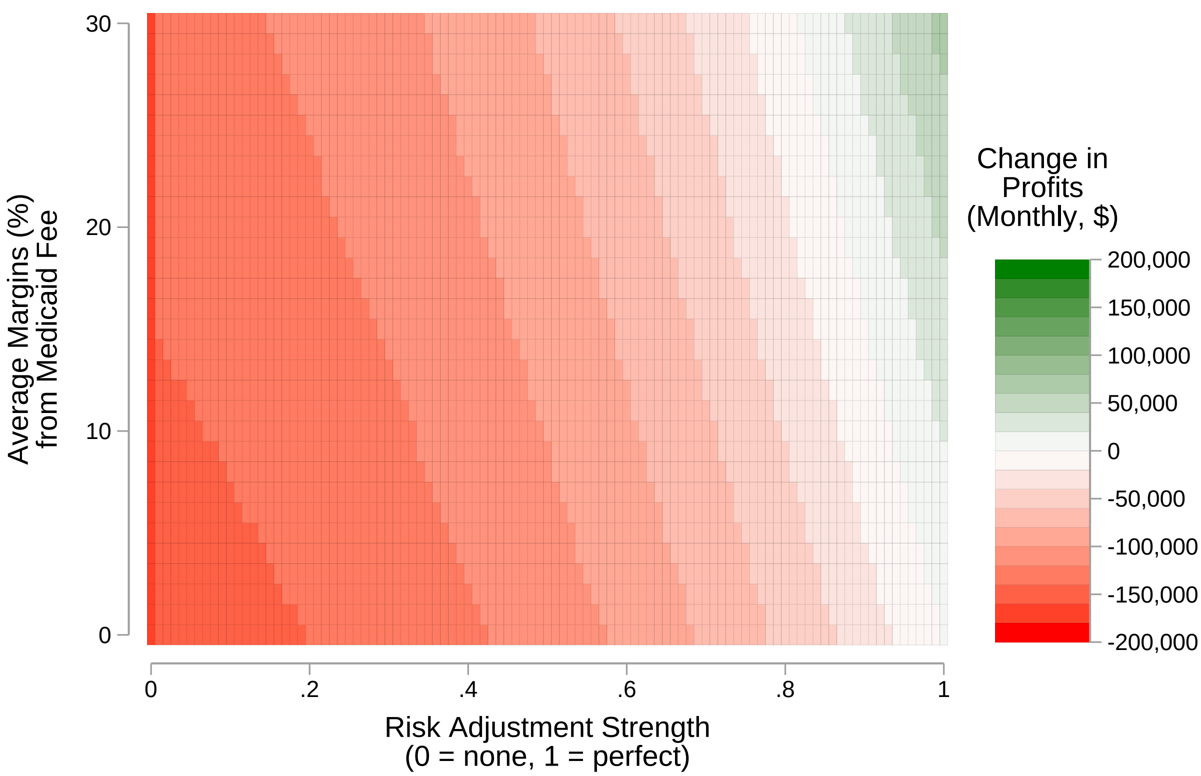


Figure 4: Profitability of Adding Cancer Hospital Coverage, by Risk Adjustment Strength and Medicaid Fee Level

Note: Figure 4 presents simulations of the selection effect of cancer hospital coverage for the focal plan under varying assumptions about: (1) the strength of risk adjustment (x-axis), and (2) the per-enrollee Medicaid fee (R) paid to insurers (y-axis). The strength of risk adjustment corresponds to the value of γ as described in Section 4.3, which ranges from 0 (no risk adjustment) to 1 (perfect risk adjustment). For Medicaid fees, we show a range of values resulting in average profit margins across all Medicaid enrollees (with and without cancer) from 0% to 30%. The heatmap colors shows the size of the selection effect on profits — corresponding to term (1) of equation (4) — ranging from red (losses) to green (profits). See Section 4.3 for a description of the method details. The simulations indicate that only with either perfect risk adjustment, or near-perfect risk adjustment ($\gamma > 0.90$) plus high fees (margins > 15%), is the payment policy strong enough to incentivize coverage of the cancer hospital.

Table 1: Summary Statistics

	No Cancer	Cancer	Total
	(1)	(2)	(3)
Unique enrollees (mean per month)	665,429	15,408	680,837
Percentage of sample (%)	97.7	2.3	100.0
Age (mean)	35.3	44.4	35.5
Female (%)	64.1	71.5	64.3
Race/ethnicity (%)			
Black	31.6	30.0	31.6
White	30.7	32.0	30.7
Asian or Pacific Islander	11.4	12.7	11.4
Hispanic	9.9	10.6	9.9
American Indian or Alaska Native	2.6	2.6	2.6
Other	13.8	12.1	13.8
Plan (%)			
Focal MCO	3.6	4.3	3.7
Other MMC plans	68.3	68.2	68.3
Fee-for-service	28.1	27.5	28.1
Monthly Medicaid spending, 2005-2008 ($)			
Total spending (FFS + MMC)	391.6	1,422.2	415.0
Monthly MMC spending, 2005-2008 ($)			
Total MMC spending	154.0	571.3	163.6
Inpatient MMC spending	67.0	285.1	72.0
Outpatient hospital MMC spending	15.2	80.2	16.7

Note: This table reports summary statistics for our sample of Medicaid enrollees ages 18-64 living in New York City who were enrolled at any time from 2004-2008. The sample excludes enrollees who were eligible for Medicaid on the basis of Supplemental Security Income (SSI) benefits. Enrollees were categorized as having cancer if at any time during their Medicaid enrollment from 2004-08 they had at least: (1) two outpatient claims on different days with a cancer diagnosis (defined as AHRQ Clinical Classifications Software (CCS) categories 11-43), or (2) one inpatient claim with a cancer diagnosis. For all spending estimates, we exclude the 2004 data due to unreliable reporting of Medicaid managed care (MMC) spending in that year. When estimating mean monthly MMC spending, we exclude enrollees in fee-for-service (FFS) Medicaid; total Medicaid spending (FFS + MMC) is estimated using the full sample.

Online Appendix

A Study Data: Additional Details

A.1 Medicaid Data

The administrative Medicaid enrollment and claims data were obtained pursuant to a Data Exchange Application & Agreement (DEAA) with New York Medicaid. The data were de-identified to protect the privacy of Medicaid enrollees. For each enrollee, we observe demographic data, monthly enrollment by plan (FFS vs. MMC, as well as which MMC plan), and claims paid by the fee-for-service program and the managed care plans for all services covered by Medicaid. The medical claims include detailed patient diagnoses, procedures, provider identifiers, and the amount paid for each claim. We also obtained a unique dataset on the physician and hospital networks of the MMC plans in New York from 2004 to 2017.

To measure health care utilization and spending for the Medicaid managed care population, we use variables provided by the New York State Department of Health (NYSDOH) to construct a set of service categories and disaggregate outpatient hospital and inpatient spending (Table 1). Finally, in order to assess the extent to which enrollees in each plan utilized the cancer specialty hospital, we use the provider IDs present in the claims to construct counts of the number of enrollee-days with a claim at the specialty hospital.

A.2 Managed Care Provider Directories

To identify changes in Medicaid managed care (MMC) plans' coverage of the specialty cancer hospital over time, we use the Provider Network Data System (PNDS), an audited database of provider networks for all managed care plans (Medicaid and non-Medicaid) in New York State. The PNDS is updated quarterly and includes an indicator for each provider-insurer pair that identifies for which insurance products the provider is "in-network" during each quarter.[7] Since several insurers serve both the Medicaid and commercial markets, this indicator allows us to isolate their Medicaid networks. Although the specialty cancer hospital we examine was out-of-network

7. Products include Medicaid, Medicare, and commercial market plans

during all quarters of the sample period for each Medicaid managed care plan other than the focal plan, it was in-network for one of the commercial HMO networks reported in our data from 2004-2007.

B Identifying Enrollees with Cancer

B.1 Cancer Cohort

Our algorithm for identifying enrollees with cancer uses Clinical Classification Software (CCS) categories 11-43 (Healthcare Cost and Utilization Project 2016), which correspond to cancer diagnoses (e.g., cancer of the head and neck, cancer of the esophagus, and cancer of the stomach). In addition to using these CCS categories to identify enrollees with a cancer diagnosis, we exclude from the estimation sample enrollees who have diagnoses mapping to CCS categories 44 (neoplasms of unspecified nature or uncertain behavior) or 45 (maintenance chemotherapy; radiotherapy), but who do not otherwise meet our criteria for a cancer diagnosis. It is unclear whether enrollees with these diagnoses, who do not also receive a clear-cut cancer diagnosis (CCS categories 11-43), belong in the treatment or control group.

B.2 Disaggregating the Cancer Cohort by Severity

To examine heterogeneity in the selection finding, we disaggregate the cancer cohort by severity. We map all diagnosis codes appearing in each enrollee's claims to U.S. Department of Health and Human Services (HHS)-defined "Condition Categories" (HHS-CCs), restricting to HHS-CCs associated with a cancer diagnosis (Centers for Medicare & Medicaid Services 2013). The HCCs associated with cancer diagnoses include (in order from most- to least-severe): Metastatic Cancer (HCC 8); Lung, Brain, and Other Severe Cancers, Including Pediatric Acute Lymphoid Leukemia (HCC 9); Non-Hodgkin's Lymphomas and Other Cancers and Tumors (HCC 10); Colorectal, Breast (Age < 50), Kidney, and Other Cancers (HCC 11); Breast (Age 50+) and Prostate Cancer, Benign/Uncertain Brain Tumors, and Other Cancers and Tumors (HCC 12); and Thyroid Cancer, Melanoma, Neurofibromatosis, and Other Cancers and Tumors (HCC 13). Once we have identified all of the HHS-CCs associated with each enrollee's diagnoses, we impose a hierarchy on the HHS-CCs, such that each enrollee is assigned to the most "severe" or expensive HHS-CC (as defined by CMS) associated with her cancer diagnoses during the sample period (2004-08). These final categorical assignments are called HHS Hierarchical Condition Categories (HCCs).

Because of differences in the ICD-9 diagnoses associated with the HCCs and the Clinical Classifications Software (CCS) categories, it was possible for an enrollee to be assigned to the cancer cohort but not to have any diagnoses associated with an HCC. When this occurred, we assigned the enrollee to a category called "Cancer, no HCC." Enrollees assigned to this category had the lowest mean spending of any of the HCC categories (see Figure 2).

C Cost of the Marginal Enrollees

To estimate the average monthly cost of the marginal enrollees who joined the focal plan, we use the following equation:

$$CostMarginals = \frac{\sum_g NumMarginals_g \cdot AvgCosts_g}{\sum_g NumMarginals_g} \tag{5}$$

In this equation, g represents the seven cancer HCCs as described in Section B.2. To calculate $NumMarginals_g$ for each HCC g, we multiply the baseline number of Medicaid enrollees in HCC g during the pre-period by the regression coefficient for HCC g for the "peak" selection period, as presented in Figure 2. This coefficient represents the percentage point increase in enrollment in the focal plan by Medicaid enrollees in HCC g relative to Medicaid enrollees without cancer. $AvgCosts_g$ represents the average monthly MMC spending for HCC g within the focal plan in 2005. Using this equation, we find that the average cost of the marginal enrollees is \$799.70/month. This cost is $\approx$ 40% higher than the cost of the average MMC enrollee with cancer (\$571.30).

D Additional Tables and Figures

D.1 Figures

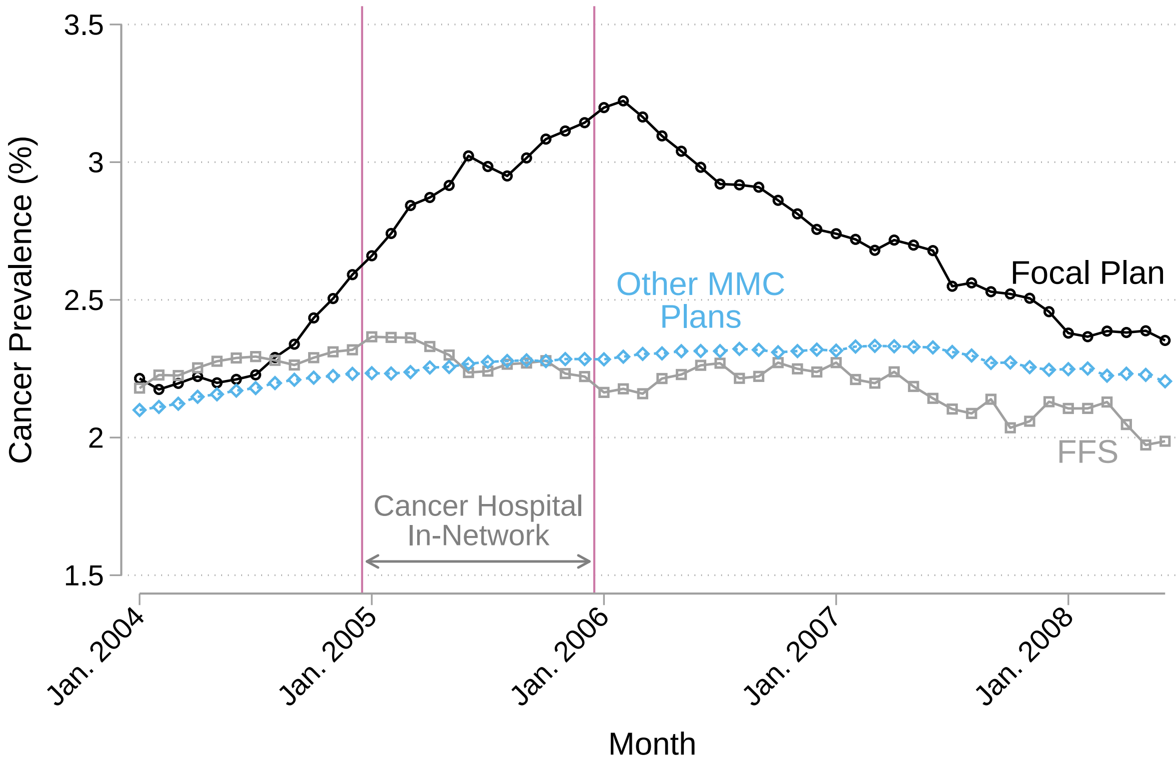
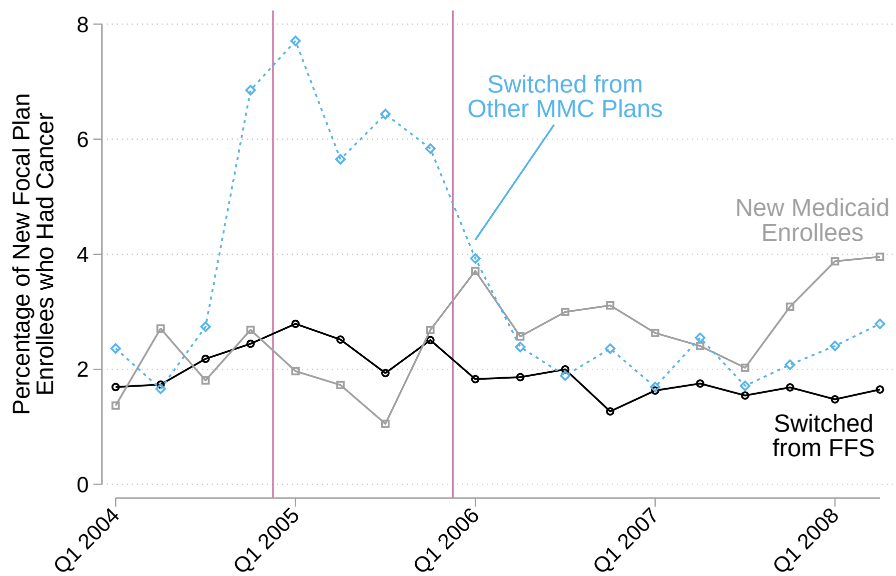


Figure A1: Cancer Prevalence within Each Medicaid Market Segment

Note: Figure A1 plots the monthly cancer prevalence within each Medicaid market segment (focal plan, other MMC plans, and fee-for-service Medicaid). Cancer prevalence is defined as the percentage of enrollees in the market segment who had cancer. The addition of the cancer hospital to the focal plan's provider network had a substantial impact on the plan's enrollee composition. Before the cancer hospital was added to the plan's network, the share of enrollees with cancer in all three market segments was $\approx 2.2-2.3\%$. Following the inclusion of the cancer center in-network, the percentage of enrollees in the focal plan who had cancer immediately began to rise, peaking at 3.2% at the beginning of 2006 (a 45% relative increase). When the cancer center was dropped from the plan's network, the percentage of the plan's enrollees who had cancer immediately began to decline, ultimately reaching $\approx 2.4\%$ at the end of the sample period. During this entire period, the percentage of enrollees in the other two market segments who had cancer remained relatively flat. This is possible because the other two market segments (FFS and other MMC plans) represent a much larger share of the overall Medicaid market; therefore, inflows and outflows of a small number of enrollees with cancer have a larger impact on the individual plan than on the overall FFS and MMC markets.

(a) Cancer Share among Enrollees Joining the Focal Plan, By Source



(b) Cancer Share among Enrollees Leaving the Focal Plan, By Destination

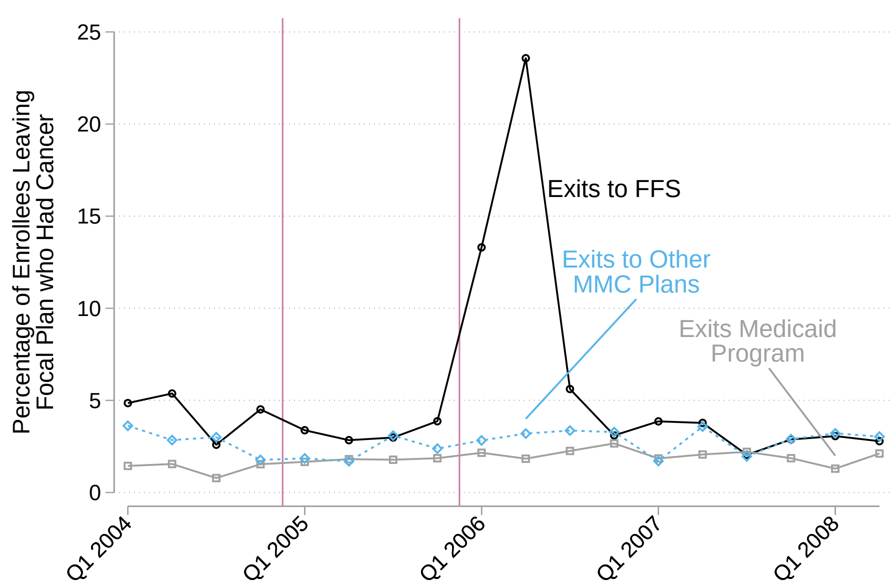
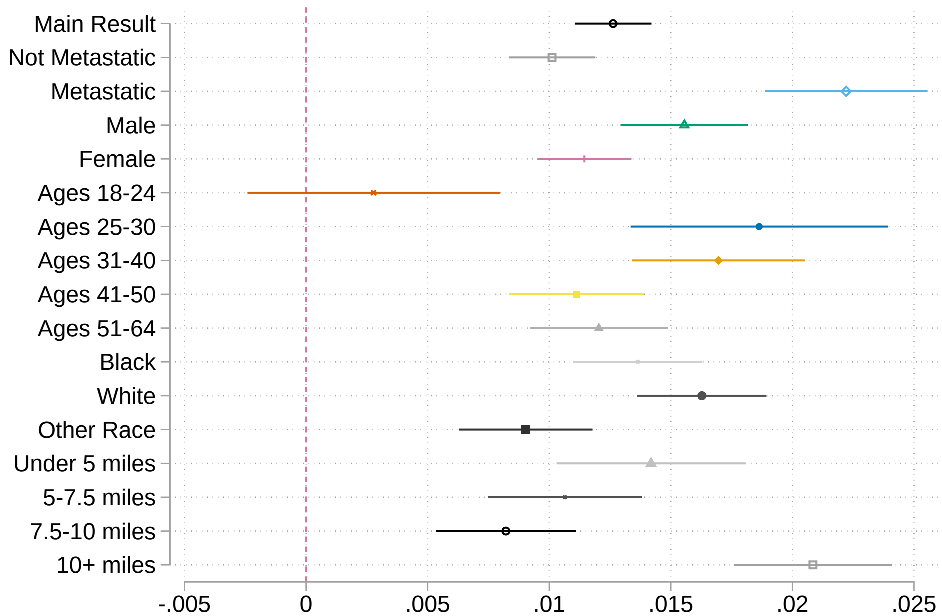


Figure A2: Understanding Flow of Cancer Enrollees into and out of Focal Plan

Note: Figure A2 examines the flow of enrollees into and out of the focal plan around the addition and subsequent removal of the specialty cancer hospital from its provider network. Figure A2a presents the share of new enrollees joining the focal plan who had cancer, by their enrollment one month prior to joining the plan. We split new plan enrollees into three groups: (1) enrollees who were not enrolled in Medicaid prior to their enrollment in the focal plan ("new Medicaid enrollees"), (2) enrollees who were enrolled in FFS Medicaid prior to their enrollment in the focal plan ("Switched from FFS"), and (3) enrollees who were enrolled in some other MMC plan prior to their enrollment in the plan ("Switched from Other MMC Plans"). Then, we examine cancer prevalence in each of these three groups, to assess where the new plan enrollees with cancer came from. It is clear from the figure that selection into the focal MCO was primarily a result of enrollees with cancer switching from other MMC plans into the focal MCO. In Figure A2b, we examine the cancer share among enrollees switching *out of* the focal plan between 2004-2008. Cancer prevalence in these three groups was relatively stable until the first quarter of 2006. Then, the cancer share among enrollees switching out of the focal plan and into FFS spiked, reaching nearly 24% during the second quarter of 2006. This indicates that the majority of the focal plan's enrollees who dropped out of the plan as a result of its removing the cancer hospital switched to FFS.

(a) Baseline Subgroups



(b) Baseline Subgroups and Prior Use

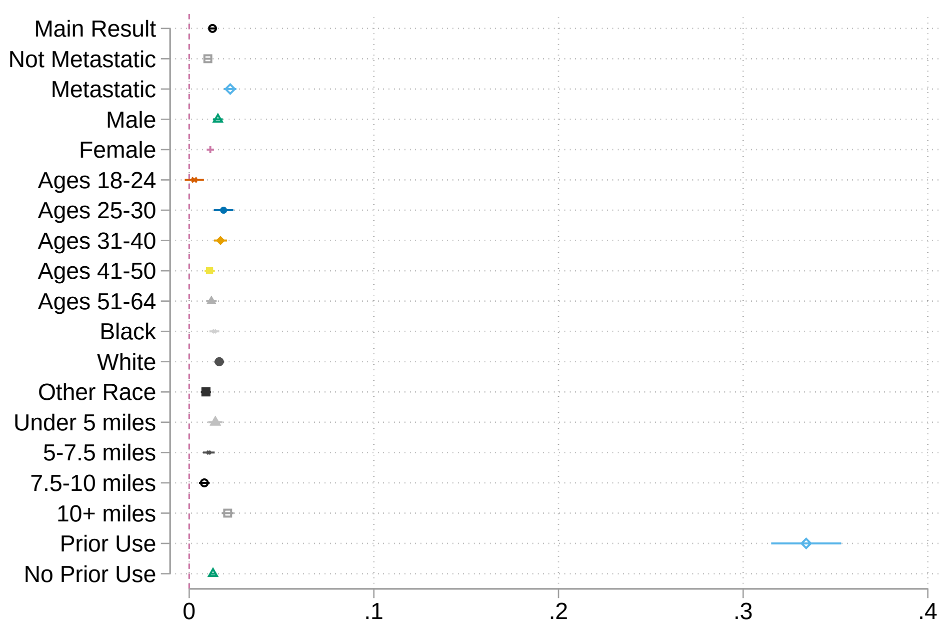
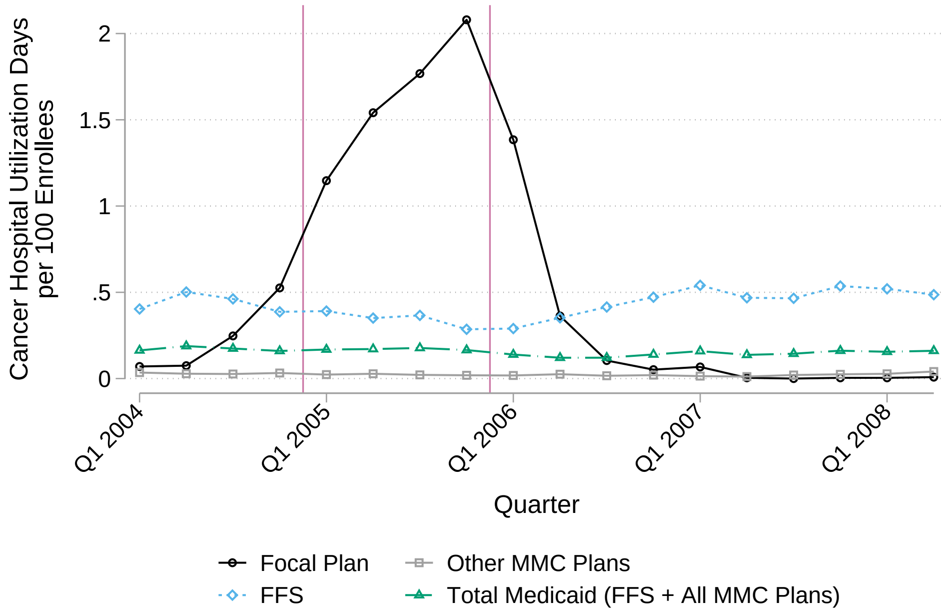


Figure A3: Heterogeneity in selection result, "Peak" coefficients, OLS specification

Note: Figure A3 reports the "peak" selection coefficients for a number of different subgroups of Medicaid enrollees with cancer. Within the cancer cohort, we find that selection into the focal plan was much more pronounced for enrollees with metastatic cancers (coefficient = 0.022) than enrollees without metastatic cancers (coefficient = 0.010), and less pronounced for younger enrollees ages 18-24 than for other age groups. The selection coefficient was similar for Black and white enrollees (0.014 and 0.016, respectively), but somewhat lower for enrollees within the other race categories (0.009). Interestingly, when disaggregating the cancer cohort by distance from the cancer hospital, the selection coefficient was highest for enrollees living furthest from the hospital (0.021, vs. 0.008-0.014 for enrollees living closer to the hospital). Finally, selection was much higher for the small number of enrollees with prior use of the specialty cancer hospital during the pre-period than for other enrollees with cancer. Due to the scale, we report this result in a separate panel (Figure A3b).

(a) Utilization of the Cancer Hospital by Medicaid Plan Type



(b) Percentage of Cancer Cohort with Utilization at the Cancer Hospital

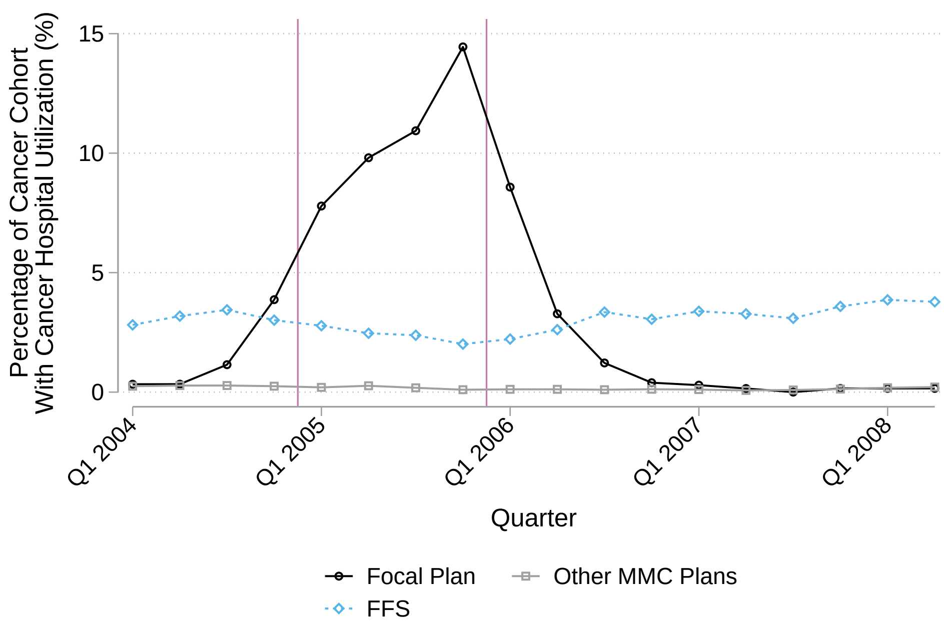


Figure A4: Utilization of the Cancer Hospital

Note: Figure A4a presents quarterly utilization of the specialty cancer hospital in enrollee-days per 100 enrollees, both overall in Medicaid (total) and disaggregated by market segment (focal plan, all other MMC plans, FFS). Utilization per 100 enrollees spiked dramatically within the focal plan during 2005, rising from 0.07 enrollee-days in mid-2004 to 2.08 in late-2005, before falling back to near-zero by late-2006. Figure A4b presents the quarterly percentage of Medicaid enrollees with cancer who used the specialty cancer hospital, disaggregated by market segment (focal plan, all other MMC plans, FFS). While some FFS enrollees used the cancer hospital throughout the study period, utilization was near-zero in MMC plans, except during 2005 when the hospital was in-network for the focal plan.

D.2 Tables

Table A1: MMC plans' network coverage of inpatient services at NYC hospitals, 2005

Plan	Cancer Hospital	Top Hospital #1	Top Hospital #2	Top Hospital #3	Top Hospital #4	All Other Hospitals (%)
Plan A (Focal MCO)	X					73
Plan B						13
Plan C						58
Plan D						31
Plan E				X		52
Plan F						37
Plan G		X		X	X	81
Plan H		X		X	X	92
Plan I						35
Plan J		X	X			26
Plan K		X		X		56
Plan L				X		58
Plan M						15
Plan N				X		27
Plan O				X		34
Plan P				X		56
Plan Q					X	24
Plan R						6

Note: Table A1 presents information on each New York City Medicaid managed care (MMC) plan's hospital coverage in 2005. Each row represents a plan, and the first five columns represent individual "top hospitals," in approximate rank order according to their U.S. News & World Report rankings in 2005. Hospitals that are in-network for a given plan are indicated by a green "X." The sixth column displays a summary measure indicating the % of other hospitals in New York City that were covered by each plan's network in 2005.

Table A2: Heterogeneity in Adverse Selection by Hierarchical Condition Category (HCC)

	HCC 8	HCC 9	HCC 10	HCC 11	HCC 12	HCC 13	Cancer, No HCC
Cancer	-0.005***	-0.001	-0.009***	0.013***	0.000	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Cancer x Pre	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Cancer x Anticipatory	0.005**	0.002	-0.001	0.002	0.001	-0.001	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
Cancer x Early	0.014***	0.005	0.013***	0.007**	0.009***	0.006	0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.002)
Cancer x Peak	0.022***	0.004	0.025***	0.010***	0.013***	0.005	0.006***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
Cancer x Late	0.008***	-0.003	0.015***	0.010***	0.007***	-0.001	0.007***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Cancer x Post	0.003	-0.007**	0.003	0.003	0.006***	-0.003	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Time Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	36099341	36014928	35998832	36072197	36080765	35974254	36123850
adj. R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table A2 presents results of the regressions described in Section 3.1 estimating heterogeneity in adverse selection by hierarchical condition category (HCC). The dependent variable is enrollment in the focal plan. Each interaction term indicates the change in enrollment since the pre-period among enrollees with a cancer HCC relative to the change in enrollment by enrollees without cancer. The "peak" coefficients (Cancer x Peak) are plotted in Figure 2.