Essays on Adverse Selection and Access to Specialty Care in Medicaid

HARVARD UNIVERSITY
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Essays on Adverse Selection and Access to Specialty Care in Medicaid

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Essays on Adverse Selection and Access to Specialty Care in Medicaid

A DISSERTATION PRESENTED
BY
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Abstract

Public health insurance programs in the United States are increasingly administered through the use of private managed care plans. Under this arrangement, private plans compete to offer coverage to beneficiaries, and the government partially or fully subsidizes the insurance premium. In Medicaid, the nation's health insurance program for low-income individuals and families, more than 70% of beneficiaries are now enrolled in managed care. By transitioning to managed care, state policymakers hoped to achieve higher value from their Medicaid programs. However, a concern in managed care markets is adverse selection, which can result in inefficiently low levels of coverage for services that are valued by sicker, higher-cost beneficiaries. My dissertation investigates whether Medicaid plans are incentivized to restrict access to specialty care due to adverse selection, the extent to which policies like risk adjustment mitigate these incentives, and whether health insurance plans respond empirically by rationing access to selected services.

Chapter 1: Adverse Selection and Access to Specialty Cancer Care

In the first chapter, my coauthors (Timothy J. Layton, Mark Shepard, and Jacob Wallace) and I investigate how adverse selection influences the decision of Medicaid managed care (MMC) plans to provide access to advanced specialty cancer care. We model a health

plan's decision to cover specialty hospitals in settings where consumers do not pay premiums and plan revenues are exogenously determined by a regulator. We demonstrate that the decision depends on two parameters: (1) the take-up of the hospital among inframarginal beneficiaries, and (2) the profitability of the marginal beneficiaries that select the plan due to its coverage of the specialty hospital. We test our model's predictions using a natural experiment. In 2005, a MMC plan added a well-known specialty cancer hospital to its provider network. We demonstrate that including the cancer center increased the plan's market share among beneficiaries with cancer by 50%, with no evidence of an increase in market share for Medicaid beneficiaries without cancer. We investigate heterogeneity in the demand response, finding that higher-cost beneficiaries, particularly those with metastatic cancers, were differentially likely to enroll in the plan. The plan dropped the cancer center from its network one year later, and its market share among beneficiaries with cancer declined substantially. While the inclusion of the hospital induced higher-cost beneficiaries with cancer to enroll in the plan, we find no evidence of take-up of the hospital among inframarginal beneficiaries. The results suggest that selection is the primary impediment to inclusion of the specialty hospital in managed care plans' networks and that the current equilibrium is inefficient.

Chapter 2: Assessing Selection Incentives by Physician Specialty

In the second chapter, I examine whether Medicaid plans are incentivized to restrict access to physician specialists due to adverse selection. I focus on one of the largest MMC markets in the United States, New York City, and quantify the selection incentives associated with 29 different physician specialties. I first measure incentives in a naive payment system with no risk adjustment. Then, I test the performance of risk adjustment at mitigating incentives. Finally, I examine the incentives associated with each provider specialty using an alternate measure from the literature that accounts for beneficiaries' ability to predict their specialty utilization, and compare this to my primary measure. I find that adverse selection creates particularly strong incentives for MMC plans to restrict access to oncologists, infectious disease specialists, thoracic surgeons, and neurosurgeons, with plans spending up to $4,000/month on beneficiaries who use these specialties. While risk adjustment and other transfers to plans mitigate these incentives, they remain, with plans losing up to $3,000/month on these beneficiaries even in a setting with risk adjustment and inpatient stop-loss payments. As managed care becomes the predominant mechanism for providing insurance benefits to low-income individuals and families in the United States, it is important that states understand which services might be most subject to under-provision in order to ensure adequate access.

Chapter 3: How Do Plans Respond?

In the final chapter, I test whether MMC plans ration access to adversely selected physician specialties. There are two primary mechanisms through which plans might restrict access to care. The first is by constructing narrow provider networks of selected specialties. Since Medicaid beneficiaries generally do not pay premiums to enroll in coverage and plan benefits are standardized, networks are a salient characteristic for plan choice; thus, plans may use their provider networks as a screening mechanism to deter unprofitable beneficiaries from enrolling. The second is through managed care utilization management techniques. Managed care plans commonly restrict access to services with strategies such as prior

authorization requirements. Plans might use such managed care strategies efficiently, in order to discourage low-value care, or inefficiently, to encourage unprofitable beneficiaries to disenroll from coverage. First, I test whether plans explicitly exclude specialists that treat unprofitable patients from their provider networks. Then, I analyze utilization of specialty care by beneficiaries in managed care plans vs. the fee-for-service Medicaid program. I find a statistically significant, but small, relationship between selection incentives and MMC plans' provider networks. In addition, I find evidence that Medicaid beneficiaries use disproportionately less care in adversely selected specialties when they are enrolled in MMC (relative to FFS).

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For Ryan, who carried me through it.

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Adverse Selection and Access to Specialty Cancer Care

1.1 Introduction

Adverse selection, the tendency of high-cost consumers to differentially demand generous insurance, is a common concern in insurance markets. Such adverse selection may lead to price distortions that cause consumers to inefficiently sort between coverage options (Einav, Finkelstein, and Cullen 2010; Hackmann, Kolstad, and Kowalski 2015; Handel, Hendel, and Whinston 2015), but it may also induce insurers to distort the contracts they offer to be more attractive to healthier, lower-cost beneficiaries and less attractive to sicker, higher-cost beneficiaries (Rothschild and Stiglitz 1976; Glazer and McGuire 2000; Veiga and Weyl 2016; Geruso and Layton 2017). Such contract distortions can lead to markets that provide limited access to products, services, and providers disproportionately used by the sick (Shepard 2016; Lavetti and Simon 2016; Carey 2017b; Geruso, Layton, and Prinz 2019).

This problem may be exacerbated in markets where plan premiums are fixed by regulators rather than endogenously set by the plans themselves. In such environments, an adversely selected health plan cannot simply react by raising its price, at least allowing some consumers to access adversely selected services (though at an inefficiently high price). The largest example of such a setting in the United States is the Medicaid program. Sixty-nine percent of Medicaid beneficiaries (53.9 million people) are now enrolled in comprehensive, risk-based managed care (Kaiser Family Foundation 2020c). Importantly, managed care plan revenues typically do not come from premiums or bids determined by the plans, but are instead equal to administratively-determined regional "capitation payments" set by a bureaucratic formula (Layton, Ndikumana, and Shepard 2017).[1]. This setting is thus similar to other government procurement settings, such as charter schools, where the government sets per-person payments and leaves the contractors to design their products within a set of pre-defined parameters. In such settings, plans (or schools) are incentivized to avoid offering services that attract higher-cost beneficiaries (or students), particularly if

1. There are some exceptions: 6 states use competitive bidding to determine the rates paid to plans, and 6 states negotiate with plans to determine rates (Layton, Ndikumana, and Shepard 2017) However, the majority of states use administered rates.

payments are not adjusted to compensate for increased average cost.

In most Medicaid markets, beneficiaries have a choice of several competing managed care plans, but do not pay premiums to enroll in coverage. Additionally, benefits are standardized, and only nominal cost-sharing is allowed. Therefore, plans are differentiated largely on their provider networks. Consistent with selection-related contract distortions, there is ample anecdotal evidence of limited access to specialty care among managed care beneficiaries in the Medicaid program (Felland, Lechner, and Sommers 2013).

In this paper, we study how adverse selection affects access to specialty hospital services in the second-largest Medicaid managed care market in the United States, New York City. We start by providing a model of a health plan's decision to include a specialty hospital in its network. We show that the decision depends critically on two parameters: (1) take-up of the (more-expensive) hospital among inframarginal beneficiaries and (2) the profitability of marginal beneficiaries.[2] The first parameter is a type of "moral hazard," or demand-response, to coverage. This demand-response could be either efficient or inefficient. It would be efficient (inefficient) if the individuals taking up the newly-covered hospital value that hospital relative to the next-best alternative more than (less than) the incremental cost of that hospital relative to the alternative. Either way, if this demand-response is large, the health plan may have difficulty providing access to this hospital while keeping costs below the administratively-set capitation payment. The second parameter is selection. If the inclusion of the hospital induces enrollment from individuals whose costs exceed the

2. By "inframarginal" beneficiaries, we refer to those Medicaid beneficiaries who would have chosen the plan regardless of its decision to include the specialty hospital in-network. "Marginal" beneficiaries refers to the Medicaid beneficiaries who choose the health plan, at the margin, when the specialty hospital is added to the plan's provider network.

administratively-set payments, health plans will again have difficulty providing access to the hospital and remaining solvent, regardless of the efficiency or inefficiency of utilization of the hospital.

We leverage a natural experiment to estimate both of the model's parameters, demand-response to coverage and the average profitability of the marginal beneficiaries. In 2005, a large, private Medicaid plan added a cancer specialty hospital to its provider network. The selection effects were clear. Prior to adding this hospital to its network, the plan had roughly equal market shares among beneficiaries with and without cancer. At the time that the hospital was added, however, we document a 50% increase in the plan's market share among beneficiaries with cancer, while its market share among beneficiaries without cancer remained relatively constant. One year after adding the hospital to its network, the plan reversed its decision and dropped the hospital. Subsequently, the plan's market share among beneficiaries with cancer immediately began to fall, ultimately dropping to a level slightly higher than its market share among beneficiaries who did not have cancer. We explore heterogeneity in the enrollment response to the addition of the cancer specialty hospital across different sub-groups of cancer patients. We find that people with more severe cancers (particularly metastatic cancers, the costliest category of cancer we study) drove a significant portion of the overall shift of beneficiaries with cancer to the health plan.

On the other hand, we show that take-up of the hospital among inframarginal beneficiaries was quite limited. Indeed, overall market-level use of the hospital was virtually unchanged during the period that the hospital was included in the plan's network. The fact that there was no change in use of the hospital when the private plan included it in-network reveals that nearly all use of the hospital in the private plan was from marginal beneficiaries, and not from take-up among inframarginal beneficiaries. These results point to selection as the primary impediment to inclusion of this specialty hospital in Medicaid managed care plans' networks. Indeed, we show that the marginal beneficiaries have average monthly health care costs that exceed monthly plan revenues by more than $350 per month. Clearly, plans have limited incentives to include such a hospital in their networks.

Our results suggest that adverse selection may make it difficult for Medicaid managed care markets (and similar markets) to provide an efficient set of options to consumers. While the exclusion of a more-expensive hospital due to take-up of that hospital among inframarginal beneficiaries could be either efficient or inefficient, selection makes it virtually impossible for a plan to provide access to this hospital either way, raising concerns about the ability of such markets to function as intended. However, our results also show the importance of a public option for providing access to adversely selected services. In the last section of the paper, we discuss how a public option can provide a backstop to protect access to these services. The same holds for non-healthcare settings like charter schools. In settings where selection makes it difficult for schools to offer specialty services and remain solvent, public schools can protect access to such services for high-need children. Importantly, the "public option" need not lead to higher costs for the government, as the government sets the rates to health plans or charter schools and can lower those rates if those plans or schools are enrolling lower-cost individuals than the public alternative.

Our results make several important contributions to the literature on adverse selection in health insurance markets. First, we provide novel and transparent evidence that adverse selection matters for network design in the Medicaid program. Prior work has shown the importance of adverse selection for contract design in other settings (Cao and McGuire 2003; Ellis and McGuire 2007; Eggleston and Bir 2009; Ellis, Jiang, and Kuo 2013; McGuire et al. 2014; Carey 2017b, 2017a; Lavetti and Simon 2016; Shepard 2016; Geruso, Layton, and Prinz 2019), but our work is the first to document this issue in Medicaid, the largest insurer in the United States. Importantly, unlike other markets, Medicaid has no premiums and no opportunity for plans to cover additional costs due to selection by charging a higher price, potentially exacerbating contract distortions due to adverse selection. Second, we contribute to the literature on how to design insurance markets in order to avoid inefficiencies caused by adverse selection. Much of the literature on contract distortions focuses on the use of risk adjustment or other features of the health plan payment system to limit insurer incentives to engage in these activities (Glazer and McGuire 2002; Layton et al. 2017). However, these payment system policies often have drawbacks such as upcoding of the diagnoses used to generate risk scores (Geruso and Layton 2015), endogeneity of payments to utilization (Geruso and McGuire 2016), and an inability to capture relevant dimensions of spending (Einav, Finkelstein, and Polyakova 2016). These drawbacks motivate a search for alternative or complementary market design features that can work to combat selection-related contract distortions. Third, while a significant body of research studies the transition from a publicly-managed fee-for-service Medicaid program to a program characterized by the outsourcing of benefits to private managed care plans, most of that work considers "managed care" to be a fixed object. Our paper thus contributes to this literature by moving beyond the public vs. private question and toward the question of how to design Medicaid programs featuring outsourcing to managed care plans, an area that has received relatively little attention despite the fact that these types of program design decisions affect millions of Americans and take place on a daily basis. Finally, we provide evidence on the particular vulnerability of advanced specialty care to adverse selection. Prior work has shown that specialty drugs are also vulnerable to contract distortions caused by selection (Geruso, Layton, and Prinz 2019). That work combines with our results here to suggest that when it comes to health care products, providers, and services that are used disproportionately by narrow yet costly segments of the population, extra care may be required to ensure that adverse selection does not inefficiently impede access.

1.2 Model

In this section, we develop a model of an insurer's decision to include a hospital in its network in a setting where plans cannot charge premiums and per-person revenues are determined administratively. Consider an insurance market in which beneficiaries (i) choose among available insurance plans $j \in \{1, ..., J\}$. Per our Medicaid setting, insurers offer a single plan, which is free to beneficiaries. The Medicaid program pays each insurer a baseline per-member fee of R, which is invariant to whether the plan covers the hospital. This fee is further risk-adjusted based on a beneficiary risk score, $\varphi_i \geq 0$, so that the plan receives $\varphi_i R$ for covering beneficiary i.

Insurers choose whether or not to cover a specialty hospital, with all other benefits fixed. Let the variable $x_j \in \{0, 1\}$ indicate this benefit decision. If insurer j does not cover the specialty hospital ($x_j = 0$), its expected cost for a given beneficiary i equals $C_{ij}(0)$. If it does cover the specialty hospital ($x_j = 1$), its expected cost is $C_{ij}(1) \equiv (1 + \eta_{ij}) C_{ij}(0)$, where η_{ij} is the scaling factor that determines the (proportional) difference in insurer costs with versus without the specialty hospital. The incremental cost varies with the relative costliness of the specialty hospital (including both its prices and its intensity of care) and the extent to which beneficiary i uses the specialty hospital. Coverage of the specialty hospital also affects beneficiary plan choices. Let $D_{ij}(x)$ be an indicator for whether beneficiary i chooses plan j, which is a function of all plans' benefit choices $x \equiv \{x_1, ..., x_J\}$. Recall that all plans are free, so premiums do not enter demand.

Putting this together, insurer profits can be represented as follows:

$$\begin{aligned}\pi_j(x) &= \sum_i \left[\varphi_i R - C_{ij}\left(x_j\right)\right] \cdot D_{ij}(x) \\ &= \sum_i \left[R - C_{ij}^{RA}\left(x_j\right)\right] \cdot \widetilde{D}_{ij}(x) \end{aligned} \tag{1.1}$$

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

PROFITABILITY OF SPECIALTY HOSPITAL COVERAGE

We now consider how profits change when one insurer j shifts from not covering to covering the specialty hospital, holding fixed all other insurers' benefits at x_{-j}. For ease of notation, we treat these other insurers' fixed 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 the $x_j = 0$ to $x_j = 1$ choice. The change in profits $\Delta\pi_j = \pi_j(1) - \pi_j(0)$ equals:

$$\Delta\pi_j = \underbrace{-\sum_i \Delta C_{ij}^{RA} \cdot \widetilde{D}_{ij}(0)}_{\text{(1) Cost increase (moral hazard)}} + \underbrace{\sum_i \left[R - C_{ij}^{RA}(1)\right] \cdot \Delta\widetilde{D}_{ij}}_{\text{(2) Profitability of marginal beneficiaries}} \tag{1.2}$$

The equation breaks down the change in profits from covering the specialty hospital into two pieces. First, the plan incurs higher costs on existing beneficiaries, as some of them shift toward using the expensive specialty hospital as opposed to alternative providers. This is a form of moral hazard that reduces insurer profits.[3] Second, the plan attracts additional beneficiaries due to its broader network. The impact of this demand change on plan profits, however, depends on the *profitability* of these marginal beneficiaries. Profitability is influenced by two factors: the generosity of Medicaid's per-member fee (R) and the selection of marginal beneficiaries on risk-adjusted costs. If marginal beneficiaries have high risk-adjusted costs – e.g., if they are differentially people who are unobservably sicker – selection will imply lower profits.

This analysis shows the challenging economics of private plans covering an expensive specialty hospital in Medicaid programs. Doing so results in direct cost increases via moral hazard among existing beneficiaries. These initial losses will only be compensated if the plan experiences a sufficiently large increase in demand among profitable beneficiaries. But if Medicaid's fees are low and/or marginal beneficiaries are adversely selected, then higher demand will actually imply lower profits.

The analysis also reveals how several policies might make it easier for private plans to cover specialty hospitals. Naturally, higher per-member fees (R) paid by the Medicaid pro-

3. We use the term "moral hazard" in the Einav and Finkelstein (2018) sense with a strictly positive (demand-response) connotation rather than a normative one. Whether this demand-response is efficient or inefficient is a targeting question in the spirit of Nichols and Zeckhauser (1982). The demand-response is efficient if the incremental value placed on care received at the specialty hospital relative to care received at the next-best included alternative hospital exceeds the incremental cost of that care for the group of consumers who take up the specialty hospital when it is included in the private plan's network but not when it is excluded. Given that, in Section 1.5, we find no additional market-wide take up of the specialty hospital when it is included versus excluded, we do not elaborate on this point here.

gram make it easier for plans to cover these hospitals. Better risk adjustment that increases the profitability of marginal beneficiaries (by decreasing C_{ij}^{RA}) can also help. The presence of a public option and the carving out of certain populations from managed care may also matter, by influencing the size and profitability of the group of marginal beneficiaries. We return to these policies in Section 1.6.

1.3 Background and Institutional Details

1.3.1 Medicaid Managed Care

The Medicaid program provides health insurance coverage to low-income and disabled Americans. It is currently the largest insurer in the United States, with over 70 million beneficiaries. Over the past three decades, Medicaid has shifted from a publicly managed fee-for-service (FFS) program to a program where the provision of benefits has been contracted out to private managed care plans for the vast majority of beneficiaries (Congressional Budget Office 2018). Today, 89% of Medicaid beneficiaries are enrolled in private managed care plans.

State Medicaid managed care programs share some attributes with the Medicare Advantage and Medicare Part D prescription drug insurance programs, as well as individual health insurance markets such as the state Health Insurance Marketplaces. However, they differ in many ways as well. In the following sections, we outline the features of Medicaid managed care programs that are relevant for selection and network design, describing each set of features generally (across all states) and indicating the specific institutions present in the New York, the state we study.

Plan Choice State Medicaid programs differ in the choice sets available to beneficiaries, including whether they require beneficiaries to enroll in a private Medicaid managed care plan. States often group beneficiaries into three categories: compulsory, voluntary, and restricted. Compulsory beneficiaries are required to enroll in one of several private managed care plans after an initial 60-90 day period in the FFS program, and typically consist of beneficiaries who are eligible for Medicaid on the basis of income. Compulsory beneficiaries who do not actively choose a managed care plan are assigned to one (Wallace 2015; Geruso, Layton, and Wallace 2020). Voluntary beneficiaries typically consist of more vulnerable groups, such as individuals with disabilities, and are allowed to choose between the publicly managed FFS program and one of several private managed care plans. Voluntary beneficiaries are often defaulted into the FFS program but can leave during an open enrollment period (similar to the Medicare program). Restricted beneficiaries typically consist of the most vulnerable beneficiaries, such as individuals using long-term services and supports and children in foster care. These individuals are required to enroll in the FFS program and do not have the option of enrolling in a managed care plan. All three categories of beneficiaries are present in the New York market that we study; however, most beneficiaries in the market are in the "compulsory" group (Forsgren 2017).[4]

Plan Payment Private managed care plans in Medicaid are typically the residual claimants on any spending incurred by their beneficiaries. The state pays the plans a fixed amount per beneficiary, which is sometimes risk-adjusted. The way in which the amount is

4. Most Medicaid beneficiaries in the market moved from the "voluntary" category to the "compulsory" category in 2005. Beneficiaries who were eligible for Medicaid on the basis of Supplemental Security Income (SSI) receipt, who are not in our sample, moved into the "compulsory" category in 2006.

set varies across states. The most common method involves an actuary taking past health care spending among Medicaid managed care beneficiaries in the region and trending it forward using regression methods, adjusting for any policy changes the actuary believes might affect insurer costs. All insurers in the region are paid the same amount for a given beneficiary, though payments may differ across beneficiaries according to age, gender, and diagnoses appearing in claims. In a small number of states, managed care plans "bid" to enter the program and enroll beneficiaries. Plans submit bids consisting of proposed payment levels as well as other details of the benefits the plan will offer. The state then selects plans based on those bids and pays each plan the proposed amount (plans with lower bids get lower payments). Finally, in some states, plans are paid negotiated rates, where the plan submits projected costs to the state and, if the state approves of the proposed costs, the state pays the plan an amount based on those costs plus a small profit margin. Under this type of system, it is not necessarily the case that the plan is just paid the amount they ask for, as there is some amount of negotiation involved around what the "true" projected costs are. While New York now pays plans according to the first method (risk-adjusted administered rates), the state paid negotiated "cost-plus" rates during our study period (2004-2008).

PLAN DESIGN Medicaid beneficiaries do not typically pay a premium to enroll in a managed care plan.[5] Additionally, benefits are tightly regulated. The package of services offered does not vary across plans, and cost-sharing, where it exists, is minimal for most

5. This is changing, with some states recently having received waivers to charge premiums to Medicaid beneficiaries. Today, five states charge premiums, and two additional states have received waivers to do so (Brooks et al. 2020).

services (e.g., up to $4 for preferred drugs) (Brooks et al. 2020). Additionally, while plans may construct "formularies" of covered drugs, Medicaid managed care plans are required to cover all drugs (or their generic equivalents) that are covered by the state Medicaid program. Therefore, the primary dimension on which managed care plans are differentiated is the provider network. There is wide variation in provider networks across plans in many Medicaid markets (Wallace 2015). When choosing plans, beneficiaries can observe the provider network, though it may not be salient to them. A more salient plan feature is the quality rating, which, because all other dimensions are highly regulated, is largely based on the network. Providers may also influence beneficiary plan choice, by encouraging patients to enroll in a plan they accept and that pays them higher rates.

1.3.2 Description of the Natural Experiment

In order to estimate the two parameters of Equation 1.2, we leverage a unique natural experiment. In 2005, one large, relatively popular managed care plan in the market we study added to its hospital network a world-renowned specialty cancer hospital. Prior to being added to this plan's network, this hospital was not included in the hospital network of any of the 19 plans present in this market.[6] This event thus shifted the MMC program in this market from a program that provided no access to this specialty cancer hospital to a program that allowed use of the hospital.

After including the hospital in its network for one year, at the beginning of 2006 the plan decided to once again remove the hospital from its network. After removing the hospital,

6. The Medicaid managed care market consolidated between 2004-2008; by the end of the study period, six plans exited or were acquired by other plans, leaving 13 plans operating in the market.

the plan allowed patients who had started episodes of care at the hospital to complete those episodes, but limited access to the hospital for other beneficiaries, eventually returning to its pre-2005 state of not allowing any patients to use the hospital.[7]

During the period before, during, and after this plan included the hospital in its network (2004-08), beneficiaries in MMC plans were sometimes able to receive out-of-network referrals to access the hospital; however, such out-of-network utilization was extremely limited. However, during this time period, individuals in the FFS program could use the hospital (to the extent that the hospital was willing to accept them). Indeed, our data show that there was modest use of the hospital among FFS beneficiaries with cancer throughout the 2004-08 period.

1.4 Data

To evaluate the natural experiment we describe in Section 1.3.2, we merge administrative health records from the New York State Department of Health (NYSDOH) with managed care provider directories. We briefly describe each data source here.

1.4.1 Administrative Enrollment and Claims Data

We obtained de-identified administrative data on enrollment, plan choice, and health care claims for the entire New York Medicaid population from 2004 to 2008.[8] For each benefi-

7. Existing plan beneficiaries in New York whose provider leaves their plan's network are allowed to continue receiving services from that provider for up to 90 days from the provider's departure from the network (New York State Department of Health 2015).

8. The 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 beneficiaries.

ciary, 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.

The enrollment data allow us to construct monthly market shares for each MMC plan available in the market, along with the FFS Medicaid program. To assess the extent to which sicker beneficiaries select into the focal plan due to the inclusion of the cancer specialty hospital in its network, we construct these market shares separately for beneficiaries with and without cancer, as described below. In addition to market shares, the available data allow us to construct a range of beneficiary-level health care use and spending measures. 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: physician, freestanding clinic, hospital outpatient, emergency department, hospital inpatient, pharmacy, lab, transportation, dental, and other. We define overall outpatient spending by aggregating spending from the physician, freestanding clinic, hospital outpatient, and emergency department service categories. We define inpatient spending as any spending in the hospital inpatient service category. Finally, we define miscellaneous spending as any spending in pharmacy, lab, transportation, dental, and other service categories. In addition to spending, we measure the extensive margin of health care use in a month with an indicator set to one if a beneficiary had positive spending for a given service category. Finally, in order to assess the extent to which beneficiaries in each plan utilized the cancer specialty hospital, we use the provider IDs present on the claims to construct measures of each type of spending *at the focal hospital*.

1.4.2 Provider Network Data

We assemble a unique dataset on the physician and hospital networks of the MMC plans in place from 2004 to 2017 using New York's Provider Network Data System (PNDS). The PNDS is an audited database of provider networks for all managed care plans (Medicaid and non-Medicaid) in the state. It is standardized across plans and reported quarterly, allowing us to identify in which quarter physicians and hospitals entered or exited each MMC plan. The focal specialty cancer hospital appears in the network of the MMC plan of interest in the first quarter of 2005 and is removed from the network in the first quarter of 2006.[9] It does not appear in the provider network of any other Medicaid plan until 2013, one year after the full implementation of risk adjustment in the New York Medicaid program.

The provider network data contain Medicaid provider identification numbers, which we use to merge the network data with the fee-for-service claims and managed care encounter data. The PNDS includes an indicator for each provider-insurer pair that identifies which insurance products the provider is "in-network" for.[10] Since many of the managed care plans 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 during all quarters of our sample period for each Medicaid managed care plan

9. Note that because the PNDS is updated quarterly, we only know network status as of the first month of a given quarter. This implies that if a hospital or provider newly appears in a plan's network in a given quarter, it may have been in the network for as few as zero months or as many as 2 months of the preceding quarter. This issue may contribute to the observed "anticipatory" effects presented in Section sec:results below.

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

other than our focal plan, it was in-network for one of the commercial HMO networks reported in our data.[11]

1.4.3 Sample Selection

We restrict our estimation sample in four ways. First, we restrict to beneficiaries in Mainstream Medicaid Managed Care plans.[12] Next, we focus on beneficiaries who live in the geographic market centered around the specialty cancer hospital.[13] Third, we restrict the sample to adult (above age 17 and below age 65) beneficiaries. We exclude individuals aged 65 and older because they become eligible for Medicare (often referred to as "dual eligibles") and are excluded from Mainstream Medicaid Managed Care. Finally, we exclude beneficiaries who are eligible for Medicaid on the basis of eligibility for Supplemental Security Income (SSI) benefits.

In order to examine the selection effects of the inclusion of the cancer specialty hospital, we categorize beneficiaries according to cancer status. To do this, we first map all diagnosis codes appearing in each beneficiary's claims to Clinical Classifications Software (CCS) categories.[14] A beneficiary is categorized as having cancer if she has at least: (1) two out-

11. One of the six commercial plans in our data included the cancer hospital in-network from 2004-2007 and from 2009-2018. A second commercial plan added the hospital to its network in 2008, but did not begin covering inpatient services at the hospital until 2009. A third commercial plan added the hospital to its network in 2009.

12. We exclude beneficiaries in Family Health Plus, Medicaid Advantage plans (integrated Medicaid/Medicare plans for beneficiaries "dually eligible" for Medicare), Managed Long-Term Care plans, and HIV Special Needs Plans (HIV SNPs).

13. We keep all beneficiaries residing in the city where the hospital is located.

14. See Healthcare Cost and Utilization Project (2016) for a list of categories.

patient claims on different days with a diagnosis that maps to one of the CCS categories corresponding to cancer (categories 11-43), or (2) one inpatient claim with a diagnosis that maps to one of the CCS cancer categories, at any time during her Medicaid enrollment between 2004-2008.[15]

Finally, to examine heterogeneity in the selection effect, we disaggregate the cancer cohort by severity of cancer diagnosis. To do this, we map all diagnosis codes appearing in each beneficiary'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).[16] Once we have identified all of the HHS-CCs associated with each beneficiary's diagnoses, we impose a hierarchy on the HHS-CCs, such that each beneficiary is assigned to the most "severe" or expensive

15. An alternative method for identifying beneficiaries with cancer would only classify an individual as having cancer *after* we observe the first cancer diagnosis. However, classifying individuals as having cancer only after the first diagnosis mechanically increases cancer prevalence among Medicaid beneficiaries over time, resulting in a more difficult interpretation of changes in market shares over time among the cancer cohort. Because of this, we opt to classify an individual as being in the cancer group if we *ever* observe them meeting the cancer criteria. At this stage, we also exclude from the estimation sample beneficiaries 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 beneficiaries with these diagnoses, who do not also receive a clear-cut cancer diagnosis (CCS categories 11-43), belong in the treatment or control group.

16. The HCCs associated with cancer diagnoses include (in order of severity 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) (Centers for Medicare & Medicaid Services 2013). Because of differences in the ICD-9 diagnoses associated with the HCCs and the Clinical Classifications Software (CCS) categories, it was possible for a beneficiary to be assigned to the cancer cohort (using the CCS categories), but not to have any diagnoses associated with an HCC. When this occurred, we assigned them to a category called "Cancer, no HCC," which we consider in our heterogeneity analysis to be the least severe sub-category of cancer.

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).

1.4.4 Outcome Measure

The primary outcome measure is plan enrollment, including the plan each beneficiary is enrolled in during each month, as well as switching between plans. Plan enrollment for each beneficiary is identified using the monthly Medicaid enrollment data. We also use these data to identify enrollment in FFS Medicaid. To identify beneficiaries who switched between MMC plans, or between FFS and a Medicaid managed care plan, we identify any plan change taking place during a Medicaid enrollment episode.

1.5 Empirical Analysis

We leverage this natural experiment to estimate the two parameters described in Equation 1.2 as determining the insurer's incentive to include the specialty hospital in its network. We start with the second parameter, selection, or the profitability of the marginal beneficiaries. We first estimate the size of the marginal group and then estimate the average profitability of the beneficiaries in the marginal group. We then move on to the first parameter, 'moral hazard' or demand-response of use of the specialty hospital to inclusion in the plan's network among inframarginal beneficiaries.

Table 1.1 presents summary statistics. For most of our analyses, we divide the population into two cohorts described in Section 1.4.3, a cohort of individuals who at some point are diagnosed with cancer and a cohort of individuals never diagnosed with cancer during the sample period (2004-2008). The cancer cohort included roughly 15,000 beneficiaries in each month ($\approx$ 2.3% of adult Medicaid beneficiaries in our sample). Beneficiaries with cancer were, on average, about 9 years older than beneficiaries without cancer (44.4 years vs. 35.3 years) and were disproportionately female (71.5% vs. 64.1%). Beneficiaries diagnosed with cancer were also slightly more likely to be categorized as white (32.0%), Asian or Pacific Islander (13.1%), or Hispanic (10.6%) relative to beneficiaries who were not diagnosed with cancer (30.7%, 11.9%, and 9.9%, respectively). Unsurprisingly, but important for our selection results, the cancer cohort tended to have much higher spending ($\approx$ \$1414 per month) than Medicaid beneficiaries who did not have cancer ($\approx$ \$390 per month). Finally, we examined spending by MMC plans (exclusive of spending by the fee-for-service Medicaid program) for beneficiaries enrolled in MMC. Medicaid beneficiaries with cancer who were enrolled in managed care also had higher MMC spending ($\approx$ \$567 per month) relative to MMC beneficiaries without cancer ($\approx$ \$153 per month).

1.5.1 Selection

Figure 1.1 presents the focal MCO's market share among beneficiaries with and without cancer during the 2004-2008 period. Market share is defined as the percentage of all Medicaid beneficiaries, in both fee-for-service and managed care, that were enrolled in the MCO. The leftmost vertical red line marks the date that the specialty cancer center was listed in the MCO's provider network, and the rightmost vertical red line marks the date that the specialty cancer center was subsequently dropped from the network.[17]

17. The network data are updated on a quarterly basis. The cancer hospital appeared in the MCO's network data for the first time in the first quarter of 2005 and for the last time in the fourth quarter of 2005.

Table 1.1: *Summary Statistics*

	No Cancer	Cancer
	(1)	(2)
N (mean per month)	665,429	15,408
Percentage of sample (%)	97.7	2.3
Age (mean)	35.3	44.4
Female (%)	64.1	71.5
Race/ethnicity (%)		
Black	31.6	30.0
White	30.7	32.0
Asian or Pacific Islander	11.9	13.1
Hispanic	9.9	10.6
American Indian or Alaska Native	2.6	2.6
Other	13.8	12.1
Plan (%)		
Focal MCO	3.6	4.3
Other MMC Plans	68.3	68.2
Fee-for-Service	28.1	27.5
Monthly spending, 2005-2008 ($)		
Total	390.2	1,414.2
Inpatient	165.4	746.5
Outpatient	90.8	260.4
ED	6.1	8.3
Miscellaneous	127.9	398.9
Monthly MMC spending, 2005-2008 ($)		
Total	153.2	567.1
Inpatient	66.7	283.4
Outpatient	59.2	220.6
ED	4.6	5.9
Miscellaneous	22.7	57.3

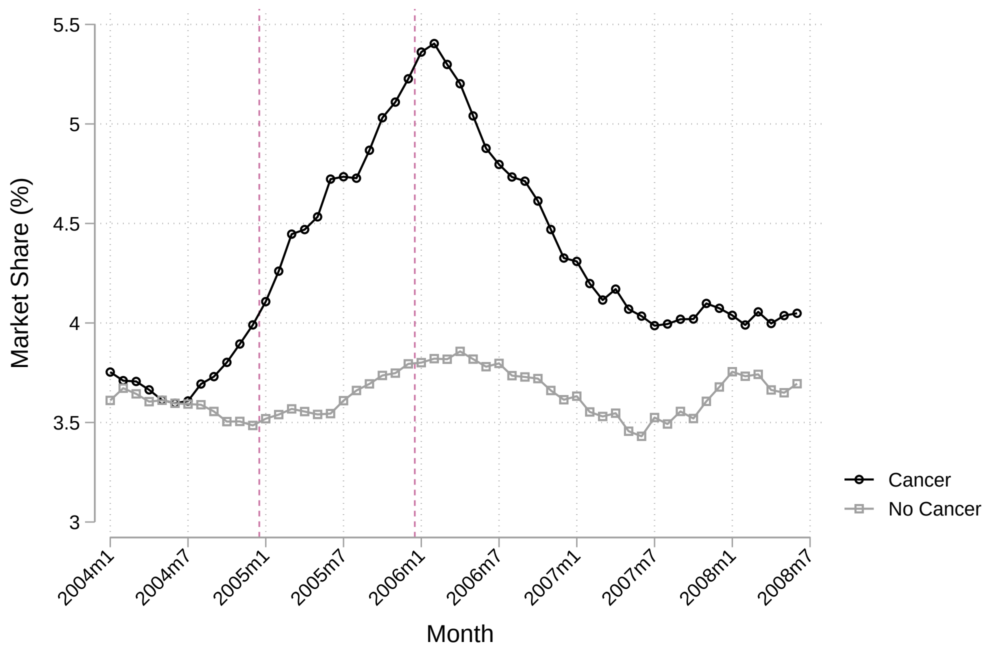


Figure 1.1: *Focal MCO's Market Share among Beneficiaries with and without Cancer*

Prior to adding the cancer center to its network, the MCO had roughly the same market shares among beneficiaries with and without cancer. In the last months of 2004, however, the plan's market share among beneficiaries with cancer began to grow rapidly while the market share among beneficiaries without cancer remained relatively flat.[18] The MCO's market share among the cancer cohort continued to grow until the cancer center was removed from the network, with market share maxing out at approximately 5.4%, a 50% increase relative to the baseline market share. As soon as the cancer center was removed, the market share among the cancer cohort plummeted, eventually settling (about 18 months

18. The gains in market share among the cancer cohort appear to predate the addition of the cancer center to the network; however, the network data prevent us from identifying the exact date that the cancer center was added to the network, which could have been as early as October 2004. Further, beneficiaries may be reacting to announcements (or informal notice) of this change in the MCOs provider network prior to it taking effect.

after the center was removed) just slightly higher than the plan's market share among beneficiaries who did not have cancer.

The addition of the cancer center to the focal MCO's provider network had a substantial impact on the plan's enrollee composition. Figure 1.2 presents the cancer prevalence within each market segment (focal MCO, other MMC, and FFS) over time. Before the cancer center was added to the MCO's network, the cancer prevalence in all three market segments was $\approx 2.2 - 2.3\%$. Following the inclusion of the cancer center in-network, the percentage of beneficiaries in the focal MCO 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 MCO plan's beneficiaries 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 beneficiaries in the other two market segments who had cancer remained relatively flat.[19]

In order to explicitly test for differences in the MCO's market share over time among Medicaid beneficiaries with and without cancer, we estimate a regression version of Figure 1.1. This regression takes the following form:

$$EnrollMCO_{it} = \sum_t \beta_t \left[Cancer_i \times Time_t\right] + \gamma Cancer_i + \alpha_t + \varepsilon_{it} \tag{1.3}$$

where $EnrollMCO_{it}$ is equal to 1 if person i was enrolled in the focal MCO in month t,

19. 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 beneficiaries with cancer have a larger impact on the individual MCO than on the overall FFS and MMC markets.

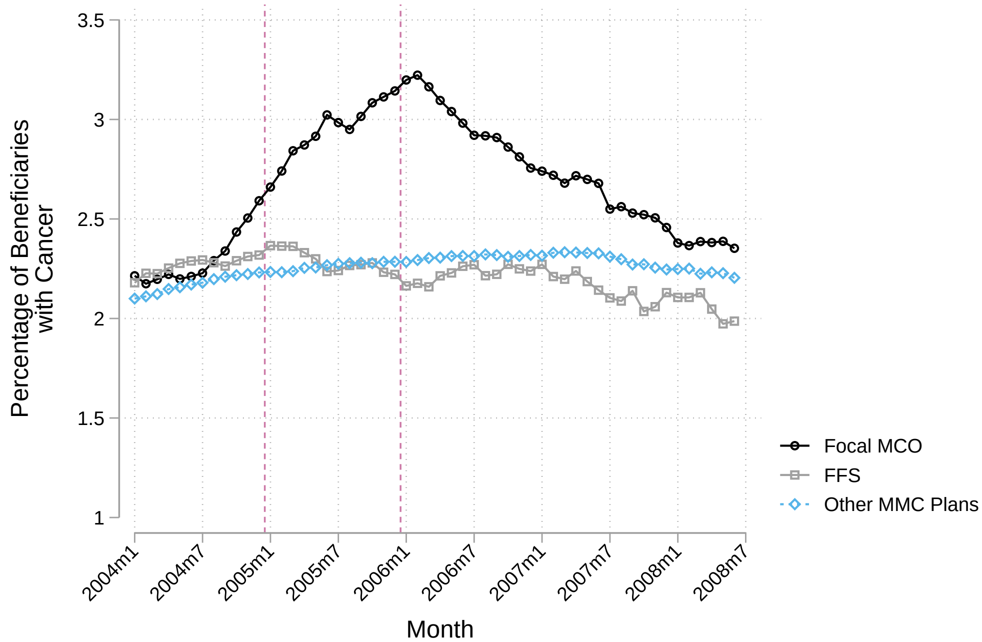


Figure 1.2: *Cancer Prevalence within Each Market Segment*

and 0 otherwise, and $Cancer_i$ is a dummy variable indicating whether person i was in the cancer cohort. $Time_t$ represents dummy variables for each month between January 2004 and June 2008 (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 MCO among the cancer cohort relative to the non-cancer cohort in each month t. α_t are time (month) fixed effects, and γ represents the difference between the cancer and non-cancer market shares in June 2004, just prior to the inclusion of the cancer hospital in the MCO's network.

Figure 1.3 presents OLS estimates of the β_t coefficients in Equation 1.3, with the shading representing a 95% confidence interval. The conclusions parallel the findings in Panel A. Following the inclusion of the specialty cancer hospital in the MCO's network, the MCO's market share among beneficiaries with cancer increased relative to its market share among beneficiaries without cancer. The MCO's market share among the cancer cohort continued to increase throughout 2005. By the end of 2005, the difference in market shares between the cancer cohort and the non-cancer cohort was 1.5 percentage points higher than the difference in market shares in the pre-period. When the cancer center was removed from the MCO's network in first quarter of 2006, the MCO's market share among beneficiaries with cancer immediately began to decline, and by 2008, the difference between the two market shares was no longer statistically significant.

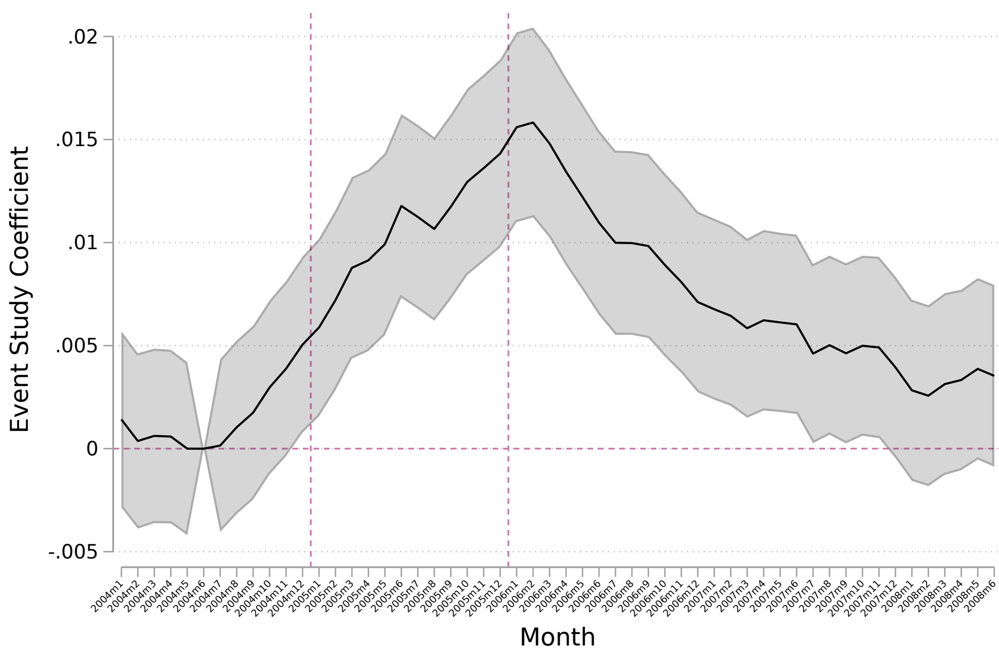


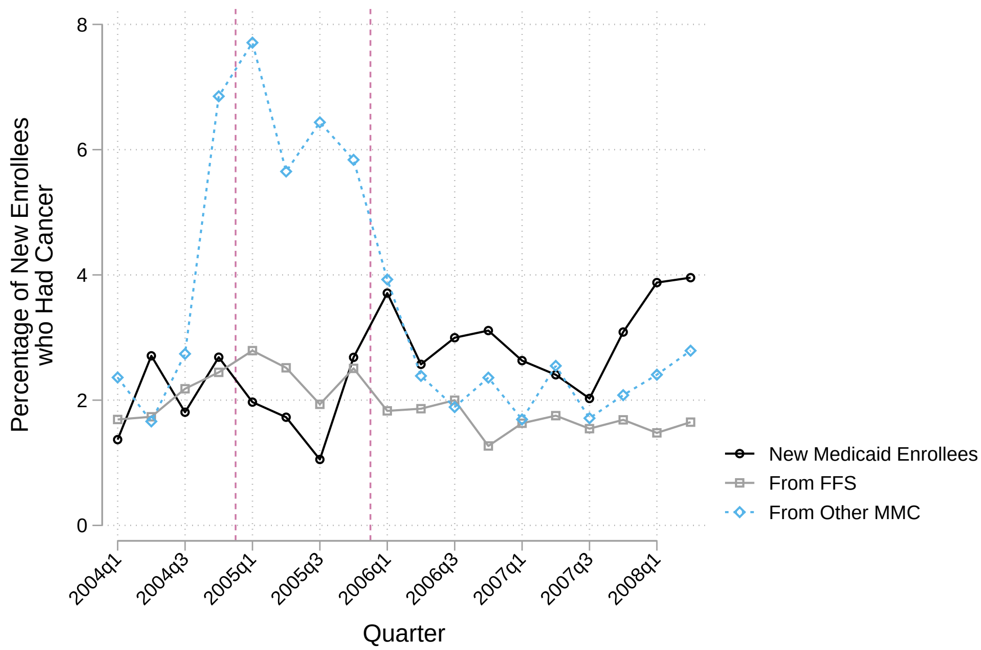
Figure 1.3: *Difference-in-Differences, Cancer vs. No Cancer*

The timing and sharp contrast of the change in the cancer cohort's market share relative to the market share among beneficiaries without cancer make a compelling case that the MCO experienced severe adverse selection as a result of adding the cancer center to its provider network. Reinforcing this finding is the sharp reversal in the market share trend among the cancer cohort as soon as the cancer center was dropped from the MCO's network in early 2006. Within one year of dropping the cancer center, approximately 80% of the MCO's market share gains among the cancer cohort had eroded. Indeed, these results, the sharp increase in market share among the cancer cohort and the stable market share among Medicaid beneficiaries without cancer, suggest that the entire marginal group described in the second component of Equation 1.2 consisted of Medicaid beneficiaries with cancer.

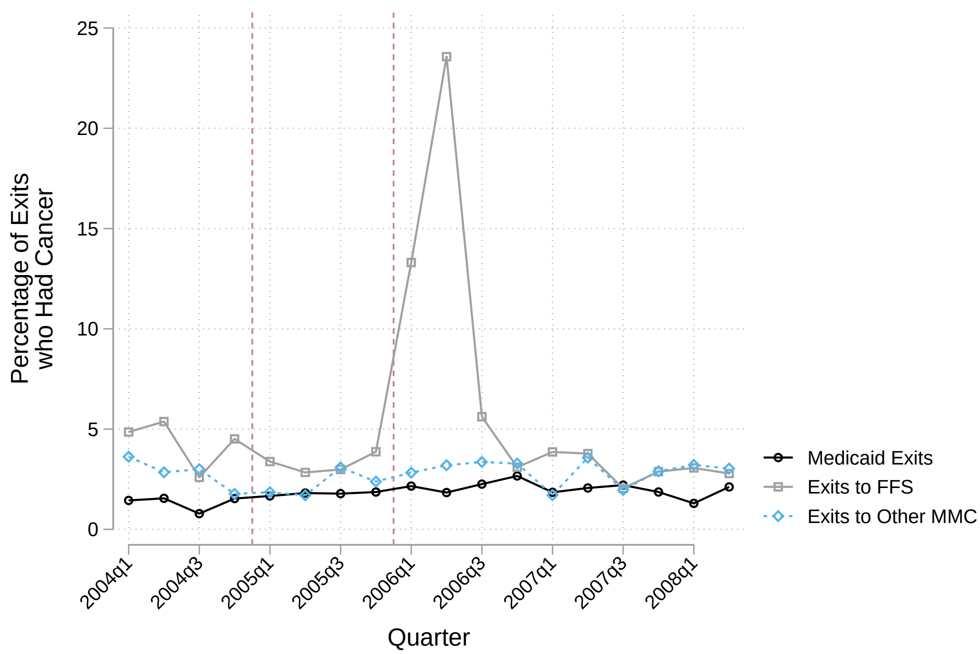
To interpret the results from Figures 1.1-1.3, it is useful to understand the flows of beneficiaries into and out of the focal MCO when it added the specialty cancer hospital to its network. We examine the share of new MCO enrollees who had cancer over time, by their enrollment one month prior to joining the MCO. We split new MCO enrollees into three groups: (1) beneficiaries who were not enrolled in Medicaid prior to their enrollment in the focal MCO ("new Medicaid enrollees"), (2) beneficiaries who were enrolled in FFS Medicaid prior to their enrollment in the focal MCO, and (3) beneficiaries who were enrolled in some other MMC plan prior to their enrollment in the MCO. Then, we examine cancer prevalence in each of these three groups, to assess which market segment the new MCO beneficiaries with cancer came from. Figure 1.4a presents the results. It is clear from the figure that selection into the focal MCO (when it added the cancer center) was primarily a result of beneficiaries with cancer switching from other MMC plans into the focal MCO. During the first half of 2004, $\approx 2\%$ of "switchers" from other MMC plans to the focal MCO had cancer (approximately equivalent to the cancer prevalence in the Medicaid sample). However, once the MCO added the cancer center to its network, this percentage rose, with

7.7% of beneficiaries switching from other MMC plans to the MCO having cancer during the first quarter when the cancer center was in-network. When the cancer center was dropped from the MCO's network at the end of 2005, this percentage promptly dropped again, with cancer prevalence among MMC "switchers" returning to $\approx$ 2.1% by the second half of 2006. In addition to selection among "switchers" from other MMC plans to the focal MCO, there was also some selection among "switchers" from FFS Medicaid to the focal MCO. During the first half of 2004, $\approx$ 1.7% of beneficiaries who moved from FFS into the focal MCO had cancer. When the MCO added the cancer center to its network, this percentage rose, reaching 2.8% in the first quarter of 2005 (approximately a 65% increase from the baseline cancer prevalence among FFS switchers). After the cancer hospital was dropped from the MCO's network, this prevalence declined again, reaching about 1.6% by the second half of 2006.

Figure 1.4b presents the cancer prevalence among beneficiaries switching *out of* the focal MCO between 2004-2008, with plan "exiters" decomposed into three groups: (1) beneficiaries who switched from the focal MCO to FFS Medicaid, (2) beneficiaries who switched to other MMC plans, and (3) beneficiaries who dis-enrolled from Medicaid altogether. Cancer prevalence in these three groups was relatively stable during most of the sample period. However, after the MCO dropped the specialty cancer hospital from its network at the end of 2005, the prevalence of cancer among beneficiaries switching out of the focal MCO and into FFS spiked, reaching nearly 24% during the second quarter of 2006. As shown in Figure 1.5, the focal MCO's beneficiaries continued to access care at the specialty hospital in the first quarter of 2006, due to a Medicaid provision requiring continuity of care for up to 90 days after a provider is dropped from a plan's network (New York State Department



(a) *Beneficiaries Entering the Focal MCO*



(b) *Beneficiaries Exiting the Focal MCO*

Figure 1.4: *Cancer Prevalence among Medicaid Beneficiaries Entering and Exiting the Focal MCO*

of Health 2015). It appears that, after this 90 day period was up, beneficiaries with cancer in the MCO were able to switch to the FFS Medicaid program to continue accessing care at the specialty hospital.

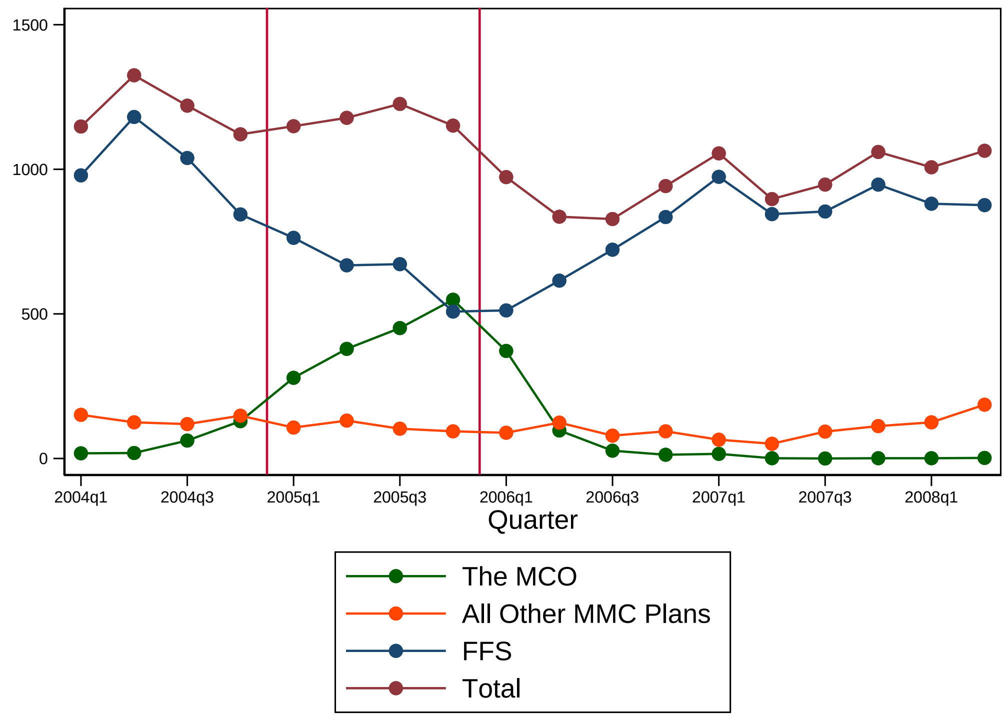


Figure 1.5: *Number of Unique Beneficiary-Visits to the Specialty Cancer Hospital, by Medicaid Market Segment*

Figure 1.6 shows the average *number* of beneficiaries with cancer who switched from each other market segment to the focal MCO between 2004-2008. While a larger *percentage* of beneficiaries who switched to the focal MCO from other MMC plans had cancer during the period when the cancer center was in-network, a larger *number* of beneficiaries with cancer switched to the focal MCO from FFS. Approximately 26 beneficiaries with cancer switched from FFS to the focal MCO each month during the first quarter of 2005, while $\approx$ 12 beneficiaries with cancer switched from other MMC plans to the focal MCO each month.

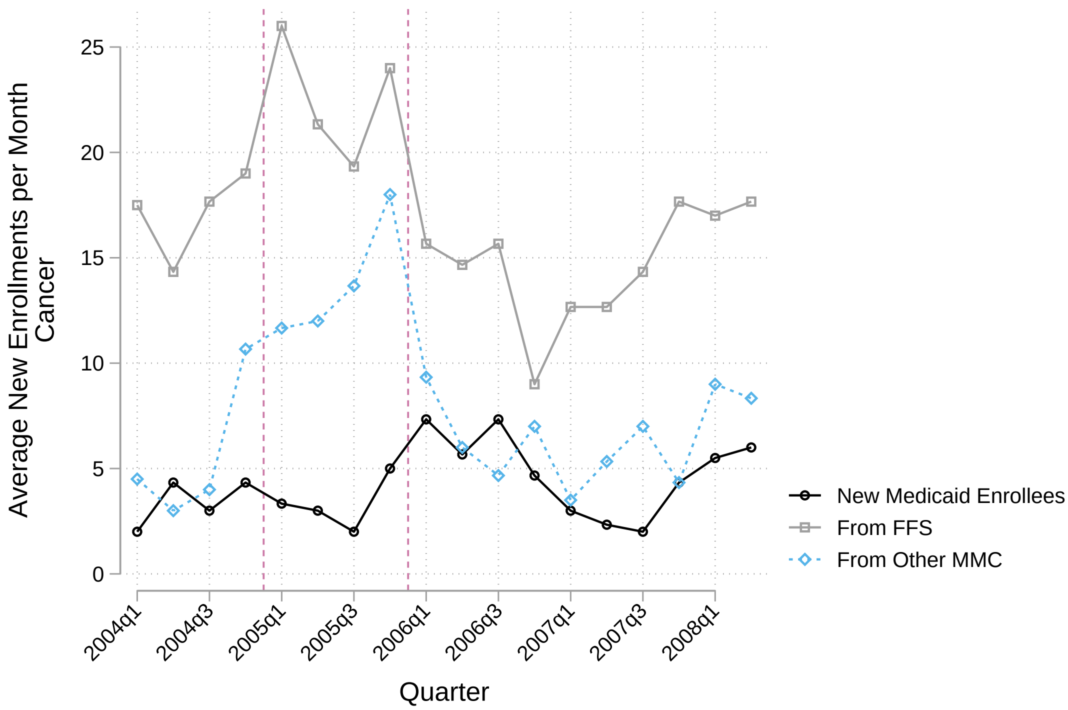


Figure 1.6: *Average Number of Beneficiaries with Cancer Switching to the Focal MCO over Time*

1.5.2 Profitability of the Marginal Beneficiaries

As described above, the addition of the cancer center to the focal MCO's provider network substantially increased the prevalence of beneficiaries with cancer in the MCO, from approximately 2.2% in the first half of 2004 to a peak of 3.2% at the beginning of 2006. Figure 1.7a presents the average monthly profitability of the MCO's beneficiaries with cancer between 2005-2008.[20] We report average monthly managed care revenues and average monthly health care spending separately. The black line in the figure represents revenues,

20. We exclude 2004 from all analyses of spending, as the MMC spending data are unreliable in that year.

the gray line represents spending, and the green bars represent the difference (profitability).[21] The average monthly profitability of the MCO's beneficiaries with cancer was $-\$353$ (representing losses to the plan of more than \$350 per month) in 2005, the year when the specialty cancer hospital was in-network. By contrast, the MCO's beneficiaries with cancer were associated with gains of $\approx$ \$79 per month (Figure 1.7b). As a back-of-the-envelope calculation, the MCO's increase in cancer prevalence from 2.2% to 3.2% when it added the cancer hospital to its network was associated with a 6.2% reduction in the plan's margins per beneficiary-month, from \$69.50/month to \$65.18/month.

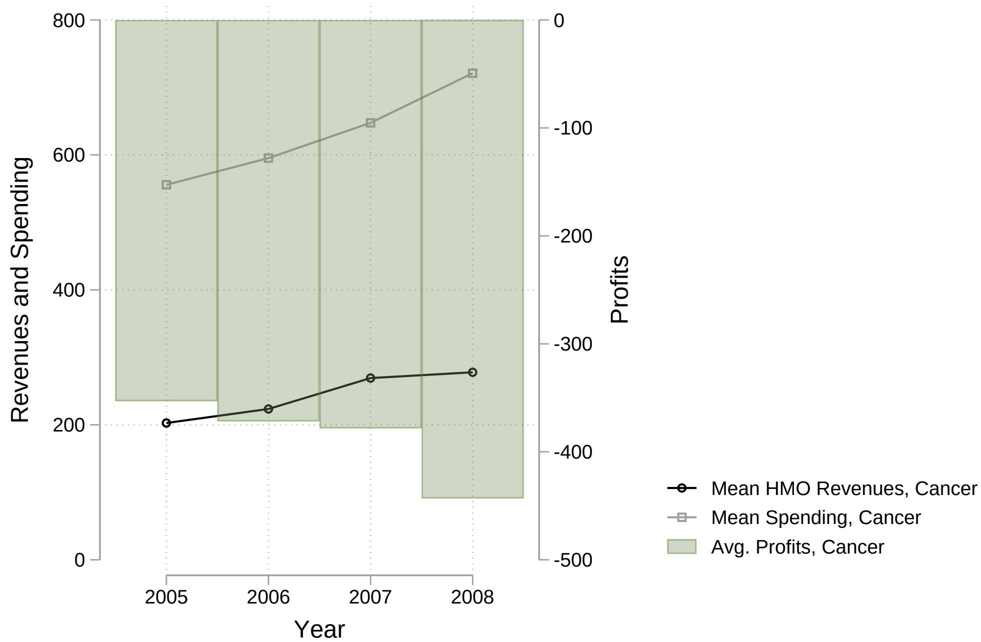
1.5.3 HETEROGENEITY

We next investigate the characteristics of the members of the cancer cohort who were induced to enroll in the MCO by the inclusion of the cancer center in its network. We do this by running a regression version of Figure 1.1. Specifically, we estimate the following regression model:

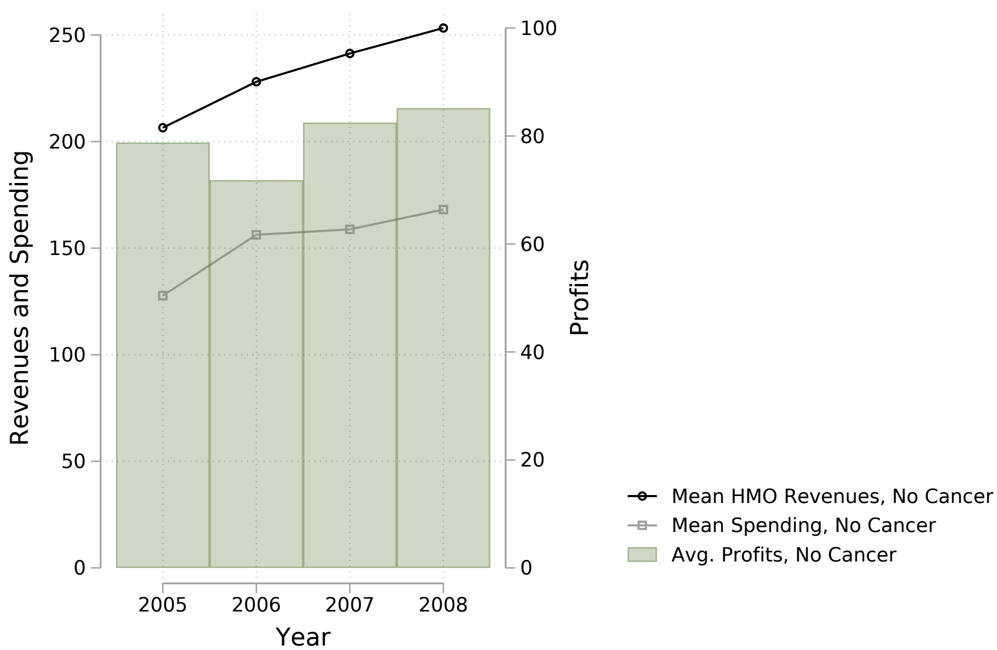
$$\begin{aligned} EnrollMCO_{it} =& \beta_1 Ant_t \times Cancer_i + \beta_2 Early_t \times Cancer_i + \beta_3 Peak_t \times Cancer_i \\ &+ \beta_4 Late_t \times Cancer_i + \beta_5 Post_t \times Cancer_i + \gamma Cancer_i + \alpha_t + \epsilon_{it} \end{aligned} \tag{1.4}$$

where $EnrollMCO_{it}$ is equal to one if person i is enrolled in the focal MCO in month t and $Cancer_i$ is equal to 1 for anyone in the cancer cohort and zero otherwise. Ant_t, $Early_t$, $Peak_t$, $Late_t$, and $Post_t$ are dummy variables capturing the different time periods surrounding the addition and removal of the cancer center from the focal MCO's network. Specifically, Ant_t

21. Since we do not include plans' administrative costs, this represents an upper bound approximation of the "profitability" of the MCO's beneficiaries.



(a) *Beneficiaries with Cancer*



(b) *Beneficiaries without Cancer*

Figure 1.7: *Average Monthly Revenues, Spending, and Profits Associated with Medicaid Beneficiaries in the Focal MCO, by Cancer Diagnosis*

represents the anticipatory period prior to the cancer center being added, July-December of 2004; $Early_t$ represents the period just after the cancer center was added, January-June of 2005; $Peak_t$ represents the peak of enrollment among the cancer cohort, July 2005-June 2006; $Late_t$ represents the period of declining enrollment among the cancer cohort, July 2006-June 2007; and $Post_t$ represents the "post-period" when enrollment among the cancer cohort has once again stabilized, July 2007-June 2008. From this regression, β_3 is our coefficient of interest, as it captures differential selection among the cancer cohort relative to the non-cancer cohort at its peak. α_t represents time period fixed effects. γ represents the difference in cancer and non-cancer market shares for the focal MCO during the pre-period (January-June 2004), allowing us to explicitly test whether the market shares were different from each other during this period.

We first estimate the regression for the full population. We then estimate the regression for subsets of the cancer cohort in order to identify which subsets responded most to the inclusion of the cancer center. The full set of coefficient estimates from these regressions is reported in Tables B.1-B.4 in the Appendix. In each of these regressions, the "control" group is all Medicaid beneficiaries who did not have cancer during the sample period, and we split the "treatment" group (the cohort with cancer) into sub-categories, estimating the selection coefficient for each. In our primary analysis of heterogeneity, we split the cancer cohort into hierarchical condition categories (HCCs) indicating the severity of the beneficiary's cancer diagnoses.[22] In secondary analyses of heterogeneity, we split the cancer cohort according to sex, age, race, whether or not the beneficiary used the specialty hospi-

22. For information on the assignment of beneficiaries with cancer to HCCs, see Section 1.4.3

tal in the pre-period (January-June 2004), and driving distance from the beneficiary's home to the cancer center.[23]

Figure 1.8 reports heterogeneity in the selection result by cancer severity (HCC). On the x-axis is the monthly adjusted "profitability" (managed care revenues minus managed care costs) of beneficiaries assigned to each cancer HCC.[24] On the y-axis is the "peak" selection coefficient from the regression in equation 1.4.[25] There is a negative correlation between profitability and selection into the MCO (correlation coefficient = -0.640); that is, MMC beneficiaries with more unprofitable (higher-cost) cancers are more likely to select into the MCO when the specialty cancer hospital is in-network. Selection into the MCO is highest among beneficiaries with Metastatic Cancers (HCC 8, coefficient = 0.022, 95% confidence interval 0.019-0.026) and Non-Hodgkin's Lymphomas and Other Cancers and Tumors (HCC 10, coefficient = 0.025, 95% CI 0.020-0.030). The only two HCCs for which the selection coefficient is not statistically significant are Lung, Brain, and Other Severe Cancers, Including Pediatric Acute Lymphoid Leukemia (HCC 9, coefficient = 0.004, 95% CI -0.001-0.008) and Thyroid Cancer, Melanoma, Neurofibromatosis, and Other Cancers and Tumors (HCC 13, coefficient = 0.005, 95% CI -0.002-0.012); the latter is considered the

23. Driving distance is estimated from the centroid of the beneficiary's home zip code to the centroid of the zip code where the cancer center is located. In the analysis of prior use of the specialty hospital, we split the cancer cohort into two groups: (1) beneficiaries who were enrolled in Medicaid during the pre-period but did not use the specialty hospital and (2) beneficiaries who were enrolled in Medicaid during the per-period and used the specialty hospital. That is, we exclude beneficiaries with cancer who were not observed during the pre-period.

24. Profitability is estimated using pooled data from all MMC plans for 2005-2006. We use an OLS regression to calculate adjusted profitability of MMC beneficiaries in each HCC category between 2005-2006, adjusting for MMC plan, calendar year, and calendar month.

25. These coefficient estimates can be found in Appendix Table B.1.

least severe (lowest-cost) of the cancer HCCs.

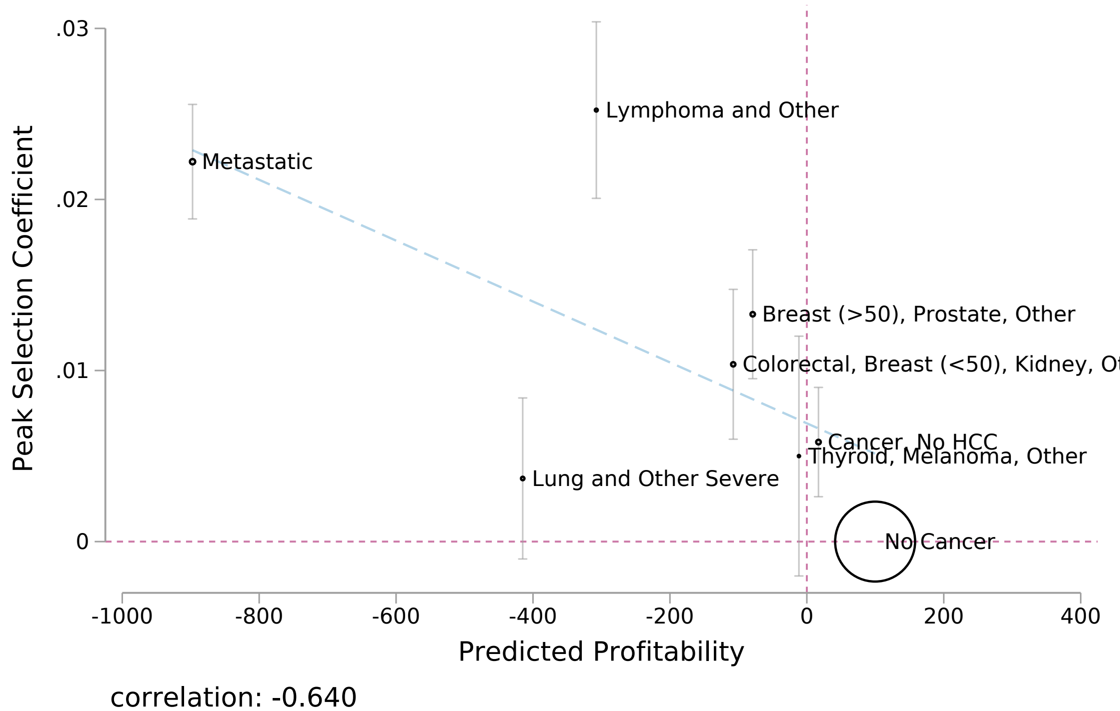


Figure 1.8: *Heterogeneity in Selection Result by Cancer Type*

Figure 1.9 reports β_3, the coefficient describing selection into the focal MCO at its peak, for a number of different subgroups of Medicaid beneficiaries with cancer. Similar to our main finding presented in Figure 1.1, we find that, at its “peak,” selection into the focal MCO was about 1.3 percentage points higher in the cancer cohort relative to the cohort without cancer (“peak” selection coefficient = 0.013). Within the cancer cohort, we find that selection into the focal MCO was much more pronounced for beneficiaries with metastatic cancers (coefficient = 0.022) than beneficiaries without metastatic cancers (coefficient = 0.010).[26] Splitting the cancer cohort by age, the selection coefficients were highest

26. Metastatic cancers are considered the highest-severity HCC cancer category, as they are associ-

for younger adult beneficiaries between the ages of 25-30 (0.019) and 31-40 (0.017), with lower levels of selection among beneficiaries above the age of 40 (0.011 for ages 41-50, and 0.012 for ages 51-64), and no statistically significant selection among beneficiaries between the ages of 18-24 with cancer. The selection coefficient was similar for Black and white beneficiaries (0.014 and 0.016, respectively), but somewhat lower for beneficiaries 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 beneficiaries living furthest from the hospital (0.021, vs. 0.008-0.014 for beneficiaries living closer to the hospital).[27] Finally, selection was much higher for the small number of beneficiaries with prior use of the specialty cancer hospital during the pre-period (0.334) than for other beneficiaries with cancer (0.013). Due to the scale, we report this final result in a separate figure, Figure B.1, in the Appendix.

1.5.4 Beneficiary Utilization of the Cancer Center

The second important component of Equation 1.2 describing the insurer's incentive to include the hospital in its network is take-up of the hospital among inframarginal beneficiaries. One way to examine this would be to focus on the focal MCO's beneficiaries with cancer who were in the plan both before and after the cancer center was added to its network, examining their utilization of the specialty cancer hospital over time. However, high rates of enrollment churn in Medicaid plus low rates of cancer make this group van-

ated with the highest spending of any of the HCC cancer categories. For raw data on spending by HCC, see Table B.5 in the Appendix.

27. The cut points for the distance bins (under 5 miles, 5-7.5 miles, etc.) were determined by splitting all beneficiaries with cancer into quartiles of distance from the cancer hospital.

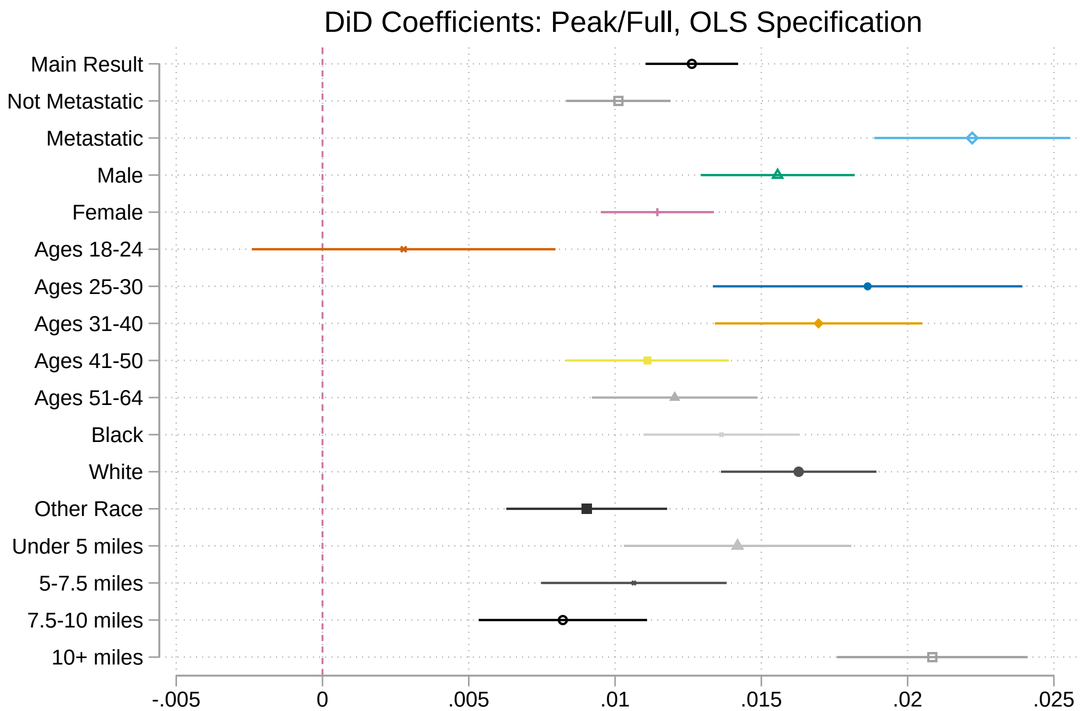


Figure 1.9: *Heterogeneity in Selection Result, "Peak" Coefficients, OLS Specification*

ishingly small, making it difficult to infer anything from changes in utilization within this group.

Instead, we opt for an alternative approach. We look at the effects of the inclusion of the cancer center in the MCO's network on utilization of the cancer center *across the entire market*. The intuition here is that if there is no change in use of the hospital across the entire market, this provides strong evidence that the MCO's inframarginal beneficiaries did not start using the cancer center. Instead, the entire change in utilization of the cancer center among the MCO's beneficiaries would be driven by *marginal* beneficiaries who enrolled in the MCO when it added the cancer hospital to its network.

Figure 1.5 plots utilization of the hospital across the entire market and across the different segments of the market, with utilization defined as a count of unique visits to the specialty hospital within each market segment (the focal MCO, all other MMC plans, or fee-for-service Medicaid) in each quarter.[28] The figure shows a large increase in use of the hospital among beneficiaries in the focal MCO when the hospital was added to the MCO's network. However, there is a corresponding decrease in use of the hospital among beneficiaries in the public FFS plan. The red line shows total market-level use of the hospital over time. This line is relatively flat between the third quarter of 2004 and the fourth quarter of 2005, indicating no change in overall use of the specialty hospital in Medicaid. This suggests that the inclusion of the hospital in the focal MCO's network had little effect on utilization of the cancer hospital by inframarginal beneficiaries; rather, the increase in utilization of the cancer hospital within the focal MCO appears to have mostly been driven by marginal beneficiaries who were already accessing the specialty cancer hospital in FFS, and who switched over from the public FFS plan when the cancer hospital was added to the MCO's network.

Figure 1.10 presents additional evidence that there was not a large amount of take-up of the specialty cancer hospital among inframarginal beneficiaries who were already enrolled in the focal MCO prior to its inclusion of the specialty cancer hospital. The figure shows the number of the MCO's beneficiaries using the specialty cancer hospital in each quarter, decomposed by what plan they were enrolled in during the pre-period (January-June 2004). From the figure, it is apparent that the vast majority of utilization of the cancer center within the MCO was by beneficiaries who were either not in Medicaid at all during the pre-period, or who were in another Medicaid market segment (other MMC plan or

28. Here, "visits" are defined as unique beneficiary-days with a claim at the cancer hospital.

FFS) in the pre-period, and who newly enrolled in the focal MCO in July 2004 or later.

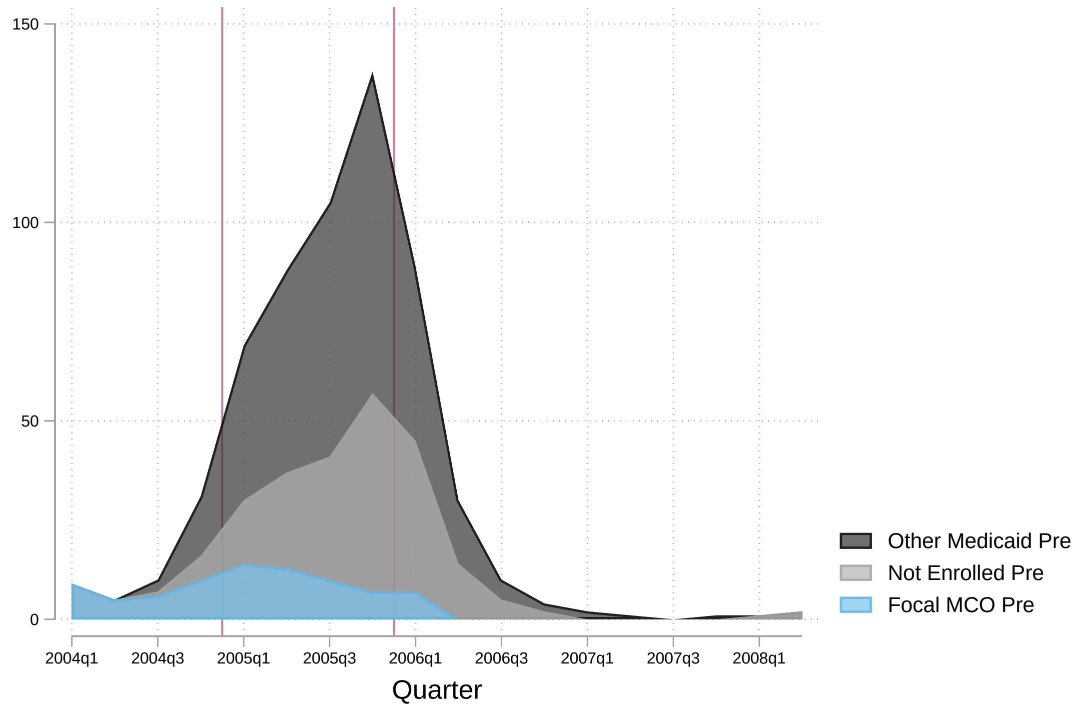


Figure 1.10: *Number of the MCO's Enrollees Using the Specialty Cancer Hospital (Stacked), by Enrollment Status in the Pre-Period (January-June 2004)*

1.6 Discussion

Medicaid covers 1 in 5 Americans, and nearly 70% of Medicaid beneficiaries are enrolled in private managed care plans (Rudowitz, Garfield, and Hinton 2019; Kaiser Family Foundation 2020b). Thus, it is important to understand how enrollment in a managed care plan affects access to advanced specialty care for these 54 million beneficiaries. In this chapter, we provide new evidence on the role of adverse selection in insurers' decisions to provide access to top specialty hospitals in Medicaid managed care (MMC). In Section 1.2 we show that there are two reasons why a plan would not want to cover a specialty hospital. The first is potential take-up of the (more expensive) specialty hospital among the plan's existing (inframarginal) beneficiaries. The second is the potential adverse selection of unprofitable (marginal) beneficiaries induced to enroll in the plan by the inclusion of the specialty hospital.

We estimate the relative importance of these two parameters using a natural experiment in which a single MMC plan added a well-known specialty cancer hospital to its provider network and dropped it a year later. We find evidence of extreme adverse selection in this setting. The marginal beneficiaries who switched to the plan when it covered the hospital cost the plan $\approx$ \$556 per month, but only brought in $\approx$ \$203 in revenues, resulting in an estimated loss of \$353 per marginal beneficiary per month (and a reduction in the plan's overall profits per marginal beneficiary of about 6.2%). Clearly, a MMC plan has little incentive to include this hospital in its network. While the inclusion of the hospital induced higher-cost beneficiaries with cancer to enroll in the plan, there was little evidence of take-up of the hospital among inframarginal beneficiaries. The results suggest that selection is the primary impediment to inclusion of the specialty hospital in managed care plans' networks.

Several policies could improve incentives for MMC plans to provide access to advanced specialty care in a setting with adverse selection. First, risk adjustment may improve incentives by increasing the revenues plans receive for enrolling high-cost beneficiaries. While risk adjustment was not present in our setting during the sample period, it was implemented later (between 2008-2012), and two of the eight MMC plans in the market subsequently added the specialty cancer hospital to their provider networks (although one of them has since dropped it again). As we note in Section 1.1, risk adjustment suffers from potential drawbacks, including upcoding of the diagnoses used to generate risk scores (Geruso and Layton 2015) and endogeneity of payments to utilization (Geruso and McGuire 2016). While most state Medicaid programs have implemented some form of risk adjustment, the extent to which risk adjustment improves incentives to provide access to advanced specialty care is an empirical question. In the next chapter, I will examine the performance of risk adjustment at mitigating the incentives associated with covering different types of physician specialists.

Medicaid programs could also improve access to specialty care by "carving out" the types of care that are known to be subject to selection incentives in MMC. For example, Medicaid programs could choose to mandate enrollment in managed care plans but carve out advanced specialty cancer care, paying for these services through the public FFS Medicaid program. A potential drawback of carve-outs is fragmentation of care, since beneficiaries do not receive all of their care from the same plan.

Finally, a public option could be an effective policy response; policymakers could give all Medicaid beneficiaries the option to remain enrolled in the public, FFS Medicaid program to ensure access to care. Indeed, in our setting, we observe that FFS Medicaid beneficiaries were able to continue accessing the cancer specialty hospital for the duration of the study period, even as MMC beneficiaries were not, indicating that the hospital was willing to accept Medicaid patients enrolled in the public program. Therefore, a public option could preserve access to services when private plans do not have a strong incentive to provide them. Although many states historically allowed Medicaid beneficiaries to enroll in public FFS coverage, few beneficiaries have this option today. While policies like a public option or carve-outs have the potential to improve access, they may also have efficiency consequences if managed care plans are able to more efficiently allocate care across beneficiaries.

In this chapter, we showed that Medicaid managed care plans face strong incentives to exclude advanced specialty cancer hospitals from their provider networks. We suggest several policy tools to ameliorate these incentives: risk adjustment, carve-outs, and a public option. While each approach has the potential to improve access to advanced specialty care, they each suffer from drawbacks as well, which we discuss above. These tradeoffs should be considered carefully as states determine how best to ensure access to advanced specialty care for Medicaid beneficiaries.

2

Assessing Selection Incentives by Physician Specialty

2.1 Introduction

Historically, state Medicaid programs paid health care providers directly, on a fee-for-service (FFS) basis, to provide health care services to beneficiaries. However, this model has changed over time, and states increasingly contract with private Medicaid managed care (MMC) plans to manage their Medicaid benefits. About 70% of Medicaid beneficiaries nationally are now enrolled in comprehensive, risk-based managed care (Kaiser Family Foundation 2017, 2020b). In adopting a managed care approach over the last few decades, states hoped to achieve higher value from their Medicaid programs – higher quality, and greater access to providers, at a lower cost (Hurley and Wallin 1998; Holahan et al. 1998). However, Medicaid managed care may also introduce concerns due to adverse selection.

Adverse selection is the tendency of individuals with higher expected health care costs to have higher willingness-to-pay for health insurance coverage, and to demand more generous coverage conditional on having insurance (Rothschild and Stiglitz 1976; Einav and Finkelstein 2011; Geruso and Layton 2017). When referring to adverse selection in the Medicaid context, I will generally be referring to the latter phenomenon: the propensity of sicker people to sort into more generous coverage.[1] In competitive health insurance markets, adverse selection can result in inefficiently low levels of coverage for services that are valued by costly beneficiaries. Particularly in settings like Medicaid with guaranteed issue, where insurers cannot turn away beneficiaries, insurers may attempt to cream skim more profitable beneficiaries by offering skimpy coverage for services that are valued by unprofitable beneficiaries (Cutler and Zeckhauser 2000; Frank, Glazer, and McGuire 2000; Glazer and McGuire 2000; Geruso and Layton 2017).

One way that MMC plans might respond to selection incentives is by excluding providers that serve high-cost beneficiaries from their networks. Historically, in FFS Medicaid, access to providers was largely a function of provider willingness to accept Medicaid pa-

1. Geruso and Layton (2017) refer to this as the "endogenous contracts" framework for thinking about selection, and it is the more relevant framework for considering adverse selection in a Medicaid context, where consumers do not pay a premium (price) to enroll in health insurance coverage.

tients. States set a fee schedule of provider prices, and providers faced a binary decision of whether or not to accept Medicaid patients at those prices. In MMC, access is instead determined by negotiations between plans and providers. MMC plans may be disincentivized to contract with providers that are disproportionately valued by unprofitable beneficiaries, particularly if provider networks are a salient feature for beneficiary plan choice. Indeed, given that Medicaid beneficiaries typically do not pay premiums to enroll in coverage, benefits are tightly regulated, and cost-sharing (where it exists) is limited, networks are likely to be important to beneficiaries making choices between MMC plans.

In this chapter, I study whether Medicaid managed care plans are incentivized to exclude particular physician specialties from their provider networks due to adverse selection. I focus on one of the largest Medicaid managed care markets in the United States, New York City. Like many other states, New York uses risk adjustment to compensate plans for differences in enrollee case-mix. If risk adjustment performs well, it should counteract selection incentives. I first replicate New York's payment system in order to simulate the risk-adjusted revenues that plans receive for each beneficiary. Then, I couple these revenues with beneficiaries' actual health care spending to derive beneficiary-specific monthly profitability. To estimate insurer incentives to attract or avoid particular beneficiaries, I group beneficiaries according to specialist utilization, calculating average monthly plan profits for beneficiaries using each physician specialist type. I compare the incentives associated with each group under risk adjustment to incentives without risk adjustment to examine how well risk adjustment performs. Finally, I examine the incentives associated with each provider specialty using an alternate measure from the literature that takes into account beneficiaries' ability to predict their own specialty utilization, and I compare this to my primary measure (Frank, Glazer, and McGuire 2000; Ellis and McGuire 2007; McGuire et al. 2014).

I find that adverse selection creates particularly strong incentives for Medicaid managed care plans to restrict access to physicians specializing in medical oncology, thoracic surgery, radiation oncology, infectious disease, neurosurgery, hematology-oncology, and nephrology. Beneficiaries who use these physician specialties are highly costly to health plans, with plans spending up to \$3,830/month on beneficiaries in the year when they visit these specialists. While risk adjustment and other transfers to plans mitigate these incentives (especially for nephrology), they remain, with plans losing up to \$2,970/month on these beneficiaries even in a setting with risk adjustment and inpatient stop-loss payments. These findings are consistent using both measures of the selection incentive. While risk adjustment generally improves incentives, it worsens the incentives associated with pediatrics and obstetrics & gynecology. For these two specialties especially, inpatient stop-loss payments and one-time maternity "kick" payments are important for ensuring beneficiaries who use these services are profitable to plans.

My work relates most closely to the literature on service-level selection (Frank, Glazer, and McGuire 2000; Glazer and McGuire 2000; Ellis and McGuire 2007; McGuire et al. 2014). Frank, Glazer, and McGuire (2000) use a model of plan profit maximization to develop an index of selection incentives, characterizing these incentives as "shadow prices" insurers can be expected to impose on different services. Ellis and McGuire (2007) build on this work, deriving an empirical measure of health plans' incentives that they show is a function of both "predictability" and "predictiveness" of service use. They show that in order for an insurer to be incentivized to over- or under-provide a service due to selection, it is necessary that individuals be able to predict their use of that service ahead of time (predictability). Additionally, the direction of the incentive depends on the correlation between predicted use of a service and gains or losses to the insurer (predictiveness). They then apply their metric to assess the magnitude of the selection incentives associated with services in Medicare. McGuire et al. (2014) use the same measure to assess selection incentives in the ACA health insurance marketplaces. I build on this prior work by using similar measures to characterize plans' incentives to ration access to specialists in a Medicaid setting. While Frank et al. (2000) characterize the incentives associated with different diagnostic groups in Medicaid in the early 1990s, there is little evidence regarding the selection incentives associated with specific provider specialties in Medicaid. Additionally, incentives in Medicaid are likely to have changed since that time due to expansions to Medicaid eligibility and technological innovation.[2] Since Medicaid managed care is now the primary mechanism for providing health insurance benefits to low-income people in the United States, it is important to understand how these incentives might affect access to specialty care for Medicaid beneficiaries.

In addition, this chapter relates to an emerging empirical literature on insurer responses to selection incentives in insurance markets. Several recent papers have demonstrated that managed care plans design insurance contracts to deter enrollment by individuals who are unprofitable to plans; for example, by offering more limited coverage of drugs used by unprofitable beneficiaries (Carey 2017b; Geruso, Layton, and Prinz 2019). In addition, Shepard (2016) documented substantial adverse selection against plans covering star hos-

2. Some diagnostic groups are likely to be much more expensive to treat now due to the emergence of new, expensive drugs (e.g., for cancer and hepatitis C).

pitals in the Massachusetts health insurance exchange, and in Chapter 1, we use a natural experiment to show that a Medicaid plan covering a specialty cancer hospital experienced adverse selection, forcing it to drop the hospital from its network. Finally, prior work has demonstrated that plans' selection activities are sophisticated – exploiting incentives embedded within the payment system. For example, a paper by Brown et al. (2014) finds that insurers respond to incentives within risk adjustment, enrolling beneficiaries with higher risk scores, but lower costs conditional on risk score, in the Medicare Advantage program. Despite this recent work, there has been little empirical work explicitly quantifying the selection incentives associated with coverage of physician specialists in Medicaid.

2.2 Setting and Institutional Details

Medicaid is the United States' public health insurance program for low-income individuals and families. Historically, the eligibility criteria for Medicaid were very strict. Prior to the Affordable Care Act (ACA), a person had to both meet income standards *and* be in one of several "categories of eligility" in order to qualify for Medicaid coverage; these categories included pregnant women, children, some parents with dependent children, and people eligible for the federal Supplemental Security Income (SSI) program on the basis of age, blindness, or a disability. The ACA, passed in 2010, was intended to expand Medicaid eligibility to all low-income individuals in the United States; however, a Supreme Court ruling determined that the ACA's Medicaid expansion was optional for states. Today, 39 states (including the District of Columbia) have expanded Medicaid, while 12 states, mostly in the Southeastern United States, have chosen not to adopt expansion (Kaiser Family Foundation 2021). In states that have expanded Medicaid, all adults with incomes below 138% of the Federal Poverty Level (FPL) are eligible, and in total, state Medicaid programs cover one out of every every five Americans (Rudowitz, Garfield, and Hinton 2019).[3]

The setting for my work is the Medicaid program in New York State. New York has one of the largest Medicaid programs in the country, accounting for nearly 1 in 10 Medicaid beneficiaries in the United States (Kaiser Family Foundation, n.d.). It also has one of the largest and oldest Medicaid managed care programs in the country, having experimented with managed care as early as 1967 (Hurley and Wallin 1998). Over time, it has expanded the array of services that are covered under the umbrella of managed care, such that most health care services are now a part of the managed care benefit (Forsgren 2017).

2.2.1 Plan Choice

In addition to carving benefits into Medicaid managed care over time, New York has been phasing in mandatory managed care since the 1990s – in other words, requiring beneficiaries to enroll in a private managed care plan. As a result, more than three-quarters of its Medicaid beneficiaries are now enrolled in managed care (Kaiser Family Foundation 2019). Beneficiaries may choose to enroll in any of the health plans operating in their county, but if they do not choose one, they are auto-assigned to a plan (New York State Department of Health 2015). Following enrollment, beneficiaries have a 90-day grace period during which they can disenroll and choose another health plan. Then, they are locked into their plan

3. As of 2019, 138% of the FPL was $17,236 for an individual. Some state Medicaid programs optionally cover pregnant women and children with incomes higher than 138% FPL; for pregnant women, this eligibility typically phases out 60 days postpartum.

for 9 months, called a "lock-in period."[4] Medicaid beneficiaries in New York City choose from a large number of competing health plans, although the market has consolidated over time. In 2004, there were 19 plans operating in the five boroughs of New York City. By the end of 2008, six plans had exited or were acquired by other plans, leaving 13 plans operating in the market. By the end of 2017, the market had consolidated further, with eight Mainstream MMC plans continuing to operate in the city.

Medicaid beneficiaries generally do not pay premiums to enroll in coverage. In addition, Medicaid plans are required to cover a defined set of benefits, and cost sharing is limited. Because of these program features, it may appear that plans are undifferentiated products from the perspective of beneficiaries. However, there are some dimensions on which plans may differentiate. First, in states where the pharmacy benefit is "carved in" to Medicaid managed care, plans may be differentiated by their drug formularies.[5] To a certain extent, drug coverage is standardized in Medicaid; plans are required to cover all medically necessary, Medicaid-covered drugs (Center for Evidence-Based Policy 2016). However, plans may place drugs on formulary "tiers," using modest levels of cost-sharing to discourage the use of non-preferred drugs. Second, while plans must cover a defined set of benefits, they may discourage the use of certain services by the use of "ordeals" – managed care techniques, such as prior authorization requirements or step therapy, that make it more

4. During the lock-in period, beneficiaries can disenroll from their MMC plan with good cause (New York State Department of Health 2015).

5. Historically, the pharmacy benefit was carved out in New York, until October 2011, when it was "carved in" to MMC (Forsgren 2017). The state planned to carve the pharmacy benefit back out of MMC in 2021; however, these plans have been postponed until 2023 (New York State Department of Health 2021). Most states cover the Medicaid pharmacy benefit through their Medicaid managed care programs (Gifford et al. 2020).

difficult to access particular health care services or drugs. Finally, plans provide different levels access to physician specialists through their provider networks. Given that drug benefits and covered services are relatively standardized in Medicaid, provider networks and ordeals remain key dimensions on which plans can differentiate themselves to beneficiaries.

2.2.2 Rate Setting and Risk Adjustment

In order to understand the relative profitability of enrolling Medicaid beneficiaries from the perspective of Medicaid managed care plans, it is necessary to understand how Medicaid plans are paid. Typically, states pay a fixed amount to plans for each beneficiary (an "administered rate"), which is risk-adjusted according to beneficiary demographics and health status (Courtot, Coughlin, and Lawton 2012; Layton, Ndikumana, and Shepard 2017).[6] While risk adjustment methods vary by state, they typically incorporate beneficiary demographics like age, sex, geography, and Medicaid eligibility category, along with beneficiaries' observed health conditions (diagnoses in the claims data) to adjust payments to plans (Courtot, Coughlin, and Lawton 2012). Some states also use prescription drug utilization in their risk adjustment formulas.[7]

6. Instead of setting an administered rate, some states use a competitive bidding process or negotiate rates with plans; however, this is much less common today (Layton, Ndikumana, and Shepard 2017). New York historically negotiated rates with plans, but today uses administered, risk-adjusted rates to pay plans.

7. Risk adjustment systems commonly used by other state Medicaid programs include the Chronic Illness and Disability Payment System (CDPS), the Combined Chronic Illness and Pharmacy Payment System (CDPS+Rx) and the Medicaid Rx (MRX) payment system, all developed by the University of California San Diego, and the Adjusted Clinical Groups (ACG) model, developed by Johns Hopkins University.

Similarly to other states, New York pays a risk-adjusted administered rate to health plans. The way the state determines this rate is as follows. The state first sets "base premiums" for each geographic rating region, which are based on the historic costs (both administrative and medical costs) of covering Medicaid beneficiaries in that region.[8] Within a geographic region, a separate base premium rate is set for each premium group. Premium groups are combinations of age and category of aid: Temporary Assistance for Needy Families (TANF) ages 0-20, TANF ages 21+, and SSI.[9] The base premium is then risk-adjusted using 3M Clinical Risk Groups (CRGs), a proprietary risk-adjustment methodology that accounts for each beneficiary's demographics, diagnoses, medical procedures, and pharmacy claims. To risk adjust premiums, the state first assigns each Medicaid beneficiary to one of 44 aggregate CRGs (CRGs). Then, it calculates a "cost weight" for each CRG, equal to the average cost of beneficiaries in that CRG relative to the average Medicaid beneficiary. Finally, it assigns each plan a premium, which is equal to the base premium times the average cost weight of the plan's beneficiaries. For more specific details on New York's risk adjustment system, see Appendix A.

In addition to its risk adjustment system, New York uses other direct transfers to compensate plans for enrolling higher-cost beneficiaries, including a stop-loss program for inpatient care and a Supplemental Newborn Capitation Payment (a "kick" payment) for inpatient newborn deliveries. The latter is a one-time, lump-sum payment that is meant to compensate MMC plans for the cost of a newborn's hospital stay (New York State Of-

8. New York City represents a single geographic region.

9. For the purposes of premium group definition, the "TANF" category includes all income-based categories of eligibility.

fice of the State Comptroller 2014). Both risk sharing arrangements and maternity "kick" payments are common in Medicaid, although their details vary by state (Schwalberg et al. 2013; Courtot, Coughlin, and Lawton 2012).

2.3 Model

In order to build intuition, I present a model characterizing a Medicaid managed care plan's incentives to include, or exclude, a specialist from its network. I borrow and adapt this model from joint work with Mark Shepard, Timothy Layton, and Jacob Wallace (see Chapter 1). The model I present here is closely related, in intuition, to the one developed first by Frank, Glazer, and McGuire (2000) to characterize plan incentives to ration services due to adverse selection.

2.3.1 Model Setup

Consider a Medicaid managed care market where beneficiaries choose from a set of plans, $j \in \{1, ..., J\}$, and do not pay premiums to enroll in coverage. As described above, each Medicaid managed care plan is paid an administratively-set premium R for each covered beneficiary, which is risk-adjusted to account for beneficiary complexity, but otherwise does not vary with plans' provider network coverage. Under a typical Medicaid risk adjustment regime, each beneficiary i is assigned a risk score $\varphi_i > 0$, based on their demographics, medical claims, and category of aid, and plan j receives $\varphi_i R$ for enrolling beneficiary i.

Insurers must decide which specialists to include in-network, subject to some network adequacy constraints. Consider a Medicaid managed care plan's decision to include or exclude a single specialist z (e.g., a single endocrinologist) from its network, holding the rest of its provider network, along with the networks of all other plans in the market, fixed. I represent the insurer's network coverage of specialist z as $n_{jz} \in \{0, 1\}$, such that $n_{jz} = 0$ means that specialist z is out-of-network, and $n_{jz} = 1$ means that specialist z is in-network. Let $D_{ij}(n_{jz})$ be an indicator for whether enrollee i chooses plan j, as a function plan j's coverage of specialist z, n_{jz}, and let $C_{ij}(n_{jz})$ represent each beneficiary's costs of medical care, conditional on choosing plan j. Plan j's profits can therefore be represented by:

$$\pi_j\left(n_{jz}\right) = \sum_i \left[\varphi_i R - C_{ij}\left(n_{jz}\right)\right] \cdot D_{ij}\left(n_{jz}\right) \tag{2.1}$$

The term $\left[\varphi_i R - C_{ij}\left(n_{jz}\right)\right]$ represents each plan enrollee's (risk-adjusted) revenues minus their costs of medical care, and $D_{ij}\left(n_{jz}\right)$ is an indicator for whether beneficiary i chooses plan j. Both are functions of whether plan j includes specialist z in its provider network.

2.3.2 The Effect of Specialist Coverage on Plan Profits

I examine the change in a plan's profits when it goes from *not covering* specialist z to covering specialist z ($\Delta\pi_j = \pi_j(1) - \pi_j(0)$), holding its coverage of other specialists fixed. In the equation below, ΔC_{ij} represents the change to beneficiary i's costs in plan j when plan j adds coverage for specialist z ($\Delta C_{ij} = C_{ij}(1) - C_{ij}(0)$). ΔD_{ij} represents the change to beneficiary i's demand for plan j when plan j adds coverage for specialist z ($\Delta D_{ij} = D_{ij}(1) - D_{ij}(0)$).

$$\Delta\pi_j = \underbrace{-\sum_i \Delta C_{ij} \cdot D_{ij}\left(0\right)}_{\text{(1) Cost increase (``moral hazard'')}} + \underbrace{\sum_i \left[\varphi_i R - C_{ij}\left(1\right)\right] \cdot \Delta D_{ij}}_{\text{(2) Profitability of marginal beneficiaries}} \tag{2.2}$$

Intuitively, there are two main ways in which network coverage of specialists affects plan profits. The first is that coverage of specialists affects the costs of medical care for the plan's existing beneficiaries (the first term in equation 2.2). One way to think about this effect is as a type of moral hazard with respect to network coverage. In my model, I will assume that $\Delta C_{ij} \geq 0$; in other words, including more specialists always increases a plan's costs (and decreases its profits) through this "moral hazard" effect. Secondly, specialist coverage affects beneficiaries' plan choices through $D_{ij}(n_{jz})$. In equation 2.2, $\Delta D_{ij} = 1$ for beneficiaries who do not choose plan j when $n_{jz} = 0$, but who choose plan j when $n_{jz} = 1$ (the "marginal" beneficiaries), and $\Delta D_{ij} = 0$ for all other Medicaid beneficiaries. Thus, in effect, the second term is simply the sum of the profitability of all of the "marginal" beneficiaries who choose plan j when specialist z is in-network. The second term in equation 2.2 represents the *selection incentive* associated with covering specialist z.

This second term, the selection incentive, is what I aim to quantify in this chapter. Assuming, as I have, that $\Delta C_{ij} \geq 0$, the only way that including the additional specialist z will be profitable to the plan is if the right-hand term in equation 2.2, $\sum_i \left[\varphi_i R - C_{ij}\left(1\right)\right] \cdot \Delta D_{ij}$, is positive. In other words, the total, risk-adjusted revenues associated with these "marginal" beneficiaries must be greater than their costs.

With this intuition in mind, a natural way to quantify the selection incentive associated with each specialist (or specialist "type") is to make some assumptions about who the "marginal beneficiaries" are – those Medicaid beneficiaries who would choose a plan based on having access to that specialist type – and calculate their profitability to Medicaid managed care plans (their risk-adjusted revenues minus their costs). In my primary specification, I will assume that the "marginal beneficiaries" associated with a physician specialty can be approximated by the individuals who are actually observed using that specialty in the data. Thus, I approximate the selection incentive associated with a physician specialty by calculating the average profitability to Medicaid managed care plans of Medicaid beneficiaries who use that specialty.

Of course, this measure is imperfect. An alternate measure would incorporate not only whether use of a specialist type is *predictive* of losses to the insurer (what the measure above does), but also whether use of that specialist type is *predictable* by beneficiaries. Intuitively, a beneficiary will choose a plan based on having access to a specialist in that plan's network only if she can *predict* that she will use that specialist in the coming year. If use of a specialist type cannot be predicted by beneficiaries, then insurers have little selection-related incentive to ration access to that specialist type. Thus, my secondary measure of the selection incentive will follow prior work by Ellis and McGuire (2007) and McGuire et al. (2014) to incorporate predictability of service use.

Ellis and McGuire (2007) use a model of plan maximization to construct a measure to quantify the direction and magnitude of selection incentives associated with different services. They demonstrate that plan incentives to ration services (in this case, access to physician specialists) are proportional to the product of measures of predictability and predictiveness of service use:

$$I_z \propto cv_z \cdot \rho_z$$

where cv_z is the coefficient of variation of predicted spending on specialist type z, and ρ_z is the correlation between predicted spending on specialist type z and plan profits or losses. In effect, cv_z measures how well beneficiaries can predict use of specialist type z. ρ_z measures the correlation between predicted spending on specialist type z and plan gains or losses. I will use this measure I_z, described in more detail below, as a secondary method for assessing selection incentives.

2.4 Data

To assess the incentives associated with each provider specialty, I merge Medicaid data from the New York State Department of Health (NYSDOH) with data from the Centers for Medicare & Medicaid Services (CMS) on all health care providers operating in the state. Both of these data sources are described below.

2.4.1 New York Medicaid Data

I obtain administrative data on enrollment and health care claims for all New York Medicaid beneficiaries enrolled between 2005-2017.[10] For each beneficiary, I observe demographics, category of aid, the MMC plan that the beneficiary was enrolled in, clinical risk group (CRG) assignment, and county of residence. I also observe the amount that the plan was paid by the state to enroll the beneficiary – both the premium that was paid, as well as any stop-loss or maternity kick payments. The claims data include diagnoses, procedures, health care provider identifiers, and the amount paid by both the managed care plan and by the FFS Medicaid program for each claim. The enrollment data allow me to categorize

10. The data were obtained pursuant to a Data Exchange Application & Agreement (DEAA) with New York Medicaid.

beneficiaries into premium groups.[11] Using the claims data, I estimate plan revenues and calculate plan spending per beneficiary. I describe the process of estimating plan revenues per beneficiary in Section 2.5. The claims data also allow me to quantify each beneficiary's utilization of each specialist type. To categorize physician claims by specialty, I map the billing provider's NPI to National Plan & Provider Enumeration System (NPPES) data (described in section 2.4.2 below).

Sample Selection

I restrict the estimation sample to beneficiaries with full Medicaid eligibility living in the five boroughs of New York City between state fiscal years (SFYs) 2012-2015.[12] I restrict to these years for several reasons. The first is that risk adjustment was not fully phased in in New York until 2012, and I am interested in MMC plans' incentives in the context of risk adjustment. The second is that CRGs, which New York uses for risk adjustment, are less reliably updated in the administrative data after 2015. The third is that observed specialist utilization declines in the encounter data after 2015, which may be due to new initiatives in New York State that encouraged capitated payments to providers (New York

11. As described in section 2.2.2, these groups include: TANF ages 0-20, TANF ages 21+, and SSI. Since I restrict to New York City, which is a distinct geographic rating region, I do not otherwise categorize beneficiaries by geography.

12. I exclude beneficiaries who received "partial" Medicaid coverage only for specific services, and those who were listed as having Family Health Plus coverage, a separate type of coverage for families with higher incomes that expired on December 31, 2013, when FHP beneficiaries were transferred into the Medicaid State Plan as part of the ACA Medicaid expansion (Forsgren 2017). I also exclude beneficiaries who were in other types of Medicaid plans, such as Special Needs Plans (SNPs) and Medicaid Advantage (MA) plans, designed for beneficiaries with HIV (SNPs) or beneficiaries who are dually eligible for Medicare. These plans are distinct from the risk adjustment system used in Mainstream Medicaid Managed Care.

State Department of Health 2019).[13] I exclude beneficiaries ages 65 and older, who are dually eligible for Medicare benefits, since such beneficiaries typically do not enroll in Mainstream Medicaid managed care plans. Finally, I exclude enrollment-months prior to the beneficiary's listed date of birth.

2.4.2 National Plan & Provider Enumeration System

I use National Plan & Provider Enumeration System (NPPES) data from the Centers for Medicare & Medicaid Services (CMS) from 2017 to construct a dataset of physicians practicing in New York City and to categorize physician claims by specialty. The NPPES is a registry of NPIs and includes data on practice location and specialty type for all individuals and organizations providing health care services in the United States (DesRoches et al. 2015).

I first check for concordance between the 2017 NPPES data and the claims data by merging a 5% random sample of the claims from 2012-2015 with the NPPES data. For this analysis, I restrict the NPPES data to providers listed as practicing in New York, New Jersey, Connecticut, or Pennsylvania (states in the vicinity of New York City). I use the the billing provider's NPI in the claims to merge with the NPPES data. Of the claim lines with a non-missing NPI (95.3% of claim lines), 97.4% match to an NPI from the New York region in the NPPES data, providing reassurance that the NPPES data adequately capture the providers practicing in the New York region during this time period.[14]

13. My concern is that I may not fully observe specialist utilization after this date, although I cannot rule out other explanations for this observed change in utilization.

14. Claim lines with missing NPIs were concentrated in service types like community & rehabilita-

Next, I use the NPPES data to construct a dataset of physicians practicing in New York City. I restrict to osteopathic and allopathic physicians with a listed practice location in a New York City zip code. To categorize physicians by specialty type, I match NPPES provider taxonomy codes to Medicare specialty codes from the Centers for Medicare & Medicaid Services (Centers for Medicare & Medicaid Services 2020).[15] I disaggregate some of the larger CMS specialty codes, such as internal medicine, using more granular codes (e.g., gastroenterology) where possible to identify physicians practicing in sub-specialties. I exclude certain sub-specialists who practice primarily within hospitals, including hospitalists, anesthesiologists, pathologists, emergency department physicians, intensive care specialists, and radiologists. Finally, I restrict the analysis to provider specialties with at least 100 providers who had New York City Medicaid claims between 2012-2015.[16]

2.5 Methods

I quantify Medicaid managed care (MMC) plans' incentives to contract with different types of physician specialists using two alternate measures. These are described below.

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tion (39.8% of claim lines with a missing NPI), transportation (19.6%), lab (11.3%), non-institutional long-term care (10.6%), and pharmacy (4.6%).

15. Gottlieb et al. (2020) also use the CMS crosswalk to categorize physicians (Gottlieb et al. 2020).

16. I exclude small sub-specialties to ensure that my analysis of selection incentives is not overly sensitive to the characteristics of a small number of providers.

2.5.1 Primary Measure: Average Profitability of Specialist Users

My primary measure of the selection incentive associated with each physician specialty is the "profitability" (revenues minus costs) of MMC beneficiaries who use that specialty. To calculate this measure for a given specialist type (e.g., endocrinologists), I first identify all MMC beneficiaries who use the specialist type during each year of the study period, 2012-2015. Then, I calculate the average monthly profitability of these beneficiaries in the year when they used the specialty, which is equal to the average (risk-adjusted) revenues the plan receives for enrolling these beneficiaries, minus the beneficiaries' average health care costs. This primary measure is analogous to the one used by Geruso, Layton, and Prinz (2019) to examine insurer responses to selection incentives in drug formularies in ACA Marketplace plans. If beneficiaries who use a particular specialist type are very profitable to plans (i.e., the average risk-adjusted revenues associated with these beneficiaries is much higher than their average health care spending), then MMC plans are incentivized to provide access to physicians of that type. By contrast, if the beneficiaries who visit a specialist type are unprofitable to Medicaid plans (i.e., their health care spending exceeds their risk-adjusted capitation payments), then plans have little incentive to include such specialists in their networks.

2.5.2 Secondary Measure: Ellis-McGuire Measure

As a second measure of the selection incentive, I use a metric developed by Ellis and McGuire (2007), which incorporates both *predictability* and *predictiveness* of specialist utilization. While the measure above assesses the ex-post profitability of beneficiaries who use each specialist type (how *predictive* use of a specialist type is of plan profits or losses), this measure also incorporates whether use of a specialist type is *predictable* by beneficiaries.

I refer to this measure as EM_z, where $EM_z = cv_z \cdot \rho_z$ for specialist type z. cv_z represents the coefficient of variation of predicted spending on specialist type z, and ρ_z represents the correlation between spending on specialist type z and plan profits or losses. In essence, cv_z quantifies the "predictability" of specialty use; a higher coefficient of variation indicates higher predictability of specialist use.[17] The correlation coefficient ρ_z between spending on specialist type z and plan gains or losses measures the "predictiveness" of specialist use.

In order to calculate cv_z for each specialist type z, I first estimate predicted (log) spending on specialist type z in year t for each Medicaid beneficiary i, $\widehat{LogSpend}_{i,z,t}$. To do this, I regress log spending on specialist type z in year t on: log spending on specialist type z, log total spending, demographics (age and sex), disability status (SSI), number of FFS enrollment months, and diagnoses in year $t-1$:[18]

$$\begin{aligned} LogSpend_{i,z,t} =& \beta_1 LogSpend_{i,z,t-1} + \beta_2 LogTotalSpend_{i,t-1} + \beta_3 Demographics_{i,t-1} + \beta_4 SSI_{i,t-1} \\ &+ \beta_5 FFS\_Months_{i,t-1} + \sum_d \beta_d 1[Diagnosis_{i,d,t-1} = 1] + \epsilon_{i,z,t} \end{aligned}$$

17. The coefficient of variation is the standard deviation divided by the mean.

18. I split age into deciles for this regression. I categorize FFS enrollment months as follows: 0 months, 1-3 months, 4-6 months, 7-9 months, or 10-12 months. For diagnoses, I include indicators for the following 14 Clinical Classifications Software (CCS) diagnosis categories: infectious and parasitic diseases; neoplasms; endocrine, nutritional, and metabolic diseases and immunity disorders; diseases of the blood and blood-forming organs; mental illness; diseases of the nervous system and sense organs; diseases of the circulatory system; diseases of the respiratory system; diseases of the digestive system; diseases of the genitourinary system; complications of pregnancy, childbirth, and the puerperium; diseases of the skin and subcutaneous tissue; diseases of the musculoskeletal system and connective tissue; and congenital anomalies.

For this regression, I restrict to Medicaid beneficiaries (both FFS and MMC) with at least 10 months of observation in at least two consecutive years between 2012-2015. Approximately 51.6% of MMC beneficiaries between 2012-2015 meet these criteria.[19]

From these regressions, I estimate $\widehat{LogSpend}_{i,z,t}$ for each beneficiary i and each specialist type z in each year t. I then calculate the coefficient of variation cv_z for this measure of predicted spending. Finally, I restrict to MMC beneficiaries and calculate the correlation coefficient ρ_z between actual average spending on each specialist type z and average monthly plan profits or losses. The selection incentive, EM_z, for each specialist type z is the product of cv_z and ρ_z, multiplied by -1 (so that the incentive is positive for adversely selected specialties).

2.5.3 Estimating Plan Revenues

I quantify Medicaid managed care (MMC) plans' incentives to contract with different types of physician specialists under three different payment regimes: (1) administered rates with no risk adjustment, (2) administered rates with risk adjustment by CRG, and (3) administered rates with risk adjustment by CRG, along with inpatient stop-loss and maternity kick payments.[20] I assume that the state makes the same total payments to MMC plans under all three payment regimes; however, in each regime, these payments are distributed differently across beneficiaries (and therefore plans) according to beneficiary risk. In the data, I observe the actual premium paid to each plan for each beneficiary in each month;

19. I use all available pairs of consecutive years of observation in the data, for beneficiaries who meet these criteria. Observations are at the level of beneficiary-pair.

20. The latter replicates the rate setting method used by New York State during the study period.

however, this observed premium is the outcome of the state's risk adjustment system, and does not vary across beneficiaries within a plan and premium group. Therefore, I simulate the state's risk adjustment system to estimate the risk-adjusted contribution of each beneficiary to her plan's revenues.

I first examine incentives under a setting with standard administered rates and no risk adjustment. For this step, I assume that MMC plans are paid the same premium for all beneficiaries in a premium group, and that plans do not receive supplemental maternity kick payments or stop-loss payments.[21] To estimate the plan revenues associated with each beneficiary under this payment regime, I calculate the average of all actual, observed payments from the state to MMC plans for each premium group in each state fiscal year (SFY).[22]

Next, I add in risk adjustment.[23] For this step, I consider the premiums calculated in the previous step to be the base premiums for each premium group. To estimate risk-adjusted plan revenues for each beneficiary, I multiply this base premium by the cost weight for the beneficiary's assigned CRG. The cost weight for each CRG is calculated by taking the ratio of average spending for beneficiaries assigned to that CRG divided by average spending

21. Premium groups, as described in section 2.2, are combinations of age and Medicaid category of aid. The three premium groups are: TANF ages 0-20, TANF ages 21+, and SSI.

22. I include kick payments and stop-loss payments in this calculation; however, I distribute them equally across all beneficiaries in a premium group. When calculating the base premium for 2015, I calculate separate premiums for the first and second half of the SFY, as New York implemented a behavioral health transition in October 2015 and added an additional amount to the base premium to cover additional mental health services under the umbrella of managed care.

23. For further information on New York's risk adjustment system, see section 2.2 and Appendix A.

for all MMC beneficiaries.[24] Intuitively, the cost weight for a CRG is a ratio of average costs of medical care for beneficiaries in that CRG to average costs for all beneficiaries.

Finally, I incorporate supplemental transfers to plans, including stop-loss payments and maternity kick payments, to simulate the revenues associated with each beneficiary under New York's *actual* MMC payment system. To estimate the plan revenues associated with each beneficiary under this payment regime, I first calculate a new base premium for each premium group and SFY, excluding stop-loss and kick payments. The base premium is the average of all actual, observed *premium* payments from the state to MMC plans for each premium group in each SFY. Then, I incorporate risk adjustment (as above). Finally, I add the supplemental transfers associated with each beneficiary to *that beneficiary's* revenues. Since I observe stop-loss and kick payments in the data, this final step is straightforward.

2.5.4 Limitations

One limitation of this study is that it assesses the performance of risk adjustment using only the prevailing risk adjustment system in New York, 3M aggregate CRGs (ACRGs). This analysis may not be generalizable to other state Medicaid programs. One alternative that would be feasible in my data would be to examine the fit of more granular CRGs, which are also present in the New York Medicaid data, but not used for risk adjustment. These more granular CRGs might offer better fit at the expense of contract power (Geruso and McGuire 2016). It is also possible that alternative risk adjustment systems commonly used by state Medicaid programs, such as the Chronic Illness and Disability Payment Sys-

24. To calculate the cost weights, I aggregate all of the claims data between SFY 2012-2015. I calculate a separate set of cost weights for each premium group.

tem (CDPS), might provide better fit. On the other hand, even within a risk adjustment system that provides good overall fit, incentives may remain to select lower-cost beneficiaries within a risk score (Brown et al. 2014).

Another limitation is that my primary measure of the selection incentive examines the ex-post profitability of Medicaid beneficiaries who access specialists, and is therefore endogenous to specialist access. This measure likely over-estimates the incentives to ration care, as it does not account for the profitability to MMC plans of beneficiaries who choose a plan in order to have access to specialty care but do not ultimately use it. If MMC plans are able to attract a sufficient number of healthy beneficiaries by offering good access to specialists, then they may be incentivized to offer such access even if the beneficiaries actually using specialty care are unprofitable. My second measure (the E-M incentive measure) attempts to address this endogeneity by correlating *predicted* spending on specialty care with beneficiary costs, and adjusting for the predictability of specialist use.

Finally, I only quantify the overall incentive associated with each specialist type; my analysis does not address whether specific physicians practicing within each specialty are more vulnerable to under-provision than others, a question that may be important in a setting where plans are required to cover a certain number of specialists, but are not required to cover specific specialists.

2.6 Results

2.6.1 Summary Statistics

I report summary statistics in Table 2.1. For the majority of the analyses, I restrict to beneficiaries enrolled in Medicaid managed care (MMC) plans; however, when estimating predictability of specialist utilization, I include beneficiaries in fee-for-service (FFS) Medicaid.[25] Therefore, I report characteristics of FFS and MMC beneficiaries separately in the table. The majority of beneficiaries in the sample were in MMC plans (89.5%), while only 10.5% were in enrolled in the public FFS Medicaid program.

There were approximately 2.3 million beneficiaries enrolled in Mainstream MMC plans in New York City in each month between 2012-2015. Of these beneficiaries, most (92.6%) were eligible for Medicaid on the basis of income (TANF).[26] The other 7.4% were eligible for Medicaid on the basis of a disability (SSI). The mean age of the MMC sample was 25.0 years, and the majority (54.2%) of beneficiaries were female. Decomposing the MMC sample by race, 26.5% of beneficiaries in MMC were white, 25.7% were Black, 16.4% were Asian or Pacific Islander, 3.4% were Hispanic, 1.4% were American Indian or Alaska Native, and 26.5% had race identified as "other" or unknown.[27] On average, Medicaid managed care beneficiaries had spending of \$352.3 per month, with \$267.5 of this paid by

25. A single beneficiary may spend some months in FFS and some months in MMC; I use all of a beneficiary's observed months in Medicaid when reporting (or predicting) specialist utilization.

26. Though not all of these beneficiaries were necessarily eligible for the Temporary Assistance for Needy Families (TANF) program, I refer to this as TANF eligibility for brevity.

27. The data were missing a variable indicating beneficiaries' ethnicity; therefore, Hispanic ethnicity is likely under-reported here.

Table 2.1: *Sample Characteristics by Market Segment, 2012-2015*

	Fee-for-Service	Medicaid Managed Care
	(1)	(2)
N (mean per month)	272,195	2,329,702
Percentage of sample (%)	10.5	89.5
Premium Group (%)		
TANF 0-20	33.8	46.2
TANF 21-64	52.6	46.4
SSI 0-64	13.6	7.4
Age (mean)	27.1	25.0
Female (%)	50.6	54.2
Race (%)		
Black	30.3	25.7
White	21.5	26.5
Asian/PI	9.2	16.4
Hispanic	2.8	3.4
AIAN	0.9	1.4
Other	7.7	6.0
Unknown	27.6	20.5
Monthly spending ($)		
Total	1,075.3	352.3
MMC	N/A	267.5
Monthly MMC payments ($)		
MMC Premiums	N/A	342.2
Maternity Payments	N/A	27.2
Inpatient Payments	N/A	3.0

Note: This table reports summary statistics by market segment (fee-for-service Medicaid vs. Mainstream Medicaid managed care) for New York City Medicaid beneficiaries between state fiscal years 2012-2015. I restrict the estimation sample to beneficiaries aged 0-64 with full Medicaid eligibility. I exclude beneficiaries who were dually eligible for Medicare; along with beneficiaries in Family Health Plus (FHP), Special Needs Plans (SNPs), Medicaid Advantage (MA) plans, and Health and Recovery (HARP) plans.

MMC plans and the other \$94.8 paid by the state FFS Medicaid progaram.[28] MMC plans received premium payments from the state averaging \$342 per beneficiary-month, maternity "kick" payments averaging \$27 per beneficiary-month, and inpatient stop-loss payments averaging \$3 per beneficiary-month. Therefore, MMC plans' average "profits" per beneficiary-month were \$104.9.[29]

Table 2.2 reports the average number (and %) of MMC beneficiaries enrolled in each month of the study period who used each specialist type at any time during the year in which they were enrolled. The bottom row reports the average number (and %) of MMC beneficiaries enrolled in each month of the study period who had a claim with *any* physician during the year. A little over half (53.7%) of MMC beneficiaries had a claim with any physician each year. The specialist types with the highest levels of utilization were those commonly associated with primary care: pediatrics (20.4%), general internal medicine (15.8%), family practice (8.4%), and obstetrics & gynecology (7.7%). The specialist types with the lowest levels of utilization were: thoracic surgery (0.08%), radiation oncology (0.09%), medical oncology (0.10%), neurosurgery (0.17%), and child & adolescent psychiatry (0.17%).

2.6.2 Selection Incentives by Specialty: Primary Measure

Figure 2.1 presents the first measure of the selection incentive (average profitability of specialist users) by physician specialty, ordered from the highest (worst) selection incentive

28. This is due, in part, to "carve outs" of certain services from the MMC program.

29. This estimate of plan profits does not include plans' administrative costs; actual plan profits per beneficiary-month are presumably lower.

Table 2.2: *Specialist Utilization by Beneficiaries in MMC, 2012-2015*

	n	%
Allergy & Immunology	19,446	0.83
Cardiology	112,685	4.84
Child & Adolescent Psychiatry	4,070	0.17
Dermatology	93,849	4.03
Endocrinology	18,695	0.80
Family Practice	194,539	8.35
Gastroenterology	78,298	3.36
General Surgery	39,738	1.71
Hematology-Oncology	12,866	0.55
Infectious Disease	13,478	0.58
Internal Medicine	368,430	15.81
Medical Oncology	2,231	0.10
Nephrology	13,035	0.56
Neurology	56,158	2.41
Neurosurgery	3,919	0.17
Obstetrics & Gynecology	180,049	7.73
Ophthalmology	158,525	6.80
Orthopedic Surgery	41,997	1.80
Otolaryngology	46,266	1.99
Pediatrics	474,913	20.39
Physical Medicine & Rehabilitation	39,022	1.67
Plastic & Reconstructive Surgery	4,708	0.20
Psychiatry	39,587	1.70
Pulmonary Disease	29,604	1.27
Radiation Oncology	2,039	0.09
Rheumatology	10,351	0.44
Thoracic Surgery	1,944	0.08
Urology	30,981	1.33
Vascular Surgery	12,866	0.55
Any Specialist Utilization	1,249,807	53.65

Note: This table reports the average number (and %) of MMC beneficiaries enrolled in each month of the study period who used each specialist type during the same year. The bottom row reports the average number (and %) of MMC beneficiaries enrolled in each month of the study period who had a claim with *any* physician during the same year.

to the lowest (best). The dark blue bar represents the incentive with no risk adjustment or other transfers; the gray bar represents the incentive with risk adjustment added; and the light blue bar represents the incentive with risk adjustment, maternity "kick" payments, and inpatient stop-loss payments. Each bar presents the average monthly profitability of beneficiaries who had a claim with a physician in that specialty, during the year when they had the claim.

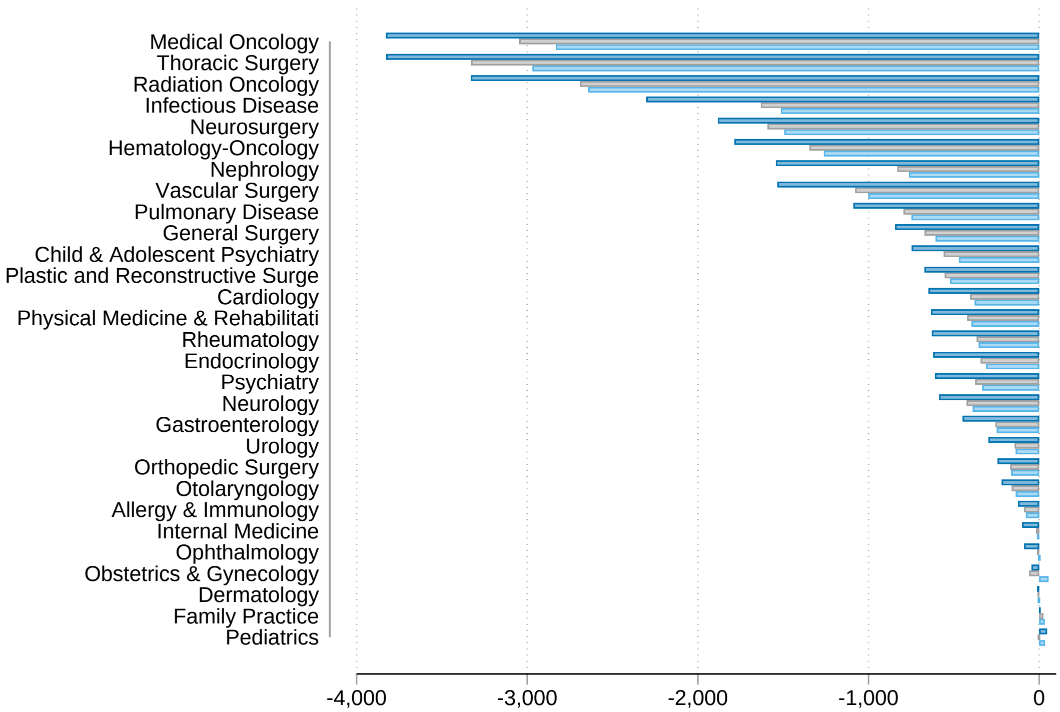

Figure 2.1: *Selection Incentive (Profitability) by Physician Specialty*

Note: This figure reports the primary selection incentive measure associated with each physician specialty under three different payment regimes: (1) administered rates with no risk adjustment (dark blue bars), (2) administered rates with risk adjustment by Clinical Risk Group (CRG) (gray bars), and (3) administered rates with risk adjustment by CRG, along with inpatient stop-loss and maternity kick payments (light blue bars). This measure represents the average monthly "profitability" (revenues minus costs, in dollars) to MMC plans associated with beneficiaries who used each specialist type. Average monthly profits are calculated over the full year when the beneficiary saw a specialist.

In a setting without risk adjustment or other transfers, beneficiaries who see a specialist are universally unprofitable to plans.[30] Certain specialties are especially unprofitable in the

30. Beneficiaries who see a primary care doctor (a family practice doctor or pediatrician) are

absence of risk adjustment, with the average beneficiary using these specialist types contributing to plan losses of more than $1,000/month during the year when they see the specialist. These include (in order from most unprofitable): medical oncology (-$3,830/month), thoracic surgery (-$3,830/month), radiation oncology (-$3,330/month), infectious disease (-$2,300/month), neurosurgery (-$1,880/month), hematology-oncology (-$1,790/month), nephrology (-$1,540/month), vascular surgery (-$1,530/month), and pulmonary disease (-$1,090/month). Specialties on the other end of the spectrum (that are only weakly unprofitable or profitable to plans) include pediatrics (gains of $50/month), family practice (+$10/month), dermatology (-$10/month), obstetrics & gynecology (-$50/month), ophthalmology (-$90/month), internal medicine (-$100/month), and allergy & immunology (-$120/month).

Risk adjustment by CRG improves the selection incentives for most physician specialties; still, it leaves in place strong incentives to ration access to many specialties (see Figure 2.1, gray bars). Thoracic surgery, medical oncology, radiation oncology, infectious disease, neurosurgery, and hematology-oncology remain the most unprofitable specialties, even with risk adjustment, with beneficiaries using these specialties contributing to plan losses of -$3,330/month, -$3,050/month, -$2,690/month, -$1,630/month, -$1,590/month, and -$1,350/month per beneficiary, respectively. On the other hand, risk adjustment greatly improves the incentives associated with nephrology, reducing insurer losses per beneficiary by $710/month, from -$1,540/month to -$830/ month, a 46% reduction. Finally, while risk adjustment alone improves incentives for almost all specialties, it worsens incentives for

profitable to plans on average.

obstetrics & gynecology (OB/GYN) (-\$60/month) and for pediatrics (-\$2/month). This is because beneficiaries who see an OB/GYN or a pediatrician tend to be healthy, on average; plans are compensated less for enrolling them in a setting with risk adjustment.

Finally, the light blue bars in Figure 2.1 present the selection incentives with risk adjustment, inpatient stop-loss payments, and maternity kick payments in place. The stop-loss and maternity kick payments improve incentives across the board for all physician specialties, but they do not significantly affect the ordering of the incentives. One exception is OB/GYN. Beneficiaries who see an OB/GYN are generally unprofitable to plans without transfer payments, contributing to plan losses of \$50/month without risk adjustment, and \$60/month with risk adjustment. However, once the transfer payments are included, these beneficiaries are profitable to plans, contributing to plan profits of about \$60/month. This is driven by the maternity "kick" payment, a one-time transfer to plans for every Medicaid birth. Beneficiaries who see primary care physicians (family practice, pediatrics, or OB/GYN) are all profitable to plans with risk adjustment and other transfers in place, contributing to plan profits of \$30/month, \$30/month, and \$60/month, respectively. However, beneficiaries seeing any other specialists (with the exception of ophthalmologists) are generally unprofitable to MMC plans in the year when they use specialty care.

2.6.3 Selection Incentives by Specialty: Ellis-McGuire Measure

Next, I estimate the selection incentive associated with each specialty using the secondary measure, the Ellis-McGuire (E-M) measure. The E-M measure takes the correlation between a beneficiary's (predicted) spending on a specialist type and profitability to Medicaid plans ("predictiveness"), and scales this by the predictability of the use of the specialist type. The measure is multiplied by -1, such that a higher (positive) value indicates a stronger incentive to ration access to specialists. The E-M measure is strongly correlated with the simpler profitability measure described above (correlation coefficient = -0.89) (see Figure 2.2).[31]

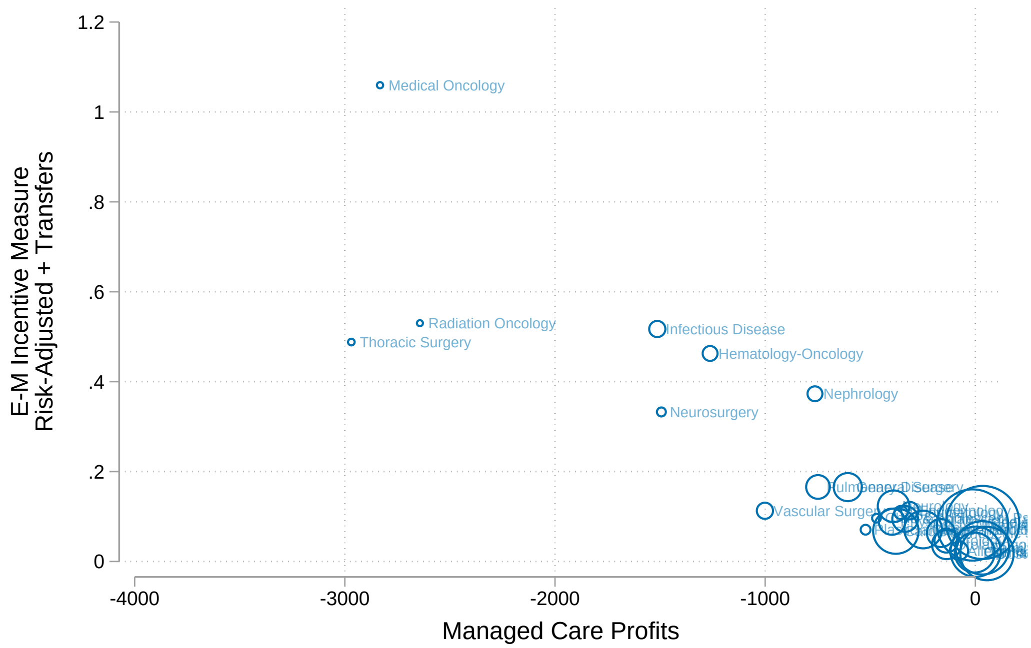

Figure 2.2: *Correlation between E-M Incentive Measure and Profitability Measure*
Note: This figure reports the primary selection incentive measure on the x-axis and the secondary (E-M) incentive measure on the y-axis.

Figure 2.3 presents the E-M incentive measure for each physician specialty. By this measure, the specialties with the worst selection incentives are the same as above, although the ordering is slightly different. By far the specialty with the worst selection incentive (E-M) is medical oncology (E-M measure = 1.17). Other specialties that Medicaid managed care plans face strong incentives to ration are: infectious disease (0.60), nephrology (0.55),

31. Incentives to ration care are indicated by negative profits (using the primary measure) and by a positive value for the E-M measure; hence, the sign on the correlation is negative.

radiation oncology (0.52), thoracic surgery (0.50), hematology-oncology (0.48), and neurosurgery (0.32). Of these specialties, risk adjustment improves the incentives the most for nephrology (from 0.55 to 0.36, a 35% reduction in the incentive to ration care).

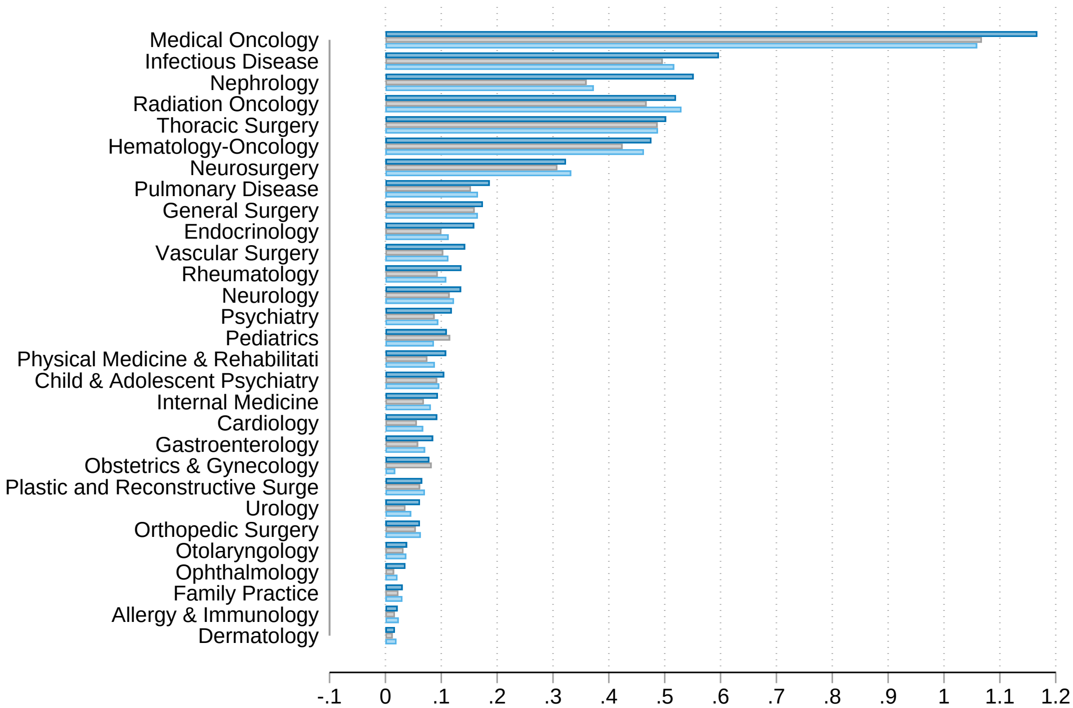

Figure 2.3: *Selection Incentive (E-M) by Physician Specialty*

Note: This figure reports the secondary (E-M) selection incentive measure associated with each physician specialty under three different payment regimes: (1) administered rates with no risk adjustment (dark blue bars), (2) administered rates with risk adjustment by Clinical Risk Group (CRG) (gray bars), and (3) administered rates with risk adjustment by CRG, along with inpatient stop-loss and maternity kick payments (light blue bars). This measure represents the correlation between beneficiary spending on a specialist type and plan profits, scaled by the predictability of specialist utilization. The measure is multiplied by -1, so that a higher positive value indicates a stronger incentive for MMC plans to ration care.

2.7 Discussion

Today, the majority of state Medicaid programs use some form of managed care to provide benefits to beneficiaries. In this chapter, I study the incentives Medicaid managed care plans face to ration access to different physician specialties due to adverse selection, and I test how well payment policies like risk adjustment and reinsurance perform at mitigating these incentives. I find that insurers face strong incentives to ration many types of specialty care, even with these payment policies in place. In particular, while Medicaid beneficiaries who see primary care providers tend to be profitable to health plans, beneficiaries with a claim for nearly any type of specialist are unprofitable to plans (i.e., the risk-adjusted payments plans receive for enrolling them are not sufficient to cover their monthly health care costs). Adverse selection creates particularly strong incentives for Medicaid managed care plans to restrict access to physicians specializing in medical and radiation oncology, thoracic surgery, neurosurgery, infectious disease, hematology-oncology, and nephrology, with beneficiaries who use these specialties contributing to plan losses of as much as $3,000 per month, even in a setting with risk adjustment.

My work highlights an important caveat of risk adjustment and other payment system policies designed to mitigate adverse selection. Even if a payment system provides good overall "fit" (as is the case in my setting), where plans are sufficiently compensated for enrolling higher-cost enrollees on average, plans may still face incentives to ration access to specific services in order to screen enrollees within a risk bin. One option for improving incentives would be to use more granular risk adjustment bins; however, plans may respond to finer risk adjustment categories by upcoding (Geruso and Layton 2015). Additionally, any efforts to improve payment system fit may come at the expense of reducing plans' cost-control incentives (Geruso and McGuire 2016), a factor that is clearly important to Medicaid programs as they transition to managed care. As discussed in Chapter 1, Section 1.6, a public option may be an appropriate alternative policy approach to ensure access to specialty care for Medicaid enrollees.

One limitation of this analysis is that my primary measure of the selection incentive may over-estimate incentives to ration care. If MMC plans are able to attract a sufficient number of healthy beneficiaries by offering broad coverage of specialists, then they may be incentivized to offer such access even if the beneficiaries who use specialty care (ex post) are unprofitable. I attempt to address the endogeneity of my primary measure by incorporating a secondary measure (the E-M incentive measure), which estimates the incentive associated with each specialty by calculating the correlation between *predicted* spending on specialty care and beneficiaries' profitability to health plans. Both meaures produce similar results.

This analysis offers a detailed accounting of the types of specialty care that may be most vulnerable to under-provision by Medicaid managed care plans. An understanding of these incentives can be a helpful guide to state policymakers as they work to ensure that Medicaid beneficiaries receive adequate access to specialist care. While Medicaid managed care has become the primary mechanism for providing health insurance benefits to low-income people in the United States, there has been little empirical work explicitly quantifying these incentives in Medicaid or examining how plans respond. In the next chapter, I test whether Medicaid plans respond to these incentives by rationing access to specialists.

3

How Do Plans Respond?

3.1 Introduction

Public health insurance programs in the United States are increasingly administered through the use of private managed care plans. Under this arrangement, private plans compete to offer coverage to beneficiaries, and the government partially or fully subsidizes the insurance premium. One prominent example of this arrangement is Medicare, the federal health insurance program for older adults, where beneficiaries have the option to enroll in private Medicare Advantage plans. Enrollment in Medicare Advantage has doubled over the last decade, with nearly 40% of all Medicare beneficiaries now enrolled in private coverage (Freed, Damico, and Neuman 2021). In contrast, the health insurance exchanges created more recently by the Affordable Care Act (ACA) offer only a choice of private coverage, with no "public option."

In Medicaid, the nation's health insurance program for low-income individuals and families, managed care has become the predominant mechanism for delivering health insurance benefits to beneficiaries. While Medicaid was historically modeled as a public fee-for-service (FFS) program, today more than 70% of beneficiaries are enrolled in managed care (Kaiser Family Foundation 2017, 2020b). By transitioning to a managed competition model, state policymakers hoped to achieve higher quality care at a lower cost (Hurley and Wallin 1998; Holahan et al. 1998). However, a common concern in competitive health insurance markets is adverse selection, or the propensity for sicker, higher-cost individuals to sort into more generous coverage. Because of the potential for adverse selection, insurers are incentivized to offer lower levels of coverage for services that are valued by higher-cost beneficiaries, in order to "cream skim" healthier beneficiaries (Rothschild and Stiglitz 1976; Cutler and Zeckhauser 2000; Frank, Glazer, and McGuire 2000; Glazer and McGuire 2000; Geruso and Layton 2017).

One feature of Medicaid that may reduce concerns about service-level selection is that plan benefits are standardized. Medicaid plans must cover a defined set of benefits, and cost sharing is limited. Plans are also required to cover all medically necessary, Medicaid-covered drugs (Center for Evidence-Based Policy 2016). In addition to contract standardization, beneficiaries typically do not pay a premium to enroll in coverage, which eliminates the price competition that can lead to adverse selection in other settings. Despite these program features, there are at least two ways that insurers might screen for less costly beneficiaries. The first is by offering "narrow networks" of providers that treat unprofitable beneficiaries. For example, if beneficiaries with cancer are unprofitable to health plans, then plans may contract with relatively few oncologists to deter beneficiaries with cancer from enrolling. Indeed, limited networks of specialists accepting new patients are a commonly reported barrier to specialty care access in Medicaid managed care (MMC) (Timbie et al. 2019). Second, plans can impose ordeals for specific services, making them more difficult to access. Using the same example as above, if beneficiaries with cancer are unprofitable from a plan's perspective, then the plan may require providers to seek prior authorization before initiating chemotherapy treatment.[1] Ordeals like prior authorization requirements generate a hassle cost for beneficiaries, which may be sufficiently high that they disenroll from the plan altogether. Importantly, plans can use such managed care strategies efficiently to discourage low-value care; however, they also may use them inefficiently, to encourage unprofitable beneficiaries to disenroll from coverage. While studies of selection incentives in health insurance have commonly focused on plan features affecting plan choice, plans may also respond to selection incentives by offering lower-quality care to costlier beneficiaries to encourage disenrollment (Kuziemko, Meckel, and Rossin-Slater 2018).

Managed care techniques for rationing care, such as prior authorization requirements,

1. Prior authorization (which is sometimes called "precertification" or "pre-authorization") is a process whereby providers must request approval from the insurer before providing a service, in order to qualify for payment. Typically, providers must submit medical documentation to prove the clinical necessity of treatment. Another type of managed care "ordeal" is step therapy for prescription drugs. Step therapy is a common requirement in health insurance contracts, and means that providers must try an alternate, usually lower-cost, medication before they can prescribe a drug.

are common in health insurance, including the Medicaid and Medicare programs, and some health care providers have argued that plans apply them in ways that are unrelated to the value of care. For example, in a survey by the American Hospital Association, providers reported that prior authorization requirements were sometimes applied to high-value (but high-cost) treatments like insulin, and that insurers sometimes imposed a higher administrative burden for higher-acuity patients than lower-acuity patients for the same service (American Hospital Association 2020). Several professional associations have lobbied against prior authorization requirements, with the American Society for Radiation Oncology arguing that they create frequent delays in care for cancer patients, and one neurosurgeon going so far as to call them the "filibuster of health care" (American Society for Radiation Oncology 2020; Menger 2021). Of all payer types, Medicaid managed care plans are reported to have the highest denial rate for prior authorizations, followed by Medicare Advantage plans (American Hospital Association 2020).

In this paper, I examine whether Medicaid managed care plans restrict access to specialist physicians when adverse selection creates strong incentives for them to do so. I first quantify the selection incentive associated with each of 29 physician specialties. The main way I quantify the incentive is by calculating the profitability to MMC plans of beneficiaries seeking treatment in each specialty, accounting for the risk adjustment and reinsurance systems present in the market. In addition, I use a second measure from the literature that accounts for how well beneficiaries can predict their specialist utilization (Frank, Glazer, and McGuire 2000; Ellis and McGuire 2007; McGuire et al. 2014). To assess the effect of the selection incentive on access to specialist care, I first examine MMC plans' provider networks, comparing them to commercial plans' networks to assess whether Medicaid plans explicitly restrict access to "adversely selected" physician specialists.[2] Using commercial HMO plans' networks as a control, I use a difference-in-differences design to compare network coverage for specialties with different selection incentives in Medicaid, while controlling for other unobservable characteristics of physician specialties that might affect their network coverage. Next, I test whether Medicaid beneficiaries in managed care plans use disproportionately less care in adversely selected specialties. This could occur either as a function of plans' provider networks, or because of other managed care utilization management techniques. For this analysis, I use a fixed-effects regression to compare Medicaid beneficiaries' specialist utilization while they are enrolled in a managed care plan to their specialist utilization while they are enrolled in the FFS Medicaid program.[3]

I find a statistically significant but small relationship between selection incentives and Medicaid managed care plans' network coverage of specialists, with MMC plans offering narrower networks of specialists serving unprofitable beneficiaries, on average, relative to commercial HMOs in the same market. In particular, while Medicaid plans cover about 23% fewer physicians than commercial plans on average, they provide much lower access to medical oncologists, covering about 41% fewer medical oncologists than commercial plans. Overall, however, the statistical relationship between selection incentives and Medicaid provider networks is small. Going from the specialty with the smallest selection incentive (OB/GYN) to the specialty with the worst selection incentive (medical oncology) is associated with at most a 5.2 percentage point predicted reduction in network coverage,

2. I use "adversely selected" throughout this chapter as shorthand for specialists that are disproportionately valued by beneficiaries who are unprofitable to managed care plans.

3. Most Medicaid beneficiaries spend some months in the FFS Medicaid program and some months in an MMC plan.

from 37.0% to 31.8%.

While I do not find a strong relationship between selection incentives and network coverage of specialists, I do find that beneficiaries in MMC plans receive disproportionately less care in adversely selected specialties than in specialties used by profitable beneficiaries. Within-beneficiary, I find that Medicaid beneficiaries receive about 90% more care in more profitable specialties when they are enrolled in MMC plans, relative to when they are enrolled in FFS Medicaid.[4] By contrast, within the most unprofitable specialties (associated with losses to the plan of $\approx \$2,640$ per month), MMC beneficiaries receive about 8.4% less care than beneficiaries in FFS Medicaid.

This paper is closely related to a recent empirical literature on insurer responses to selection incentives in markets for health insurance. Several recent papers demonstrate that managed care plans design insurance contracts to deter enrollment by unprofitable individuals. For example, Shepard (2016) documents substantial adverse selection against plans covering star hospitals in the Massachusetts health insurance exchange, and in Chapter 1, we use a natural experiment to show that a Medicaid plan covering a specialty cancer hospital experienced adverse selection, forcing it to drop the hospital from its network. Recent work also demonstrates that insurers respond to selection incentives by distorting their drug formularies to avoid enrolling unprofitable beneficiaries (Carey 2017b; Geruso, Layton, and Prinz 2019). A related literature has demonstrated that plans use the channel of *dis*enrollment to shed unprofitable beneficiaries. A recent paper by Kuziemko, Meckel, and Rossin-Slater (2018) presents a framework in which Medicaid managed care plans

4. By "more profitable," I am referring to specialties at the 90th percentile of the selection incentive distribution, which are associated with gains to the plan of $\approx \$30$ per month on average.

provide worse care to beneficiaries who are costlier ex-post, allowing them to favorably select beneficiaries by disenrolling the unprofitable ones. They demonstrate that infant Black-Hispanic health disparities widened following the introduction of managed care in Texas, and provide evidence that this finding is consistent with their model. Additionally, Marton, Yelowitz, and Talbert (2017) demonstrate that high-cost Medicaid beneficiaries disproportionately disenroll from lower-quality health plans, contributing to adverse selection.

Despite this recent work, there remains little empirical evidence on insurer responses to selection incentives in Medicaid, or on whether insurers use their networks of physician specialists to screen profitable beneficiaries. Since Medicaid managed care is now the primary mechanism for providing health insurance benefits to low-income people in the United States, it is important to understand how these incentives might affect access to specialty care for Medicaid beneficiaries.

3.2 Setting and Institutional Details

The setting for my work is the New York Medicaid program. For an overview of key program details, see Section 2.2. Below, I provide additional details on the distribution of enrollment between the public, FFS Medicaid program and private MMC plans. I also provide detail on utilization management techniques, like prior authorization, that are common in health insurance markets.

3.2.1 Medicaid Enrollment by Market Segment

Most New York Medicaid beneficiaries are required to choose a Medicaid managed care plan. Beneficiaries may choose to enroll in any of the health plans operating in their county, but if they do not choose one, they are auto-assigned to a plan after 90 days (New York State Department of Health 2015). Because of this mandate, more than three-quarters of Medicaid beneficiaries in New York are now enrolled in MMC (Kaiser Family Foundation 2019). This percentage is even higher when excluding beneficiaries who are dually eligible for Medicare, as well as other beneficiaries, like those in the Medicaid Cancer Treatment Program (MCTP), who obtain their benefits from the FFS program. When I exclude such beneficiaries from my study sample, 89.5% of remaining beneficiaries in New York City are enrolled in MMC.[5]

Importantly for my study design, while 89.5% of Medicaid beneficiaries are in MMC at any given time, most beneficiaries actually spend some time in FFS and some time in MMC over the course of an enrollment episode. Of beneficiaries whose full enrollment-episode I observe in the sample data, about 75.8% spend some months in FFS and some months in MMC. About 20.4% of beneficiaries are always enrolled in MMC, and the remaining 3.8% of beneficiaries are always enrolled in FFS. Beneficiaries who are always enrolled in FFS are, on average, higher-acuity beneficiaries that the state has granted exceptions from the MMC mandate. These beneficiaries are disproportionately eligible for Medicaid on the basis of having a disability. For more details on beneficiary characteristics

5. I exclude dual eligibles and beneficiaries in certain categories of aid, such as the MCTP, in order to develop a comparable set of beneficiaries in FFS and MMC.

by market segment, see Section 3.5.1 and Appendix Table C.1.

Figure 3.1 reports the percentage of New York City Medicaid beneficiaries in the analysis sample who were enrolled in FFS vs. MMC at each month of their Medicaid enrollment episode. "Month of their Medicaid enrollment episode" refers to the length of time since a beneficiary first enrolled in Medicaid (i.e., first month of enrollment, second month, etc.).[6] When beneficiaries first enroll in Medicaid, they typically enroll in FFS ($\approx$ 80% of beneficiaries). Over time, beneficiaries choose managed care plans, and the pool of beneficiaries remaining in FFS shrinks. By the tenth month of an enrollment episode, fewer than 10% of beneficiaries remain in FFS. Of these beneficiaries, some are enrolled in FFS for their full enrollment episode, and others are temporarily enrolled in FFS between enrollment in MMC plans.

3.2.2 Prior Authorization Requirements and Other Utilization Management Techniques

Health insurance plans commonly use utilization management techniques, such as prior authorization, to ration care, discourage the use of low-value care, or to target care appropriately to individuals for whom it is medically necessary. New York Medicaid is no different. According to plan documentation, MMC plans in New York City require prior authorization for a number of different services, which vary by plan, but include such services as inpatient admissions, certain radiology and cardiology services, medical oncology

6. A new enrollment episode begins when a beneficiary enrolls in Medicaid for the first time or re-enrolls after a lapse in coverage of one month or more.

Figure 3.1: *Enrollment in FFS and MMC by Month of Medicaid Enrollment Episode*

services, radiation therapy, physical and occupational therapy, and transplant services.[7] At least three Medicaid managed care plans in New York City partner with vendors for utilization management, outsourcing prior authorization requests for medical oncology, radiation therapy, cardiology, radiology, and other services.

In addition to imposing prior authorization requirements for specific services, health insurance plans may sometimes deny payment for claims altogether. These denials may occur either because a service was deemed not to be medically necessary, or because the provider did not seek the required prior authorization. Health care providers have reported an increase in claims payment denials over time, with MMC plans having claims

7. In order to preserve plans' anonymity, I do not cite plan documentation here. These citations are available upon request.

denial rates of nearly 20% (American Hospital Association 2020).

3.3 Data

I use administrative data from New York Medicaid, National Plan & Provider Enumeration System (NPPES) data from the Centers for Medicare & Medicaid Services (CMS), and the New York State Department of Health's Provider Network Data System (PNDS). I use each physician's National Provider Identifier (NPI) to merge the three data sources.

3.3.1 New York Medicaid Data

I obtain administrative data on enrollment and health care claims for all New York Medicaid beneficiaries enrolled between 2005-2017.[8] For each beneficiary, I observe demographics, category of aid, the MMC plan that the beneficiary was enrolled in, clinical risk group (CRG) assignment, and county of residence. I also observe the amount that the plan was paid by the state to enroll the beneficiary. The claims data include diagnoses, procedures, health care provider identifiers, and the amount paid by both the managed care plan and by the FFS Medicaid program for each claim. The enrollment data allow me to categorize beneficiaries into premium groups.[9] Using the claims data, I estimate plan revenues and calculate plan spending per beneficiary. The claims data also allow me to quantify each beneficiary's utilization of each specialist type. To categorize physician claims by spe-

8. The data were obtained pursuant to a Data Exchange Application & Agreement (DEAA) with New York Medicaid.

9. As described in Section 2.2.2, these groups include: TANF ages 0-20, TANF ages 21+, and SSI. Since I restrict to New York City, which is a distinct geographic rating region, I do not otherwise categorize beneficiaries by geography.

cialty, I map the billing provider's NPI to National Plan & Provider Enumeration System (NPPES) data (described in Section 3.3.2 below).

Sample Selection

I restrict the estimation sample to beneficiaries with full Medicaid eligibility living in the five boroughs of New York City between state fiscal years (SFYs) 2012-2015.[10] I restrict to these years for several reasons. The first is that risk adjustment was not fully phased in in New York until 2012, and I am interested in insurer responses to incentives in the context of risk adjustment. The second is that CRGs, which New York uses for risk adjustment, are less reliably updated in the administrative data after 2015. The third is that observed specialist utilization declines in the encounter data after 2015, which may be due to new initiatives in New York State that encouraged capitated payments to providers (New York State Department of Health 2019).[11] I exclude beneficiaries ages 65 and older, who are dually eligible for Medicare benefits, since such beneficiaries typically do not enroll in Mainstream MMC plans. Finally, I exclude enrollment-months prior to the beneficiary's listed date of birth.

10. I exclude beneficiaries who received "partial" Medicaid coverage only for specific services, and those who were listed as having Family Health Plus coverage, a separate type of coverage for families with higher incomes that expired on December 31, 2013, when FHP beneficiaries were transferred into the Medicaid State Plan as part of the ACA Medicaid expansion (Forsgren 2017). I also exclude beneficiaries who were in other types of Medicaid plans, such as Special Needs Plans (SNPs) and Medicaid Advantage (MA) plans, designed for beneficiaries with HIV (SNPs) or beneficiaries who are dually eligible for Medicare. These plans are distinct from the risk adjustment system used in Mainstream Medicaid Managed Care.

11. My concern is that I may not fully observe specialist utilization after this date, although I cannot rule out other explanations for this observed change in utilization.

3.3.2 National Plan & Provider Enumeration System

I use National Plan & Provider Enumeration System (NPPES) data from the Centers for Medicare & Medicaid Services (CMS) from 2017 to construct a dataset of physicians practicing in New York City and to categorize physician claims by specialty. The NPPES is a registry of NPIs and includes data on practice location and specialty type for all individuals and organizations providing health care services in the United States (DesRoches et al. 2015).

I first check for concordance between the 2017 NPPES data and the claims data by merging a 5% random sample of the claims from 2012-2015 with the NPPES data. For this analysis, I restrict the NPPES data to providers listed as practicing in New York, New Jersey, Connecticut, or Pennsylvania (states in the vicinity of New York City). I use the the billing provider's NPI in the claims to merge with the NPPES data. Of the claim lines with a non-missing NPI (95.3% of claim lines), 97.4% match to an NPI from the New York region in the NPPES data, providing reassurance that the NPPES data adequately capture the providers practicing in the New York region during this time period.[12]

Next, I use the NPPES data to construct a dataset of physicians practicing in New York City. I restrict to osteopathic and allopathic physicians with a listed practice location in a New York City zip code. To categorize physicians by specialty type, I match NPPES provider taxonomy codes to Medicare specialty codes from the Centers for Medicare &

12. Claim lines with missing NPIs were concentrated in service types like community & rehabilitation (39.8% of claim lines with a missing NPI), transportation (19.6%), lab (11.3%), non-institutional long-term care (10.6%), and pharmacy (4.6%).

Medicaid Services (Centers for Medicare & Medicaid Services 2020).[13] I disaggregate some of the larger CMS specialty codes, such as internal medicine, using more granular codes (e.g., gastroenterology) where possible to identify physicians practicing in sub-specialties. I exclude certain sub-specialists who practice primarily within hospitals, including hospitalists, anesthesiologists, pathologists, emergency department physicians, intensive care specialists, and radiologists. Finally, I restrict the analysis to provider specialties with at least 100 providers who had New York City Medicaid claims between 2012-2015.[14]

3.3.3 Provider Network Data

Finally, I use the New York State Department of Health's Provider Network Data System (PNDS) to construct a dataset of the physician networks of Medicaid and commercial plans operating in New York City between 2012-2015. The PNDS an audited database of all managed care organizations' (MCOs') provider networks in New York State, and includes data on Medicaid, Medicare, and some commercial plans. All MCOs that are certified by the New York State Department of Health (NYSDOH) are responsible for submitting provider network data to the PNDS (New York State Department of Health 2012).[15] Eight MMC plans and four commercial HMOs operated in New York City during the full study

13. Gottlieb et al. (2020) also use the CMS crosswalk to categorize physicians (Gottlieb et al. 2020).

14. I exclude small sub-specialties to ensure that my analysis of selection incentives is not overly sensitive to the characteristics of a small number of providers.

15. These plans include health maintenance organizations (HMOs), prepaid health services plans (PHSPs) that primarily service Medicaid beneficiaries, and preferred provider organizations (PPOs), as well as specialty plans that serve individuals with HIV and individuals who are dually eligible for Medicare.

period and reported network data for all four years.[16] For a listing of MCOs operating in New York during the study period, see New York State Department of Health Division of Managed Care and Program Evaluation (2012). Networks are reported on a quarterly basis, and I use the 4th quarter PNDS data to construct the network measures.

3.3.4 Outcome Measures

Specialist Network Breadth

Using the PNDS data and the NPPES data, I construct a measure of network breadth for each plan and specialist type for each year of the study period. I use the NPPES data to construct a denominator of all physician specialists practicing in New York City during the study period, and I use the PNDS data to calculate the percentage of doctors in each specialty that were covered by each plan's network in each year. I link the two datasets using the provider's NPI.

As a secondary measure of network breadth, I use the claims data and the PNDS data to calculate the percentage of total specialist claims (within each specialty) in Medicaid between 2012-2015 that would have been covered by the network of each Medicaid plan in each year between 2012-2015. Similar simple measures of network breadth, such as the percentage of hospital admissions covered by a plan's network, have been found in other work to be highly correlated with more sophisticated measures of consumer demand

16. While two additional commercial plans also offered HMO coverage in New York City during the sample period, they are excluded from the analysis due to inconsistent reporting of provider networks in the PNDS. Each of the four commercial HMOs shares joint ownership with, or is a sister company of, one of the MMC plans in the market, and in some cases the commercial plan negotiates its provider networks out of the same business unit as its sister MMC plan (Newell, Aziz, and Gorman 2013).

(Ericson and Starc 2015).

3.4 Methods

I first quantify Medicaid plans' incentives to contract with different types of physician specialists under the prevailing New York risk adjustment system. Then, I test: (1) whether plans explicitly exclude doctors practicing in adversely selected (or "unprofitable") specialties from their networks, and (2) whether beneficiaries in Medicaid managed care receive disproportionately less care in unprofitable specialties, relative to beneficiaries in fee-for-service Medicaid.

3.4.1 Quantifying the Selection Incentive

I first quantify MMC plans' incentives to ration access to each specialist type due to adverse selection. I quantify the incentive using two alternate measures. The primary measure of the selection incentive associated with each specialist type is the average monthly profitability to MMC plans of beneficiaries who use the specialist type. Profitability is equal to average monthly risk-adjusted revenues minus average monthly health care spending, and is calculated using all months in the year when the beneficiary had specialist utilization. Intuitively, if beneficiaries who use a particular specialist type are very profitable to plans (i.e., the average risk-adjusted revenues associated with these beneficiaries is much higher than their average health care spending), then MMC plans are incentivized to provide access to specialists of that type. By contrast, if the beneficiaries who visit a specialist type are unprofitable to Medicaid plans (i.e., their health care spending exceeds their risk-adjusted capitation payments), then plans have little incentive to provide access to that specialist type.

As a second measure of the selection incentive, I use a metric developed by Ellis and McGuire (2007), which incorporates both *predictability* and *predictiveness* of specialist utilization. While the primary measure assesses the ex-post profitability of beneficiaries who use each specialist type (how *predictive* use of a specialist type is of plan profits or losses), this measure also incorporates whether use of a specialist type is *predictable* by beneficiaries. I describe how I calculate each measure in Chapter 2, Section 2.5.

3.4.2 The Effect of Selection Incentives on Access to Specialty Care

Once I have quantified the selection incentives associated with each specialty, I test whether MMC plans respond to these incentives. There are two ways that plans could respond: (1) by explicitly excluding physicians practicing in unprofitable specialties from their provider networks, or (2) by rationing care in unprofitable specialties (for example, using prior authorization requirements and other managed care utilization management techniques to limit access to services).

Provider Networks

First, I use a linear regression and a difference-in-differences approach to assess whether MMC plans differentially exclude physicians practicing in unprofitable specialties from their provider networks relative to commercial HMOs operating in the same market. I model this analysis after the one used by Geruso, Layton, and Prinz (2019) to test whether health plans in the ACA's health insurance exchanges use drug formularies to screen enrollees. This analysis allows me to examine whether Medicaid plans cover differentially fewer physicians that treat unprofitable beneficiaries (within the context of the Medicaid managed care payment system), while differencing out average specialist coverage rates in a similar managed care setting with plausibly different selection incentives. As described in Section 3.3, all of the commercial HMOs I study are co-owned (or are sister plans) with MMC plans in the market, and they sometimes negotiate their networks out of the same business unit as the MMC plan. However, the New York Medicaid program uses its own risk adjustment formula to adjust plan premiums according to beneficiary health risk; therefore, the actual incentives to cover specialists should be different in the two markets.[17]

These regressions take the following form:

$$Y_{zjt} = \beta[S_z \times MMC_j] + \gamma_z + \alpha_j + \delta_t + \epsilon_{zjt} \tag{3.1}$$

The dependent variable Y_{zjt} is the percentage of New York City physicians practicing in specialty z who are in the network of plan j at time t. S_z is the Medicaid selection incentive for physician specialty z. MMC_j is an indicator for whether the plan is a Medicaid managed care plan. β is the coefficient of interest, representing the correlation between the Medicaid selection incentive and inclusion in Medicaid provider networks. γ_z, α_j, and δ_t are specialty, plan, and year fixed effects. I estimate the regressions using heteroskedasticity-robust standard errors, and apply frequency weights equal to the total

17. My identification strategy relies upon the assumption that selection incentives are different in MMC vs. commercial insurance. If the observed health care spending of beneficiaries who use each specialty in Medicaid is uncorrelated with their average (risk-adjusted) profitability to MMC plans, then this is a reasonable assumption. If, in my setting, spending is strongly correlated with risk-adjusted profits, then the analysis will be poorly identified (and biased to the null). In fact, the two measures are strongly correlated in my data, presenting a problem for identification. I discuss this problem in later sections.

number of physicians practicing in each specialty in New York City.

UTILIZATION

As a second test, I examine whether Medicaid beneficiaries in MMC plans use disproportionately less care in adversely selected specialties, relative to beneficiaries in FFS Medicaid. As described in Section 3.2.1, most New York Medicaid beneficiaries spend some time in both FFS Medicaid and MMC. While MMC plans face incentives to ration access to certain types of specialty care due to adverse selection, beneficiaries' utilization in FFS Medicaid is not subject to these incentives. Therefore, I hypothesize that beneficiaries receive less care in adversely selected specialties in MMC relative to FFS.

A simple comparison of beneficiaries in MMC and FFS would be subject to confounding, as the characteristics of beneficiaries in MMC and FFS may differ in ways that are correlated with their specialist utilization (e.g., FFS beneficiaries may be more likely to have a disability that requires access to specialists). Therefore, I use a fixed effects regression analysis to examine within-beneficiary differences in specialist utilization between MMC and FFS. Even within-beneficiary, there remains the potential for confounding, because beneficiaries who spend time in both FFS and MMC often enroll in FFS at the beginning of their Medicaid enrollment episode before choosing an MMC plan. Specialist utilization may be either higher or lower when a person first gains access to health insurance coverage than when she has already been enrolled for many months. To adjust for confounding by length of time enrolled in Medicaid, I also control for the month of the beneficiary's enrollment episode.

These regressions take the following form:

$$Util_{i,t} = \beta_1 MMC_{i,t} + \beta_2 EpisodeMonth_{i,t} + \gamma_t + \mu_t + \alpha_i + \epsilon_{i,t} \tag{3.2}$$

where $Util_{i,t}$ is an indicator for whether beneficiary i had a specialist claim in month t; $MMC_{i,t}$ is an indicator for whether beneficiary i was enrolled in an MMC plan in month t; $EpisodeMonth_{i,t}$ is a categorical variable indicating the month of beneficiary i's Medicaid enrollment episode (how long she has been enrolled in Medicaid: 1 month, 2 months, 3 months, 4-6 months, 7-12 months, or 13+ months); γ_t and μ_t are year and calendar month fixed effects; and α_i are beneficiary fixed effects. Observations are at the level of the beneficiary-month, and I run a separate regression for each specialist type. I exclude emergency department (ED) claims from the outcome measure, $Util_{i,t}$, since Medicaid managed care plans must allow beneficiaries to go out-of-network for emergency care, and to my knowledge emergency care is not subject to utilization management. For tractability, I run the regressions in a 20% random sample of beneficiaries enrolled in Medicaid between 2012-2015.

To aid in interpretation, I use predictive margins to calculate predicted monthly probabilities of specialist utilization separately for beneficiaries in MMC and in FFS Medicaid. From these predictions, I calculate ratios of predicted specialist utilization in MMC relative to FFS for each specialty. I then assess the correlation between these ratios and the selection incentive for each speciality, to determine whether MMC beneficiaries receive disproportionately less care in specialties for which there is a strong incentive to under-provide care.

3.4.3 Limitations

A limitation of the provider networks analysis, which compares networks of Medicaid and commercial plans, is that selection incentives might overlap between the two markets. In particular, I find that even with risk adjustment, selection incentives are strongly correlated with beneficiaries' underlying health care costs. If selection incentives are similar in the two markets, then commercial plans would be expected to ration the same types of care as in Medicaid plans, which would bias my findings to the null. Additionally, Medicaid and commercial networks may vary in ways that are unrelated to selection; for example, certain physician specialist types might be less willing to accept Medicaid rates. If such differences are correlated with my measure of the selection incentive, then the results will be biased.

Specialist network coverage may also be a poor indicator of access. For example, a report by the Office of Inspector General found that many providers listed as in-network by MMC plans were not accepting new Medicaid patients, or were not actually participating in the plan at the listed location (U.S. Department of Health and Human Services, Office of Inspector General 2014a). This may be less of a concern in New York, as the state conducts direct audits of MMC plans' provider networks (U.S. Department of Health and Human Services, Office of Inspector General 2014b).

One limitation of the utilization analysis is that there may be other factors that contribute to relative specialist utilization in MMC compared with FFS, aside from rationing by MMC plans. For example, certain specialists may be more willing to accept MMC patients than others. If provider-side decisions are correlated with the selection incentive measure, then my results will be biased.

3.5 Results

3.5.1 Summary Statistics

I report summary statistics in Table 3.1. In the analysis of specialist utilization, I compare beneficiaries in fee-for-service (FFS) Medicaid to beneficiaries in Medicaid managed care (MMC); therefore, I report summary statistics separately for each of these two market segments. The majority of beneficiaries in the sample are in MMC (89.5%), while only 10.5% remain in FFS.

I first describe differences between FFS and MMC beneficiaries. Beneficiaries in FFS are more likely to be eligible for Medicaid on the basis of a disability than are MMC beneficiaries (13.6% vs. 7.4%).[18] Beneficiaries in FFS are, on average, about 2 years older than beneficiaries in MMC (27.1 years vs. 25.0 years) and are less likely to be female (50.6% vs. 54.2%). Examining beneficiaries' reported race, beneficiaries in FFS are more likely to be categorized as Black (30.3%) or as having unknown (27.6%) or "some other" race (7.7%), relative to beneficiaries in MMC (25.7%, 20.5%, and 6.0%, respectively).[19] Monthly spending in FFS Medicaid ($1,075 per month) is about three times the amount of monthly spending in MMC Medicaid ($352 per month). Of total spending by MMC beneficiaries ($352

18. Beneficiaries with a disability are eligible for Medicaid on the basis of Supplemental Security Income (SSI) receipt.

19. The fact that almost 30% of FFS beneficiaries have missing race data may be a feature of reporting of race data in FFS Medicaid. It is my understanding that race data are often not collected for FFS beneficiaries. Therefore, I do not control for race in comparisons between FFS and MMC beneficiaries.

Table 3.1: *Sample Characteristics by Market Segment, 2012-2015*

	Fee-for-Service	Medicaid Managed Care
	(1)	(2)
N (mean per month)	272,195	2,329,702
Percentage of sample (%)	10.5	89.5
Premium Group (%)		
TANF 0-20	33.8	46.2
TANF 21-64	52.6	46.4
SSI 0-64	13.6	7.4
Age (mean)	27.1	25.0
Female (%)	50.6	54.2
Race (%)		
Black	30.3	25.7
White	21.5	26.5
Asian/PI	9.2	16.4
Hispanic	2.8	3.4
AIAN	0.9	1.4
Other	7.7	6.0
Unknown	27.6	20.5
Monthly spending ($)		
Total	1,075.3	352.3
MMC	N/A	267.5
Monthly MMC payments ($)		
MMC Premiums	N/A	342.2
Maternity Payments	N/A	27.2
Inpatient Payments	N/A	3.0

Notes: This table reports summary statistics by market segment (FFS Medicaid and Mainstream MMC) for state fiscal years 2012-2015.

per month), $268 was paid by the MMC plans; the FFS program covered the rest.[20] Finally,

20. This is due, in part, to "carve outs" of certain services from the MMC program. For example,

MMC plans receive premium payments from the state averaging $342 per beneficiary-month, maternity "kick" payments averaging $27 per month, and inpatient stop-loss payments averaging $3 per month per beneficiary. Therefore, MMC plans' average "profits" per beneficiary-month are $104.9 during the study period.[21]

3.5.2 Incentives in Medicaid Managed Care

Figures 3.2 and 3.3 report MMC plans' incentives to ration access to different physician specialties in the context of New York's risk adjustment and reinsurance systems. Using the primary incentive measure, the three specialist types with the strongest incentives to ration care are thoracic surgery (with beneficiaries using thoracic surgeons contributing to insurer losses of $2,970 per month in the year when they see a thoracic surgeon), medical oncology (-$2,830 per month), and radiation oncology (-$2,640 per month). Additionally, insurers face strong incentives to restrict access to infectious disease specialists (-$1,510 per month), neurosurgeons (-$1,490 per month), hematologist-oncologists (-$1,260 per month), and vascular surgeons (-$1,000 per month). The Ellis-McGuire (E-M) incentive measure, which also accounts for differences in predictability of specialist use, generates mostly the same results. However, when using this measure, medical oncology is a major outlier, with by far the strongest incentives to restrict access (E-M measure = 1.06). Using the E-M measure, medical oncology is followed by radiation oncology (E-M measure = 0.53), infectious disease (0.52), thoracic surgery (0.49), hematology-oncology (0.46), nephrology

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mental health benefits were carved out for SSI beneficiaries for the majority of the study period.

21. This estimate of plan profits does not include plans' administrative costs; actual plan profits per beneficiary-month are presumably lower.

(0.37), and neurosurgery (0.33). A more detailed discussion of the incentives associated with each specialty can be found in Chapter 2, Section 2.6.

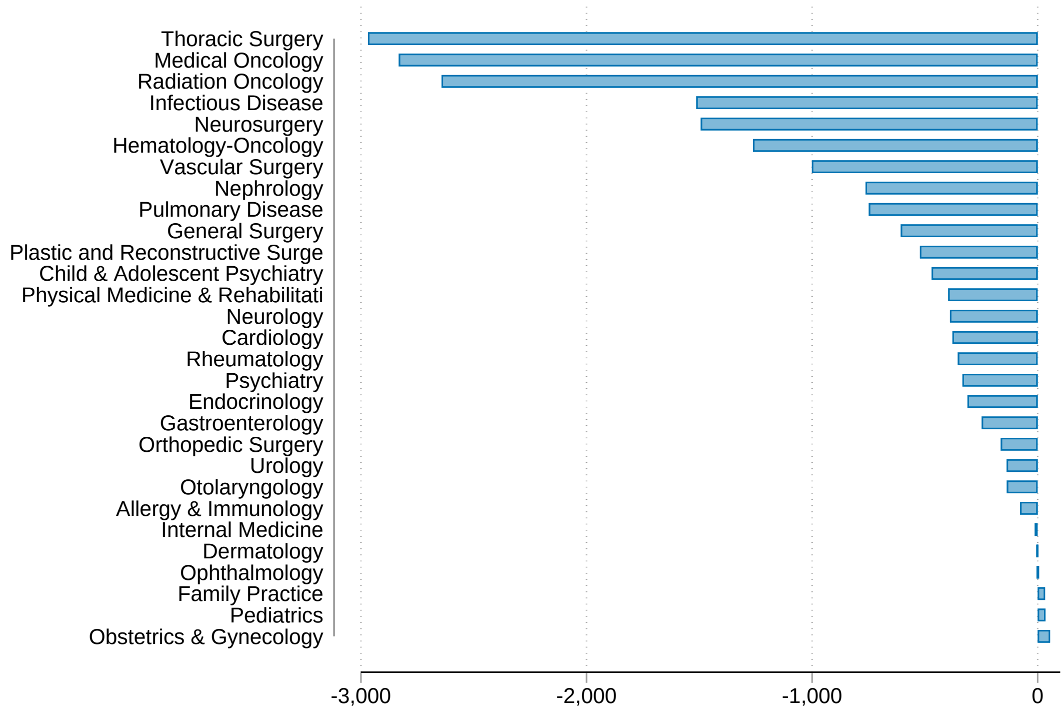

Figure 3.2: *Selection Incentive (Profitability) by Physician Specialty*

Note: This figure reports the primary selection incentive measure associated with each physician specialty in New York Medicaid. This incentive measure represents the average monthly "profitability" (revenues minus costs, in dollars) to MMC plans associated with beneficiaries who use each specialist type. Average monthly profits are calculated over the full year when the beneficiary saw a specialist. In New York Medicaid, plans are paid an administered rate for enrolling each beneficiary, which is risk-adjusted according to beneficiary health risk. Additional transfer payments to plans include inpatient stop-loss payments and a one-time maternity "kick" payment for each Medicaid birth.

Figure 3.4 plots the Medicaid selection incentive associated with each specialty against a simple measure of monthly spending (costs to the MMC plan) by beneficiaries using each specialty. It is apparent from the figure that, while New York Medicaid's payment system mitigates selection incentives, it does not strongly affect the ordering of the incentive across physician specialties. Therefore, the selection incentive associated with each

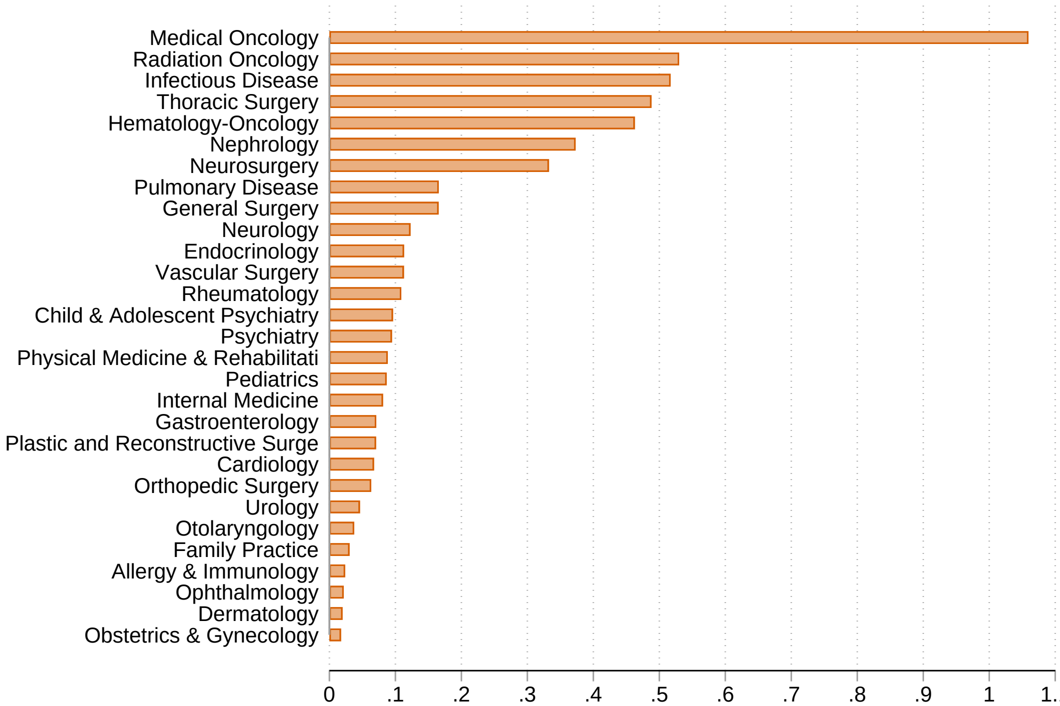

Figure 3.3: *Selection Incentive (E-M) by Physician Specialty*

Note: This figure reports the secondary (E-M) selection incentive measure associated with each physician specialty in New York Medicaid. This measure represents the correlation between beneficiary spending on a specialist type and plan profits, scaled by the predictability of specialist utilization. The measure is multiplied by -1, so that a higher positive value indicates a stronger incentive for MMC plans to ration care.

specialty is likely to be similar in the Medicaid and commercial markets. As a result, the analysis of provider networks described below is not well-identified. I will proceed to describing the results of this analysis, but after that I will focus primarily on the analysis of specialist utilization by market segment within Medicaid (MMC vs. FFS).

3.5.3 Insurer Responses to Selection Incentives: Provider Networks

I first test whether Medicaid managed care plans respond to selection incentives by explicitly excluding providers practicing in "unprofitable" specialties from their networks.

Figure 3.4: *Profitability (Risk-Adjusted Revenues Minus Costs) vs. Costs for Beneficiaries Using Each Specialist Type*

Note: This figure reports the average monthly costs (health care spending) for beneficiaries using each specialist type on the x-axis and the primary selection incentive measure (monthly "profitability" of beneficiaries using each specialist type) on the y-axis. Each circle represents a specialist type, and the size of the circles is weighted by the number of beneficiaries who used that specialist type during the sample period.

Descriptives: Network Coverage of Specialists

First, I present descriptive data on plans' network coverage of specialists. Figure 3.5 displays the percentage of all specialists in New York City that were in-network for MMC and commercial plans (on average) between 2012-2015.[22] Commercial plans offered broader network coverage for nearly all specialties than did MMC plans; about 33.3% of all New York City physicians were covered by Medicaid plans' networks (on average) between

22. This represents a simple average across plan-years.

2012-2015, while about 43.4% of physicians were covered by the networks of commercial HMOs. One exception was child and adolescent psychiatry, which had similar rates of coverage in MMC and commercial insurance (17.6% in MMC; 17.0% in commercial). Several specialties had very low levels of insurance coverage in both MMC and commercial plans, including psychiatry (16.5% of psychiatrists in-network in MMC plans; 19.2% in commercial plans), child & adolescent psychiatry (17.6% in MMC; 17.0% in commercial), and plastic and reconstructive surgery (19.3% in MMC; 25.5% in commercial).

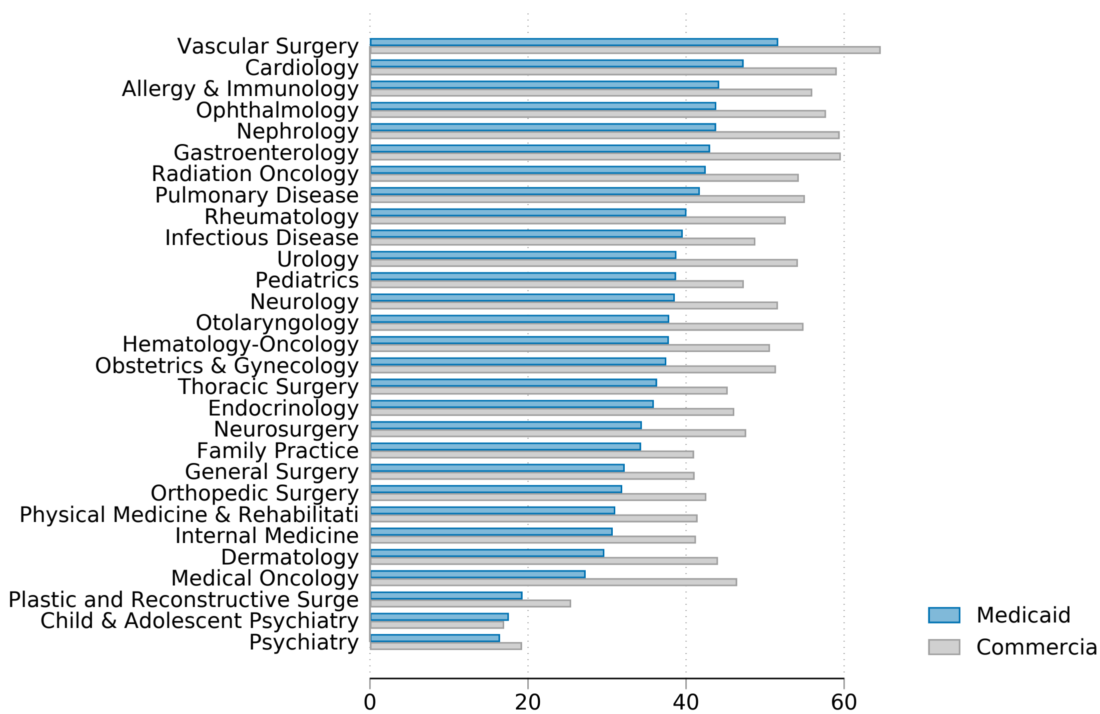

Figure 3.5: *Percentage of New York City Specialists In-Network in Medicaid Managed Care Plans and Commercial HMOs, 2012-2015*

Next, I compare network coverage of specialists in MMC vs. commercial insurance by calculating coverage ratios for each specialty, dividing the number of physicians in-network in MMC plans (on average) by the number of physicians in-network in commercial plans (on average). Figures 3.6 and 3.7 report the results. On the y-axis is the coverage ratio, and on the x-axis is the selection incentive for MMC plans to ration coverage. Each circle represents a single specialty, with the size of the circle weighted by the number of physicians practicing in the specialty in New York City between 2012-2017. Figure 3.6 presents the primary selection incentive measure, and Figure 3.7 presents the E-M measure.

Examining Figure 3.6, Medicaid plans cover approximately 76.7% as many specialists as commercial plans, on average.[23] There is little correlation between the "profitability" of specialties and their coverage in Medicaid (relative to commercial coverage) (correlation coefficient=0.15). However, Figure 3.7, which uses the E-M incentive measure, presents a slightly different result, with stronger selection incentives being associated with (weakly) lower network coverage in Medicaid (correlation coefficient = -0.31). This correlation appears to be driven by medical oncology, an outlier associated with a much stronger incentive for MMC plans to ration care than other physician specialties. Medicaid plans cover 41% fewer medical oncologists, on average, than do commercial plans.

Difference-in-Differences Results

Table 3.2 presents the results of the difference-in-differences regression specified in Equation 3.1. This analysis formally assesses whether MMC plans offer differentially lower coverage of adversely selected specialist types relative to commercial plans. I report coefficient estimates for β, the coefficient on the interaction between the selection incentive S_z

23. This is a simple average of the coverage ratios across all 29 specialties.

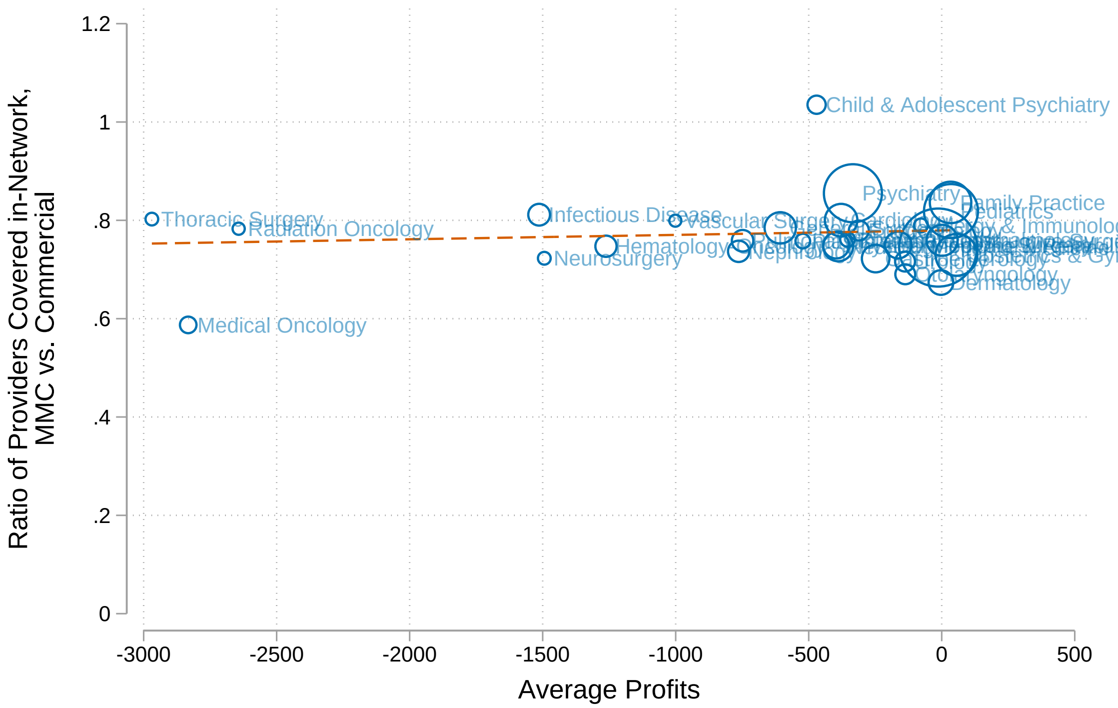

Figure 3.6: *Ratio of Providers Covered In-Network, Medicaid Managed Care vs. Commercial Plans, by Profitability of Specialty*

and the indicator variable for Medicaid plans, MMC_j. Column 1 presents the results of the regression using primary measure of the selection incentive, and Column 2 presents the results for the E-M incentive measure.

The selection incentive is significantly correlated with network coverage in Medicaid, with Medicaid plans providing differentially less coverage (relative to commercial plans) of physician specialists where there is a strong incentive to under-provide care under the prevailing Medicaid payment system. On the other hand, while this effect is statistically significant, it is small. The coefficient on the interaction term is 0.001 for the primary measure ($p < 0.001$), and -4.920 ($p < 0.001$) for the secondary E-M measure. To aid in interpretation, going from the specialty with the smallest E-M selection incentive in the data

Figure 3.7: *Ratio of Providers Covered In-Network, Medicaid Managed Care vs. Commercial Plans, by E-M Incentive Measure*

(OB/GYN, 0.02) to the largest (medical oncology, 1.06) is associated with only a 5.2 percentage point predicted reduction in network coverage, from 37.0% to 31.8%. The estimated relationship between the primary incentive measure and network coverage is even smaller. Going from the specialty with the most profitable patients (OB/GYN, with gains of $\approx$ \$60 per beneficiary-month under risk adjustment) to the specialty with the least profitable patients (thoracic surgery, with losses of $\approx \$2,970$ per beneficiary-month under risk adjustment) results in only about a 2.4 percentage point predicted reduction in network coverage, from 36.9% to 34.5%.

Unfortunately, as discussed in Sections 3.4.3 and 3.5.2, this analysis is not well-identified, as the selection incentives in the Medicaid and commercial markets are likely strongly

Table 3.2: *Regression Results: Difference-in-Differences Analysis Comparing Networks of Medicaid and Commercial Plans*

	(1)	(2)
	Primary Measure	E-M Measure
Selection Incentive x Medicaid	0.001***	-4.920***
	(0.000)	(0.134)
Plan FE	Yes	Yes
Year FE	Yes	Yes
Specialty FE	Yes	Yes
Observations	1343760	1343760
Adjusted R^2	0.882	0.883

Standard errors in parentheses

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

Note: This table reports results of the regression analysis specified in Equation 3.1.

correlated, biasing the result to the null. In the next section, I compare utilization of specialists in the FFS Medicaid program vs. MMC plans, an analysis that is not subject to this limitation.

3.5.4 Insurer Responses to Selection Incentives: Do Medicaid Managed Care Plans Ration Care?

I next test whether Medicaid beneficiaries in managed care plans use disproportionately less care in adversely selected specialties, relative to beneficiaries in FFS Medicaid.

Utilization Ratios, MMC vs. FFS

Figure 3.8 presents preliminary evidence that beneficiaries in MMC use relatively less care in adversely selected specialties, as compared with beneficiaries in FFS Medicaid. On the y-axis is a raw ratio of the total number of specialist claims per beneficiary-month in MMC between 2012-2015, relative to the total number of claims per beneficiary-month in FFS. The primary selection incentive is on the x-axis. Each circle represents a single specialty, with the size of the circle weighted by the number of beneficiaries who had a claim for that specialty in New York City between 2012-2015. Beneficiaries who use specialties to the right of the vertical red line are profitable to MMC plans (having monthly health care spending that is lower than their risk-adjusted premium), while beneficiaries who use specialties to the left of the vertical red line are unprofitable to plans. MMC beneficiaries receive more care than FFS beneficiaries in specialties above the horizontal red line, and less care in specialties below it.

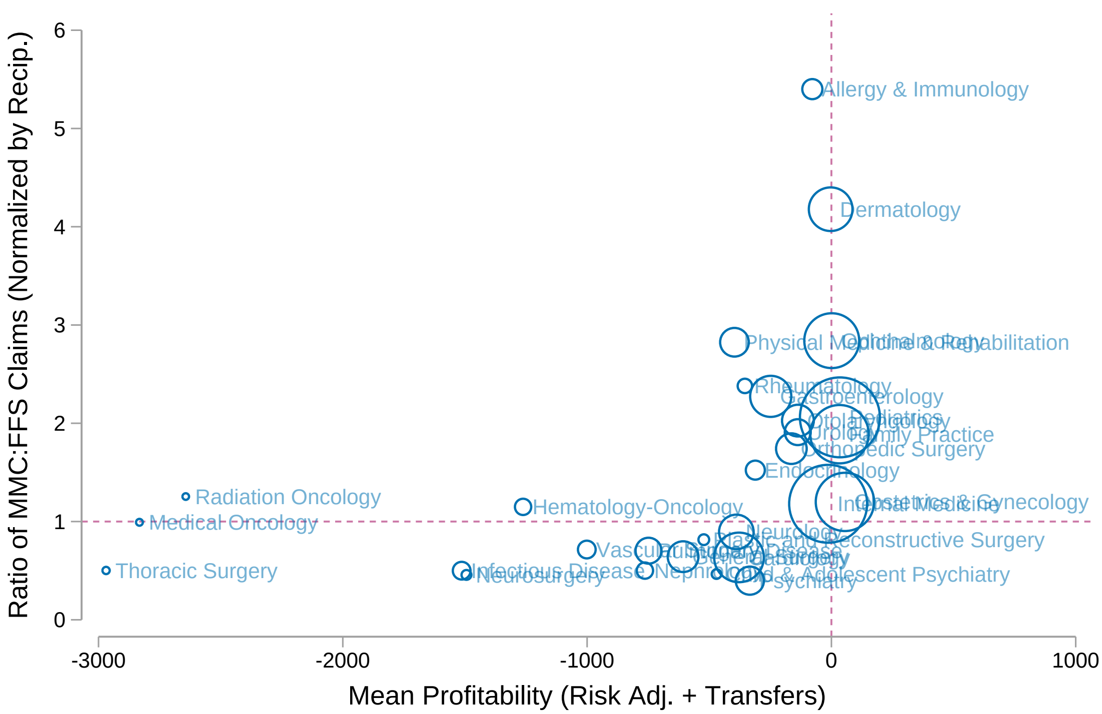

Figure 3.8: *Raw Ratio of MMC Claims:FFS Claims, by Profitability of Physician Specialty*

There is a clear pattern, whereby MMC beneficiaries receive disproportionately less care in adversely selected specialties, relative to FFS beneficiaries (correlation coefficient = 0.42). As an example, within the top 5 specialties with the most favorable selection incentives (OB/GYN, pediatrics, family practice, ophthalmology, and dermatology), MMC beneficiaries use on average 2.4 times as much care as FFS beneficiaries. By contrast, within the 5 specialties with the worst selection incentives (thoracic surgery, medical oncology, radiation oncology, infectious disease, and neurosurgery), MMC beneficiaries use on average about 25% less care than FFS beneficiaries.

Adjusted Utilization Ratios, MMC vs. FFS

To adjust for confounders that could contribute to differences in care between beneficiaries in FFS and MMC, I use a fixed effects regression approach. These regressions, described in Equation 3.2, allow me to compare within-beneficiary utilization of different specialist types when beneficiaries are enrolled in MMC vs. FFS, while controlling for the month of the beneficiary's enrollment episode, calendar month fixed effects, and year fixed effects.[24] I use predictive margins to estimate predicted monthly probabilities of specialist utilization when beneficiaries are enrolled in MMC and FFS, and I calculate new, adjusted ratios of utilization in MMC relative to FFS.

The full regression results are reported in Tables C.2-C.7 in the Appendix. Figure 3.9 plots the adjusted utilization ratios (y-axis) against the primary selection incentive measure (x-axis). Beneficiaries who use specialties to the right of the vertical red line are profitable to MMC plans (having health care spending that is lower than their risk-adjusted

24. I estimate separate regressions for each specialty.

premium), while beneficiaries who use specialties to the left of the vertical red line are unprofitable to plans. Beneficiaries receive more care in MMC than in FFS in specialties above the horizontal red line, and less care in specialties below it.

The adjusted, within-beneficiary results are qualitatively quite similar to the descriptive results reported above. Medicaid beneficiaries have more physician claims overall when they are enrolled in MMC, relative to FFS (mean ratio = 1.39, representing about 39% more beneficiary-months with a claim). However, they do not have more physician claims in specialties that are highly unprofitable to MMC plans, such as medical oncology, radiation oncology, thoracic surgery, infectious disease, hematology-oncology, neurosurgery, and vascular surgery. Therefore, beneficiaries use relatively less care in “unprofitable” specialties than “profitable” ones when they are enrolled in MMC (as compared with months when they are enrolled in FFS) (correlation coefficient = 0.52). Within the five specialties with the most favorable selection incentives (OB/GYN, pediatrics, family practice, ophthalmology, and dermatology), MMC beneficiaries use on average 1.9 times as much care as beneficiaries in FFS Medicaid. Within the 5 specialties with the worst selection incentives (thoracic surgery, medical oncology, radiation oncology, infectious disease, and neurosurgery), MMC beneficiaries use on average $\approx$ 8.4% less care than beneficiaries in FFS.

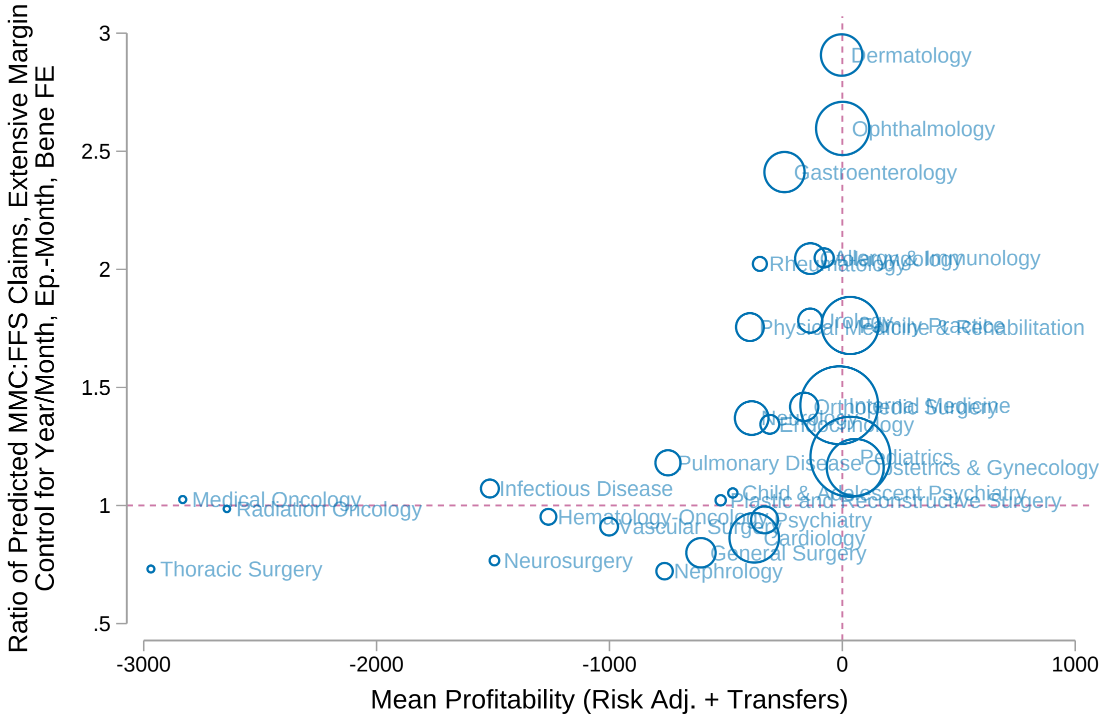

Figure 3.9: *Adjusted Ratios of Specialist Utilization in MMC vs. FFS, by the MMC Selection Incentive*

3.6 Discussion

Public health insurance coverage in the United States is increasingly administered using competitive, private health insurance markets. In such markets, plans may be incentivized to offer lower levels of coverage for services that are valued by high-cost beneficiaries due to adverse selection. In this chapter, I test whether private Medicaid managed care (MMC) plans ration access to physician specialists when adverse selection creates strong incentives for them to do so.

I first compare MMC plans' provider networks to commercial HMOs' networks in New York City to assess whether Medicaid plans offer lower levels of network coverage of specialties that serve high-cost (unprofitable) Medicaid beneficiaries. I find a statistically significant but small relationship between selection incentives and Medicaid managed care plans' network coverage of specialists, with MMC plans offering slightly narrower networks of specialists serving unprofitable beneficiaries, on average, relative to commercial HMOs in the same market. In particular, Medicaid plans offer much lower coverage of medical oncologists, a specialty with strong incentives to ration care, than do private plans. However, I find that incentives in Medicaid are likely not very different from the incentives faced by commercial insurers in this market, biasing the result to the null.

I conduct a second test to examine whether MMC plans explicitly ration access to adversely selected specialties. In addition to restricting access to specialists using their provider networks, MMC plans could ration access to specialty care using utilization management techniques like prior authorization. To test this, I compare Medicaid beneficiaries' specialist utilization when they are enrolled in MMC plans to their utilization in fee-for-service (FFS) Medicaid using a regression approach with beneficiary fixed effects. I find that MMC beneficiaries use differentially less care in specialties with strong selection incentives, which may indicate rationing by MMC plans.

Interestingly, Medicaid beneficiaries have about 39% more physician claims overall when they are enrolled in MMC relative to FFS; however, this is not the case for specialties that are highly unprofitable to MMC plans, like oncology and thoracic surgery. One interpretation of this result is that FFS enrollment is transitory for many Medicaid beneficiaries in New York, occurring either for a few months at the beginning of an enrollment episode or for brief periods between enrollment in different MMC plans. Therefore, physician utilization might be expected to be relatively low during these periods and to increase when beneficiaries enroll in an MMC plan. The fact that utilization does not increase for unprofitable specialties may represent rationing of these services by MMC plans. A limitation of this analysis is that I cannot rule out alternative explanations for this result; for example, it is possible that utilization of specialties like oncology is less sensitive to the type of Medicaid coverage, due to the relative severity or urgency of these types of care.

In sum, I find evidence that MMC plans may ration access to physician specialists when adverse selection creates strong incentives for them to do so. In particular, I find that Medicaid plans offer disproportionately lower network coverage of medical oncologists than commercial HMOs. Additionally, while Medicaid beneficiaries use more specialty care overall during months when they are enrolled in an MMC plan, they use the same amount or less of the types of care that are subject to selection incentives, including oncology and thoracic surgery. Future work should seek to better understand the mechanisms driving within-beneficiary differences in utilization between FFS and MMC.

A

New York's Rate Setting and Risk Adjustment Methodology

The New York State Department of Health (DOH) uses the following process to construct risk-adjusted premiums for each Medicaid managed care plan.[1] First, the state sets a base premium for each geographic rating region using cost data from previous years. Next, the state assigns each Medicaid beneficiary to a clinical risk group (CRG), using that benefi-

1. New York began using administered rates in 2008, and phased in risk adjustment between fiscal years 2008-2011.

ciary's demographics, diagnoses, procedures, and pharmacy claims. Third, it calculates the average cost of beneficiaries in each CRG relative to the average Medicaid beneficiary; this is the "cost weight" for the CRG. Finally, it assigns each plan a region- and premium group-specific premium, which is equal to the base premium times the average cost weight of the plan's beneficiaries. I describe these steps in more detail below.

A.1 Base Premiums

New York State first sets a base premium for each of its nine rating regions. It does so using two years of plan-reported Medicaid Managed Care Operating Report (MMCOR) data, which incorporate plans' administrative and medical costs on a per member per month (PMPM) basis (Duchessi and Dembrosky 2016; New York State Department of Health 2018; New York State Office of the Comptroller, Division of State Government Accountability 2016).[2] Base rates are set prospectively using data from prior years, and they vary by age and category of aid (TANF vs. SSI); there are separate rates for TANF ages 0-20, TANF ages 21+, and SSI. From here on, I will call these three groups "premium groups."

2. The five counties of New York City are a single rating region. These counties include: Bronx County (the Bronx), Kings County (Brooklyn), New York County (Manhattan), Queens County (Queens), and Richmond County (Staten Island). The administrative cost component is calculated by using actual plan administrative costs from the MMCOR reports, but is subject to a cap (New York State Office of the Comptroller, Division of State Government Accountability 2016).

A.2 Clinical Risk Groups

Next, DOH stratifies all Medicaid beneficiaries by health condition severity using 3M Clinical Risk Groups (CRGs) (New York State Department of Health 2018). The 3M model incorporates demographics, diagnosis codes, procedure codes, and pharmacy codes from the encounter data to assign each individual beneficiary to one of more than 1,000 mutually exclusive risk categories, or CRGs (Conroy 2008; Borok 2011). These CRGs are then aggregated into three levels: ACRG1, ACRG2, or ACRG3; with ACRG3 being the highest level of aggregation (least detailed) (Averill et al. 1999; Conroy 2008). New York uses 44 aggregate CRGs (ACRG3s) in its risk adjustment methodology (Borok 2011; Conroy 2008).[3]

A.3 Cost Weights

DOH calculates a "cost weight" or "relative weight" for each aggregate CRG category (ACRG3), stratified by premium group, using actual beneficiary costs from the managed care encounter data.[4] DOH does this by dividing the average cost for beneficiaries in each ACRG3 and premium group by the average cost for all beneficiaries in that premium group (Conroy 2008).[5] To calculate average costs, the state uses encounter data from the managed care plans, but standardizes prices in order to account for missing payment

3. See also: New York State Department of Health (2016).

4. See New York State Department of Health (2016).

5. For example, if the average monthly cost for TANF beneficiaries ages 21 years and older is \$144.39, while the average cost for healthy (ACRG3 = 10) TANF beneficiaries ages 21 years and older is \$49.36, then the cost weight for 10 (healthy) is \$49.36/\$144.39 = 0.3419. This specific example is from a presentation by Mary Beth Conroy (Conroy 2008).

amounts, as well as unusually high- or low-priced services (Conroy 2008).[6] The state excludes beneficiaries with fewer than three months of Medicaid eligibility when developing the cost weights (Borok 2011; Conroy 2008).

A.4 Plan-Specific Risk Scores

Finally, once the state has calculated cost weights for each ACRG3, it assigns each plan a region- and premium group-specific relative risk score. The DOH first calculates a raw risk score for each plan, which is the weighted average acuity of plan beneficiaries, calculated by combining the ACRG3-specific cost weights with the distribution of beneficiaries across ACRG3 categories (New York State Department of Health 2016). Separately, the state calculates a regional risk score for all plans in the region. A relative risk score is computed for each plan by dividing its raw risk score by the regional risk score. This relative risk score is multiplied by the base payment to determine the premiums paid to each plan (Conroy 2008).

6. Encounters with missing payment data are assigned the mean for the given service, and encounters above and below certain "trim points" are adjusted to the trim point (25th percentile for the low end trim point; high end varies by inpatient vs. outpatient/pharmacy), with service defined using procedure codes, revenue codes, DRGs, or NDC codes (Conroy 2008)

B

Appendix to Chapter 1

B.1 Supplemental Tables

Table B.1: *Heterogeneity in "Peak" Coefficient by HCC*

	(1) HCC 8	(2) HCC 9	(3) HCC 10	(4) HCC 11	(5) HCC 12	(6) HCC 13	(7) 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

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

The interaction terms in each of these regressions compare changes over time in the focal MCO's market share among beneficiaries with cancer (disaggregated by HCC) to changes over time in the focal MCO's market share among all beneficiaries who did not have cancer. See Equation 1.4 for the regression specification.

Table B.2: *Heterogeneity in "Peak" Coefficient (Other Sub-Categories of the Cancer Cohort, Part 1)*

	(1) Main	(2) Prior Use	(3) No Prior Use	(4) Not Metastatic	(5) Metastatic
Cancer	0.000	-0.028***	0.001	0.002**	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Cancer x Pre	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Cancer x Anticipatory	0.002*	0.021***	0.006***	0.001	0.005**
	(0.001)	(0.005)	(0.001)	(0.001)	(0.002)
Cancer x Early	0.008***	0.167***	0.011***	0.007***	0.014***
	(0.001)	(0.010)	(0.001)	(0.001)	(0.002)
Cancer x Peak	0.013***	0.334***	0.013***	0.010***	0.022***
	(0.001)	(0.010)	(0.001)	(0.001)	(0.002)
Cancer x Late	0.007***	0.130***	0.012***	0.007***	0.008***
	(0.001)	(0.008)	(0.001)	(0.001)	(0.002)
Cancer x Post	0.003***	0.062***	0.008***	0.003***	0.003
	(0.001)	(0.007)	(0.001)	(0.001)	(0.002)
Time Period FE	Yes	Yes	Yes	Yes	Yes
N	36765195	35944127	36507622	36599016	36099341
adj. R^2	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

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

The interaction terms in each of these regressions compare changes over time in the focal MCO's market share among beneficiaries with cancer who fall into the sub-category in the column heading (e.g., "metastatic," "not metastatic") to changes over time in the focal MCO's market share among all beneficiaries who did not have cancer. See Equation 1.4 for the regression specification.

Table B.3: *Heterogeneity in "Peak" Coefficient (Other Sub-Categories of the Cancer Cohort, Part 2)*

	(1) Ages 18-24	(2) Ages 25-30	(3) Ages 31-40	(4) Ages 41-50	(5) Ages 51-64	(6) Male	(7) Female
Cancer	0.003	-0.002	-0.002	-0.000	0.003*	-0.009***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cancer x Pre	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Cancer x Anticipatory	0.002	0.003	-0.001	0.003	0.003	0.003*	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Cancer x Early	0.004	0.010***	0.007***	0.009***	0.009***	0.009***	0.008***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Cancer x Peak	0.003	0.019***	0.017***	0.011***	0.012***	0.016***	0.011***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Cancer x Late	-0.004	0.011***	0.014***	0.005***	0.007***	0.013***	0.005***
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Cancer x Post	-0.012***	0.009***	0.008***	-0.000	0.004**	0.006***	0.002*
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Time Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	35996107	36005225	36083430	36179689	36233392	36169881	36528476
adj. R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

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

The interaction terms in each of these regressions compare changes over time in the focal MCO's market share among beneficiaries with cancer who fall into the sub-category in the column heading (e.g., "ages 18-24" or "ages 25-30") to changes over time in the focal MCO's market share among all beneficiaries who did not have cancer. See Equation 1.4 for the regression specification.

Table B.4: *Heterogeneity in "Peak" Coefficient (Other Sub-Categories of the Cancer Cohort, Part 3)*

	(1) Black	(2) White	(3) Other Race	(4) <5 Miles	(5) 5-7.5 Miles	(6) 7.5-10 Miles	(7) 10+ Miles
Cancer	-0.005***	-0.006***	0.009***	0.004**	0.005***	-0.003*	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Cancer x Pre	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Cancer x Anticipatory	0.002	0.002	0.002	0.003	0.001	0.000	0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cancer x Early	0.010***	0.009***	0.007***	0.011***	0.007***	0.003	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cancer x Peak	0.014***	0.016***	0.009***	0.014***	0.011***	0.008***	0.021***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Cancer x Late	0.011***	0.007***	0.005***	0.008***	0.005**	0.006***	0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Cancer x Post	0.005***	0.004**	0.003	0.003	0.002	0.004*	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Time Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	36182964	36199502	36249053	34739318	34813553	34819212	34778953
adj. R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

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

The interaction terms in each of these regressions compare changes over time in the focal MCO's market share among beneficiaries with cancer who fall into the sub-category in the column heading to changes over time in the focal MCO's market share among all beneficiaries who did not have cancer. See Equation 1.4 for the regression specification.

Table B.5: *Spending by Hierarchical Condition Category (HCC)*

Cancer HCC	N (mean)[1]	Mean MMC Spending ($)[2]	Mean Total Spending ($)[3]
HCC 8: Metastatic Cancer	3,077.0	1,403.0	3,063.8
HCC 9: Lung, Brain, Other Severe	1,514.0	790.2	2,045.9
HCC 10: Non-Hodgkin's Lymphomas, Other	1,216.0	563.1	1,776.2
HCC 11: Colorectal, Breast (Age<50), Kidney, Other	2,575.0	395.9	875.9
HCC 12: Breast (Age 50+), Prostate, Other	2,733.0	366.4	824.6
HCC 13: Thyroid, Melanoma, Neurofibromatosis, Other	761.0	282.2	660.6
Cancer, No HCC Assignment[4]	3,531.0	235.3	624.5

[1] The N in this table represents average monthly enrollment between 2004-2008.

[2] Mean monthly spending by managed care plans for beneficiaries in the sample who were enrolled in Medicaid managed care between 2005-2008. For spending calculations, 2004 data were dropped due to unreliable reporting of spending in Medicaid managed care in that year.

[3] Mean monthly total Medicaid spending for all beneficiaries in the sample between 2005-2008.

[4] These beneficiaries met our criteria for inclusion in the cancer cohort (which was based on Clinical Classifications Software categories), but did not have a diagnosis corresponding to a cancer HCC code.

B.2 Supplemental Figures

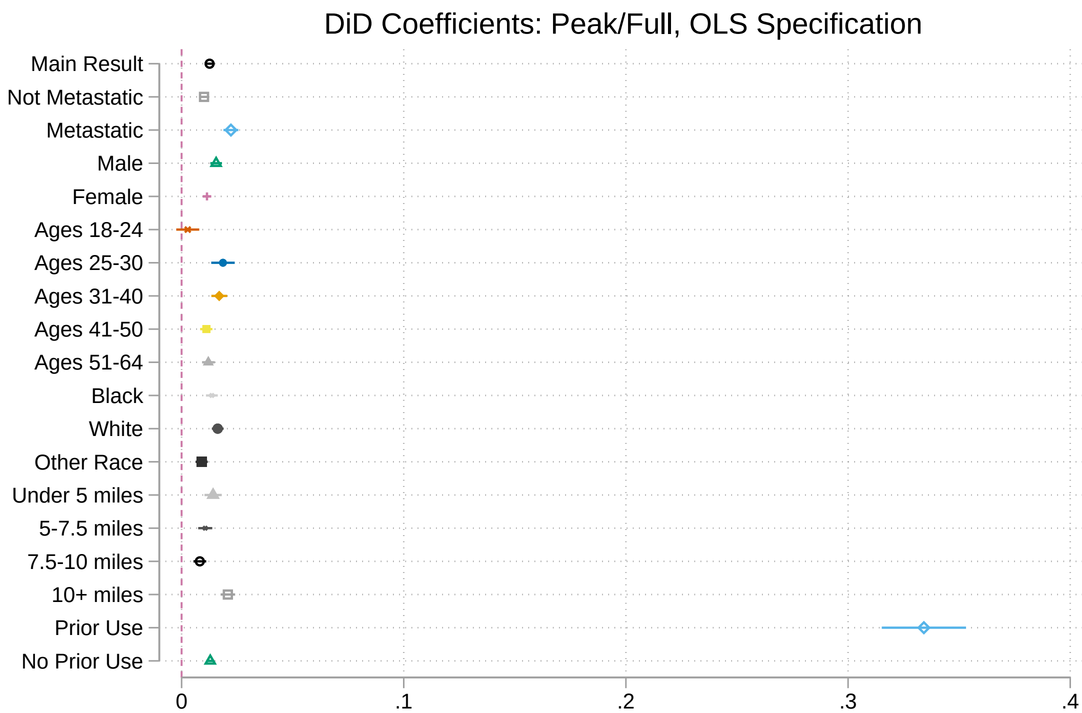

Figure B.1: *Heterogeneity in Selection Result, "Peak" Coefficients, OLS Specification*

C

Appendix to Chapter 3

C.1 Supplemental Tables

Table C.1: *Spending and Demographics by Market Segment, SFY 2012-2015*

	Start FFS Always FFS	Start FFS Mix	Start MMC Always MMC	Start MMC Mix	Unobs. Always FFS	Unobs. Always MMC	Unobs. Mix
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N (mean per month)	46,133	874,301	246,398	42,939	40,778	1,076,950	274,397
Percentage of sample (%)	1.8	33.6	9.5	1.7	1.6	41.4	10.5
Episode-Month (%)							
Months 1-3	35.9	17.8	16.0	12.2	0.5	0.1	1.0
Months 4-6	19.2	16.5	14.8	12.0	1.4	0.7	2.3
Months 7-12	25.5	27.6	25.9	23.0	4.6	3.5	5.9
Months 13+	19.4	38.1	43.4	52.8	93.5	95.6	90.8
Medicaid Eligibility (%)							
TANF/SN	75.9	96.2	97.5	97.4	21.3	87.0	88.7
SSI-Disabled	7.7	1.9	1.5	1.6	52.7	12.1	10.5
SSI-Aged	0.2	0.0	0.0	0.0	1.6	0.3	0.1
SSI-Blind	0.0	0.0	0.0	0.0	0.2	0.0	0.0
Foster Care and CW	13.6	0.1	0.0	0.0	24.0	0.5	0.2
Pregnant	1.7	1.4	0.9	0.7	0.2	0.1	0.4
Prenatal	0.9	0.4	0.0	0.3	0.0	0.0	0.0
Female (%)	49.3	53.1	54.7	56.8	44.1	54.4	55.0
Age (mean)	26.5	27.8	24.2	26.4	25.3	23.6	24.0
Monthly spending ($)							
Total	873.5	347.4	459.4	508.9	3,536.8	325.0	510.3
MMC	7.2	215.0	353.3	347.4	4.5	240.9	276.8

Note: This table reports summary statistics by market segment for the full analysis sample.

Table C.2: *Results of the Fixed Effects Regression Analyses of Utilization, MMC vs. FFS (Part 1)*

	(1) Allergy & Immunology	(2) Cardiology	(3) Child & Adolescent Psychiatry	(4) Dermatology	(5) Endocrinology
MMC	0.0006***	-0.0011***	0.0000	0.0036***	0.0003***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
First Month	-0.0003***	0.0011***	-0.0000	-0.0010***	-0.0002***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Second Month	-0.0002***	0.0012***	-0.0000	-0.0004***	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Third Month	-0.0002***	0.0023***	-0.0001**	0.0001	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Months 4-6	-0.0001**	0.0022***	-0.0000	0.0006***	0.0002***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Months 7-12	-0.0001**	0.0007***	-0.0000	0.0003***	0.0001***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Months 13+	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Bene FE	Yes	Yes	Yes	Yes	Yes
Mean Outcome Var.	0.0011	0.0072	0.0003	0.0049	0.0011
Observations	1.31e+07	1.31e+07	1.31e+07	1.31e+07	1.31e+07

Standard errors in parentheses

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

Note: This table reports results of the regression analyses specified in Equation 3.2 for the first 5 specialties.

Table C.3: *Results of the Fixed Effects Regression Analyses of Utilization, MMC vs. FFS (Part 2)*

	(1) Family Practice	(2) Gastroenterology	(3) General Surgery	(4) Hematology-Oncology	(5) Infectious Disease
MMC	0.0067***	0.0030***	-0.0005***	-0.0000	0.0001*
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
First Month	-0.0020***	-0.0001	0.0002**	-0.0004***	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Second Month	0.0026***	0.0008***	-0.0001	-0.0001**	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Third Month	0.0047***	0.0020***	0.0003***	0.0000	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Months 4-6	0.0033***	0.0025***	0.0005***	0.0001***	0.0001*
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Months 7-12	0.0013***	0.0012***	0.0002***	0.0001*	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Months 13+	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Bene FE	Yes	Yes	Yes	Yes	Yes
Mean Outcome Var.	0.0145	0.0046	0.0019	0.0010	0.0010
Observations	1.31e+07	1.31e+07	1.31e+07	1.31e+07	1.31e+07

Standard errors in parentheses

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

Note: This table reports results of the regression analyses specified in Equation 3.2 for specialties 6-10.

Table C.4: *Results of the Fixed Effects Regression Analyses of Utilization, MMC vs. FFS (Part 3)*

	(1) Internal Medicine	(2) Medical Oncology	(3) Nephrology	(4) Neurology	(5) Neurosurgery
MMC	0.0101***	0.0000	-0.0004***	0.0009***	-0.0001***
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
First Month	-0.0036***	-0.0001***	-0.0004***	-0.0001	-0.0000
	(0.0003)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Second Month	0.0057***	-0.0001**	-0.0002***	0.0002*	-0.0000
	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Third Month	0.0103***	-0.0000*	0.0001**	0.0004***	-0.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Months 4-6	0.0078***	0.0000	0.0002***	0.0006***	0.0000
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Months 7-12	0.0024***	0.0000	0.0001***	0.0003***	0.0000*
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Months 13+	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Bene FE	Yes	Yes	Yes	Yes	Yes
Mean Outcome Var.	0.0324	0.0002	0.0011	0.0031	0.0002
Observations	1.31e+07	1.31e+07	1.31e+07	1.31e+07	1.31e+07

Standard errors in parentheses

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

Note: This table reports results of the regression analyses specified in Equation 3.2 for specialties 11-15.

Table C.5: *Results of the Fixed Effects Regression Analyses of Utilization, MMC vs. FFS (Part 4)*

	(1) Obstetrics & Gynecology	(2) Ophthalmology	(3) Orthopedic Surgery	(4) Otolaryngology	(5) Pediatrics
MMC	0.0021***	0.0041***	0.0006***	0.0011***	0.0053***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0002)
First Month	0.0014***	-0.0004**	-0.0004***	-0.0004***	0.0010***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Second Month	0.0063***	0.0017***	-0.0000	-0.0001	0.0062***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Third Month	0.0057***	0.0030***	0.0001	0.0003***	0.0046***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Months 4-6	0.0051***	0.0022***	0.0003***	0.0003***	0.0012***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0002)
Months 7-12	0.0019***	0.0006***	0.0002***	0.0001*	0.0007***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Months 13+	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Bene FE	Yes	Yes	Yes	Yes	Yes
Mean Outcome Var.	0.0147	0.0060	0.0018	0.0020	0.0301
Observations	1.31e+07	1.31e+07	1.31e+07	1.31e+07	1.31e+07

Standard errors in parentheses

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

Note: This table reports results of the regression analyses specified in Equation 3.2 for specialties 16-20.

Table C.6: *Results of the Fixed Effects Regression Analyses of Utilization, MMC vs. FFS (Part 5)*

	(1) Physical Medicine & Rehabilitation	(2) Plastic and Reconstructive Surgery	(3) Psychiatry	(4) Pulmonary Disease	(5) Radiation Oncology
MMC	0.0013***	0.0000	-0.0002***	0.0003***	-0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
First Month	-0.0005***	-0.0001*	-0.0010***	-0.0003***	-0.0000*
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Second Month	-0.0001	-0.0000	-0.0008***	-0.0000	0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Third Month	0.0001	-0.0000	-0.0007***	0.0001	-0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Months 4-6	0.0005***	0.0000	-0.0002***	0.0003***	0.0000**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
Months 7-12	0.0003***	0.0000	-0.0000	0.0001***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Months 13+	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Bene FE	Yes	Yes	Yes	Yes	Yes
Mean Outcome Var.	0.0027	0.0002	0.0038	0.0016	0.0001
Observations	1.31e+07	1.31e+07	1.31e+07	1.31e+07	1.31e+07

Standard errors in parentheses

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

Note: This table reports results of the regression analyses specified in Equation 3.2 for specialties 21-25.

Table C.7: *Results of the Fixed Effects Regression Analyses of Utilization, MMC vs. FFS (Part 6)*

	(1) Rheumatology	(2) Thoracic Surgery	(3) Urology	(4) Vascular Surgery
MMC	0.0003***	-0.0000**	0.0008***	-0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
First Month	-0.0001**	0.0000*	-0.0003***	0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Second Month	-0.0001	0.0000	-0.0002*	0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Third Month	-0.0000	0.0000**	0.0001	0.0001**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Months 4-6	0.0000	0.0000***	0.0005***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Months 7-12	0.0000	0.0000**	0.0002***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Months 13+	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Bene FE	Yes	Yes	Yes	Yes
Mean Outcome Var.	0.0006	0.0001	0.0016	0.0007
Observations	1.31e+07	1.31e+07	1.31e+07	1.31e+07

Standard errors in parentheses

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

Note: This table reports results of the regression analyses specified in Equation 3.2 for specialties 26-29.

References

American Hospital Association. 2020. *Addressing Commercial Health Plan Abuses to Ensure Fair Coverage for Patients and Providers.* White Paper. December. Accessed May 22, 2021. https://www.aha.org/white-papers/2020-12-01-addressing-commercial-health-plan-abuses-ensure-fair-coverage-patients-and.

American Society for Radiation Oncology. 2020. Re: CMS-9123-P: Medicaid Program; Patient Protection and Affordable Care Act; Reducing Provider and Patient Burden by Improving Prior Authorization Processes, and Promoting Patients' Electronic Access to Health Information for Medicaid Managed Care Plans, State Medicaid Agencies, CHIP Agencies and CHIP Managed Care Entities, and Issuers of Qualified Health Plans on the Federally-Facilitated Exchanges; Health Information Technology Standards and Implementation Specifications. December 24, 2020. Accessed May 13, 2021. https://www.astro.org/ASTRO/media/ASTRO/Daily%20Practice/PDFs/ASTROComments_ReducingProviderPatientBurdenbyImprovingPriorAuthProcesses.pdf.

Averill, Richard F., Norbert I. Goldfield, Jon Eisenhandler, John H. Muldoon, John S. Hughes, John M. Neff, James C. Gay, et al. 1999. *Development and Evaluation of Clinical Risk Groups (CRGs).* 3M HIS Research Report 9-99. 3M.

Borok, Lawrence. 2011. "The Use of Predictive Modeling by New York State Medicaid." *Predictive Modeling News* 4, no. 1 (January): 1–8.

Brooks, Tricia, Lauren Roygardner, Samantha Artiga, Olivia Pham, and Rachel Dolan. 2020. *Medicaid and CHIP Eligibility, Enrollment, Renewal, and Cost Sharing Policies as of January 2020: Findings from a 50-State Survey.* Kaiser Family Foundation, March.

Brown, Jason, Mark Duggan, Ilyana Kuziemko, and William Woolston. 2014. "How Does Risk Selection Respond to Risk Adjustment? New Evidence from the Medicare Advantage Program." *American Economic Review* 104 (10): 3335–3364.

Cao, Zhun, and Thomas G. McGuire. 2003. "Service-Level Selection by HMOs in Medicare." *Journal of Health Economics* 22, no. 6 (November): 915–931.

Carey, Colleen. 2017a. *A Time to Harvest: Evidence on Consumer Choice Frictions from a Payment Revision in Medicare Part D.* Working Paper, March 17, 2017.

———. 2017b. "Technological Change and Risk Adjustment: Benefit Design Incentives in Medicare Part D." *American Economic Journal: Economic Policy* 9, no. 1 (February): 38–73.

Center for Evidence-Based Policy. 2016. *Medicaid and Specialty Drugs: Current Policy Options.* Brief. Center for Evidence-Based Policy, June. Accessed May 18, 2021. http://centerforevidencebasedpolicy.org/wp-content/uploads/2018/12/MED_Medicaid_and_Specialty_Drugs_Current_Policy_Options_Final_Sept-9-2016.pdf.

Centers for Medicare & Medicaid Services. 2013. *HHS-Developed Risk Adjustment Model Algorithm Software: Technical Details,* May 7, 2013. Accessed May 30, 2021. https://web.archive.org/web/20131224175132/http://www.cms.gov/CCIIO/Resources/Regulations-and-Guidance/Downloads/ra_tables_04_16_2013xlsx.xlsx.

———. 2020. "Crosswalk Medicare Provider/Supplier to Healthcare Provider Taxonomy," November 3, 2020. Accessed November 15, 2020. https://data.cms.gov/Medicare-Enrollment/CROSSWALK-MEDICARE-PROVIDER-SUPPLIER-to-HEALTHCARE/j75i-rw8y/data.

Congressional Budget Office. 2018. *Exploring the Growth of Medicaid Managed Care.* August. https://www.cbo.gov/publication/54235.

Conroy, Mary Beth. 2008. "New York State Medicaid Managed Care Risk Assessment." MMIS 2008, Nashville, TN, September 17, 2008.

Courtot, Brigette, Teresa A. Coughlin, and Emily Lawton. 2012. *Medicaid and CHIP Managed Care Payment Methods and Spending in 20 States.* Washington, D.C.: U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation, December. Accessed December 9, 2020. https://aspe.hhs.gov/basic-report/medicaid-and-chip-managed-care-payment-methods-and-spending-20-states.

Cutler, David M., and Richard J. Zeckhauser. 2000. "The Anatomy of Health Insurance." In *Handbook of Health Economics,* edited by Anthony J. Culyer and Joseph P. Newhouse, vol. 1A, 563–643. Amsterdam: Elsevier.

DesRoches, Catherine M., Kirsten A. Barrett, Bonnie E. Harvey, Rachel Kogan, James D. Reschovsky, Bruce E. Landon, Lawrence P. Casalino, Stephen M. Shortell, and Eugene C. Rich. 2015. "The Results Are Only as Good as the Sample: Assessing Three National Physician Sampling Frames." *Journal of General Internal Medicine* 30, no. 3 (August 1, 2015): 595–601.

Duchessi, Torrey, and Michael Dembrosky. 2016. "Rate Setting for Transition into Managed Care." New York State Department of Health, November 16, 2016. Accessed April 15, 2020. https://www.health.ny.gov/health_care/medicaid/redesign/mrt90/nhtd-tbi/2016-11-16_overview.htm.

Eggleston, Karen, and Anupa Bir. 2009. "Measuring Selection Incentives in Managed Care: Evidence from the Massachusetts State Employee Insurance Program." *The Journal of Risk and Insurance* 76 (1): 159–175. JSTOR: 40247546.

Einav, Liran, and Amy Finkelstein. 2011. "Selection in Insurance Markets: Theory and Empirics in Pictures." *Journal of Economic Perspectives* 25, no. 1 (March): 115–138.

———. 2018. "Moral Hazard in Health Insurance: What We Know and How We Know It." *Journal of the European Economic Association* 16 (4): 957–982.

Einav, Liran, Amy Finkelstein, and Mark R. Cullen. 2010. "Estimating Welfare in Insurance Markets Using Variation in Prices." *Quarterly Journal of Economics* 125, no. 3 (August): 877–921.

Einav, Liran, Amy Finkelstein, and Maria Polyakova. 2016. *Private Provision of Social Insurance: Drug-Specific Price Elasticities and Cost Sharing in Medicare Part D.* Working Paper 22277. National Bureau of Economic Research.

Ellis, Randall P., Shenyi Jiang, and Tzu-Chun Kuo. 2013. "Does Service-Level Spending Show Evidence of Selection across Health Plan Types?" *Applied Economics* 45, no. 13 (May 1, 2013): 1701–1712. Accessed March 5, 2021. https://doi.org/10.1080/00036846.2011.636023.

Ellis, Randall P., and Thomas G. McGuire. 2007. "Predictability and Predictiveness in Health Care Spending." *Journal of Health Economics* 26, no. 1 (January): 25–48.

Ericson, Keith Marzilli, and Amanda Starc. 2015. "Measuring Consumer Valuation of Limited Provider Networks." *American Economic Review* 105, no. 5 (May): 115–119.

Felland, Laurie E., Amanda E. Lechner, and Anna Sommers. 2013. *Improving Access to Specialty Care for Medicaid Patients: Policy Issues and Options.* The Commonwealth Fund, June 6, 2013. Accessed February 12, 2021. https://www.commonwealthfund.org/publications/fund-reports/2013/jun/improving-access-specialty-care-medicaid-patients-policy-issues.

Forsgren, Ethan. 2017. *New York Medicaid History, 1991 to Present.* Unpublished Report. July 26, 2017.

Frank, Richard G., Jacob Glazer, and Thomas G. McGuire. 2000. "Measuring Adverse Selection in Managed Health Care." *Journal of Health Economics* 19, no. 6 (November): 829–854.

Freed, Meredith, Anthony Damico, and Tricia Neuman. 2021. "A Dozen Facts About Medicare Advantage in 2020." Kaiser Family Foundation, January 13, 2021, 7:00 p.m. (Z). Accessed May 21, 2021. https://www.kff.org/medicare/issue-brief/a-dozen-facts-about-medicare-advantage-in-2020/.

Geruso, Michael, Timothy J Layton, and Jacob Wallace. 2020. *Are All Managed Care Plans Created Equal? Evidence from Random Plan Assignment in Medicaid.* NBER Working Paper No. 27762. National Bureau of Economic Research, August. Accessed October 1, 2020. http://www.nber.org/papers/w27762.

Geruso, Michael, and Timothy J. Layton. 2015. *Upcoding: Evidence from Medicare on Squishy Risk Adjustment.* Working paper 21222. National Bureau of Economic Research.

———. 2017. "Selection in Health Insurance Markets and Its Policy Remedies." *Journal of Economic Perspectives* 31, no. 4 (November): 23–50.

Geruso, Michael, Timothy J. Layton, and Daniel Prinz. 2019. "Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges." *American Economic Journal: Economic Policy* 11, no. 2 (May): 64–107.

Geruso, Michael, and Thomas G. McGuire. 2016. "Tradeoffs in the Design of Health Plan Payment Systems: Fit, Power and Balance." *Journal of Health Economics* 47 (May): 1–19. pmid: 26922122.

Gifford, Kathleen, Anne Winter, Linda Wiant, Rachel Dolan, Marina Tian, and Rachel Garfield. 2020. *How State Medicaid Programs Are Managing Prescription Drug Costs:*

Results from a State Medicaid Pharmacy Survey for State Fiscal Years 2019 and 2020. Kaiser Family Foundation, April 29, 2020. Accessed May 19, 2021. https://www.kff.org/report-section/how-state-medicaid-programs-are-managing-prescription-drug-costs-pharmacy-benefit-administration/.

Glazer, Jacob, and Thomas G. McGuire. 2000. "Optimal Risk Adjustment in Markets with Adverse Selection: An Application to Managed Care." *American Economic Review* 90, no. 4 (September): 1055–1071.

———. 2002. "Setting Health Plan Premiums to Ensure Efficient Quality in Health Care: Minimum Variance Optimal Risk Adjustment." *Journal of Public Economics* 84 (2): 153–173.

Gottlieb, Joshua D., Maria Polyakova, Kevin Rinz, Hugh Shiplett, and Victoria Udalova. 2020. *Who Values Human Capitalists' Human Capital? Healthcare Spending and Physician Earnings.* Center for Economic Studies (CES) Working Paper 20-23. Washington, D.C.: United States Census Bureau, July. Accessed November 15, 2020. https://www2.census.gov/ces/wp/2020/CES-WP-20-23.pdf.

Hackmann, Martin B., Jonathan T. Kolstad, and Amanda E. Kowalski. 2015. "Adverse Selection and an Individual Mandate: When Theory Meets Practice." *American Economic Review* 105 (3): 1030–1066.

Handel, Benjamin R., Igal Hendel, and Michael D. Whinston. 2015. "Equilibria in Health Exchanges: Adverse Selection vs. Reclassification Risk." *Econometrica* 83 (4): 1261–1313.

Healthcare Cost and Utilization Project. 2016. "Appendix A - Clinical Classification Software-DIAGNOSES (January 1980 through September 2015)." Agency for Healthcare Research and Quality, March 24, 2016. Accessed October 16, 2020. https://hcup-us.ahrq.gov/toolssoftware/ccs/AppendixASingleDX.txt.

Holahan, John, Stephen Zuckerman, Alison Evans, and Suresh Rangarajan. 1998. "Medicaid Managed Care In Thirteen States." *Health Affairs* 17, no. 3 (May): 43–63.

Hurley, Robert E., and Susan Wallin. 1998. *Adopting and Adapting Managed Care for Medicaid Beneficiaries: An Imperfect Translation.* Urban Institute Occasional Paper Number 7. Washington, D.C.: The Urban Institute, June. Accessed April 15, 2020. https://www.

urban.org/sites/default/files/publication/70571/307473-Adopting-and-Adapting-Managed-Care-for-Medicaid-Beneficiaries.PDF.

Kaiser Family Foundation. 2017. “Total Medicaid MCO Enrollment,” July 1, 2017. Accessed April 13, 2020. https://www.kff.org/other/state-indicator/total-medicaid-mco-enrollment/.

———. 2019. “Share of Medicaid Population Covered under Different Delivery Systems,” July 1, 2019. Accessed April 13, 2020. https://www.kff.org/medicaid/state-indicator/share-of-medicaid-population-covered-under-different-delivery-systems/.

———. n.d. “Medicaid Enrollees by Enrollment Group.” Accessed April 13, 2020. https://www.kff.org/medicaid/state-indicator/distribution-of-medicaid-enrollees-by-enrollment-group/.

———. 2020b. “Medicaid Managed Care Market Tracker.” Accessed April 13, 2020. https://www.kff.org/data-collection/medicaid-managed-care-market-tracker/.

———. 2020c. *Total Medicaid MCO Enrollment.* https://www.kff.org/other/state-indicator/total-medicaid-mco-enrollment/.

———. 2021. *Status of State Medicaid Expansion Decisions: Interactive Map.* Issue Brief. May 13, 2021. Accessed May 18, 2021. https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/.

Kuziemko, Ilyana, Katherine Meckel, and Maya Rossin-Slater. 2018. “Does Managed Care Widen Infant Health Disparities? Evidence from Texas Medicaid.” *American Economic Journal: Economic Policy* 10, no. 3 (August): 255–283.

Lavetti, Kurt, and Kosali Simon. 2016. *Strategic Formulary Design in Medicare Part D Plans.* Working Paper No. 22338. National Bureau of Economic Research.

Layton, Timothy J., Randall P. Ellis, Thomas G. McGuire, and Richard van Kleef. 2017. “Measuring Efficiency of Health Plan Payment Systems in Managed Competition Health Insurance Markets.” *Journal of Health Economics* 56 (December): 237–255.

Layton, Timothy J., Alice K. Ndikumana, and Mark Shepard. 2017. *Health Plan Payment in Medicaid Managed Care: A Hybrid Model of Regulated Competition.* NBER Working

Paper No. 23518. June. Accessed November 21, 2017. https://www.nber.org/papers/w23518.pdf.

Marton, James, Aaron Yelowitz, and Jeffery C. Talbert. 2017. "Medicaid Program Choice, Inertia and Adverse Selection." *Journal of Health Economics* 56 (December 1, 2017): 292–316. Accessed December 9, 2020. http://www.sciencedirect.com/science/article/pii/S016762961730406X.

McGuire, Thomas G., Joseph P. Newhouse, Sharon-Lise Normand, Julie Shi, and Samuel Zuvekas. 2014. "Assessing Incentives for Service-Level Selection In Private Health Insurance Exchanges." *Journal of Health Economics* 35 (May): 47–63. pmid: 24603443.

Menger, Richard. 2021. "Streamlining the Process of Prior Authorization for Medical and Surgical Procedures." The Hill, January 14, 2021. Accessed May 13, 2021. https://thehill.com/blogs/congress-blog/healthcare/534334-streamlining-the-process-of-prior-authorization-for-medical.

New York State Department of Health. 2012. "MCOs Certified by NYS Department of Health," October. Accessed May 24, 2021. https://www.health.ny.gov/health_care/managed_care/mcodefs.htm.

———. 2015. "Medicaid Managed Care/Family Health Plus/HIV Special Needs Plan/Health and Recovery Plan Model Contract," October 1, 2015. Accessed April 15, 2020. https://www.health.ny.gov/health_care/managed_care/docs/medicaid_managed_care_fhp_hiv-snp_model_contract.pdf.

———. 2016. *Request for Proposals: Rate and Fiscal Management Consultant.* RFP #16501. February 26, 2016. Accessed May 18, 2021. https://www.health.ny.gov/funding/rfp/inactive/16501/16501.pdf.

———. 2018. *A Path toward Value Based Payment: Annual Update: New York State Roadmap for Medicaid Payment Reform.* June. Accessed April 24, 2020. https://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Waivers/1115/downloads/ny/medicaid-redesign-team/ny-medicaid-rdsgn-vbp-roadmap-apprvl-20190501.pdf.

———. 2019. "DSRIP - Value Based Payment Reform (VBP)," September. Accessed April 16, 2020. https://www.health.ny.gov/health_care/medicaid/redesign/dsrip/vbp_reform.htm.

New York State Department of Health. 2021. "Medicaid Pharmacy Program," April. Accessed May 18, 2021. https://www.health.ny.gov/health_care/medicaid/redesign/mrt2/pharmacy_carve_out/.

New York State Department of Health Division of Managed Care and Program Evaluation. 2012. *Managed Care Plan Directory.* January 3, 2012. Accessed May 25, 2021. https://web.archive.org/web/20120131191601/http://www.health.ny.gov/health_care/managed_care/pdf/hmo_dir.pdf.

New York State Office of the Comptroller, Division of State Government Accountability. 2016. *Mainstream Managed Care Organizations: Administrative Costs Used in Premium Rate Setting.* Report 2014-S-55. October. Accessed May 18, 2021. https://www.osc.state.ny.us/files/state-agencies/audits/pdf/sga-2017-14s55.pdf.

New York State Office of the State Comptroller. 2014. *Overpayments to Managed Care Organizations and Hospitals for Low Birth Weight Newborns.* 2013-S-57. October. Accessed May 18, 2021. https://www.osc.state.ny.us/state-agencies/audits/2014/10/02/medicaid-program-overpayments-managed-care-organizations-and-hospitals-low-birth-weight.

Newell, Peter, Miriam Aziz, and Don Gorman. 2013. *Networks in New York and the Affordable Care Act.* New York: United Hospital Fund.

Nichols, Albert L., and Richard J. Zeckhauser. 1982. "Targeting Transfers through Restrictions on Recipients." *American Economic Review* 72 (2): 372–377.

Rothschild, Michael, and Joseph E. Stiglitz. 1976. "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information." *The Quarterly Journal of Economics* 90, no. 4 (November 1, 1976): 629–649.

Rudowitz, Robin, Rachel Garfield, and Elizabeth Hinton. 2019. *10 Things to Know about Medicaid: Setting the Facts Straight.* Issue Brief. Kaiser Family Foundation, March 6, 2019. Accessed May 18, 2021. https://www.kff.org/medicaid/issue-brief/10-things-to-know-about-medicaid-setting-the-facts-straight/.

Schwalberg, Renee, Sheryl Anderson Mathis, Mary Giffen, Larissa Mohamadi, Beth Zimmerman, and Erin Sines. 2013. *Medicaid Coverage of Perinatal Services: Results of a National Survey.* Washington, D.C.: Kaiser Family Foundation, January. Accessed

March 8, 2021. https://www.kff.org/wp-content/uploads/2013/01/medicaid-coverage-of-perinatal-services-results-of-a-national-survey-report.pdf.

Shepard, Mark. 2016. *Hospital Network Competition and Adverse Selection: Evidence from the Massachusetts Health Insurance Exchange.* NBER Working Paper No. 22600. September. Accessed April 13, 2020. https://www.nber.org/papers/w22600.

Timbie, Justin W., Ashley M. Kranz, Ammarah Mahmud, and Cheryl L. Damberg. 2019. "Specialty Care Access for Medicaid Enrollees in Expansion States." *The American Journal of Managed Care* 25, no. 3 (March 1, 2019): e83–e87. Accessed May 27, 2021. pmid: 30875176. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6986199/.

U.S. Department of Health and Human Services, Office of Inspector General. 2014a. *Access to Care: Provider Availability in Medicaid Managed Care.* OEI-02-13-00670. Washington, D.C., November 8, 2014. Accessed May 27, 2021. https://oig.hhs.gov/oei/reports/oei-02-13-00670.asp.

———. 2014b. *State Standards for Access to Care in Medicaid Managed Care.* OEI-02-11-00320. Washington, D.C., September 25, 2014. Accessed May 27, 2021. https://oig.hhs.gov/oei/reports/oei-02-11-00320.asp.

Veiga, André, and E. Glen Weyl. 2016. "Product Design in Selection Markets." *Quarterly Journal of Economics* 131 (2): 1007–1056.

Wallace, Jacob. 2015. *Do Provider Networks Impact Health Care Use and Spending? Evidence from Random Assignment in Medicaid Managed Care.* Job Market Paper. Harvard University, November 17, 2015.

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