Essays on Private Health Insurance in Public Programs

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Abstract

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Over 100 million people in the US now have public health insurance that is administered by a private company. This dissertation consists of three essays that analyze various outcomes in private health insurance markets inside of US public programs. Chapter 1 of this dissertation outlines the role of private insurers in public health insurance programs in the US. It also summarizes the key lessons learned from the remaining chapters of the dissertation. Chapter 2 of this dissertation examines the effect of insurer entry in the health insurance marketplaces, started by the Patient Protection and Affordable Care Act, on total costs for the insured. In the first year of the marketplaces, each insurer decreased patient costs by 5 percent or more. In the second year of the marketplaces, however, additional insurers had no average effects on patient costs. Chapter 3 examines the implications of private versus public administration of Medicare for elderly cancer patients. Having privately, rather than publicly, administered insurance at the time of initial cancer diagnosis increased mortality for patients with brain cancer, lung cancer, or prostate cancer in a health service area with at least 500,000 people. Insurance choices also suggested a preference among cancer patients for the public Medicare plan. Finally, Chapter 4 examines the relationship between private Medicare plans and preventive care and how that relationship may be affected by modern risk adjustment policies that adjust insurer revenues according to patients' chronic medical conditions. Before modern risk adjustment, private Medicare plans increased patients' use of pneumonia and flu shots. However, the introduction of modern risk adjustment reduced patients' use of pneumonia shots and colorectal cancer screening.

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Chapter 1

Introduction

This dissertation consists of three essays that analyze various outcomes in private health insurance markets inside of US public programs. Over 100 million people in the US now have public health insurance that is administered by a private company. The first chapter analyzes consumers' out-of-pocket risk in the health insurance marketplaces that began after the Patient Protection and Affordable Care Act (ACA). The second and third chapters analyze private Medicare plans in terms of quality of post-diagnosis cancer care and facilitation of preventive care, respectively.

1.1 Background

Medicare, health insurance for the elderly and disabled, and Medicaid, health insurance for the poor, are the two largest public health insurance programs in the US. Both programs began in 1965. Medicare currently covers over 55 million people and Medicaid currently covers over 74 million people. Originally, Medicare was administered only by the federal goverment and Medicaid was administered only by state governments. Over time, however, the federal and state governments began to contract with privately-owned managed care organizations to administer the insurance. In Medicare, beneficiaries choose if they want to receive their health insurance from a private company. Medicare administered by private companies is referred to as "Medicare Advantage." Private Medicare Advantage plans offer health insurance coverage beyond what traditional Medicare covers, but also restrict patients' access to medical providers. The Medicare Advantage program has been steadily

increasing in popularity over the past decade. Currently, nearly one-third of Medicare beneficiaries choose a Medicare Advantage plan over traditional Medicare. The landscape of public versus private administration of Medicaid varies by state. Some states contract with private managed care organizations to serve all or some of their Medicaid beneficiaries and some states do not contract with private managed care organizations at all. Currently, over three-fourths of Medicaid beneficiaries are insured by a private insurer.

In 2014, as a result of the ACA, a third major public health insurance program began in the US. Online health insurance marketplaces were set up in each state that provided consumers with a one-stop shop to purchase health insurance. The federal government provided both premium and cost-sharing subsidies for qualifying individuals who purchased marketplace plans. The subsidies were paid to low-income people who did not quality for Medicaid or for sufficiently affordable employer-sponsored health insurance. Importantly, for my purposes, the health insurance marketplaces are fully privatized. To be insured through the marketplaces, individuals must choose a plan administered by a private company. The choice of plans is dependent on the insurers that decide to participate in each county.

Relying on private companies to administer health insurance is a promising way to reduce wasteful health spending. For example, Curto et al. (2015) showed that Medicare Advantage plans reduce health insurance claims cost by 12 percent. However, insurer costs are only one of several important policy considerations. To inform the best policies, we also need to know how private health insurers influence patients' costs and quality of care. In the health insurance marketplaces, particularly because there is no public plan option, patient and taxpayer costs are heavily dependent on competition amongst private insurers. The efficiency of the marketplaces is thus dependent on the optimal number of private insurers participating. In chapter 2 of this dissertation, I examine the effect of insurer participation on patient costs. By program design, private insurers in Medicare must reduce patient costs. However, their influence on quality of care requires careful empirical analysis. In chapters 3 and 4 of this dissertation, I using traditional publicly-administered Medicare as a benchmark to examine private Medicare Advantage plans' influence on post-diagnosis care and preventive care.

1.2 Summary

To examine the effect of insurer entry in the health insurance marketplaces on total costs for the insured (chapter 2), I measure costs as a patient's premium plus cost-sharing expenditures. The latter is a function of the patients' medical utilization, which is unobserved. I thus measure costs from a range of utilization scenarios. Because insurers bargain with medical providers over reimbursement rates, the effect of insurer entry on patient costs is theoretically ambiguous. To estimate the effect empirically, I use an instrumental variables approach. Regulatory costs, which influence entry but not pricing, are paid at the state level and likely to be large in the first year an insurer participates in the marketplaces. I thus use the number and size of residual geographic markets in a state to instrument for insurer entry in a county. In the first year of the marketplaces, each insurer decreased patient costs by 5 percent or more. In the second year of the marketplaces, additional insurers had no average effects on patient costs for most utilization scenarios. However, in counties with three or more incumbent insurers, a new insurer actually increased patient cost-sharing for emergency room services. This was likely driven by a shift of bargaining power away from insurers towards emergency departments; most markets have few emergency departments and the estimate varies with the number of emergency departments in a market. The take-away of the analysis is that the optimal number of private insurers in a county is finite and may be, on average, as small as 2 or 3.

To examine the implications of private versus public administration of Medicare for elderly cancer patients (chapter 3), I look at cancer mortality and health insurance switching as outcomes. Because private Medicare plans restrict provider access (in exchange for offering supplemental insurance coverage), it is possible that cancer patients with private Medicare plans experience a lower quality of cancer care in situations where there is variation in quality of cancer care providers. Health service areas with less than 500,000 people typically only have one hospital with an accredited cancer program, while the average number of hospitals with accredited cancer programs in larger health services areas is 9. In the larger health service areas, I estimate that having privately, rather than publicly, administered Medicare at

the time of initial cancer diagnosis increased mortality for brain cancer, lung cancer, and prostate cancer patients. The size of the effect was 0.9 months of median life expectancy for brian cancer patients, 0.4 months of median life expectancy for lung cancer patients, and 4.0 months of median life expectancy for prostate cancer patients. The mortality results are striking, but do not account for quality of life. However, insurance choices after cancer diagnosis also suggest a preference among cancer patients for the public Medicare plan. While switching between the public plan and a private plan is rare, patients are 37 percent more likely to switch away from private insurance and 29 percent less likely to switch into private insurance after a cancer diagnosis. The take-away of the analysis is that the use of private insurers in Medicare constitutes at least some trade-off between reducing medical costs and improving health outcomes.

To examine the relationship between private Medicare plans and preventive care (chapter 4), I use individual-level data on the use of preventive care. Importantly, the data covers multiple years that span two different risk adjustment policy regimes. In the first four years of data, from 2000 through 2003, private Medicare insurers were paid independent of their enrollees' chronic conditions and thus had a financial incentive to prevent chronic illness. In the last seven years of data, from 2004 through 2010, Medicare adjusted its payments to private Medicare insurers to reflect each enrollees' chronic conditions. While this gave private insurers more incentive to cover sicker individuals, it may have also lessened their incentive to prevent chronic illness. To measure the effect of private insurers on preventive care in these two policy regimes, I use plausibly exogenous changes over time in the popularity of private Medicare plans. Before modern risk adjustment, a 10 percentage point increase in the market share of private Medicare plans increased the probability of a Medicare beneficiary in that county having a pneumonia shot by 1.8 percentage points and having a flu shot by 1.5 percentage points. After modern risk adjustment, however, there was no detectable influence of private insurers on patients' use of preventive care. In particular, the same 10 percentage point increase in the market share of private Medicare plans after modern risk adjustment led to a *lesser* increase in the probabilty of getting a pneumonia shot by 1.2 percentage points and the probablity of screening for colorectal cancer by 1.2 percentage points. The take-away of the

analysis is that, by changing the financial incentives of private insurers, modern risk adjustment may decrease the use of preventive care, particularly services that prevent conditions (like pneumonia and colorectal cancer) that are included in the risk adjustment formula.

Chapter 2

Three's a Crowd? The Effect of Insurer Participation on Premiums and Cost-Sharing Parameters in the Initial Years of the ACA Marketplaces

2.1 Introduction

Since 2014, as a result of the Patient Protection and Affordable Care Act (ACA), non-elderly adults in the US can access online marketplaces to purchase private health insurance. In their first two years the marketplaces facilitated enrollment for 10 million individuals, about 85 percent of whom received financial assistance. Because federal subsidies are defined so that the government pays less when insurers offer plans with lower premiums, both consumers and taxpayers depend on insurer competition to minimize their respective costs. However, because insurers rely on bargaining power over medical providers to maintain low costs for medical services, it is not clear that additional insurers always benefit consumers and taxpayers. In this chapter I provide new evidence on insurer competition in the marketplaces. In particular, I estimate the marginal effect of insurer entry on premiums and cost-sharing parameters in both the first and second years of the marketplaces.

Premium plus cost-sharing is the total cost of health care for insured consumers

as a function of the cost of medical services that they use. It is the combination of their plan's premium and the amount of cost-sharing they are required to contribute toward their medical expenses according to the parameters defined by their plan. I study the 34 states with federally facilitated marketplaces, where insurers have considerable latitude to vary cost-sharing parameters even within plans that provide the same actuarial value of benefits. In this setting, insurers could compete by offering plans with similar cost-sharing parameters but lower premiums, or they could compete by offering plans with similar premiums but more specialized cost-sharing parameters. Since additional insurers could lower patient costs under either scenario, an important contribution of this research is to incorporate both premiums and cost-sharing parameters in the outcome variables.

Since data on plan choices and medical utilization for enrollees in the marketplaces has not been made available, I define outcome variables that measure "premium plus cost-sharing" parameters, realizations of offered premium plus cost-sharing for various hypothetical medical service costs. First, I choose service costs to represent medical services that patients might use, as motivated by the distribution of medical service costs in the 2012 Medical Expenditure Panel Survey. Second, for each "silver" plan, I compute premium plus cost-sharing for the various service costs based on the plan's premium and cost-sharing parameters indicated by publicly-available healthcare.gov data. Third, for each service cost, I summarize premium plus cost-sharing at the county level by either taking the minimum of premium plus cost-sharing across all plans in the county or the premium plus cost-sharing from the plan with the lowest premium.[1] I refer to the outcome array of premium plus cost-sharing for the various service costs as premium plus cost-sharing parameters.

In the first year of the marketplaces, premium plus cost-sharing parameters were lower in counties with more insurers. This is not necessarily a causal relationship, because more insurers might have participated in counties where their variable costs

[1] Insurer participation in the marketplaces varies by county even though premiums for a given plan can only vary by rating area. See section 2.4 for details.

(e.g., expected claim reimbursements) were lower. In order to estimate a causal effect, I rely on an instrumental variables approach. The instruments measure variation in insurers' fixed costs of regulatory compliance from participating in different markets. Insurers make entry decisions at the county level but regulatory compliance costs are paid at the state level. Insurers that decide to enter a state due to high expected profits in other counties are thus more likely to enter a marginal county in that state. Consequently, all else equal, average insurer participation should be greater in states with more and larger geographic markets. Using the number, average market size, and total market size of residual rating areas in the state as instruments for insurer participation in a county, I estimate that an additional insurer induced premium plus cost-sharing parameters to be around 5 percent lower. The decrease, between 10 and 15 percent depending on the service cost amount, was greatest for service costs associated with inpatient care. These estimates represent causal effects as long as the number and size of residual rating areas is uncorrelated with unobserved components of demand and insurer variable costs. The identification assumption is supported by falsification tests that show the instruments are not correlated with pre-ACA premiums, claims, or utilization.

In the second year of the marketplaces there was a large increase in insurer entry due to new entry by Assurant Health and UnitedHealth. Consistent with the cross-sectional pattern from the first year of the marketplaces, premium plus cost-sharing parameters generally decreased the most in counties where the number of insurers increased the most. However, this relationship is again not necessarily causal because new insurers could have entered in counties where their variable costs decreased. To establish a causal link I separately use two sets of instruments for changes in insurer entry between 2014 and 2015. The first set of instruments includes the same variables used as instruments in the 2014 analysis. The second set of instruments measures pre-ACA market shares for Assurant and United. Estimates with either set of instruments represent causal effects as long as the instruments are uncorrelated with changes in demand or insurer variables costs between 2014 and 2015. Falsification tests support the identification assumptions because none of the instruments are correlated with pre-ACA changes in premiums, claims, utilization.

The estimates are similar with either set of instruments and reveal several interesting conclusions. First, there is no statistically distinguishable evidence that insurer entry lowered premiums. However, entry did increase risk protection for inpatient services because premium plus inpatient cost-sharing parameters decreased by 10 to 20 percent due to each new insurer. Second, the marginal effect of each new insurer varied according to the number of incumbent insurers. I split the sample into two subsamples, one with counties where two or fewer insurers participated in 2014 and one with counties where three or more insurers participated in 2014. For all 36 of my outcome variables, the estimate for the effect of insurer entry is lower in the sample of counties with fewer incumbent insurers. Additionally, in the counties with three or more incumbent insurers, each new insurer *increased* premium plus emergency room cost-sharing parameters by 4 to 8 percent. I find suggestive evidence that this might have occurred because new entry decreased insurer bargaining power with emergency departments.

Of the early research on insurer competition in the marketplaces, Dafny, Gruber, and Ody (2015) use the most credible identification strategy to address the potential endogeneity of insurer competition and find that it lowered premiums in 2014. This chapter builds on their work by expanding both the time period and the range of outcomes. My results show that both of these added dimensions are important. In particular, insurer entry influences cost-sharing parameters in addition to premiums and the influence varies according to baseline insurer participation. My analysis of the second year of the marketplaces is most similar to work by Sheingold, Nguyen, and Chappel (2015), but they do not address the potential endogeneity of new insurer entry and do not include outcomes that incorporate cost-sharing. To my knowledge, Taylor et al. (2015) provide the only prior work that examines the relationship between insurer participation and an outcome related to cost-sharing. However, they do not address the potential endogeneity of insurer participation, do not incorporate all cost-sharing parameters, and do not examine the second year of the marketplaces.

The rest of the chapter is organized as follows. Section 2.2 provides the relevant background for the marketplaces. Section 2.3 outlines literature related to the competing effects of health insurer competition on patient costs. Section 2.4 summarizes

the data, Section 2.5 develops the empirical strategy, and Section 2.6 presents the results. Finally, Section 2.7 concludes with a discussion of the implications of the results.

2.2 Background

In this section I provide background about the marketplaces and the different marketplace plans. I start by noting the horizontal differentiation among plans, particularly with respect to cost-sharing parameters. I then outline the key features of the marketplaces and discuss changes in insurer participation as the marketplaces have evolved.

2.2.1 Horizontal Plan Differentiation

Each marketplace plan has a certified vertical quality, measured by the actuarial value of its plan benefits. In particular, all plans must cover a certain percentage of expected medical expenses, within a 2 percent margin of error, for a standard population of potential enrollees. The following are the four main allowable vertical qualities of plans, called metal tiers, with their required actuarial values in parentheses: bronze (60 percent), silver (70 percent), gold (80 percent), and platinum (90 percent).[2] Insurers must offer at least one silver and at least one gold plan in every county in which they participate, and are allowed to offer plans in other metal tiers if they choose.

Due to horizontal differentiation, plans in the same metal tier are not identical. There are several sources of horizontal differentiation across plans, but in this chapter I focus on differences in cost-sharing parameters. Together with the plan's premium, though the premium does not vary with the use of medical services, cost-sharing parameters define a multi-dimensional and non-linear relationship between medical utilization and total patient cost. The main cost-sharing variables are the deductible, out-of-pocket maximum, and any copays and coinsurance rates. Copays and coinsurance rates can, and often do, vary by category of medical service

[2] Individuals younger than 30 or with hardship exemptions also have the option to purchase a catastrophic plan with actuarial value below 60 percent.

and whether or not the deductible has been reached. In practice, silver plans define cost-sharing parameters that are very different from one another. As long as the expected amount of total reimbursements implied by the plan design meets the required actuarial value, any combination of cost-sharing parameters can be used. The only exception is that the out-of-pocket maximum is not allowed to exceed a certain threshold, $6,350 for a 2014 plan sold to an individual. To give a sense of the variation, some marketplace plans set a deductible of zero while others set the deductible equal to the highest possible out-of-pocket maximum.

Besides variation in cost-sharing parameters, the main source of differentiation across marketplace plans is likely provider networks.[3] Each plan's provider network must meet minimum ACA standards, but some plans have broader networks than others. Ericson and Starc (2015) find that consumers value health insurance plans with broader provider networks, but there is anecdotal evidence that many marketplace plans cut costs by setting narrow networks.[4] Since I measure premium plus cost-sharing parameters from the plans with the lowest premiums and most generous cost-sharing parameters, my estimates likely reflect patient costs for plans with relatively narrow provider networks.

2.2.2 Key Features of the Marketplaces

Each marketplace is a website for a particular state that allows individuals and families a one-stop shop to view their health insurance options and ultimately purchase a health insurance plan. States have some ability to regulate their own marketplace, but the ACA mandates a minimum set of regulations for all states. There are 34 states that elected to have the federal government at least partially manage their marketplace in the first two years, and the regulations that apply to marketplaces in these states are similar.[5]

[3] Plans may also differ because insurers may have different reputations due to differences in claims adjudication or financial solvency. Miller, Eibner, and Gresenz (2013) discuss the potential for variation in claims adjudication and financial solvency in health insurance plans, but these are at least somewhat regulated by the state and not likely to be salient to consumers.

[4] See "Regulators Urge Broader Health Networks," published online in the New York Times on November 8, 2015.

[5] There are some regulatory differences across the 34 states. I address the major ones with a robustness exercise in section 2.6.2.

To interpret the effect of insurer entry on premium plus cost-sharing parameters, it is important to remember that premiums and cost-sharing are paid jointly by consumers and the government. Roughly 85 percent of enrollees in the marketplaces are individuals and families that qualify for federal subsidies. There are two different kinds of subsidies. The first is a premium subsidy, which is available to consumers with income between 100 percent and 400 percent of the federal poverty level (FPL).[6] The premium subsidy is based on a cap for the premium the consumer pays if they purchase the "benchmark" silver plan in their county, which is the one with the second-lowest premium. The lower is a consumer's income, the lower is their cap. Consumers can apply their subsidy to any marketplace plan.

The second subsidy is a cost-sharing subsidy, and is only available to consumers that purchase a silver plan and have income between 100 percent and 250 percent of the FPL. For silver plans, insurers define baseline cost-sharing parameters and alternative, more generous, cost-sharing parameters for people that qualify for cost-sharing subsidies. Like the premium subsidy, the increased generosity of the cost-sharing parameters is greater for consumers with lower incomes. For any medical services used during the year, the consumer pays only the cost-sharing defined by the parameters that they qualify for. Any additional cost-sharing defined by the plan's baseline cost-sharing parameters is paid by the government directly to the insurer.

2.2.3 Key Changes in Insurer Participation

Insurer participation has fluctuated in the early years of the marketplaces. In my analysis of the second year of the marketplaces, I rely on changes in insurer entry between 2014 and 2015, particularly due to the new entry of Assurant and United.

Assurant and United are both national insurers that were major players in the pre-ACA individual market. United is also a major player in the much larger employer-sponsored health insurance market, while Assurant is not. Assurant and United both declined to enter any counties in the states with federally facilitated marketplaces in 2014. Besides Aetna (854 counties), Assurant (934 counties) and United

[6]The FPL was $11,490 for a single-family household in the 2014 benefit year. Individuals with income less than 100 percent of the FPL either qualify for Medicaid or a hardship exemption from the insurance mandate, depending on the state in which they live.

(760 counties) both participated in more counties than any other insurer in 2015. However, both Assurant and United decreased their participation in the marketplaces after 2015. Assurant closed its plans to new entrants after just one year and plans to shut down by the end of 2016.[7] United has said it will exit most of the federally facilitated marketplaces in 2017.[8]

Despite their exits after 2015, it does not appear that Assurant and United pursued different pricing strategies than other national insurers. United offered the plan with the lowest premium in 30 percent of the counties in which it participated, similar to Aetna and Humana. On the other hand, Assurant offered the plan with the lowest premium in less than 1 percent of the counties in which it participated. Similarly, though, Cigna did not offer the plan with the lowest premium in any of the counties in which it participated. There were also no noticeable differences in the cost-sharing parameters used by Assurant and United versus other national insurers. Thus, entry by Assurant and United appears representative of entry by other national insurers.

2.3 Competing Effects of Insurer Entry on Patient Costs

Even though additional insurer entry should lower markups, the excess of premiums over expected insurer costs, it does not necessarily benefit consumers and taxpayers. Insurers rely on bargaining power over medical providers to minimize service costs and, all else equal, insurers have less bargaining power when medical providers have more insurers to potentially negotiate with. Thus, as shown by Ho and Lee (2016), Melnick, Shen, and Wu (2011), and Moriya, Vogt, and Gaynor (2010), increased insurer competition increases service costs that patients and insurers owe to medical providers. Particularly for patients who owe coinsurance for their marginal medical services, higher service costs directly implies higher patient costs. It does not necessarily imply a shift of premiums or cost-sharing parameters, however, which is what my outcomes would measure. My premium plus

[7] See http://www.chicagobusiness.com/article/20150610/NEWS03/150619979/sell-off-or-close-up-assurant-health-opts-for-costly-market-exit, accessed on 6/1/16.

[8] See https://www.washingtonpost.com/news/wonk/wp/2016/04/19/unitedhealth-group-to-exit-obamacare-exchanges-in-all-but-a-handful-of-states/, accessed on 6/1/16.

cost-sharing parameters measure will only shift due to higher service costs if insurers pass through their share of the higher service costs to patients by shifting cost-sharing parameters or by increasing premiums.

In employer-sponsored health insurance, researchers have found that higher service costs are partially passed through to consumers via higher premiums (Town et al., 2006; Trish and Herring, 2015). However, researchers looking both at employer-sponsored health insurance (Dafny, Duggan, and Ramanarayanan, 2012; Ho and Lee, 2016) and the first year of the marketplaces (Dafny, Gruber, and Ody, 2015) agree that the net effect of an additional insurer is to lower health insurance premiums. Still, there are those that support limiting insurer competition in order to make health insurance more affordable. For example, most state Medicaid agencies contract with only a small number of managed care organizations to serve their Medicaid patients. The marketplace for California, Covered California, also selectively contracts with insurers. Within Covered California, Scheffler et al. (2016) found that premium growth from 2014 to 2015 was positively correlated with increases in insurer participation.

2.4 Data and Descriptive Analysis

My empirical analysis relies on data from healthcare.gov for the first two years of the marketplaces. For each year of the marketplaces, the publicly-available data from healthcare.gov contain information about issuing insurer, service area, premiums, and cost-sharing parameters for all plans in the states with federally facilitated marketplaces.[9] Each plan has been approved by the federal government and is defined by its issuer, premiums, benefit and cost-sharing parameters, provider network, and drug formulary. The same plan is often available in multiple counties and sometimes even in multiple states. The same issuer often offers multiple plans, even within the same metal tier. There are 34 states included in the data, encompassing 395 rating areas and 2,512 counties. Since my empirical strategy relies on

[9] I downloaded the data from `https://www.healthcare.gov/health-and-dental-plan-datasets-for-researchers-and-issuers/` on 12/2/2014. The 2015 data has since been updated to exclude plans issued by Assurant, because it stopped enrolling new members as of 6/15/15. The participation of Assurant in the 2015 marketplaces is critical for my empirical analysis, so I am happy to share my version of the data upon request.

variation from residual rating areas in a state, I exclude data from three states that have only one rating area. The excluded states are Delaware, New Hampshire, and New Jersey. The final data set covers 2,478 counties in 392 rating areas in 31 states.

I make three notable decisions with respect to measuring premiums and cost-sharing parameters with the healthcare.gov data. First, I follow the previous literature and focus only on silver plans.[10] Silver plans are convenient to study because offering at least one silver plan is mandatory for all participating insurers and silver is the only metal tier for which consumers can obtain subsidized cost-sharing. Likely for those reasons, silver plans are also the most commonly selected plans.[11] Second, I measure premiums for a 27-year old non-smoker who purchases coverage only for himself or herself. Dafny, Gruber, and Ody (2015) and Burke, Misra, and Sheingold (2014) examine premiums for the same class of consumers. Plan premiums for all classes of consumers exhibit similar patterns since ACA regulations impose a scale of allowable differentiation in premiums based on age, family size, and smoking status. Third, I use counties as the unit of observation rather than rating areas. While Dafny, Gruber, and Ody (2015) and Burke, Misra, and Sheingold (2014) define rating areas as markets, Dickstein et al. (2015) and Sheingold, Nguyen, and Chappel (2015) use counties. The fundamental issue is that insurer entry and plan menus can vary at the county-level, but premiums for the same plan can only vary across rating areas. Since nearly half of the multi-county rating areas in my data exhibit variation in insurer participation across counties, and this often leads to substantial differences when measuring the offered premium plus cost-sharing parameters, I define counties as markets but cluster standard errors by rating area.

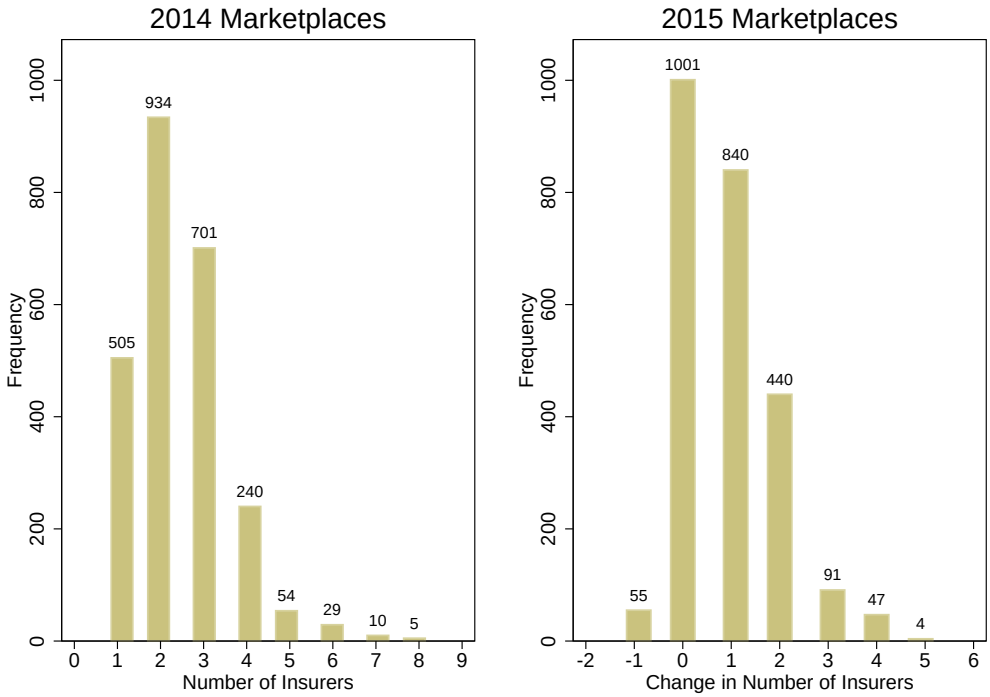
2.4.1 Insurers

Since issuers defined in the healthcare.gov data sometimes share the same parent company, I use supplementary information on company ownership from SNL

[10] I also only focus on the standard (i.e. 70 percent actuarial value) cost-sharing parameters. For consumers between 100 and 250 percent of the FPL, this represents the total cost-sharing that is split between the consumer and the government.

[11] In 2014, according to the April 2014 enrollment report, roughly two-thirds of Marketplace enrollees purchased a silver plan. See `http://aspe.hhs.gov/health/reports/2014/MarketPlaceEnrollment/Apr2014/ib_2014apr_enrollment.pdf`, accessed on 1/16/2015.

FIGURE 2.1: Insurer Participation in 2014 and 2015 Marketplaces



The histogram on the left summarizes insurer participation in the first year of the marketplaces. The histogram on the right summarizes the change in insurer participation in the second year of the marketplaces. In each histogram an observation is a county in the 31 states with federally facilitated marketplaces that also have more than one rating area. There are 2,478 observations.

Financial in order to aggregate issuers into unique insurers. For example, Coventry has been owned by Aetna since April 2013 but is denoted as a separate issuer from Aetna in the healthcare.gov data. Another example is Florida Blue, Florida Blue HMO, and Florida Health Care Plans, which are all separately-denoted companies in the healthcare.gov data that are owned by the same parent, Blue Cross Blue Shield of Florida. In the first year of the marketplaces, there are 90 unique insurers serving the 31 states in my data. The left panel of Figure 2.1 illustrates the variation in insurer entry across the 2,478 counties. Most counties had between one and three insurers, but some had as many as eight.

There was a large increase in insurer participation in the second year of the marketplaces. 1,422 of the 2,478 counties experienced an increase in insurer entry and only 55 counties experienced a decrease. The right panel of Figure 2.1 illustrates variation in the change in insurer participation from 2014 to 2015. Many counties

experienced one or two new insurers because of Assurant and United, that together accounted for nearly 80 percent of the total change in insurer participation.

2.4.2 County Characteristics

The challenge in identifying a causal effect of insurer entry on premium plus cost-sharing parameters is that unobserved characteristics about the market, related to demand or insurer variable costs, could affect both entry and pricing. Since I use cross-sectional variation to examine the first year of the marketplaces, it is important to control for county characteristics related to demand and insurer variable costs. I use several data sources to construct variables that are motivated by previous literature and related to the cost of health care, demand for health care, characteristics of potential consumers, and negotiation of medical service costs. The variable for market size is particularly important for my empirical strategy because I also use it to characterize residual rating areas. Since most marketplace enrollees qualify for federal subsidies, I define market size as the number of individuals in the county projected to be eligible for federal subsidies. I calculate this variable in two steps. First, I use the 2012 American Community Survey to approximate the percentage of individuals within each county who are eligible for federal subsidies.[12] I assume someone is eligible for a federal subsidy if they are (1) a U.S. citizen, (2) younger than 65 and without Medicare coverage, (3) not insured through an employer, and (4) between 100 percent and 400 percent of the federal poverty level. Second, I multiply the percent subsidy-eligible by the projected county population for 2013, taken from the Census QuickFacts.

For county characteristics besides market size, Appendix A provides motivation for their inclusion and contains details on their construction and definition. All of the county characteristic variables are summarized in Table 2.1. Most of them are measured at the county level except the average hospital price variable, which is constructed to replicate the hospital price variable used by Dafny, Gruber, and Ody

[12]The American Community Survey only identifies geographic units that contain at least 100,000 people. Thus, many of the subsidy eligibility rates are constant across small, neighboring counties.

TABLE 2.1: Summary of County Characteristics

	Mean	St Dev	Min	Max
Market Size (millions)	0.06	0.90	0.00	27.62
Per Capita Income ($)	37,428.47	9,422.65	17,922.00	116,978.05
Average Hospital Price ($)	10,609.87	2,249.19	1,310.04	22,435.42
% Black	0.11	0.16	0.00	0.85
% Hispanic	0.08	0.13	0.00	0.96
% Previously Uninsured	0.44	0.09	0.12	0.70
Urbanity	5.36	3.47	1.00	12.00
# Hospitals	1.75	3.46	0.00	69.00
# Hospitals in Largest System	0.58	0.83	0.00	10.00
# Top-30 Medical Schools	0.01	0.08	0.00	1.00
Medicare Advantage penetration	0.18	0.12	0.00	0.66

There are 2,478 observations, one for each county in the 31 states with federally facilitated marketplaces that also have more than one rating area. Market size is defined as the number of individuals projected to be eligible for federal subsidies. Hospital price is defined as net revenue per case-mix adjust discharge, excluding Medicare revenues and discharges, constructed using Medicare's HCRIS database per Dafny, Gruber, and Ody (2015) and Dafny (2009). Average hospital price is the discharge-weighted average of hospital prices for all hospitals in the rating area. It is thus equivalent for all counties within a rating area. Urbanity is from the Area Health Resources File and is measured on a scale of 1 to 12, 1 for the most urban and 12 for the most rural areas. Medicare Advantage penetration is the proportion of Medicare beneficiaries enrolled in a private Medicare Advantage plan.

(2015) and measured at the rating area level.[13] The summary statistics indicate a lot of variation in market size, particularly because some counties are very large. The average county has about 65,000 individuals eligible for federal subsidies while the median county has less than 4,000.

2.4.3 Outcome Variables

I define 36 outcome variables in order to summarize premium plus cost-sharing parameters for the available silver plans in a county. The outcome variables cover a range of 18 different service costs. For example, there is an outcome variable for premium plus cost-sharing if no medical services are used during the year. In this case, the premium plus cost-sharing, for a patient enrolled in a particular silver plan, is the plan's premium. There is also an outcome variable for premium plus cost-sharing if unlimited in-network medical services are used, in which case premium plus cost-sharing is the plan's premium plus out-of-pocket maximum.[14] The other 16 service costs cover intermediate levels of services a patient might incur. They

[13] A higher level of geographic aggregation for hospital prices is consistent with consumers often visiting hospitals outside of their county. Even though I replicate their methodology, my hospital price variable is generally higher in most rating areas as compared to the hospital price variable used by Dafny, Gruber, and Ody (2015). My estimates for the relationship of hospital price and premiums of silver plans are very similar to theirs, however. This holds true not only when I run my regressions, but also when I mimic theirs.

[14] If consumers use uncovered, out-of-network services, their cost could be much higher than the out-of-pocket maximum.

TABLE 2.2: Summary of Premium + Cost-Sharing in the 2014 and 2015 Marketplaces

Service Cost ($)	Service Category	Lowest-Possible Premium + Cost-Sharing ($)				Lowest-Premium Premium + Cost-Sharing ($)			
		2014		2015		2014		2015	
		Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
0	N/A	2,620	485	2,684	477	2,620	485	2,684	477
125	Primary Care	2,677	497	2,734	491	2,681	497	2,741	492
125	Specialist	2,707	496	2,769	486	2,709	496	2,773	487
250	Emerg. Room	2,750	495	2,844	496	2,771	497	2,867	496
1,500	Inpatient	3,525	709	3,549	755	3,771	794	3,914	775
500	Primary Care	2,745	533	2,778	523	2,823	566	2,873	570
500	Specialist	2,836	553	2,875	530	2,938	605	2,873	570
650	Emerg. Room	2,867	541	2,984	572	2,984	579	3,136	579
3,000	Inpatient	3,981	922	3,997	977	4,735	1,241	4,963	1,203
1,000	Primary Care	2,808	549	2,833	533	3,027	701	3,062	711
1,000	Specialist	2,976	614	2,996	553	3,204	702	3,271	688
1,400	Emerg. Room	2,999	697	3,137	751	3,388	872	3,712	1,042
5,600	Inpatient	4,533	1,102	4,493	1,127	5,515	1,487	5,771	1,507
1,500	Primary Care	2,867	565	2,884	536	3,228	861	3,248	874
1,500	Specialist	3,104	675	3,106	568	3,493	853	3,562	840
2,900	Emerg. Room	3,111	937	3,249	966	3,998	1,404	4,482	1,400
9,750	Inpatient	5,205	1,261	5,110	1,282	6,311	1,658	6,458	1,637
∞	N/A	7,361	1,040	7,206	1,042	8,156	1,052	8,313	1,086

N = 2,478 for each year. Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The left panel summarizes lowest possible premium + cost-sharing in any silver plan in the county and the right panel summarizes premium + cost-sharing in the silver plan in the county with the lowest premium. All amounts shown are annual.

cover four different service costs each for four different categories of in-network services: primary care, specialist care, emergency room care, and inpatient care. The four service costs within each category represent the distribution of service costs observed in the Medical Expenditure Panel Survey for the non-elderly population in 2012. For more details on the outcome variables, see Appendix A.

Given a particular service cost, because plans have different premiums and cost-sharing parameters, a patient's premium plus cost-sharing will vary depending on which plan he or she chose. I summarize premium plus cost-sharing parameters across silver plans in the county in two ways. First, for a given service cost, I take the lowest premium plus cost-sharing among all silver plans in the county. Second, I measure the premium plus cost-sharing parameters from the silver plan in the county with the lowest premium.

Table 2.2 summarizes the lowest-possible premium plus cost-sharing (left panel) and premium plus cost-sharing in the plan with the lowest premium (right panel) for the various service costs in each of the first two years of the marketplaces. There are a few notable patterns. First, cost-sharing parameters vary in generosity for the different categories of services. Cost-sharing parameters for primary care are the

most generous while cost-sharing parameters for inpatient care are the least generous. Second, there is substantial savings available to consumers from plans with higher premiums if they are able to anticipate their medical utilization.[15] For example, in 2014 it would have been possible for someone with a $5,600 visit to the hospital to save almost $1,000 had they enrolled in the silver plan with the lowest-possible premium plus cost-sharing for that service rather than the silver plan with the lowest premium. Third, cost-sharing parameters changed from 2014 to 2015 differentially by category of service. For example, inpatient cost-sharing parameters decreased while emergency room cost-sharing parameters increased.

2.5 Empirical Strategy

The goal of this chapter is to estimate the marginal effect of an additional insurer on premium plus cost-sharing parameters available to consumers from silver plans in their county. The challenge of this exercise is that demand and insurer variable costs can influence both entry and pricing. In this section I develop an identification strategy involving instrumental variables. I then examine the identification assumptions and discuss how the estimates should be interpreted.

2.5.1 Regression Models

I use three separate instrumental variables regression models. I start with a model that relies on cross-sectional variation to estimate the effect of an additional insurer on premium plus cost-sharing parameters in the first year of the marketplaces. I then introduce two additional and separate models that rely on panel variation to estimate the effect of an additional new insurer on premium plus cost-sharing parameters in the second year of the marketplaces.

2014 Marketplaces

If y_m is one of the patient cost variables (e.g. the lowest-possible premium plus cost-sharing for a visit to the emergency room with service cost of $650) for county

[15] Of course, it is also possible that the service costs for the same medical procedures might differ substantially across silver plans. It is not clear if this variation would be correlated with premiums or cost-sharing parameters.

m, an example OLS regression equation to relate insurer entry and premium plus cost-sharing parameters would be:

$$ln(y_m) = \alpha X_m + \beta N_m + \varepsilon_m \tag{2.1}$$

Observations are the 2,478 counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. X_m is a vector containing characteristics of county m, N_m is the number of insurers participating in county m, and ε_m contains all other county-specific variables that affect insurer pricing. The variables in X_m are the same as those in Table A1 plus a constant. Since premiums for an identical plan cannot vary across multiple counties within a rating area, ε_m is clustered by rating area.

The problem with using OLS to estimate equation 2.1 is that any components of demand or insurer variable costs contained in ε_m can affect both insurer pricing and entry, which would bias the estimate of β. The direction of the bias is theoretically ambiguous. Unobserved insurer variable costs would influence pricing and entry in opposite directions while unobserved demand would influence premiums and entry in the same direction. Variation in insurer fixed costs would be an ideal instrument for insurer entry because fixed costs influence profits, and thus entry, but not pricing.

We can decompose fixed costs for insurers into two components, a local component and a state component. Examples of local fixed costs include marketing and establishing a network of medical providers. The state fixed costs are costs associated with regulatory compliance, which are likely to be substantial for insurers in their first year of participating in the marketplaces. They include navigating the plan approval process, providing brochures defining plan benefits, and eventually submitting enrollee risk scores.[16] The state fixed costs imply that insurers are more likely to enter a marginal county if they expect high profits in other counties in that state. This leads to plausibly exogenous variation across states that can be used to instrument for insurer entry. For example, suppose that two counties are identical in every way except that county A is in Arizona and county B is in Wyoming. If the counties in Arizona besides county A are more lucrative to an insurer than the

[16]The dimensions of each plan that are subject to approval include provider network, benefits, actuarial value, and premiums.

counties in Wyoming besides county B, the insurer is more likely to enter county A than county B.

I use three instruments for the number of insurers in a county: (1) the number of residual rating areas, (2) the average market size of the residual rating areas, and (3) the total market size of the residual rating areas.[17] The residual markets are defined as rating areas rather than counties because residual counties in the same rating area are likely to influence demand or insurer variable costs. All else equal, more and larger residual rating areas increase the likelihood that insurers already pay the state fixed cost in a residual rating area and thus incrementally lower their total fixed cost. The total residual market size, the product of the other two instruments, controls for negative cross-derivatives. Additional residual rating areas are likely to be most important when their average market size is small. Similarly, increased average market size for residual ratings is likely to be most important when there are only a few of them. My preferred specification for estimating the effect of an additional insurer on premium plus cost-sharing parameters in the 2014 marketplaces extends equation 2.1 by using the vector of three instruments Z_m for the number of insurers:

$$\begin{aligned} ln(y_m) &= \alpha X_m + \beta N_m + \varepsilon_m \\ N_m &= \gamma X_m + \pi Z_m + \nu_m \end{aligned} \tag{2.2}$$

2015 Marketplaces

Adding data from the second year of the marketplaces allows me to estimate the effect of new insurer entry on changes to premium plus cost-sharing parameters. The advantage of this variation is that all time-invariant components of demand and insurer variable costs can be differenced out. The following equation represents an example first-differences OLS specification:[18]

$$ln(y_{m2}) - ln(y_{m1}) = \alpha + \beta(N_{m2} - N_{m1}) + \varepsilon_m \tag{2.3}$$

[17]The instruments are of similar spirit to instruments for airline entry used by Berry (1992) and Ciliberto and Tamer (2009).

[18]With only two time periods, the first-differences and pooled fixed effects approaches are equivalent. I add a constant term, that does not difference out, in order to allow for a mean inflation rate from 2014 to 2015.

Similar to equations 2.1 and 2.2, observations are counties indexed by m. The numeric subscripts denote either the first year of the marketplaces or the second. Any variable associated with county m besides the number of insurers that changes from 2014 to 2015 is captured in ε_m. Sheingold, Nguyen, and Chappel (2015) use a similar OLS specification in their analysis of premium changes from the first to the second year of the marketplaces. The problem with using OLS, however, is that β will be biased if new insurer entry occurred in counties where demand or insurer variable costs changed from 2014 to 2015. I address this potential endogeneity by separately using two sets of instruments for changes in insurer entry from 2014 to 2015.

The first set of instruments is the residual rating areas instruments used for the cross-sectional 2014 analysis. Since most of the new entry in 2015 was due to Assurant and United joining the marketplaces for the first time, the variation in state fixed costs associated with regulatory compliance are still applicable. The instrumental variables regression equation extends equation 2.3 with the same vector Z_m of instruments used in equation 2.2:

$$\begin{aligned} ln(y_{m2}) - ln(y_{m1}) &= \alpha + \beta(N_{m2} - N_{m1}) + \varepsilon_m \\ N_{m2} - N_{m1} &= \gamma + \pi Z_m + \nu_m \end{aligned} \tag{2.4}$$

The second set of instruments measures pre-ACA market shares for Assurant and United. The idea is that pre-ACA market shares measure variation in local fixed costs, as opposed to state fixed costs, for Assurant and United. Each insurer is likely to have lower local fixed costs in markets where they had a larger presence before the ACA due to pre-existing relationships with providers and reputation with consumers. The are three pre-ACA market shares instruments. The first two are the 2012 shares in the individual market for Assurant and United. The available data, which I take from the Medical Loss Ratio files, dictates that the shares be measured at the state level.[19] Because Assurant and United are competitors, however, I also include the product of their 2012 market shares as a third instrument. All else equal, one insurer is most likely to enter a county where it previously had a large presence and

[19]The Medical Loss Ratio files are published by CMS's Center for Consumer Information and Insurance Oversight. See `https://www.cms.gov/CCIIO/Resources/Data-Resources/mlr.html`, accessed on 2/20/16.

TABLE 2.3: Instrument Values in Every State

	Residual Rating Areas:					Pre-ACA Shares:		
	No.	Avg. Size (millions)		Tot. Size (millions)		Assurant	United	Assurant ×
State		Mean	St. Dev.	Mean	St. Dev			United
AK	2	0.061	0.014	0.121	0.028	0.083	0.045	0.004
AL	12	0.073	0.011	0.871	0.126	0.009	0.046	0.000
AR	5	0.079	0.011	0.476	0.064	0.022	0.086	0.002
AZ	6	3.219	0.878	19.313	5.267	0.041	0.198	0.008
FL	66	0.231	0.010	15.242	0.645	0.019	0.176	0.003
GA	15	0.142	0.033	2.131	0.495	0.043	0.052	0.002
IA	6	0.049	0.004	0.294	0.021	0.034	0.035	0.001
IL	12	2.218	0.203	26.615	2.436	0.046	0.063	0.003
IN	16	0.124	0.016	1.979	0.258	0.069	0.124	0.009
KS	6	0.073	0.007	0.437	0.045	0.047	0.055	0.003
LA	7	0.137	0.015	0.959	0.105	0.020	0.034	0.001
ME	3	0.042	0.005	0.126	0.015	0.000	0.004	0.000
MI	15	0.378	0.036	5.665	0.537	0.048	0.139	0.007
MO	9	0.212	0.034	1.904	0.309	0.073	0.184	0.013
MS	5	0.065	0.015	0.323	0.077	0.056	0.166	0.009
MT	3	0.048	0.004	0.143	0.012	0.229	0.000	0.000
NC	15	0.229	0.019	3.439	0.280	0.017	0.027	0.001
ND	3	0.015	0.003	0.046	0.010	0.082	0.002	0.000
NE	3	0.133	0.023	0.399	0.068	0.077	0.108	0.008
OH	16	0.307	0.039	4.919	0.626	0.032	0.112	0.004
OK	4	0.202	0.040	0.808	0.159	0.077	0.062	0.013
PA	8	0.695	0.121	5.556	0.971	0.018	0.048	0.001
SC	45	0.015	0.000	0.682	0.022	0.060	0.188	0.011
SD	3	0.032	0.005	0.095	0.015	0.024	0.009	0.000
TN	7	0.308	0.039	2.157	0.271	0.053	0.082	0.004
TX	25	2.114	0.249	52.839	6.230	0.057	0.088	0.005
UT	5	0.305	0.102	1.525	0.511	0.022	0.007	0.000
VA	11	0.090	0.011	0.995	0.117	0.017	0.049	0.001
WI	15	0.111	0.008	1.668	0.118	0.091	0.164	0.015
WV	10	0.023	0.001	0.233	0.005	0.060	0.186	0.011
WY	2	0.016	0.008	0.032	0.016	0.154	0.114	0.018

Size represents the number of people projected to be eligible for federal subsidies, measured in millions of people. Rating areas are geographic areas over which an identical plan cannot charge different premiums.

the other insurer previously had a small presence. Accounting for competition between Assurant and United is important in order to capture variation in the number of new entrants.[20] Of the 1,307 counties in my data that either Assurant or United entered in 2015, both insurers entered 30 percent of those counties. If we denote the three pre-ACA shares with a vector Q_m, the instrumental variables regression equation is identical to equation 2.4 except that Q_m replaces Z_m.

2.5.2 Addressing Threats to Identification

Table 2.3 presents the mean value for each instrument in each state. Since the instruments measure cross-state variation, any unobserved state-level heterogeneity that is correlated with the instruments would compromise identification.

[20]Results are similar, though less precise, if the product term is excluded. Results are also similar if the endogenous variable is an indicator for at least one new insurer rather than the count of new insurers. In this case, indicators for the maximum number of pre-ACA lives, covered by Assurant or United, exceeding thresholds of 500 and 10,000 are sufficiently predictive instruments in the first stage.

2014 Marketplaces

The identification assumption in equation 2.2 is that the instruments Z_m are orthogonal to any unobserved components of demand and insurer variable costs. One reason to worry about the orthogonality assumption is that consumers may frequently visit medical providers outside of their own rating area. In particular, the estimate of β will be biased if hospitals in larger rating areas tend to charge different service costs than hospitals in smaller rating areas. When aggregated to the rating area level, however, the market size and hospital price variables have a very weak correlation coefficient of ρ = -0.03. Of course, there may be other mechanisms by which more and larger residual rating areas could be correlated with demand or insurer variable costs. In section 2.6.2, I perform a falsification test to show that the residual rating areas instruments are uncorrelated with premiums, claims, and utilization in the pre-ACA individual insurance market.

We might also worry about state-specific regulations that took effect in 2014. While an advantage of examining only the federally facilitated marketplaces is the general uniformity of the marketplaces across states, there are a few institutional differences across states that existed in 2014 but not in 2013. For example, Kowalski (2014) reports the states that expanded Medicaid and the states that allowed individuals to keep coverage from previously purchased non-ACA-compliant "non-grandfathered" plans. In section 2.6.2, I demonstrate the robustness of my estimates to controlling for which states expanded Medicaid and which states allowed non-grandfathered plans.

2015 Marketplaces

Though equation 2.4 uses the same set of instruments as equation 2.2, the identification assumption is different. In equation 2.4, the instruments Z_m must be orthogonal to any changes to demand or insurer variable costs between 2014 and 2015. For the version of equation 2.4 that uses the pre-ACA shares instruments in place of the residual rating areas instruments, the identification assumption is similar.

Any component of demand or insurer variable cost that has been changing over time would be a threat to identification. For example, we might be concerned about

the recent trend of provider consolidation. In section 2.6.2, I perform a falsification test and find reassuring evidence that variables in both sets of instruments are uncorrelated with changes in premiums, claims, and utilization in the pre-ACA individual insurance market in the years leading up to 2014. Of course, this does not rule out the correlation of the instruments with any sharp changes to demand or insurer variable costs during 2014. As long as the results are similar whether the residual rating areas or pre-ACA shares instruments are used, however, these sharp changes would have to correlated with *both* sets of instruments in order to make the estimates of β unreliable.

2.5.3 Addressing Limitations to Interpretation

There are a few important caveats to interpreting estimates from the regression models presented in this section. First, the number of insurers is not necessarily a reflection of market competitiveness. A market with many insurers is not competitive if one insurer serves most of the market. This matters for my estimates because a small insurer may induce a different effect than a large insurer. In my cross-sectional analysis of the first year of the marketplaces, the estimates of β reflect the effect of entry by the average marginal insurer. In my analysis of the second year of the marketplaces, since the variation primarily comes from the new entry of Assurant and United, the estimates of β should be interpreted as the effect of new entry by a national insurer.

Second, my estimates reflect the effect of an additional insurer on offered premiums and cost-sharing parameters. They cannot be interpreted as an effect of insurer entry on premiums and cost-sharing parameters in purchased plans without strong assumptions about how patients choose among offered plans. The two ways I measure the offered premium plus cost-sharing parameters represent two extreme plan selection rules. The lowest-possible premium plus cost-sharing is the relevant measure for patients who perfectly anticipate their medical utilization and choose the plan with lowest combined premium and cost-sharing. The lowest-premium plan's premium plus cost-sharing is the relevant measure for patients who choose the plan with the lowest premium. Since plan-level enrollment data has not been made available for the marketplaces, it is not possible to empirically evaluate the

validity of either plan selection rule. Recent studies, that examine either employer-sponsored health insurance or Medicare, demonstrate that plan selection rules are difficult to model. Abaluck and Gruber (2011) find that consumers value premium dollars more than expected cost-sharing dollars. Bhargava, Loewenstein, and Sydnor (2015) find that the majority of consumers choose financially dominated plans when given the option to build their own cost-sharing parameters. Many other researchers (e.g. Handel, 2013; Ericson, 2014; Miller, 2014; Polyakova, 2016) find that consumers do a poor job of re-optimizing their health plan selection every year. Given this literature, it is possible that only a small number of consumers follow one of the two plan selection rules my outcome variables represent.

Third, interpreting my estimates as an effect of insurer entry on offered *unconditional* patient costs, rather than offered premium plus cost-sharing parameters, requires that service costs are unaffected by insurer entry. This is likely not a good assumption, because a broad literature (e.g. Ho and Lee, 2016; Melnick, Shen, and Wu, 2011; Moriya, Vogt, and Gaynor, 2010) shows that increased insurer competition increases service costs. For patients who owe coinsurance for marginal medical spending, higher service cost implies a higher *unconditional* patient cost that my estimates do not capture. Thus, my estimates likely overstate the effect of insurer entry to decrease offered *unconditional* patient costs and understate the effect of insurer entry to increase offered *unconditional* patient costs.

2.6 Results

In this section I discuss my estimates for the marginal effect of insurer entry on premium plus cost-sharing parameters. I also perform falsification and robustness checks. Finally, I include a supplementary analysis to examine the importance of insurer entry influencing insurer bargaining power over medical providers.

2.6.1 Main Estimates

I start by examining the effect of insurer entry on the benchmark premium, the second-lowest silver premium, in order to compare my results to previous work. I then examine the effect of insurer entry on premium plus cost-sharing parameters.

TABLE 2.4: Effect of Insurer Entry on (Log) Benchmark Premiums in the 2014 and 2015 Marketplaces

	(1) OLS Dep. Var. = ln(Benchmark Premium)	(2) First Stage Dep. Var. = # Insurers or Δ # Insurers	(3) Red. Form Dep. Var. = ln(Benchmark Premium)	(4) IV Dep. Var. = ln(Benchmark Premium)
2014 Marketplaces				
Residual Rating Areas Instruments (F = 88)				
# Insurers	-0.031***			-0.051***
	(0.008)			(0.015)
Avg. Residual Market Size		1.498***	-0.049**	
		(0.103)	(0.025)	
# Residual Markets		0.004	0.001*	
		(0.003)	(0.001)	
Total Residual Market Size		-0.062***	0.000	
		(0.006)	(0.001)	
2015 Marketplaces				
Residual Rating Areas Instruments (F = 30)				
Δ # Insurers	-0.034***			-0.005
	(0.006)			(0.017)
Avg. Residual Market Size		0.436***	-0.002	
		(0.128)	(0.014)	
# Residual Markets		0.036***	0.000	
		(0.004)	(0.000)	
Total Residual Market Size		-0.036***	0.001*	
		(0.009)	0.001	
2015 Marketplaces				
Pre-ACA Shares Instruments (F = 20)				
Δ # Insurers	-0.034***			-0.021
	(0.006)			(0.020)
Assurant Pre-ACA Share		2.973***	-0.292	
		(0.803)	(0.188)	
United Pre-ACA Share		11.712***	-0.277	
		(1.543)	(0.260)	
Assurant Pre-ACA Share ×		-142.800***	5.228**	
United Pre-ACA Share		(26.755)	(2.459)	

Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The top panel includes data from the first year of the marketplaces only. The middle and bottom panels include data from the first and second years of the marketplaces in a first-differences framework. The residual rating areas instruments are (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. Market size is the projected number of individuals eligible for federal subsidies, measured in millions. The pre-ACA shares instruments are (1) the 2012 market share for Assurant Health in the state, (2) the 2012 market share for UnitedHealth in the state, (3) the product of the 2012 market shares for Assurant Health and UnitedHealth in the state. The unreported covariates (top panel only) are: market size, fraction previously uninsured, log of per-capita income, log of hospital price, percent black, percent Hispanic, urbanity on a scale of 1 to 12, Medicare Advantage penetration, number of hospitals, and number of top-30 medical schools. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

All estimates are computed separately for the first and second years of the marketplaces.

Effect of Insurer Entry on Benchmark Premiums

Table 2.4 reports OLS, first stage, reduced form, and IV estimates related to the effect of an additional insurer on benchmark premiums in the 2014 (top panel) and 2015 (bottom two panels) marketplaces. The coefficients for the county characteristic variables are omitted from the top panel. Estimates in the bottom panel come from first-differences regressions, which difference out the county characteristic variables.

The OLS estimates in the first column of Table 2.4 are similar for both years and match analogous estimates from Burke, Misra, and Sheingold (2014) and Sheingold, Nguyen, and Chappel (2015). All else equal, an additional insurer in a county was associated with roughly a 3 percent lower benchmark premium.

The first stage estimates for the residual rating areas instruments are similar for both years and consistent with the motivation presented in section 2.5.1. All else equal, more and larger residual rating areas were associated with more insurer participation. For a county with the median number of residual rating areas (7), a 1 million increase (corresponding to 1.1 standard deviations) in the average market size of the residual rating areas was associated with 1.064 (1.498 - 7*0.062) additional insurers in 2014. In 2015, the same increase in average market size was associated with 0.184 new insurers. More residual rating areas in the state were associated with more insurers, but the coefficient is only statistically distinguishable from zero for the 2015 marketplaces. For a county with the median market size of residual rating areas (0.16 million), an additional residual rating area was associated with 0.03 new insurers. The total market size in the residual rating areas of a state, the product of the other two instruments, has a negative and statistically significant coefficient for both years. The overall F-statistic for relevance of the residual rating areas instruments is 88 in the 2014 marketplaces and 30 in the 2015 marketplaces.

The first stage estimates for the pre-ACA shares instruments are also consistent with the motivation presented in section 2.5.1. Larger pre-ACA shares for Assurant and United were associated with more new entry, particularly where only one insurer had a strong pre-ACA presence. In a state where United had no presence in the 2012 individual market, a 10 percentage point increase (about 2.7 standard deviations) in Assurant's 2012 share was associated with 0.3 additional new insurers entering in 2015. In a state with the median United share of the 2012 individual market (0.082), however, the same 10 percentage point increase in Assurant's 2012 share was associated with 0.8 fewer new insurers in 2015. A 10 percentage point increase (about 1.8 standard deviations) in United's 2012 share was associated with 1.2 new insurers in states where Assurant had no 2012 presence and 0.5 new insurers in states with the median Assurant share of the 2012 individual market (0.047). The F-statistic for the pre-ACA shares instruments is 20.

The main takeaways from Table 2.4 are the IV estimates in the fourth column. In the first year of the marketplaces, an additional insurer induced benchmark premiums to be 5 percent lower on average. The estimate is remarkably similar to the conclusion of Dafny, Gruber, and Ody (2015), who use a different identification strategy to address the potential endogeneity of insurer competition. Since United did not participate in any counties in 2014, they use local variation in United's pre-ACA market share as a source of cross-sectional variation in the predicted effect of United's exit. They estimate that the participation of an additional insurer in all 2014 marketplaces would have lowered benchmark premiums by 5 percent. While the IV estimate in the first column serves as an identification check based on previous estimates, the IV estimates in the bottom two panels of Table 2.4 are a new addition to the literature. On average, a new insurer in the second year of the marketplaces had no statistically distinguishable effect on benchmark premiums.

Effect of Insurer Entry on Premium + Cost-Sharing Parameters: 2014 Marketplaces

Table 2.4 presents OLS and IV estimates for the effect of an additional insurer in the first year of the marketplaces on premium plus cost-sharing parameters. In columns (1) and (2), the outcome variables measure the lowest-possible premium plus cost-sharing for various service costs. In columns (3) and (4), the outcome variables measure premium plus cost-sharing for various service costs in the plan with the lowest premium. Coefficients for the county characteristic variables are not reported. The estimates generally indicate that an additional insurer decreased premium plus cost-sharing parameters by 5 percent or more. The only exception is that an additional insurer had no effect on the parameters' tail, where the patient uses enough medical services so that the out-of-pocket maximum is binding. The largest reductions in premium plus cost-sharing parameters due to an additional insurer, which ranged from 10 to 15 percent, were for inpatient services. Not only did competition in the first year of the marketplaces lower premiums, it also lowered inpatient cost-sharing parameters.

TABLE 2.5: Effect of Insurer Entry on (Log) Premium + Cost-Sharing in the 2014 Marketplaces

Service Cost ($)	Service Category	Outcome = ln(Lowest-Possible Premium + Cost-Sharing) Variable = # Insurers				Outcome = ln(Lowest-Premium Premium + Cost-Sharing Variable = # Insurers			
		OLS		IV		OLS		IV	
0	N/A	-0.038***	(0.008)	-0.055***	(0.015)	-0.038***	(0.008)	-0.055***	(0.015)
125	Primary Care	-0.038***	(0.008)	-0.056***	(0.015)	-0.037***	(0.008)	-0.055***	(0.015)
125	Specialist	-0.038***	(0.008)	-0.055***	(0.015)	-0.038***	(0.008)	-0.055***	(0.015)
250	Emerg. Room	-0.034***	(0.008)	-0.058***	(0.014)	-0.034***	(0.008)	-0.059***	(0.014)
1,500	Inpatient	-0.047***	(0.009)	-0.110***	(0.024)	-0.036***	(0.010)	-0.092***	(0.031)
500	Primary Care	-0.042***	(0.008)	-0.056***	(0.015)	-0.038***	(0.008)	-0.057***	(0.016)
500	Specialist	-0.043***	(0.008)	-0.060***	(0.016)	-0.037***	(0.009)	-0.058***	(0.020)
650	Emerg. Room	-0.035***	(0.008)	-0.062***	(0.014)	-0.029***	(0.008)	-0.070***	(0.017)
3,000	Inpatient	-0.059***	(0.010)	-0.144***	(0.028)	-0.044***	(0.013)	-0.126***	(0.044)
1,000	Primary Care	-0.043***	(0.008)	-0.055***	(0.015)	-0.038***	(0.009)	-0.059***	(0.020)
1,000	Specialist	-0.046***	(0.009)	-0.058***	(0.015)	-0.044***	(0.009)	-0.072***	(0.020)
1,400	Emerg. Room	-0.050***	(0.009)	-0.066***	(0.015)	-0.023*	(0.012)	-0.090***	(0.028)
5,600	Inpatient	-0.066***	(0.010)	-0.154***	(0.026)	-0.042***	(0.015)	-0.129***	(0.050)
1,500	Primary Care	-0.044***	(0.008)	-0.054***	(0.015)	-0.039***	(0.011)	-0.061**	(0.025)
1,500	Specialist	-0.049***	(0.009)	-0.056***	(0.015)	-0.047***	(0.010)	-0.078***	(0.025)
2,900	Emerg. Room	-0.068***	(0.012)	-0.075***	(0.017)	-0.024	(0.018)	-0.128***	(0.042)
9,750	Inpatient	-0.069***	(0.010)	-0.161***	(0.020)	-0.038***	(0.014)	-0.117**	(0.048)
∞	N/A	-0.027***	(0.007)	0.002	(0.017)	-0.008	(0.007)	0.010	(0.014)

N = 2,478. Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The coefficients (β) reported are for the number of insurers variable. The instruments for the number of insurers are (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. Market size is the projected number of individuals eligible for federal subsidies, measured in millions. The unreported covariates are: market size, fraction previously uninsured, log of per-capita income, log of hospital price, percent black, percent Hispanic, urbanity on a scale of 1 to 12, Medicare Advantage penetration, number of hospitals, and number of top-30 medical schools. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

TABLE 2.6: Effect of Insurer Entry on (Log) Lowest-Possible Premium + Cost-Sharing in the 2015 Marketplaces

Service Cost ($)	Service Category	Outcome = ln(Lowest -Possible Premium + Cost-Sharing) Variable = Δ # Insurers					
		OLS		IV: Residual Rating Areas		IV: Pre-ACA Shares	
0	N/A	-0.016***	(0.006)	0.005	(0.017)	-0.017	(0.022)
125	Primary Care	-0.018***	(0.006)	0.006	(0.018)	-0.005	(0.022)
125	Specialist	-0.015**	(0.006)	0.006	(0.017)	-0.009	(0.022)
250	Emerg. Room	-0.010*	(0.006)	0.002	(0.015)	-0.006	(0.023)
1,500	Inpatient	-0.032***	(0.006)	-0.095***	(0.014)	-0.093***	(0.025)
500	Primary Care	-0.024***	(0.007)	0.003	(0.019)	0.011	(0.022)
500	Specialist	-0.017***	(0.006)	-0.002	(0.017)	-0.002	(0.022)
650	Emerg. Room	-0.005	(0.007)	0.009	(0.015)	0.005	(0.024)
3,000	Inpatient	-0.048***	(0.007)	-0.156***	(0.025)	-0.161***	(0.035)
1,000	Primary Care	-0.027***	(0.007)	-0.008	(0.018)	0.006	(0.022)
1,000	Specialist	-0.019***	(0.007)	-0.007	(0.017)	0.004	(0.022)
1,400	Emerg. Room	0.002	(0.008)	0.024	(0.017)	0.007	(0.025)
5,600	Inpatient	-0.048***	(0.007)	-0.160***	(0.025)	-0.161***	(0.033)
1,500	Primary Care	-0.029***	(0.007)	-0.017	(0.016)	0.002	(0.022)
1,500	Specialist	-0.023***	(0.008)	-0.013	(0.017)	0.008	(0.023)
2,900	Emerg. Room	0.001	(0.009)	0.029	(0.018)	0.001	(0.028)
9,750	Inpatient	-0.047***	(0.008)	-0.210***	(0.035)	-0.177***	(0.036)
∞	N/A	-0.022***	(0.005)	-0.047***	(0.011)	-0.064***	(0.021)

N = 2,478. Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The coefficients (β) reported are for the change in the number of insurers variable, taken from first-differences regressions. The instruments for the change in the number of insurers in the middle panel are: (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. The instruments for the change in the number of insurers in the right panel are: (1) 2012 share for Assurant Health in the state, (2) 2012 share for UnitedHealth in the state, and (3) the product of the 2012 shares for Assurant Health and UnitedHealth in the state. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

TABLE 2.7: Effect of Insurer Entry on (Log) Premium + Cost-Sharing from the Lowest Premium Plan in the 2015 Marketplaces

Service Cost ($)	Service Category	Outcome = ln(Lowest-Premium Premium + Cost-Sharing) Variable = Δ # Insurers					
		OLS		IV: Residual Rating Areas		IV: Pre-ACA Shares	
0	N/A	-0.016***	(0.006)	0.005	(0.017)	-0.017	(0.022)
125	Primary Care	-0.018***	(0.006)	0.006	(0.018)	-0.004	(0.022)
125	Specialist	-0.015**	(0.006)	0.007	(0.017)	-0.008	(0.022)
250	Emerg. Room	-0.009	(0.006)	0.005	(0.015)	0.004	(0.023)
1,500	Inpatient	-0.024***	(0.007)	-0.047***	(0.014)	-0.036	(0.024)
500	Primary Care	-0.024***	(0.008)	0.017	(0.022)	0.046*	(0.026)
500	Specialist	-0.018**	(0.008)	0.013	(0.018)	0.047	(0.030)
650	Emerg. Room	0.002	(0.008)	0.003	(0.015)	0.037	(0.028)
3,000	Inpatient	-0.028***	(0.009)	-0.089***	(0.025)	-0.089***	(0.029)
1,000	Primary Care	-0.030***	(0.010)	0.025	(0.027)	0.099***	(0.034)
1,000	Specialist	-0.013	(0.009)	0.019	(0.022)	0.057*	(0.032)
1,400	Emerg. Room	0.011	(0.016)	-0.020	(0.028)	0.061	(0.048)
5,600	Inpatient	-0.023	(0.010)	-0.144***	(0.038)	-0.204***	(0.041)
1,500	Primary Care	-0.036***	(0.013)	0.031	(0.032)	0.143***	(0.042)
1,500	Specialist	-0.012	(0.011)	0.025	(0.026)	0.085**	(0.040)
2,900	Emerg. Room	0.050**	(0.024)	-0.004	(0.038)	0.138**	(0.061)
9,750	Inpatient	-0.023**	(0.010)	-0.185***	(0.045)	-0.264***	(0.048)
∞	N/A	0.006	(0.008)	-0.064***	(0.022)	-0.125***	(0.031)

N = 2,478. Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The coefficients (β) reported are for the change in the number of insurers variable, taken from first-differences regressions. The instruments for the change in the number of insurers in the middle panel are: (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. The instruments for the change in the number of insurers in the right panel are: (1) 2012 share for Assurant Health in the state, (2) 2012 share for UnitedHealth in the state, and (3) the product of the 2012 shares for Assurant Health and UnitedHealth in the state. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

Effect of Insurer Entry on Premium + Cost-Sharing Parameters: 2015 Marketplaces

Table 2.6 presents OLS and IV estimates for the effect of a new insurer in the 2015 marketplaces on lowest-possible premium plus cost-sharing parameters. The estimates come from first-differences regressions and there are no unreported coefficients. The OLS estimates are in the left panel, the residual rating areas IV estimates are in the middle panel, and the pre-ACA shares IV estimates are in the right panel. The IV estimates with either set of instruments are similar. A new insurer had no statistically distinguishable effect on the lowest-possible premium plus cost-sharing parameters except for inpatient services and services with sufficiently large service costs. For a patient using inpatient services, a new insurer reduced premium plus cost-sharing parameters by 10 to 20 percent on average, with larger reductions for more expensive inpatient stays. A new insurer reduced premium plus out-of-pocket maximum by 5 or 6 percent on average. Table 2.7 reports analogous estimates using outcome variables that measure premium plus cost-sharing parameters from the silver plan with the lowest premium. The estimates are noisier but similar to the ones in Table 2.6. A notable difference is that the pre-ACA shares instruments indicate that a new insurer *increased* premium plus cost-sharing parameters for expensive primary care, specialist, and emergency room visits.

The implication of the estimates in Table 2.6 and Table 2.7 is that new insurers in 2015 did not lower premiums, but did lower inpatient cost-sharing parameters.[21] This might be because average insurer participation was substantially greater in 2015 versus 2014. I investigate this explanation further in Table 2.8. In particular, I run first-difference regressions separately for two subsamples of counties: (1) counties with two or fewer insurers in the first year of the marketplaces and (2) counties with three or more insurers in the first year of the marketplaces. All 36 IV estimates are lower for the set of counties with fewer insurers in 2014. The most striking estimates in Table 2.8 are those for premium plus cost-sharing parameters associated

[21] This does not necessarily mean that patient costs for using inpatient services decreased, because insurer entry also could have increased inpatient service costs. In Appendix B, I describe a simulation exercise I used to check how the estimates would change if each additional insurer increased the inpatient service cost by 7.5 percent, which is consistent with estimates from Ho and Lee (2016). The estimates were, as expected, lower than my main estimates that hold service cost constant, but only by a very small amount. Thus, it is likely that insurer entry lowered offered *unconditional* patient costs for inpatient services.

TABLE 2.8: Effect of Insurer Entry on (Log) Lowest-Possible Premium + Cost-Sharing in the 2015 Marketplaces by 2014 Insurer Participation

Service Cost ($)	Service Category	Outcome = ln(Lowest-Possible Premium + Cost-Sharing) Variable = Δ # Insurers							
		IV: Residual Rating Areas				IV: Pre-ACA Shares			
		2014 Insurers ≤ 2 N = 1,439		2014 Insurers > 2 N = 1,039		2014 Insurers ≤ 2 N = 1,439		2014 Insurers > 2 N = 1,039	
0	N/A	-0.005	(0.024)	0.028	(0.020)	-0.021	(0.025)	0.021	(0.019)
125	Primary Care	-0.008	(0.024)	0.030	(0.020)	-0.009	(0.023)	0.026	(0.020)
125	Specialist	-0.005	(0.024)	0.031	(0.019)	-0.018	(0.024)	0.029	(0.020)
250	Emerg. Room	-0.015	(0.019)	0.037*	(0.020)	-0.029	(0.024)	0.047*	(0.024)
1,500	Inpatient	-0.083***	(0.014)	-0.057**	(0.025)	-0.136***	(0.034)	-0.002	(0.030)
500	Primary Care	-0.024	(0.023)	0.030	(0.020)	0.014	(0.025)	0.030	(0.021)
500	Specialist	-0.022	(0.022)	0.023	(0.019)	-0.012	(0.024)	0.036	(0.022)
650	Emerg. Room	-0.015	(0.017)	0.056***	(0.022)	-0.037	(0.028)	0.073**	(0.030)
3,000	Inpatient	-0.150***	(0.028)	-0.073***	(0.026)	-0.230***	(0.059)	-0.013	(0.030)
1,000	Primary Care	-0.037*	(0.021)	0.025	(0.020)	0.012	(0.027)	0.028	(0.020)
1,000	Specialist	-0.029	(0.021)	0.024	(0.020)	-0.003	(0.027)	0.046*	(0.024)
1,400	Emerg. Room	-0.011	(0.017)	0.077***	(0.022)	-0.038	(0.032)	0.068**	(0.033)
5,600	Inpatient	-0.147***	(0.025)	-0.087***	(0.022)	-0.236***	(0.056)	-0.034	(0.023)
1,500	Primary Care	-0.046**	(0.020)	0.020	(0.019)	0.011	(0.028)	0.025	(0.020)
1,500	Specialist	-0.036*	(0.021)	0.026	(0.020)	0.001	(0.029)	0.053**	(0.025)
2,900	Emerg. Room	-0.009	(0.021)	0.081***	(0.023)	-0.040	(0.038)	0.062*	(0.034)
9,750	Inpatient	-0.180***	(0.031)	-0.191***	(0.041)	-0.216***	(0.056)	-0.066**	(0.033)
∞	N/A	-0.051***	(0.016)	-0.039**	(0.016)	-0.126***	(0.032)	-0.018	(0.020)

Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The sample is split between counties where there were two or fewer insurers in 2014 and counties where there were more than two insurers in 2014. The coefficients reported are for the number of total insurers, taken from first-differences regressions. The instruments for the change in the number of insurers in the left panels are: (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. The instruments for the change in the number of insurers in the right panels are: (1) 2012 share for Assurant Health in the state, (2) 2012 share for UnitedHealth in the state, and (3) the product of the 2012 shares for Assurant Health and UnitedHealth in the state. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

with emergency room visits. In counties with three or more insurers in 2014, a new insurer increased premium plus emergency room cost-sharing parameters by 4 to 8 percent on average.[22] The increase is statistically distinguishable from zero with at least a 10 percent threshold for all eight estimates that incorporate four service cost scenarios and two sets of instruments. The estimates using the residual rating areas instruments and the outcome variables for emergency room visits with service costs of $650, $1,400, and $2,900 are statistically distinguishable from zero at a 1 percent threshold. In section 2.6.3, I explore lost insurer bargaining power over emergency departments as a potential mechanism for the emergency room cost-sharing parameters to increase in the counties where new insurers entered.

2.6.2 Falsification and Robustness Tests

Causal interpretation of the estimates in the previous subsection relies on the exogeneity of the instruments. If the instruments are truly exogenous to unobserved components of demand and insurer variable costs (equation 2.2) and changes in demand and insurer variable costs (equation 2.4), they should be uncorrelated with insurer pricing outcomes prior to the ACA. In order to assess the validity of the instruments, I thus test for their correlation with pre-ACA premiums, claims, and utilization. Since most of the variation in the instruments occurs across states, these falsification tests are all run at the state level. The pre-ACA data are for the individual insurance market and come from SNL Financial.

The falsification tests of the residual rating areas instruments in the analysis of the 2014 marketplaces are presented in Table 2.9. The first column uses the weighted (by market size) benchmark premium as the outcome to confirm that the instruments are predictive of 2014 insurer pricing. The estimates are similar to the reduced form estimates at the county level presented in column 3 of Table 2.4. The remaining columns in Table 2.9 demonstrate no evidence that any of the instruments are correlated with pre-ACA premiums, claims, or utilization. The measures of utilization are

[22] It is important to note that emergency room care has likely become more expensive in recent years due to increased entry of for-profit standalone emergency departments and increased out-of-network physician charges for emergency room care. Due to lack of data I am unable to control for these secular trends in my analysis. To explain the results, it would have to be the case that increases in emergency room service costs between 2014 and 2015 were correlated with both the residual rating areas instruments and the pre-ACA shares instruments.

TABLE 2.9: Relationship Between Residual Rating Areas Instruments and Pre-ACA Outcomes

	2014 Outcome: ln(Benchmark Premium)	2013 Outcomes (Per Member Month):				
		ln(Premiums)	ln(Claims)	Hospital Days	Physician Encounters	Non-Phys. Encounters
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Residual Market Size	-0.167**	0.114	0.002	-0.010	-0.017	-0.038
	(0.073)	(0.228)	(0.098)	(0.038)	(0.111)	(0.065)
# Residual Markets	-0.002	0.002	-0.004	-0.001	-0.003	-0.003
	(0.003)	(0.008)	(0.004)	(0.001)	(0.004)	(0.002)
Total Residual Market Size	0.005	-0.007	-0.002	0.000	0.002	0.003
	(0.005)	(0.017)	(0.007)	(0.003)	(0.008)	(0.005)

N = 31. Observations are states with federally facilitated marketplaces that also have more than one rating area. Data for 2013 outcomes are taken from insurer reports to the NAIC furnished by SNL Financial. The residual rating areas instruments are (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. Market size is the projected number of individuals eligible for federal subsidies, measured in millions. Standard errors are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

number of days spent in the hospital, number of physician ambulatory encounters, and number of non-physician ambulatory encounters.

Table 2.10 contains estimates from falsification tests of the residual rating areas instruments (top panel) and pre-ACA shares instruments (bottom panel) in the analysis of the 2015 marketplaces. The first two columns confirm that the instruments are correlated with changes in premium plus cost-sharing parameters between the first and second year of the marketplaces. The remaining columns show little evidence that any of the instruments are correlated with annual changes in pre-ACA premiums or claims. Two of the 24 estimates are statistically significant at a 10 percent threshold, which is consistent with random chance. The outcomes used for the falsification tests are percentage changes in premiums and claims from (a) 2012 to 2013 and (b) 2011 to 2012.

It would be useful to check the robustness of my estimates to the inclusion of state fixed effects. Unfortunately, this is not possible with my IV estimates because the instruments do not capture within-state variation.[23] It is encouraging, however, that the OLS estimates do not vary whether or not state fixed effects are included. One aspect of cross-state variation that is potentially problematic for my 2014 analysis is that states made different decisions on expanding Medicaid and allowing consumers to keep non-grandfathered plans. However, I find that variation in these

[23]The only instrument that varies within a state is the average market size of residual rating areas. Conditional on state fixed effects in the first stage, this variable measures average market size in the county's own rating area.

TABLE 2.10: Relationship Between Instruments and Growth of Pre-ACA Outcomes

	2014-15 Outcome:		2012-13 Outcome:		2011-12 Outcome:	
	Benchmark Premium	$5,600 Inpatient Prem. + C-S	Premiums	Claims	Premiums	Claims
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Residual Market Size	-0.035*	-0.123***	0.013	-0.001	-0.014	-0.005
	(0.017)	(0.043)	(0.084)	(0.024)	(0.021)	(0.027)
# Residual Markets	-0.001	-0.005***	0.001	-0.000	-0.000	0.000
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Total Residual Market Size	0.001	0.003	0.001	0.001	0.000	0.000
	(0.001)	(0.003)	(0.006)	(0.002)	(0.002)	(0.002)
Assurant Pre-ACA Share	-0.111	-0.047	0.675	0.115	0.249	-0.111
	(0.197)	(0.570)	(0.938)	(0.272)	(0.210)	(0.309)
United Pre-ACA Share	-0.546**	-1.682**	1.349	0.221	-0.446*	0.203
	(0.215)	(0.622)	(1.024)	(0.297)	(0.229)	(0.338)
Assurant Pre-ACA Share ×	7.739**	13.726	-12.146	-0.429	5.444*	-2.942
United Pre-ACA Share	(2.972)	(8.602)	(14.153)	(4.108)	(3.169)	(4.667)

N = 31. Observations are states with federally facilitated marketplaces that also have more than one rating area. Data for 2013 outcomes are taken from insurer reports to the NAIC furnished by SNL Financial. The residual rating areas instruments are (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. Market size is the projected number of individuals eligible for federal subsidies, measured in millions. Standard errors are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

regulations does not drive my estimates.

2.6.3 Assessing the Importance of Insurer Bargaining Power

Perhaps the most surprising finding of the analysis is that entry of new insurers in the second year of the marketplaces increased emergency room cost-sharing parameters. This could be because insurers adjusted cost-sharing parameters to account for lost bargaining power in negotiating emergency room service costs. It might make sense that this effect would be particularly apparent for emergency room parameters, since geographic areas typically have fewer emergency departments than doctor's offices, specialty practices, or hospitals. As a rough test of the bargaining mechanism, I allow the effect of new insurers to increase emergency room cost-sharing parameters to vary according to the number of emergency departments in the county. In particular, I interact the variable for number of new insurers with a variable from the Area Health Resources File measuring the number of hospitals with emergency departments in 2012, the most recent year with this data. Since there are a handful of outlier counties with many emergency departments, I focus on counties with three or fewer emergency departments.

TABLE 2.11: Effect of Insurer Entry on (Log) Lowest-Possible Premium + Cost Sharing for Emergency Room Visit in the 2015 Marketplaces by Number of Emergency Departments

Service Cost ($)	Variable	Outcome = ln(Lowest-Possible Premium + ER Cost-Sharing) 2014 Insurers > 2, 2012 Emerg. Dept.'s < 4 N = 973					
		OLS		IV: Residual Rating Areas		IV: Pre-ACA Shares	
0	Δ # Insurers	-0.002	(0.008)	0.007	(0.021)	0.007	(0.025)
	Δ # Insurers $\times$ # EDs	0.002	(0.003)	0.003	(0.004)	0.003	(0.007)
250	Δ # Insurers	0.011	(0.009)	0.022	(0.022)	0.045	(0.030)
	Δ # Insurers $\times$ # EDs	-0.001	(0.002)	0.000	(0.004)	-0.005	(0.007)
650	Δ # Insurers	0.016	(0.012)	0.053**	(0.026)	0.080**	(0.038)
	Δ # Insurers $\times$ # EDs	-0.005	(0.003)	-0.007	(0.005)	-0.012	(0.008)
1,400	Δ # Insurers	0.014	(0.014)	0.095***	(0.030)	0.074*	(0.042)
	Δ # Insurers $\times$ # EDs	-0.007	(0.004)	-0.018**	(0.008)	-0.011	(0.009)
2,900	Δ # Insurers	0.006	(0.016)	0.111***	(0.035)	0.075*	(0.042)
	Δ # Insurers $\times$ # EDs	-0.006	(0.005)	-0.025**	(0.010)	-0.015	(0.010)

Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The sample only includes counties where there were more than two insurers in 2014 and, according to the Area Health Resources File, less than four emergency departments in 2012. The coefficients reported are for the number of total insurers and the number of total insurers multiplied by the number of emergency departments. The "Residual Rating Areas" instruments are: (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. The instruments for the change in the number of insurers in the "Pre-ACA Shares" panels are: (1) 2012 share for Assurant Health in the state, (2) 2012 share for UnitedHealth in the state, and (3) the product of the 2012 shares for Assurant Health and UnitedHealth in the state. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

Since insurer bargaining power increases with insurer concentration but decreases with provider concentration, more insurer entry should lead insurers to increase emergency room cost-sharing parameters the most in areas with the fewest emergency departments. The estimates in Table 2.11 are consistent with this pattern. All 12 estimates of the interaction variable are (weakly) negative, and the residual rating areas IV estimates for the two most expensive service costs are statistically distinguishable from zero using a 5 percent threshold. These results should be viewed as suggestive, rather than definitive, in favor of the bargaining mechanism. An important limitation of this analysis is the lack of data on emergency department diffusion since 2012, particularly for for-profit standalone emergency departments. To the extent that the recent spread of for-profit standalone emergency departments is correlated with new insurer entry in 2015 and the number of hospitals with emergency departments in 2012, the estimates may be biased.

2.7 Conclusion

In this chapter, I estimated the marginal effect of insurer entry on premium plus cost-sharing parameters separately for the first and second years of the ACA's health insurance marketplaces. In 2014, an additional insurer lowered premiums and inpatient cost-sharing parameters. In the second year of the marketplaces, however, new insurers lowered inpatient cost-sharing parameters but did not lower premiums or cost-sharing parameters for primary care, specialists, or the emergency room. A likely explanation for the different results is the substantial increase in the average number of insurers from 2014 to 2015. Consistent with this explanation, I find that a new insurer in 2015 was more likely to lower premium plus cost-sharing parameters if it was joining a county with two or fewer incumbent insurers versus a county with three or more incumbent insurers.

From a policy perspective, it would be useful to know the optimal number of insurers to provide marketplace plans in each county. The optimal number is likely to be a function of provider concentration, which has been changing in recent years. Additionally, without the assumptions indicated in section 2.5.3, my estimates are not necessarily informative about how insurer entry influences actual patient and

taxpayer costs. Once more marketplace data regarding patients' plan choices and medical utilization become available, it will be important for future research to revisit this issue. While it is difficult to predict how insurer participation may continue to evolve in the marketplaces, it is not difficult to imagine a rationale for regulators to exercise control over the insurers serving different counties. States already exercise this control in their Medicaid managed care markets. Additionally, California, which fully manages its own marketplace, set a precedent for direct regulation of insurer participation in the marketplaces by not allowing United to serve many of its counties in 2015.[24]

[24]See "California rejects UnitedHealth's bid to sell Obamacare statewide," published online in the Los Angeles Times on January 15, 2015.

Chapter 3

Does Public Administration of Health Insurance Improve Cancer Care? Plan Choices and Mortality for Older Cancer Patients

What is the best way for policymakers to design health insurance markets in order to promote the efficient use of health care? Some advocate for regulated privatization of public insurance programs, pointing out that private companies have an incentive to manage medical utilization in order to reduce costs of paying medical claims. Others argue that single-payer, publicly administered insurance is simpler and avoids market inefficiencies related to risk selection. There has been a recent policy shift in the US to favor the use of private companies to administer health insurance. Between Medicare Parts A and B (inpatient and outpatient medical care), Medicare Part D (prescription drugs), Medicaid, and the new health insurance marketplaces, over 100 million people in the US now have public health insurance that is administered by a private insurer. In this chapter, I explore implications of the privatization trend by comparing quality of post-diagnosis cancer care in private versus publicly administered Medicare.

Nearly everyone aged 65 and older in the US is eligible for Medicare. The medical (Part A and Part B) component of Medicare is an ideal setting to evaluate private versus public administration of health insurance because, unlike the other public

programs in the US, private and publicly administered insurance operate in parallel. Some Medicare beneficiaries have medical coverage administered by a private Medicare Advantage (MA) plan and the rest have medical coverage administered by the public plan, traditional Medicare. MA plans offer coverage beyond what is provided by traditional Medicare in exchange for restricting access to medical providers. Medicare pays the private companies that issue MA plans a fixed payment for each of their enrollees. The payment adjusts for county-level variation in the cost of providing care and some individual-level variation in medical risk, but the private companies bear the full financial risk of reimbursing their enrollees' medical claims. Curto et al. (2015) provide the most recent and comprehensive evaluation of the MA program. They determine that the program reduces medical costs and increases social welfare.[1] In particular, private companies save $77 (12 percent) per member per month in costs relative to traditional Medicare and MA patients only incur a disutility from restricted provider access of $27 per member per month.

Curto et al. (2015) inferred patient disutility from MA plans based on a model of health insurance choice. While patients' revealed preferences are important, it is also important to consider any differences in health outcomes between MA plans and traditional Medicare. There is an emerging literature (e.g. Abaluck and Gruber, 2011; Handel, 2013; Miller, 2014; Ericson, 2014; Bhargava, Loewenstein, and Sydnor, 2015; Polyakova, 2016) that documents substantive inefficiencies in patients' health insurance choices, particularly with respect to health insurance switching. To the extent that patients' relative preferences for MA plans evolve over time, possibly due to bad health shocks, health outcomes may be more policy-relevant than revealed preferences. Relatedly, while average differences in insurer costs and patient utility between MA plans and traditional Medicare are important, they may not hold for all patients. Health insurance is specifically meant to provide financial protection in the case of a bad health shock, so it is important to consider the implications of the MA program for patients newly diagnosed with a chronic condition.[2]

[1] However, taxpayers do not capitalize on any of the savings and instead contribute substantial funds ($95 per member month) to pay insurers that offer MA plans.

[2] As an example of the importance of evaluating health policy's distributional effects, the introduction of Medicare had no distinguishable effect on mean out-of-pocket spending, but reduced the top quartile of out-of-pocket spending by 40 percent (Finkelstein and McKnight, 2008).

Cancer is one of the deadliest and costliest chronic conditions. The US government spends nearly $5 billion every year to support cancer research and recently launched an additional $1 billion "Cancer Moonshot" initiative to further accelerate cancer research.[3] The large amount of cancer research leads to frequent advances in cancer care. However, there is theory (Goodman and Stano, 2000) and empirical evidence (e.g., Baker, 2001; Baker and Phibbs, 2002; Mobley et al., 2011) suggesting that managed care organizations discourage the use or adoption of high-cost, innovative treatments. For these reasons, cancer patients are an important population for which to compare private versus public administration of health insurance. The timing of cancer diagnosis is also plausibly unpredictable, which leads to useful identifying variation.

My empirical analyses use individual-level data from the Surveillance, Epidemiology, and End Results Program (SEER) cancer registries that are linked to Medicare administrative records. The linked data are referred to as SEER Medicare. The most important aspect of the SEER Medicare data is that, unlike medical claims information in standard Medicare data, the cancer-related information is provided for all patients regardless of whether they are enrolled in an MA plan or traditional Medicare. This is because the information is collected and reported by the SEER registries, which rely directly on medical providers rather than insurance claims. Unlike the unlinked SEER data, the SEER Medicare data also indicate (historical) MA enrollment for each cancer patient.

My first empirical objective is to estimate the effect of MA enrollment, relative to enrollment in traditional Medicare, on cancer patients' mortality. My preferred approach is to use a stratified Cox proportional hazards model. Though Medicare beneficiaries can choose a different health insurance plan every year, switches between MA and traditional Medicare are rare.[4] I thus define MA enrollment as a static variable at the time of cancer diagnosis. This reflects a decision made by the patient prior to the severity of their cancer being revealed. Given controls in the model for patient

[3] See the website for the National Cancer Institute: `http://www.cancer.gov/about-nci/budget` and `http://www.cancer.gov/research/key-initiatives/moonshot-cancer-initiative`.

[4] On average, about 3 percent of patients with one type of health insurance in one year switched to the opposite type of health insurance in the following year. Between 2000 and 2013, 79 percent of patients never switched between an MA plan and traditional Medicare.

characteristics, cancer severity, and cause of death, I treat MA enrollment at the time of diagnosis as plausibly exogenous to cancer mortality. Based on the extensive risk selection literature, summarized nicely by Newhouse et al. (2015), any residual selection bias is likely in the (conservative) direction of decreased cancer mortality for MA patients. For patients with brain, lung, or prostate cancer living in relatively large health service areas, I estimate that MA enrollment increased cancer mortality. 73 percent of the patients in my sample lived in a health service area with at least 500,000 people. In these areas, my estimates imply that MA enrollment lowered median life expectancy after diagnosis by 0.9 months for brain cancer patients, by 0.4 months for lung cancer patients, and by 4.0 months for prostate cancer patients. For patients with other cancers and patients living in smaller health service areas, MA enrollment had no distinguishable effect on mortality.

My second empirical objective is to use the time-varying MA enrollment information in the data in order to estimate the effect of having cancer on patients' preferences for MA plans relative to traditional Medicare. After controlling for the increasing MA enrollment trend in the non-cancer population, the data show that patients were relatively less likely to be enrolled in an MA plan after being diagnosed with cancer. This does not necessarily mean that a cancer diagnosis reduced patients' relative preferences for MA plans because a cancer diagnosis might increase the cost of switching health insurance. A more useful approach is to relate a cancer diagnosis to the likelihood of switching, in both directions, between an MA plan and traditional Medicare. The raw data indicate compelling evidence that more patients switched out of MA plans and fewer patients switched into MA plan after cancer diagnosis. I quantify the change in switching behavior by running an event study using linear probability models. In particular, I estimate the difference in the likelihood of switching from an MA plan to traditional Medicare, or vice-versa, in the calendar year immediately after cancer diagnosis relative to the calendar year three years before diagnosis. A cancer diagnosis increased the probability of switching from an MA plan to traditional Medicare by 1.1 percentage points (37 percent) and decreased the probability of switching from traditional Medicare to an MA plan by 0.8 percentage points (29 percent). Unlike the mortality effect, the switching effect was consistent across health service areas and cancer sites.

This chapter makes several contributions to the debate surrounding the privatization of public health insurance. Most of the literature evaluating the MA program (e.g., Curto et al., 2015; Miller, 2014; Town and Liu, 2003; Hall, 2011) has focused on cost outcomes rather than health outcomes.[5] The previous studies that have examined mortality differences between MA and traditional Medicare patients are inconclusive about any non-immediate differences unrelated to risk selection.[6] Curto et al. (2015) documented that life expectancy, conditional on observable risk, was greater for MA patients than traditional Medicare patients. Given the wealth of literature on risk selection in Medicare, the relationship was not interpreted as causal and was instead used to help infer MA plan costs. Researchers that have addressed risk selection have focused on immediate differences in mortality for the general Medicare population. These researchers conclude either that MA enrollment reduces (Dowd et al., 2011; Afendulis, Chernew, and Kessler, 2013) or has no distinguishable effect (Gowrisankaran, Town, and Barrette, 2011; Duggan, Gruber, and Vabson, 2015) on short-term mortality.[7] There are some researchers (Potosky et al., 1997; Potosky et al., 1999; Merrill et al., 1999; Roetzheim et al., 2000a; Roetzheim et al., 2000b) who compared longer-term mortality for cancer patients with traditional Medicare patients versus cancer patients insured by some of the first Medicare HMOs. These studies examined specific geographic areas and cancer sites and found mixed results for the effect of Medicare HMOs on cancer mortality.[8] In comparison, I focus on a more modern regulatory regime in Medicare and larger data that incorporates more geographic areas and cancer sites.

My approach is most similar to the approach of Cutler, McClellan, and Newhouse (2000), who famously estimated similar health outcomes for heart disease patients with managed care versus patients with fee-for-service insurance. However, the current Medicare setting is quite different from the employer-sponsored insurance setting they studied. In their setting, Cutler, McClellan, and Newhouse

[5]This is likely due to challenges with unobserved differences in health status (Newhouse et al., 2012) and the general lack of claims data for MA patients.

[6]Einav and Levin (2015) also discussed the lack of definitive research measuring health outcome differences between MA plans and traditional Medicare, having stated that "better data and more research will be needed to establish if there are measurable differences in health outcomes."

[7]Gowrisankaran, Town, and Barrette (2011) and Dowd et al. (2011) examined older time periods, before private Medicare plans were referred to as Medicare Advantage plans.

[8]Section 3.4.2 contains further discussion of the results from the most relevant of these studies.

(2000) found that managed care plans paid prices to medical providers that were 30 to 40 percent lower than what fee-for-service plans paid for the same services. Conversely, in Medicare, private companies reimburse medical providers about the same amount that traditional Medicare pays for the same services (Berenson et al., 2015; Baker et al., 2016).

Within the broader literature pertaining to privatized public health insurance, this chapter also makes a contribution to the understanding of risk selection in Medicare. Previous work (e.g., Morrissey et al., 2013; Newhouse et al., 2012; Brown et al., 2014) suggests that MA plans enroll patients who are healthier, even conditional on risk adjustment for chronic conditions, than patients in traditional Medicare. However, Newhouse et al. (2015) raise important concerns with the methodologies used in the risk selection literature. Most of the existing studies rely on comparing patients who switched between an MA plan and traditional Medicare versus patients who stayed. One concern is that switching could be driven by changes in health that are unaccounted for. By showing that switching behavior changed around a cancer diagnosis, this chapter reinforces the concern of endogenous switching. This chapter also finds little evidence that plan switching after cancer diagnosis is correlated with variation in costs of treating cancer. In particular, I find no evidence that low-cost cancer patients select into MA plans.

The rest of the chapter is organized as follows. Section 3.1 outlines the relevant background, section 3.2 discusses a conceptual framework, and section 3.3 describes the data. Section 3.4 examines the effect of MA enrollment on cancer survival. Section 3.5 analyzes the effect of having cancer on patients' switching between MA plans and traditional Medicare. A discussion and concluding remarks are in section 3.6.

3.1 Background

Medicare is a public program that has provided nearly universal health insurance to elderly individuals in the US ever since 1966. The program provides insurance for inpatient (Part A) and outpatient (Part B) medical care and, since 2006, prescription drugs (Part D). Besides individuals with end-stage renal disease or a

qualifying disability, eligibility for Medicare starts at age 65. Once eligible, Medicare beneficiaries elect to receive their combined Part A and Part B coverage in one of two ways. About 70 percent of current beneficiaries enroll in the public plan, traditional Medicare. The remaining 30 percent enroll in an MA plan offered by a private company.

3.1.1 Medicare Advantage versus Traditional Medicare

MA plans must cover the same services, and provide at least the same level of coverage for those services, as traditional Medicare. In general, traditional Medicare covers almost all of a patient's inpatient expenses and about 80 percent of their outpatient expenses. The choices for a private company offering an MA plan can be summarized as follows.[9] First, it chooses the counties in which to offer the plan. Any Medicare beneficiary living in one of the chosen counties is then able to enroll in the plan. Second, the private company chooses what supplemental coverage to provide in the plan. In most cases, the supplemental coverage is some combination of reduced cost-sharing for outpatient care and added dental, vision, and prescription drug coverage. The private company can also choose to charge enrollees a premium in excess of the standard Part B premium owed to Medicare. The premium, however, must be the same for every enrollee. Third, the private company defines a network of medical providers for the plan. The plan's coverage only applies for enrollees who visit a provider in the plan's network. The private company is able to negotiate possibly different rates to pay each provider in the plan's network. Traditional Medicare, on the other hand, defines reimbursement rates that any medical provider can accept.

The trade-off for patients in choosing health insurance is more coverage, but less access to medical providers, in an MA plan versus traditional Medicare. Provider networks for MA plans are subject to approval and audit by the Centers for Medicare and Medicaid Services.[10] Due to data constraints, researchers have very limited understanding of what these provider networks look like. Jacobson et al. (2016)

[9] Many private companies offer multiple MA plans, but these choices can be made separately for each plan.

[10] A recent report from the Government Accountability Office revealed that the Centers for Medicare and Medicaid Services reviews less than one percent of the provider networks. See `http://www.gao.gov/products/GAO-15-710`.

provided the first broad-based characterization. They manually collected provider network data, from pdf files or searchable directories embedded within company websites, for the MA plans in 20 counties in 2015. They found that provider network breadth varied significantly by plan. Using enrollment totals for each plan, they determined that about one-sixth of MA enrollees had coverage that applied to less than 30 percent of the hospitals in their county, about two-thirds of MA enrollees had coverage that applied to somewhere between 30 and 70 percent of the hospitals in their county, and the remaining one-sixth had coverage that applied to more than 70 percent of the hospitals in their county. The limited provider networks in MA plans could have major implications for the use of medical services. Curto et al. (2017) show that MA plans reduce medical utilization and substitute less expensive primary care in place of more expensive specialist care. In other contexts, other researchers have also found that limited provider networks reduce the use of specialty care (Gruber and McKnight, 2016; Atwood and LoSasso, 2016).

While MA plans are one source of supplemental coverage for Medicare beneficiaries, they are not the only option. Some patients qualify for supplemental coverage through a previous employer or Medicaid at no extra cost.[11] For everyone else, there are two options. First, one can buy a Medigap plan for $2,000 or more per year (Huang et al., 2013). Second, one can sacrifice provider access and enroll in an MA plan for little, if any, extra monetary cost.

3.1.2 Payments to Medicare Advantage Plans

Most of the revenue for MA plans comes from Medicare's capitation payments. For each of its MA enrollees, a private company is reimbursed by Medicare for taking on the risk associated with paying medical claims. The capitation payment roughly reflects the cost Medicare would have expected to pay for that patient had he or she instead enrolled in traditional Medicare. It is determined based on a formula consisting of a county multiplier and a patient-specific risk adjustment. Notably, the formula does not include any retroactive adjustment based on the patient's utilization or health outcome. MA plans thus make the most profit from MA patients

[11] According to (Cubanski et al., 2015), about 86 percent of 2010 Medicare beneficiaries had some form of supplemental coverage. Of that 86 percent, about half had supplemental coverage through a previous employer or Medicaid.

who spend less on medical services than comparable patients with traditional Medicare.

In a broad sense, there are two avenues through which MA plans can influence their enrollees to spend less on medical services than comparable patients with traditional Medicare. First, MA plans can use supplemental coverage to shift patient care from an inpatient setting to a cheaper outpatient setting. For example, prior to the Affordable Care Act's requirement of full coverage by MA plans and traditional Medicare, many MA plans offered supplementary coverage of preventive care. Second, private companies can steer their patients toward lower-cost medical services. For example, Friedman and Jiang (2010) found that MA enrollees are admitted to hospitals with lower costs than the hospitals to which traditional Medicare beneficiaries are admitted. Those lower-cost hospitals, however, also had higher risk-adjusted mortality measures.

3.1.3 Regulatory Changes Over Time

There have been several important regulatory changes in Medicare over the past ten to fifteen years. The time period of my data mostly fits into the regulatory regime after the Medicare Modernization Act of 2003 (MMA) and prior to the Patient Protection and Affordable Care Act of 2011 (ACA). McGuire, Newhouse, and Sinaiko (2011) provide an excellent historical perspective of the MA program.[12] I discuss the changes that are most relevant for my analysis below.

The MMA is best known for introducing Medicare Part D prescription drug coverage starting in 2006. Individuals can now purchase a standalone prescription drug plan, enroll in an MA plan that includes prescription drug coverage, or choose to forgo the Part D benefit entirely. However, the MMA made several other notable changes. First, it changed the capitation formula by starting a competitive bidding system for the county multipliers (in 2006) and implementing a new risk adjustment formula that accounted for chronic medical conditions (in 2004). The new risk adjustment implies that private companies are reimbursed more, in order to offset higher average claims cost, for insuring patients with cancer versus patients without

[12]The terminology for the MA program has changed over time. The program has historically also been referred to as Medicare Part C. It was not referred to as Medicare Advantage until the MMA. After the Balanced Budget Act of 1997 and before the MMA, it was also referred to as Medicare+Choice.

chronic conditions. For details about the competitive bidding for county multipliers, see Curto et al., 2015. Medicare continues to set benchmarks that are critical to the bidding process, and these benchmarks increased after the MMA. Second, whereas Medicare beneficiaries were previously allowed to switch health insurance every month, the MMA introduced calendar-year plan-lock beginning in 2006.[13] In total, the MMA led to a substantial increase in the popularity of MA plans. The proportion of Medicare beneficiaries enrolled in an MA plan increased from 13 percent in 2004 to 25 percent in 2011.

There were two notable changes in Medicare resulting from the ACA. Because these changes occurred at the very end of my sample period, they are not reflected in the results of my analysis. First, starting in 2011, the ACA required traditional Medicare and all MA plans to provide full coverage of recommended preventive care. This requirement may lessen the ability of private companies to save money by shifting inpatient care to outpatient care. Second, since 2012, payments to MA plans now adjust for "star-ratings", a composite measure of quality.[14] The star-ratings take into account management of chronic conditions and consumer satisfaction, which could give private companies some incentive to facilitate better cancer care.

3.2 Conceptual Framework

In this section, I provide a brief conceptual framework for my analysis. I first outline the potential for quality variation within the spectrum of cancer care. I then discuss the reasons and ways that private companies might facilitate lower quality of cancer care for their enrollees.

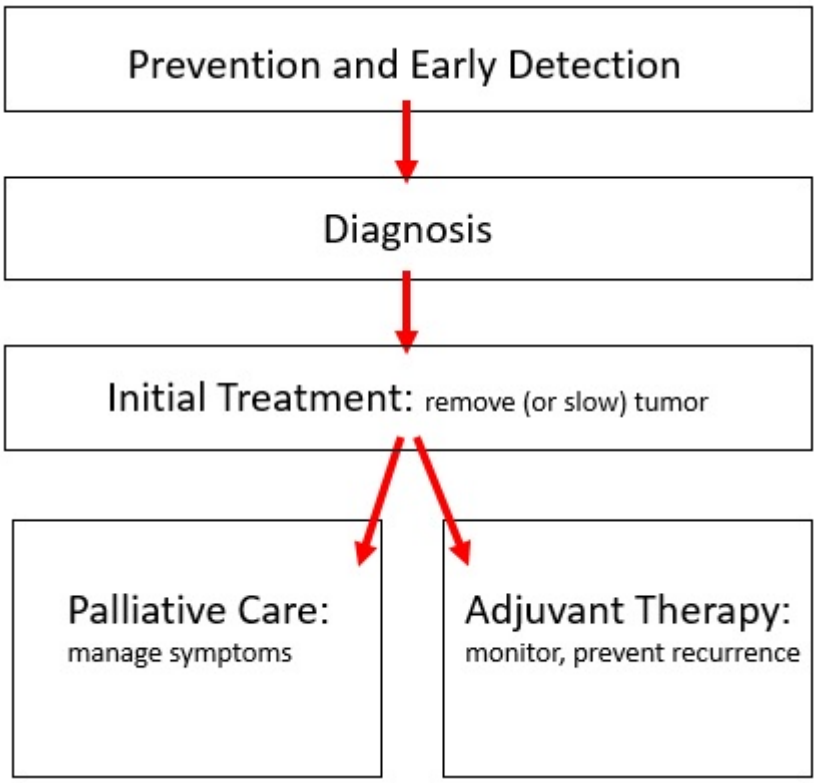
3.2.1 Variation in Quality of Cancer Care

There are several phases of cancer care, as illustrated in Figure 3.1. While prevention and diagnosis of cancer are certainly important within the spectrum of cancer care, this chapter focuses only on post-diagnosis cancer care. An important aspect of post-diagnosis cancer care is that there are many different types of treatments and many different doctors that can be involved in those treatments. A typical course of

[13] I examine calendar-year plan-lock in detail in C.

[14] The star-ratings began in 2009, but were not used to adjust payments to MA plans until 2012.

FIGURE 3.1: Phases of Cancer Care



The flow chart illustrates the various phases of cancer care. The pre-diagnosis goal is to prevent cancer or detect it at an earlier, more treatable stage. The post-diagnosis goal is to remove the tumor, or at least slow its growth. If the tumor is successfully removed, adjuvant therapy is used to reduce the chance of cancer recurrence. After unsuccessful initial treatments, palliative care is used to manage symptoms.

cancer treatment might involve some combination of surgery, radiation, chemotherapy, and immunotherapy. Surgery can be performed by a general surgeon or a surgical oncologist. Radiation oncologists specialize in radiation therapy, and medical oncologists specialize in therapies besides surgery and radiation. There are also oncologists that specialize in treating patients with particular types of cancer. The medical literature provides evidence that more specialized cancer care leads to better outcomes. The best survival outcomes for ovarian cancer patients result from treatment by a gynecologic oncologist (Chan et al., 2007). Similarly, surgeon specialization improves survival for breast cancer (Gillis and Hole, 1996), colorectal cancer (McArdle and Hole, 2004), and lung cancer (Goodney et al., 2005; Sahni et al., 2016).

There are also medical facilities that specialize in cancer care. The most prestigious cancer treatment facilities are specifically designated for research funding

by the National Cancer Institute (NCI). There are 69 NCI-designated cancer centers spread across 35 states and the District of Columbia. The medical literature shows that NCI-designated cancer centers improve cancer outcomes. In particular, they lead to lower mortality rates than other hospitals (Birkmeyer et al., 2015; Pfister et al., 2015). According to Pfister et al. (2015), NCI-designated cancer centers decrease overall short and long-term mortality for cancer patients by 5-10 percent relative to community hospitals. Compared to stand-alone academic medical centers, they decrease mortality by 3-7 percent.

3.2.2 Private Companies May Facilitate Lower Quality Cancer Care

Since private companies have a profit incentive to manage the medical utilization of their enrollees, proponents of privately administered health insurance argue that it helps make the health care market more efficient. Profit and efficiency would ideally align so that private insurers steer their enrollees toward beneficial medical care and away from wasteful medical care. It is both more profitable to an insurer and more efficient to society when patients use cheaper alternatives for medical care that result in the same health benefits. In cases where there are cheaper alternatives for medical care that result in worse health outcomes, however, health outcomes may differ between patients with private and publicly administered insurance.

While private MA plans have a financial incentive to reduce future costs and keep profitable patients alive, they have no direct financial incentive related to the future health of their patients. There are several examples where this distinction could be important. First, private companies must account for the possibility that patients leave their plan in the future. Goodman and Stano (2000) constructed a theoretical model that demonstrates how "HMOs self-insure against future disenrollment by reducing current costs through (low-cost) continuing care rather than high-tech treatment" (see page 253). Only about 3 percent of patients switch from an MA plan to traditional Medicare in a given year. However, private companies would also account for the possibility of their patients switching to a different MA plan. Miller (2014) estimated that the cost of switching from one MA plan to another is slightly lower than the cost of switching from an MA plan to traditional Medicare. Second, some treatments may improve health outcomes without increasing profit. Consider

a treatment that is effective at slowing the growth of a tumor, thus extending patients' life expectancy. Many of these treatments (for example, immunotherapies) are continually administered, potentially making the patients' additional life-years unprofitable.

Even though private companies may prefer not to pay for some cancer treatments, they are legally required to cover (nearly) all the treatments covered by traditional Medicare with at least the same generosity.[15] This does not mean that private companies cannot reduce the use of specialized care in other ways. Perhaps the most obvious way for a private MA plan to facilitate a lower quality of cancer care is to exclude specialized cancer care providers from its network. In the 15 counties they examined with an NCI-designated cancer center, Jacobson et al. (2016) found that only 15 percent of MA plans in those counties specifically named the cancer center as being included in their networks. 43 percent of MA plans clearly excluded the cancer center from their networks. The remaining MA plans were unclear about whether or not the cancer center was included. They did not specifically list the cancer center as being in their networks, but did list the academic medical center affiliated with the cancer center. There are also other potential tools, besides provider network construction, through which a private company can influence treatments. For example, private insurers can directly communicate information to their enrollees. Private insurers can also negotiate reimbursement contracts with doctors and hospitals in order to directly transfer their financial incentives to medical providers.

3.3 SEER Medicare Data

The analysis in this chapter uses SEER Medicare data, a large database of cancer patients from the SEER cancer registries linked with Medicare administrative records. For each patient, the data indicate historical MA enrollment, detailed characteristics of the cancer at the time of diagnosis, and any date and cause of death prior to 2014. The data include all Medicare-eligible individuals living in a county within a SEER registry region who were diagnosed with one of eight cancers between 2004 and 2011. The SEER registry regions cover a representative 28 percent

[15] Exceptions are that MA plans are not required to cover hospice care or participation in clinical trials. In these cases, traditional Medicare provides coverage even to patients with an MA plan.

of the US population and the eight cancers included are breast, lung, colorectal, prostate, brain, cervical, ovarian, and leukemia.[16] Together, these eight cancers account for approximately 60 percent of all cancer diagnoses.

The original data include over 1.3 million unique cancer patients, but I drop a substantial number of patients for the purposes of my analysis. Most (76 percent) of the excluded patients were first diagnosed with cancer before turning age 65. MA enrollment around the time of cancer diagnosis is undefined for these people. Patients were also excluded if they were ever eligible for Medicare due to a disability or end-stage renal disease (10 percent of drops) or were diagnosed at an age older than 90 (4 percent). The other 10 percent of drops were patients who never enrolled in both Medicare Parts A and B, were missing critical information such as county of residence or date of diagnosis, or had their diagnosis information taken from a death certificate, autopsy, or nursing home. The remaining sample consists of 591,615 cancer patients. In some parts of my analysis, I drop an additional 110,818 patients who died too soon after their diagnosis to have been able to switch health insurance. To have been able to switch, since enrollment generally lasts a full calendar year and because I cannot discern MA enrollment in the month of death, a patient would have had to survive at least until the first day of February following their diagnosis.

The biggest obstacle to studying patients in MA plans is that researchers typically cannot observe their medical claims. Medicare keeps record of claims only for patients in traditional Medicare. The advantage of the linked SEER Medicare data is that the information from the SEER registries is available for all cancer patients, including those enrolled in an MA plan. The SEER registries provide rich information about cancer severity and survival to complement the MA enrollment data provided by Medicare.

3.3.1 Health Insurance Data

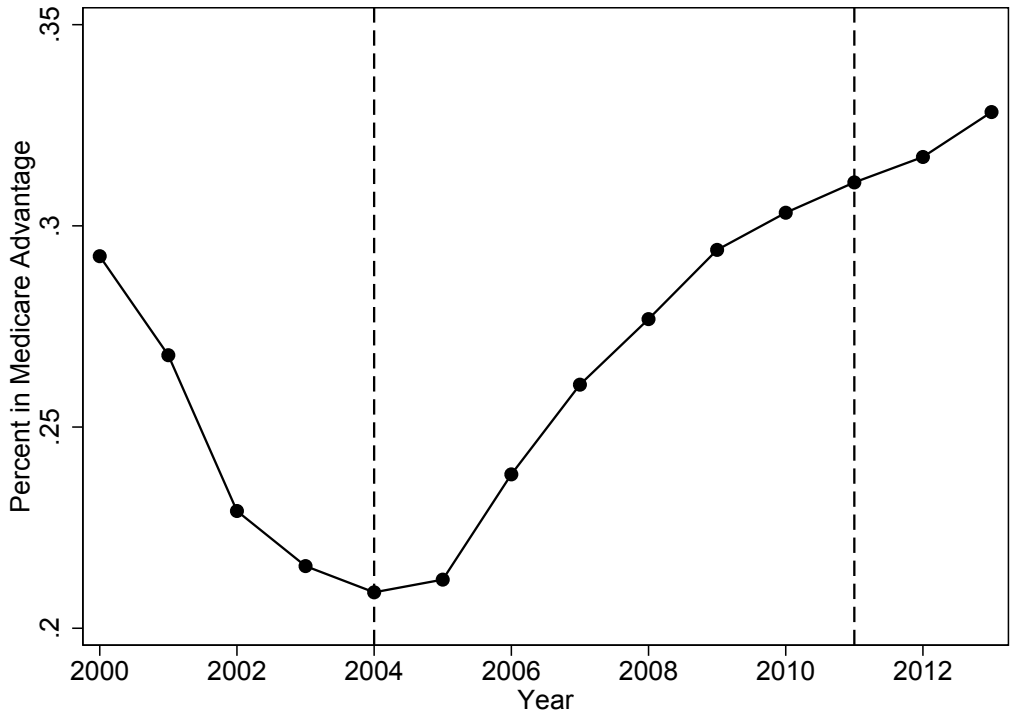
For each month between January 1991 and December 2013, Medicare provides a variable indicating whether or not the individual was enrolled in an MA plan.[17]

[16] Researchers must request specific cancer sites when using the SEER Medicare data. These eight cancers include the major cancer sites (breast, colorectal, lung, prostate) and other sites that researchers at UVa were interested in. I particularly thank Aaron Yao for helping me to access this data.

[17] In my analysis of plan switching, the earliest year for which I measure MA enrollment is 2000, at least four years prior to cancer diagnosis for all patients in the sample.

Unfortunately, the variable does not indicate which MA plan the individual was enrolled in. It is likely that there is important variation in facilitation of cancer care within MA plans, but I am not able to capture that variation in this study. Though the MA enrollment indicator is provided on a monthly basis, I measure MA enrollment on a yearly basis. Switching between an MA plan and traditional Medicare within a calendar year was allowed, but infrequent, prior to 2006. Since 2006, it is only possible under rare circumstances.[18] Less than 2 percent of individual-year observations in my data include some months where the individual was enrolled in an MA plan and some months where he or she was enrolled in traditional Medicare. In these cases, I assign enrollment based on the plan type with the greater number of months within the year.

FIGURE 3.2: Popularity of Medicare Advantage Over Time



The graph illustrates the proportion of the (eventual) cancer patients in the sample who were enrolled in a Medicare Advantage plan in each year from 2000 to 2013. The first vertical dashed line marks the first year of cancer diagnoses. The second vertical dashed line marks the last year of cancer diagnoses.

[18]First, patients dually eligible for Medicaid and Medicare can still switch health insurance every month. Second, patients who move to a new county can switch health insurance immediately after their move. Third, MA patients are allowed to switch to traditional Medicare (but not a different MA plan) any time during January and the beginning of February.

For the full sample of 591,615 patients, Figure 3.2 illustrates the proportion enrolled in an MA plan (conditional on being alive and in Medicare) in each year between 2000 and 2013. Depending on the year, the proportion of the sample enrolled in an MA plan ranged from 21 to 32 percent. The trough of MA popularity was in 2004 and the peak was in 2013, consistent with the pattern of MA enrollment in the overall population. In much of the analysis I will categorize patients based on MA enrollment in the year of their cancer diagnosis. At diagnosis, 157,485 (27 percent) of the 591,615 cancer patients in my sample were enrolled in an MA plan.

3.3.2 Cancer and Mortality Data

The SEER registries provide variables indicating month and year of cancer diagnosis, primary cancer site, and detailed information about cancer severity at the time of diagnosis. The dates of diagnosis range from January 2004 to December 2011 and are usually the date of a biopsy, but sometimes are the date of a clinical diagnosis or positive cytology.[19] The primary site, or cancer type, is either the brain, breast, cervix, colon or rectum, blood cells (leukemia), lung or bronchus, ovary, or prostate.

There are several variables that describe cancer severity. The main variable I use is an indicator for tumor metastasis, which identifies cancer that have spread to multiple organs. For example, colon cancer that has spread to the liver is classified as a metastatic colorectal cancer. The frequency of metastasis varies by primary cancer site. None of the brain cancers or leukemias are considered metastatic, but the majority of lung cancers are. There is another useful measure of cancer severity, cancer grade, that is coded for all cancer sites. Cancer grade measures how differentiated the cancer cells are from normal cells and serves as the clinical proxy for aggressiveness in future growth. For breast cancers only, there are also useful variables describing estrogen receptor and progesterone receptor status. Receptor-positive breast cancers receive signals from estrogen or progesterone that can promote growth. I do not use the variables for cancer grade and hormone receptivity in my preferred models, but use them in robustness exercises.

[19] In cases where a cancer is diagnosed more than once, the SEER registries report the earliest date of unambiguous diagnosis.

TABLE 3.1: Summary of Cancer Types and 2-Year Survival

	TM Patients			MA Patients		
Cancer	N	% Survived 2 Years	% Deaths from Cancer	N	% Survived 2 Years	% Deaths from Cancer
Brain	6,415	0.13*	0.91	2,215	0.11	0.92
Breast	92,684	0.90***	0.56	35,986	0.91	0.57
Cervical	2,113	0.57	0.80	674	0.56	0.76
Colorectal	75,381	0.67***	0.71***	27,920	0.69	0.74
Leukemia	17,779	0.53	0.77***	6,094	0.53	0.80
Lung	105,724	0.26	0.87***	35,950	0.26	0.89
Ovarian	9,318	0.46	0.88	3,421	0.46	0.89
Prostate	124,716	0.918**	0.42***	45,225	0.922	0.46

Total N = 591,615. TM patients are those diagnosed with cancer while enrolled in traditional Medicare. MA patients are those diagnosed with cancer while enrolled in a Medicare Advantage plan. Survival is summarized in the first two years because all patients have at least two years of follow-up. The "% Deaths from Cancer" column indicates the percentage of deaths within 2 years that were due to cancer. Asterisks represent statistically significant (two-sided) differences between TM and MA patients.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Medicare and SEER both provide month and year of death for patients who died by the end of 2013. SEER additionally provides information about cause of death. In particular, SEER indicates all deaths that were caused by cancer. I use the date of death from Medicare, because Medicare collects death data directly from the Social Security Administration. I distinguish whether or not cancer was the cause of death using the information from SEER.

Table 3.2 summarizes outcomes for patients with particular types of cancers. For each of the eight cancer types, it lists the number of patients diagnosed in an MA plan and the number of patients diagnosed in traditional Medicare. For each set of patients, it also indicates the proportion who died within 2 years of their diagnosis and the proportion of those deaths that were caused by cancer. Some cancers were much more deadly than others. Almost 90 percent of brain cancer patients died within the first two years. Of those deaths, over 90 percent were due to the brain cancer. Lung cancer was the next deadliest, followed by cervical, ovarian, and then colorectal cancer. Breast and prostate cancers were the least deadly. Only about 10 percent of patients with these cancers died within the first two years, approximately half of whom died from something other than their cancer. There were not enough

TABLE 3.2: Summary of Patient Characteristics at time of Cancer Diagnosis

Variable	**TM Patients N = 434,130** Mean	**MA Patients N = 157,485** Mean
Age	75.83***	75.73
Female	0.48***	0.49
Black	0.086***	0.090
Hispanic	0.05***	0.10
Married	0.54	0.54
Widowed	0.24***	0.22
CT Per-Capita Income ($1000)	24.896***	24.644
CT Median Income ($1000)	51.152***	52.882
CT Percent Poverty	0.11	0.11
CT Percent No High School Degree	0.19	0.19
CT Percent College Degree	0.27	0.27

The sample consists of 434,130 cancer patients diagnosed in traditional Medicare (TM) and 157,485 cancer patients diagnosed in a Medicare Advantage (MA) plan. Age at diagnosis is measured in whole years and the variables that start with "CT" are socioeconomic measures of the census tract where the patient lives. These are the only variables in the table that are non-binary. Asterisks represent statistically significant (two-sided) differences between TM and MA patients.
* p<0.10, ** p<0.05, *** p<0.01

cervical cancer patients for meaningful inferences between MA patients and traditional Medicare patients. In the remainder of the chapter, I include cervical cancer patients in my sample of aggregate cancer patients, but do not disaggregate them as a separate sample. There were some statistically distinguishable differences in survival, based on MA enrollment, for patients with other types of cancer. MA patients with breast, colorectal, or prostate cancers were more likely than traditional Medicare patients with the same cancers to survive at least two years. These relationships are not necessarily causal due to potentially endogenous selection into MA plans. Another important observation from the data is that MA patients with colorectal cancer, leukemia, lung cancer, or prostate cancer who died within two years were more likely to have died from cancer than traditional Medicare patients with the same cancers. This pattern is consistent with MA cancer patients having better non-cancer health than cancer patients with traditional Medicare.

3.3.3 Patient Characteristic Data

Medicare and SEER both report some demographic characteristics for each patient. Since age is a crucial determinant of Medicare eligibility, I give precedence to the date of birth information provided by Medicare. For the race and ethnicity

TABLE 3.3: Summary of Geographic Areas of Residence

Variable	**HSA Population $<$ 500,000 N = 159,206** Mean	**HSA Population $\geq$ 500,000 N = 432,409** Mean
% of Cancer Patients in MA	0.13	0.32
# Physicians	152.28	2,292.88
# Surgeons	96.46	1,650.44
# Radiaton Oncologists	3.04	46.95
# Hospitals	6.47	34.33
# Hospitals w/ Cancer Programs	1.23	9.54
# Hospitals w/ Medical Schools	0.90	9.09
Any NCI Cancer Center	0.00	0.42

The sample consists of 159,206 cancer patients who lived in HSAs with fewer than 500,000 people at the time of diagnosis (left panel) and 432,409 cancer patients who lived in HSAs with 500,000 or more people. The mean for the percent of the cancer patients in Medicare Advantage (MA) plans is taken directly from the SEER Medicare data, the information about number of providers is taken from the Area Health Resources File, and the information needed to classify the presence of an NCI Cancer Center is taken from the National Cancer Institute's website. Using any conventional cutoff, all of the means are statistically different between the two groups of patients.

variables, however, I use the information provided by SEER because it is likely to be more accurate (Waldo, 2004). I also give precedence to the gender variable and, since there is no equivalent variable from Medicare, the marital status variable provided by SEER. The top panel of Table 3.2 provides the summary statistics for the main patient characteristics, separately for patients diagnosed with cancer in MA plans versus traditional Medicare.[20] For most variables, MA cancer patients and traditional Medicare cancer patients were similar, except that MA cancer patients were about twice as likely to be Hispanic as traditional Medicare cancer patients.

Two of the most important differences between MA and traditional Medicare cancer patients are in terms of geography of residence and year of diagnosis.[21] Figure 3.2 shows how the popularity of MA plans varied over time, and Table 3.3 shows important differences between geographic areas where MA plans tend to be least popular and geographic areas where MA plans tend to be most popular. Since MA plans tend to be most popular in large urban areas, Table 3.3 splits the main sample into groups of patients who live in areas with relatively small or large populations. These subsamples are used throughout the mortality analysis. Recent studies of the MA program (Afendulis, Chernew, and Kessler, 2013; Duggan, Starc, and Vabson, 2014; Starc and Town, 2015; Cabral, Geruso, and Mahoney, 2015) have compared

[20]The data includes additional variables for Medicaid and Part D coverage, but only in years 2006 and after.

[21]For a good discussion of the likely sources of spatial heterogeneity (and time trends) in the popularity of MA plans, see McGuire, Newhouse, and Sinaiko (2011).

patients in MSAs with fewer than 250,000 people to patients in MSAs with at least 250,000 people in regression discontuinity frameworks. I choose a cutoff for HSA population of 500,000 people. This cutoff is consistent with the cutoffs used in the other studies; MSAs with populations between 150,000 and 350,000 have an average HSA population of 536,000.[22]

The first row of Table 3.3 summarizes the geographic variation in MA popularity. Only 13 percent of cancer patients in the smaller HSAs were enrolled in an MA plan, but 32 percent of cancer patients in larger HSAs were enrolled in an MA plan. Unsurprisingly, there are also large differences in the supply of cancer treatment between the two sets of cancer patients. Notably, patients living in HSAs with fewer than 500,000 people had only about 3 radiation oncologists, 1 hospital with a certified cancer program, and 1 hospital with a medical school affiliation in their HSA. Patients in the larger HSAs had approximately 47 radiation oncologists, 9 hospitals with certified cancer programs, and 9 hospitals with medical school affiliations to choose from. Similarly, less than 1 percent of the cancer patients in smaller HSAs had an NCI cancer center in their HSA, but 42 percent of cancer patients in larger HSAs did. In section 3.2, I discussed how MA plans might reduce quality of cancer care in situations where there is variation in the quality of cancer care. Due to the differences in number of cancer providers available, the supply-side statistics indicate that larger HSAs are much more likely to exhibit variation in quality of cancer care than smaller HSAs.

3.4 Effect of Health Insurance on Cancer Mortality

The first objective of this research is to estimate the effect of MA enrollment on cancer patients' mortality. The main challenge is that MA enrollment is potentially endogenous. Likely due to selection, MA patients tend to live longer than traditional Medicare patients (Curto et al., 2015). Using a stratified Cox proportional hazards model, I take several steps to minimize this bias.

[22]The average of HSA population is somewhat sensitive to the bandwidth used for MSA population, but MSA population and HSA population are very strongly correlated.

3.4.1 Empirical Strategy

Estimating the effect of MA enrollment on cancer mortality is complicated by potentially endogenous selection into MA plans and right-censoring of survival times. I first discuss how I address selection in the context of a simplified linear model. I then introduce the Cox proportional hazards model to address censoring.

Addressing Selection into Medicare Advantage

Ignoring the important issue of censoring for now, the simplest form of my analysis is to regress survival time on an indicator for MA enrollment. Let T_{iym} indicate the number of months individual i survived after being diagnosed with cancer in month m of year y while living in county c. Let MA_{iy} indicate if the patient was enrolled in an MA plan in the year of diagnosis. The timing of the MA enrollment variable is the first way that I address selection. In particular, the variable reflects a decision that the patient made before learning about their cancer. The second way I address selection is to condition on patient characteristics X_{iy}, geographic fixed effects d_c, and year of diagnosis fixed effects d_y. The geographic fixed effects are especially important because, as shown in the bottom panel of Table 1, MA plans are much more popular in places that likely have better medical care available. Using these covariates, a naive regression to estimate the effect of MA enrollment on cancer survival would be:

$$T_{icym} = \alpha X_{iy} + \beta MA_{iy} + d_y + d_c + d_m + \varepsilon_{icym} \tag{3.1}$$

The concern with equation 3.1, besides the censoring in the data, is that MA enrollment is still likely to be endogenous. Evidence suggests that MA patients are residually healthier (Newhouse et al., 2012) and perhaps more likely to screen for cancer (e.g., Baker et al., 2004; Rizzo, 2005) than patients with traditional Medicare.[23] A naive estimate of β is thus likely to be biased in the direction of indicating that MA enrollment decreases cancer mortality. Unfortunately, there is no obvious candidate for an instrument in this context. Some researchers (Afendulis, Chernew, and Kessler, 2013; Duggan, Starc, and Vabson, 2014; Starc and Town, 2015; Cabral,

[23] In the final chapter of this dissertation, I find evidence that the relationship is not causal.

Geruso, and Mahoney, 2015) have instrumented for MA enrollment using plausibly exogenous changes to payment benchmarks across counties. Such variation cannot be used in conjunction with geographic fixed effects, which are important in order to flexibly control for spatial heterogeneity in quality of cancer care providers. The ideal instrument would be predictive of variation in MA enrollment within a locality over time and be orthogonal to changes over time in cancer care. Additionally, due to the non-linearity of the Cox proportional hazards model discussed in the next subsection, I would need to introduce additional assumptions in order to address the censoring in the data.[24] In the absence of an instrumental variables approach, the goals of my empirical model are to minimize bias and ensure that the estimates are conservative with respect to testing whether MA enrollment increases cancer mortality.

The omitted variables that are most likely to influence cancer mortality include cancer severity, non-cancer health, financial resources, determination, health literacy, and home support. Especially because the model can control for marital status, Medicaid eligibility, and census-tract-level socioeconomic characteristics, perhaps the most potentially concerning omitted variables are cancer severity and non-cancer health. However, as mentioned above, both of these omitted variables are likely to result in a conservative bias.

Through the timing of the MA enrollment variable, equation 3.1 already addresses endogeneity due to cancer severity that the patient learns after being diagnosed with cancer. However, it does not address selection correlated with pre-cancer health or behavior that might also influence cancer severity. To minimize this bias, I use the rich information in the SEER Medicare data and control for cancer severity that is clinically measurable. My preferred models only include an indicator for tumor metastasis, but in alternative models I also include cancer grade, and, for breast cancers, estrogen and progesterone receptivity.

There are two important caveats regarding the conditioning on observed cancer severity. First, it wipes out a potential effect of MA plans to improve early detection

[24]Stukel et al. (2007) used estimates from linear IV models to back out an estimate for the hazard rate. MacKenzie et al. (2014) proposed an instrumental variables approach with the standard Cox proportional hazards model, but their approach assumes that any omitted variable affects the hazard rate additively even though the observed variables are assumed to affect the hazard rate multiplicatively.

of cancer via reduced cost-sharing for cancer screening and other preventive services. It is thus important to remember that the estimates can only be interpreted as an effect of MA enrollment on post-diagnosis cancer care.[25] Second, conditioning on observed cancer severity does not eliminate the conceptual possibility that β could be biased in the undesirable direction of MA enrollment increasing cancer mortality. Related to the first caveat, patients who are particularly worried about a future (first) cancer diagnosis may enroll in an MA plan in order to reduce the out-of-pocket cost associated with cancer screening and other preventive care. It is possible that whatever makes a patient particularly worried about a future diagnosis also eventually results in a cancer that is more severe in ways that are not clinically measurable. Similarly, suppose that there are unmeasurable dimensions of tumor aggression. If MA patients screen more regularly for cancer, their later stage cancers, which may have grown too fast to be detected early, may spread more rapidly than otherwise similar cancers for patients with traditional Medicare. These concerns are most plausible for patients with cancers that are preventable (i.e., lung cancer) or have screening technology (i.e., breast and colorectal cancers).[26] They are perhaps least plausible for brain cancer patients; there is no brain cancer screening technology and the only known lifestyle risk factor for brain cancer is exposure to radiation.

Addressing the potential endogeneity of MA enrollment due to non-cancer health requires a different approach. Unfortunately, besides the patient characteristics, there is no information in the data related to non-cancer health at the time of cancer diagnosis.[27] However, for people who died during the study period, I know whether their death was due to cancer or due to other causes. A convenient way to address the potential endogeneity of MA enrollment due to non-cancer health is thus to treat non-cancer deaths as a source of censoring. The implied assumption is that MA enrollment and non-cancer deaths are only related due to differences in pre-existing health stocks for MA patients and traditional Medicare patients at the time of cancer diagnosis. Health differences between MA patients and traditional

[25] Even without conditioning on cancer severity, because MA plans may improve cancer prevention, the estimates can only be interpreted as an effect of MA enrollment on post-diagnosis cancer care.

[26] According to Song and Giovannucci (2016), about 80 percent of lung cancer diagnoses could be prevented with a healthier lifestyle. Breast and colorectal cancers are the only cancers for which routine cancer screening is recommended by the US Preventive Services Task Force.

[27] I excluded cancer patients aged 91 and older and those known to have a disability, end-stage renal disease, or need for a nursing home.

Medicare patients are generally attributed to selection.[28] It is possible, however, that there is some causal influence of MA enrollment to improve non-cancer health. To the extent that MA enrollment might prevent non-cancer deaths in my follow-up period, my cancer-mortality models attribute that to an influence that occurred prior to cancer diagnosis. I also estimate all-causes mortality models for comparison.

Stratified Cox Proportional Hazards Model

To account for right-censoring of survival times in the data, I use a stratified Cox proportional hazards model to estimate the effect of MA enrollment on the mortality hazard rate. The mortality hazard rate, denoted $\lambda(t)$, measures the conditional probability of death in each month t given survival up until month t. The standard way to estimate the effect of a covariate on a hazard rate is to use a semi-parametric approach developed by Cox, 1972. If we assume that the mortality hazard rate for MA patients is proportional to the mortality hazard rate for patients with traditional Medicare, i.e. $\lambda(t|MA = 1) = \kappa\lambda(t|MA = 0)$ for some $\kappa > 0$, then we can estimate the parameter of interest κ without making any assumptions about the baseline hazard function $\lambda(t|MA = 0)$. We can also examine the validity of the proportional hazards assumption by testing whether the true effect of MA enrollment on the mortality hazard rate varies with t, the number of months the person has had cancer.

Due to potentially endogenous selection into MA plans, it is important that the model controls for patient characteristics, geography, cancer severity, and year of cancer diagnosis. Since it is not necessarily important to estimate coefficients for any of these variables, there are two ways to incorporate them in the Cox model. First, if their true effect on the mortality hazard rate is proportional over time, they can enter as proportional covariates with coefficients to be estimated. For most of the variables, this turned out to not be a reasonable assumption. For example, the ratio of mortality hazards for patients diagnosed with cancer at different ages varied with the elapsed time since diagnosis. The second option is to include the variables as stratifying covariates, where each strata (combination of the covariates) is associated with a different baseline hazard function. This is convenient, and a less

[28] With respect to a greater life expectancy conditional on Medicare's risk score for MA patients versus traditional Medicare patients, Curto et al. (2015) indicated that "private plans offering superior care" is a "relatively unlikely explanation for the differential mortality."

parametric approach, because there are no underlying assumptions about the baseline hazard functions in the Cox model. However, over-stratifying the model will result in limited statistical power and could cause some strata to be ignored in the estimation.[29]

My general approach is to stratify the baseline hazard function in a way that does not lead to many small strata but also includes the control variables that (1) violate the proportionality assumption and (2) most influence selection in MA plans and/or cancer mortality. This approach leads to a preferred model in which the baseline hazard function is stratified by age band at diagnosis, an indicator for being married, health service area (HSA), cancer site and metastasis, and year of diagnosis.[30] These are the only controls used in the preferred model, but other strata are added in some alternative models. If we let g index the strata and $\widetilde{X_{iy}}$ any characteristics for patient i diagnosed in year y that are assumed to be proportional, the estimating equation can be written as:

$$ln\lambda_{igy}(t) = ln\lambda_g^0(t) + \alpha\widetilde{X_{iy}} + \beta MA_{iy} + \varepsilon_{igyt} \tag{3.2}$$

3.4.2 Main Results

Table 3.4 reports estimates for the aggregate effect of MA enrollment on the hazard rates of all-causes mortality (panel A) and cancer mortality (panel B) for all cancer patients. Consistent with MA cancer patients have better non-cancer health than traditional Medicare cancer patients, the cancer-mortality estimates are consistently larger than the estimates for all-causes mortality. The first column of the table shows descriptive estimates from a model that stratifies the baseline hazard only by cancer site. Controlling only for cancer site, in HSAs with populations less than 500,000, MA cancer patients have lower hazards of all-causes mortality and cancer mortality than do traditional Medicare cancer patients. In HSAs with populations of at least 500,000, MA cancer patients have similar hazard of all-causes mortality but *higher*

[29]The Cox model is estimated with partial likelihood. The likelihood meausures the probability that a particular individual died in a particular month, given that someone (still alive and in that individual's stratum) died in that month. If a person dies at a time when there was nobody else alive in their stratum, that person will not contribute to estimation at all.

[30]The age bands are for ages 65-69, 70-74, 75-79, 80-84, and 85 and older. Health service areas are defined by the National Cancer Institute. See `https://seer.cancer.gov/seerstat/variables/countyattribs/hsa.html`, accessed on 3/10/17.

TABLE 3.4: Aggregate Effect of Medicare Advantage Enrollment on the Mortality Hazard Rate for Cancer Patients

	(1)	(2)	(3)	(4)
(A) All-Causes Mortality				
HSA Population $<$ 500K	-0.0720***	-0.0379***	-0.0010	-0.0130
N = 159,206	(0.0114)	(0.0123)	(0.0154)	(0.0179)
	[0.4927]	[0.1700]	[0.7237]	[0.3768]
HSA Population $\geq$ 500K	-0.0054	0.0008	0.0165**	0.0218***
N = 432,409	(0.0080)	(0.0082)	(0.0081)	(0.0082)
	[0.0000]	[0.0965]	[0.8650]	[0.9728]
(B) Cancer Mortality				
HSA Population $<$ 500K	-0.0661***	-0.0086	0.0265	0.0098
N = 159,206	(0.0141)	(0.0144)	(0.0185)	(0.0206)
	[0.1123]	[0.1074]	[0.4486]	[0.5308]
HSA Population $\geq$ 500K	0.0369***	0.0412***	0.0555***	0.0631***
N = 432,409	(0.0105)	(0.0101)	(0.0106)	(0.0107)
	[0.0000]	[0.0184]	[0.6458]	[0.1543]
HSA, Year of DX Strata		✓	✓	✓
Age, Sex, Married Strata			✓	✓
Metastatic Tumor Strata				✓

An observation is an individual. Each panel contains two rows of estimates for two different subsamples of the data. The estimates are computed using Cox partial likelihood and the Breslow approximation for ties. HSA is the National Cancer Institute's definition of hospital service area, and HSA Population is taken from the 2010 census for all years of diagnosis. In addition to the variables noted in the table, all models stratify the baseline hazard by cancer site. Standard errors, in parentheses, are clustered by county$\times$year-of-diagnosis. The p-values in brackets are for the proportionality test, based on Schoenfield residuals, testing the null hypothesis that the variable has a true effect on the stratified baseline hazard that does not vary over time.
* p$<$0.10, ** p$<$0.05, *** p$<$0.01

hazards of cancer mortality than traditional Medicare cancer patients. None of these estimates should be interpreted as causal because selection into MA plans, most importantly with respect to geography and year of diagnosis, is unaccounted for. The proportionality assumption is also violated for the sample of patients in highly populated HSAs, as indicated by the small p-values in brackets.

The next columns in the table sequentially add additional stratifying covariates into the model. The first step, in column 2, is to stratify the baseline hazard function by the HSA of residence and year of diagnosis. Compared to the estimates in column 1, all four of the estimates in column 4 are larger. The pattern of increasing estimates continues in column 3 (additional stratification by age band and indicator for female and married) and column 4 (additional stratification by tumor metastasis). The preferred specification is the one in column 4, as it conditions on important covariates without overstratifying the model.[31] Using either all-causes or cancer-mortality, there is no evidence that MA enrollment influenced the hazard rate for patients in HSAs with fewer than 500,000 people. However, for patients in larger HSAs, MA enrollment increased the hazard of both all-causes mortality (by 2.2 percent) and cancer mortality (by 6.3 percent).

Table 3.5 presents estimates for the effect of MA enrollment on the mortality hazard rates for patients with particular types of cancer. Cervical cancer is not included due to its small sample size. The table reports estimates from the preferred specification only, but for both subsamples of patients and for both all-causes and cancer mortality. For patients in HSAs with fewer than 500,000 people, none of the 14 estimates are statistically distinguishable from zero using a 5 percent threshold and only one is statistically distinguishable from zero using a 1 percent threshold. For patients in larger HSAs, the estimates indicate that MA enrollment increased mortality for patients with several types of cancers. Three cancer sites (brain, lung, and prostate) exhibit a statistically distinguishable effect of MA enrollment to increase both all-causes mortality and cancer mortality. In particular, MA enrollment increased the hazard of brain cancer mortality by 20.7 percent, increased the hazard of lung cancer mortality by 6.8 percent, and increased the hazard of prostate cancer mortality by

[31] A useful signal of overstratification is the standard error. The standard errors in column 4, particularly for the patients in highly populated HSAs, are similar to the standard errors in column 1. This is reassuring evidence that most patients in smaller strata are still contributing to estimation.

TABLE 3.5: Effect of Medicare Advantage Enrollment on Mortality Hazard Rate for Patients with a Particular Cancer

	(A) All-Causes Mortality		(B) Cancer Mortality	
Cancer Type	HSA Pop. $< 500K$	HSA Pop. $\geq 500K$	HSA Pop. $< 500K$	HSA Pop. $\geq 500K$
Brain	-0.0786	0.1869***	-0.1817	0.2074***
	(0.2026)	(0.0475)	(0.2184)	(0.0502)
	N = 2,371	N = 6,259	N = 2,371	N = 6,259
Breast	0.0392	-0.0150	0.1404*	0.0059
	(0.0485)	(0.0155)	(0.0729)	(0.0207)
	N = 31,923	N = 95,747	N = 31,923	N = 95,747
Colorectal	-0.0439	-0.0198	0.0366	0.0339**
	(0.0461)	(0.0121)	(0.0631)	(0.0161)
	N = 27,987	N = 75,314	N = 27,987	N = 75,314
Leukemia	-0.2975**	-0.0147	-0.1925	0.0193
	(0.1247)	(0.0304)	(0.1417)	(0.0383)
	N = 6,488	N = 17,385	N = 6,488	N = 17,385
Lung	-0.0204	0.0428***	0.0039	0.0677***
	(0.0237)	(0.0107)	(0.0248)	(0.0121)
	N = 41,251	N = 100,423	N = 41,251	N = 100,423
Ovarian	-0.0225	0.0533	-0.2126	0.0947**
	(0.1771)	(0.0352)	(0.1959)	(0.0393)
	N = 3,340	N = 9,399	N = 3,340	N = 9,399
Prostate	0.0290	0.0385**	0.0035	0.1536***
	(0.0423)	(0.0157)	(0.0854)	(0.0316)
	N = 44,099	N = 125,842	N = 44,099	N = 125,842

An observation is an individual. Estimates in panel A and panel B are computed separately for each geographic subsample (columns) and cancer site rows) using specification (4) from Table 3.4. Standard errors, in parentheses, are clustered by county×year-of-diagnosis.
* p<0.10, ** p<0.05, *** p<0.01

15.4 percent. For two of the other cancer sites (colorectal and ovarian), MA enrollment had no effect on the hazard of all-causes mortality but may have increased the hazard of cancer mortality. The increases to the cancer-mortality hazard rate were statistically distinguishable from zero using a 5 percent cutoff, but not a 1 percent cutoff. For the other two cancer sites (breast and leukemia), there is no evidence that MA enrollment influenced all-causes mortality or cancer mortality.

The estimates for breast, colorectal, and prostate cancer in Table 3.5 can be compared to similar estimates from previous studies that focused on the earliest years of Medicare HMOs. Overall, my estimates for previously-studied cancer sites are more robust than the results from these older studies. The studies most similar to mine examined the relationship between Medicare HMO enrollment, with one of two private companies, and mortality hazard rates for patients living in the San Francisco and Seattle SEER registry regions who were diagnosed with cancer between 1985 and 1992. Potosky et al. (1997) estimated lower (all-causes and cancer) mortality hazard rates for breast cancer patients enrolled in one of the HMOs versus traditional Medicare, but no distinguishable difference in mortality hazard rates between breast cancer patients enrolled in the other HMO versus traditional Medicare. Merrill et al. (1999) estimated a negative relationship between HMO enrollment and all-causes mortality for colorectal cancer patients, but no relationship between HMO enrollment and colorectal cancer mortality. Finally, Potosky et al. (1999) estimated no relationship between HMO enrollment and all-causes mortality for prostate cancer patients, but a *positive* relationship between HMO enrollment and prostate cancer mortality.

3.4.3 Robustness and Magnitude

Table 3.6 shows the stability of the main results, for patients living in HSAs with at least 500,000 people, to a variety of alternative model specifications, . Columns 1 and 2 alleviate any concerns that the estimated effect of MA enrollment on mortality could be driven by switches in health insurance around the time of diagnosis. In column 1, MA enrollment is defined from the year prior to cancer diagnosis rather than the year of cancer diagnosis. In column 2, all cancer patients who ever, in some year between 2000 and 2013, switched between an MA plan and traditional Medicare are

TABLE 3.6: Robustness of the Aggregate Effect of Medicare Advantage Enrollment on the Mortality Hazard Rate for Cancer Patients in HSAs with at least 500,000 People

	(0) Base	(1) Prior Year MA Enroll.	(2) Exclude Switchers	(3) Part D Strata	(4) Medicaid Strata	(5) Severity Strata
(A) All-Causes Mortality						
MA Enrollment	0.0218***	0.0278***	0.0258***	0.0213**	0.0064	0.0349***
	(0.0082)	(0.0081)	(0.0091)	(0.0098)	(0.0092)	(0.0107)
(B) Cancer Mortality						
MA Enrollment	0.0631***	0.0637***	0.0762***	0.0598***	0.0390***	0.0794***
	(0.0107)	(0.0105)	(0.0115)	(0.0129)	(0.0123)	(0.0115)
N	432,409	432,409	337,081	321,015	321,015	432,409

An observation is an individual. The estimates in specification (0) match the estimates in specification (4) from Table 3.4. Subsequent specifications are adjusted as described in the table. The Part D and Medicaid strata specifications additionally stratify the baseline hazard by an indicator for having Medicare Part D or Medicaid coverage, respectively. The severity strata, in addition to tumor metastasis, are: tumor grade, estrogen-receptivity for breast tumors, and progesterone-receptivity for breast tumors. Standard errors, in parentheses, are clustered by county×year-of-diagnosis.
* p<0.10, ** p<0.05, *** p<0.01

excluded. By including a control for Medicare Part D coverage, column 3 demonstrates that the estimates are unlikely to be driven by differences in prescription drug coverage, as Gowrisankaran, Town, and Barrette, 2011 argued in the context of their results.[32] The estimates in column 4 are most different from the estimates in column 0. Column 4 address potential unobserved heterogeneity in patients' financial resources conditional on health insurance by including a control for Medicaid coverage. This control makes the all-causes mortality effect indistinguishable from zero and reduces the cancer mortality effect to 3.9 percent. Conversely, column 5 shows that controlling for more measures of cancer severity, notably including measures that proxy for tumor aggression, results in estimating larger mortality effects. If the controls in column 4 (for Medicaid coverage) and column 5 (for additional cancer severity measures) are included in the same model, the resulting estimate is similar to the main estimate in column 0.[33]

The conclusion that MA enrollment increased mortality for cancer patients in large HSAs is also robust to using survival models besides the Cox model. Besides

[32]Since Medicare Part D coverage and Medicaid coverage are only coded starting in 2006, the models in columns 3 and 4 exclude patients diagnosed in 2004 and 2005.

[33]The estimate is 1.9 percent ($p < 0.1$) for all-causes mortality and 5.6 percent ($p < 0.01$) for cancer mortality.

TABLE 3.7: Effect of Medicare Advantage Enrollment on Post-Diagnosis Life Expectancy in HSAs with Over 500,00 People

	Censored Quantile Regression: Laplace Quantiles (1)		Parametric Hazard Model: Log-logistic Hazard No Frailty (2)	Gamma Frailty (3)
Combined (N = 432,409)				
Median L.E. (in months)	-0.6291***	Average L.E. (percent)	-0.0520***	-0.0469***
$S_{30} = 43$ months	(0.1287)	$S_{30} = 43$ months	(0.0116)	(0.0114)
Brain Cancer (N = 6,259)				
Median L.E. (in months)	-0.9177***	Average L.E. (percent)	-0.1575***	-0.1282***
$S_{50} = 6$ months	(0.1959)	$S_{50} = 6$ months	(0.0285)	(0.0273)
Breast Cancer (N = 95,747)				
Median L.E. (in months)	-1.2621	Percentage L.E.	-0.0229	-0.0246
$S_{10} = 58$ months	(1.1664)	$S_{10} = 58$ months	(0.0340)	(0.0335)
Colorectal Cancer (N = 75,314)				
Median L.E. (in months)	-0.6788	Percentage L.E.	-0.0195	-0.0098
$S_{30} = 42$ months	(0.7666)	$S_{40} = 42$ months	(0.0245)	(0.0244)
Leukemia (N = 17,385)				
Median L.E. (in months)	-1.6912	Percentage L.E.	-0.0881*	-0.0181
$S_{50} = 72$ months	(1.0308)	$S_{50} = 72$ months	(0.0508)	(0.0427)
Lung (N = 100,423)				
Median L.E. (in months)	-0.4006***	Percentage L.E.	-0.0525***	-0.0443***
$S_{50} = 10$ months	(0.0957)	$S_{50} = 10$ months	(0.0138)	(0.0133)
Ovarian (N = 9,399)				
Median L.E. (in months)	-0.5152	Percentage L.E.	-0.0217	-0.0139
$S_{50} = 26$ months	(0.7670)	$S_{50} = 26$ months	(0.0457)	(0.0460)
Prostate (N = 125,842)				
Median L.E. (in months)	-3.9505***	Percentage L.E.	-0.1236***	-0.1193***
$S_{05} = 40$ months	(0.8354)	$S_{05} = 40$ months	(0.0288)	(0.0287)

An observation is an individual. Each panel represents a separate model and only includes patients living in HSAs with populations that exceeded 500,000 people in 2010. When it exists, the median of survival times for these patients (S_{50} is provided in each panel. When it does not exist due to censoring, the highest calculable quantile is provided. In the first column, the dependent variable is median life expectancy, measured in whole months. The model is estimated using Laplace regression (Bottai and Zhang, 2010). In the second and third columns, the dependent variable is the log of survival time. The model is estimated by maximum likelihood, assuming the hazard rate follows a log-logistic distribution. In the third column only, unobserved heterogeneity (i.e., frailty) is explicitly modeled and assumed to follow a gamma distribution. All models control for female, black, Hispanic, married, widowed, socioeconomic characteristics of the census tract of residence, and fixed effects for age, year, cancer severity, and HSA. The cancer severity fixed effects are for tumor metastasis, tumor grade, and (for breast cancers only) estrogen and progesterone receptivity. Standard errors, clustered by county×year-of-diagnosis, are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

serving as additional robustness checks, there are two important benefits of the parametric estimates in Table 3.7. First, the estimates are more easily interpreted since they directly measure life expectancy. Column 1 presents estimates from a parametric censored quantile regression model. The model assumes a Laplace distribution of the conditional quantiles, as suggested by Bottai and Zhang (2010). The estimates from this model are interpreted as effects on median post-diagnosis life expectancy. Columns 2 and 3 present estimates from parametric hazard models. These models assume a log-logistic hazard function and, in column 3 only, a gamma distribution for unobserved heterogeneity (frailty).[34] The estimates from these models are interpreted as average percentage effects on post-diagnosis life expectancy. The second benefit of the parametric estimates is that, since covariates enter directly into the models rather than as stratifying covariates, more covariates are included as controls. In particular, I use the full set of patient characteristics from Table 3.2 and the full set of cancer severity variables, which include cancer grade (all cancers) and hormone-receptivity variables (breast cancers).

The first row of Table 3.7 combines all of the cancer patients living in HSAs with at least 500,000 people. In these areas, I estimate (column 1) that MA enrollment decreased median life expectancy by 0.6 months. Relatedly, I also estimate (columns 2 and 3) that MA enrollment decreased life expectancy for cancer patients in these areas by 5 percent on average. The remaining rows show that, similar to the results from the Cox model, the mortality effects are concentrated on patients with cancers of the brain, lung, or prostate. In particular, I estimate that MA enrollment decreased brain cancer life expectancy by 0.9 months (13 to 16 percent), decreased lung cancer life expectancy by 0.4 months (4 to 5 percent), and decreased prostate cancer life expectancy by 4.0 months (12 percent).

In this section, I presented estimates indicating that MA enrollment decreased life expectancy for patients with brain, lung, and prostate cancers living in HSAs with at least 500,000. In section 3.2, I discussed how MA plans might faciliate a

[34] In the Cox proportional hazards model, unobserved heterogeneity can bias the estimates even if it is uncorrelated with the proportional covariates. All else equal, patients who survive longer contribute more to estimation and may be affected differently by a particular variable. Unobserved heterogeneity can be incorporated into a hazard model, but only separately identified if the baseline hazard is estimated. Thus, I explore robustness of the estimates to unobserved heterogeneity with a parametric hazard model and not with the Cox model.

lower quality of care than traditional Medicare for conditions and regions where there is variation in the quality of care. It is possible that the heterogeneous effects I find, by HSA size and cancer site, are consistent with my theoretical hypothesis. In particular, there is likely to be little variation in quality of cancer care in smaller HSAs because there are not many cancer care providers to choose from (Table 3.3). It would be beneficial to dig into the mechanism of how MA plans influence cancer mortality further, but I am unfortunately limited by the available data. Ideally, in order to better assess a mechanism, I would like to know the precise treatments that patients receive and who they are treated by. At least some level of this information could be inferred from medical claims data, but the claims information in SEER Medicare is only provided for traditional Medicare patients. One rough mechanism test I have tried is to test whether the mortality effect varies within larger HSAs according to the presence of an NCI cancer center. MA plans often exclude NCI cancer centers from their provider networks (Jacobson et al., 2016) and NCI cancer centers likely provide the highest quality of cancer care (Pfister et al., 2015). My (unreported) estimates, however, did not significantly differ based on residence in an HSA with an NCI cancer center. This is not overly surprising, since I do not know which MA patients were blocked from visiting an NCI cancer center and am unable to precisely measure, in each HSA, the quality of the NCI cancer center relative to other cancer treatment facilities.

3.5 Effect of Having Cancer on Health Insurance Choice

The analysis in the previous section treated MA enrollment as a static variable. To the extent that patients recognize and value differences in quality of post-diagnosis cancer care, however, patients may choose different health insurance before versus after a cancer diagnosis. The second objective of this research is to estimate the effect of a cancer diagnosis on patients' relative preference for MA plans. The main approach is an event study for switching between MA plans and traditional Medicare.

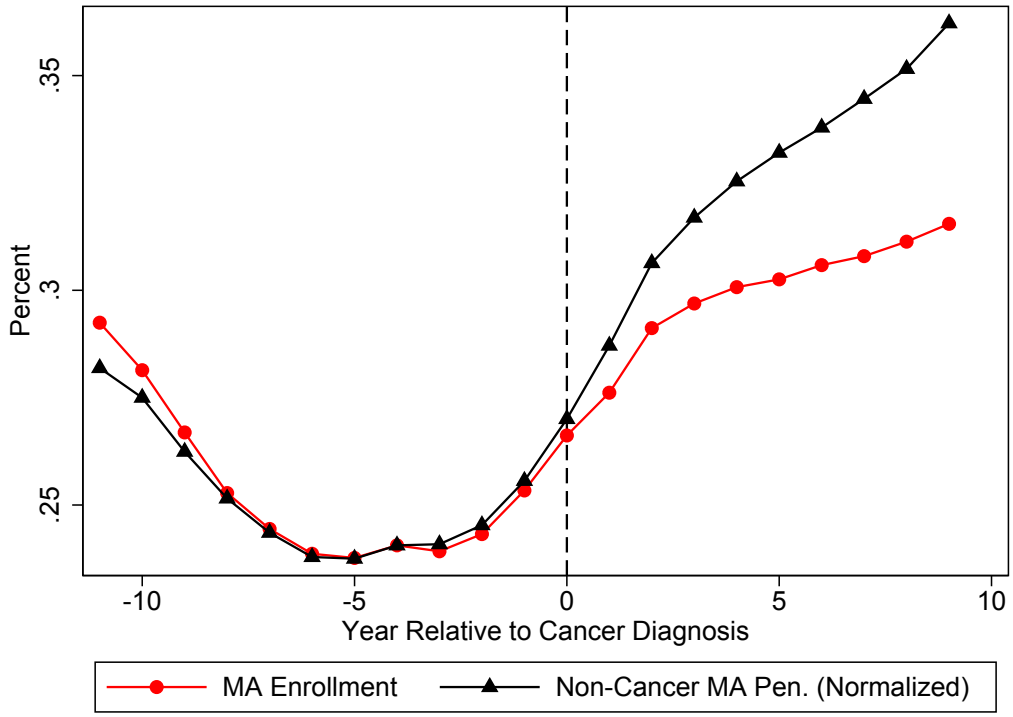
3.5.1 Descriptive Analysis

As depicted in Figure 3.2, starting in 2004, the proportion of the patients in my sample who were enrolled in an MA plan increased over time. While their cancer diagnoses started in 2004 too, 2004 was also when the popularity of MA plans in the general population started to increase substantially. To gain a better sense of the relationship between cancer diagnosis and MA enrollment, it is important to control for changes in MA enrollment in the non-cancer population. While this can be done fairly well with county and year fixed effects in a regression, to show the relationship graphically I link the SEER Medicare data with county-by-year MA penetration data released by the Centers for Medicare and Medicaid Services. For each county-year, I subtract the patients in the SEER Medicare data in order to calculate the proportion of non-cancer Medicare beneficiaries enrolled in an MA plan. This results in a new variable "non-cancer MA penetration" that has a value for each cancer patient and serves as a baseline for the trend of MA enrollment in my sample.

In Figure 3.3, I graph the means of the MA enrollment and non-cancer MA penetration variables by calendar year relative to cancer diagnosis. The calendar year when the patient is diagnosed with cancer is year zero. In order to facilitate easier comparison between the two variables, I normalize the means for non-cancer MA penetration so that the mean non-cancer MA penetration in the fourth year preceding cancer diagnosis equals the mean MA enrollment in the fourth year preceding diagnosis.[35] The take-away from the graph is that the two variables follow a similar trajectory in years prior to cancer diagnosis and diverge quickly after cancer diagnosis. One interpretation of this pattern is that having cancer reduced patients' valuation of coverage in an MA plan relative to traditional Medicare. This is the interpretation I will more formally test for in the remainder of the section. An alternative interpretation is that having cancer reduced patients' propensity to switch health insurance. Since MA popularity was increasing in the general population in the period after the diagnoses for the eventual cancer patients, increased inertia for cancer patients would imply more inclination to stay in traditional Medicare.

[35] Without this normalization, the means for non-cancer MA penetration are substantially less than the means for MA enrollment because non-cancer MA penetration includes people with disability, end-stage renal disease, and very old age.

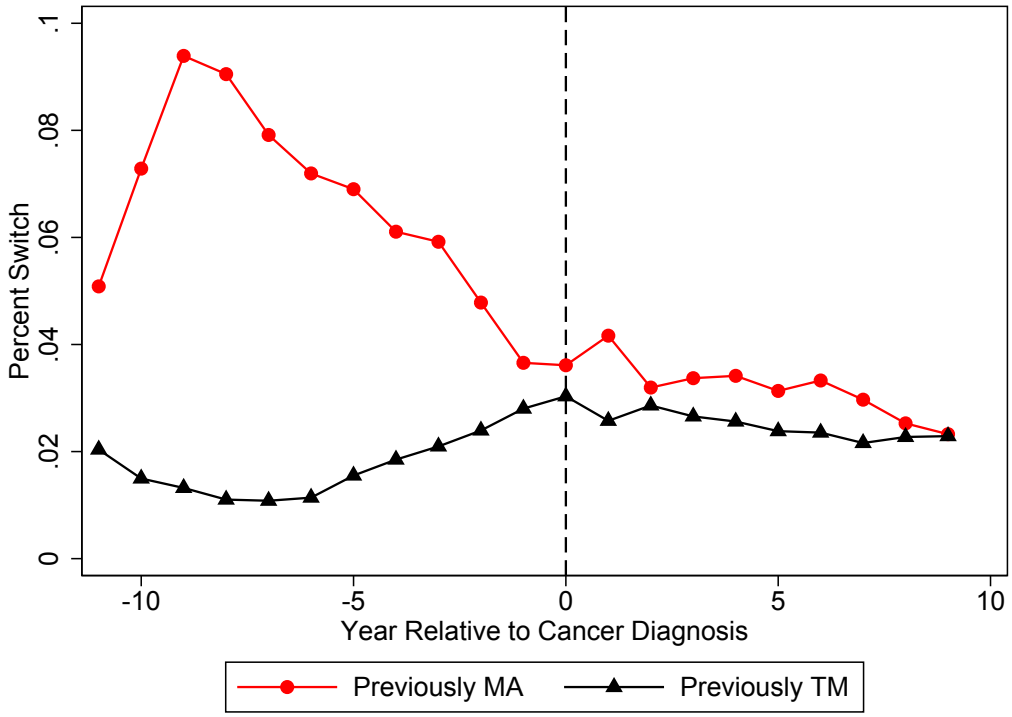
FIGURE 3.3: Popularity of Medicare Advantage Around Cancer Diagnosis



The graph summarizes two variables in the data. The horizontal axis measures years relative to one's cancer diagnosis. Year 0 is the calendar year of cancer diagnosis, year -1 is the first full calendar year preceding cancer diagnosis, year 1 is the first full calendar year after cancer diagnosis, and so on. The line with circular markers represents average Medicare Advantage (MA) enrollment. The line with triangular markers represents average non-cancer MA penetration. The non-cancer MA penetration variable is normalized to have the same mean as the MA enrollment variable in the fourth full year preceding cancer diagnosis.

In support of the first interpretation that having cancer reduced the relative value of MA coverage, Figure 3.4 shows some evidence that patients were both less likely to switch from traditional Medicare to an MA plan and *more likely to switch from an MA plan to traditional Medicare* in the year immediately following a cancer diagnosis. The vertical axis represents the proportion of patients who switched between an MA plan and traditional Medicare. The line with circular markers represents switching from an MA plan to traditional Medicare and the line with triangular markers represents switching from traditional Medicare to an MA plan. Neither graph is flat because of the regulatory changes to MA plans over the time period. The years at least two years prior to diagnosis are particularly influenced by the abnormally large

FIGURE 3.4: Health Insurance Switching Around Cancer Diagnosis (by Year)

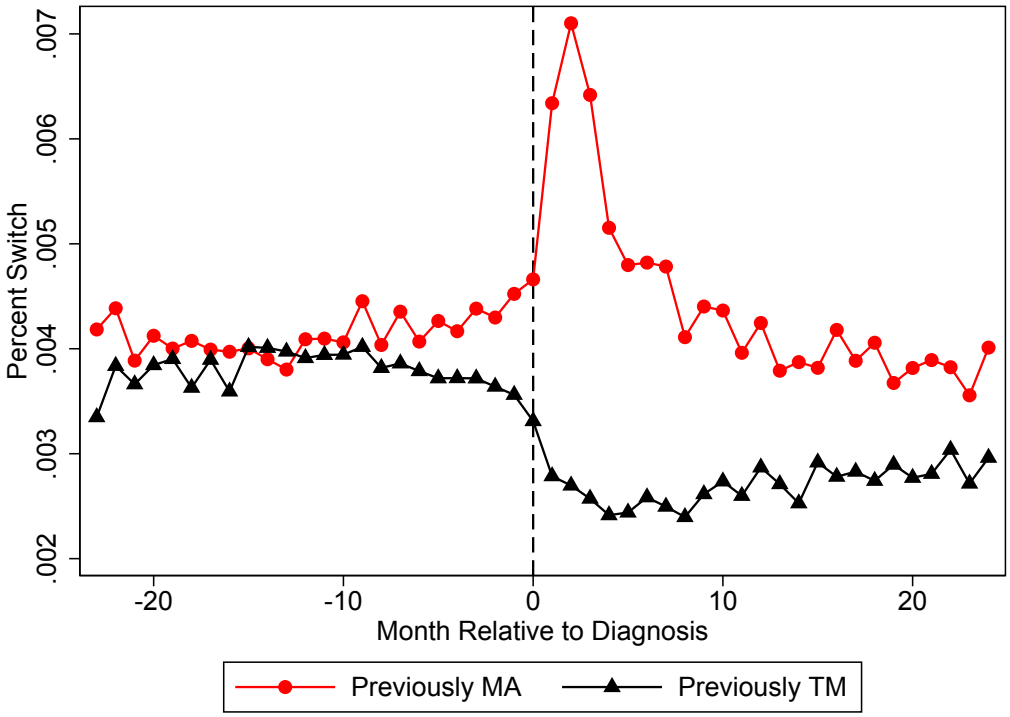


The graph illustrates the frequency of switches between Medicare Advantage (MA) plans and traditional Medicare (TM) around cancer diagnosis. Year 0 is the calendar year of cancer diagnosis, year -1 is the calendar year immediately preceding cancer diagnosis, year 1 is the calendar year immediately after cancer diagnosis, and so on. The line with circular markers indicates the proportion of patients with a MA plan in the prior year who switched to traditional Medicare. The line with triangular markers indicates the proportion of patients previously with traditional Medicare who switched to an MA plan.

rate of switching from an MA plan to traditional Medicare in the year 2002, which was nearly 15 percent. In spite of the noise, in the calendar year immediately following cancer diagnosis there is a noticeable upward spike in switches out of MA plans and a mirroring downward spike in switches into MA plans.

Figure 3.5 shows a similar, starker pattern with less noise. It plots monthly switches within a window of two years before and after cancer diagnosis. Aside from the main pattern of more switches out of MA plans and less switches into MA plans after cancer diagnosis, there are two interesting observations from the figure. First, patients seem to be more interested in switching out of an MA plan in the first several months after cancer diagnosis rather than subsequent months. Health insurance switching is, since 2006, generally only allowed at the start of a calendar year,

FIGURE 3.5: Health Insurance Switching Around Cancer Diagnosis (by Month)



The graph illustrates the frequency of switches between Medicare Advantage (MA) plans and traditional Medicare (TM) around cancer diagnosis. Month 0 is the month of cancer diagnosis, month -1 is the month immediately preceding cancer diagnosis, month 1 is the month immediately after cancer diagnosis, and so on. The line with circular markers indicates the proportion of patients with a MA plan in the prior year who switched to traditional Medicare. The line with triangular markers indicates the proportion of patients previously with traditional Medicare who switched to an MA plan.

which could have influenced switching behavior. Second, and perhaps relatedly, Figure 3.5 emphasizes that changes in the trend of switching between MA plans and traditional Medicare began as many as 10 months prior to cancer diagnosis. This is not overly surprising, given that many patients go a long time between first experiencing symptoms and officially being diagnosed with cancer. The median time between the start of symptoms and diagnosis for lung cancer patients is 180 days, with 25 percent of lung cancer patients being diagnosed more than 300 days after their first sign of symptoms (Koo, Zhou, and Lyratzopoulos, 2015). Similarly, 25 percent of patients with chronic lymphocytic leukemia are diagnosed 251 days or more after their first sign of symptoms (Friese et al., 2011) and about 20 percent of colorectal cancer patients are diagnosed 8 months or more after their first sign of symptoms

(Pruitt et al., 2013). Long diagnosis delays have also been documented for breast, ovarian, prostate, and other cancers (Allgar and Neal, 2005).

3.5.2 Empirical Strategy

There are several challenges to estimating the effect of having cancer on patients' relative preference for MA plans. First, people who get cancer may be inherently different, in unobservable ways, from people who do not get cancer. My model thus only uses variation from individuals' switching their health insurance. Since the timing of cancer diagnosis is plausibly random, switches around the time of diagnosis that cannot be attributed to other factors, such as aging or the changing popularity of MA plans in the general population, can be attributed to having cancer. Because some cancer patients may have long diagnosis delays, I use several years before cancer diagnosis as a baseline and run an event study.

The second challenge is that health insurance switching is only relevant for individuals who live long enough to be able to switch. I thus only estimate the effect of having cancer on health insurance switching *conditional on being alive*. In particular, I exclude patients who died before having the opportunity to switch health insurance. Elkin et al. (2008) and Riley, Feuer, and Lubitz (1996) took a different approach, using a Cox proportional hazards model to account for censoring due to death. The drawback of their approach, besides having to simulate placebo diagnosis dates for non-cancer patients, is that the censoring itself is influenced by having cancer. Cancer patients are more likely to die, and thus exit the sample, than non-cancer patients. While Elkin et al. (2008) and Riley, Feuer, and Lubitz (1996) estimated that having cancer reduced the likelihood of switching from an MA plan to traditional Medicare, some of their estimate is explained by cancer reducing the opportunities to switch by increasing the likelihood of death.[36]

The unit of observation for my analysis is an individual-year. The outcome is a dummy variable S_{icy} that equals 1 if and only if individual i living in county c

[36]For example, see Table 3 created by Elkin et al. (2008). Of the people who survived 2 years, 24 percent of MA lung cancer patients switched to traditional Medicare while only 16 percent of matched MA non-cancer patients switched to traditional Medicare. Because the MA cancer patients were much less likely to survive the two years, however, the Cox estimate indicates that the effect of having lung cancer was to reduce the hazard of switching to traditional Medicare.

switched from an MA plan in year $y-1$ to traditional Medicare in year y or vice-versa. I index years so that T_0 represents the calendar year in which cancer diagnosis occurred. I define year T_{-3}, the third calendar year preceding diagnosis, as the baseline year and include all subsequent calendar years up to T_1, the calendar year immediately following diagnosis. I estimate two separate linear probability models in order to quantify the effect of cancer diagnosis ($y = T_1$) on switching. One model is for patients initially enrolled in an MA plan and the other model is for patients initially enrolled in traditional Medicare. For both estimation samples, I exclude patients not enrolled in that type of health insurance for at least two years before the baseline year (i.e., at least T_{-5} and T_{-4}). I only model initial health insurance switches. For a given patient, any years after a switch in health insurance are excluded from the sample. If a patient switched from traditional Medicare to an MA plan in year T_{-2}, for example, their years T_{-1} through T_1 would not contribute to estimation in either sample. Besides year relative to cancer diagnosis, the linear probability models control for patient characteristics X_{icy}, county fixed effects d_c, and year fixed effects d_y:

$$S_{icy} = \sum_{j=-2}^{1} \beta_j I(y = T_j) + \alpha X_{icy} + d_c + d_y + \varepsilon_{icy} \tag{3.3}$$

The vector of patient characteristics X_{icy} controls for non-cancer factors that may influence an individual's propensity to switch health insurance. The variables were discussed in detail in section 3.3 and include age, gender, race, ethnicity, marital status, and census tract socioeconomic variables.[37] The year fixed effects control for regulatory changes over time and the county fixed effects control for geographic variation in the availability of particular MA plans. Since the growth over time in general popularity of the MA program likely varied by county, I also explore two variations of equation 3.3. First, I add the non-cancer MA penetration variable (created for Figure 3.3) as a continuous measure of growth in general MA popularity over time for each county. Second, I control for county-specific growth in general MA popularity more flexibly by adding county-by-year fixed effects. In all three

[37]Health insurance switching could also be influenced by changes to an individual's income or wealth, which might be correlated, though perhaps not immediately, with cancer diagnosis. I mitigate concerns that this could drive my results by including a robustness check with Medicaid entitlement in the model.

specifications, the error term ε_{icy} is clustered by county-year. The coefficient β_j represents the increased chance of switching health insurance from the $(j-1)^{th}$ to j^{th} year after cancer diagnosis, relative to the chance of switching health insurance from the fourth to the third year prior to cancer diagnosis. The identification assumption is that, at least in the omitted year, patients are unable to anticipate the year of their cancer diagnosis. Thus, people who were diagnosed with cancer should not have been able to predict the timing of their diagnosis three or more calendar years before being diagnosed. The diagnosis delay literature (Koo, Zhou, and Lyratzopoulos, 2015; Friese et al., 2011; Pruitt et al., 2013; Allgar and Neal, 2005) suggests that very few patients experience cancer symptoms more than one year in advance. To the extent this is true, β_{-2} acts as a placebo parameter and should be estimated as zero.

The switching regressions do not separately identify an effect of having cancer on the relative value of MA coverage versus an effect of having cancer on a cost of switching health insurance. However, measuring switching in both directions allows me to discern between these mechanisms. Any effect of a cancer diagnosis on switching costs would affect the estimate for both samples in the same direction, while any effect of a cancer diagnosis on the relative value of MA coverage would affect both samples in opposite directions. In addition, the switching regressions do not separately identify duration dependence from an effect of a cancer diagnosis on plan switching. To test whether duration dependence might confound my estimates, I run a falsification test that examines plan switching around a placebo diagnosis year.

3.5.3 Results

To be consistent with the mortality analysis in section 3.4, I first estimated equation 3.3 separately for patients living in HSAs with small and large populations. However, unlike the mortality results, the switching estimates were similar for each subsample. Thus, Table 3.8 presents the estimates for all patients in the sample. The estimates are stable and have similar precision across the three specifications. I treat the third specification, which controls for county-by-year fixed effects, as the preferred specification. The estimates indicate that a cancer diagnosis led to more

TABLE 3.8: Aggregate Effect of a Cancer Diagnosis on Switching Health Insurance

	MA to TM			TM to MA		
	(1)	(2)	(3)	(1)	(2)	(3)
2^{nd} Year prior to Diagnosis (β_{-2})	0.0000	0.0001	0.0002	-0.0007*	-0.0005	-0.0007
	(0.0011)	(0.0011)	(0.0011)	(0.0004)	(0.0004)	(0.0004)
1^{st} Year prior to Diagnosis (β_{-1})	0.0024**	0.0025**	0.0018*	-0.0009**	-0.0008*	-0.0008*
	(0.0011)	(0.0011)	(0.0011)	(0.0004)	(0.0004)	(0.0004)
Year of Diagnosis (β_0)	0.0063***	0.0061***	0.0045***	-0.0024***	-0.0024***	-0.0025***
	(0.0011)	(0.0011)	(0.0011)	(0.0005)	(0.0005)	(0.0005)
1^{st} Year after Diagnosis (β_1)	0.0131***	0.0124***	0.0107***	-0.0075***	-0.0075***	-0.0075***
	(0.0013)	(0.0013)	(0.0012)	(0.0006)	(0.0006)	(0.0005)
County FE	✓	✓		✓	✓	
(Calendar) Year FE	✓	✓		✓	✓	
Non-Cancer MA Penetration		✓			✓	
County×Year FE			✓			✓
Observations	370,211	370,211	370,211	1,273,867	1,273,867	1,273,867
Unique Individuals	80,855	80,855	80,855	265,904	265,904	265,904

An observation is an individual-year. The outcome variable is a binary indicator for switching between a Medicare Advantage (MA) plan and traditional Medicare (TM). All individuals in the estimation samples were enrolled in the same type of health insurance for both the 4th and 5th (calendar) years prior to their diagnosis, and all have Medicare enrollment data in each subsequent year up through at least one year following their diagnosis. The years included in the sample range from the third year before diagnosis to the first year after diagnosis. After a switch occurs, the individual is dropped from the sample. The estimates are computed using linear probability models. Besides those indicated in the table, the only unreported covariates are the patient characteristics: age, sex, black, Hispanic, married, widowed, and census tract socioeconomic variables. Standard errors, in parentheses, are clustered by county-year.
* p<0.10, ** p<0.05, *** p<0.01

switching out of MA plans and less switching into MA plans. On average, a patient with an MA plan was 1.1 percentage points more likely to switch to traditional Medicare in the year following cancer diagnosis versus three years prior to diagnosis. Patients with an MA plan in the years 2004 through 2009, who were at least two years prior to their cancer diagnosis, switched to traditional Medicare at a rate of 3 percent per year. Thus, the 1.1 percentage point increase represents a 37 percent increase. As expected, there is no statistically distinguishable difference in the likelihood of switching two years prior to diagnosis versus three years prior to diagnosis. There is statistical evidence of increased switching in the calendar year of diagnosis and even weak evidence of increased switching in the calendar year preceding diagnosis. Given that some patients experience long diagnosis delays, this is not overly surprising. The estimates for the traditional Medicare patients reflect a pattern that is opposite to the pattern for MA patients. On average, a patient with traditional Medicare was 0.8 percentage points (29 percent) less likely to switch to an MA plan in the year after cancer diagnosis versus three years prior.

Table 3.9 tests whether the results might be explained by duration dependence. In particular, patients may be more or less likely to switch health insurance the longer they are enrolled in the same type of plan. The falsification test examines calendar years between eight and three years prior to cancer diagnosis. There is no evidence of duration dependence for patients in traditional Medicare. However, the estimates suggest that patients in MA plans are less likely to switch to traditional Medicare the longer they have an MA plan. This means that the estimates in Table 3.8 likely *understate* the effect of a cancer diagnosis on the desire to switch out of an MA plan, as some cancer patients find it particularly costly to switch out of an MA plan that they have had for a long time.

It is possible that some of the effect I find of a cancer diagnosis on health insurance switching could be explained by cancer increasing the likelihood of Medicaid eligibility. Since Medicaid essentially offers free supplemental insurance, most dually eligible beneficiaries choose traditional Medicare. I test the ability of Medicaid eligibility to explain my results in Table 3.10. Since the variable for Medicaid coverage is only available in the SEER Medicare data starting in 2006, I restrict the sample

TABLE 3.9: Falsification Test for Duration Dependence - Event Study of Switching Health Insurance in Years At Least Three Years Prior to Cancer Diagnosis

	MA to TM	TM to MA
6^{th} Year prior to Diagnosis (β_{-6})	-0.0060*	0.0006
	(0.0032)	(0.0004)
5^{th} Year prior to Diagnosis (β_{-5})	-0.0089***	0.0005
	(0.0030)	(0.0005)
4^{th} Year prior to Diagnosis (β_{-4})	-0.0076**	-0.0000
	(0.0034)	(0.0007)
3^{rd} Year prior to Diagnosis (β_{-3})	-0.0070**	-0.0008
	(0.0035)	(0.0009)
Observations	145,130	424,965
Unique Individuals	29,026	84,993

An observation is an individual-year. The outcome variable is a binary indicator for switching between a Medicare Advantage (MA) plan and traditional Medicare (TM). All individuals in either sample were enrolled in the same type of plan for both the 8th and 9th (calendar) years prior to their diagnosis, and all have Medicare enrollment data in each subsequent year up through at least the third year prior their diagnosis. The years included in the sample range from the seventh year before diagnosis to the third year before diagnosis. After a switch occurs, the individual is dropped from the sample. The estimates are computed using linear probability models. The unreported covariates are county-by-year fixed effects and the patient characteristics: age, sex, black, Hispanic, married, widowed, and census tract socioeconomic variables. Standard errors, clustered by county-year, are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

TABLE 3.10: Robustness Check - Aggregate Effect of Having Cancer on Switching Health Insurance for Diagnoses After 2007

	MA to TM		TM to MA	
	(1)	(2)	(1)	(2)
1^{st} Year prior to Diagnosis (β_{-1})	0.0014	0.0012	0.0002	0.0002
	(0.0014)	(0.0014)	(0.0008)	(0.0008)
Year of Diagnosis (β_0)	0.0001	-0.0001	-0.0014*	-0.0014*
	(0.0016)	(0.0016)	(0.0008)	(0.0008)
1^{st} Year after Diagnosis (β_1)	0.0058***	0.0053***	-0.0071***	-0.0071***
	(0.0019)	(0.0019)	(0.0010)	(0.0010)
Medicaid Indicator		✓		✓
Observations	159,661	159,661	526,954	526,954
Unique Individuals	41,154	41,154	139,218	139,218

An observation is an individual-year. The outcome variable is a binary indicator for switching between a Medicare Advantage (MA) plan and traditional Medicare (TM). All individuals in either sample were enrolled in the same type of health insurance for both the 3rd and 4th (calendar) years prior to their diagnosis, and all have Medicare enrollment data in each subsequent year up through at least one year following their diagnosis. The years included in the sample range from the third year before diagnosis to the first year after diagnosis. After a switch occurs, the individual is dropped from the sample. The estimates are computed using linear probability models. Besides the Medicaid variable indicated in the table, the unreported covariates are county-by-year fixed effects and the patient characteristics: age, sex, black, Hispanic, married, widowed, and census tract socioeconomic variables. Standard errors, clustered by county-year, are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

to diagnoses that occurred after 2007 and include years from two years prior to cancer diagnosis to one year after diagnosis. The estimates are nearly the same whether or not the regression controls for time-varying Medicaid entitlement, so Medicaid eligibility is unlikely to be the culprit.

It is also possible that cancer diagnosis would have a greater influence on health insurance switching if patients were not constrained by calendar-year plan lock. In C, I examine this hypothesis using a difference-in-differences approach that relies on variation due to month of diagnosis and a 2006 policy change implementing calendar-year plan-lock.[38] My preferred model finds a small, but statistically significant, effect of an additional month of plan-lock to decrease the probability of switching out of an MA plan in the first year after cancer diagnosis. Calendar-year plan-lock may deter some patients from switching out of their MA plans, but it does not seem to explain why the vast majority of MA cancer patients do not switch health

[38]One might think that a difference-in-differences approach is not needed because month of cancer diagnosis is plausibly random. As explained in the Appendix, there are seasonal patterns in month of cancer diagnosis that make the difference-in-differences approach preferable.

insurance. Further, there is no evidence that calendar-year plan-lock influences cancer mortality.

It is interesting to examine whether certain types of cancer influence health insurance switching more than others. Table 3.11 presents separate sets of estimates for patients diagnosed with each type of cancer, excluding cervical cancer. While any type of cancer diagnosis generally increased switching out of MA plans and decreased switching into MA plans, there are a few estimates which are not distinguishable from zero using a 5 percent threshold. There are also some types of cancer for which the effect on switching out of an MA plan was larger than others. The pattern appears roughly related to cancer severity; MA patients with deadlier cancers were somewhat more likely to switch to traditional Medicare. For example, being diagnosed with lung cancer increased the likelihood of switching from an MA plan to traditional Medicare by an average of 2.1 percentage points (70 percent). Conversely, a diagnosis of prostate cancer only increased the likelihood of switching from an MA plan to traditional Medicare by an average of 0.4 percentage points (13 percent).

The estimates in Table 3.11 can be used to examine risk selection, conditional on Medicare's risk adjustment, into MA plans. This exercise is motived by a similar one used by Brown et al. (2014).[39] Some of the cancers that are grouped together in the risk adjustment formula, and thus generate the same revenue adjustment for private companies, have different average costs of treatment. In the time period of my study, breast, colorectal, and prostate cancers were grouped together in the risk adjustment formula.[40] According to Yabroff et al. (2008), the average cost of initial treatment for colorectal cancer is more than double the average cost of initial treatment for breast and prostate cancer. If cancer patients select into MA plans differentially based on risk-adjusted cost, colorectal cancer patients would select out of MA plans but breast and prostate cancer patients would select into MA plans. However, this is not what the estimates show. There is some evidence that the least profitable (i.e., colorectal cancer) patients were more likely to switch out of MA plans, but no evidence that the

[39]Brown et al. (2014) examined gender differences in switching into MA plans among people who had a risk score that indicated breast, prostate, or colorectal cancer. Their motivation was an incrementally larger average cost of treating prostate cancer rather than breast cancer. They found that women with this risk score were more likely than men to switch into MA plans.

[40]Colorectal cancer was moved to a different risk adjustment category starting in 2015.

TABLE 3.11: Effect of a Particular Cancer Diagnosis on Switching Health Insurance

	(1) Brain	(2) Breast	(3) Colorectal	(4) Leukemia	(5) Lung	(6) Ovarian	(7) Prostate
Panel A: MA to TM							
2^{nd} Year prior to DX (β_{-2})	0.0071	0.0019	-0.0005	0.0006	0.0044*	0.0053	-0.0043**
	(0.0148)	(0.0018)	(0.0023)	(0.0062)	(0.0025)	(0.0086)	(0.0021)
1^{st} Year prior to DX (β_{-1})	0.0246*	0.0026	-0.0001	-0.0028	0.0057**	0.0032	-0.0011
	(0.0140)	(0.0018)	(0.0021)	(0.0054)	(0.0024)	(0.0074)	(0.0020)
Year of DX (β_0)	0.0196	0.0030*	0.0044**	0.0014	0.0080***	0.0134*	0.0014
	(0.0128)	(0.0017)	(0.0021)	(0.0058)	(0.0027)	(0.0072)	(0.0020)
1^{st} Year after DX (β_1)	0.0295*	0.0070***	0.0143***	0.0078	0.0212***	0.0177**	0.0043**
	(0.0160)	(0.0019)	(0.0024)	(0.0061)	(0.0030)	(0.0078)	(0.0021)
Observations	2,180	101,144	73,410	13,449	58,337	6,865	113,563
Unique Individuals	486	21,902	15,969	2,955	12,828	1,490	24,950
Panel B: TM to MA							
2^{nd} Year prior to DX (β_{-2})	0.0023	-0.0008	-0.0015	-0.0021	-0.0005	0.0038	-0.0003
	(0.0085)	(0.0008)	(0.0010)	(0.0023)	(0.0010)	(0.0036)	(0.0007)
1^{st} Year prior to DX (β_{-1})	0.0021	-0.0007	-0.0001	-0.0013	-0.0010	-0.0025	-0.0013
	(0.0079)	(0.0009)	(0.0011)	(0.0024)	(0.0011)	(0.0042)	(0.0008)
Year of DX (β_0)	-0.0073	-0.0022**	-0.0026**	-0.0053*	-0.0024*	-0.0021	-0.0028***
	(0.0087)	(0.0009)	(0.0011)	(0.0027)	(0.0012)	(0.0044)	(0.0009)
1^{st} Year after DX (β_1)	-0.0144	-0.0072***	-0.0064***	-0.0100***	-0.0103***	-0.0077*	-0.0066***
	(0.0093)	(0.0010)	(0.0013)	(0.0030)	(0.0012)	(0.0043)	(0.0010)
Observations	9,011	366,827	265,909	55,362	240,584	25,153	429,998
Unique Individuals	1,880	68,249	49,936	10,034	43,893	4,821	85,917

An observation is an individual-year. The outcome variable is a binary indicator for switching between a Medicare Advantage (MA) plan and traditional Medicare (TM). All individuals in the estimation samples were enrolled in the same type of health insurance for both the 4th and 5th (calendar) years prior to their diagnosis, and all have Medicare enrollment data in each subsequent year up through at least one year following their diagnosis. The years included in the sample range from the third year before diagnosis to the first year after diagnosis. After a switch occurs, the individual is dropped from the sample. The estimates are computed using linear probability models. The unreported covariates are county-by-year fixed effects and the patient characteristics: age, sex, black, Hispanic, married, widowed, and census tract socioeconomic variables. Standard errors, in parentheses, are clustered by county-year.
* p<0.10, ** p<0.05, *** p<0.01

most profitable (i.e., breast and prostate) patients tended to stay in, or switch into, MA plans. In total, there is little evidence of risk selection conditional on Medicare's risk adjustment.

The estimates in this section indicate that a cancer diagnosis lowered patients' relative preference for MA plans. At least at a high level, the results are consistent with the effect of MA enrollment to increase cancer mortality from section 3.4. Something about the quality of post-diagnosis cancer care in MA plans, relative to traditional Medicare, appears to result in increased mortality and patients switching their health insurance. However, the two findings are not perfectly complementary for several reasons. First, recall that the mortality effect was robust to excluding patients who ever switched health insurance. Thus, some MA cancer patients do not switch to traditional Medicare even though they seemingly could extend their life expectancy by doing so. Second, MA enrollment only definitively decreased life expectancy for patients with brain, lung, or prostate cancer who also lived in an HSA with at least 500,000 people. Table 3.11 shows that the other types of cancer diagnoses, for which there was no detectable mortality effect, also influenced switching. I also found, in unreported results, that the switching effect did not vary according to HSA population. These discrepancies imply that the cancer patients who switched health insurance were not necessarily the ones with the most life expectancy to gain by switching.

3.6 Conclusion

In this chapter, I examined private versus publicly administered health insurance for elderly cancer patients. Private MA plans provide at least the same coverage as the public plan, traditional Medicare, but manage care primarily by restricting access to medical providers. I estimated that enrollment in an MA plan at cancer diagnosis increased mortality relative to enrollment in traditional Medicare, but only for patients with certain types of cancers who lived in areas with relatively large populations. In health service areas with at least 500,000 people, I estimated that MA enrollment decreased median life expectancy by 0.9 months for brain cancer

patients, 0.4 months for lung cancer patients, and 4.0 months for prostate cancer patients. The presumed mechanism is that MA plans steered patients to lower quality cancer care, though I was unable to directly confirm that mechanism with the data at hand. My results indicate that there is a trade-off between reducing health costs and improving health outcomes in MA plans versus traditional Medicare.

Does enrollment in traditional Medicare, rather than an MA plan, improve life expectancy for cancer patients by a clinically meaningful amount in a cost-effective way? It is helpful to compare the costs of additional life expectancy in traditional Medicare, rather than an MA plan, to the costs of additional life expectancy implied by recent advances in cancer care. For example, Genentech's famous drug Avastin increased median life expectancy for high-risk colorectal cancer patients by 4.7 months for a cost of $50,000 (Mayer, 2004) and increased median life expectancy for high-risk lung cancer patients by 2 months for a projected price for a projected cost of $100,000.[41] If we assume that Medicare pays for 80 percent of the cost of Avastin, in 2004 dollars, Avastin costs Medicare $8,638 per month of additional median life expectancy for colorectal cancer patients and an alarming $34,094 per month of additional median life expectancy for lung cancer patients.[42] I estimated that traditional Medicare enrollment increased median life expectancy for brain, lung, and prostate cancer patients living in large HSAs. Due to data limitations, I did not estimate the cost of this additional life expectancy. For the average Medicare beneficiary, who admittedly may differ from a typical cancer patient, Curto et al. (2015) estimated that traditional Medicare costs are greater than private Medicare Advantage costs by 12 percent.[43] Using their cost estimate, and the cost of the first 12-months of treating different cancer in traditional Medicare estimated by Yabroff et al. (2008), along with my life expectancy estimates from Table 3.7, back-of-the-envelope calculations indicate favorable cost-effectiveness ratios of switching health insurance. In particular, I calculate that traditional Medicare enrollment costs Medicare $7,060

[41] See `http://www.gene.com/media/product-information/avastin-lung` and "Costly Cancer Drug Offers Hope, but Also a Dilemma," written by Gina Kolata and Andrew Pollack and published online in the New York Times on July 6, 2008.

[42] All cost-effectiveness ratios in this paragraph are quoted in 2004 dollars. The projected price of Avastin for lung cancer patients was converted from 2008 to 2004 dollars using the medical inflation calculator from `http://www.halfhill.com/inflation_js.html`.

[43] The 12 percent ignores differences in taxpayer costs to pay MA plans rather than fund traditional Medicare. If differences in taxpayer costs are included, then traditional Medicare increases median life expectancy *and saves money.*

per month of additional median life expectancy for brain cancer patients, $8,460 per month of additional median life expectancy for lung cancer patients, and $258 per month of additional median life expectancy for prostate cancer patients.

Since Medicare cancer patients are able to freely choose between an MA plan and traditional Medicare, it is not obvious that MA cancer patients are being harmed by lower life expectancy. If MA cancer patients valued the additional life expectancy they could gain by switching to traditional Medicare, then presumably they would switch. While I estimated that MA patients were 37 percent more likely to switch to traditional Medicare after a cancer diagnosis, because the baseline switching probability was so low, this represented only a 1.1 percentage point increase in the probability of switching to traditional Medicare. Future work is needed to determine why more cancer patients do not enroll in traditional Medicare. It is possible that many patients cannot afford the extra out-of-pocket costs in traditional Medicare or do not value the additional life expectancy it offers. Given the extent of health insurance switching frictions estimated in recent studies (e.g. Handel, 2013; Ericson, 2014; Miller, 2014; Polyakova, 2016), it is also possible that some cancer patients would make different health insurance choices if policies were able to reduce their switching costs.

It is important to remember that this study only compares quality of care in private and public Medicare plans for one dimension of care, post-diagnosis cancer care. Other studies have found favorable effects of private Medicare plans on quality of care along other dimensions. For example, Huckfeldt et al. (2017) uncovered a higher quality of postacute care in MA plans versus traditional Medicare. It is also important to remember that this study did not compare *costs* of post-diagnosis cancer care in private and public Medicare plans.

There are several other important limitations of my results that provide promising areas for future work. First, I was not able to examine any heterogeneity within types of MA plans. It is possible that Special Needs Plans, Programs of All-Inclusive Care for the Elderly, and even PPOs allow patients better access to specialized cancer care than HMOs. Second, recent changes in Medicare due to the ACA were too recent to be incorporated into my analysis. It is possible that the new star-ratings have induced more MA plans to encourage the use of specialized cancer care. Third, this

research focused on a particular chronic medical condition and a particular health insurance market. It is possible that MA enrollment increases mortality for Medicare patients with chronic conditions besides cancer. It is also possible that private companies facilitate lower quality of post-diagnosis cancer (or other) care in other health insurance markets. The regulation of MA plans in Medicare is similar to the regulation of private insurance plans in Medicaid, Medicare Part D, and the health insurance marketplaces. However, unlike the medical component of Medicare I studied in this chapter, none of these markets currently offers a public plan as an option to consumers. It will be important to ensure that the health insurance plans in these markets provide adequate coverage of appropriate care for sickly patients.

Chapter 4

Does Risk Adjustment Prevent Prevention? Evidence from Medicare Advantage

4.1 Introduction

Economic theory shows that risk-based selection can undermine the usefulness of insurance markets. Public policy has recently turned to risk adjustments to combat risk selection in health insurance. Beginning in 2004, as a result of the Medicare Modernization Act (MMA), Medicare started to adjust payments to private Medicare Advantage insurers based on the chronic conditions of enrollees. Beginning in 2014, the Patient Protection and Affordable Care Act (ACA) implemented similar diagnosis-based risk adjustment in the private health insurance markets for individuals and small groups.[1] As has been pointed out in the literature, these risk adjustment models transform incentives for insurers and thus have implications for strategic insurer behavior. In this chapter, I examine the implications of modern risk adjustment for insurer investment in preventive care.

Eggleston, Ellis, and Lu (2012) provided a model demonstrating the theoretical link between risk adjustment and preventive care. Their two-period model shows that risk adjustment has the theoretical benefit of removing incentives for health insurers to invest in selection, but also the undesirable consequence of removing their incentives to invest in prevention. Without risk adjustment, health insurers are

[1] The ACA risk adjustment program is different in that it is a zero-sum game. Insurers with low-risk enrollees are required transfer money to insurer with higher-risk enrollees.

willing to invest in prevention because they bear financial risk for their enrollees developing medical conditions. Because risk adjustment transfers that financial risk to the regulator, it leaves insurers with no incentive to invest in preventive care. I am the first, to my knowledge, to test this theoretical relationship between risk adjustment and prevention with an empirical analysis.

I use individual-level data for the use of various types of preventive services from the 2000 through 2010 waves of the Medicare Current Beneficiary Survey (MCBS). The MCBS includes administrative Medicare data and survey responses. The key independent variable I use is the proportion of Medicare beneficiaries in a county who are enrolled in a private Medicare Advantage (MA) plan in a given year. County-level MA penetration rates varied differentially over time, most likely in response to regulations regarding the generosity of payments to MA plans. I thus examine the relationship between changes in MA penetration over time, both before and after the 2004 risk adjustment policy change, and the use of preventive care.

Before 2004, when revenues for MA insurers did not adjust for their enrollees' chronic conditions, I estimate that increases in MA penetration increased vaccination rates for pneumonia and influenza. The estimates for the effect of increases in MA penetration on blood pressure and cholesterol checks, as well as rates of recommended screening for breast and colorectal cancers, were positive but not statistically distinguishable from zero. After 2004, when revenues for MA insurers began to adjust for their enrollees' chronic conditions, I estimate that increases in MA penetration had less of an effect to increase rates for pneumonia shots, cholesterol checks, and screening for colorectal cancer. Estimates in the post period for flu shots, blood pressure checks and breast cancer screening were also negative, but indistinguishable from zero. In fact, the overall effect of changes in MA penetration on the use of preventive care after 2004 was indistinguishable from zero for all of the outcomes I studied.

This chapter contributes to two bodies of literature. The first is the implications of modern risk adjustment in health insurance. Brown et al. (2014), Newhouse et al. (2012), and Newhouse et al. (2015) examined the implications for risk selection and Geruso and Layton (2015) examined the implications for the diagnosis/coding of chronic conditions. I examine the implications of modern risk adjustment on a

different outcome, preventive care. The second body of literature I contribute to is the influence of health insurers on the use of preventive care. This literature (e.g., Rizzo, 2005; Greene, Blustein, and Laflamme, 2001; Landon et al., 2004) has relied on cross-sectional analyses. In contrast, I use plausibly exogenous changes in local MA popularity over time to measure the influence of MA plans on the use of preventive care.

The rest of the chapter is organized as follows. Section 4.2 provides background for Medicare and risk adjustment. Section 4.3 discusses the theoretical link between risk adjustment and prevention. Section 4.4 describes the data and develops my empirical strategy. Section 4.5 presents the results of my analysis. Concluding remarks are in Section 4.6.

4.2 Background

The United States has administered Medicare, a social health insurance program that covers elderly individuals, since 1966.[2] The Medicare program has reimbursed private insurance companies in exchange for providing Medicare Parts A (inpatient care) and B (outpatient care) benefits ever since the 1980's. The monthly reimbursement from Medicare to a private insurance company is called a capitation payment, and is allowed under Medicare Part C. Capitation payments are adjusted for the patient's ex-ante medical risk, but independent of their ex-post medical utilization. The Medicare Part C program is currently referred to as Medicare Advantage (MA), which is the term I will use throughout the chapter.[3] In contrast to MA, I will refer to the fee-for-service benefits paid directly from Medicare to medical providers as traditional Medicare.

4.2.1 Capitation Payments

Capitation payments are the main source of revenue for MA plans. CMS publishes capitation rates every April for the following year. MA insurers receive a

[2] In this chapter I will focus only on elderly Medicare beneficiaries. Younger individuals with specialized health needs (disability, end stage renal disease, or amyotrophic lateral sclerosis) can also qualify for Medicare. An examination of the influence of MA insurers on their use of preventive care would be informative, but is outside the scope of this current research.

[3] From 1997 to 2003, the Medicare Part C program was referred to as Medicare+Choice.

capitation payment, based on the published rates for that year, for each one of their enrollees. The capitation rate is a function of two components: the county in which the enrollee resides (county multiplier) and some characteristics of the enrollee (risk score). Notably, the capitation payment is independent of the enrollee's medical utilization. Thus, because capitation rates are generally set to offset the expected cost of health insurance coverage provided by MA plans, MA plans bear the residual financial risk associated with health expenses incurred by their enrollees.

There have been several notable changes in the methodology CMS uses to calculate capitation rates. I provide a brief summary in the following paragraphs. McGuire, Newhouse, and Sinaiko (2011) provide a more comprehensive review of the changes and their effects.

County Multipliers

Changes to annual county multipliers have created noticeable changes in the popularity of MA over time. Prior to 1997, county multipliers were set to reflect 95 percent of medical costs in the county. From 1997 to 2003, in an effort to save money for Medicare, multipliers for each county were set equal to the greater of a minimum floor and a 2 or 3 percent increase over the county's multiplier for the previous year.[4] The dominant effect of the methodology change was a decline in MA popularity, particularly in urban areas. The trend was not reversed until after the Medicare Modernization Act (MMA) in 2003. Starting in 2004, county multipliers were set to reflect 100 percent of medical costs in the county, subject to lower bounds that favored areas with low or slow-growing medical costs. The result was inflated capitation payments that led to an increase in the popularity of MA plans, but also caused the Medicare program to lose money. In 2006, the introduction of Medicare Part D, for which there is no public option, may have further increased MA penetration.[5]

[4]The maximum increase was 2 percent from 1997 to 1999 and 3 percent from 2000 to 2003.

[5]Medicare Part D coverage is available only through an MA-PD plan, which covers Medicare Parts A, B, and D, or a prescription drug plan (PDP) that only covers Medicare Part D.

Risk Scores

Changes in the calculation of individual risk scores over time have potentially important implications for the financial incentives of MA plans. Between 2000 and 2003, individual risk scores were calculated based on a blend of a demographic risk score (90 percent weight) and an inpatient diagnosis risk score (10 percent weight).[6] The demographic risk score accounted for the individual's gender, age, disability status, and Medicaid status. The inpatient diagnosis risk score came from a risk adjustment model (PIP-DCG) that adjusted for risk associated with medical conditions, but was not given much weight due to concerns of excluding outpatient diagnoses. Starting in 2004, after the MMA, both inpatient and outpatient diagnoses were included in a new Medicare Hierarchical Condition Category (CMS-HCC) risk adjustment model.[7] The new risk adjustment model calculates risk scores for each MA enrollee according to their demographic characteristics and their chronic conditions. There are seventy chronic condition (HCC) categories, which are distilled from around 4,000 ICD-9-CM procedure codes for inpatient and outpatient visits. The model is calibrated using data on medical claims and demographics from traditional Medicare beneficiaries. The main benefit of the CMS-HCC model was to increase predictive power that could potentially correct for risk-based selection into MA plans. According to Pope et al. (2004), the CMS-HCC risk adjustment model alone explains eleven percent of the variation in medical expenses for traditional Medicare beneficiaries, while the Demographic and PIP-DCG risk adjustment models only explained one percent and six percent respectively, on their own.

4.2.2 Medicare Advantage and Preventive Care

The appeal of MA plans over traditional Medicare is that they reduce patient cost-sharing, particularly for Part B (outpatient) services. Perhaps not surprisingly, a plethora of studies have found higher rates of preventive care for MA patients versus traditional Medicare patients. For 1996, Greene, Blustein, and Laflamme (2001)

[6] Prior to 2000, only the demographic risk score was used.

[7] Though CMS introduced diagnosis-based risk adjustment in 2004, it was not fully implemented until 2007. Risk scores contained a 30, 50, and 75 percent blend of the new CMS-HCC model in 2004, 2005, and 2006, respectively. The remaining fraction of the risk score in these years came from the previous demographic model.

found that MA patients had higher rates for mammography screening, pap smears, eye exams, and flu vaccination. Rizzo (2005) found the same pattern for other preventive care measures, such as checking blood pressure and cholesterol. For 2000 and 2001, Landon et al. (2004) found that MA patients had higher rates of vaccination for pneumonia and influenza. They also found that MA smokers were more likely to get counseling to quit smoking than smokers with traditional Medicare. The pattern in these studies could reflect a causal effect of MA plans to increase the use of preventive care. Alternatively, it could reflect a correlational effect where patients who most value preventive care tend to sign up for MA plans.

This study complements previous literature in at least two ways. First, it addresses causality in the relationship between MA enrollment and the use of preventive care by exploiting variation over time. Rizzo (2005) used instrumental variables, with instruments similar to those used in this study, to argue that there was some causal effect of MA enrollment on prevention. However, Rizzo (2005) only had one year of data and thus relied only on spatial variation. Second, this study examines a more recent time period than the previous literature. This is important because the new risk adjustment methodology implemented in 2004 introduced financial incentives that could have changed how MA insurers influence preventive care.

4.3 Theoretical Effect of Risk Adjustment on Prevention

Eggleston, Ellis, and Lu (2012) provide the theoretical framework for how risk adjustment, accounting for patients' chronic conditions, can influence the use of preventive care. Without risk adjustment, insurers have incentive to encourage their enrollees to use preventive care because insurers bear financial responsibility for enrollees developing medical conditions. With "perfect" risk adjustment, however, insurers have no incentive to encourage the use of preventive care because their financial responsibility is transferred to the government. An imperfect risk adjustment model, like the CMS-HCC model, may still leave some incentives for insurers to encourage preventive care. For example, there is no HCC category for influenza, since it is not considered to be a chronic condition. There is an HCC category for pneumonia (HCC 111). Thus, Medicare's new risk adjustment model should not

influence how insurers may attempt to prevent the flu, but could influence how insurers attempt to prevent pneumonia.[8]

There are several implicit assumptions in the model presented by Eggleston, Ellis, and Lu, 2012 that are important for an empirical analysis. First, even in the absence of risk adjustment, insurers only have incentive to encourage preventive care to the extent that patients remain insured in their plan over time. Researchers have discovered substantial amounts of inertia in health plan choice in many health insurance markets, including employer-sponsored health insurance (Handel, 2013), Medicare Part D (Ericson, 2014), and MA plans (Miller, 2014). According to the Government Accountability Office (2008), about 9 percent of MA enrollees switch out of their MA plan (either to traditional Medicare or a different MA plan) each year. Second, risk adjustment will only influence the use of preventive care to the extent that insurers can influence the use of preventive care. The most obvious way that insurers might influence utilization is to adjust the out-of-pocket cost for the patient. The randomized RAND health insurance experiment showed that out-of-pocket cost influences utilization (Manning et al., 1987), but recent evidence indicates that patients may be relatively unsophisticated in their response to out-of-pocket cost. In particular, patients appear to adjust utilization of preventive care in response to aggregate cost-sharing parameters rather than parameters that are relevant to the use of preventive care (Brot-Goldberg et al., 2015). Aside from out-of-pocket cost, insurers could hypothetically influence the use of preventive care through financial contracts with physicians or communications with patients.

Finally, empirical examples of pure preventive care are relatively rare. Many services that are considered preventive, like cancer screening, are also diagnostic. This is relevant in the context of modern risk adjustment, because modern risk adjustment provides insurers with a strong financial incentive to record chronic conditions every year. Geruso and Layton (2015) showed that this has led to increased diagnoses, or "upcoding", for MA patients. To the extent that preventive services also allow more diagnoses of chronic conditions, the theoretical impact of modern

[8]However, it is not necessarily true that flu shots are a placebo outcome in my empirical analysis. It is possible that a flu shot plays some role in preventing pneumonia.

risk adjustment on prevention would be ambiguous. The theory would only be unambiguous for vaccines and other types of pure preventive care.

4.4 Empirical Strategy

There are two empirical goals in this paper. The first is to measure a causal effect of MA plans on patients' use of preventive care *in the absence of diagnosis-based risk adjustment*. The second goal is to measure how that effect changed *once revenues for MA plans began to adjust for patients' chronic conditions in 2004*. I examine a broad range of preventive care outcomes using the 2000 through 2010 waves of the Medicare Current Beneficiary Survey (MCBS).

4.4.1 Medicare Current Beneficiary Survey

The MCBS surveys a rotating panel of Medicare beneficiaries. Each sampled beneficiary is interviewed for four consecutive years. The data have a survey component and an administrative component. I use administrative Medicare enrollment data to classify patients in MA plans, but use individuals' survey responses to measure the use of preventive care. In years prior to 2004, individuals were only considered to be enrolled in an MA plan if they were enrolled with a risk-based, rather than cost-based, HMO.[9] The types of preventive care I measure are a pneumonia vaccine (ever), flu vaccine (last winter), smoking (currently), blood pressure check (in last year), blood cholesterol check (in last year), mammogram (in last year), pap smear (in last year), prostate cancer screening (in last year), and colorectal cancer screening (in last year).[10]

The unit of observation in the MCBS data is an individual-year. However, due to strong and irregular serial correlation in the use of preventive care within individuals, I modify the data to include only one observation per individual.[11] In particular,

[9] The MA program evolved out of the Medicare+Choice program. The risk-based Medicare+Choice plans were compensated similarly to the way MA plans are compensated, but the cost-based plans did not bear financial risk for their patients.

[10] Mammograms screen for breast cancer. An individual is defined to have screened for prostate cancer if he had a digital rectal exam or a blood test. An individual is defined to have screened for colorectal cancer if he or she had a colonoscopy, sigmoidoscopy, or fecal-occult blood test.

[11] For example, some patients tend to use preventive services every year while others use them every other year.

TABLE 4.1: Summary Statistics

	Traditional Medicare (N = 43,527)		Medicare Advantage (N = 9,526)	
	Mean	St Dev	Mean	St Dev
Age	77.27	7.58	76.69	7.19
Female	0.58	0.49	0.58	0.49
Black	0.08	0.27	0.10	0.30
Other Minority	0.05	0.22	0.06	0.24
Hispanic	0.05	0.21	0.10	0.30
Married	0.50	0.50	0.53	0.50
Widowed	0.37	0.48	0.34	0.47
Number of Children	2.91	2.10	2.96	2.04
High School Graduate	0.69	0.46	0.70	0.46
Some College	0.40	0.49	0.40	0.49
College Graduate	0.17	0.38	0.14	0.35

Summary statistics are for individuals aged 65 to 95 in the 2000 through 2010 survey waves of the Medicare Current Beneficiary Survey. The variables are collected from the last of the survey years in which the individual was present. All variables are binary with the exception of age, which is measured in integer years, and number of children, which is top-coded at 6.

I only include the last year each individual was surveyed (between 2000 and 2010). After excluding individuals younger than 65 or older than 95, I arrive at a final estimation sample of 53,053 Medicare beneficiaries.[12] 9,526 (18 percent) of these had a Medicare Advantage plan, and the rest had traditional Medicare. Table 4.1 summarizes the characteristics for each set of patients. The two sets of patients are generally similar on observables, though MA patients are more likely than traditional Medicare patients to be Hispanic.

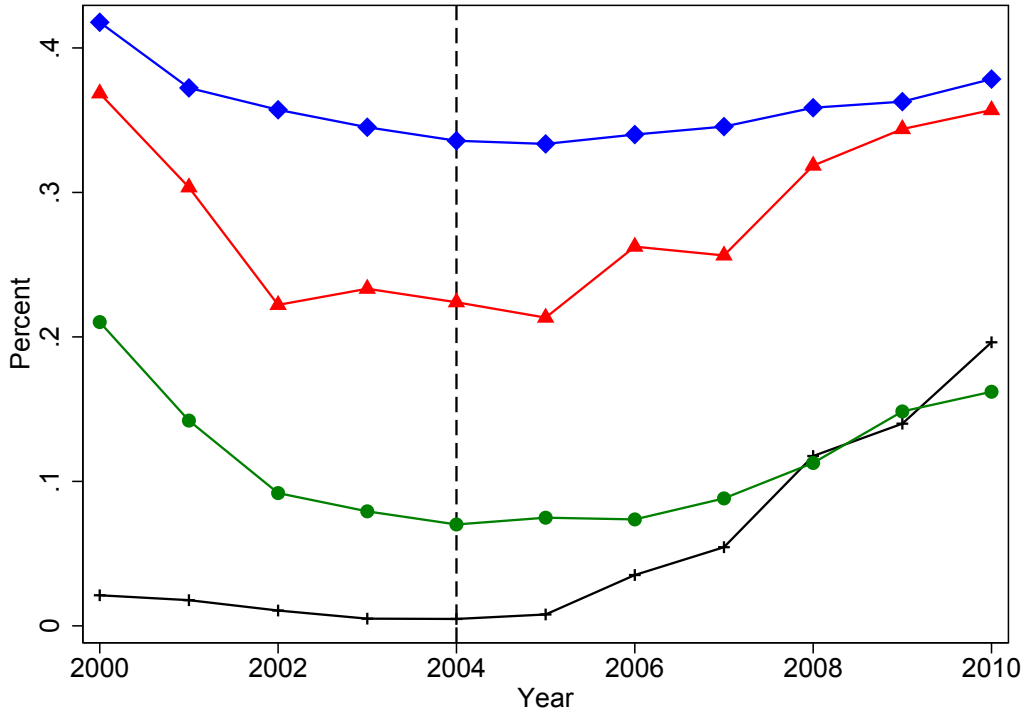
4.4.2 Econometric Model

The ways through which MA plans could influence the use of preventive care can be categorized into two channels. First, MA plans might directly influence how patients value preventive services. This "enrollment effect" would only influence patients enrolled in MA plans. Second, MA plans might influence the willingness of suppliers to provide preventive services. In particular, MA plans should have larger influence on suppliers in areas where they have greater market share. This "penetration effect" would affect all Medicare patients, even those with traditional Medicare, within a geographic area. The theoretical existence of the penetration effect is

[12]The exclusions based on age are in order to avoid combining "typical" Medicare beneficiaries with disabled and extremely elderly Medicare beneficiaries. The latter populations are no less important to study, but are too small for their own analyses.

important in defining an appropriate econometric model. If there were no penetration effect, then traditional Medicare patients would represent a control group and a difference-in-differences approach would be suitable. However, previous work indicates that the penetration effect is not zero. For example, Baker et al. (2004) showed that HMO penetration influenced the use of cancer screening in 1996. In the same period I study, Mobley et al. (2011) showed that MA penetration influenced colorectal cancer screening and Baicker, Chernew, and Robbins (2013) showed that MA penetration influenced costs and lengths of hospital stays. In my context, I demonstrate that the penetration effect is substantial in section 4.5.

FIGURE 4.1: Variation in Medicare Advantage Penetration



There are four different trend lines shown for four different counties, the four counties with the largest number of sample participants. Each point on a trend line represents the proportion of Medicare patients in the county who were enrolled in an MA plan in a given year. Data are taken from the Centers for Medicare and Medicaid Services' public-use files.

The goal of my identification strategy is to measure how patients' use of preventive care responds to changes in MA penetration in their county of residence. The key source of variation is the changes over time in county-level MA penetration. According to McGuire, Newhouse, and Sinaiko, 2011 and Baicker, Chernew, and

Robbins (2013), the changes to MA penetration were largely driven by regulatory changes to the county multipliers in the formula determining the payments to MA plans. Thus, changes in MA penetration over time are plausibly exogenous to the use of preventive services. At the national level, MA penetration dipped in the early 2000s and has been gradually increasing ever since 2004. The trend of penetration rates has varied by county, however, as illustrated in Figure 4.1. Figure 4.1 plots the trend of MA penetration rates for the four counties with the largest number of sample participants.

To formalize the model, let y_{ict} denote a prevention outcome for individual i living in county c in year t. The preventive care outcomes are all binary. For example, did the individual have their blood pressure checked last year? The main controls in the model are for the county's MA penetration ($MApen_{ct}$) and the county's MA penetration interacted with an indicator for years after the risk adjustment policy change in 2004 ($MApen_{ct} \times Post_t$). The model also controls for a vector of the individual's characteristics (X_i), county fixed effects (μ_c), and year fixed effects (γ_t). The equation is written:

$$y_{ict} = \pi X_i + \alpha MApen_{ct} + \beta MApen_{ct} \times Post_t + \gamma_t + \mu_c + \varepsilon_{ict} \tag{4.1}$$

The observed individual characteristics X_i are age fixed effects, number of children, and indicator variables for female, black, other minority, Hispanic, married, widowed, high school degree, some college, and college degree. All other variables that influence an individual's decision to use preventive care are in the error term ε_{ict}. The parameters of interest from equation 4.1 are α and β. The coefficient α measures the effect of MA penetration on preventive care *prior to modern risk adjustment*. Adding the coefficient β to the coefficient α measures the effect of MA penetration on preventive care *with modern risk adjustment*. Note that the parameters measure a total effect of MA plans on the use of preventive care that includes (1) the enrollment effect of having more patients enrolled in MA plans and (2) the penetration effect of MA plans having more influence over suppliers of preventive care. Identification of α and β relies on the exogeneity of changes in MA penetration over time. It would be problematic, for example, if underlying geographic trends in the use of preventive

TABLE 4.2: Effect of Medicare Advantage Penetration on Use of Preventive Care: Before and After 2004 Risk Adjustment Policy Change

		(A) All Patients			(B) Only TM Patients		
		N	MA Pen.	MA Pen. × Post	N	MA Pen.	MA Pen. × Post
(1)	Pneumonia Shot (ever)	53,053	0.1761***	-0.1153***	43,470	0.1472**	-0.1206***
			(0.0577)	(0.0405)		(0.0654)	(0.0466)
(2)	Flu Shot	53,053	0.1471***	-0.0731*	43,470	0.1231**	-0.1008**
			(0.0545)	(0.0381)		(0.0603)	(0.0427)
(3)	Smoke (now)	53,053	0.0212	-0.0167	43,470	0.0431	-0.0216
			(0.0402)	(0.0234)		(0.0402)	(0.0269)
(4)	Check Blood Pressure	45,477	0.0503	-0.0310	37,222	0.0194	-0.0361
			(0.0382)	(0.0231)		(0.0447)	(0.0303)
(5)	Check Cholesterol	45,477	0.0813	-0.0958***	37,222	0.0690	-0.1356***
			(0.0538)	(0.0360)		(0.0642)	(0.0442)
(6)	Mammogram	30,741	0.1557*	-0.0481	25,187	0.1735*	-0.0285
			(0.0825)	(0.0634)		(0.0902)	(0.0646)
(7)	Pap Smear	30,741	-0.0493	0.0240	25,187	-0.1303	0.0714
			(0.0840)	(0.0591)		(0.0833)	(0.0615)
(8)	Prostate Cancer Screening	22,312	0.0409	-0.0596	18,283	0.0501	-0.0870
			(0.0699)	(0.0482)		(0.0826)	(0.0617)
(9)	Colorectal Cancer Screening	42,693	0.0670	-0.1221***	35,002	0.0578	-0.1487***
			(0.0652)	(0.0419)		(0.0745)	(0.0464)

Each row represents a separate preventive care outcome. Unless otherwise noted, the preventive care outcomes are measured within the most recent year. The data come from the 2000 through 2010 waves of the Medicare Current Beneficiary Survey, using one observation per individual. MA Pen. is the proportion of Medicare beneficiaries enrolled in an MA plan, measured for each county-year. Post is an indicator for survey years after 2003, when payments to Medicare Advantage plans began to adjust for patients' chronic conditions. Besides the variables for which estimates are reported, all specifications also include dummy variables for: county of residence, year, age, female, black, other race, Hispanic, married, widowed, number of children, high school degree, some college, and a college degree. Standard errors, in parentheses, are clustered by county of residence.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

services were correlated with changes over time in MA penetration.

4.5 Results

In this section, I present the main estimates for the effect of MA penetration on the use of preventive care, both before and after the risk adjustment policy change in 2004. I also test the robustness of the main estimates to alternative model specifications.

4.5.1 Main Estimates

Table 4.2 contains the estimates of α and β from specification of equation 4.1 with all patients (panel A) and only patients with traditional Medicare (panel B). Each row corresponds to a different regression with a different preventive care outcome variable. Within each panel, the sample size and estimates of α and β are reported. While there are 53,053 unique patients in the main estimation sample, several of the regressions, even in Panel A, have smaller sample sizes. For the blood pressure and cholesterol regressions (rows 4 and 5), patients last surveyed in the year 2000 are omitted from the sample because questions about checking blood pressure and cholesterol were not asked until 2001. The mammogram and pap smear regressions (rows 6 and 7) ignore male patients. Similarly, the prostate cancer screening regression (row 8) ignores female patients. Finally, the colorectal cancer screening regression (row 9) has a slightly smaller sample size because questions about colorectal cancer screening were not asked in every survey year.[13]

With the exception of smoking and pap smears, the signs for the estimates of α are positive and the signs for the estimates of β are negative. A positive estimate of α implies that MA plans increased the use of preventive care prior to 2004, before modern risk adjustment. A negative estimate of β implies that the effect of MA plans to increase the use of preventive care was lessened after 2004, when modern risk adjustment was implemented.

The estimates of α for pneumonia shots and flu shots are statistically distinguishable from zero at any conventional threshold. Prior to 2004, a 10 percentage point increase in MA penetration in the county induced a 1.8 percentage point increase, on average, in the probability of a Medicare patient getting a pneumonia shot. Similarly, a 10 percentage point increase in MA penetration in the county induced a 1.5 percentage point increase in the probability of getting a flu shot. We saw in Figure 4.1 that the difference between MA penetration amongst the most highly-populated counties was 0.4. Based on the estimates in Panel A of Table 4.2, we would expect

[13] For the colorectal cancer screening outcome, data comes from the last survey year containing the colorectal cancer screening questions. There were, however, some patients in the main sample who were only surveyed in years without the colorectal cancer screening questions.

this difference in MA penetration to imply a 7.2 percentage point difference in pneumonia vaccination rates and a 6.0 percentage point difference in flu vaccination rates. Note that the estimates are quite similar for all patients (Panel A) and just traditional Medicare patients (Panel B), implying that the penetration effect is much larger than the enrollment effect.

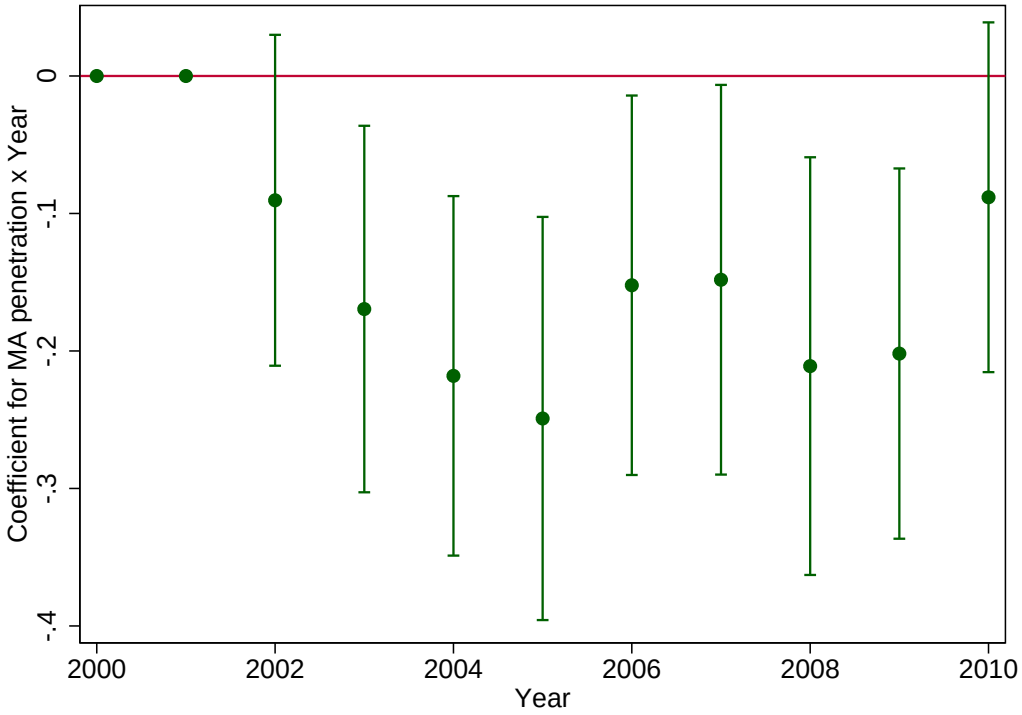
The estimates of β for pneumonia shots, cholesterol checks, and colorectal cancer screening are statistically distinguishable from zero at any conventional threshold. A 10 percentage increase in MA penetration after 2004 (with modern risk adjustment) induced 1.2 percentage points less of an increase in the probability of getting a pneumonia shot than the same increase in MA penetration before 2004 (without modern risk adjustment). Similarly, the new risk adjustment policy reduced the effect of a 10 percentage increase in MA penetration on the probability of having cholestorol checked by 1.0 percentage points and on the probability of screening for colorectal cancer by 1.2 percentage points. The sum of the estimates for α and β indicates the total effect of MA penetration on the use of preventive care with modern risk adjustment. For all of the prevention outcomes, there is no statistically significant evidence that MA penetration influenced the use of preventive care after 2004. There is, however, suggestive evidence that MA penetration still may have influenced the use of flu shots and mammograms.

Overall, the main estimates are quite consistent with the theoretical relationship between risk adjustment and prevention discussed in section 4.3. Without modern risk adjustment, MA plans appear to have induced more pneumonia shots and flu shots. Out of the nine prevention outcomes I look at, these are the two purest forms of preventive care. With modern risk adjustment, MA plans appeard to have had less positive influence on pneumonia shots, cholesterol checks, and colorectal cancer screening. It is particularly reassuring to see more of a distinguishable effect for pneumonia shots than flu shots, because pneumonia is specifically included in the risk adjustment formula while influenza is not.

4.5.2 Robustness

The key identification assumption underlying the main estimates is the exogeneity of changes in MA penetration over time. With this assumption in mind, there are

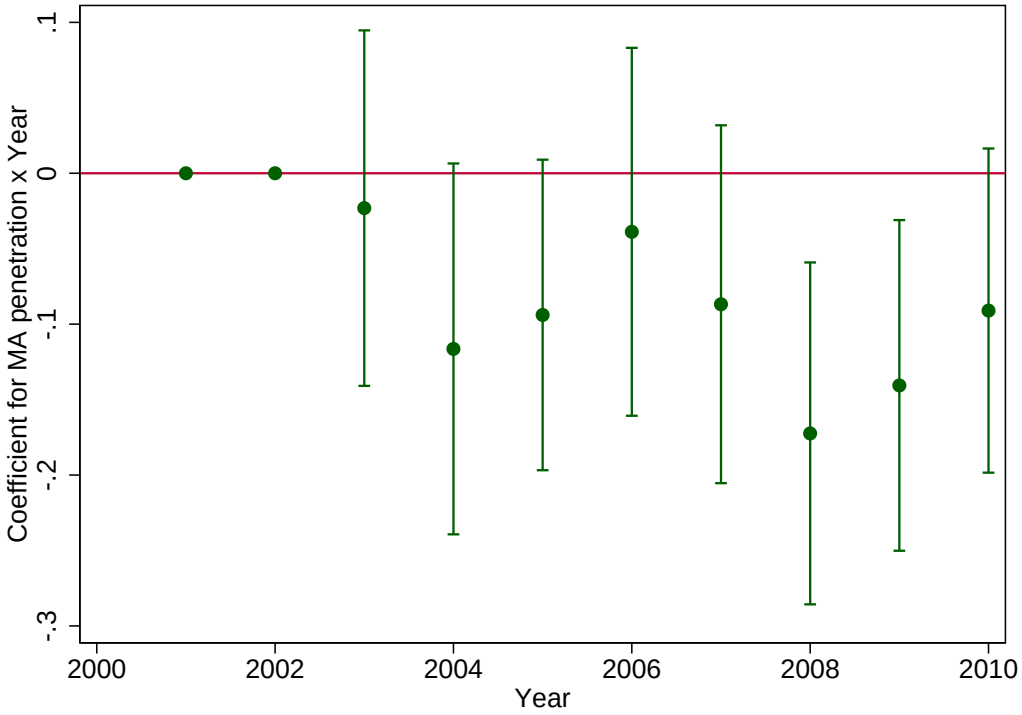
FIGURE 4.2: Event Study Estimates for β - Pneumonia Shots



The graph plots coefficients and 95 percent confidence intervals from an event study regression. The effect of MA penetration in years 2000 through 2002 is normalized to zero. Coefficients are the estimates of MA penetration interacted with each year between 2003 and 2010. The event study model also includes the uninteracted MA penetration variable and dummy variables for: county of residence, year, age, female, black, other race, Hispanic, married, widowed, number of children, high school degree, some college, and a college degree. Standard errors are clustered by county of residence.

several useful ways to test the robustness of the main estimates to alternative model specifications. First, it is helpful to estimate an event study in order to check that the estimates of β correspond to a sharp change at the time of the policy change. The new risk adjustment model was implemented as part of the Medicare Modernization Act, which passed in the House and the Senate in the summer of 2003 and was signed into law in December of 2003. By the end of 2003, MA plans would have known that their future payments would adjust for patients' chronic conditions. Figure 4.2 shows that the event study estimates of β for pneumonia shots started in 2003 and are reasonably constant from 2003 through 2010. Since MA plans could have anticipated in 2003 how their future revenues would adjust for patients with pneumonia, the timing is consistent with the policy change.

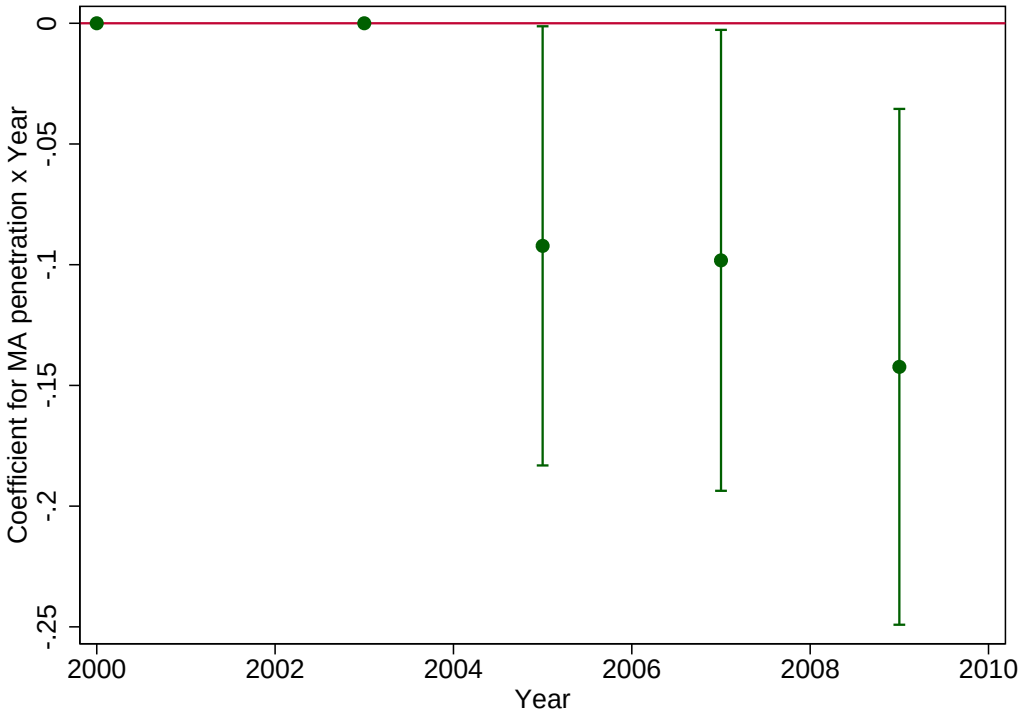
FIGURE 4.3: Event Study Estimates for β - Cholesterol Checks



The graph plots coefficients and 95 percent confidence intervals from an event study regression. The effect of MA penetration in years 2001 and 2002 is normalized to zero. Coefficients are the estimates of MA penetration interacted with each year between 2003 and 2010. The event study model also includes the uninteracted MA penetration variable and dummy variables for: county of residence, year, age, female, black, other race, Hispanic, married, widowed, number of children, high school degree, some college, and a college degree. Standard errors are clustered by county of residence.

In contrast to the estimates for pneumonia shots, the event study estimates of β for cholesterol checks (Figure 4.3) are somewhat inconsistent with the timing of the policy change. The estimates are only statistically distinguishable from zero for the years 2008 and 2009, at least four years after MA plans learned about the new risk adjustment policy. It is thus possible that the relationship between MA penetration and cholesterol checks from 2004 through 2010 was driven, at least partially, by underlying trends unrelated to risk adjustment policy. The event study estimates of β for colorectal cancer screning (Figure 4.4) are constant in all of the post-years, but there are not enough pre-years to assess precisely when the effect started.

FIGURE 4.4: Event Study Estimates for β - Colorectal Cancer Screening



The graph plots coefficients and 95 percent confidence intervals from an event study regression. The effect of MA penetration in years 2000 and 2003 is normalized to zero. Coefficients are the estimates of MA penetration interacted with years 2005, 2007, and 2009. The event study model also includes the uninteracted MA penetration variable and dummy variables for: county of residence, year, age, female, black, other race, Hispanic, married, widowed, number of children, high school degree, some college, and a college degree. Standard errors are clustered by county of residence.

Since MA plans tend to be most popular in urban areas, particularly in the western part of the US, it is also useful to check the robustness of the estimates to underlying trends specific to metropolitan areas or particular regions of the country. Table 4.3 reports estimates from variations of equation 4.1 that include metro-by-year fixed effects (Panel A) and region-by-year fixed effects (Panel B). The main estimates are robust to these alternative specifications in the sense that there is no statistically distinguishable difference between the estimates in Table 4.2 and the estimates in Table 4.3. There are, however, some patterns worth mentioning. The estimates of α for pneumonia shots and flu shots are statistically distinguishable from zero in Panel A, but not (at least with a standard 5 percent cutoff) in Panel B. The lack of statistical

significance in Panel B is partly explained by lower point estimates and partly explained by larger standard errors. Similarly, the estimate of β for pneumonia shots is statistically distinguishable from zero in Panel A but not Panel B, and the estimates of β for cholesterol checks and colorectal cancer screening are statistically distinguishable from zero in Panel B but not Panel A. Overall, in cases where the main estimates are statistically distinguishable from zero, the robustness tests in Table 4.3 do not introduce major concern for their sign. If anything, the robustness tests provide suggestive evidence that the true parameters may be slightly more attenuated than the statistically significant estimates of α and β in Table 4.2.

4.6 Conclusion

In this chapter, I examined the role of private MA insurers in patients' use of preventive care, and how that role has been affected by modern risk adjustment. Before modern risk adjustment, I estimated that increases in MA penetration in a county increased the rate of vaccination for pneumonia and influenza for Medicare patients in that county. However, I also estimated that the implementation of modern risk adjustment reduced the effect of MA penetration on rates of vaccination for pneumonia and screening for colorectal cancer.[14] Pneumonia vaccines and colorectal cancer screening are both good examples of services that can prevent chronic conditions included in the risk adjustment formula. Pneumonia vaccines prevent pneumonia, and colorectal cancer screening can detect and remove precancerous polyps in order to prevent colorectal cancer. My results are thus consistent with the theoretical hypothesis of this paper: insurers may be willing to invest in preventing conditions when future revenues do not adjust for the future costs of treating those conditions, but they are less willing to invest in preventing risk-adjusted conditions.

In terms of risk adjustment policy, this chapter evaluated only one of several outcomes that are important. A comprehensive policy evaluation would need to consider the effect of modern risk adjustment on outcomes related to risk selection and diagnosis of chronic conditions. Newhouse et al. (2012) showed that modern

[14] My estimates indicated that the implementation of modern risk adjustment also reduced the effect of MA penetration on rates of cholesterol checks, but I found the timing of that effect to be inconsistent with the timing of the policy change.

TABLE 4.3: Robustness of the Effect of Medicare Advantage Penetration on Use of Preventive Care: Before and After 2004 Risk Adjustment Policy Change

		(A) Metro-Year Fixed Effects			(B) Region-Year Fixed Effects		
		N	MA Pen.	MA Pen. × Post	N	MA Pen.	MA Pen. × Post
(1)	Pneumonia Shot (ever)	53,053	0.1825***	-0.1353***	53,053	0.1211*	-0.0839*
			(0.0564)	(0.0428)		(0.0647)	(0.0482)
(2)	Flu Shot	53,053	0.1540***	-0.0877**	53,053	0.0848	-0.0507
			(0.0536)	(0.0422)		(0.0622)	(0.0439)
(3)	Smoke (now)	53,053	0.0168	-0.0018	53,053	0.0310	-0.0277
			(0.0410)	(0.0259)		(0.0437)	(0.0274)
(4)	Check Blood Pressure	45,477	0.0570	-0.0380	45,477	-0.0114	-0.0229
			(0.0394)	(0.0259)		(0.0424)	(0.0265)
(5)	Check Cholesterol	45,477	0.0688	-0.0824*	45,477	0.0491	-0.1089***
			(0.0551)	(0.0425)		(0.0611)	(0.0393)
(6)	Mammogram	30,741	0.1606*	-0.0575	30,741	0.1782**	-0.0423
			(0.0840)	(0.0665)		(0.0888)	(0.0673)
(7)	Pap Smear	30,741	-0.0507	0.0172	30,741	-0.0331	0.0134
			(0.0842)	(0.0616)		(0.0806)	(0.0590)
(8)	Prostate Cancer Screening	22,312	0.0119	-0.0369	22,312	0.0838	-0.0887
			(0.0705)	(0.0521)		(0.0861)	(0.0588)
(9)	Colorectal Cancer Screening	42,693	0.0486	-0.0842*	42,693	-0.0170	-0.1003**
			(0.0665)	(0.0458)		(0.0744)	(0.0469)

Each row represents a separate preventive care outcome. Unless otherwise noted, the preventive care outcomes are measured within the most recent year. The data come from the 2000 through 2010 waves of the Medicare Current Beneficiary Survey, using one observation per individual. MA Pen. is the proportion of Medicare beneficiaries enrolled in an MA plan, measured for each county-year. Post is an indicator for survey years after 2003, when payments to Medicare Advantage plans began to adjust for patients' chronic conditions. The estimates in Panel A come from models that control for dummies indicating metropolitan areas interacted with year dummies. The estimates in Panel B come from models that control for dummies indicating census region interacted with year dummies. Besides the variables for which estimates are reported, all specifications also include dummy variables for: county of residence, year, age, female, black, other race, Hispanic, married, widowed, number of children, high school degree, some college, and a college degree. Standard errors, in parentheses, are clustered by county of residence.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

risk adjustment has helped risk selection and Geruso and Layton (2015) showed that modern risk adjustment has led to more diagnoses of chronic conditions.[15] My results show that there are examples of preventive care, particularly pneumonia shots and colorectal cancer screening, that may respond negatively to modern risk adjustment. The use of other types of preventive services that are intended to detect, rather than prevent, chronic conditions, however, do not appear to respond to modern risk adjustment. As researchers continue to make progress on quantifying the positive and negative consequences of modern risk adjustment methodology, it will be important for policymakers to improve that methodology.

[15] It remains unclear if the extra diagnoses are due to extra and beneficial medical care, relaxed medical coding standards, or both.

Bibliography

Abaluck, Jason and Jonathan Gruber (2011). "Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program". In: *American Economic Review* 101.4, pp. 1180–1210.

Afendulis, Christopher C., Michael E. Chernew, and Daniel P. Kessler (2013). "The Effect of Medicare Advantage on Hospital Admissions and Mortality". In: *NBER Working Paper No. 19101*.

Allgar, V. L. and R. D. Neal (2005). "Delays in the Diagnosis of Six Cancers: Analysis of Data from the Nationaly Survey of NHS Patients: Cancer". In: *British Journal of Cancer* 92.11, pp. 1959–1970.

Atwood, Alicia and Anthony T. LoSasso (2016). "The Effect of Narrow Provider Networks on Health Care Use". In: *Journal of Health Economics* 50, pp. 86–98.

Baicker, Katherine, Michael E. Chernew, and Jacob A. Robbins (2013). "The Spillover Effects of Medicare Managed Care: Medicare Advantage and Hospital Utilization". In: *Journal of Health Economics* 32.6, pp. 1289–1300.

Baker, Laurence C. (2001). "Managed Care and Technology Adoption in Health Care: The Adoption of Neonatal Intensive Care". In: *Journal of Health Economics* 20.3, pp. 395–421.

Baker, Laurence C. and Ciaran S. Phibbs (2002). "Managed Care, Technology Adoption, and Health Care: Evidence from Magnetic Resonance Imaging". In: *RAND Journal of Economics* 33.3, pp. 524–548.

Baker, Laurence C. et al. (2004). "The Effect of Area HMO Market Share on Cancer Screening". In: *Health Services Research* 39.6, pp. 1751–1772.

Baker, Laurence C. et al. (2016). "Medicare Advantage Plans Pay Hospitals Less Than Traditional Medicare Pays". In: *Health Affairs* 35.8, pp. 1444–1451.

Berenson, Robert A. et al. (2015). "Why Medicare Advantage Plans Pay Hospitals Traditional Medicare Prices". In: *Health Affairs* 34.8, pp. 1289–1295.

Berry, Steven T. (1992). "Estimation of a Model of Entry in the Airline Industry". In: *Econometrica* 60.4, pp. 889–917.

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor (2015). "Do Individuals Make Sensible Health Insurance Decisions? Evidence from a Menu with Dominated Options". In: *NBER Working Paper No. 21160*.

Birkmeyer, N. J. et al. (2015). "Do Cancer Centers Designated by the National Cancer Institute Have Better Surgical Outcomes?" In: *Cancer* 103.3, pp. 435–441.

Bottai, Matteo and Jiajia Zhang (2010). "Laplace Regression with Censored Data". In: *Biometric Journal* 52.4, pp. 487–503.

Brot-Goldberg, Zarek C. et al. (2015). "What Does a Deductible Do? The Impact of Cost-Sharing on Health Care Prices, Quantities, and Spending Dynamics". In: *NBER Working Paper No. 21632*.

Brown, Jason et al. (2014). "How Does Risk Selection Respond to Risk Adjustment? New Evidence from the Medicare Advantage Program". In: *American Economic Review* 104.10, pp. 3335–3364.

Burke, Amy, Arpit Misra, and Steven Sheingold (2014). *Premium Affordability, Competition, and Choice in the Health Insurance Marketplace, 2014*. URL: http://aspe.hhs.gov/health/reports/2014/Premiums/2014MktPlacePremBrf.pdf.

Cabral, Marika, Michael Geruso, and Neale Mahoney (2015). "Does Privatized Health Insurance Benefit Patients or Producers? Evidence from Medicare Advantage". In: *SSRN Working Paper No. 248999*.

Chan, J. K. et al. (2007). "Influence of the Gynecologic Oncologist on the Survival of Ovarian Cancer Patients". In: *Obstetric and Gynecology* 109.6, pp. 1342–1350.

Ciliberto, Federico and Elie Tamer (2009). "Market Structure and Multiple Equilibria in Airline Markets". In: *Econometrica* 77.6, pp. 1791–1828.

Cox, D. R. (1972). "Regression Models and Life-Tables". In: *Journal of the Royal Statistical Society. Series B (Methodological)* 4.2, pp. 187–220.

Cubanski, Juliette et al. (2015). *A Primer on Medicare: Key Facts About the Medicare Program and the People it Covers*. URL: http://kff.org/report-section/a-primer-on-medicare-what-types-of-supplemental-insurance-do-beneficiaries-have/.

Curto, Vilsa et al. (2015). "Can Health Insurance Competition Work? Evidence from Medicare Advantage". In: *NBER Working Paper No. 20818*.

Curto, Vilsa et al. (2017). "Healthcare Spending and Utilization in Public and Private Medicine". In: *NBER Working Paper No. 23090*.

Cutler, David M., Mark McClellan, and Joseph P. Newhouse (2000). "How Does Managed Care Do It?" In: *RAND Journal of Economics* 31.3, pp. 526–548.

Dafny, Leemore S. (2009). "Estimation and Identification of Merger Effects: An Application to Hospital Mergers". In: *Journal of Law and Economics* 53.3, pp. 523–550.

Dafny, Leemore S., Mark Duggan, and Subramaniam Ramanarayanan (2012). "Paying a Premium on Your Premium? Consolidation in the U.S. Health Insurance Industry". In: *American Economic Review* 102.2, pp. 1161–1185.

Dafny, Leemore S., Jonathan Gruber, and Christopher Ody (2015). "More Insurers Lower Premiums: Evidence from Initial Pricing in the Health Insurance Marketplaces". In: *American Journal of Health Economics* 1.1, pp. 53–81.

Dickstein, Michael J. et al. (2015). "The Impact of Market Size and Composition on Health Insurance Premiums: Evidence from the First Year of the Affordable Care Act". In: *American Economic Review Papers and Proceedings*, pp. 120–125.

Dowd, Bryan et al. (2011). "Health Plan Enrollment and Mortality in the Medicare Program". In: *Health Economics* 20.6, pp. 645–659.

Duggan, Mark, Jonathan Gruber, and Boris Vabson (2015). "The Efficiency Consequences of Health Care Privatization: Evidence from Medicare Advantage Exits". In: *NBER Working Paper No. 21650*.

Duggan, Mark, Amanda Starc, and Boris Vabson (2014). "Who Benefits When the Government Pays More? Pass-Through in the Medicare Advantage Program". In: *NBER Working Paper No. 19989*.

Eggleston, Karen, Randall P. Ellis, and Mingshan Lu (2012). "Risk Adjustment and Prevention". In: *Canadian Journal of Economics* 45.4, pp. 1586–1607.

Einav, Liran and Jonathan Levin (2015). "Managed Competition in Health Insurance". In: *Journal of the European Economic Association* 13.6, pp. 998–1021.

Elkin, Elena B. et al. (2008). "Disenrollment From Medicare Managed Care Among Beneficiaries With and Without a Cancer Diagnosis". In: *Journal of the National Cancer Institute* 100.14, pp. 1013–1021.

Ericson, Keith Marzilli (2014). "Consumer Inertia and Firm Pricing in the Medicare Part D Prescription Drug Insurance Exchange". In: *American Economic Journal: Economic Policy* 6.1, pp. 38–64.

Ericson, Keith Marzilli and Amanda Starc (2015). "Measuring Consumer Valuation of Limited Provider Networks". In: *American Economic Review Papers and Proceedings*, pp. 115–119.

Finkelstein, Amy and Robin McKnight (2008). "What Did Medicare Do? The Initial Impact of Medicare on Mortality and Out of Pocket Medical Spending". In: *Journal of Public Economics* 92.7, pp. 1644–1668.

Friedman, Bernard and H. Joanna Jiang (2010). "Do Medicare Advantage Enrollees Tend to be Admitted to Hospitals with Better or Worse Outcomes Compared with Fee-for-Service Enrollees?" In: *International Journal of Health Care Finance and Economics* 10.2, pp. 171–185.

Friese, Christopher R. et al. (2011). "Timeliness and Quality of Diagnostic Care for Medicare Recipients with Chronic Lymphocytic Leukemia". In: *Cancer* 117.7, pp. 1470–1477.

Geruso, Michael and Timothy Layton (2015). "Upcoding: Evidence from Medicare on Squishy Risk Adjustment". In: NBER Working Paper No. 21222.

Gillis, Charles R. and David J. Hole (1996). "Survival Outcome of Care by Specialist Surgeons in Breast Cancer: A Study of 3786 Patients in the West of Scotland". In: *BMJ* 312.7024, pp. 145–148.

Goodman, Allen C. and Miron Stano (2000). "HMOs and Health Externalities: A Local Public Good Perspective". In: *Public Finance Review* 28.3, pp. 247–269.

Goodney, P. P. et al. (2005). "Surgeon Specialty and Operative Mortality with Lung Resection". In: *Annals of Surgery* 241.1, pp. 179–184.

Government Accountability Office (2008). "Medicare Advantage: Characteristics, Financial Risks, and Disenrollment Rates of Beneficiares in Private Fee-for-Service Plans". In: GAO-09-25. URL: `http://www.gao.gov/new.items/d0925.pdf`.

Gowrisankaran, Gautam, Robert Town, and Eric Barrette (2011). "Managed Care, Drug Benefits and Mortality: An Analysis of the Elderly". In: *The B.E. Journal of Economic Analysis and Policy* 11.2, pp. 1–30.

Greene, Jessica, Jan Blustein, and Kelly A. Laflamme (2001). "Use of Preventive Care Services, Beneficiary Characteristics, and Medicare HMO Performance". In: *Health Care Financing Review* 22.4, pp. 141–153.

Gruber, Jonathan and Robin McKnight (2016). "Controlling Health Care Costs through Limited Network Insurance Plans: Evidence from Massachusetts State Employees". In: *American Economic Journal: Economic Policy* 8.2, pp. 219–250.

Hall, Anne E. (2011). "Measuring the Return on Government Spending on the Medicare Managed Care Program". In: *B. E. Journal of Economic Analysis and Policy* 11.2, pp. 1–43.

Handel, Benjamin R. (2013). "Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts". In: *American Economic Review* 103.7, pp. 2643–2682.

Ho, Kate and Robin S. Lee (2016). "Insurer Competition in Health Care Markets". In: NBER Working Paper No. 19401.

Ho, Katherine (2009). "Insurer-Provider Networks in the Medical Care Market". In: *American Economic Review* 99.1, pp. 393–340.

Holmberg, Lars et al. (2009). "Seasonal of Diagnosis and Prognosis in Breast and Prostate Cancer". In: *Cancer Causes And Control* 20.5, pp. 663–670.

Huang, Jennifer T. et al. (2013). *Medigap: Spotlight on Enrollment, Premiums, and Recent Trends*. URL: https://kaiserfamilyfoundation.files.wordpress.com/2013/04/8412-2.pdf.

Huckfeldt, Peter J. et al. (2017). "Less Intense Postacute Care, Better Outcomes for Enrolles in Medicare Advantage than those in Fee-For-Service". In: *Health Affairsl* 36.1, pp. 91–100.

Jacobson, Gretchen A. et al. (2016). *Medicare Advantage Hospital Networks: How Much Do They Vary?* URL: http://files.kff.org/attachment/Report-Medicare-Advantage-Hospital-Networks-How-Much-Do-They-Vary.

Koo, M. M., Y. Zhou, and G. Lyratzopoulos (2015). "Delays in Diagnosis and Treatment of Lung Cancer: Lessons from US Healthcare Settings". In: *Cancer Epidemiology* 39.6, pp. 1145–1147.

Kowalski, Amanda E. (2014). "The Early Impact of the Affordable Care Act State-by-State". In: NBER Working Paper No. 20597.

Lambe, M., P. Blomqvist, and R. Belloco (2003). "Seasonal Variation in the Diagnosis of Cancer: A Study Based on National Cancer Registration in Sweden". In: *British Journal of Cancer* 88.9, pp. 1358–1360.

Landon, Bruce E. et al. (2004). "Comparison of Performance of Traditional Medicare vs Medicare Managed Care". In: *JAMA* 291.14, pp. 1744–1752.

Lewis, Matthew S. and Kevin E. Pflum (2015). "Diagnosing Hospital System Bargaining Power in Managed Care Networks". In: *American Economic Journal: Economic Policy* 7.1, pp. 243–274.

MacKenzie, Todd A. et al. (2014). "Using Instrumental Variables to Estimate a Cox's Proportional Hazards Regression Subject to Additive Confounding". In: *Health Services and Outcomes Research Methodology* 14.1-2, pp. 54–68.

Manning, Willard G. et al. (1987). "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment". In: *American Ecnomic Review* 77.3, pp. 251–277.

Mayer, Robert J. (2004). "Two Steps Forward in the Treatment of Colorectal Cancer". In: *New England Journal of Medicine* 350.23, pp. 2406–2408.

McArdle, C. S. and D. J. Hole (2004). "Influence of Volume and Specialization on Survival Following Surgery for Colorectal Cancer". In: *British Journal of Surgery* 91.5, pp. 610–617.

McGuire, Thomas G., Joseph P. Newhouse, and Anna D. Sinaiko (2011). "An Economic History of Medicare Part C". In: *The Milbank Quarterly* 89.2, pp. 289–332.

Melnick, Glenn A., Yu-Chu Shen, and Vivian Yaling Wu (2011). "The Increased Concentration Of Health Plan Markets Can Benefit Consumers Through Lower Hospital Prices". In: *Health Affairs* 30.9, pp. 1728–1733.

Merrill, Ray M. et al. (1999). "Survival and Treatment for Colorectal Cancer Medicare Patients in Two Group/Staff Health Maintenance Organizations and the Fee-for-Service Setting". In: *Medical Care Research and Review* 56.2, pp. 177–196.

Miller, Amalia R., Christine Eibner, and Carole Roan Gresenz (2013). "Financing of Employer Sponsored Health Insurance Plans Before and After Health Reform: What Consumers Don't Know Won't Hurt Them?" In: *International Review of Law and Economics* 36, pp. 36–47.

Miller, Keaton (2014). "Do Private Medicare Firms Have Lower Costs?" In: *Mimeo, University of Minnesota*.

Mobley, Lee Rivers et al. (2011). "Managed Care and the Diffusion of Endoscopy in Fee-for-Service Medicare". In: *Health Services Research* 46.6 (Part 1), pp. 1905–1927.

Moriya, Asako S., William B. Vogt, and Martin Gaynor (2010). "Hospital Prices and Market Structure in the Hospital and Insurance Industries". In: *Health Economics, Policy and Law* 5.4, pp. 459–479.

Morrissey, Michael A. et al. (2013). "Favorable Selection, Risk Adjustment, and the Medicare Advantage Program". In: *Health Services Research* 43.3, pp. 1039–1056.

Newhouse, Joseph P. et al. (2012). "Steps to Reduce Favorable Risk Selection in Medicare Advantage Largely Succeeded, Boding Well for Health Insurance Exchanges". In: *Health Affairs* 31.12, pp. 2618–2628.

Newhouse, Joseph P. et al. (2015). "How Much Favorable Selection is Left in Medicare Advantage?" In: *American Journal of Health Economics* 1.1, pp. 1–26.

Pfister, David G. et al. (2015). "Risk Adjusting Survival Outcomes in Hospitals That Treat Patients With Cancer Without Information on Cancer Stage". In: *JAMA Oncology* 1.9, pp. 1303–1310.

Polyakova, Maria (2016). "Regulation of Insurance with Adverse Selection and Switching Costs: Evidence from Medicare Part D". In: *American Economic Journal: Applied Economics* 8.3, pp. 165–195.

Pope, Gregory C. et al. (2004). "Risk Adjustment of Medicare Capitation Payments Using the CMS-HCC Model". In: *Health Care Financing Review* 25.4, pp. 119–141.

Potosky, Arnold L. et al. (1997). "Breast Cancer Survival and Treatment in Health Maintenance Organization and Fee-for-Service Settings". In: *Journal of the National Cancer Institute* 89.22, pp. 1683–1691.

Potosky, Arnold L. et al. (1999). "Prostate Cancer Treatment and Ten-Year Survival Among Group/Staff HMO and Fee-for-Service Medicare Patients". In: *Health Services Research* 34.2, pp. 525–546.

Pruitt, Sandi L. et al. (2013). "Do Diagnostic and Treatment Delays for Colorectal Cancer Increase Risk of Death?" In: *Cancer Causes and Control* 24.5, pp. 961–977.

Riley, Gerald F., Eric J. Feuer, and James D. Lubitz (1996). "Disenrollment of Medicare Cancer Patients from Health Maintenance Organizations". In: *Medical Care* 34.8, pp. 826–836.

Riley, Gerald F. et al. (2008). "Comparison of Cancer Diagnosis and Treatment in Medicare Fee-for-Service and Managed Care Plans". In: *Medical Care* 46.10, pp. 1108–1115.

Rizzo, John A. (2005). "Are HMOs Bad for Health Maintenance?" In: *Health Economics* 14, pp. 1117–1131.

Roetzheim, Richard G. et al. (2000a). "Effects of Health Insurance and Race on Breast Carcinoma Treatments and Outcomes". In: *American Journal of Public Health* 89.11, pp. 2202–2213.

Roetzheim, Richard G. et al. (2000b). "Effects of Health Insurance and Race on Colorectal Cancer Treatments and Outcomes". In: *Cancer* 90.11, pp. 1746–1754.

Sahni, Nihkil R. et al. (2016). "Surgeon Specialization and Operative Mortality in United States: Retrospective Analysis". In: *BMJ* 354, pp. 1–9.

Scheffler, Richard M. et al. (2016). "Differing Impacts Of Market Concentration On Affordable Care Act Marketplace Premiums". In: *Health Affairs* 35.5, pp. 880–888.

Sheingold, Steven, Nguyen Nguyen, and Andre Chappel (2015). *Competition and Choice in the Health Insurance Marketplaces, 2014 - 2015: Impact on Premiums*. URL: http://aspe.hhs.gov/basic-report/competition-and-choice-health-insurance-marketplaces-2014-2015-impact-premiums.

Song, Mingyang and Edward Giovannucci (2016). "Preventable Incidence and Mortality of Carcinoma Associated With Lifestyle Factors Among White Adults in the United States". In: *JAMA Oncology* 2.9, pp. 1154–1161.

Starc, Amanda and Robert J. Town (2015). "Internalizing Behavioral Externalities: Benefit Integration in Health Insurance". In: *NBER Working Paper No. 21783*.

Stukel, T. A. et al. (2007). "Analysis of Observational Studies in the Presence of Treatment Selection Bias: Effects of Invasive Cardiac Management on AMI Survival Using Propensity Score and Instrumental Variable Methods". In: *JAMA* 297.3, pp. 278–285.

Taylor, Erin A. et al. (2015). "More Choice in Health Insurance Premiums May Reduce the Value of the Subsidies Available to Low-Income Enrollees". In: *Health Affairs* 34.1, pp. 104–110.

Town, Robert and Su Liu (2003). "The Welfare Impact of Medicare HMOs". In: *RAND Journal of Economics* 34.4, pp. 719–736.

Town, Robert et al. (2006). "The Welfare Consequences of Hospital Mergers". In: *NBER Working Paper No. 12244*.

Trish, Erin E. and Bradley J. Herring (2015). "How Do Health Insurer Market Concentration and Bargaining Power with Hospitals Affect Health Insurance Premiums". In: *Journal of Health Economics* 42, pp. 104–114.

Waldo, Daniel R. (2004). "Accuracy and Bias of Race/Ethnicity Codes in the Medicare Enrollment Database". In: *Health Care Financing Review* 26.2, pp. 61–72.

Yabroff, K. Robin et al. (2008). "Cost of Care for Elderly Cancer Patients in the United States". In: *Journal of the National Cancer Institute* 100.9, pp. 630–641.

Appendix A

Variable Construction

This appendix provides details about how variables were constructed for the analysis in Chapter 2.

County Variables

In my analysis of the 2014 marketplaces I include county-level controls related to the cost of health care, demand of health care, characteristics of potential enrollees, and provider reimbursement rates. To control for the cost of health care in a county, I follow the methodology in Dafny, Gruber, and Ody (2015) and Dafny (2009) to construct a measure of acute-care hospital prices for potential marketplace enrollees. The data source is the Healthcare Cost Report Information System (HCRIS) from the Center for Medicare and Medicaid Statistics. Like the other two papers, I use data from the 2007-2009 reports. The ultimate measure of health care cost is the average net revenue per non-Medicare case-mix-adjusted discharge for hospitals in the rating area containing the county.[1]

I control for the demand of health care in a county using market size and the number of hospitals. The market size variable is described in section 2.4. The number of hospitals comes from the 2010 American Hospital Association (AHA) survey.

To measure the characteristics of potential marketplace enrollees in a county, I control for the percentages of the population that are black and Hispanic, respectively, according to Census projections for 2013. I approximate the fraction of the subsidy-eligible population that was uninsured prior to the implementation of the

[1] Like Dafny, Gruber, and Ody (2015), I use each hospital's Medicare Case-Mix Index to adjust for admissions severity and I exclude all hospitals not paid under Medicare's Prospective Payment System.

marketplaces using data from the 2012 ACS. I also control for per-capita income using estimates from the Bureau of Economic Analysis for 2012. Finally, I include a measure of how urban or rural the county is. I use the urbanity variable in the Area Health Resources File, which is measured on a 12-point scale from most urban (1) to most rural (12).

The last set of variables I include are related to the negotiation of medical service costs between providers and insurers. This is important to control for because more bargaining power for insurers might induce both (1) more insurers to participate and (2) lower service costs. Including the number of hospitals already helps to control for bargaining power. Further, Ho (2009) argues that insurers have less bargaining power in areas with top medical schools or large hospital systems.[2] I thus include the number of top-30 medical schools in a county, using the 2015 rankings issued by the U.S. News and World Report, and the number of hospitals in the largest hospital system in a county, using the 2010 AHA survey.[3] Finally, McGuire, Newhouse, and Sinaiko (2011) propose that regional variation in insurer bargaining power and costs of marketing contribute to regional variation in popularity of private Medicare Advantage plans. I thus include the proportion of Medicare beneficiaries enrolled in a Medicare Advantage plan as an additional proxy for insurer bargaining power.

Premium + Cost-Sharing Variables

I use variables in the healthcare.gov data to construct measures of premium plus cost-sharing for a variety of service costs in each silver plan. For premiums, I use the premium for an individual 27-year old non-smoker. For cost-sharing, I use the following variables reported for standard (i.e., 70 percent actuarial value) cost-sharing: individual medical deductible and descriptions of the copays and/or coinsurance related to a primary care physician, specialist, emergency room, inpatient facility, and inpatient physician. For each category of service, there are several different ways that copays and/or coinsurance can apply:

[2] See Lewis and Pflum (2015) for an analysis of differences in reimbursement rates negotiated by system and non-system hospitals.

[3] See `http://grad-schools.usnews.rankingsandreviews.com/best-graduate-schools/top-medical-schools/research-rankings/page+2`, accessed on 8/19/14.

1. No charge

   When an individual uses the service, the insurer covers the full cost. This is somewhat common for a visit to a primary care physician but uncommon for the other categories.

2. No charge after deductible

   If the individual's total medical spending in the calendar year (excluding premium and copays) has not exceeded the deductible, the individual pays the full cost of the service. All expenses within the category beyond the deductible are fully covered by the insurer.

3. $X copay

   If the individual's total medical spending in the calendar year (excluding premium) has not exceeded the out-of-pocket maximum, the individual pays $X each time they use the category of service independent of the cost of their visit. For hospital visits, the plan chooses to have the copay charged either per day or per stay, which could cover multiple days. Once the out-of-pocket maximum is reached, all expenses are fully covered by the insurer.

4. $X copay before deductible, $Y copay after deductible

   If the individual has not met the deductible, the individual pays $X for each time they use the category of service independent of the cost of their visit. If the individual has met the deductible but has not exceeded the out-of-pocket maximum, the individual pays $Y for each time they use the category of service independent of the cost of their visit.

5. X percent coinsurance (after deductible)

   Coinsurance only ever applies after any deductible has been met. Before the deductible has been met, the individual is responsible for the full cost of the service. After the deductible has been met and before the out-of-pocket maximum has been met, the individual is responsible for X percent of the cost of the service.

6. $X copay before deductible, Y percent coinsurance after deductible

If the individual has not met the deductible, the individual pays $X each time they use the category of service independent of the cost of their visit. If the individual has met the deductible but has not exceeded the out-of-pocket maximum, the individual pays Y percent of the cost of their visit.

The outcome variables I use represent premium plus cost-sharing conditional on some hypothetical service cost. An example of a service cost is a visit to a primary care provider where the provider bills the insurer and patient a combined $125. Aside from two extreme scenarios where the patient uses no medical services or unlimited in-network medical services, I choose four service costs within each service category to represent the distribution of service costs for that category. The service costs for each category are described below.

- Primary Care

  According to the Medical Expenditure Panel Survey (MEPS), the median service cost per primary care visit was $125 for non-disabled adults between the ages of 27 and 64. The mean service cost per visit was $216. The median number of primary care visits was 1, the 75th percentile was 3, and the 90th percentile was 6. I define the four primary care service costs to incorporate variation primarily in the number of visits.

  1. 1 visit that costs $125 $\implies$ $125
  2. 2 visits that cost $250 each $\implies$ $500
  3. 4 visits that cost $250 each $\implies$ $1,000
  4. 6 visits that cost $250 each $\implies$ $1,500

- Specialist Care

  The distribution of service costs for specialist visits in the MEPS is similar to the distribution of service costs for primary care visits. The median service cost per specialist visit was $108 and the mean was $197. The median number of specialist visits was 0, the 75th percentile was 1, and the 90th percentile was 3. I thus use the same four service costs for primary care and specialist care.

  1. 1 visit that costs $125 $\implies$ $125

2. 2 visits that cost \$250 each $\implies$ \$500
3. 4 visits that cost \$250 each $\implies$ \$1,000
4. 6 visits that cost \$250 each $\implies$ \$1,500

- Emergency Room Care

  According to the MEPS, emergency room visits for this population are rare. Only 11 percent of the people in the MEPS had one or more emergency room visits. I thus focus on the variation in the service cost for one emergency room visit. I use the 25th percentile, 50th percentile, 75th percentile, and 90th percentile of service costs for one emergency room visit.

  1. 1 visit that costs \$250
  2. 1 visit that costs \$650
  3. 1 visit that costs \$1,400
  4. 1 visit that costs \$2,900

- Inpatient Care

  Like emergency room visits, the MEPS indicates that inpatient stays are also rare for this population. Over 94 percent of the people in the MEPS had no inpatient discharges. I thus focus on the variation in the service cost for one day spent in the hospital. For inpatient care there are separate service costs for the inpatient facility and the inpatient physicians. According to the MEPS the inpatient facility service cost typically comprises about 85 percent of the total service cost (median is 0.86 and mean is 0.8). I thus use the 85 percent split for each of my four outcomes that represent the 25th percentile, 50th percentile, 75th percentile, and 90th percentile of service costs for one night spent in the hospital.

  1. 1 night that costs \$1,500
  2. 1 night that costs \$3,000
  3. 1 night that costs \$5,600
  4. 1 night that costs \$9,750

Appendix B

Additional Analysis: Simulated Effect of Insurer Entry on Medical Service Costs

As discussed in section 2.5.3, the results of the first chapter can only be interpreted as an effect of insurer entry on offered *unconditional* patient costs if insurer entry does not influence medical service costs. However, because insurers have less bargaining power over hospitals when hospitals have more insurers to negotiate with, insurer entry is likely to increase medical service costs. In order to infer anything about the effect of insurer entry on offered *unconditional* patient costs, one must therefore keep in mind that, for this purpose, my estimates are likely to be biased in the direction of insurer entry lowering patient costs. In terms of the main result of the paper, that there mostly does not seem to be a marginal benefit of insurer entry beyond three insurers, this bias won't reverse the result. However, the results in the paper that show insurer entry lowers premiums and cost-sharing parameters (i.e. the 2014 results and the results for inpatient cost-sharing parameters in 2015) could be misleading due to possibly greater service costs. The 2014 effect of insurer entry to lower premiums and cost-sharing parameters, however, arises primarily because insurer entry lowered premiums rather than cost-sharing parameters. Thus, the main estimate in the paper that might change, if we are interested in offered *unconditional* patient costs as the outcome, is the estimate suggesting that additional insurer entry in 2015 lowered patient costs for using inpatient services.

Ho and Lee (2016) estimated that the effect of insurer exit on inpatient service

TABLE B.1: Effect of Insurer Entry on (Log) Lowest-Possible Premium + Cost-Sharing in the 2015 Marketplaces: Simulated Effect of Entry on Inpatient Service Costs

Service Cost ($) ($\times 1.075^{\Delta \# \text{ Insurers}}$)	Service Category	Outcome = ln(Lowest-Possible Premium + Cost-Sharing) Variable = Δ # Insurers					
		OLS		IV: Residual Rating Areas		IV: Pre-ACA Shares	
1,500	Inpatient	-0.025***	(0.006)	-0.073***	(0.014)	-0.082***	(0.025)
3,000	Inpatient	-0.038***	(0.007)	-0.149***	(0.026)	-0.156***	(0.036)
5,600	Inpatient	-0.032***	(0.007)	-0.155***	(0.027)	-0.154***	(0.034)
9,750	Inpatient	-0.027***	(0.008)	-0.203***	(0.037)	-0.166***	(0.038)

N = 2,478. Observations are counties in the 31 states with federally facilitated marketplaces that also have more than one rating area. The coefficients (β) reported are for the change in the number of insurers variable, taken from first-differences regressions. The inpatient service cost (first column) varies with the number of new insurers in the county. Each new insurer is assumed to increase the inpatient service cost by 7.5 percent, based on Ho and Lee (2016). The instruments for the change in the number of insurers in the middle panel are: (1) the number of residual rating areas in the state, (2) the average market size of the state's residual rating areas, and (3) the total market size of the state's residual rating areas. The instruments for the change in the number of insurers in the right panel are: (1) 2012 share for Assurant Health in the state, (2) 2012 share for UnitedHealth in the state, and (3) the product of the 2012 shares for Assurant Health and UnitedHealth in the state. Standard errors, in parentheses, are clustered by rating area.
* p<0.10, ** p<0.05, *** p<0.01

costs varies according to market conditions and identity of the exiting insurer. Because Kaiser is not a typical insurer in my data, the most relevant scenario in their Table 8 for my analysis is the effect of removing Blue Cross on Blue Shield's hospital prices. In this scenario the effect of removing an insurer on hospital prices ranged from -5% to -12% across geographic markets, and was -7.5% across all markets.

To examine how much changes in medical service costs that also likely occurred due to changes in insurer entry might influence my estimates, I performed a simulation assuming that inpatient service costs increased by 7.5% with each new insurer in 2015. For example, suppose that one new insurer entered county A in 2015. Instead of using X as the inpatient service cost in county A in 2015, I instead use 1.075X. The calculation is similar for counties where more than one new insurer entered in 2015. The estimates from this simulation are presented in Table B.1. As expected, the estimates are all lower than the estimates with constant inpatient service cost in Table 2.6. However, the differences between the estimates in Table B.1 and the estimates in Table 2.6 are very small and not statistically distinguishable from zero using any conventional cutoff. Thus, one could fairly confidently use my results to infer that insurer entry lowered cost-sharing in 2015 for patients who used inpatient services.

Appendix C

Effect of Plan-Lock on Switching and Mortality

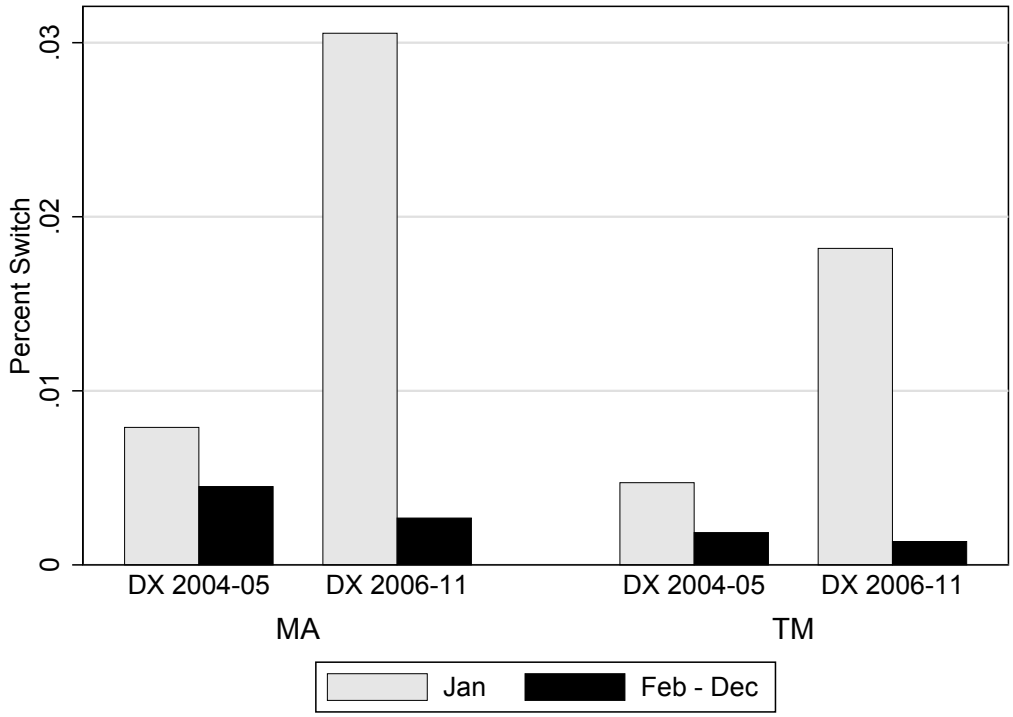
Given the effect of MA enrollment to increase cancer mortality estimated in section 3.4, it is perhaps surprising that more MA cancer patients do not switch to traditional Medicare. Even though MA patients were 37 percent more likely to switch to traditional Medicare after being diagnosed with cancer, only 4.2 percent of them actually switched. One possible reason for infrequent switches after cancer diagnosis is that most patients are not legally allowed to switch to traditional Medicare immediately after being diagnosed with cancer. Since 2006, Medicare beneficiaries are generally locked into a health insurance plan for a full calendar year. Before that, they were able to change their enrollment every month. I examine the importance of plan-lock on health insurance switching and cancer survival first with a descriptive analysis and then with a difference-in-differences approach.

Descriptive Analysis

Figure C.1 illustrates the first-stage effect of plan-lock. Before 2006, switching health insurance was about twice as common from December to January (gray bars) as compared to all other months (black bars). For patients diagnosed with cancer in 2006 or later, however, nearly all switches occurred from December to January. Because more patients initially enrolled in MA plans, the overall frequency of switches also increased.

Calendar-year plan-lock may have deterred some patients, with longer times to wait until being able to switch, from switching health insurance. Figure C.2 plots the

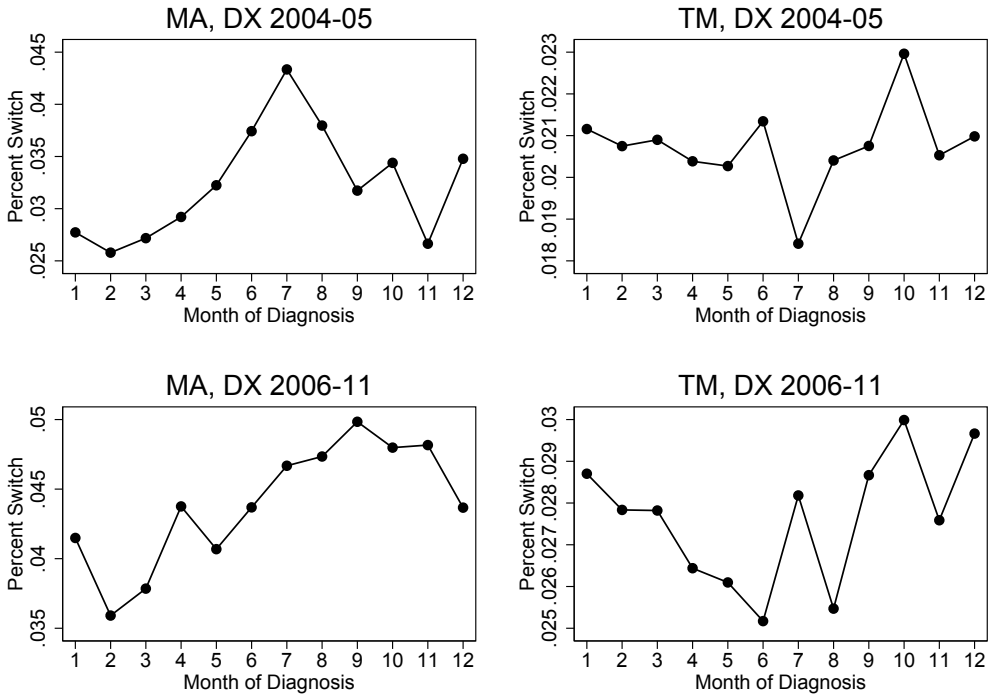
FIGURE C.1: Health Insurance Switching by Month and Regulatory Regime



The graph summarizes average monthly switching rates between Medicare Advantage (MA) plans and traditional Medicare (TM) in the 12 months following cancer diagnosis. A switch in January, for example, means that the patient was covered by a Medicare Advantage plan in December but covered by traditional Medicare in January. The averages are split by diagnoses before versus after calendar-year plan-lock began in 2006. After 2006, nearly all switches occurred in January.

rates of switching health insurance after cancer diagnosis by month of diagnosis. It only includes patients who survived long enough after their diagnosis to have the opportunity to switch. For MA patients diagnosed after 2006 (bottom left graph), there appears to be an approximately linear, modest trend of fewer switches by patients diagnosed at the beginning of the year and more switches by patients diagnosed at the end of the year. The linearity is clearer if diagnoses in December and January are ignored, which makes sense based on the timing of Medicare's open enrollment and special disenrollment periods. Most diagnoses in December occur after open enrollment ends on December 7. Additionally, there is a special disenrollment period throughout January and the beginning of February that allows individuals to switch from an MA plan to traditional Medicare (but not in the other direction).

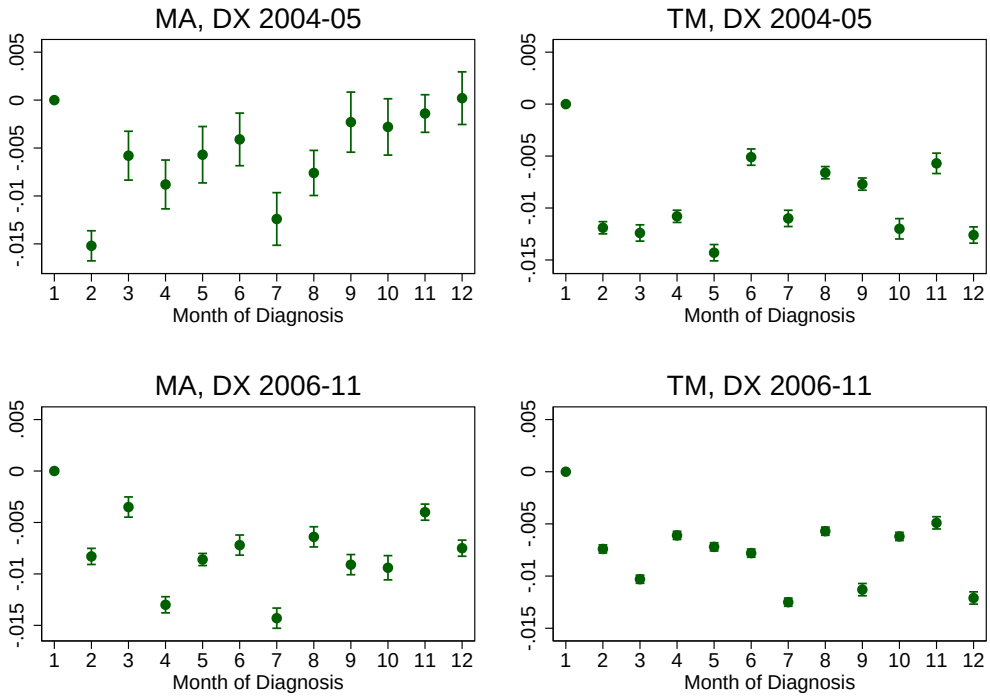
FIGURE C.2: Switching Health Insurance After Cancer Diagnosis by Month of Diagnosis



The graphs summarize switching between Medicare Advantage (MA) plans and traditional Medicare (TM) in the calendar year after cancer diagnosis. The switch frequency is reported for each month of diagnosis and split by diagnoses before versus after calendar-year plan-lock began in 2006. For patients diagnosed in an MA plan after 2006 (bottom left graph), there appears to be an increasing relationship between month of diagnosis and switching to traditional Medicare.

It is also possible that plan-lock influences cancer mortality. Besides possibly influencing some patients to not switch health insurance, plan-lock could also cause some patients to delay treatment until a switch is allowed, or even die before a switch is allowed. Figure C.3 plots estimates of diagnosis month fixed effects from linear probability models for the outcome of surviving at least two years after cancer diagnosis. Regardless of health insurance or regulatory regime, it is clear that month of diagnosis was correlated with two-year survival probability. However, it seems that the pattern is driven by something other than plan-lock. Lambe, Blomqvist, and Belloco (2003) examined seasonality of cancer diagnosis and found, particularly for breast and prostate cancers, that month of diagnosis is not random. Diagnoses are less common in December, presumably due to the holidays, and more common in

FIGURE C.3: Switching Health Insurance After Cancer Diagnosis by Month of Diagnosis



The figure illustrates estimates for month fixed effects in four separate regressions, based on four subsamples of the data. The regressions are linear probability models. The outcome variable indicates if the patient survived at least 2 years after their cancer diagnosis. The dependent variables, other than the month fixed effects, are year of diagnosis fixed effects, county of residence fixed effects, cancer severity fixed effects, and patient characteristics: age, sex, black, Hispanic, married, widowed, and census tract socioeconomic variables.

January. Similarly, diagnoses are less common in the summer months. Holmberg et al. (2009) showed that the seasonality of breast and prostate cancer diagnosis matters for cancer survival. In particular, diagnoses that occur over the summer are more severe and associated with greater hazard rates than diagnoses that occur in January. The patterns in Figure C.3 seem to be consistent with these seasonal trends.

Empirical Strategy

To account for non-random month of diagnosis, I use a difference-in-differences approach to estimate the effects of plan-lock on plan switching and the cancer-mortality hazard rate. I separately estimate the effects of being locked into an MA plan and the effects of being locked into traditional Medicare. The treatment variable $stuckmonths$

is the number of months between month of diagnosis and the start of the next calendar year. The main independent variable $stuckmonths \times post$ is the treatment variable interacted with an indicator for years after 2006, when calendar-year plan-lock was introduced.[1] The unit of observation is an individual i diagnosed with cancer in month m of year y while living in county c. To estimate the effect of plan-lock on switching health insurance S_{icym}, I use a linear probability model:

$$S_{icym} = \alpha X_{it} + \beta\ stuckmonths_m \times post_y + d_c + d_y + d_m + \varepsilon_{icym} \tag{C.1}$$

To estimate the effect of plan-lock on cancer mortality, I use a Cox proportional hazards model. For simplicity and to preserve power, I do not include any covariates for patient characteristics or cancer severity:[2]

$$ln\lambda_{icym}(t) = ln\lambda^0(t) + \beta\ stuckmonths_m \times post2006_y + d_c + d_y + d_m + \varepsilon_{icymt} \tag{C.2}$$

The key identifying assumption for the models in equations C.1 and C.2 is that the seasonal factors that influence month of diagnosis are the same before and after 2006. Unfortunately, there are only two years of diagnoses before 2006 in order to examine pre-trends. In unreported estimates that use 2005 as a placebo treatment year, I find no strong evidence of differential pre-trends. There is some suggestive evidence that my estimates may understate the effect of plan-lock to decrease switches out of MA plans and also understate its effect to increase the cancer-mortality hazard rate for traditional Medicare patients.

Results

The difference-in-differences estimates are reported in Table C.1. The models, for both MA patients and traditional Medicare patients, are estimated separately to include or exclude diagnoses in December and January. Due to the timing of Medicare's open enrollment and special disenrollment periods, diagnoses in these

[1] There was a brief phase-in period, which I do not control for in my analysis. The estimates are not sensitive to excluding diagnoses that occurred during the phase-in years.

[2] The estimates are similar, but less precise, if covariates are added as in the preferred specifiction in 3.4.

TABLE C.1: Effect of Plan-Lock on Switching Health Insurance After Cancer Diagnosis and the Cancer-Mortality Hazard Rate

	Prob. Switch (to TM)		Cancer-Mortality Hazard Rate	
	(1)	(2)	(3)	(4)
Panel A: MA Patients				
# Months Locked In	-0.0004	-0.0009**	0.0018	0.0011
	(0.0003)	(0.0004)	(0.0020)	(0.0032)
Exclude DX in Dec, Jan		✓		✓
N	129,097	107,686	157,485	132,137
	Prob. Switch (to MA)		Cancer-Mortality Hazard Rate	
	(1)	(2)	(3)	(4)
Panel B: TM Patients				
# Months Locked In	-0.0001	-0.0001	-0.0007	-0.0007
	(0.0002)	(0.0002)	(0.0011)	(0.0016)
Exclude DX in Dec, Jan		✓		✓
N	351,700	292,993	434,130	363,649

An observation is an individual. In the first two columns, only individuals who survived long enough after their cancer diagnosis to switch health insurance are included. The sample is split between patients enrolled in a Medicare Advantage (MA) plan at diagnosis (top panel) and patients enrolled in traditional Medicare (TM) at diagnosis (bottom panel). The estimates in the first two columns are computed using difference-in-differences linear probability models. The unreported covariates are the patient characteristics (age, sex, black, Hispanic, married, widowed, and the census tract socioeconomic variables) and fixed effects for cancer type, county of residence, year of diagnosis, and month of diagnosis. The estimates in the last two columns are computed using difference-in-differences Cox proportional hazards models. The only unreported covariates are year of diagnosis and month of diagnosis fixed effects. Standard errors, in parentheses, for all models are clustered by month of diagnosis.

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

months are not subject to calendar-year plan-lock in the same way as diagnoses in other months.

The estimates in Table C.1 are consistent with the evidence from the descriptive analyses. Plan-lock seems to have decreased the likelihood of switching from an MA plan to traditional Medicare after cancer diagnosis (Panel A, column 2), but only by a small amount. Excluding December and January, an additional month of lock-in led to a 0.1 percentage point (2 percent) decrease in the probability of switching to traditional Medicare. The estimate is statistically distinguishable from zero using a 5 percent threshold. There is no evidence that plan-lock affected switching from traditional Medicare to an MA plan after cancer diagnosis (Panel B, columns 1 and 2). There is also no evidence that plan-lock influenced cancer survival for either set of patients (columns 3 and 4).[3] The conclusion is that calendar-year plan-lock appears unlikely to explain why most MA cancer patients do not switch to traditional Medicare, and also appears to have no influence on cancer mortality.

[3]The zero effect is robust to using non-linear measures of plan-lock. For example, there is also no statistically distinguishable effect of being locked into an MA plan for at least 6 months on the cancer-mortality hazard rate.