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Author
Valdez, Samuel

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Essays on The Industrial Organization of Health Care

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

Samuel V. Valdez

Dissertation Committee:
Associate Professor Jiawei Chen, Co-Chair
Associate Professor Mireille Jacobson, Co-Chair
Professor David Brownstone
Professor Matthew Harding

2020

DEDICATION

To my loving and supportive wife

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CURRICULUM VITAE

Samuel V. Valdez

EDUCATION

University of California, Irvine
Ph.D. in Economics, June 2020

California State University, Long Beach
M.A. in Economics, December 2013

University of California, Los Angeles
B.S. in Mathematics/Economics, June 2012

RESEARCH FIELDS

Health Economics, Empirical Industrial Organization, Applied Microeconomics

RESEARCH EXPERIENCE

Health Policy Research Institute and Paul Merage School of Business, University of California, Irvine
Research Assistant to Mireille Jacobson, 2016-20

Nicholas C. Petris Center on Health Care Markets and Consumer Welfare, University of California, Berkeley
Graduate Student Researcher, Summer 2019

Los Angeles County Economic Development Corporation
Contracted Employee working under Senior Vice President Dr. Christine Cooper at the Institute for Applied Economics, 2012-15

TEACHING EXPERIENCE

University of California, Irvine
Teaching Assistant: Probability and Statistics for the Social Sciences (Summer I 2016), Intermediate Macroeconomics (Summer II 2016), Intermediate Microeconomics (Summer II 2015), Basic Economics I (Spring 2015, Fall 2015), Computer Research in Social Science (Winter 2015), Basic Economics II (Fall 2014)

California State University, Long Beach
Instructor: Introduction to Econometrics and Statistical Economics, Lab (Spring 2013)
Tutor: Managerial Economics, 2012-13

PUBLICATIONS

Yabroff, K. R., Valdez, S., Jacobson, M., Han, X., and Fendrick, A. M. "The Changing Health Insurance Coverage Landscape in the United States." *American Society of Clinical Oncology Educational book. American Society of Clinical Oncology. Annual Meeting.* Vol. 40. 2020.

WORKING PAPERS

"Asymmetric Information in Health Insurance: Replication and Re-specification"
"How Medicare's Facility Fee Payments Affect the Vertical Integration of Hospitals and Physicians"
"The Impact of Hospital-Physician Integration on Referral Networks: Evidence from Oncologists"

WORKS IN PROGRESS

"The Role of Academic Medical Centers on Incentivizing Hospital-Physician Integration"
"Hospital-Physician Integration: Response to Private Insurance Concentration"

HONORS AND AWARDS

Economics Summer Research Fellowship, UCI, 2017-18
Social Science Tuition Fellowship, UCI, 2014-18
Microeconomics Qualifying Exam, Distinctions, UCI, 2015
Merit Fellowship in Economics, UCI, 2014
Graduate Dean's List, CSULB, 2013
Ray and Marge Lancaster Graduate Scholarship Award Recipient, CSULB, 2013
National Science and Mathematics Access to Retain Talent (SMART) Grant Recipient, UCLA, 2009-11
Blue and Gold Scholarship Recipient, UCLA, 2009-11
Phi Theta Kappa International Honor Society, 2008-09
ALPFA Scholarship Award Recipient, 2007

PRESENTATIONS AND WORKSHOPS

UCI Department of Economics seminar, UCI, November 2019
NBER Summer Institute 2019, Health Care Workshop, Invited Attendee, July 2019
Transportation, Urban, and IO seminar, UCI, May 2019
NBER Health Economics Research Boot Camp, Invited Participant, December 2018
Transportation, Urban, and IO seminar, UCI, May 2018
California State University, Chico, Guest Speaker, April 2018
Workshop in Industrial Organization/Corporate Welfare, UCI, November 2018
Annual Economics Poster Session, UCI, October 2018
Annual Economics Poster Session, UCI, October 2017

PROFESSIONAL AFFILIATIONS

American Economic Association (AEA)

ABSTRACT OF THE DISSERTATION

Essays on The Industrial Organization of Health Care

By

Samuel V. Valdez

Doctor of Philosophy in Economics

University of California, Irvine, 2020

Associate Professor Jiawei Chen, Co-Chair

Associate Professor Mireille Jacobson, Co-Chair

The first chapter of this dissertation replicates, re-specifies, and re-estimates Cardon and Hendel's 2001 RAND Journal of Economics article "Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey." This article presented the first structural model to study adverse selection in the health insurance market—finding no evidence of informational asymmetries. I demonstrate, however, that after normalizing residual income, correcting an inconsistency in the construction of a health good, and accounting for corner solutions of the maximization problem, asymmetric information in fact exists in the health insurance market studied.

The second chapter examines whether hospitals strategically choose to vertically integrate with physicians in order to capture facility fees. To address this question, I match data on hospitals' ownership of clinical oncologist practices with Medicare payment data disaggregated to the physician and specific service level. I leverage a 2014 policy change that drastically altered the payment structure of Medicare's facility fees paid to hospitals for evaluation and management services—and yet, it did not alter the direct payments made to physicians. Contrary to popular belief, I find no evidence that the financial incentives of facility fees have an effect on the probability that a hospital and clinical oncologist vertically integrate.

The third chapter explores how hospital-physician integration in the United States has the potential to restrict patient referral pattern flows within specific referral networks. I first empirically illustrate these referral network restrictions that result from hospital-physician integration and then consider their implications for newly integrating oncologists as well as for independent oncologists. Utilizing detailed longitudinal data that cover the complete U.S. shared patient patterns for oncologists' Medicare beneficiaries along with oncologists' integration status with hospitals in geographically-defined market boundaries, I find that the average integrating oncologist increases his or her share of referrals made to health system partners by 36 percentage points following integration; these effects are most pronounced in markets with highly concentrated levels of integrated oncologists employed by a single health system. In addition, hospital-physician integration increases the probability of referral foreclosure—with respect to the referrals made to oncologists outside of a health system—by 14 percentage points in unconcentrated markets and by 23 percentage points in highly concentrated markets. As a single health system increases its market share of integrated oncologists, independent oncologists in the market shift their referrals to oncologists of lower quality. These findings suggest broader access issues for patients of independent oncologists in markets that experience high levels of consolidation that result from hospital-physician integration.

Chapter 1

Asymmetric Information in Health Insurance: Replication and Re-specification

1.1 Introduction

How to effectively structure consumer choice in the health insurance market is one of the most frequently posed policy questions in health economics. A major concern of the health insurance market is inefficient sorting. Due to asymmetric information between consumers and insurers, the health insurance market runs the risk of healthy policyholders declining or terminating coverage when faced with increased insurance costs. Insurers can be left with a disproportional number of high-risk individuals in generous plans—leading to higher than anticipated claims. This phenomenon is defined as adverse selection. As a result of adverse selection, more generous plans will charge a higher premium than benefit differences would dictate in order to not disproportionately attract less healthy individuals. As shown by Rothschild and Stiglitz (1976), when adverse selection is large it could completely destroy the market for generous plans. Even when equilibria do exist, efficiency is limited due to inefficient sorting.

In recent years, a vast amount of literature has examined adverse selection in insurance markets through reduced-form analysis. While reduced-form analyses afford convenient estimation strategies for demonstrating correlations, they have limitations in making statements regarding market efficiency, welfare impact of potential market interventions, and the separation of adverse selection from moral hazard (Einav et al., 2009). Without a clearly specified model of consumer preferences, counterfactuals cannot be generated to forecast the effects of interventions that have never been experienced. In order to rectify these limitations, recent work has built structural models to guide the choices of estimators and to incorporate theoretically grounded specifications of consumer preferences.

Cardon and Hendel's 2001 RAND Journal of Economics article "Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey"—henceforth, CH—is the first demonstration of a structural model to study adverse selection in the health insurance market. The model is of a two-stage decision made by expected-utility maximizing consumers who face uncertainty about their future health state. Consumers choose the health insurance plan and level of health care expenditure that maximizes their expected utility conditional on their health risk distribution; estimates of health care expenditure, plan choice, and ex ante health risk are obtained.[1] The model is used to test if private information plays a large role in an individual's choice of health insurance plan and of health care expenditure. The model is specified such that the main estimate obtained is the variance of simulated private risk signals given to each individual in the first stage of the model. If this variance is large, consumers receive dispersed risk signals. This implies that for a given level of demographics, those receiving a signal of high risk expect their health to be relatively poor—thus, anticipating large second-stage health care expenditure. As a result, these individuals will have a higher willingness to pay for insurance in the first stage relative to those who received a signal indicating good health. If the variance of the simulated private risk signal is low or zero, then risk type can be categorized by observable demographics—implying that consumers receive essentially the same risk information as insurers. CH find the variance of the simulated private risk signal to be statistically indistinguishable from zero; this suggests an absence of informational asymmetries and adverse selection in the market.

[1] This structural approach provides a quantitative framework for welfare and policy study that builds directly on the underlying theory of expected utility and choice of optimizing agents. While the tightly specified model imposes strict assumptions, it provides the benefits of identifying direct measures of the extent of asymmetric information that would not be available in a reduced-form analysis.

This paper, while primarily a replication, extends CH in the following ways. First, I demonstrate that by not normalizing residual income, identifying variation only originates from the continuous dimension of health care expenditure choice—rather than from both the intended continuous and discrete dimensions of health care expenditure and health insurance plan choice. Second, I correct an inconsistency in the construction of the health state variable that allowed for individuals to be rewarded for excess expenditure. Third, I refine the specification of the model by imposing additional constraints in the maximization problem in order to account for corner solutions. By re-specifying model characteristics presented in CH, this paper produces contradictory evidence—indicating the presence of adverse selection that resulted from asymmetric information. Estimates from the re-specification of the model are more in line with recent reduced-form and structural analyses that indicate significant evidence of adverse selection in health insurance markets.

Analysis is based on a subsample from The National Medical Expenditure Survey (NMES) of employed single individuals—age 18 to 65 years old—which I create to match the original data set used in CH as closely as possible. The NMES is the most complete and reliable medical survey of the late eighties; it offers data on health care utilization, the complete menu of health insurance plans offered to employees, and the plans the employees enrolled in. By focusing on employed individuals, the study is narrowed to employer-based health coverage. Employer-based health coverage is the predominant form of private health insurance in the United States that covers around 60 percent of the population (McGuire, 2012).[2]

The next section provides an overview of related literature. Section 1.3 and Section 1.4 present a detailed description of the econometric model and estimation procedure that are presented in CH. Construction of the data set used in this paper as well as descriptive statistics are presented in Section 1.5. Section 1.6 analyzes the structural estimates from the model and contrasts the obtained replication and re-specification results to the published CH's results. Concluding remarks are made in Section 1.7.

[2]The following salient features of employer-based insurance demonstrate its historical importance in the U.S. health care system. First, enrollment in employer-based insurance is explicitly promoted through tax subsidies. Employees do not pay state or federal income taxes on the employer contribution to health insurance (Breyer et al., 2012). Second, employees in firms of all sizes are uniformly offered health insurance as a benefit of employment. 99 percent of large firms—defined as over 200 employees—and 68 percent of smaller firms offer health insurance coverage (McGuire, 2012).

1.2 Literature Review

While the implications of adverse selection in insurance markets have been widely recognized, evidence on its quantitative importance has been limited due to the difficulty of empirically demonstrating adverse selection and its effects (Bundorf et al., 2012). Recent empirical advances in insurance markets began with the development of reduced-form analyses to test for the existence of asymmetric information. Chiappori and Salanie (2000) are credited with the first of such studies; they describe a set of positive correlation tests for asymmetric information that compare risk indicators to claims of consumers who self-selected into different insurance contracts.

Cutler and Zeckhauser (2000) present a detailed summary of the recent literature that examines adverse selection in health insurance markets through reduced-form analysis. Regardless of the type of identification strategy implemented, these studies near uniformly suggest that adverse selection is quantitatively large. Eighteen studies utilize data sets from employers who offered choices of different health insurance plans with varying generosity; seventeen of these studies result in findings of adverse selection. Studies focusing on the Medicare market find adverse selection is present in eight out of twelve studies.

Notably, the model constructed in CH serves as a baseline for similar structural approaches used in Bajari et al. (2006), Carlin and Town (2009), and Bundorf et al. (2012). Bajari et al. (2006) propose a two-step semi-parametric estimation strategy to identify and to estimate a canonical model of asymmetric information in health care markets. With this method, they estimate a structural model of demand for health care. Using confidential information from a large self-insured employer, they find significant evidence of adverse selection. Carlin and Town (2009) assess the welfare impact of adverse selection in health insurance choices. Their estimates suggest that adverse selection plays an important role in explaining cost differentials. The distortionary consequences of asymmetric information, however, are modest because individuals are premium inelastic in their data set.

Recently, structural studies have attempted to address physician access, network restrictions, consumer heterogeneity, search or switching costs, and consumer errors in expected utility calculations within the context of the health insurance market that earlier studies previously ignored. Bundorf et al. (2012) develop a simple econometric model to study physician access and network's scope; they present estimates on the impact of risk rating using a model of consumer demand.[3] Cutler et al. (2009) assess the factors influencing the movement of people across health plans. In a similar vein of research, Hendel (2013) develops a structural choice model that jointly quantifies inertia and allows for heterogeneity in risk preferences.[4]

Moving beyond simple testing for the presence of adverse selection in the health insurance market, Einav et al. (2009) provide a summary of studies that evaluate market efficiency and examine the welfare consequences of certain types of government policies when adverse selection is present. Importantly, Einav et al. (2009) find that even in markets in which there appear to be substantial evidence of adverse selection, the welfare costs from misallocation are relatively limited.

1.3 Econometric Model

In this section, I present details on CH's model of a two-stage decision made by an expected-utility maximizing consumer who faces uncertainty about his or her future health state.[5]

First stage: In the first stage, an individual i receives a private risk signal, ω_i, about his or her uncertain future health state, s_i.[6] After observing ω_i—but prior to the realization of s_i—each individual i incorporates all private information available and maximizes his or her first-stage indirect expected utility, V_{ij}, by choosing one of the health insurance plans j in his or her choice set or by remaining uninsured:

[3]This article is pertinent because plans vary not only in financial characteristics such as copayments, premiums, and deductibles, but also in physician access and in the scope of provider networks. This suggests that insights based on purely risk-based selection may not adequately capture the dynamics of today's health insurance market.

[4]Theoretically, search or switching costs may be important as well; such costs arise if the insured are concerned with maintaining continuity with their physicians or with their health insurance plan. There can be efficiency loss from consumers not maximizing their individual utility as well as a long-term efficiency loss from not transmitting the appropriate price signals to the competitive marketplace.

[5]The framework enables estimation of demand and risk parameters for a collection of employed individuals across a multitude of firms.

[6]See Section 1.4.2 for the specification of s_i that incorporates the presence of asymmetric information through the variance of the private risk signal, σ^2_ω—given to each individual i in the first stage of the model.

$$\max_j (V_{ij}(\omega_i, a_{ij})) \quad j = 0, ..., J_i$$

where V_{ij}—conditional on ω_i and plan-specific random tastes, a_{ij}[7]—incorporates second-stage optimal indirect utility, U^*_{ij}, and is calculated by integrating over the conditional distribution of s_i represented by π_i.[8] Thus, for each health insurance plan j:

$$V_{ij}(\omega_i, a_{ij}) \equiv E(U^*_{ij}(s_i)|\omega_i) + a_{ij} = \int U^*(y_i, s_i, Z_i)\pi_i(s_i|\omega_i, D_i) + a_{ij}$$

where

$$\begin{aligned} V_{ij}(\omega_i, a_{ij}) &= \text{individual } i's \text{ indirect expected utility from plan } j, \text{ conditional on a private} \\ &\quad \text{signal } \omega_i \text{ and tastes } a_{ij}, \\ U^*_{ij} &= \text{second-stage indirect utility of individual } i \text{ holding plan } j, \\ \pi_i &= \text{distribution of the realized health state } s_i \text{ conditional on the signal } \omega_i \\ &\quad \text{and the demographics of of individual, } D_i. \end{aligned}$$

Second stage: In the second stage—after s_i is realized and health insurance plan j has been selected—an individual i chooses the level of health care expenditure, x_i, that maximizes his or her second-stage indirect utility, U_{ij}, subject to a budget constraint:[9]

$$\begin{aligned} U^*_{ij}(s_i) = U^*(y_i, s_i, Z_i) &= \max_{x_i}(U(m_i, h_i)) \\ &\qquad \text{subject to } m_i + C_j(x_i) = y_i - p_j \end{aligned}$$

where

[7] It is assumed that a_{ij} enter additively and do not affect second-stage behavior.

[8] Individual demographics, D_i, may affect the need for care and are incorporated in π_i.

[9] Note that the budget constraint is influenced by the first-stage decision of which plan an individual i enrolls in after receiving ω_i.

$$
\begin{aligned}
y_i &= \text{annual income of individual } i,\\
p_j &= \text{annual premium of plan } j,\\
C_j(x_i) &= \text{annual out of pocket expenditure under plan } j,\\
Z_j &= [p_j, DED_j, c_j] = \text{plan } j's \text{ characteristics.}
\end{aligned}
$$

The model assumes that individuals have preferences given by $U(m_i, h_i)$—where $h_i = x_i + s_i$ represents a health good and $m_i = y_i - p_j - C_j(x_i)$ represents a composite good comprised of all other goods other than the health good.[10]

1.4 Estimation Strategy

The parameters of the model laid out in the previous section are estimated using Generalized Method of Moments (GMM). In this section, I describe the construction of the moment conditions. With the structure of the moment conditions in place, focus is shifted to the algorithm used to estimate the parameter vector $\hat{\theta}_{GMM}$.

1.4.1 Moment Conditions

For each individual i, a vector of indicators, $I_{i0}, ..., I_{iJ}$, is created from the observed plan choice of that individual—where $I_{ij} = 1$ if plan j is chosen and $I_{ij} = 0$ otherwise. The vector of indicators is then multiplied by the actual observed expenditure under an individual's chosen plan, x_{ij}—resulting in the vector of products, $I_{i0}x_i, ..., I_{iJ}x_i$. Predicted expenditure under each plan offered to an individual, x^e_{ij}, as well as the probability an individual chooses the offered plan, P_{ij}, is constructed, as detailed in Section 1.4.2. Finally, using predicted and actual expenditure, a vector of prediction errors is formed—where θ is the vector of parameters to be estimated:

[10]The health good is a linear combination of the health state and health care expenditure. Thus, a poor health state can be perfectly compensated with increased medical care.

$$u_i(\theta, D_i) = \begin{pmatrix} P_{i0}(\theta, D_i)x^e_{i0}(\theta, D_i) - I_{i0}x_{i0} \\ \vdots \\ P_{iJ}(\theta, D_i)x^e_{iJ}(\theta, D_i) - I_{iJ}x_{iJ} \\ P_{i0}(\theta, D_i) - I_{i1} \\ \vdots \\ P_{iJ}(\theta, D_i) - I_{iJ} \end{pmatrix}$$

Assuming there exists a set of instruments, W_i, such that $E(u_i(W_i, \theta_0)) = 0$, "moment conditions" are constructed:

$$G(\theta_0) = E(W_i \otimes u_i(\theta_0, D_i)|I_i, D_i) = 0$$

If the model is correctly specified, $G(\theta_0)$ has a mean of zero at the true parameter vector θ_0. For the system to be just identified—with a unique θ_0—there must be an equal number of moment conditions as there are parameters to be estimated in θ. When implementing the estimation algorithm, however, the system is over-identified—therefore, the parameters that are estimated instead minimize the distance from $G(\theta)$ to zero measured by the quadratic form:

$$Q(\theta) = G(\theta)'WG(\theta)$$

where W is a symmetric and positive definite weighting matrix. The weighting matrix is set to the identity matrix—implying that each moment condition carries equal weight. The GMM estimator is then estimated:

$$\hat{\theta}_{GMM} = arg \min_{\theta}(G(\theta)'WG(\theta))$$

1.4.2 Estimation Algorithm

The first step in solving the model presented in Section 1.3 is to specify a distribution for s_i. In any given year, the majority of individuals do not experience major negative shocks to their health—which would require large medical costs.[11] This motivates the literature's use of a negative log-normal distribution to approximate health care expenditure. Following this logic, it is assumed that:

$$s_i = -exp(K(D_i) + \omega_i + \epsilon_i)$$

where $K(D_i)$ is a deterministic function of demographics. $\omega_i \sim N(0, \sigma_\omega^2)$ represents an individual's private risk signal, and $\epsilon_i \sim N(0, \sigma_\epsilon^2)$ represents the remaining uncertainty realized after a health insurance plan has been chosen. ω_i and ϵ_i are assumed independent.[12]

To obtain second-stage optimal expenditure, x_{ij}^*—conditional on each plan j and s_i—a functional form must be placed on $U(m_i, h_i)$. The unknown true form $U(m_i, h_i)$ is approximated by a second-order Taylor series expansion:

$$U(m_i, h_i) \approx \beta_1 m_i + \beta_2 h_i + \beta_3 m_i h_i + \beta_4 m_i^2 + \beta_5 h_i^2$$

$U(m_i, h_i)$ is maximized subject to the budget constraint, $m_i + C_j(x_i) = y_i - p_j$, and the health good, $h_i = x_i + s_i$.[13] Out of pocket expenditure, $C_j(x_i)$, is modeled to incorporate deductibles and coinsurance rates:

$$C_j(x_i) = \begin{cases} x_i & \text{if } x_i \leq DED_j \\ DED_j + c_j(x_i - DED_j) & \text{if } x_i > DED_j \end{cases}$$

[11] As seen in Figure 1.2, annual health expenditure is relatively low for all but the sickest individuals.
[12] For each individual in the data set, I simulate ω_i between 20-1000 times—each with a corresponding 25-100 ϵ_i.
[13] Individuals experience negative health shocks, which they then compensate for with second-stage health care expenditure.

The above piecewise equation implies an individual pays the full cost of health care up to his or her deductible, DED_j, and above that amount, he or she is only responsible for c_j of every dollar spent. Solving the first order condition of the constrained maximization problem with respect to x_i leads to the following first-order condition:

$$x_{ij}(y_i - p_j - DED_j, s_i, c_j) = \frac{(\beta_2 + \beta_3((y_i - p_j - DED_j + 2\beta_5 s_i)}{2(\beta_3 c_j - \beta_4 c_j^2 - \beta_5)} - \frac{c_j(\beta_1 + \beta_3 s_i + 2\beta_4(y_i - p_j - DED_j)}{2(\beta_3 c_j - \beta_4 c_j^2 - \beta_5)}$$

The structure of $C_j(x_i)$ leads to a piecewise linear budget set that is not linear or convex when $DED_j > 0$. Thus, there are two possible interior solutions: 1) the case where the individual pays the full cost of care $x_{ij}(y_i - p_j, s_i, 1)$ and 2) the case where the individual pays c_j of every dollar after paying his or her deductible $x_{ij}(y_i - p_j - DED_j, s_i, c_j)$. There is also the possibility of two corner solutions at: 1) $x_{ij} = 0$ and 2) $m_i = 0$. For each j in an individual's choice set and s_i, utility is calculated at these four points. The point which yields the highest utility is selected as x_{ij}^*.

Now that x_{ij}^* has been calculated, I can solve the first stage of the model for the probability that one health insurance plan is chosen over another—conditional on ω_i. By assuming a_{ij} are independent and identically distributed type 1 extreme value random variables, the probability that individual i chooses plan j conditional on ω_i, takes the well-known logistic probability:

$$P_{ij}(\omega_i) = \frac{e^{E(U_{ij}^*(s_i)|\omega_i)}}{\sum_{j=0}^{J_i} e^{E(U_{ij}^*(s_i)|\omega_i)}}$$

P_{ij} is calculated by numerically integrating with respect to ω_i.[14] The final step of the algorithm is to calculate predicted expenditure x_{ij}^e under each plan offered to an individual. x_{ij}^e is constructed as:

$$x_{ij}^e = \int\int_{(\omega|V_{ij}(\omega_i,a_{ij})\geq V_{ik}(\omega_i,a_{ik})\,\forall k)} x_{ij}^*(y_i - p_j, K(D_i) + \omega_i + \epsilon_i) f(\omega) f(\epsilon)\, d\omega\, d\epsilon$$

[14]Monte Carlo integration is performed in order to calculate P_{ij}.

x^e_{ij} is calculated by numerically integrating over the values of ω_i and a_{ij} that make plan j the optimal health insurance plan. This is accomplished by only recording optimal expenditure levels for each plan when the plan has the highest logit probability of selection given a ω_i.[15] With the algorithm now complete, the vector of prediction errors is fully specified. The parameters θ are estimated using a hill climbing algorithm—such that the model's predicted probabilities match the observed choices as closely as possible.

1.5 Data and Descriptive Statistics

I begin by discussing the data set replication of CH. This paper uses a subsample from the National Medical Expenditure Survey (NMES) of 880 employed single individuals who are ages 18 to 65 years old.[16] The NMES was collected in 1987 by the Agency of Health Care Policy Research; it builds on the earlier National Medical Care Expenditure Survey and the National Medical Care Utilization and Expenditure Survey. The NMES requested detailed health care expenditure and demographics for a sample of roughly 36,000 individuals. To increase reliability of an individual's self-reported health care expenditure and to control for omitted expense details, the NMES collected actual health care expenditure reported by health care providers. Additionally, employers and insurers provided data on health insurance plans that were then cross-checked with the information reported by individuals. As a supplementary follow-up to the NMES, the Health Insurance Plans Survey (HIPS) verified health insurance status in order to provide supplementary information on private coverage.[17]

NMES and HIPS data were obtained from the Interuniversity Consortium for Political and Social Research.[18] Each survey provides both individual identifiers and potential source of employment-related health insurance identifiers. These identifiers allow linkages that enable construction of the analysis sample that will be used in estimation. For each of the plans offered to the individuals in

[15] Monte Carlo integration is performed in order to calculate $E(U^*_{ij}(s_i)|\omega_i)$.

[16] As seen in Table 1.1, the subset of 826 individuals used in CH was not perfectly replicated. A subset of 880 individuals was created after I obtained the publicly available data sources and processed the data to match what is described in CH.

[17] The HIPS is implemented to provide information on employer-based health insurance plans that were offered and not chosen by employees.

[18] The two surveys have been archived as a combined 40 public use tapes.

the sample, linkages are used to identify the characteristics of that plan. I isolated the subsample of unmarried individuals with single coverage plans that is used to represent single individuals. Observations that contained missing data on premium, coinsurance rate, or deductibles for any of the plans offered were omitted from the analysis sample.[19]

The model does not require that each individual is offered the same choice set; the heterogeneity of the menus offered to different individuals is exploited to create variation across similar individuals at different firms. For the purpose of estimation, the choice set of each individual is constrained—circumventing the problem of each employee having varying choice sets. The number of employer-offered health insurance plans in the sample is reduced to at most four options. Each individual's choice is limited to two Health Maintenance Organization (HMO) plans and two Fee-for-Service (FFS) plans. Non-chosen alternatives were randomly selected for each individual from his or her reported employer-offered plans. Therefore, the choice set contains: 1) the individual's chosen health insurance plan, 2) at most two HMO plans, 3) at most two FFS plans, 4) and the option of remaining uninsured. Few individuals are affected by this aggregation.[20] Because the choice sets of individuals not offered health insurance and who remain uninsured are not observed, a plan chosen by those who purchased a private health insurance plan is randomly assigned as a plan offered—yet not chosen by these individuals. A maintained assumption of the model is that employment choice is unrelated to health status; it is critical to the exclusion assumption that workers do not self-select into firms based off observables or unobservables.[21]

Table 1.1 presents a comparison of the demographics and health insurance plan characteristics reproduced alongside the original table from CH. Table 1.1 is further broken down by those who are insured and uninsured. While some discrepancies exist between the sample reproduced and what was reported by CH, the reproduced sample overall is similar in all the main features of the original sample. It is not believed that the differences between the two samples lead to biased

[19]The motivation for the restriction to single individuals is that families face extremely complex choice sets. Such a complex choice set would make estimation extremely difficult. If one wished to study household behavior, coverage offered to an employee's spouse and dependents must be considered under each of the different plans offered. It should be noted, however, that restricting the sample reduces this paper's external validity.

[20]Plan choice is not common under employer-based insurance. 48 percent of workers are offered a single plan type; while 35 percent have a choice among only two plans (McGuire, 2012).

[21]CH perform reduced-form probit regressions of the probability that an individual's employer offers insurance. After controlling for income, job characteristics, and self-reported health status, there appears to be little evidence of self-selection into jobs based on insurance offerings.

results of this replication. The two largest discrepancies between the CH's reported tables and those reproduced are in reported premiums and coinsurance rates offered to individuals in the sample.

Information on premiums offered to employees was obtained from a constructed variable of annual premium amounts for single plan holders from the HIPS.[22] Coinsurance rates for a single health insurance plan differ depending on the procedure performed. For each plan, the HIPS reports coinsurance rates for thirty-three procedures such as physician inpatient visits, outpatient surgery, and diagnostic x-ray/labs. In order to report a single coinsurance rate per plan, I aggregated and weighed the coinsurance rates of each of the thirty-three procedures. An equally weighted average of all procedures was used to create a single coinsurance rate for each health insurance plan.[23]

Table 1.2 presents descriptive statistics of the reproduced sample—along with CH's original tables—separated by insurance status conditional on being offered health insurance. It can be immediately noted from both original and replicated tables that individuals not being offered employer-sponsored health insurance work at smaller firms and tend to have lower annual income. Employer-based health insurance is less expensive than individual insurance offered in the market ($139 versus $758). As a result, over 90 percent of those offered health insurance by their employer purchase insurance, and over 90 percent of those not offered remain uninsured. Replication is consistent with CH—83 percent insured when offered health insurance by their employer and 88 percent uninsured when not offered. The degree to which employer-based health insurance is less expensive than private health insurance was found to be less severe ($578 versus $672).

Both CH's and the reproduced descriptive statistics are suggestive of possible adverse selection in the health insurance market; insured individuals spend roughly double on health care expenditures than uninsured individuals. Individuals with private information about their risk may have selected health insurance plans with higher coverage when they perceived their risks as high. When their risks are perceived as low, individuals may have declined buying health insurance and used less health care.[24]

[22] I have concerns regarding the degree of cost sharing that is observed between employer and employee when paying this premium to insurers; it is possible the variable used in replicating the data set does not capture this cost sharing—leading to higher offered premiums relative to what is reported in CH.

[23] The methodology for this aggregation is not detailed in CH, and differing weights is the most probable explanation for coinsurance discrepancies.

[24] This difference, however, may also be contributed to observable demographic differences or the cost differences

1.6 Results

In Table 1.3 Columns 1-4, I present the published point estimates from CH; point estimates that are statistically significant at the 5 percent significance level are presented in bold. The preferred specification of CH is reported in Column 2, which includes individual demographics. By including individual demographics, the standard error of the simulated private risk signal, σ_ω, substantially drops relative to Column 1; σ_ω is estimated to have a mean of 0.12 and is no longer statistically significant at conventional significance levels. This result indicates that risk type can be categorized by observable demographics—implying consumers have essentially the same risk information as insurance companies, and thus adverse selection is not present.[25] I was graciously provided the code used in CH. This allowed me to replicate the point estimates almost identically.[26] Replication results are presented in Table 1.3 Columns 3-4.

In the course of replicating the results presented in CH, I discovered three peculiarities that when accounted for greatly reduce the evidence supporting the claim that informational asymmetries are not present in the market studied. In the following subsections, I describe each in greater detail. I then propose a re-specification of the model and present the results.

1.6.1 Comments

Failure to Normalize Residual Income

A lack of normalization of residual income is highlighted by the simple exercise of running the estimation algorithm with CH's published estimates of Table 1.3 Columns 1-2 as initial values. By construction, h_i is orders of magnitude smaller than m_i. The logit probabilities of P_{ij} demonstrate a case of perfect prediction. Plan choice simplifies into a binary probability of zero or one that is not sensitive to fluctuations of σ_ω that determine h_i. Thus, identifying variation only comes from x^e_{ij}, and no contribution is made from moment conditions derived from P_{ij}. The vector of

of health care for those insured relative to those uninsured.

[25]See CH pg. 421-422 for a more detailed discussion on how adverse selection is captured by σ_ω and on how σ_ω is distinguished from σ_ϵ.

[26]Standard errors were not replicated for computational reasons.

prediction errors is reduced to:

$$u_i(\theta, D_i) = \begin{pmatrix} x^e_{i0}(\theta, D_i) - I_{i0}x_{i0} \\ \vdots \\ x^e_{iJ}(\theta, D_i) - I_{iJ}x_{iJ} \end{pmatrix}$$

h_i is Permitted to Take Both Positive and Negative Values

CH remark that the sign of the coefficient on the health good, β_2, in Table 1.3 Columns 1-2 seems peculiar. CH write, "The reason β_2 is negative is that the health state s_i, and thus h_i, are negative." While it is true that s_i is strictly negative—as it is drawn from a negative log-normal distribution—this is not true of h_i. Using the published estimates of Columns 1-2 to calculate the mean value of s_i, I obtain -0.34 and -0.06, respectively. Comparing this to the published mean predicted expenditure of $749, it seems highly probable that h_i takes positive values for many individuals.[27] Given the nature of the model, allowing the health good to take on positive values is illogical because it results in individuals being rewarded a higher utility for excess expenditure above and beyond their negative health shock.

Consideration of Corner Solutions

The estimation algorithm of optimal expenditure calls for consideration of two interior and two corner solutions to account for the piecewise linear budget set that is generated by deductibles. Contrary to the description in CH, inspection of their code indicates that instead of manually checking the corner solutions the authors simply bounded expenditure above zero and below the highest feasible amount one could spend given income and insurance characteristics. While this simplification is benign in itself—as it would rarely be optimal for an individual to spend all of his or her income on health care—complications in the maximization problem arise due to the potential convexity of the utility function during the parameter search. In the case of a convex utility function, it will always be optimal to select a corner solution to generate the highest level of

[27]Recall $h_i = x_i + s_i$.

utility—even when an interior solution exists. Therefore, it is critical to properly account for the possibility of corner solutions in the estimation algorithm.

1.6.2 Re-specification

I make three changes to CH's original model and estimation algorithm. First, I normalize both the health good and the composite good. Second, I restrict $x_i \leq |s_i|$.[28] Finally, utility is calculated at both the interior and corner solutions. The estimation results after re-specification are reported in Table 1.4 Columns 1-2.[29,30,31] Column 1 reports σ_ω to be 1.25 and statistically significant at the 1 percent significance level. Column 2 includes demographics and reports σ_ω to be 0.46 and no longer statistically significant. While the finding that σ_ω loses statistical significance remains consistent with that of CH, the relative magnitude of the point estimate of σ_ω is substantially greater. CH's published point estimates of σ_ω when estimated with demographics is one-fifteenth of the point estimates of the commonly observed error σ_ϵ in comparison to one-half without demographics. Under the re-specified model point estimates of σ_ω when estimated with demographics is one-half of the point estimates of σ_ϵ in comparison to one-half without demographics. Because σ_ϵ and σ_ω determine an individual's health state in an exponential manner—as well as being bounded strictly above zero—it is highly probable that ω_i plays a pivotal role in health insurance plan choice. Additionally, it is suspected that the standard errors are estimated imprecisely due to the

[28]The majority of individuals face no negative health shocks as there is a substantial mass of s_i at zero. Thus, these individuals are constrained to have low health expenditure, and therefore h_i hovers near zero. The individuals that do face large negative health shocks—captured by a large draw of s_i—attempt to compensate by increasing x_i in order to push h_i back to near zero.

[29]By normalizing residual income, plan choice is no longer perfectly separated in x_{ij}^e. Appendix Table A.1 Columns 1-2 present estimates of the model after normalization of residual income. In Column 1, σ_ω doubles in magnitude. Additionally, the two other variables that make up the distribution of an individual's health state—σ_ϵ and Constant—increase by magnitudes of 3.5 and 2, respectively. Because these variables enter the model in an exponential fashion, normalization of residual income alone has profound implications. Column 2 reports σ_ω to be 0.08 and to be statistically insignificant at the 1 percent significance level.

[30]The numerical integration performed in the estimation algorithm in CH is based on 20 generated values of σ_ω and 25 values of σ_ϵ. In supplemental work, I increase the number of simulations of σ_ω to 1000 and σ_ϵ to 100. Results are presented in Appendix Table A.1 Columns 3-4. Increasing the number of simulations greatly reduces the standard errors of select variables yet had a minimal effect on the point estimates.

[31]CH's preferred specification reported in Table 1.3 Columns 1-2 has a corresponding J test of the overidentifying restrictions test statistic that is greater than the 5 percent critical value of 25.0. This suggests that the instruments are not jointly exogenous; there are 30 moment conditions arising from 6 instruments and 15 parameters that yield 15 overidentifying restrictions. Appendix Table A.1 Columns 5-6 report estimates of the re-specified model with 3 instruments race, sex, and a constant—a reduced subset of the instruments used in CH. Estimates appear to be sensitive to instrument selection.

numerical gradient being poorly scaled. I propose further refinements to the model in the following subsection that improves the specification of the model.

1.6.3 Additional Refinements

The choice of a second-order Taylor series approximation for the utility function in CH is motivated by a desire to obtain a specification flexible enough to fit the data and simple enough to provide an analytic solution for the demand function. I argue, however, that this utility function is too general as it leads to the potential for non-monotonicity and convexity that could invalidate the utility maximization calculations performed in the estimation algorithm. Figure 1.1 plots utility of the two goods over their relevant ranges using CH's published point estimates of Table 1.3 Columns 1-2. For many values of h_i and m_i, utility is non-monotonic for the parameters estimated. Thus, I impose additional constraints to the maximization problem to guarantee the utility function is monotonic and concave in the two goods.[32] The second-stage maximization problem of Section 1.3 becomes:

$$
\begin{aligned}
U^*_{ij}(s_i) = \max_{x_i} & (\beta_1 m_i + \beta_2 h_i + \beta_3 m_i h_i + \beta_4 m_i^2 + \beta_5 h_i^2) \\
\text{subject to } & m_i + C_j(x_i) = y_i - p_j \\
& \beta_1 + \beta_3 h + 2\beta_4 m > 0 \\
& \beta_2 + \beta_3 m + 2\beta_5 h > 0 \\
& 2\beta_4, 2\beta_5 < 0
\end{aligned}
$$

Table 1.4 Columns 3-4 present estimation results after: 1) imposing additional constraints on the maximization problem, 2) normalizing both goods, and 3) restricting $x_i \leq |s_i|$. This is the preferred specification of this paper.[33] According to the main estimates—with and without demographics—the null hypothesis that σ_ω is zero can be rejected at the 1 percent significance level. As a result, I find evidence suggesting that unobservables do in fact link health insurance status and health

[32] Ongoing future work imposes a Cobb-Douglas utility function and re-solves the first order condition of the constrained maximization problem with respect to x_i.

[33] The estimation algorithm is ran with all 6 instruments, 200 simulated σ_ω, and 100 simulated σ_ϵ.

care consumption—suggestive of asymmetric information and adverse selection. The evidence presented in this paper raises questions regarding the validity of the model and the robustness of the conclusions obtained in CH.

1.6.4 Model Performance

To evaluate the fit of the model, I compare predicted and observed behavior in Table 1.5 and Table 1.6. In Table 1.6, I define the model's predicted insurance plan as the one with the highest probability of being chosen after 200 individual health shocks. The i,j cell gives the number of instances in which plan i was predicted and plan j chosen. Diagonal elements are correct predictions. Row totals are aggregate predictions. Column totals are aggregate observed choices. At the individual level, the model correctly predicts about 66.8 percent of the cases. Table 1.6 shows that the model under predicts mean health care expenditure by about 55.9 percent. Figures 1.2-1.3 show predicted and observed log expenditure. Figure 1.3 is a simulated sample using individual characteristics and model estimates. The spikes at zero show the frequency of zero expenditure. While the distributions are similar, the model under predicts expenditures of those who do not have zero consumption.

1.7 Conclusion

In this paper, I re-examine the question of whether or not asymmetric information exists in the employer-sponsored health insurance market. The evidence I present in this paper raises questions regarding the structural model used in CH as well as their published estimates. In particular, when I estimate the model using a re-specified health good and additional constraints, I obtain evidence suggesting that asymmetric information exists in the health insurance market studied. Therefore, this paper refutes the only structural model to my knowledge that indicates adverse selection is not present in health insurance markets. The findings presented in this paper reaffirm more recent structural studies' assertion that adverse selection is alive and well and that focus should not be placed on its presence—but rather its implications for market performance.

Even after re-specification, several assumptions are made to handle the problem of individual choice under uncertainty, and biases may arise from misspecification and simplifications. Critical modeling choices about the nature of both the utility function and individuals' private information can have non-trivial effects on the estimates. Moreover, the modeling assumptions are specific to the health insurance market—making it difficult to meaningfully compare estimates of asymmetric information across other insurance settings.

1.8 Figures

Figure 1.1
Utility of the two goods

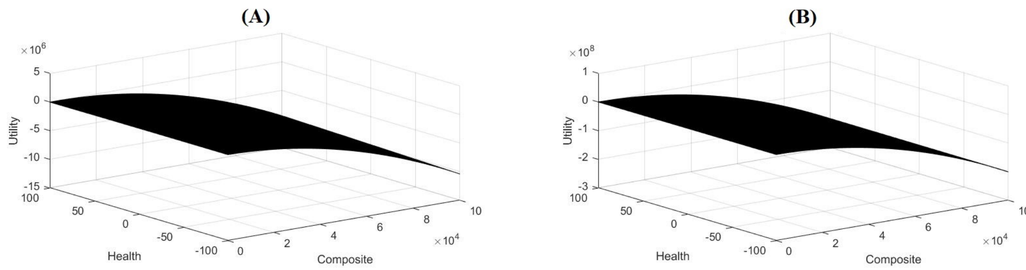


Figure 1.2
Observed expenditure

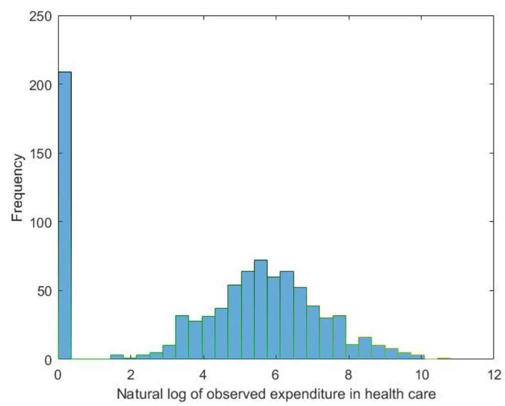
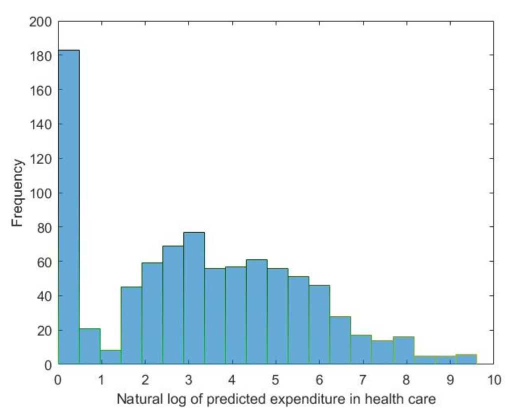


Figure 1.3
Predicted expenditure



1.9 Tables

Table 1.1
Descriptive statistics

	Cardon & Hendel			Replicated		
	All	Insured	Uninsured	All	Insured	Uninsured
Age	34.0	35.3	31.5	32.6	33.8	31.0
Female (%)	44.7	50.4	33.3	50.2	56.4	42.1
Annual income	18,280	22,059	10,632	15,660	20,110	9,907
Ann. health expenditure	901	1,019	660	838	1,064	547
Coinsurance rate (offered)	0.12	0.12	0.13	0.22	0.21	0.24
Premium (offered)	360	171	745	638	585	1,073
Deductible (offered)	140	124	173	100	98	123
Total employees	638	878	153	375	624	55
Northeast (%)	20.4	23.1	14.9	18.7	24.3	11.5
Midwest (%)	25.4	27.8	20.5	22.7	25.8	18.7
West (%)	21.8	20.9	21.5	19.6	15.3	25.1
South (%)	33.2	28.3	43.1	39.0	34.6	44.7
Hispanic (%)	7.4	4.9	12.4	8.4	4.2	13.8
Black (%)	12.0	9.3	17.7	11.4	7.9	15.9
Urban core (%)	32.3	33.4	30.0	24.7	26.4	22.6
Urban metropolitan area (%)	51.1	52.9	47.5	50.1	50.0	50.3
Nonurban (%)	16.7	13.8	22.5	25.1	23.6	27.2
Self-reported health state (%)						
Excellent	34.3	38.0	26.8	33.6	37.1	29.1
Good	54.0	52.2	57.6	54.7	53.4	56.4
Fair	10.9	8.8	15.0	11.3	9.1	14.1
Poor	0.8	0.9	0.6	0.4	0.3	0.4
Number of observations	826	516	310	880	470	410
Weight	100	67	33	100	56	44

Notes: Annual health expenditure includes the total cost of care no matter who paid for it and excludes insurance premiums. Coinsurance, Premium and Deductible are the mean of those offered to the individual. Health states are self-reported assessments that fall into the four categories.

Table 1.2
Means conditional on offered and insurance status

	Cardon & Hendel			
	Offered		Not offered	
	Insured	Uninsured	Insured	Uninsured
Annual expenditure	1,005	716	1,270	654
Age	35.2	29.5	35.9	31.7
Annual income	22,302	11,889	17,557	10,488
Annual premium	139	440	758	-
Employer size	924	1,093	11	45
N	492	33	24	277
Weight	66	3	3	30
	Replicated			
	Offered		Not offered	
	Insured	Uninsured	Insured	Uninsured
Annual expenditure	1,074	470	972	566
Age	33.8	28.8	34.3	31.6
Annual income	20,657	9,844	15,020	9,924
Annual premium	578	1,073	672	-
Employer size	687	148	30	31
N	428	88	42	322
Weight	51	9	5	35

Notes: Observations are separated according to if an individual was offered/not offered insurance by his or her employer. Employer size is the number of employees working for the employer. Observations are further separated by insured and uninsured.

Table 1.3
Replication

	Parameters	Cardon & Hendel Estimate	Estimate	Replicated Estimate	Estimate
		(1)	(2)	(3)	(4)
1	σ_ω(Private signal)	**0.52**	0.12	0.44	0.13
2	σ_ϵ(Error)	**0.99**	**1.75**	1.30	1.69
3	$\beta_1(m)$	1	-	1	-
4	$\beta_2(h)$	-0.94	-0.70	-0.87	-0.73
5	$\beta_3(mh)$	0.04	0.11	0.05	0.14
6	$\beta_4(m^2)$	-0.001	**-0.015**	-0.001	-0.01
7	$\beta_5(h^2)$	-7.27	-6.39	-2.19	-2.50
8	Age		-0.05		-0.05
9	Age^2		**0.001**		0.001
10	Female		0.67		0.73
11	Northwestern		-0.17		-0.18
12	Nonmetro		-0.57		-0.55
13	Black		**1.28**		1.51
14	Clerical		-0.23		-0.25
15	Constant	-1.07	**-2.37**	-0.98	-2.25
$J \sim \chi^2$		52.16	29.79	33.92	25.00

Notes: The first two rows present the estimated standard errors of the private risk signal and error term. The next five rows present the coefficients of the second-order Taylor series approximation of the utility function (with the linear term in M normalized to one). Rows 8 to 15 present the demographics in the function $K(D_i)$, i.e. the deterministic component of the health state. t-statistics are based on a covariance matrix of the estimators computed using numerical gradients.

Table 1.4
Re-specification

	Parameters	Re-specification				Preferred specification			
		Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
		(1)		(2)		(3)		(4)	
1	σ_ω(Private signal)	1.25	14.53	0.46	0.41	1.33	10.31	2.23	7.21
2	σ_ϵ(Error)	2.50	12.92	0.88	60.98	1.61	14.60	0.45	1.53
3	$\beta_1(m)$	1	-	1	-	1	-	1	-
4	$\beta_2(h)$	-1.56	-0.01	-0.27	-0.003	-0.98	-0.007	-0.99	-0.005
5	$\beta_3(mh)$	0.05	0.05	0.09	3.25	-2.82	-0.01	-4.09	-0.08
6	$\beta_4(m^2)$	-0.0002	-59.46	-0.04	-3.19	-1.00	-0.01	-0.80	-0.08
7	$\beta_5(h^2)$	-8.04	-0.02	-0.42	-0.06	-1.01	-0.01	-0.85	-0.06
8	Age			1.18	0.19			0.80	0.22
9	Age^2			1.21	0.57			0.56	0.19
10	Female			0.73	1.05			1.00	1.96
11	Northwestern			-1.07	-0.87			0.34	1.30
12	Nonmetro			0.28	0.12			1.06	3.49
13	Black			-0.02	-0.06			-0.11	-0.55
14	Clerical			-1.47	-0.39			0.79	0.56
15	Constant	3.20	6.33	0.55	0.10	4.56	13.16	1.29	1.12
$J \sim \chi^2$		33.92		24.99			33.92		24.99

Notes: The first two rows present the estimated standard errors of the private risk signal and error term. The next five rows present the coefficients of the second-order Taylor series approximation of the utility function (with the linear term in M normalized to one). Rows 8 to 15 present the demographics in the function $K(D_i)$, i.e. the deterministic component of the health state. t-statistics are based on a covariance matrix of the estimators computed using numerical gradients.

Table 1.5
Model fit: insurance choice

	Observed			
	Uninsured	FFS	HMO	Total
Predicted				
Uninsured	385	17	1	403
FFS	225	196	6	427
HMO	34	9	7	50
Total	664	222	14	880
Correct predictions:	66.8%			

Notes: Cells present the number of observations that fall into each specific predicted/observed pair. Observations in the diagonal are those with insurance status correctly predicted by the model.

Table 1.6
Model fit: expenditure

	Predicted	Actual
Mean expenditure	468.3	838.3
Insured	507.7	1,064.0
Uninsured	137.3	546.6

Notes: Comparisons of model predictions with sample values.

Chapter 2

Do Medicare's Facility Fees Incentivize Hospitals to Vertically Integrate with Physicians?

2.1 Introduction

Physicians practice in a variety of organizational settings such as independent practices and large integrated health systems. Under a vertically integrated arrangement like hospital-physician integration, physicians work as hospital employees rather than receiving admitting privileges from hospitals. Within the past decade, the U.S. health care market has undergone massive vertical integration. This increase in physician employment is driven by recent trends in which hospitals both acquire existing physician practices and employ new physicians[1]—leading economists to further inquire as to what exactly are the underlying causes and consequences of hospital-physician integration.

Economic theory is ambiguous regarding the effects of vertical integration, and there is no consensus as to why hospitals and physicians vertically integrate (Gaynor, 2006). Many prominent cited rationales for vertical integration are unique to the health care marketplace and diverge from traditional

[1] 49 percent of physicians hired out of residency or fellowship were placed in hospital-owned practices (Medical Group Management Association, 2010).

economic literature. Early research from the 1990s, for example, posited that hospital-physician integration aimed to improve bargaining positions as health maintenance organization/managed care penetration became more prevalent (Gaynor et al., 2015). Modern rationales, however, vary somewhat; whereas some recent scholars specify that physicians possess an increased desire to reduce administrative burden,[2] others comment on how physician work-life preferences have drastically changed.[3] In addition, economists have argued that financial incentives such as 340B programs,[4,5] insurer contracts, and facility fees have spurred consolidation. An often discussed explanation is that hospitals make a concerted effort to integrate with physicians to capture facility fee payments; this rent-seeking behavior has been a particular concern for Medicare.[6]

Irrespective of whether a physician is vertically integrated or unintegrated—that is, hospital-employed or independent with hospital admitting privileges—when a patient is provided a service in a facility that is part of a hospital, payors such as Medicare typically designate provider-based facility fees in addition to a standard service payment.[7] The only requirement for a facility fee payment is that the physician bills the service as hospital-based rather than as freestanding office-based. As expected, the vast majority of unintegrated physicians bills standard patient visits as freestanding office-based; a standard patient visit does not require a hospital's infrastructure, and there is little reason for an unintegrated physician to perform this type of service in a hospital-based setting. This, however, is not the case for integrated physicians. Integrated physicians often bill standard patient visits as hospital-based services through which they take advantage of the Medicare rules that allow them to bill as though they are working in a hospital, even for services provided in their offices—in turn, generating a facility fee. As a result, vertically integrated health systems may capture the increase in rents despite the fact that there is no physical change as to

[2]Compliance with the HITECH Act (2009) requires physicians to demonstrate meaningful use of electronic medical records. Researchers have noted that this has led to hospital-physician integration (Burns et al., 2014).

[3]Younger doctors tend to work fewer hours and to display decreased willingness to take call and work in the emergency room (Kirchhoff, 2013).

[4]As discussed in Alpert et al. (2017), one of the most commonly cited explanations for consolidation in the market for cancer care is that it is a response to a reduction in reimbursement for Part B drugs and subsequent expansions in hospitals' eligibility for pharmaceutical discounts under the 340B Drug Discount Program, as laid out in section 340B of the Public Health Service Act.

[5]See Desai and McWilliams (2018).

[6]See Dranove and Ody (2019), Koch et al. (2017), and Medicare Payment Advisory Commission (2012, 2013, 2014, 2015, 2016, 2017).

[7]These facility fees are provided in order to help offset costs for operating hospitals that freestanding offices do not encounter; hiring extensive support staff, meeting accreditation requirements, and maintaining a standby capacity of on-call physicians for handling emergencies are a few examples of these costs.

where the acquired physicians treat patients. Thus, facility fees' financial incentives may promote hospital-physician integration if hospitals attempt to capture these facility fees by acquiring physicians and converting their previous freestanding office-based services to hospital-based services. In their March 2016 report, the Medicare Payment Advisory Commission (MedPAC) demonstrated that a large portion of growth in outpatient volume can be attributed to the actions of hospitals first acquiring physicians then converting physician billing from previous freestanding office-based evaluation and management (E&M) services to hospital-based E&M services:

> Approximately one-quarter of the growth in outpatient volume in 2014 was due to an increase in the number of evaluation and management (E&M) visits billed as outpatient services. This growth in part reflects hospitals purchasing freestanding physician practices and converting the billing from the physician fee schedule to higher paying hospital outpatient department (HOPD) visits (Medicare Payment Advisory Commission, 2016).

Defined as new or existing patient office or other outpatient visits, E&M services have garnered much attention by federal agencies and policy makers—due to the fact that these services have been found to be comparable across sites of care and provide substantial facility fees. MedPAC estimated that in 2015 the Medicare program spent $1.6 billion more than it would have if prices for E&M services in a hospital-based setting were the same as freestanding office-based prices—an increase of about 42 percent off the base of physician new patient E&M services' payments (MedPAC, 2017).[8]

Court cases have demonstrated that hospitals are cognizant of the financial incentives of facility fees when proposing vertical integration with physicians. The Federal Trade Commission (FTC) recently challenged St. Luke's Hospital's acquisition of a physician group practice in Idaho. In the trial, the FTC presented an internal document obtained from the physicians, listing "fundamental reasons" why the physician practice should integrate with the hospital. The reasons listed included "control market share[s]," "one competition compared to two," and "facility fee[s] for Medicare"

[8]Payment for new patient evaluation and management services was calculated from the Medicare National Healthcare Common Procedure Coding System Aggregate Report, Calendar Year 2015. In 2015, the Medicare program spent approximately $3.8 billion on physician new patient E&M services.

(United States District Court for the District of Idaho, 2013). This paper seriously considers the above statements—illustrating that policy makers believe that the mechanism of hospital-physician integration is predicated on hospitals strategically targeting physicians in order to capture facility fees.

I empirically assess this mechanism with an econometric strategy that accounts for observed and unobserved differences between the hospital-physician pairs that integrated and the pairs that remained separate entities. By leveraging a 2014 policy change introduced by the Centers for Medicare & Medicaid Services (CMS), my paper analyzes whether or not facility fees incentivize hospitals to vertically integrate with physicians. The 2014 policy collapsed the previous facility fee rates for the five levels of physician E&M services into a single rate for each hospital-based E&M service.[9] While the goal of the 2014 policy was to eliminate incentives to up-code, empirically I find no change in physicians' billing behavior. What the policy did, however, is differentially affect the facility fees that a hospital can capture for these services by integrating with a physician. Specifically, certain physicians are more affected by this policy than others due to the heterogeneity in the acuity of E&M services billed by physicians. This heterogeneity creates variation that allows me to assess the role of facility fees in hospital-physician integration. When hospitals and physicians decide to participate in hospital-physician integration, they engage in a two-sided bargaining process amongst each other. A unique feature of the 2014 policy I implement is that it directly altered facility fee payments made to hospitals, yet it left the direct payments made to physicians for these services (physician professional fees) unaltered—thereby, not changing physicians' incentives to integrate. This allows direct study through which I inquire whether or not facility fees incentivize hospitals to vertically integrate with physicians. If the perceived wisdom is true—that is, if facility fees are in fact a driving force in hospital-physician integration—it is expected that physicians who experienced large reductions in potential facility fees should be less attractive to a hospital and thereby less likely to integrate. On the other hand, physicians who experienced gains in their potential facility fees should be more attractive to a hospital and thus, more likely to be targeted for hospital-physician integration.

[9] The policy this research leverages was announced on July 18, 2013, and it took effect 6 months later on January 1, 2014.

This research focuses specifically on clinical oncologists—a physician group that is highly exposed to and strongly affected by the consequences originating from the 2014 policy change. Their exposure to this policy originates along two dimensions; U.S. oncologists have faced some of the most dramatic increases in vertical integration within the past 15 years—from roughly 30 percent in the early 2000s to 57 percent in 2016—and they primarily serve the age 65 and over population who are near-universally covered by Medicare. Given the fact that E&M service payments account for 16 percent of all Medicare revenues of clinical oncologists in the period of study, and E&M services provide a disproportionately large amount of facility fees relative to other service types—22 percent of all facility fee payments—the 2014 policy has a significant effect on this physician group.[10] Furthermore, by restricting my study to clinical oncologists, I alleviate concerns relating to other confounding factors that typically exist in a setting where physicians receive the majority of their revenues from private health insurance payors.[11]

Importantly, I have 2012-2016 data on the ownership status of the practices of the universal set of U.S. oncologists. I identify clinical oncologists who are newly acquired by hospitals and match this information to data on 100 percent of final-action Medicare payments disaggregated to each physician and specific service. To identify the effects of facility fees on hospitals' incentives to integrate with physicians, I construct an index of the dollar change in potential facility fees that can be captured by a hospital integrating with a clinical oncologist—projecting the future fee schedule change occurring from the 2014 policy on prior year billings. This index accounts for the two sources of facility fee revenues an integrating clinical oncologist can generate for an acquiring hospital: 1) the facility fees that a clinical oncologist can generate if he or she converts all previous freestanding office-based E&M services to hospital-based E&M services and 2) the facility fees from previous hospital-based E&M services that a clinical oncologist may have billed at other hospitals. In effect, this index serves as an intensity of treatment measure that captures the incremental effect of a reduction or an increase in facility fees generated under the recent 2014 policy, and it can be

[10] Analysis of the Medicare Fee-For-Service Provider Utilization and Payment Data: Physician and Other Supplier Public Use File indicates that in 2013, E&M services accounted for upwards of 16 percent of the total Medicare payments to clinical oncologists.

[11] The Medicare program covers less than 15 percent of the U.S. population (Cooper et al., 2018). Thus, by focusing on clinical oncologists—a physician group in which a change in Medicare facilities fees will most likely have the largest effect out of all physician groups since they primarily serve those 65 and older—this research alleviates some of the potential bias concerns due to omitted factors that would be present in other physician groups.

used to study the role of facility fees in hospital-physician integration. Operationally, I estimate a linear probability model that specifies the probability of a clinical oncologist integrating with a hospital as a function of this constructed index as well as a vector of physician characteristics.

Contrary to the received wisdom, the evidence of my research does not support the view that facility fee capture is a primary motive for hospitals integrating with physicians. Instead, I find the change in potential facility fees is associated with statistically and economically insignificant changes in the probability of hospital-physician integration. While the simplest way to address the excess expenditures facility fees generate is to set payment rates equal wherever a service is provided, hospitals face a unique set of licensing and accreditation requirements that increase their cost structure. Hospitals incur costs to maintain standby capacity for handling emergencies and must comply with more stringent regulatory requirements than a free-standing office (MedPAC, 2012). If hospitals are not strategically targeting physicians in order to capture excess rents generated by Medicare's payment structure, then the current perception—that is, payment incentives have led to exacerbated hospital-physician integration—should be reconsidered. These findings make important contributions to two research literatures: 1) the rationale for vertical consolidation and 2) the effect of financial incentives introduced through policy on hospital-physician integration.

The next section provides an overview of related literature and describes the Medicare billing framework that can lead to the exploitation of facility fees. Section 2.3 details data and descriptive statistics. The empirical strategy for estimating hospital integration incentives is presented in Section 2.4. Section 2.5 analyzes the findings at the physician and hospital levels. Concluding remarks are made in Section 2.6.

2.2 Background and Related Literature

While a great deal of analysis concerning horizontal consolidation in the health care market exists—see Gaynor et al. (2015) and Dranove and Sfekas (2009) for excellent reviews—vertical relations, more specifically, hospital-physician integration, has been understudied. Rationales for hospital-physician integration can be traced to academic theories such as minimizing transaction costs, reducing the threat of opportunistic behavior by trading partners, securing stable distribution systems for finished products, pooling of complementary assets, ensuring access to needed inputs, blocking competitor access to the same inputs, and creating market power over buyers and suppliers. These different explanations are associated with contradictory implications for economic outcomes (Katz, 1989). The potential benefits from hospital-physician integration are accompanied with the challenges brought forth when hospitals and physicians together attempt to align their interests.

From a physician's perspective, vertical integration with a hospital limits his or her business risk through a guaranteed salary. Hospital employment, in particular, benefits young physicians seeking a more favorable work-life balance as well as older physicians planning for near-term retirement. Hospital-physician integration grants the physician convenient access to the hospital's capital and technologies; it also provides greater market power when negotiating rates with insurers and safety from the impacts of policy reform. These benefits, however, are counterbalanced by the loss of autonomy (Burns et al., 2014).

A hospital's rationale to employ physicians centers on capturing inpatient and outpatient market shares, maximizing hospital profits, increasing hospital leverage over pricing, and improving care outcomes. Furthermore, physician acquisitions can both generate increased admissions/consultations through referral networks[12] and help hospitals deal with shortages of on-call physicians. However, newly acquired physicians come with a set of difficulties such as coordinating their practices and their management. Additionally, some economists have suggested that physicians salaried by hospitals exhibit lower productivity because they lack income incentives due to their salary guarantees (Gans, 2012).

Other studies have examined the effects of hospital-physician integration without specifically focusing on the underlying reasons as to why hospitals and physicians vertically integrate or the specific mechanisms of its effects. In fact, there are no general results in economic theory that determine if vertical consolidation tends to increase efficiency or to enhance firms' market power. The specifics of the situation dictate which occurs, as discussed by Gaynor and Haas-Wilson (1998) within the

[12] In the absence of hospital-physician integration, a hospital may be concerned that physicians will affiliate with another hospital, develop their own risk contracting capacity through IPAs, or invest in physician-owned competitors such as ambulatory surgery centers or specialty hospitals. Each of these actions could divert patients and revenues, especially in competitive markets (MedPAC, 2008).

health care context. Additionally, as seen in the recent survey by Burns et al. (2014), the existing literature has done little to settle the debate on whether vertical integration of health services increases or decreases welfare.

Cuellar and Gertler (2006) and Ciliberto and Dranove (2006) were the first authors to provide empirical economic research in this area. These authors analyze if vertical integration is either efficiency-enhancing or anti-competitive. Cuellar and Gertler (2006), in particular, investigate the impact of hospital-physician integration on hospital efficiency, prices, quantities, and quality; they find hospital-physician integration increased market power in hospital markets. Ciliberto and Dranove (2006), however, find limited evidence that hospitals on average charge higher prices when they are integrated.[13]

Recent data coupled with a rapid growth in vertical integration have increased the number of studies that analyze the effects of hospital-physician integration.[14] Capps et al. (2017) find that because of vertical integration, physician prices were higher in 2013 than they would have been had hospital ownership of physician groups remained at its 2007 level. The authors estimate that approximately 1 quarter of the price increases is due to the increased exploitation of reimbursement rules that allow hospitals to charge "facility fees" for services by hospital-owned physicians.[15] Koch et al. (2017) assess the behaviors subsequent to hospital systems' acquisitions of twenty-seven large physician groups; the authors' analysis exploits claims-level data from the CMS. Notably, Koch et al. (2017) find that financial integration systematically produces economically large changes in the acquired physicians' behavior yet has less consistent effects at the acquiring system level.[16] Baker et al. (2014), on the other hand, measure hospital-physician integration by combining information on

[13]While the two studies arrive at seemingly contradictory results, they use data from substantially different markets. As pointed out by Gaynor (2006), because theory is ambiguous in regards to the effects of vertical integration, it is no surprise that these first wave studies arrived at differing results. It is entirely plausible that hospital-physician integration increased market power in hospital markets in Arizona, Florida, and Wisconsin from 1994 to 1998, but did not do so in California from 1994 to 2001.

[14]Data collected by SK&A, IMS Health, and the MarketScan Research Database represent a large improvement over past measures of physician markets; recent studies have implemented these data (Neprash et al., 2017, Baker et al., 2014, Koch et al., 2017, Dunn and Shapiro, 2016, Dunn et al., 2014, Capps et al., 2017, Baker et al., 2016, and Alpert et al., 2017).

[15]Capps et al. (2017) conclude that price increases are larger when the acquiring hospital has a larger share of its inpatient market.

[16]Overall, the results indicate that vertical mergers have effects on both the intensive and extensive margin. On the intensive margin, vertical mergers induce affected physicians to shift their place and mode of practice in ways associated with significantly higher expenditures by CMS. On the extensive margin, the authors find that acquired physicians may cease to practice.

physician and hospital relationships from the American Hospital Association Annual Survey with patient-flow information from Medicare. The authors find that an increase in the market share of hospitals with the tightest vertically integrated physician relationships was directly associated with higher hospital prices and spending.[17]

Currently, there is no consistent answer as to what the consequences of hospital-physician integration are—let alone as to why hospitals and physicians vertically integrate. What remains clear, however, is MedPAC's current perception that payment incentives created by the Medicare payment structure have exacerbated integration and contributed to wasteful spending. MedPAC, an independent U.S. federal body of seventeen members charged with providing recommendations to Congress in order to improve Medicare, has for the past five years recommended adjusting Medicare payment for E&M office visits to equal the Medicare payment for freestanding physicians' offices and HOPDs (Medicare Payment Advisory Commission, 2012, 2013, 2014, 2015, 2016, 2017).[18] In their March 2017 report, MedPAC writes:

> While some integrated entities report strong cost or quality performance, in other cases, systems may financially integrate for the tangible financial benefits of market power and Medicare's facility fees rather than a cultural commitment to affordable integrated care (Medicare Payment Advisory Commission, 2017).

As seen in the quote above, it is the perceived wisdom of MedPAC that facility fees play a large role in hospital-physician integration. CMS currently reimburses outpatient (i.e., not requiring an overnight stay in a hospital) Medicare claims billed as hospital-based at a substantially higher rate than those billed as freestanding office-based.[19,20] Thus, the structure of provider reimbursement for

[17] Whereas the vertical integration of physicians and hospitals is a relatively understudied area in the economics literature, the health care management literature has been prolific in its study on physician and hospital relationships. Almost all of these studies, however, have been descriptive in nature, making any causal inference difficult to assess. Burns et al. (2014) provide the first comprehensive review of the scale and scope economies of physician practices since their prior review of physician organizations (Burns and Wholey, 2000). While the authors' analysis includes no original data, it synthesizes all known surveys of physician practice characteristics and group practice formation.

[18] About MedPAC. May be accessed at http://www.medpac.gov/-about-medpac- (accessed January 2, 2019).

[19] For example, in 2012 CMS paid a doctor $68.97 for a 15-minute visit to an established patient in the physician's office. The same visit in an HOPD would cost CMS $124.40, of which $75.13 went to the hospital in the form of facility fees and $49.27 to the physician.

[20] In 2015, Congress moved partially towards the Commission's recommendations by equalizing rates between new

publicly insured patients remains intimately connected with the debate concerning the integration of hospitals and physicians; this topic continues to garner attention despite little empirical evidence that hospitals target physicians in order to capture the excess rents produced by facility fees.

My primary goal, in contrast to prior literature, is to analyze whether or not facility fees are a major cause of vertical integration as well as to study the role that policy has on incentivizing integration. To my knowledge, the only prior study that empirically examines the relationship between Medicare's reimbursement structure and hospital-physician integration is Dranove and Ody (2019). In contrast to what is presented in this paper, Dranove and Ody (2019) direct their focus on a different perspective of hospital-physician integration; they argue that "payment differentials" incentivize physicians to engage in vertical integration with hospitals in order to negotiate over excess rents. Dranove and Ody (2019) exploit a plausibly exogenous 2010 policy that changed the methodology used to calculate these overhead practice expenses while leaving Medicare's facility fee rates unaltered. This 2010 policy, on average, led to lowered prices for procedures delivered by independent physicians in their offices relative to the prices for the same procedures performed in a hospital-based setting. The price shock from Dranove and Ody (2019) lowered physician prices, but left prices in facilities the same. Therefore, it is plausible that the effect of a decrease in the benefits from being an independent physician incentivizes physicians to integrate with a hospital and to convert all their freestanding office-based billing to hospital-based billing—creating higher relative revenues that could then be split between hospital employer and physician employee. This revenue sharing is possible only because when a hospital employs a physician, anti-kickback and Stark laws no longer apply; thus, it is plausible that physicians' salaries could include facility fee incentives. Using private insurance claims data and a measure of the intensity of the price change in a hospital-based setting that resulted from the 2010 policy, Dranove and Ody (2019) estimate that the change in Medicare's methodology explains 20 percent of the increase in physician employment.

To shed new light on this topic, my research takes a different approach to studying facility fees' role in hospital-physician integration. The 2014 policy that I leverage explicitly alters facility fee payments for E&M services while leaving direct payments to physicians unaltered. Rather than

off-campus HOPDs and physician offices. On-campus HOPDs as well as existing off-campus HOPDs, however, will continue to receive the higher HOPD facility fees under the Bipartisan Budget Act of 2015.

studying the effect of policy on a physician's opportunity cost and his or her desire to integrate with a hospital, my research focuses on whether or not hospitals attempt to capture facility fees by specifically acquiring physicians. This approach is realistic for the environment physicians face in two aspects: 1) in physician focus groups conducted by MedPAC in 2016, nearly all physicians reported that they had been approached by a hospital about affiliation within the last year, and 2) the assumed mechanism is not predicated on the assertion that once hospital-physician integration occurs, a hospital transfers some of the additional relative revenues it receives to the physician. This is appropriate considering nearly half of employed physicians only receive a straight salary from the hospitals employing them; Medscape's Employed Physicians Report (2014) demonstrated that the most common contractual arrangements of hospital-owned physicians are straight salaries lacking any productivity bonuses, making up 46 percent of those surveyed.

Additionally, my decision to study E&M services has a noteworthy benefit; E&M services have been identified by MedPAC as one of the service groups in which outpatient billing by hospital-owned physicians is increasingly prevalent. E&M services are not captured in the analysis performed by Dranove and Ody (2019) due to data limitations. As mentioned previously, E&M services are of significance because they characterize a sizable portion of clinical oncologists' Medicare revenues. Also, E&M services have few cost differences dependent on location because they primarily involve medical history, examination, and medical decision making[21]—each of which is defined similarly in both a hospital-based setting and a freestanding office-based setting. And yet, E&M services are subject to large Medicare reimbursement differentials dependent on location. This makes E&M services ideal for the study of hospital-physician integration because the reimbursement differentials should not reflect any differences in service costs.

My research is relevant to policy makers concerned with the functioning of existing health care markets as well as the validity of MedPAC's focus on equalizing payments. I build on a modeling strategy formerly used in a long literature that specifically investigates the determinants of hospital

[21]The descriptors for the levels of E&M services recognize three key components. These components are medical history, examination, and medical decision making. Medical history is defined as: 1) the reason for the patient encounter or chief complaint, 2) the history of present illness, 3) the review of systems based on the patient's perspective, and 4) past, family, and social history. The examination is an assessment of body areas or organ systems performed by the physician. The examination along with the medical history aid in determining the correct diagnosis and in devising a treatment plan. Medical decision making refers to the complexity of establishing a diagnosis and/or selecting a management option (Evaluation and Management Services Guide, 2017).

choice (Gaynor and Town, 2012).[22] In addition, I extend this standard choice model to distinctly address hospital-physician integration.

2.3 Data

2.3.1 Integrated Physicians

My analysis utilizes 2012-2016 SK&A data to identify the vertical integration of hospitals and clinical oncologists. SK&A is a private company that conducts commercial surveys of physicians and sells its extensive database primarily for marketing purposes. More specifically, SK&A's database contains information on the universal set of U.S. physicians' office-based practices as well as practices that are owned by or located in hospitals; via phone every six months, SK&A attempts to verify information for all physician practices. Moreover, SK&A provides practice-level variables such as National Provider Identifier (NPI), office address, patient volume, number of providers, site specialty, and ownership. The 2014 single payment policy this research leverages was announced on July 18, 2013, and it took effect 6 months later on January 1, 2014. Thus, by using the 2012-2016 SK&A data, I account for 3.5 calendar years after the change to Medicare's facility fees was announced—allowing sufficient time for the consequences of the 2014 single payment policy to affect hospital-physician integration decisions. The issue of timing regarding this data set is particularly important for interpreting a result of no effect. According to the Brief of the Appellants in the St. Luke's case previously cited,[23] negotiations for the acquisition started in 2009; the deal was completed in 2012. Theoretically speaking, there could have been negotiations between hospitals and oncologists once CMS signaled it was going to make these changes in the Federal Register. In preliminary work not presented in this research, I find that the results are not being contaminated by anticipatory effects.

Studies of the completeness of the SK&A data set have found it to provide reasonably accurate up-to-date address and ownership information of physicians. It also possesses substantive overlap

[22] Most papers investigate patient hospital choice; typically, these papers specify a patient's hospital of admission as a conditional logit function of hospital characteristics and interaction between hospital and patient characteristics.

[23] Dated June 12, 2014; see FTC's website.

with the American Medical Association Physician Masterfile and the National Plan and Provider Enumeration System (NPPES) file (Gresenz et al., 2013, DesRoches, 2015). The SK&A data have been increasingly implemented in studies that examine oncologists. Alpert et al. (2017) find that the level and trends in the number of oncologists by sub-specialty in the SK&A data are similar to those reported by the American Society of Clinical Oncology.

2.3.2 Utilization

To quantify the impact of vertical integration on clinical oncologists' utilization, I use the Medicare Fee-For-Service Provider Utilization and Payment Data Physician and Other Supplier Public Use File (PUF). PUF is a public data set prepared by CMS; it contains information on utilization, payment (allowed amount and Medicare payment), and submitted charges organized by NPI, Healthcare Common Procedure Coding System (HCPCS) code, and place of service. Additionally, for all PUF data years, provider demographics such as name, physician specialty, credentials, gender, complete address, and NPIs are derived from the NPPES. Each health care provider's demographic information is collected at the time of enrollment and updated periodically. Data in the PUF cover the calendar years from 2012 to 2016 and contain 100 percent of final-action Medicare payments (The Centers for Medicare and Medicaid Services, Office of Enterprise Data and Analytics, 2017).

CMS created two supplementary data sets that are provided with the PUF: 1) Medicare Physician and Other Supplier Aggregate Table by Physician and 2) Medicare Physician and Other Supplier Aggregate Table by State/National and HCPCS. The aggregated data are not restricted to the redacted data reported in the PUF but are instead aggregated based on all Medicare Part B non-institutional claims. I make use of the aggregated data by physician; the data include beneficiary demographics and health characteristics including age, sex, race, Medicare and Medicaid entitlement, chronic conditions, and risk scores.

2.3.3 Facility Fees and Hospital-Based Data

Data in the PUF only represent the physician's professional fee and do not include the facility fee payment. To account for this, I construct a data set of hospital facility fees. My data set is created from the Hospital Outpatient Prospective Payment System (OPPS) Addendum A and Addendum B that are provided by CMS. The quarterly updates of Addendum A and Addendum B reflect the OPPS price changes that are part of the quarterly OPPS recurring update notification transmittals (The Centers for Medicare and Medicaid Services, 2017). The OPPS pays a hospital a predetermined amount per service. CMS assigns each outpatient service to 1 of approximately 850 ambulatory payment classification (APC) groups. Each APC has a relative weight based on its median cost of service compared with the median cost of a mid-level clinic visit. Data are obtained from 2012 to 2016.

2.3.4 Constructing the Analysis Sample

I construct the final analysis sample in three steps. First, I link beneficiary demographics contained in the OPPS Addendum A and Addendum B to the PUF on NPI.[24] Second, I link the SK&A 2012-2016 data to the PUF on NPI.[25] Information on a physician's address and specialty are contained in both data sets. Because some inconsistencies exist between a physician's sub-specialty within the two data sets, I use the specialty information provided in the PUF when constructing the analysis sample. Finally, the SK&A data contain multiple observations for a physician only if the physician works in multiple settings over the course of 1 year. Thus, I construct a weight for these physicians based on the number of patients seen in each location. Utilization values are then assigned to physicians with multiple observations based on the value of the constructed weight.[26] The final analysis sample is then balanced—keeping only the physicians who appear in each year from 2012-

[24]Both these files are provided by CMS, and 100 percent of observations can be matched on NPI.

[25]On average, across the years in the sample, 18.8 percent of observations do not have matching NPIs between the SK&A and PUF data sets or a missing NPI in one of these two files. These observations are removed from the analysis sample.

[26]For my analysis of physician integration, 2.8 percent of observations corresponds to physicians who practice in multiple settings where one setting is integrated with a hospital and the other setting is not integrated. To account for this, I remove these observations from the analysis sample.

2016.[27] Considering that this study focuses on hospital acquisitions of clinical oncologists, the physicians that integrated with a hospital prior to 2014 are dropped from the sample. The final analysis sample contains approximately 3,850 unique observations for each year of study.

2.3.5 Descriptive Statistics

I define a clinical oncologist as any physician falling under the following specialties: Gynecological/Oncology, Hematology/Oncology, and Medical Oncology. Surgical Oncology and Radiation Oncology physicians are excluded from the analysis sample because they bill few E&M services and are unlikely the target of a hospital's effort to integrate with physicians to capture E&M facility fees. Table 2.1 provides descriptive statistics of clinical oncologists used in the analysis sample. The most numerous of these specialties is Hematology/Oncology. These physicians experienced the largest percentage change in integration status—increasing 25 percent from just 2012 to 2016 alone. Overall, clinical oncologists experienced a 23 percentage increase in hospital ownership during the sample period.

Table 2.2 presents clinical oncologists' demographics broken down by integration status. Integrated and unintegrated clinical oncologists appear to treat similar patients; key measures such as the average age of patients and the average HCC risk score of patients are comparable across the two groups. Concentration of hospitals and clinical oncologists in the market is modeled through the number of hospitals and other clinical oncologists in a physician's 3-digit ZIP code and 5-digit ZIP code. Appendix Figure B.1 presents the distribution of these concentration measures. The concentration of clinical oncologists varies drastically by geographic location; this is shown in Appendix Figure B.2. In the subsequent section, I discuss the identification strategy that I implement in an effort to determine the extent to which facility fees affect hospital ownership of clinical oncologists by exploiting a 2014 policy introduced by CMS.

[27] Hospitals in Maryland, in the District of Columbia, and in U.S. territories outside the 50 states, are not paid under the OPPS. As a result, any physician with an address in these locations are removed from the analysis sample. 2 percent of observations are removed.

2.4 Methods

2.4.1 Institutional Setting

Medicare fee-for-service outpatient services are subject to two payment rates—one rate for when a physician bills a service as freestanding office-based and another rate for when a physician bills a service as hospital-based. Regardless of integration status, an outpatient service billed as freestanding office-based generates a single payment; however, when a service is billed as hospital-based, including an HOPD, Medicare makes a payment to the hospital (facility fee) in addition to a payment to the physician (physician professional fee). Table 2.3 provides a visual representation of Medicare's payment structure by integration status and service location.

As displayed in Table 2.3, if a physician bills for a service provided to a patient as freestanding office-based, he or she will be reimbursed a physician's professional fee at the freestanding office-based physician rate.[28] On the other hand, if a physician bills for a service provided to a patient as hospital-based, he or she will be reimbursed a physician's professional fee at the hospital-based physician rate; the facility's owner will receive the associated facility fee for the service.

I limit my study to a single category of services, E&M, for clinical oncologists from 2012-2016. E&M services are comparable across freestanding office-based settings and hospital-based settings; due to this fact, these services are appropriate to specifically study whether or not hospitals strategically choose to integrate with physicians in order to capture Medicare's facility fees.[29] As displayed in Appendix Table B.1, E&M services account for 16 percent of all Medicare payments made to clinical oncologists in the period of study. Additionally, as displayed in Appendix Table B.2, E&M services account for a disproportionately large amount of facility fees relative to other service types—E&M services generate 22 percent of all facility fee payments. Thus, E&M services make up a sizable portion of clinical oncologists' revenues and an even larger portion of facility fees this physician

[28]Freestanding office-based and hospital-based physician payment rates can be found in the Medicare physician fee schedule.

[29]The OPPS packages many ancillary services and supplies with their associated services for payment purposes; the Physician Fee Schedule often pays separately for ancillary items and services. The level of packaging, however, is relatively low for E&M services—about 2.5 percent of the total cost (Medicare Payment Advisory Commission, 2011).

group generates. Figure 2.1 presents the distribution of E&M services billed by clinical oncologists by sub-specialty in 2013. All three sub-specialties bill a large number of yearly E&M services with a rightward skewed distribution.

For illustrative purposes, Table 2.4 presents the payments made by CMS for HCPCS code 99214—the most commonly billed E&M service for clinical oncologists that accounts for 47 percent of their E&M billings. Appendix Table B.3-B.6 show the full range of E&M codes. In 2013, CMS reimbursed $78.46 to a physician for a 25-minute established patient visit billed as freestanding office-based. The same service billed as hospital-based or in an HOPD is reimbursed $153.87 for this service—$56.91 paid to the physician and $96.96 paid to the hospital. Because a "facility" can be an "office" owned by a hospital, the implication is that hospital-physician integration can result in a total Medicare payment that is almost doubled for the exact same service in the exact same location.

Two institutional characteristics are important for my identification strategy. The first characteristic is that facility fees are only paid to a hospital if a physician bills for a service provided to a patient as hospital-based. Medicare billing locations, however, are determined by ownership status rather than by physical location. This allows hospital-employed physicians to bill as though they are working in a hospital-based setting—even for services provided in their offices. Therefore, the incentive exists for hospitals to acquire physicians and to convert E&M services previously billed as freestanding office-based to hospital-based—thus, capturing facility fee payments.

Empirical evidence demonstrates that clinical oncologists bill a drastically higher portion of their E&M services as hospital-based rather than as freestanding office-based once they vertically integrate. Figure 2.2 illustrates two distributions separated by integration status of E&M services billed as hospital-based by clinical oncologists. Approximately 60 percent of integrated clinical oncologists bill all of their E&M services as hospital-based. Of the remaining 40 percent of integrated clinical oncologists, 35 percent of them bill all of their E&M services as freestanding office-based; 5 percent of integrated clinical oncologists bill their E&M services as a mix of the two. In contrast, 90 percent of unintegrated clinical oncologists bill none of their E&M services as hospital-based. Rather, they bill all of their E&M services as freestanding office-based. As a result, when hospitals integrate with clinical oncologists, they can expect newly acquired clinical oncologists to shift a large percentage of previously billed freestanding office-based E&M services to hospital-based E&M services—even if, as previously mentioned, the location of the service is unchanged. At first glance it appears puzzling that 40 percent of integrated clinical oncologists do not bill all of their E&M services as hospital-based services since these services generate a higher payment; thus, these physicians are "leaving money on the table." Based on discussions with newly acquired physicians, my informed (but not well-documented) understanding is that newly acquired physicians are ignorant of the complex Medicare reimbursement rules that generate facility fees. Considering that facility fees are paid to a hospital and not to a physician—in many cases, the integrated physicians' physical office location remains unchanged—many physicians continue to bill services as they had previously done only until instructed otherwise by their employer hospital.

Due to data limitations, this research focuses on the acquisition of individual clinical oncologists by hospitals rather than physician practices by hospitals. Figure 2.3 shows the distribution of potential facility fees a hospital can capture when integrating with an unintegrated clinical oncologist—instructing him or her to bill all previously freestanding office-based E&M services as hospital-based E&M services. On average, a hospital can capture $104,132 in facility fee payments for E&M services by vertically integrating with a clinical oncologist. The highest billing clinical oncologist can generate as much as $974,830 in facility fees for a hospital.

There exists two sources of facility fee revenues an integrating clinical oncologist can generate for an acquiring hospital. In addition to the facility fees a hospital can generate by moving the billed place of physician service, the hospital can also capture the facility fees from previous hospital-based E&M services that a clinical oncologist may have billed at <u>other</u> hospitals. Figure 2.4 shows the distribution of potential facility fees a hospital can capture from unintegrated clinical oncologists—assuming that previous hospital-based E&M services were performed at a different hospital prior to integration. On average, a hospital can capture $5,511 per year in facility fee payments for E&M services by vertically integrating with a clinical oncologist. The highest billing clinical oncologist can generate as much as $265,764 per year in facility fees for a hospital.

A critical point that is frequently ignored in the assertion that facility fees are a driving factor in hospital-physician integration is that the Medicare provider payment rate is higher for services billed as freestanding office-based. This is because when a service is provided in a freestanding office-based setting, a physician is responsible for providing clinical staff, supplies, and equipment. Recall from Table 2.4 that for a 25-minute established outpatient office visit, Medicare pays a physician \$78.46 for the service when billed as freestanding office-based and \$56.91 for the service when billed as hospital-based. Thus, while the total payments made by CMS for a hospital-based 25-minute established outpatient office visit is \$75.41 greater than when it is freestanding office-based, the raw payments to physicians are reduced by \$21.55. Because anti-kickback and Stark laws do not apply to entities that employ physicians (Koch et al., 2017), physicians may still be willing to integrate if they can capture some of the gains in facility fees or are otherwise "compensated" for their loss.[30] This type of agreement would have to be explicit in a physician's contract; anecdotal evidence demonstrates this type of arrangement does not always occur. Therefore, the potential gains in facility fees to a hospital from hospital-physician integration are counterbalanced by the loss of payments to a physician. Figure 2.5 presents the distribution of Medicare payments that a clinical oncologist could lose when integrating with a hospital. In 2013, the mean losses to a clinical oncologist due to billing all his or her previously freestanding office-based E&M services as hospital-based E&M services were \$22,197 per year; the clinical oncologist with the highest potential losses could lose \$175,526 in Medicare payments.

The second institutional characteristic that is critical to my identification strategy is that clinical oncologists do not alter the ratio of the acuity of E&M services they perform once vertically integrating. This allows for the projection of a clinical oncologist's prior year billings to future year billings—even after hospital-physician integration occurs. I estimate separate pre-treatment and post-treatment event studies by including leads and lags for the integration of a clinical oncologist with a hospital. I do so to empirically verify parallel trends and to demonstrate that billing behavioral changes do not occur in my sample of clinical oncologists. The coefficients on these lags will reveal whether hospital-physician integration is associated with endogenous behavioral changes in a clinical oncologist's billing patterns. The estimation equations take the following form:

[30] When a physician integrates with a hospital, he or she often sells his or her practice and collects a onetime lump sum payment.

$$y_{ij} = \alpha_i + \lambda_j + \sum_{j=m}^{-2} \pi_j T_{ij} + \sum_{j=0}^{g} \phi_j K_{ij} + \epsilon_{ij}$$

where y_{it} is the outcome for clinical oncologist i in year j, α_i are physician dummies, and λ_j are year dummies. T_{ij} are interactions of the treatment indicator (which equals one if clinical oncologist i has integrated) with time dummies for all periods before time -1. Likewise, K_{ij} is the treatment indicator interacted with time dummies for all periods after time -1.

Figure 2.6 presents the results of these event studies in which I model the outcome variable to be the share of clinical oncologists' billings of HCPCS code 99214—the most commonly billed E&M service for clinical oncologists. While not reported, I individually estimate this model for all E&M HCPCS codes; the results are quantitively similar. To facilitate interpretation, I plot the estimated coefficients and their 95 percent confidence intervals. Individual point estimates give the overall effect of hospital-physician integration on the shares of E&M services clinical oncologists bill in a specific year after the 2014 policy's implementation date. All lag coefficients are statistically indistinguishable from zero—implying that clinical oncologists do not alter billing behaviors post-integration. Additional descriptive evidence is presented in Appendix Table B.6-B.7; it appears that after 3 years of implementing the 2014 single payment policy, the billing behavior of integrated clinical oncologists did not change.

2.4.2 Identification

The increase in overall Medicare reimbursements generated from facility fees, however, is a mechanical consequence of hospital-physician integration; facility fees are perfectly correlated with utilization measures of physicians. In order to systematically link facility fees to hospital-physician integration, exogenous variation in the amount of facility fees a physician generates is required. Therefore, to assess whether or not hospitals strategically choose to vertically integrate with clinical oncologists in order to capture Medicare's facility fees, I leverage a 2014 policy change introduced by CMS that exogenously altered the facility fee payment structure for E&M services while leaving payments to physicians for these services unchanged. Prior to 2014, 10 separate facility fee reimbursement rates existed. Each rate varied by the acuity of a physician's visit—5 reimbursement rates for new patients (patient clinic visit codes 99201-99205) and 5 reimbursement rates for established patients (patient clinic visit codes 99211-99215). On July 18, 2013, CMS proposed collapsing facility fees for all physician E&M services into a single rate for each outpatient hospital visit. The intended goal of introducing the G0463 code was to discourage up-coding as well as to reduce administrative burden. CMS states, "We believe that the spectrum of hospital resources provided during an outpatient hospital clinic visit is appropriately captured and reflected in the single level payment for clinic visits. We also believe that a single visit code is consistent with a prospective payment system, where payment is based on an average estimated relative cost for the service, although the cost of individual cases may be more or less costly than the average."[31] As previously demonstrated, the 2014 policy did not change billing behavior—thereby allowing me to exploit it to assess how heterogeneous alterations to facility fees affect the probability of the occurrence of hospital-physician integration.

This new payment policy (hereafter, 2014 single payment policy), which introduced billing code G0463, became effective 6 months later at the start of 2014. The payment rate for the new G0463 code was based on the mean reimbursement rate of new and established patient clinic visit codes from the 2012 OPPS claims data and was set at $92.53. Table 2.5 presents Medicare's 2012-2014 facility fee schedule for established patient E&M services—see Appendix Table B.8 for full tables.[32] Column 5 displays the percent change associated with the move to the single payment rate for G0463 in comparison to the established patient clinic visit codes used for the years prior. The associated facility fee for the most commonly billed E&M service by clinical oncologists, HCPCS code 99214, decreased from $96.96 in 2013 to $92.53 in 2014—a decrease of 4.57 percent. Whereas the previous lowest reimbursed E&M service, HCPCS code 99211, facility fee increased by 62.99 percent, the previously highest reimbursed E&M service, HCPCS code 99215, facility fee experienced a reduction

[31] https://www.aapc.com/blog/26475-cms-adopts-one-code-fits-all-for-hospital-clinic-visits/ (accessed January 2, 2019).

[32] As previously mentioned, a goal of introducing the G0463 code was to discourage up-coding as CMS feared the previous payment structure incentivized billing for a higher reimbursed service. For instance, in 2013, HCPCS code 99215, facility fee was $71.71 more than HCPCS code 99211. However, it is worth noting with much concern that the new payment structure provides incentives for hospitals to instruct physicians to shift patient visits of 25 minutes and 40 minutes to the equally lucrative 15-minute visit. Extensive preliminary work was performed to alleviate concern of any behavioral response to this policy. It should be mentioned that while the 2014 single payment policy equalizes reimbursements to a hospital, physicians still receive higher payments for services of higher acuity. This provides one explanation for the lack of change in physician billing behavior.

of 27.98 percent.

The implementation of the 2014 single payment policy had the unintended consequence of altering the potential gains in facility fees a hospital can capture when integrating with a clinical oncologist. Because there exists heterogeneity in the acuity of E&M services billed by clinical oncologists, certain clinical oncologists are more affected by this 2014 single payment policy than others. Correspondingly, the variation introduced by this policy creates a unique opportunity to identify whether or not hospitals strategically integrate with clinical oncologists who generate large amounts of facility fees. I construct an index of the dollar change to potential facility fees that a clinical oncologist can generate for an acquiring hospital. This is accomplished by using 2013 billing patterns and projecting the change in facility fees for E&M services that resulted from the 2014 single payment policy. Details are presented in subsection 2.4.4.

Figure 2.7 Panel A presents the distribution of my constructed index; it demonstrates how the 2014 single payment policy altered the potential facility fees a hospital can capture from each clinical oncologist in the sample. The 2014 single payment policy decreased the mean value of a clinical oncologist to a hospital by \$212 for the year; the most negatively affected clinical oncologist lost \$133,102 in value, and the most positively affected clinical oncologist gained \$174,008 in value.[33] Finally, the percentage change in potential facility fees caused by the 2014 single payment policy is presented as an alternative measure displayed in Figure 2.7 Panel B. The 2014 single payment policy reduced the potential facility fees a hospital can capture from hospital-physician integration for the majority of clinical oncologists. The most negatively affected clinical oncologist lost 63 percent of his or her potential facility fee value to a hospital.

2.4.3 "Bite" of the 2014 Single Payment Policy

While the mean effect of the policy is near zero, the wide variation around the mean is critical. This variation allows the constructed index to be interpreted as an intensity of treatment measure.

[33] In comparison, data from 2011 indicate median losses among hospital-owned groups were \$174,430 per full-time physician (Gans, 2012). Considering this policy, at the extremes, can double or negate the yearly losses of a new physician to a hospital, it is plausible to posit that these changes in potential facility fees may affect the probability of a hospital integrating with certain physicians.

Clinical oncologists near the mean can be viewed as having received low intensity of treatment, and clinical oncologists at the extreme tails of the distribution can be viewed as having received high intensity of treatment. Figure 2.8 Panel A presents the distribution of my constructed index for clinical oncologists in the 10th percentile of those affected by the 2014 single payment policy. Figure 2.8 Panel B displays the percentage change in facility fees a clinical oncologist—in the 10th percentile of those affected by the 2014 single payment policy—generates for his or her acquiring hospital. In contrast, Figure 2.9 Panel A presents the distribution of my constructed index for clinical oncologists in the 90th percentile of those affected by the 2014 single payment policy. Figure 2.9 Panel B displays the percentage change in facility fees a clinical oncologist—in the 90th percentile of those affected by the 2014 single payment policy—generates for his or her acquiring hospital.

My constructed index can then be used to study testable hypotheses of facility fees' role in hospital-physician integration—particularly, in the tails of the distribution for clinical oncologists most affected by the 2014 single payment policy. In my econometric specification, I include interaction terms that allow the model to flexibly capture discontinuous changes in incentives for hospitals to integrate with clinical oncologists (discussed in more detail below). If facility fees promote hospital-physician integration, it is expected that clinical oncologists with a large negative value of my constructed measure will be less attractive to a hospital and thereby less likely to integrate. On the contrary, clinical oncologists with large positive values of my constructed measure will be more attractive to a hospital and more likely the target of hospital-physician integration. Additionally, a natural counterfactual exists for clinical oncologists who received a low intensity of treatment; it is expected that if this policy is exogenous there will be no effect on their probability of integration with a hospital. I now turn to the econometric specification that allows me to make claims on whether or not the financial incentives of Medicare's facility fees have an effect on the probability of hospital-physician integration.

2.4.4 Econometric Specification

I employ a linear probability model to estimate the effect of a change in projected $t+1$ potential facility fees that resulted from the 2014 single payment policy on the probability of clinical oncologist i integrating with a hospital in period $t+k$. The estimating equation takes the following form:

$$\begin{aligned} y_{ist+k} =& \alpha + \mathbf{V}_{it}\beta + \mathbf{W}_{it}\Theta + \nu_1 Tail_{it}^{lower} + \nu_2 Tail_{it}^{upper} + (Tail_{it}^{lower} \cdot \mathbf{V}_{it})\Psi + (Tail_{it}^{upper} \cdot \mathbf{V}_{it})\Omega \\ &+ \mathbf{Z}_{it}\Lambda + \mathbf{X}_{it}\Pi + \sigma_s + \epsilon_{ist} \end{aligned} \tag{2.1}$$

where y is an indicator of the integration status of clinical oncologist i in state s at time $t+k$. Hospital and physician concentration measures are incorporated in vector $\mathbf{Z}$. $\mathbf{X}$ is a set of physician covariates aimed at controlling patient demographics, and σ are state fixed effects. $\mathbf{V}$, $\mathbf{W}$, $Tail^{upper}$, and $Tail^{lower}$ are detailed below. It is assumed that $E(\epsilon_{ist}|\mathbf{V}_{it}, \mathbf{W}_{it}, \mathbf{Z}_{it}, \mathbf{X}_{it}) = 0$.

The coefficient of interest in Eq. (2.1) is the effect of vector $\mathbf{V}$ on the probability of hospital-physician integration, where $\mathbf{V} = [Office, Hospital]'$ indexes the change in potential facility fees a hospital can capture by integrating with a clinical oncologist caused by the 2014 single payment policy. Specifically, $\mathbf{V}$ projects the induced change in fee schedule rates resulting from the 2014 single payment policy on 2013 year billings. Thus, the estimates capture the incremental effect of a reduction or an increase in potential facility fees generated under this policy. From this variation, inference can be drawn as to whether or not hospitals make a concerted effort to capture facility fees when integrating with clinical oncologists.

To test for heterogeneous effects and to control for other determinants of hospital-physician integration—that if omitted may bias my estimates—I interact $\mathbf{V}$ with indicator variables denoting whether or not a clinical oncologist was in the upper or lower tails of the distribution of those affected by the 2014 single payment policy. Depending on the regression specification, I vary the level of $Tail^{lower}$ and $Tail^{upper}$ to be an indicator of the 5th/10th and 95th/90th percentile of those affected respectively.

The first element of $\mathbf{V}$, (*Office*), represents the change in potential facility fees that can in principle be captured by a hospital integrating with clinical oncologist i—that is, if clinical oncologist i moves all of his or her office visits to a hospital:

$$Office_{it} = \sum_{j=99201}^{99215} EM(office\_based)_{ijt}(facility\_fee_{jt+1} - facility\_fee_{jt})$$

where $EM(office\_based)_{ijt}$ is the number of freestanding office-based E&M services j that clinical oncologist i billed in time t, and $(facility\_fee_{jt+1} - facility\_fee_{jt})$ measures the change in potential facility fee payments caused by the 2014 single payment policy. This index is an upper bound of potential facility fees that can be captured because it assumes all E&M services get switched from freestanding office-based to hospital-based post-integration.

The second element of $\mathbf{V}$, (*Hospital*), represents the change in potential facility fees that can be captured by a hospital integrating with clinical oncologist i—collecting facility fees from hospital-based E&M services that clinical oncologist i may have previously billed at other hospitals:

$$Hospital_{it} = \sum_{j=99201}^{99215} EM(hospital\_based)_{ijt}(facility\_fee_{jt+1} - facility\_fee_{jt})$$

where $EM(hospital\_based)_{ijt}$ represents the number of hospital-based E&M services j that clinical oncologist i billed in time t.

The vector $\mathbf{W}$ =[*Physician losses*, *Baseline facility fees*]$'$ includes other monetary variables that may critically contribute to the integration decision and yet are independent of the variation in facility fees brought about by the 2014 single payment policy.

As previously stated, physicians stand to lose large amounts of Medicare payments by converting all of their freestanding office-based E&M services to hospital-based E&M services. Thus, the first element of $\mathbf{W}$, (*Physician losses*), is a potential physician loss index. This is constructed as follows:[34]

[34] This is a constructed index of the upper bound of potential losses to a clinical oncologist when integrating with a

$$Physician\ losses_{it} = \sum_{j=99201}^{99215} EM(office\_based)_{ijt}(physician\_rate_{jt} - physician\_facility\_rate_{jt})$$

where $physician\_rate_{jt}$ represents the reimbursement rate for freestanding office-based E&M services j that clinical oncologist i billed in time t, and $physician\_facility\_rate_{jt}$ represents the reimbursement rate for hospital-based E&M services j that clinical oncologist i billed in time t.

The second element of vector $\mathbf{W}$, (*Baseline facility fees*), captures the baseline level of E&M facility fees a clinical oncologist generates. This is a measure of utilization as it is directly correlated with the number of E&M services billed in 2013; this is required to establish a relative base from which the incremental effect of the 2014 single payment policy on facility fees is measured:[35]

$$\begin{aligned} Baseline\ facility\ fees_{it} = \sum_{j=99201}^{99215} & EM(office\_based)_{ijt}(facility\_fee_{jt}) \\ & + EM(hospital\_based)_{jt}(facility\_fee_{jt}) \end{aligned}$$

Large values of *Baseline facility fees* are indicative of a clinical oncologist being more attractive to a hospital that seeks to capture facility fees, irrespective of the change brought forth by the 2014 single payment policy. Large values of *Physician losses* imply that integration would be costly to a clinical oncologist.

The policy underlying my paper's analysis is a consolidation of codes for different lengths of E&M services into one code—i.e., it used to be that a hospital was paid more for a 40-minute visit than for a 10-minute visit. After the policy change, that was no longer true. For physician payments, no consolidation of codes occurs; the policy change just affects facility fee payments. Therefore, the policy change is going to be correlated with the severity of the patients that a clinical oncologist is treating. The vectors $\mathbf{X}$ and $\mathbf{W}$ together act akin to physician fixed effects—controlling for these time invariant factors that may influence the attractiveness of hospital-physician integration.

hospital; subsequently, billing all of his or her freestanding office-based E&M services as hospital-based E&M services.

[35]This is a constructed index of the upper bound of potential facility fees an integrating clinical oncologist can generate for a hospital using his or her 2013 billing patterns.

The main caveat to the interpretation of my results is the concern that my constructed indexes are an imperfect proxy for the underlying mechanisms that occur when a hospital and physician integrate. Critical to my analysis is that the only variation being used to make inference on the role of facility fees in integration decisions is the 2014 single payment policy. Alternative model specifications are explored in Section 2.5.2, attempting to alleviate concerns that the results are biased.

2.5 Empirical Findings

2.5.1 Physician Integration

Initial estimates from Eq. (2.1) are presented in Table 2.6 Column 1; it should be noted that all monetary variables are reported in hundreds of thousands.[36] These estimates do not consider heterogeneous effects of the 2014 single payment policy (i.e., indicators of being in the upper or lower tails of the index distribution and associated interaction terms are omitted from Eq. (2.1)) and only identify integration 1 year after the 2014 single payment policy was implemented. Virtually all coefficients relating to facility fees are statistically insignificant at conventional levels. Considering the vast majority of clinical oncologists were only marginally affected by the 2014 single payment policy, it is not surprising that on average the 2014 single payment policy had no effect. For this reason, I next estimate specifications that capture the heterogeneous effects of the 2014 single payment policy. As previously discussed, by including an interaction of vector **V** with an indicator variable of whether or not the clinical oncologists are in the tail percentile of those affected by the policy, I incorporate heterogeneous effects of the 2014 single payment policy. These interaction terms account for the fact that the 2014 single payment policy drastically changed the incentives for hospitals to integrate with certain clinical oncologists, if not the average. If hospitals are strategically targeting clinical oncologists to generate facility fees, it is expected that the coefficient on $Tail^{upper} * \mathbf{V}$ should have a positive and significant effect on hospital-physician integration. For clinical oncologists in the lower tail, the expected effect should be negative and significant.

[36] Appendix Table B.10 provides a comprehensive description of all variables used in this analysis while Appendix Table B.11 provides all acronym definitions.

Additionally, the structure of the constructed intensity of treatment measure has the added benefit that those not in the tails of the distribution—and thus not highly exposed to the consequences of the 2014 single payment policy—should have estimated effects of zero. This fact provides a testable validity check of the measure. Table 2.6 Columns 2-3 provide regression results from the model specified by Eq. (2.1) with these interactions included.

Column 2 specifies the tails of the distribution of the affected clinical oncologists to be at the 5th and 95th percentile. The estimated coefficient for *Office* is statistically insignificant. According to the estimates, a clinical oncologist not in the tails of the distribution of those affected by the 2014 single payment policy would have to experience a change of $100,000 in *Office* facility fees in order to have a 1 percentage point change in the probability of hospital-physician integration. At the 95 percent confidence interval, the estimates indicate a change of $100,000 in *Office* facility fees increases the probability of vertical integration by 8 percentage points or decreases the probability of vertical integration by 10 percentage points. This effect is not only statistically insignificant but also economically insignificant as it requires the change in *Office* facility fees to be upwards of $100,000 in order to experience single digit percentage point changes in the probability of hospital-physician integration. Refer to Figure 2.7 to observe that the 2014 single payment policy decreased the mean value of a clinical oncologist to a hospital by $212 for the year; therefore, the likelihood that a clinical oncologist would ever experience hundreds of thousands of dollars in altered potential facility fee payments is highly unlikely.

Similarly, the estimated coefficient for *Hospital* is positive and statistically insignificant. According to the estimates, a clinical oncologist not in the tails of the distribution of those affected by the 2014 single payment policy would have to experience a change of $10,000 in *Hospital* facility fees in order to have a 3 percentage point change in the probability of hospital-physician integration. Analogous to how the coefficient for *Office* is economically insignificant, these estimates are as well. These estimated coefficients on *Office* and *Hospital* are in line with a priori reasoning that the 2014 single payment policy's effect is minimal for those only marginally treated. What is critical to my analysis, however, is what occurs for those most affected by the 2014 single payment policy—which is where I will now turn my attention.

The estimated coefficient for *Office*, *Hospital*, and their respective interactions with the indicators for being in the upper and lower tails of the distribution of those most treated by the 2014 single payment policy show magnitudes and significance levels that are not significant at conventional levels. The estimated coefficients corresponding to all four interaction variables possess the expected sign. It is important to note, however, that the estimates are statistically and economically insignificant in all cases and should be interpreted as a null effect. According to the estimate of the coefficient on $Tail^{lower}$ * *Office* and $Tail^{lower}$ * *Hospital*, a clinical oncologist in the lower 5th percentile of the 2014 single payment policy's effect receives an additional 3 percentage point reduction in the probability of hospital-physician integration for each reduction of $100,000 in potential facility fees he or she may generate by converting previous freestanding office-based E&M services to hospital-based E&M services and an additional 3 percentage point reduction in the probability of hospital-physician integration for each reduction of $10,000 in potential facility fees from hospital-based E&M services he or she may have performed at other hospitals. According to the estimate of the coefficient on $Tail^{upper}$ * *Office* and $Tail^{upper}$ * *Hospital* a clinical oncologist in the upper 5th percentile of the 2014 single payment policy's effect receives an additional 16 percentage point increase in the probability of hospital-physician integration for each increase of $100,000 in potential facility fees he or she may generate by converting previous freestanding office-based E&M services to hospital-based E&M services and an additional 0.2 percentage point increase in the probability of hospital-physician integration for each increase of $10,000 in potential facility fees from hospital-based E&M services he or she may have performed at other hospitals.

Column 3 specifies the tails to be the 10th and 90th percentile. In this specification, estimates of interest retain their magnitude and statistical and economic insignificance. The estimates of the interactions are statistically indistinguishable from zero. Overall, the evidence in my research makes it abundantly clear that hospitals do not prioritize the capture of facility fees when proposing vertical integration. This contradicts the current perception of scholars and policy makers alike who deem that facility fees' financial incentives in the Medicare payment structure have exacerbated integration.

Next, I demonstrate that many other monetary variables included in the regression analysis—

which may critically contribute to the integration decision yet are independent of the variation resulting from the 2014 single payment policy—have the anticipated sign and play the role one would expect in hospital-physician integration. According to Column 2, the coefficient on *Physician losses* has a positive sign and is highly statistically significant. $10,000 Medicare payment losses for a clinical oncologist are associated with a 11 percentage point reduction in the probability of hospital-physician integration. Refer to Figure 2.5 to observe that the mean losses to a clinical oncologist due to billing all his or her previously freestanding office-based E&M services as hospital-based E&M services were $16,092 per year. Both coefficients on hospital and physician market concentration indexes have the expected sign; both, however, are economically insignificant in all cases and should be interpreted as a null effect.

In Column 4-9, I check the robustness of my estimates to the inclusion of an additional 1 year or 2 years of integration. For these specifications, integration status is extended 2-3 years after the 2014 single payment policy was implemented. The estimated coefficients for *Office* remain positive, statistically insignificant, and similar in magnitude. The estimated coefficients for *Hospital* remain positive, statistically insignificant, and similar in magnitude; both remain economically insignificant. The estimated coefficient corresponding to $Tail^{upper}$ * *Office*—i.e., highly treated in the direction of the policy increasing potential facility fees—is the only one of the four interaction variables to gain statistical significance in Column 5 and Column 8. According to the estimate of the coefficient of Column 5 on $Tail^{upper}$ * *Office*, a clinical oncologist in the upper 5th percentile of the 2014 single payment policy's effect receives an additional 33 percentage point increase in the probability of hospital-physician integration—2 years after the 2014 single payment policy was implemented—for each increase of $100,000 in potential facility fees he or she may generate by converting previous freestanding office-based E&M services to hospital-based E&M services.

Lastly, I explore the robustness of the results by transforming all monetary variables with either a logistic or inverse hyperbolic sine transformation. The results using these alternative specifications, which I report in Appendix Table B.9 for brevity, are qualitatively identical to the estimates from my baseline regression. Overall, the results provide strong suggestive evidence that altering the payments for E&M services' facility fees does not have an effect on hospital-physician integration.

2.5.2 Robustness

I take a number of steps to reduce the possibility that the results of the previous subsection are being misinterpreted. A major concern of my paper is that the constructed indexes are not picking up the effects of altered facility fees on hospital-physician integration; rather, what is occurring is that clinical oncologists who experienced altered facility fees already had a predisposition to future integration. To ensure that the conclusions of my research are robust, I implement an alternative model that includes physician fixed effects; this controls for potential underlying unobservables of clinical oncologists. I do this through a first-difference estimator approach. For two-time periods, first-difference estimators and fixed effects are numerically equivalent. By implementing first-differences, however, I lose precision as well as all non-physician time invariant variables. With this caveat in mind, I estimate Eq. (2.1) after first-differencing the model. The results are reported in Table 2.7 Panel A. The coefficients on *Office* and *Hospital* retain their sign and magnitude as well as remain statistically and economically insignificant. Additionally, after transforming monetary variables with either a logistic or inverse hyperbolic sine transformation, I report the estimates of the model in Table 2.7 Panel B. Overall, I find the conclusions pertaining to hospital-physician integration to be robust to these alternate specifications.

As an additional check, I test the robustness of my baseline results to an alternative definition of vertical integration. In my research, the dependent variable in all previous analyses is based on hospital ownership data of physician practices obtained by SK&A. As previously mentioned, while the SK&A data set has been found to provide reasonably accurate up-to-date address and ownership information for physicians, it is limited considering the fact that it is a commercial survey intended for marketing purposes. I numerically construct integration status by defining clinical oncologists who bill 100 percent of their E&M services as hospital-based as vertically integrated. Using this alternative definition of vertical integration, I re-estimate Eq. (2.1). Table 2.8 presents the regression results. The findings are similar to all previous specifications. If facility fees are in fact a driving force in hospital-physician integration, then these estimates should have indicated that clinical oncologists who had experienced significant losses or gains to their potential facility fees were more or less attractive to hospitals—and yet, the results of my paper demonstrate this is not the case.

2.6 Conclusion

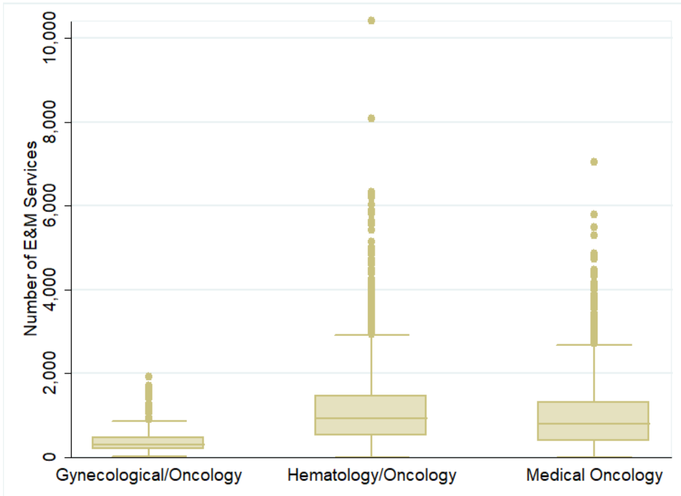
Recent economic literature and policy interest have focused on the integration of hospitals and physicians—asking what the consequences of vertical integration are on physicians, patients, and payors. Few papers, however, have addressed the underlying reasons as to why hospitals and physicians vertically integrate. The received wisdom put forth in the Medicare literature maintains systems are integrating for the tangible financial benefits of Medicare's facility fees. The exploitation of the facility fee payment structure is assumed to be an impetus in hospital-physician integration. However, the incentive to capture the mechanical increase in Medicare reimbursements generated from facility fees is just one possible explanation for the increase in hospital-physician integration.

My paper empirically examines whether hospitals make a concerted effort to integrate with physicians to capture facility fees. I leverage a 2014 policy change that collapsed facility fee rates for E&M services into a single rate for each hospital-based service—thereby, altering the amount of facility fees a hospital can capture when integrating with an unintegrated clinical oncologist. The evidence found in this paper demonstrates that facility fees do not lead to significant alteration in the probability of a hospital and a clinical oncologist vertically integrating. In other words, hospitals do not prioritize capturing facility fees' financial incentives when proposing vertical integration with physicians.

My results provide empirical evidence against the claims made by MedPAC that state facility fees are a likely contributor to the movement towards care that is billed in an outpatient setting. The results of this research are relevant to two recent MedPAC policies that intended to curb the increased movement towards care billed in an outpatient setting. The first policy focused on site-neutral reimbursement for procedures that could reasonably be performed in either setting. The second policy limited the ability of newly hospital-acquired physicians to bill as if they are part of a hospital outpatient facility.

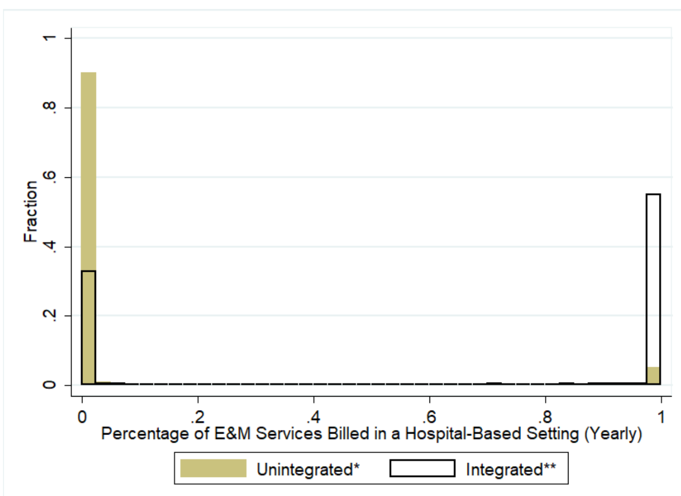
2.7 Figures

Figure 2.1
Distribution of E&M services billed by clinical oncologists



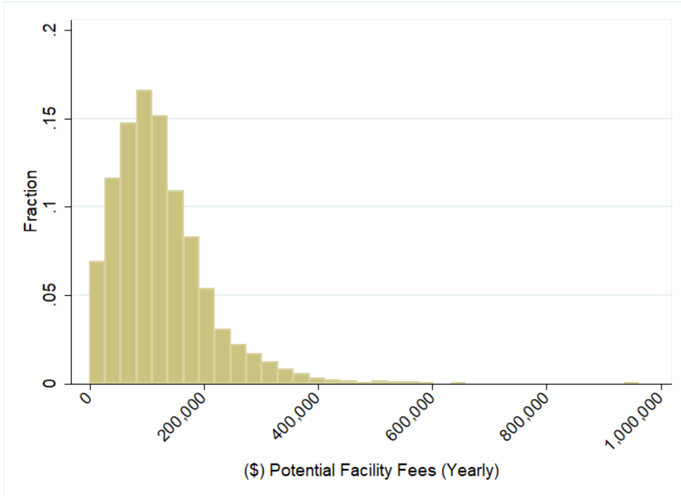
Notes: This figure presents box plots of the distribution of E&M services billed by clinical oncologist sub-specialty.
Source: PUF and SK&A, 2013

Figure 2.2
Location where clinical oncologists' E&M services were billed by integration status



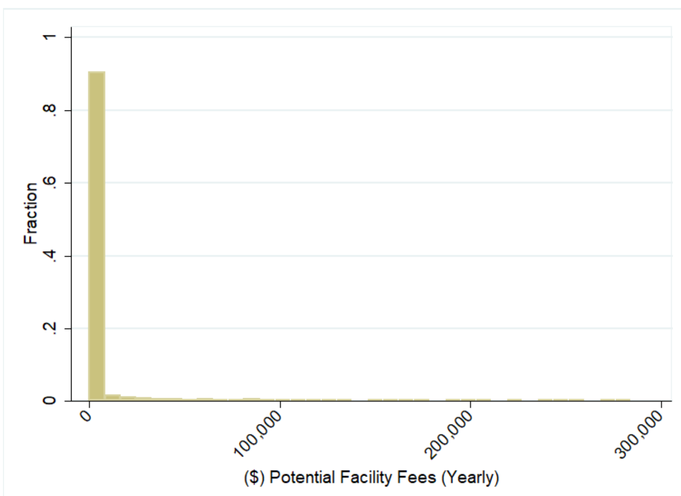
Notes: This figure presents histograms of the distribution of the location where clinical oncologists' E&M services were billed by integration status.
* Clinical oncologist works in a freestanding physician office
** Clinical oncologist works as an integrated employee of a hospital or a health system
Source: PUF and SK&A, 2013

Figure 2.3
Facility fees: freestanding office-based E&M services



Notes: This figure presents a histogram of the distribution of facility fees that a hospital can capture by integrating with a clinical oncologist and converting all his or her previous freestanding office-based E&M services to hospital-based E&M services.
Source: PUF and SK&A, 2013

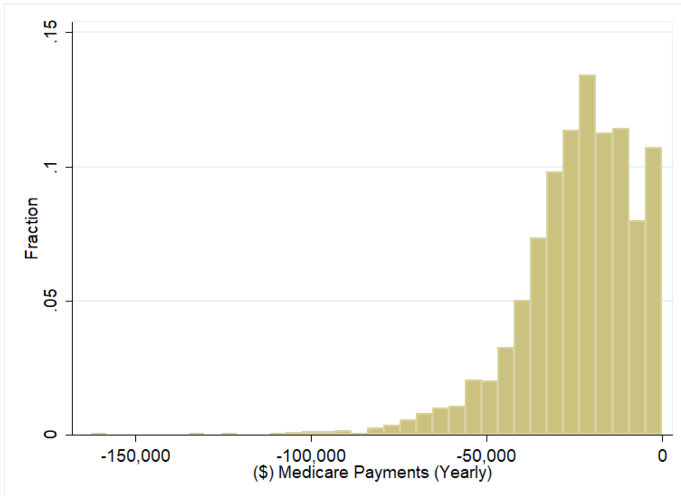
Figure 2.4
Facility fees: E&M services billed at other hospitals



Notes: This figure presents a histogram of the distribution of facility fees that a hospital can capture by integrating with a clinical oncologist and collecting previous hospital-based E&M services that he or she may have billed at other hospitals.
Source: PUF and SK&A, 2013

Figure 2.5

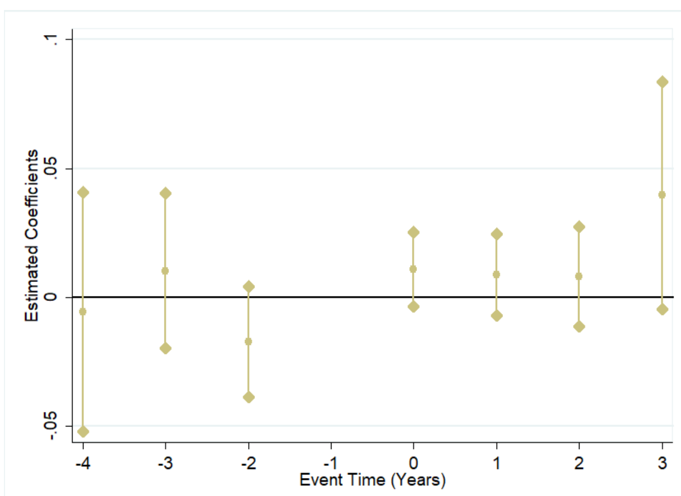
Medicare payments that a clinical oncologist could lose by vertically integrating



Notes: This figure presents a histogram of the distribution of Medicare payments that a clinical oncologist could lose by integrating with a hospital and billing all his or her freestanding office-based E&M services as hospital-based E&M services.
Source: PUF and SK&A, 2013

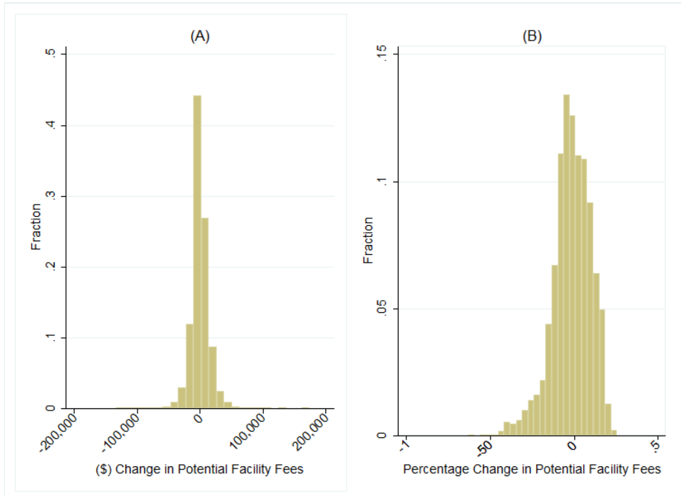
Figure 2.6

Post-integration effect on the shares of 25-minute established outpatient office visits



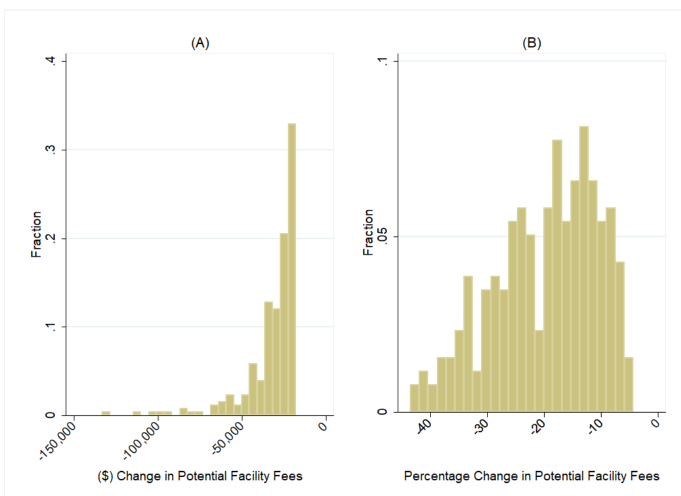
Notes: The point estimates show the effect of integration relative to the effect during the year prior to integration occurring. The 95 percent confidence intervals are illustrated by bars stemming from the point estimates. Robust standard errors are presented.
Source: PUF and SK&A

Figure 2.7
Effect of the 2014 single payment policy



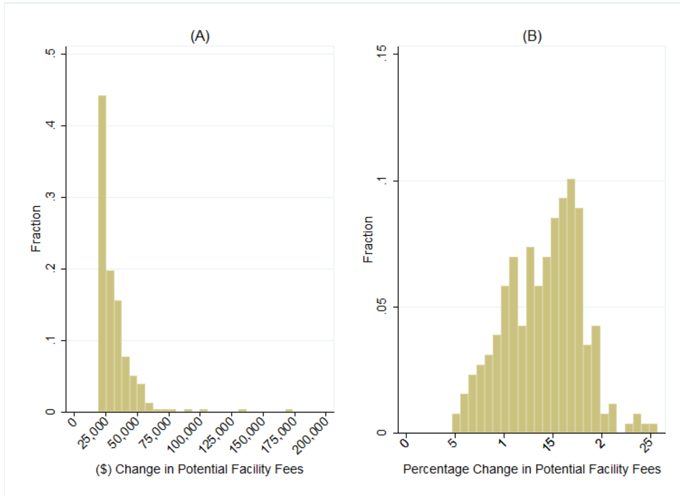
Notes: This figure presents histograms of the distribution of changes in facility fees that can be captured by a hospital integrating with a clinical oncologist, projecting the 2014 single payment policy fee schedule on 2013 year billings.
Source: PUF and SK&A

Figure 2.8
Effect of the 2014 single payment policy, $Tail^{lower}$



Notes: This figure presents histograms of the distribution of changes in facility fees that can be captured by a hospital integrating with a clinical oncologist—projecting the 2014 single payment policy fee schedule on 2013 year billings. This figure has been truncated to only display clinical oncologists in the 10th percentile of the distribution of those affected by the 2014 single payment policy.
Source: PUF and SK&A

Figure 2.9
Effect of the 2014 single payment policy, $Tail^{upper}$



Notes: This figure presents histograms of the distribution of changes in facility fees that can be captured by a hospital integrating with a clinical oncologist—projecting the 2014 single payment policy fee schedule on 2013 year billings. This figure has been truncated to only display clinical oncologists in the 90th percentile of the distribution of those affected by the 2014 single payment policy.
Source: PUF and SK&A

2.8 Tables

Table 2.1
Descriptive statistics

	Number of physicians in 2012	Share hospital or health system owned in: 2012	2013	2014	2015	2016	Percent change in hospital or health system owned from 2012 to 2016
Gynecological/Oncology	564	0.61	0.62	0.63	0.64	0.69	13%
Hematology/Oncology	6,106	0.46	0.50	0.54	0.56	0.55	25%
Medical Oncology	2,081	0.55	0.56	0.60	0.63	0.62	19%
Clinical Oncology	**8,751**	**0.49**	**0.52**	**0.56**	**0.59**	**0.57**	**23%**

Total number of practicing physicians in 2012: 925,328

Source: PUF and SK&A

Table 2.2
Demographic characteristics of clinical oncologists

	All	Unintegrated	Integrated
Observations	9,528	4,514	5,004
Average age of patients	72.2	73.1	71.3
Number of patients age less than 65	56.1	63.9	47.9
Number of patients age 65 to 74	159.9	202.0	121.5
Number of patients age 75 to 84	134.6	170.0	98.4
Number of patients age greater than 84	60.4	74.6	43.8
Number of female patients	234.2	301.2	172.1
Number of male patients	154.3	196.8	114.7
Number of Non-Hispanic White patients	338.3	423.5	251.2
Number of Black or African American patients	63.5	72.0	51.5
Number of Asian Pacific Islander patients	31.1	36.2	23.9
Number of Hispanic patients	48.8	59.1	32.1
Number of American Indian/Alaska Native patients	1.8	2.6	1.0
Number of patients with race not elsewhere classified	11.6	13.4	8.9
Number of patients with Medicare only entitlement	324.7	414.5	239.3
Number of patients with Medicare and Medicaid entitlement	76.2	94.3	58.9
Percent of patients identified with atrial fibrillation	10.8	11.7	9.7
Percent of patients identified with Alzheimer's disease or dementia	8.7	8.5	8.8
Percent of patients identified with asthma	13.5	14.0	13.1
Percent of patients identified with cancer	43.0	42.4	43.6
Percent of patients identified with heart failure	34.2	34.7	33.8
Percent of patients identified with chronic kidney disease	21.2	21.9	20.5
Percent of patients identified with chronic obstructive pulmonary disease	23.2	22.2	24.2
Percent of patients identified with depression	33.8	35.3	32.5
Percent of patients identified with diabetes	24.3	25.4	23.1
Percent of patients identified with hyperlipidemia	53.6	55.5	51.8
Percent of patients identified with hypertension	68.4	69.5	67.3
Percent of patients identified with ischemic heart disease	38.9	40.6	37.4
Percent of patients identified with osteoporosis	11.1	11.4	10.8
Percent of patients identified with rheumatoid arthritis/osteoarthritis	37.1	38.4	35.9
Percent of patients identified with schizophrenia/other psychotic disorder	4.9	4.7	5.1
Percent of patients identified with stroke	6.5	6.6	6.4
Average HCC risk score of patients	2.0	1.9	2.0

Source: Medicare Physician and Other Supplier NPI Aggregate, PUF, and SK&A, 2013

Table 2.3
Medicare payments: freestanding office-based vs. hospital-based

	Services billed as freestanding office-based	Services billed as hospital-based
Integrated or Unintegrated	Physician professional fee (freestanding office-based rate)	Physician professional fee (hospital-based rate) + facility fee

Notes: Under the MPFS, some procedures have a separate Medicare fee schedule for physicians' professional services when billed in a facility (hospital-based setting) or in a non-facility (freestanding office-based setting). Generally, Medicare provides additional payments to physicians and to other health care professionals for procedures performed in their freestanding offices because they are responsible for providing clinical staff, supplies, and equipment.

Table 2.4
Differences in Medicare payments for a 25-minute established outpatient office visit

		Service billed as hospital-based		
	Service billed as freestanding office-based*	Physician professional fee (hospital-based rate)*	OPPS rate (facility fee)**	Total, hospital-based setting rate
Medicare payment	78.46	56.91	96.96	153.87

Notes: PPS (prospective payment system). The Current Procedural Terminology code for this visit is 99214.
* Paid under the Medicare physician fee schedule
** Paid under the outpatient PPS
Source: PUF and OPPS, 2013

Table 2.5
Medicare's facility fee payments for established patient E&M services

HCPCS code	Description	Average annual facility fee payment 2012	2013	2014*	%Δ in payments between 2013-2014
99211	Established patient office or other outpatient visit, typically 5 minutes	53.82	56.77	92.53	62.99%
99212	Established patient office or other outpatient visit, typically 10 minutes	72.15	73.68	92.53	25.58%
99213	Established patient office or other outpatient visit, typically 15 minutes	72.15	73.68	92.53	25.58%
99214	Established patient office or other outpatient visit, typically 25 minutes	95.16	96.96	92.53	-4.57%
99215	Established patient office or other outpatient visit, typically 40 minutes	130.47	128.48	92.53	-27.98%

* Effective Jan. 1, 2014, facilities are required to report outpatient clinic visits using a new HCPCS level II code, G0463 (hospital outpatient clinic visit for assessment and management of a patient), rather than using E&M codes 99201-99205 (new patient) and 99211-99215 (established patient). The payment rate for G0463 is based on the mean reimbursement rate of new and established patient clinic visit codes (99201-99205/99211-99215) from the 2012 Outpatient Prospective Payment System (OPPS) claims data.
Source: OPPS

Table 2.6
Baseline

Dependent variable:	Integration indicator								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Facility fees									
Office	0.0215	-0.0113	0.0000	0.0090	0.0063	0.0267	0.0087	0.0497	0.0680
	(0.0218)	(0.0476)	(0.0761)	(0.0328)	(0.0707)	(0.1070)	(0.0366)	(0.0777)	(0.1190)
Hospital	0.2250	0.2910	0.0000	0.3610	0.5550	0.1820	0.4880	0.8450**	0.5320
	(0.2590)	(0.3960)	(0.5420)	(0.2690)	(0.4220)	(0.6170)	(0.2760)	(0.4200)	(0.6190)
Bargaining indexes									
Physician losses	1.0700***	1.0500***	0.0000***	1.2700***	1.2500***	1.0900***	1.2200***	1.2500***	1.1300***
	(0.1570)	(0.1780)	(0.1920)	(0.1710)	(0.1990)	(0.2120)	(0.1750)	(0.2020)	(0.2190)
Baseline facility fees	0.1830***	0.1740***	0.0000***	0.1990***	0.1860***	0.1530***	0.1880***	0.1850***	0.1600***
	(0.0344)	(0.0393)	(0.0423)	(0.0375)	(0.0440)	(0.0468)	(0.0000)	(0.0447)	(0.0481)
Concentration indexes									
Number of hospitals 3-ZIP	0.0019	0.0019	0.0018	0.0066***	0.0065***	0.0065***	0.0077***	0.0076***	0.0076***
	(0.0015)	(0.0015)	(0.0015)	(0.0018)	(0.0018)	(0.0018)	(0.0019)	(0.0019)	(0.0019)
Number of physicians 3-ZIP	-0.0015**	-0.0015***	-0.0015**	-0.0029***	-0.0029***	-0.0029***	-0.0036***	-0.0037***	-0.0036***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Indicators									
$Tail^{lower}$		-0.0051	-0.0105		-0.0212	-0.0367		-0.0334	-0.0466
		(0.0268)	(0.0172)		(0.0371)	(0.0229)		(0.0454)	(0.0271)
$Tail^{upper}$		-0.0250	-0.0423***		-0.1006***	-0.0546**		-0.0908***	-0.0411
		(0.0247)	(0.0161)		(0.0285)	(0.0240)		(0.0323)	(0.0264)
Interactions									
$Tail^{lower}$ * Office		-0.0326	0.0000		-0.1440	-0.1920		-0.2340	-0.2730
		(0.0756)	(0.0910)		(0.1100)	(0.1270)		(0.1400)	(0.1500)
$Tail^{lower}$ * Hospital		-0.3020	0.0000		-0.6690	-0.5740		-0.7840	-0.6120
		(0.6580)	(0.7070)		(0.7170)	(0.7880)		(0.7160)	(0.7950)
$Tail^{upper}$ * Office		0.1590	0.0000		0.3330***	0.1850		0.2620**	0.1100
		(0.0806)	(0.0971)		(0.1080)	(0.1370)		(0.1170)	(0.1490)
$Tail^{upper}$ * Hospital		0.0173	0.0000		0.0383	0.8870		-0.4000	0.3300
		(0.6240)	(0.7090)		(0.6350)	(0.7920)		(0.6370)	(0.7940)
Constant	1.14065***	1.12709***	1.14012***	1.40655***	1.37575***	1.42159***	1.54695***	1.50733***	1.54269***
	(1.1407)	(0.3295)	(0.6299)	(0.3461)	(0.3520)	(0.3684)	(0.3544)	(0.3556)	(0.3676)
Tail		5%	10%		5%	10%		5%	10%
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 2	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year 3	No	No	No	No	No	No	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,857	3,857	3,857	3,857	3,857	3,857	3,857	3,857	3,857
R-squared	0.1367	0.1374	0.1383	0.1707	0.1725	0.1726	0.1788	0.1807	0.1800

Notes: The dependent variable is a binary indicator taking the value of 1 if a clinical oncologist vertically integrated with a hospital over the course of the sample period or the value 0 if he or she did not. Observations are at the physician level. Robust standard errors are in parentheses.
* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Table 2.7
First-difference (FD)

	(A)				(B)		
Dependent variable:	Integration indicator			Dependent variable:	Integration indicator		
	(1)	(2)	(3)		(4)	(5)	(6)
Facility fees				**Facility fees**			
Office	0.0718**	0.1380**	0.3120***	IHS(Office)	0.0007	0.0010*	0.0014
	(0.0313)	(0.0579)	(0.0930)		(0.0005)	(0.0006)	(0.0006)
Hospital	0.2080	-0.1840	0.2390	IHS(Hospital)	0.0006	0.0001	0.0019
	(0.3560)	(0.5390)	(0.7260)		(0.0031)	(0.0034)	(0.0037)
Indicators				**Indicators**			
$Tail^{lower}$		-0.0139	-0.0200	$Tail^{lower}$		-0.2859	-0.2387
		(0.0339)	(0.0229)			(0.3299)	(0.1979)
$Tail^{upper}$		-0.0846***	-0.0783***	$Tail^{upper}$		0.0347	0.0456
		(0.0257)	(0.0190)			(0.1784)	(0.1475)
Interactions				**Interactions**			
$Tail^{lower}$ * Office		-0.2430**	-0.4030***	$Tail^{lower}$ * Office		-0.0272	-0.0234
		(0.0976)	(0.1160)			(0.0300)	(0.0186)
$Tail^{lower}$ * Hospital		-0.5120	-1.1600	$Tail^{lower}$ * Hospital		-0.0277	-0.0291*
		(0.8800)	(0.9240)			(0.0270)	(0.0161)
$Tail^{upper}$ * Office		0.2680***	0.0586	$Tail^{upper}$ * Office		-0.0052	-0.0069
		(0.0910)	(0.1160)			(0.0163)	(0.0139)
$Tail^{upper}$ * Hospital		1.3700*	0.9120	$Tail^{upper}$ * Hospital		0.0065	0.0009
		(0.7460)	(0.8720)			(0.0078)	(0.0061)
Tail		5%	10%	Tail		5%	10%
Bargaining measures	Yes	Yes	Yes	Bargaining measures	Yes	Yes	Yes
Concentration measures	Yes	Yes	Yes	Concentration measures	Yes	Yes	Yes
Patient characteristics	Yes	Yes	Yes	Patient characteristics	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Constant	Yes	Yes	Yes
Observations	2,565	2,565	2,565	Observations	2,565	2,565	2,565
R-squared	0.0593	0.0676	0.0703	R-squared	0.1407	0.1426	0.1449

Notes: The dependent variable is a binary indicator taking the value of 1 if a clinical oncologist vertically integrated with a hospital over the course of the sample period or the value 0 if he or she did not. Observations are at the physician level. Robust standard errors are in parentheses.
* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Table 2.8
Alternative measures of integration status

(A)		(B)	
Dependent variable:	Integration indicator	Dependent variable:	Integration indicator
Facility fees		**Facility fees**	
Office	0.0178**	IHS(Office)	0.0001
	(0.0077)		(0.0001)
Hospital	0.9400	IHS(Hospital)	0.0012
	(0.0000)		(0.0026)
Bargaining indexes	Yes	Bargaining indexes	Yes
Concentration indexes	Yes	Concentration indexes	Yes
Patient characteristics	Yes	Patient characteristics	Yes
State FE	Yes	State FE	Yes
Constant	Yes	Constant	Yes
Observations	4,113	Observations	4,113
R-squared	0.1040	R-squared	0.1040

Notes: The dependent variable is a binary indicator taking the value of 1 if a clinical oncologist vertically integrated with a hospital over the course of the sample period or the value 0 if he or she did not. Observations are at the physician level. Robust standard errors are in parentheses.
* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Chapter 3

The Impact of Hospital-Physician Integration on Referral Networks: Evidence from Oncologists

3.1 Introduction

Historically, the U.S. health care market has been dominated by physicians who practice in small "physician practice" groups. These groups operate with few formal contractual links to hospitals or to other physicians outside their practice.[1] In recent years, however, hospitals have both acquired existing physician practices and have begun employing new physicians at an increasing rate.[2] When a hospital directly employs a physician, this is known as "hospital-physician integration." This type of vertically integrated arrangement has led economists and health care scholars to recognize that the health care delivery system can be thought of not as a collection of standalone physician practices but as an organizational health system—that is, as a system of contractually interconnected entities (referring physicians, physicians receiving referrals, and hospitals).

Due to the specialized nature of health care, there is typically not one individual and often not

[1] According to a 2009 American Medical Association survey, 60 percent of physicians practice in groups with fewer than five physicians.

[2] 49 percent of physicians hired out of residency or fellowship were placed in hospital-owned practices (Medical Group Management Association, 2010).

one organization that can provide all necessary care to a given patient. Therefore, health care providers are linked together by the relationship of "shared patients"—referrals being one of the most common and important forms of shared patients.[3] The networks constructed from physicians who care for the same patients are referred to as "referral networks."[4] While the importance of referral networks to the health care delivery system remains prominent, knowledge as to how hospital-physician integration restricts patient pattern flows within these referral networks remains limited.

Early research on integrated health systems during the 1980s envisioned a type of organizational system in which physicians and hospitals were linked by membership in a formal, tightly structured hierarchy—thus, fully restricting referrals within the health system (Everson, 2017). In reality, most physicians are allowed to refer outside the health system if a patient requests it or if it is in his or her best interest. Typically, the only limiting factor is whether or not the patient's insurance will pay for his or her care. Thus, independent entities can act as a destination for referrals pertaining to the complex care that a health system may not provide. Anecdotal evidence, however, demonstrates health systems often attempt to dissuade physicians from referring patients to outside competitors—a practice commonly referred to as "patient leakage." Policies discouraging outside referrals are legal and extremely common. Health systems incentivize modest financial benefits to physician practices that maintain or increase the percentage of patients who remain within the health system. Extreme practices aimed at restricting referral networks have also been documented. A 2018 whistle-blower lawsuit filed against Steward Health Care alleged that the health system exerted undue pressure in an attempt to restrict referrals outside the organizational system.[5] As a result, the degree to which hospital-physician integration truly isolates physicians and hospitals within a health system from outside physicians and hospitals in the geographic area likely varies across system arrangement. This degree of isolation has the potential of profoundly restricting referral networks of both independent entities and integrated entities.

[3] Physicians decide to refer patients to other physicians for a multitude of reasons. The top three reasons for a primary care physician to refer a patient to a specialist are: 1) to seek advice on a diagnosis or a treatment (52.1 percent), 2) to request surgical management (37.8 percent), and 3) to ask a specialist to directly manage a patient (25.1 percent) (An et al., 2017).

[4] These networks have also been variously described as collaboration networks, informal physician networks, and patient-sharing networks (An et al., 2017).

[5] See http://www0.bostonglobe.com/metro/2018/05/24/doctor-lawsuit-says-steward-health-care-exerted-undue-pressure-restrict-referrals-outside-chain/xSLjUn27mhmF3NDltkeZgO/story.html

This paper contributes to the literature on how hospital-physician integration shapes referral networks.[6] A benefit of restricting referrals within a health system post hospital-physician integration is that physicians and hospitals are potentially better positioned to monitor and to adjust quality and costs of the entire episode of care through the use of streamlined electronic medical records and appointment scheduling; this may lead to improvement in care translations and to reductions in redundant care. Potential adverse effects of hospital-physician integration, however, include and are not limited to: 1) integrated physicians referring patients only to physicians in the same health system at the patients' expense, 2) an increase in referrals for medically unnecessary care aimed at increasing revenue for the health system, and 3) the referral foreclosure of physicians outside of a health system in which they experience a decrease in the referrals received from newly integrating physicians. This paper largely focuses on outcomes that can be measured at the physician or hospital level since individual patient data are not available. I begin this paper by empirically defining referral networks. I then investigate the implications of these referral networks on patient pattern flows between integrated and independent physicians—paying special attention to adverse anticompetitive effects and referral foreclosure.

There are two key challenges in empirically estimating hospital-physician integration's effect on referral patterns: 1) adequate data and 2) plausibly exogenous variation in the integration status of physicians. Regarding the first issue, comprehensive data on referral patterns have been difficult to obtain due to the highly confidential nature of the physician-patient relationship and the lack of a standardized reporting system. Moreover, physicians practice in a variety of settings—both geographic and organizational. The complicated nature of these organizational systems has made measuring the market structure for physician services particularly difficult. Furthermore, referral patterns may vary based on the demographics, market concentration, health risks, and expenditure history of the geographic population. With respect to the second challenge, physicians who decide to integrate with a hospital are likely to differ from those who choose to remain independent in unobservable ways—making it difficult to separately identify the effect of hospital-physician integration on referral patterns from other factors.

[6] I define a referral as the event that a patient encounters a first physician followed by a second within 30 days. Although this may not fully capture formal referrals from one physician to another, this is a standard definition in the literature.

I address these challenges as follows. First, this paper utilizes detailed longitudinal data that cover the complete U.S. shared patient patterns for oncologists' Medicare beneficiaries along with oncologists' integration status with hospitals in geographically-defined market boundaries to empirically define referral networks. This allows for an analysis as to how hospital-physician integration changes the referral patterns of those inside and outside of a health system. Oncologists serve as an ideal physician specialty for this paper for two reasons: 1) U.S. oncologists have faced some of the most dramatic increases in vertical integration within the past 15 years from roughly 30 percent in the early 2000s to 57 percent in 2016, and 2) they primarily serve the age 65 and over population who are near-universally covered by Medicare. This means I can capture a high observable share of oncologists' referrals in Medicare data alone; based on my calculations of the 2015 sample of office visits, on average, 94 percent of patients seen by oncologists were Medicare patients. Additionally, roughly 85 percent of oncologists in the sample exclusively saw Medicare patients. Furthermore, by restricting my study to oncologists, I alleviate concerns relating to other confounding factors that typically exist in a setting where physicians receive the majority of their revenues from private health insurance payors.[7] The data span the 6 years between 2009 and 2015 and represent approximately 2.8 million patient referrals in each year. I analyze the structure of oncologists' referral networks and consider how they vary by market concentration defined at the Hospital Referral Region level.[8] Care should be taken, however, when generalizing the results of this study to privately insured patients.

After defining referral networks and documenting trends in the level and growth of various characteristics of markets, I implement empirical strategies to compare changes in referral patterns of newly integrating oncologists to those oncologists who remain independent. Timing of hospital-physician integration is used for identification. My primary approach is to utilize: 1) a difference-in-differences strategy that uses non-integrating oncologists and differential timing of integration as controls to estimate the effect of hospital-physician integration on various referral outcomes and 2) an event study analysis that displays estimates by year relative to year of integration to assess the credibility that my estimates are causal. My analysis takes advantage of the unique structure of the

[7]The Medicare program covers less than 15 percent of the U.S. population (Cooper et al., 2018). Oncologists disproportionally serve the 65 and older.

[8]In robustness checks, key analyses are repeated at the Hospital Service Area and at the Metropolitan Statistical Area and are available upon request.

referral panel data to control for time-invariant differences between integrating and non-integrating physicians.

In order to understand the impact of hospital-physician integration on referral networks, it is necessary to examine several different patterns of patient referrals. I first estimate the impact of hospital-physician integration on the share of referrals made to current or future health system partners. I find that the average integrating oncologist increases his or her share of referrals made to health system partners by 36 percentage points off of a base of 9 percent following integration;[9] these effects are most pronounced in markets with highly concentrated levels of integrated oncologists employed by a single health system—which I measure by the sum of squared market shares of integrated oncologists affiliated with a single health system. Throughout the remainder of this paper, I refer to this as a market's "referral network Herffndahl-Hirschman Index (HHI)." The above finding is significant and robust using both the difference-in-differences and the event study methodologies. On average, this increase results from a higher referral volume per patient to health system partners post hospital-physician integration rather than from a decrease in the number of referrals made to oncologists outside the health system. These new referrals are on average made to oncologists of similar quality and of similar distance for the patient. These results are robust regardless of a market's referral network HHI.

Notably, however, across my sample roughly 25 percent of newly integrating oncologists made no referrals to oncologists inside a health system before integrating. Once vertically integrated with the health system, these oncologists shift the entirety of their referrals from oncologists outside of the health system to health system partners—thereby engaging in referral foreclosure. To understand this phenomenon, I implement a linear probability model that estimates the probability that an oncologist participates in referral foreclosure after hospital-physician integration. I find that hospital-physician integration increases the probability of referral foreclosure by 14 percentage points in markets with a referral network HHI below 1,500[10] and by 23 percentage points in markets

[9]This share, which I later define as *Referral share*, is calculated by dividing referrals made to current or future health system partners by the total referrals of an oncologist. An increase in *Referral share* occurs by either 1) a shift in referrals—that were previously made to oncologists outside of the health system prior to hospital-physician integration—to health system partners and/or 2) an increase in referral volume to health system partners relative to referrals made to oncologists outside of the health system

[10]This is derived from the Department of Justice's and Federal Trade Commission's definition of an unconcentrated market.

with a referral network HHI above 2,500.[11] This finding suggests that health systems have greater leverage to implement practices aimed at restricting patient leakage in markets with a high referral network HHI.

The referral patterns of newly integrating oncologists do not fully capture the impact of hospital-physician integration. Thus, I also estimate complementary models of the relationship between market level referral patterns of independent oncologists and a market's referral network HHI. I find evidence that independent oncologists experience an increase in the volume of referrals made to integrated oncologists as health systems increase their share of integrated physicians within a market; independent oncologists do not experience a change in the volume of referrals made to independent oncologists as a market's referral network HHI increases. The referrals independent oncologists made, however, are shifted to more distant oncologists and oncologists of lower quality. There are two potential mechanisms in which this realignment of referrals could occur. First, as the referral network HHI of a market increases—thereby the market power of a single health system increases—other health systems in the market may experience a loss in referrals they previously received from newly integrating oncologists. These competing health systems may increase incentives to independent oncologists in the market in order to make up for their loss in market power and thereby referrals—which may come at the patient's expense. Second, if the health systems with the greatest market power of integrated oncologists become capacity constrained—through increased within health system referrals—independent oncologists in the market may be forced to refer patients elsewhere (Walden, 2018).

The rest of the paper is organized as follows. The next section provides an overview of related literature. Section 3.3 describes the data in detail. I discuss study measures and present associations between hospital-physician integration and referral patterns in Section 3.4. Section 3.5 includes a discussion of my empirical strategy. The results are presented in Section 3.6. Section 3.7 concludes.

[11] This is derived from the Department of Justice's and Federal Trade Commission's definition of a highly concentrated market.

3.2 Background and Related Literature

Within the past decade, the U.S. health care market has undergone massive vertical integration. A growing literature has begun investigating the underlying reasons as to why hospitals and physicians vertically integrate. Early research from the 1990s posited that hospital-physician integration aimed to improve bargaining positions as health maintenance organization/managed care penetration became more prevalent (Gaynor et al., 2015). Modern rationales explaining the fundamental reasons for increased hospital-physician integration specify that: 1) physicians possess an increased desire to reduce administrative burden (Burns et al., 2014), 2) physician work-life preferences have drastically changed (Kirchho, 2013), and 3) financial incentives such as 340B programs (Alpert et al, 2017), insurer contracts, and facility fees (the Medicare Payment Advisory Commission, 2012-2017, Koch et al., 2017, Dranove and Ody, 2019, and Valdez, 2020) have spurred consolidation—and yet, a definite conclusion on why hospitals and physicians vertically integrate has not been reached.

Additionally, there are no general results in economic theory that determine if vertical consolidation tends to increase efficiency or to enhance firms' market power. The specifics of the situation dictate which occurs, as discussed by Gaynor and Haas-Wilson (1998) within the health care context. As seen in the recent survey by Burns et al. (2014), the existing literature has done little to settle the debate on whether vertical integration of health services increases or decreases welfare. Several papers consider the effect of hospital-physician integration on hospital efficiency, prices, quantities, and quality. The first authors to provide empirical economic research in this area find mixed results. Whereas Cuellar and Gertler (2006) find hospital-physician integration increased market power in hospital markets, Ciliberto and Dranove (2006) find limited evidence that hospitals on average charge higher prices when they are integrated.[12]

More recent work investigating the effects of hospital-physician integration has been robust in finding evidence of increased prices. Capps et al. (2017) find that because of vertical integration, physician prices were higher in 2013 than they would have been had hospital ownership of physician

[12]While the two studies arrive at seemingly contradictory results, they use data from substantially different markets. As pointed out by Gaynor (2006), because theory is ambiguous in regards to the effects of vertical integration, it is no surprise that these first wave studies arrived at differing results. It is entirely plausible that hospital-physician integration increased market power in hospital markets in Arizona, Florida, and Wisconsin from 1994 to 1998, but did not do so in California from 1994 to 2001.

groups remained at its 2007 level.[13] Koch et al. (2017) assess the behaviors subsequent to hospital systems' acquisitions of twenty-seven large physician groups; the authors' analysis exploits claims-level data from the Centers for Medicare & Medicaid Services. Notably, Koch et al. (2017) find that financial integration systematically produces economically large changes in the acquired physicians' behavior yet has less consistent effects at the acquiring system level.[14] Baker et al. (2014), on the other hand, measure hospital-physician integration by combining information on physician and hospital relationships from the American Hospital Association Annual Survey with patient-flow information from Medicare. The authors find that an increase in the market share of hospitals with the tightest vertically integrated physician relationships was directly associated with higher hospital prices and spending.

This study is the first to use panel data containing complete records of U.S. Medicare shared patient patterns for oncologists and to link this data to integration status with hospitals in geographically-defined market boundaries. This allows for not only the study of the effect of hospital-physician integration on an entire physician sub-specialty but also for the incorporation of heterogeneous market concentration effects. Prior studies have not been able to provide insight regarding hospital-physician integration's effect on referral patterns—such as whether integrated physicians alter their volume or their choice of physicians they refer to once integrated. In addition, they have not made claims about whether or not independent physicians experience changes in referral patterns when faced with a growing influx of newly integrating outside physicians. Huckman (2006), Nakamura et al. (2007), and Nakamura (2010) have examined the effects of hospital mergers on hospital admissions. Although related, hospital admissions fundamentally differ from the referral relationship of physicians. Studies explicitly examining the effect of hospital employment on referrals have only implemented either cross-sectional data (Baker et al., 2016) or a case study (Carlin et al., 2016). Walden (2018) studies the impact of mergers between primary care physician practices (PCPs) and hospitals on referral patterns—finding that the average acquired PCP increases referrals to specialists employed by the acquirer by 52 percent after acquisition; primary care services, however,

[13] Capps et al. (2017) conclude that price increases are larger when the acquiring hospital has a larger share of its inpatient market.

[14] Overall, the results indicate that vertical mergers have effects on both the intensive and extensive margin. On the intensive margin, vertical mergers induce affected physicians to shift their place and mode of practice in ways associated with significantly higher expenditures. On the extensive margin, the authors find that acquired physicians may cease to practice.

account for only 6 percent of total health care spending (McWilliams et al., 2014). In contrast, oncologists disproportionally serve patients age 65 and over who are near-universally covered by Medicare. The novelty of this work is seen in the scale of analysis and in the investigation of the implications of referral networks.

3.3 Data

3.3.1 Primary Data Sources

This paper combines data from commercial physician surveys that capture integration status with count data from the Centers for Medicare and Medicaid Services on patients encountered by one physician and then another physician within a 30-day time interval.

Integrated Oncologists and Market Definitions

Data on oncologists and their integration status are from SK&A—a private company that conducts commercial surveys of physicians and sells its extensive database primarily for marketing purposes. More specifically, SK&A's database contains information on the near-universal set of U.S. physicians' office-based practices as well as practices that are owned by or located in hospitals; via phone every six months, SK&A attempts to verify information for all physician practices.[15] Moreover, SK&A provides practice-level variables such as National Provider Identifier (NPI), office addresses, patient volume, number of offices a physician practices in, and physician specialty. Studies of the completeness of the SK&A data set have found it to provide reasonably accurate up-to-date address and ownership information of physicians. It also possesses substantive overlap with the American Medical Association Physician Masterfile and the National Plan and Provider Enumeration System file (Gresenz et al., 2013, DesRoches, 2015). The SK&A data have been increasingly implemented in studies that examine oncologists. Alpert et al. (2017) find that the level and trends in the

[15] Data collected by SK&A, IMS Health, and the MarketScan Research Database represent a large improvement over past measures of physician markets; recent studies have implemented these data (Neprash et al., 2017, Baker et al., 2014, Koch et al., 2017, Dunn and Shapiro, 2016, Dunn et al., 2014, Capps et al., 2017, Baker et al., 2016, and Alpert et al., 2017).

number of oncologists by sub-specialty in the SK&A data are similar to those reported by the American Society of Clinical Oncology.

I obtain 2009 to 2015 SK&A data on oncologists.[16] I categorize oncologists into three specialties based on physician specialty information found in the SK&A data: 1) clinical oncology, 2) surgical oncology, and 3) radiation oncology. The most numerous of these specialties is clinical oncology. Table 3.1 provides descriptive statistics of oncologists over the sample period. The table shows a dramatic increase in hospital and health system ownership of oncologists' practices during the study period. Roughly 30 percent of clinical oncologists' practices and 40 percent of radiation and surgical oncologists' practices were owned by a hospital or health system before 2009. By 2015 nearly 70 percent of these practices were vertically integrated. Appendix Tables C.1-C.3 present additional descriptive statistics of integrated oncologists found in the SK&A data.

Utilizing the five-digit ZIP code of a practice's office address found in the SK&A data, each oncologist in the sample is assigned to a geographic market. I define a market as a Hospital Referral Region (HRR). In supplementary analyses, I test the sensitivity of my results to alternative market definitions such as a Hospital Service Area (HSA) and a Metropolitan Statistical Area (MSA); results remain quantitatively and qualitatively similar. Results of the analysis at the HSA and MSA levels are available upon request.

The definition of an HRR is taken from the 1996 edition of the Dartmouth Atlas of Health Care.[17] HRRs are defined by the documentation of where patients were referred for major cardiovascular surgical procedures and for neurosurgical procedures as described in the Dartmouth Atlas of Health Care.[18] Each HRR had at least one city where both major cardiovascular surgical procedures and neurosurgical procedures were performed. HRRs were constructed by examining each HSA and aggregating the 1,608 HSAs into 306 HRRs.[19]

[16]The unbalanced panel across the time span of 6 years accounts for 116,550 unique oncologists' observations that practice in 151,994 office locations.

[17]The Dartmouth Atlas Project documents how medical resources are distributed and used in the United States. The project utilizes Medicare data to provide comprehensive information and analysis about national, regional, and local markets as well as individual hospitals and their affiliated physicians. See https://www.dartmouthatlas.org/about/

[18]The Medicare program maintains exhaustive records of hospitalizations—which makes it possible to define the patterns of hospital care utilization. When Medicare enrollees are admitted to hospitals, the program's records identify both the patients' places of residence and the hospitals where the admissions took place.

[19]HSAs are defined in the 1996 edition of the Dartmouth Atlas of Health Care as local health care markets for hospital care. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the

At the HRR level, on average 6 percent of markets in my data set fail to possess both integrated and independent oncologists and/or are markets in which all oncologists are integrated with the same health system—making the study of their referral networks inappropriate. For a market to experience anticompetitive effects or foreclosure it is required that: 1) The entire market cannot be fully integrated with the same health system to begin with, or 2) if there is a mix of integrated and independent oncologists it is required that the independent oncologists are not already sending all their referrals to integrated oncologists belonging to the health system they will join in the future.[20] However, of the 94 percent remaining markets—287 geographically-defined markets—that contain a blend of oncologists in different health systems, the data set demonstrates that there is significant variation across markets in the number of health systems, the number of oncologists, and referral network HHIs. Table 3.2 provides descriptive statistics of the HRRs in my sample by concentration, averaged across years. The number of health systems varies from 1 to as many as 28 for the 3 to 777 oncologists in these markets. Additionally, referral network HHIs vary wildly from 64 in some markets to as much as 9,798 in other markets.

Figure 3.1 presents a visual representation of key descriptive statistics at the HRR level for the most populous MSA in the U.S.—New York-Newark-Jersey City, NY. This figure illustrates that the number of health systems, number of oncologists, share of integrated oncologists, and referral network HHIs vary drastically by HRRs—even within a single MSA. While levels of these measures are not primarily used in the analysis of this paper, it is important to illustrate how sensitive descriptive key measures are to market definitions.[21]

hospitals in that specific area. HSAs are defined by assigning ZIP codes to the hospital area where the greatest proportion of their Medicare residents were hospitalized. Most hospital service areas contain only one hospital. 1,608 HSAs result from this process. While HSAs provide clarity on the patterns of local hospital utilization, a significant proportion of care, however, is provided by referral hospitals that serve a larger region.

[20]Appendix Figure C.1 presents a visual representation of the markets that are appropriate for study.

[21]The U.S. Office of Management and Budget's definition of an MSA is incorporated in this paper. MSAs account only for areas of high population density—thus, removing potential issues of lumping rural communities with their urban counterparts. The 427 MSAs are less restrictive than HRRs, and they allow patients to seek care at a greater distance.

Referral Data

To analyze referral networks, I need data on common patients shared between the members of networks. This paper makes use of CMS Physician Shared Patient Patterns data from 2009 to 2015, which I link on NPI to the SK&A data.[22] Patient sharing is defined as "an organization or provider participating in the delivery of health services to the same patient within a 30 days, 60 days, 90 days and finally a 180 days period after another organization or provider participated in providing health services to the same patient." For institutions such as hospitals and non-institutions such as freestanding physician offices, this data set contains initial physician NPI, secondary physician NPI, shared count, number of unique beneficiaries, and number of same day visits.

I utilize the 30-day interval data set because it judges the existence of direct referrals between two physicians with the most rigorous criteria. For example, if a patient visits physician A two months after a visit to physician B, the record will not be counted in the 30-day data set, but instead will be counted in the data sets with longer time windows. Table 3.3 presents the number of average referrals made by oncologists in the sample by specialty. The nearly 20,000 oncologists account for approximately 2.8 million patient referrals each year. Approximately 85 percent of referrals clinical oncologists made are to fellow clinical oncologists; my construction of clinical oncologists, however, includes 311 unique specialties found in the SK&A data such as "Oncologist/Hematologist," "Pathologist Hematologist," "Urologist Oncologist," and "Neurologist Oncologist." While not a homogenous group, the key feature of all clinical oncologists in this sample is that they do not perform surgical or radiation services. It is important to recognize the most common referrals are not made to surgical oncologists but rather to other subspecialties of clinical oncology.[23]

[22] On average, across the years in the sample, 18.7 percent of observations do not have matching NPIs between the SK&A and PSPP data sets or a missing NPI in one of these two files. These observations are removed from the analysis sample.

[23] Data were only obtained for 7 months of the year in 2015. The end-date of the data is 10/1/2015, and so the last date for a first visit in which a full 30-days is available for a second visit is 8/31/2015. Accordingly, I expect a reduction in the average number of referrals between two oncologists in 2015 compared to years prior. I perform sensitivity analysis that focuses solely on the 2009-2014 sample—results remain quantitatively and qualitatively similar and are available upon request.

3.3.2 Supplemental Data

I supplement my primary data set with time-varying measures of oncologists' demographics and quality. Oncologists' demographics information is obtained from Medicare Fee-For-Service Provider Utilization and Payment Data Physician and Other Supplier Public Use File (PUF), and oncologists' quality information is obtained from Physician Compare. The years in which the two data sets contain available data are limited and thus are used only in complementary analysis.

Oncologists' Demographics and Quality

PUF is a public data set prepared by CMS; it contains provider demographics such as name, physician specialty, credentials, gender, complete address, and NPIs. Each health care provider's demographic information is collected at the time of enrollment and is updated periodically. Data in the PUF cover the calendar years from 2012 to 2015 (The Centers for Medicare and Medicaid Services, Office of Enterprise Data and Analytics, 2017). CMS created two supplementary data sets that are provided with the PUF: 1) Medicare Physician and Other Supplier Aggregate Table by Physician and 2) Medicare Physician and Other Supplier Aggregate Table by State/National and HCPCS. The aggregated data are not restricted to the redacted data reported in the PUF but are instead aggregated based on all Medicare Part B non-institutional claims. I make use of the aggregated data by physician; the data include beneficiary demographics and health characteristics including age, sex, race, Medicare and Medicaid entitlement, chronic conditions, and risk scores.

Additionally, I utilize the Physician Compare 2014 to 2015 data sets that have been released as part of the CMS Physician Compare Initiative. These data sets contain a select list of physicians registered with Medicare and their accompanying NPI. Physician Compare data include Individual EP Physician Quality Reporting System (PQRS) performance rates that are implemented in this paper.

Table 3.4 presents oncologists' demographics broken down by integration status. Integrated and unintegrated oncologists appear to treat similar patients. Key measures such as the average age of patients and the average HCC risk score of patients are comparable across the two groups.

Integrated oncologists possess noticeably higher average PQRS performance rates, 87.8, compared to their independent counterparts, 77.4.

3.4 Key Study Measures

To illustrate the effects of hospital-physician integration on referral patterns, I present a stylized market with three oncologists and one health system in Figure 3.2. The arrows represent patients referred from one oncologist to another oncologist, and oncologists encompassed by the red dotted line represent members of a health system. Panel (A) displays an example of an oncologist who experiences no alteration in his or her referral patterns post hospital-physician integration. The left side of Panel (A) visually demonstrates an oncologist who prior to hospital-physician integration made referrals only to the oncologist—within his or her market—outside of the health system that he or she will be integrating with in the future. After hospital-physician integration, this newly integrating oncologist continues to make referrals only to the oncologist outside of the health system he or she is now integrated with—as seen in the right side of Panel (A).

Panel (B) demonstrates the most extreme alteration in referral patterns post hospital-physician integration an oncologist can experience. The left side of Panel (B) is identical to the left side of Panel (A). Unlike the right side of Panel (A), however, in the right side of Panel (B), the newly integrating oncologist now shifts all his or her referrals to the oncologist inside the health system that he or she is now integrated with. In both Panel (A) and Panel (B) of Figure 3.2, it is assumed that before hospital-physician integration, the integrating oncologist only made referrals to the oncologist outside of the health system that he or she will be integrating with in the future. Appendix Figure C.2 reproduces Figure 3.2 when altering this assumption.

In order to assign a numerical value to the phenomenon described in Figure 3.2, I construct the index *Referral share*. This index is calculated by dividing referrals made to current health system partners as well as referrals made to oncologists employed by the health system that an oncologist will integrate with in the future by the total referrals of an oncologist. *Referral share* takes a value ranging from [0,1]. An oncologist who never engages in hospital-physician integration will always possess a corresponding *Referral share* of 0. The *Referral share* of an unintegrated oncologist who will integrate with a health system over the sample can range from [0,1]. A value of 0 indicates that all the referrals an unintegrated oncologist made during a given period are to oncologists who are not employed by the health system that he or she will integrate with in the future. A value of 1 indicates all the referrals an unintegrated oncologist made during a given period are to oncologists who are employed by the health system that he or she will be integrating with in the future. An integrated oncologist's *Referral share* can range from [0,1]. A value of 0 indicates that all referrals an integrated oncologist made during a given period are to oncologists outside the health system he or she is employed by. A value of 1 indicates all the referrals an integrated oncologist made during a given period are to health system partners. In effect, this index serves as a measure of the degree of isolation of integrated oncologists—and thereby their patients—from oncologists outside of a health system in the market. This index can be used to study hospital-physician integration's effect on referral patterns.

Throughout this paper, I analyze the change in *Referral share*—Δ*Referral share*—a value ranging from [-1,1] that results from hospital-physician integration.[24] When an oncologist integrates with a health system he or she may experience: 1) no change in his or her *Referral share*—a Δ*Referral share* of 0—or 2) a positive or negative change in his or her *Referral share*—a non-zero value of Δ*Referral share.*

A Δ*Referral share* of 0 implies that hospital-physician integration has no effect on referral patterns. Panel (A) of Figure 3.2 is just one of a myriad of scenarios that would result in Δ*Referral share* of 0 for an integrating oncologist. A Δ*Referral share* of 0 represents any situation in which the referral patterns of an integrating oncologist do not change post hospital-physician integration.

A positive value of Δ*Referral share* implies that an oncologist *Referral share* has increased from one period to the next. This can occur by either shifting referrals previously made to oncologists outside of the health system prior to integration to health system partners and/or by increasing referral volume to health system partners relative to prior levels; whereas a negative value of Δ*Referral share* occurs in the reverse situation. A value of 1 of Δ*Referral share* uniquely corresponds to

[24]Operationally, this is accomplished through regression analysis that includes time and individual fixed effects.

what was visually demonstrated in Panel (B) of the previous figure—that is, 1) an integrating oncologist who prior to hospital-physician integration made no referrals to other oncologists within the market who are currently employed by the acquiring health system (a *Referral share* of 0 prior to hospital-physician integration) and 2) once integrated, he or she only made referrals to health system partners (a *Referral share* of 1 post hospital-physician integration). A value of -1 of Δ*Referral share* uniquely corresponds to the reverse situation.

Figure 3.3 presents key features of my constructed index. Panel (A) of this figure presents a histogram of the distribution of Δ*Referral share*. The upper portion of the figure represents the sample of newly integrating oncologists whereas the bottom portion represents the sample of independent oncologists. Panel (B) presents an additional histogram for those oncologists in the sample experiencing $\Delta \textit{Referral share} = 0$. A value of 0 indicates that an oncologist continues to refer to the same oncologists outside of the health system pre and post hospital-physician integration. A value of 1, on the other hand, indicates that the oncologists who previously received referrals were already members or subsequently became members with the health system the oncologist integrated with.

As seen in the upper portion of Panel (A) in Figure 3.3, roughly 25 percent of newly integrating oncologists across my sample made no referrals to oncologists inside a health system before integrating. Once vertically integrated with the health system, these oncologists shift the entirety of their referrals from oncologists outside of the health system to health system partners. Roughly 25 percent of newly integrating oncologists experienced a Δ*Referral share* of 0 as shown in the upper portion of Panel (B); for 85 percent of these newly integrating oncologists, this occurs because they continue to refer to the same oncologists outside of the health system pre and post hospital-physician integration whereas the other 15 percent were already referring to members of the health system the oncologist integrated with. For the most part, the remainder of newly integrating oncologists experienced a positive increase in Δ*Referral share*. This pattern appears unique to newly integrating oncologists—as seen in the lower portion of Figure 3.3. I now turn to the econometric specifications that allow me to make claims on the effect of hospital-physician integration on referral patterns.

3.5 Econometric Specifications

The basis of my empirical strategy is to estimate the effect of hospital-physician integration on referral pattern outcomes. Referral pattern outcomes are measured by: 1) the share of referrals made to current or future health system partners, *Referral share*, and 2) various referral volumes of interest such as the volume of referrals made to oncologists inside of the health system, the volume of referrals made to oncologists outside of the health system, the number of patients an oncologist sees, the distance patients must travel for referrals, and the quality of referrals. While I regard studying changes in the levels of referral patterns useful, I also seek to make claims on whether or not referral foreclosure after hospital-physician integration occurs; thus, in a supplementary analysis, I incorporate an alternative outcome measure that enables estimation of the probability that an oncologist participates in referral foreclosure after hospital-physician integration. My primary approach is to use: 1) a difference-in-differences strategy and 2) an event study analysis. Finally, I estimate the association between market-level referral patterns of independent oncologists and markets' referral network HHIs.

My first approach, the traditional difference-in-differences framework, compares changes in referral pattern outcomes of integrating oncologists to those who remain independent. I implement this strategy by including individual fixed effects and year fixed effects in the following specification:

$$Y_{imt} = \alpha + \beta_1 VI_{imt} + \phi C_{mt} + \tau_t + \lambda_i + \epsilon_{imt} \tag{3.1}$$

where Y_{imt} represents an outcome such as *Referral share* for oncologist i within market m at time t. VI_{imt} represents a binary indicator that takes the value of 1 if oncologist i vertically integrated with a health system within the last year or the value 0 if he or she did not. C_{mt} is a vector of time-varying demand and supply side covariates that include the number of health systems in the market, the number of hospitals in the market, the number of newly integrating oncologists in the market, the number of newly independent oncologists in the market, the number of integrated oncologists in the market, and the number of independent oncologists in the market. All estimation is performed on the full sample of markets as well as separately for three levels of market referral network

HHIs. I perform these separate estimations to test for heterogeneous effects of health systems' market power of integrated oncologists on hospital-physician integration. I define a market as: 1) unconcentrated if a market's referral network HHI is below 1,500, 2) moderately concentrated if a market's referral network HHI is between 1,500 and 2,500, and 3) highly concentrated if a market's referral network HHI is above 2,500. Standard errors are clustered at the market level to adjust for correlation in unobserved components of referral patterns for oncologists within geographic locations. My second econometric specification specifies the outcome variable of Eq. (3.1) as a binary indicator $Foreclosure_{imt}$ that takes the value of 1 if referral foreclosure occurs post hospital-physician integration. Referral foreclosure is defined as integrating oncologist i possessing: 1) a corresponding *Referral share* not equal to 1 prior to hospital-physician integration and 2) a corresponding *Referral share* equal to 1 post hospital-physician integration. When including $Foreclosure_{imt}$, Eq. (3.1) becomes a linear probability model, and the regression coefficients are interpreted as the percentage point change in the probability of referral foreclosure occurring that resulted from hospital-physician integration.

$$Foreclosure_{imt} = \alpha + \beta_1 VI_{imt} + \phi C_{mt} + \tau_t + \lambda_i + \epsilon_{imt} \tag{3.2}$$

My third approach employs an event study analysis to estimate lagged effects while testing for pre-existing trends—both of which are ignored in the difference-in-differences framework. For this approach, I modify Eq. (3.1) to allow for differential effects of VI_{imt} based on the time relative to hospital-physician integration. The estimating equation takes the following form:

$$Y_{imt} = \alpha + \beta_1 VI_{imt} + \sum_{j=0}^{5} \delta_j VI_{imt+j} + \sum_{j=2}^{5} \pi_j VI_{imt-j} + \phi C_{mt} + \tau_t + \lambda_i + \epsilon_{imt} \tag{3.3}$$

Unlike a difference-in-differences model—which estimates the effect of hospital-physician integration relative to the pre-period—an event study estimates effects relative to a single omitted year. For this paper, I specify this omitted year as the year prior to hospital-physician integration.

Finally, I estimate OLS regressions through which I relate market-level referral patterns of independent oncologists to corresponding market referral network HHIs. The longitudinal nature of the data set used allows for the inclusion of market fixed effects in my models—resulting in the coefficient of interest being identified using referral network HHI variation within each market over time.[25] Year fixed effects are incorporated to control for any time trends.[26] The estimating equation is as follows:

$$Y_{mt}^{NonInt} = \alpha + \beta_1 HHI_{mt} + \phi C_{mt} + \tau_t + \lambda_m + \epsilon_{mt} \tag{3.4}$$

where Y_{mt}^{NonInt} represents market m level outcomes for independent oncologists at time t. HHI_{mt} represents a market's referral network HHI. Time-varying demand and supply side covariates C_{mt} remain as previously specified.

3.6 Empirical Findings

3.6.1 Hospital-Physician Integration's Effect on Referral Patterns

Table 3.5 presents estimates from Eq. (3.1) when the outcome variable is specified as *Referral share*—the share of referrals made to current or future health system partners. Estimates without time-varying market specific covariates are presented in Panel (A), and estimates with time-varying market specific covariates are presented in Panel (B). Estimates with time-varying market specific covariates are the preferred specification and will be referenced throughout the remainder of the paper. The estimated coefficient on hospital-physician integration, VI, for the entire sample is 0.355 and is statistically significant at the 1 percent significance level. This implies that the average integrating oncologist increases his or her share of referrals made to health system partners through either a shift of referrals from oncologists outside of the health system to health system partners or an increase in referral volume to health system partners—by 35.5 percentage points off of a base of 8.8 percent following integration. When incorporating heterogeneous effects of health systems'

[25] The inclusion of fixed effects controls for the average differences across markets in any observable or unobservable predictors such as differences in quality—leaving only within market variation.

[26] As with all fixed effects regressions, it must be assumed that there are no changes over time within each market that cannot be controlled for such as changes in quality or demand. The richness of the data permits me to control for important time-varying within market changes; however, it is dubious to believe that the implemented OLS regression adequately controls for all omitted variable bias. Thus, while interesting as a descriptive exercise, this supplementary analysis is unlikely to yield unbiased estimates of the causal impact of market-level concentration.

market concentration of integrated oncologists, the estimated coefficient on VI remains statistically significant at the 1 percent significance level. The magnitude of the coefficient varies from 0.319 in unconcentrated markets to 0.283 in moderately concentrated markets and finally 0.354 in highly concentrated markets. According to the estimates, the effect of hospital-physician integration is greatest for markets with a referral network HHI that exceeds 2,500. I next examine what factors prompt oncologists to increase their share of referrals made to oncologists inside a health system post hospital-physician integration.

Table 3.6 presents estimates from Eq. (3.1) when the outcome variable is specified as *Inside referrals*—the volume of referrals to oncologists inside a health system. The estimated coefficient on VI is 81.817 and is statistically significant at the 1 percent significance level. The estimate implies that in the year immediately following hospital-physician integration, an integrating oncologist increases his or her referral volume made to health system partners by 82 referrals annually. The estimated coefficients remain similar in magnitude as market concentration varies.

In Table 3.7, *Outside referrals*—the volume of referrals made to oncologists outside a health system—is specified as the outcome variable of Eq. (3.1). The estimated coefficient on VI is 5.547 and is robust across market concentration. The results from Table 3.6 and Table 3.7 when taken together suggest that, on average, oncologists increase their share of referrals made to partners inside a health system through a higher referral volume to health system partners post hospital-physician integration rather than through shifting referrals away from oncologists outside of the health system.

The results of the regression when the outcome variable is specified as *Patient volume*—the volume of patients seen by oncologists—are presented in Table 3.8. Across market concentrations, the estimated coefficient on VI is statistically and economically insignificant. This result is quite interesting as it suggests that despite making more referrals post hospital-physician integration, an integrating oncologist is not increasing his or her patient's visits over the course of a year. This implies that patients are receiving more care—necessary or unnecessary—once their oncologist becomes a member of a health system. Regardless of the necessity of the referrals, hospital-physician integration will result in increased Medicare expenditures by CMS due to Medicare's service-based reimbursement structure.

A defining feature of the health care market is the information asymmetry that exists between patients and oncologists. Because patients may be unable to accurately evaluate health services, they depend on their physicians to recommend services they need. Hospital-physician integration has the potential to exacerbate oncologists maximizing their own payoffs at the expense of patients' utility—if for example an oncologist's motivation to refer to health system partners is to keep revenues within the system rather than to refer a patient to someone who is better equipped to provide care. I find no evidence to support this hypothesis; the referrals made by newly integrating oncologists post hospital-physician integration are on average of similar quality and of similar distance for patients relative to referrals made prior to hospital-physician integration. The estimated coefficient on VI in Table 3.9 when the outcome variable is specified as *Distance*—the share of referrals made to oncologists within the same five-digit ZIP code—is statistically indistinguishable from zero.

Similarly, as seen in Table 3.10, the estimated coefficient on VI when the outcome variable is specified as *Quality*—the average of Physician Quality Reporting System (PQRS) measures of the oncologists that referrals are made to—is insignificant at conventional levels of statistical significance. These results provide evidence that the welfare of patients of integrating oncologists do not decrease as a result of hospital-physician integration.

3.6.2 Hospital-Physician Integration's Effect on Referral Foreclosure

Estimates from Eq. (3.2) are presented in Table 3.11. The estimated coefficient for VI is 0.166 for the full sample, 0.140 for the sample of newly integrating oncologists in unconcentrated markets, and 0.231 for the sample of newly integrating oncologists in highly concentrated markets. These estimates imply that hospital-physician integration increases the probability of referral foreclosure by 14.0 percentage points in markets with unconcentrated levels of integrated oncologists and by 23.1 percentage points in markets with highly concentrated levels of integrated oncologists. Referral foreclosure may result for a variety of reasons such as: 1) hospital-physician integration may give integrating oncologists a financial stake in health system referrals or 2) hospital-physician integration may reduce the cost of referring within the network by streamlining electronic medical records and appointment scheduling. The specific mechanism that leads to increased referral foreclosure cannot be determined with the data in this paper; the finding, however, that the estimated coefficient on VI is 9 percentage points greater in highly concentrated markets relative to unconcentrated markets is suggestive that health systems—in markets with a high concentration of oncologist ownership—have greater leverage to implement practices aimed at restricting patient leakage.

3.6.3 Event Studies

I take a number of steps to assess whether the conclusions of the previous subsection are causal. A major concern of the difference-in-differences estimates is that they do not pick up pre hospital-physician integration or capture other unobservable changes in trends of referral patterns correlated with hospital-physician integration. Rather, what is occurring is that oncologists who are integrating already had a predisposition to alter their referral pattern behaviors. To ensure that the conclusions of my research are robust, I implement event studies; this allows for the identification of pre-trends.

Figure 3.4 plots the event study coefficients for the treatment of an oncologist participating in hospital-physician integration when the outcome variable is specified as *Referral share*. All of the treatment coefficients after the year of integration are positive and significant at the 1 percent level. There exists no significant positive or negative trend prior to hospital-physician integration. Once integration occurs, there is roughly a 30 percentage point shock to *Referral share*, and this effect persists throughout the remainder of the post-adoption period. Overall, I observe no evidence that the effect of hospital-physician integration on *Referral share* documented in the previous subsection is driven by pre-existing trends.

Figure 3.5 and Figure 3.6 present the corresponding event studies when the outcome variable is specified as *Inside referrals* and *Outside referrals* as well as *Inside referrals* and *Outside referrals* separated by market concentration. These figures suggest that there exists no significant positive or negative trend prior to integration, and once integration occurs the shock persists throughout the remainder of the post-adoption period.

These estimates demonstrate the absence of pre-existing trends in the volume of referrals made to oncologists post hospital-physician integration. These findings are robust with that of the previous subsection insofar that hospital-physician integration on average leads to increased referral volumes to health system partners while retaining previous levels of referrals to oncologists outside of the health system.

Figure 3.7 demonstrates the corresponding event study when the outcome variable is specified as *Patient volume*. The figure suggests that there exists no significant positive or negative trend prior to integration for unconcentrated and moderately concentrated markets. For highly concentrated markets, there appears to be a positive trend upwards in *Patient volume* for integrating oncologists that continues post hospital-physician integration.

Figure 3.8 plots the event study coefficients for VI when the outcome variable is specified as *Foreclosure*. There exists no significant positive or negative trend prior to integration. Once integration occurs, there is an 18 percentage point shock to *Foreclosure* in unconcentrated markets and a 25 percentage point shock to *Foreclosure* in highly concentrated markets—each of which are significant at the 1 percent level. During the post-adoption period, the event study coefficients experience a roughly 50 percent reduction. While the point estimates of the post-adoption period remain positive, they are no longer statistically significant at conventional levels.

3.6.4 Market Consolidation of Integrated Oncologists' Effect on Independent Oncologists' Referral Patterns

Finally, estimates from Eq. (3.4) for the subsample of independent oncologists are presented in Tables 3.12-3.15. Table 3.12 presents estimates from Eq. (3.4) when the outcome variable is specified as *Referrals to integrated oncologists*. The estimated coefficient on HHI is 0.005 and is statistically significant at the 1 percent significance level. This implies that independent oncologists, on average, increase their volume of referrals made to integrated oncologists by 6 for each increase of 100 in the HHI of market shares of oncologists a health system controls. This result is driven entirely by those independent oncologists in unconcentrated markets. The estimated coefficient on HHI in highly concentrated markets is statistically indistinguishable from zero.

Table 3.13 presents estimates from Eq. (3.4) when the outcome variable is specified as *Referrals to independent oncologists*. The estimated coefficients on HHI are statistically indistinguishable from zero and robust across market concentration. This implies that independent oncologists do not experience a change in the volume of referrals made to independent oncologists as health systems increase their share of integrated oncologists within a market.

While I find no evidence that hospital-physician integration leads to newly integrating oncologists making lower quality and further distance referrals, I find that independent oncologists in highly concentrated markets shift their referrals to oncologists of lower quality and of further distance in the face of increased consolidation. Although the results regarding the distance of referrals are statistically significant, they lack economic significance. Table 3.14 presents estimates from Eq. (3.4) when the outcome variable is specified as *Distance*. The estimated coefficient on HHI is -0.000010. This estimate is economically insignificant as it requires the change in HHI to be upwards of 10,000 in order to experience a single digit change in the share of referrals made to oncologists within the same digit ZIP code.

Table 3.15 presents estimates from Eq. (3.4) when the outcome variable is specified as *Quality*. The estimated coefficient on HHI is -0.008 for the full sample and is -0.084 for the sample of independent oncologists in highly concentrated markets. The estimate in highly concentrated markets is statistically significant at the 1 percent significance level and implies that, on average, independent oncologists' physician quality of referrals is decreased by 8.4 for each increase of 100 in the HHI of market shares of oncologists a health system controls.

3.7 Conclusion

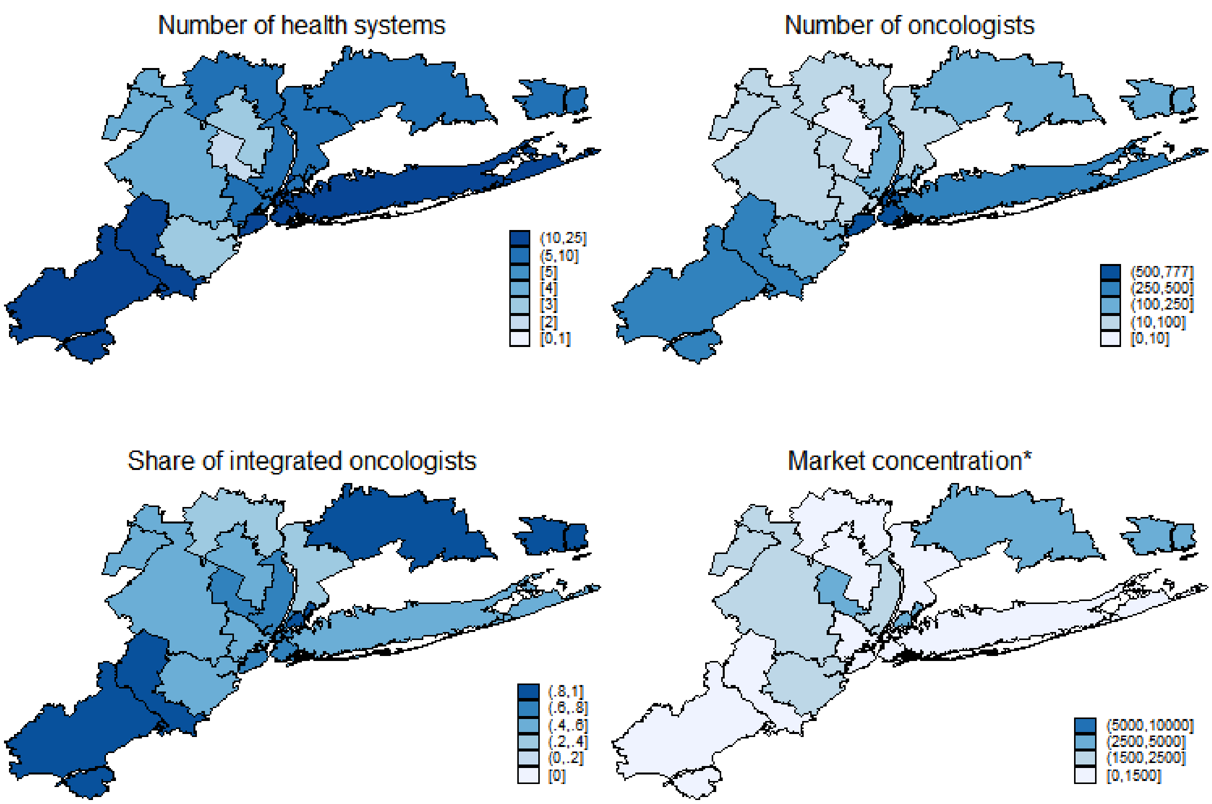
Recent economic literature and policy interest have focused on the integration of hospitals and physicians—asking what the consequences of vertical integration are on hospital efficiency, prices, quantities, and quality. Few papers, however, have addressed how hospital-physician integration shapes referral networks. My paper empirically examines the impact of hospital-physician integration on referral patterns. I find strong and robust evidence using difference-in-differences and event study methods that hospital-physician integration does indeed alter the referral patterns of integrating oncologists.

In addition, I find evidence that hospital-physician integration increases the probability of referral foreclosure with respect to the referrals made to oncologists outside of a health system; I find that this effect is greater in markets with a high concentration of integrated oncologists affiliated with a single health system. Therefore, when evaluating anticompetitive effects of hospital-physician integration in highly concentrated markets, additional scrutiny should be applied.

While the welfare of patients of integrating oncologists appears unaltered, this paper demonstrates that this is not the case for independent oncologists' patients. In response to increased market concentration of integrated oncologists, independent oncologists shift referrals of their patients to oncologists of lower quality.

3.8 Figures

Figure 3.1
HRR market descriptive statistics of New York-Newark-Jersey City, NY



Notes: *Market concentration is defined as the HHI of market shares of integrated oncologists affiliated with a single health system. For the purposes of this calculation, independent oncologists are assigned to their own unique health system along with any other oncologists in the same physician practice.
Source: SK&A, 2015

Figure 3.2
Potential referral impact of hospital-physician integration

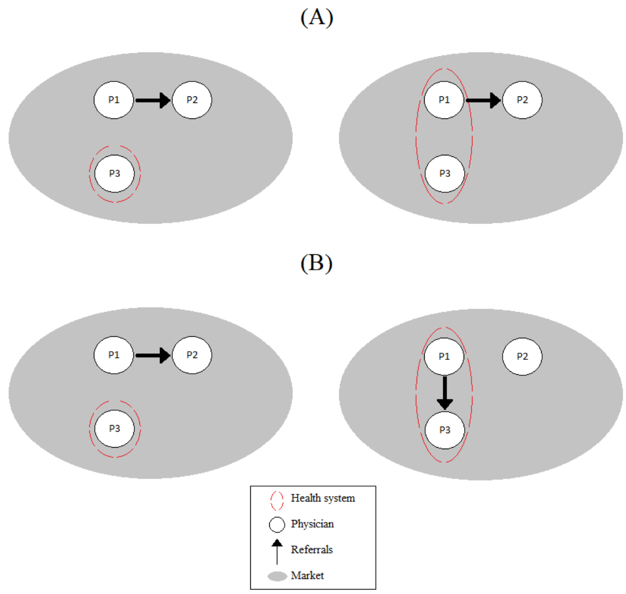


Figure 3.3
Δ*Referral share*

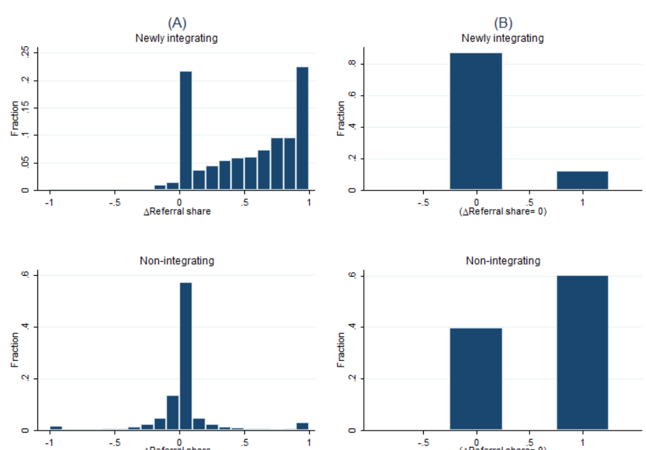
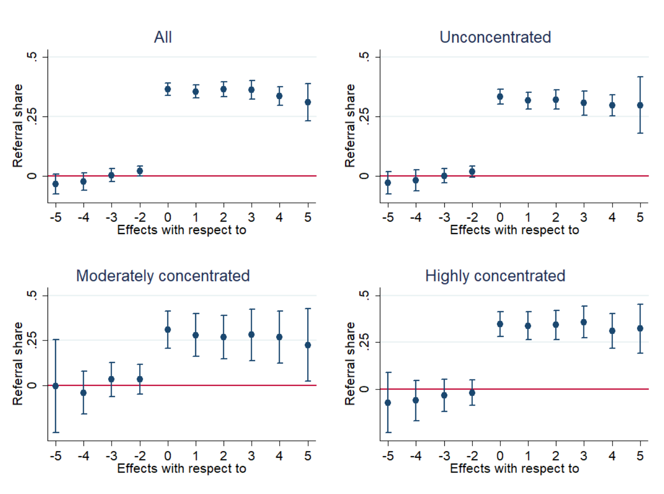


Figure 3.4

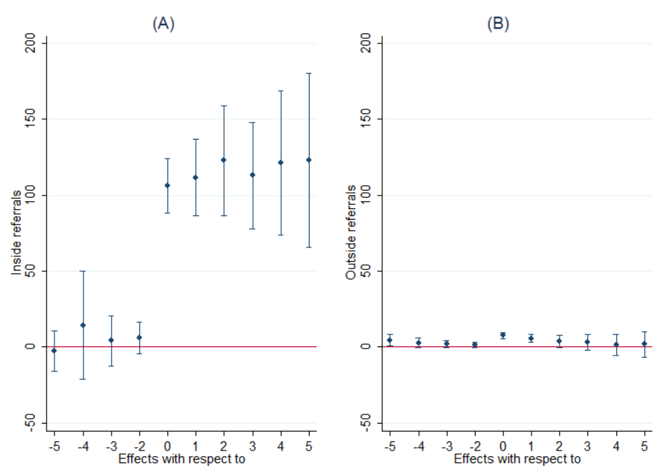
Event studies for *Referral share*



Notes: Outcome is *Referral share*. Confidence intervals adjusted for within-HRR clustering. All time-varying covariates discussed in text included in regression.

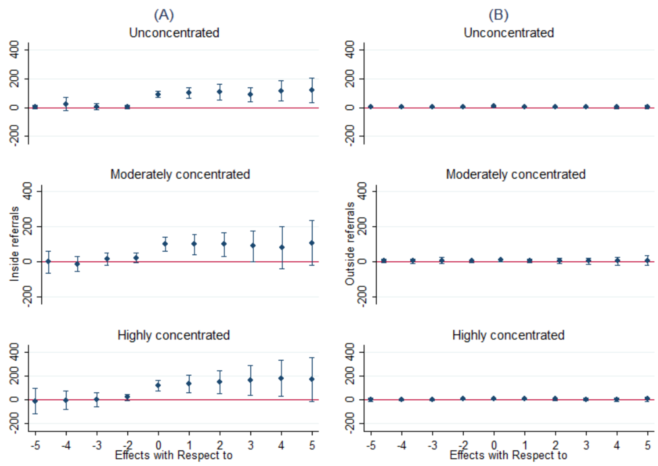
Figure 3.5

Event studies for Inside referrals and *Outside referrals*



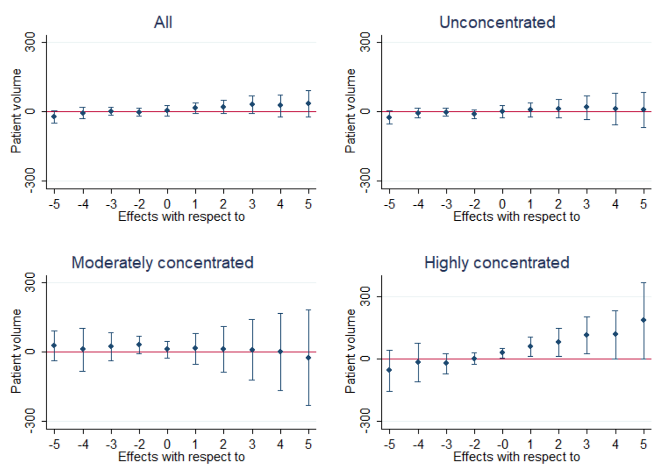
Notes: Panel (A) outcome is *Inside referrals*. Panel (B) outcome is *Outside referrals*. Confidence intervals adjusted for within-HRR clustering. All time-varying covariates discussed in text included in regression.

Figure 3.6
Event studies for *Inside referrals* and *Outside referrals* by market concentration



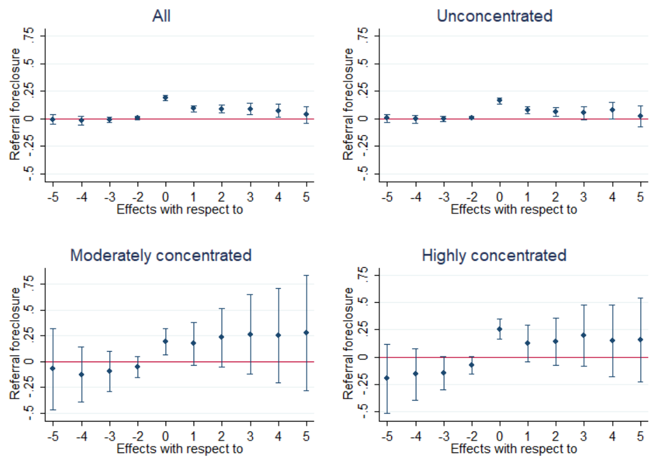
Notes: Panel (A) outcome is *Inside referrals*. Panel (B) outcome is *Outside referrals*. Confidence intervals adjusted for within-HRR clustering. All time-varying covariates discussed in text included in regression.

Figure 3.7
Event studies for *Patient volume*



Notes: Outcome is *Patient volume*. Confidence intervals adjusted for within-HRR clustering. All time-varying covariates discussed in text included in regression.

Figure 3.8
Event studies for *Foreclosure*



Notes: Outcome is *Foreclosure*. Confidence intervals adjusted for within-HRR clustering. All time-varying covariates discussed in text included in regression.

3.9 Tables

Table 3.1
Integrated oncologists

Specialization	Number of oncologists in 2015	Share hospital or health system owned in:							Percent change in hospital or health system owned from 2009 to 2015
		2009	2010	2011	2012	2013	2014	2015	
Clinical oncology	15,219	0.32	0.34	0.44	0.55	0.60	0.63	0.66	105%
Radiation oncology	3,519	0.42	0.40	0.48	0.58	0.61	0.61	0.68	62%
Surgical oncology	1,006	0.41	0.48	0.61	0.60	0.66	0.68	0.72	77%

Notes: The total number of practicing physicians in 2015 was 1,019,442.
Source: SK&A (office level), 2009-2015

Table 3.2
Descriptive statistics (market-year): HRR

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Level				
Referral network HHI*	1,876.78	756.52	1,945.08	4,566.15
	(1,808.34)	(367.74)	(270.23)	(1,774.34)
Health systems	4.41	4.91	4.48	3.13
	(3.85)	(4.20)	(3.52)	(2.72)
Hospitals	4.66	4.95	5.15	3.57
	(5.24)	(5.39)	(5.31)	(4.62)
Oncologists	59.20	67.07	55.32	42.96
	(84.91)	(90.58)	(70.12)	(78.59)
Integrated oncologists	32.20	29.34	37.00	35.43
	(59.29)	(57.45)	(50.34)	(69.14)
Independent oncologists	27.00	37.73	18.31	7.52
	(35.44)	(40.58)	(22.79)	(12.71)
Change in levels				
Referral network HHI*	9.10	-290.03	74.05	632.17
	(1,331.76)	(895.35)	(894.25)	(2,035.32)
Health systems	-0.02	-0.11	0.25	-0.02
	(2.60)	(2.62)	(3.04)	(2.12)
Hospitals	-0.04	-0.29	0.44	0.12
	(3.67)	(3.59)	(4.38)	(3.18)
Oncologists	61.33	69.63	58.24	45.08
	(88.26)	(94.94)	(72.51)	(81.37)
Integrated oncologists	0.35	-3.36	5.71	4.52
	(37.70)	(36.67)	(36.58)	(39.93)
Independent oncologists	0.33	2.23	-1.73	-2.34
	(19.70)	(22.10)	(18.34)	(13.64)
Observations	1,935	1,119	359	457
Share of markets	1.00	0.58	0.19	0.24

Notes: *Market concentration is defined as the HHI of market shares of integrated oncologists affiliated with a single health system. For the purposes of this calculation, independent oncologists are assigned to their own unique health system along with any other oncologists in the same physician practice.
Source: SK&A, 2009-2015 (office level)

Table 3.3
Average annual referrals

Specialization	Referrals	Specialization	Referrals	Specialization	Referrals
Clinical oncology	**2,108,414**	**Radiation oncology**	**650,243**	**Surgical oncology**	**14,701**
to clinical oncology	0.852	to clinical oncology	0.451	to clinical oncology	0.724
to radiation oncology	0.141	to radiation oncology	0.533	to radiation oncology	0.158
to surgical oncology	0.004	to surgical oncology	0.002	to surgical oncology	0.114

Notes: This table presents the average annual referrals oncologists in the sample made by specialty along with the share of total referrals each specialty receives.
The total number of practicing oncologists in 2015 was 19,744.
Source: SK&A (office level), PSPP, 2009-2015

Table 3.4
Demographic characteristics of oncologists and their patients

	All	Integrated	Independent
Average age of patients	72.3	71.7	73.2
Number of patients:			
Age less than 65	49.1	42.5	58.3
Age 65 to 74	149.3	120.4	196.2
Age 75 to 84	116.5	89.6	156.5
Age greater than 84	52.3	39.1	69.2
Female patients	199.2	153.5	272.1
Male patients	144.3	115.0	190.9
Non-Hispanic white patients	299.2	233.0	396.2
Number of Black or African American patients	57.3	49.8	65.2
Asian Pacific Islander patients	24.9	18.9	32.3
Hispanic patients	41.4	31.9	49.8
Number of American Indian/Alaska Native patients	1.6	1.0	2.5
Patients with race not elsewhere classified	14.2	11.6	16.1
Patients with Medicare only entitlement	292.6	227.9	394.5
Patients with Medicare and Medicaid entitlement	64.5	52.9	82.7
Share of patients identified with:			
Atrial fibrillation	13.2	12.8	13.8
Alzheimer's disease or dementia	10.2	9.5	11.2
Asthma	14.6	14.6	14.7
Cancer	48.8	49.8	47.3
Heart failure	22.1	21.2	23.4
Chronic kidney disease	34.5	34.1	35.3
Chronic obstructive pulmonary disease	21.3	21.1	21.7
Depression	23.7	24.5	22.4
Diabetes	32.9	31.9	34.5
Hyperlipidemia	54.4	53.1	56.4
Hypertension	68.5	67.9	69.4
Ischemic heart disease	37.4	36.5	38.9
Osteoporosis	10.7	10.4	11.1
Rheumatoid arthritis/osteoarthritis	37.8	37.1	39.0
Schizophrenia/other psychotic disorder	4.4	4.5	4.3
Stroke	7.0	6.9	7.2
Average HCC risk score of patients	2.0	2.0	1.9
Average PQRS performance rates	83.1	87.8	77.4

Source: PUF and SK&A (office level), 2015

Table 3.5
Referral share†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	0.356***	0.321***	0.294***	0.335***
	(0.0152)	(0.0197)	(0.0494)	(0.0317)
Panel B: with state and year fixed effects and covariates				
VI	0.355***	0.319***	0.283***	0.354***
	(0.0122)	(0.0142)	(0.0476)	(0.0323)
Observations	147,327	98,779	24,834	23,714

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Referral share* represents the share of referrals made to current or future health system partners. *Referral share* takes a value ranging from [0,1].
All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.6
Inside referrals†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	83.812***	86.069***	68.652***	89.862***
	(8.8040)	(14.445)	(15.0627)	(12.2613)
Panel B: with state and year fixed effects and covariates				
VI	81.817***	83.726***	68.143***	89.169***
	(8.4681)	(13.4607)	(14.8630)	(12.1876)
Observations	149,360	99,883	25,329	24,148

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Inside referrals* represents the volume of referrals to oncologists inside a health system.
All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.7
Outside referrals†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	5.741***	6.831***	7.592**	6.876***
	(0.6518)	(0.9587)	(3.0383)	(1.9794)
Panel B: with state and year fixed effects and covariates				
VI	5.547***	6.693***	6.964**	6.996***
	(0.6472)	(0.9737)	(2.8082)	(2.0015)
Observations	149,360	99,883	25,329	24,148

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Outside referrals* represents the volume of referrals made to oncologists outside a health system.
All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.8
Patient volume†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	-6.212	-3.988	15.0167	-8.990
	(6.2013)	(8.4058)	(10.2408)	(10.7273)
Panel B: with state and year fixed effects and covariates				
VI	-5.973	-3.524	14.238	-6.170
	(6.2272)	(8.3750)	(10.4405)	(9.0224)
Observations	149,360	99,883	25,329	24,148

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Patient volume* represents the volume of patients seen by oncologists.
All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.9
Distance†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	0.008**	0.005	0.005	0.002
	(0.0040)	(0.0047)	(0.0104)	(0.0129)
Panel B: with state and year fixed effects and covariates				
VI	0.008	-0.000	0.013	0.007
	(0.0088)	(0.0097)	(0.0229)	(0.0338)
Observations	94,443	5,398	15,629	13,416

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Distance* represents the share of referrals made to oncologists within the same 5-digit ZIP code. *Distance* takes a value ranging from [0,1].
All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.10
Quality†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	-2.887	2.369	6.400	-23.540
	(10.1267)	(6.2297)	(7.6211)	(20.2815)
Panel B: with state and year fixed effects and covariates				
VI	1.203	7.183	0.012	-12.578
	(8.8602)	(6.3156)	(6.9212)	(16.4263)
Observations	2,698	1,683	575	440

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Quality* represents the average of Physician Quality Reporting System (PQRS) measures of the oncologists that referrals are made to. *Quality* ranges from [0,100].
All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.11

Foreclosure†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
VI	0.169***	0.140***	0.155***	0.236***
	(0.0079)	(0.0097)	(0.0311)	(0.0209)
Panel B: with state and year fixed effects and covariates				
VI	0.166***	0.140***	0.148***	0.231***
	(0.0080)	(0.0101)	(0.0305)	(0.0212)
Observations	149,360	99,883	25,329	24,148

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

† *Foreclosure* represents the probability that an oncologist participates in complete referral foreclosure after hospital-physician integration.

All regressions include individual and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. VI is a binary indicator that takes the value of 1 if an oncologist vertically integrated with a hospital within the last year and takes the value of 0 if he or she did not. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.12

Referrals to integrated oncologists†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
HHI	0.006***	0.018***	0.002	0.002
	(0.0018)	(0.0056)	(0.2400)	(0.0045)
Panel B: with state and year fixed effects and covariates				
HHI	0.005***	0.017***	0.000	0.005
	(0.0018)	(0.0051)	(0.0084)	(0.0065)
Observations	73,409	59,549	9,241	4,619

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

† *Referrals to integrated oncologists* represents the volume of referrals made by the sample of independent oncologists to integrated oncologists.

All regressions include HRR and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. HHI takes a value ranging from (0,10000]. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.13
Referrals to independent oncologists†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
HHI	-0.006	-0.007	0.018	-0.012
	(0.0086)	(0.0208)	(0.0278)	(0.0090)
Panel B: with state and year fixed effects and covariates				
HHI	-0.004	0.004	0.002	-0.009
	(0.0092)	(0.0219)	(0.0300)	(0.0090)
Observations	73,409	59,549	9,241	4,619

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Referrals to independent oncologists* represents the volume of referrals made by the sample of independent oncologists to independent oncologists.
All regressions include HRR and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. HHI takes a value ranging from (0,10000]. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.14
Distance†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
HHI	-0.000010***	-0.000006	0.000017	-0.000015***
	(0.000004)	(0.000008)	(0.000020)	(0.000012)
Panel B: with state and year fixed effects and covariates				
HHI	-0.000010***	-0.000004	0.000021	0.001815***
	(0.000005)	(0.000009)	(0.000028)	(0.000602)
Observations	52,433	43,150	6,404	2,879

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Distance* represents the share of referrals made by the sample of independent oncologists to oncologists within the same 5-digit ZIP code. *Distance* takes a value ranging from [0,1].
All regressions include HRR and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. HHI takes a value ranging from (0,10000]. Standard errors allow for clustering at the HRR level and are reported in parentheses.

Table 3.15
Quality†

	All	Unconcentrated	Moderately concentrated	Highly concentrated
Panel A: with state and year fixed effects only				
HHI	-0.009***	-0.0116***	-0.005	-0.007
	(0.0032)	(0.0040)	(0.0118)	(0.0048)
Panel B: with state and year fixed effects and covariates				
HHI	-0.008***	-0.008*	-0.006	-0.084***
	(0.0028)	(.0050)	(0.0027)	(0.0210)
Observations	1,081	750	200	131

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
† *Quality* represents the average of Physician Quality Reporting System (PQRS) measures of the oncologists that referrals are made to by independent oncologists. *Quality* ranges from [0,100].
All regressions include HRR and year fixed effects. Time-varying HRR covariates include: number of health systems, number of hospitals, number of newly integrated oncologists, number of newly independent oncologists, number of integrated oncologists, and number of independent oncologists. Observations are at the physician level. HHI takes a value ranging from (0,10000]. Standard errors allow for clustering at the HRR level and are reported in parentheses.

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Appendix A

Appendix for Chapter 1

A.1 Tables

Table A.1
Additional tables

	Parameters	Normalized				Increased Monte Carlo draws				Fewer instruments			
		Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
		(1)		(2)		(3)		(4)		(5)		(6)	
1	σ_ω(Private signal)	1.06	4.17	0.08	0.08	1.31	3.43	0.56	0.80	1.22	4.96	0.14	0.01
2	σ_ϵ(Error)	3.48	9.66	3.41	9.01	2.49	5.05	0.29	0.22	2.48	8.47	0.39	0.03
3	$\beta_1(m)$	1	-	1	-	1	-	1	-	1	-	1	-
4	$\beta_2(h)$	-1.01	-0.004	-0.80	-0.0001	-1.13	-0.0003	-0.71	-0.0002	-1.54	-0.01	-0.84	-0.005
5	$\beta_3(mh)$	0.003	0.08	-0.05	-0.05	0.04	0.11	0.38	0.65	0.05	0.75	0.21	0.08
6	$\beta_4(m^2)$	-0.001	-0.08	-0.01	-6000.2	-0.0002	0.03	-0.12	-3.58	-0.0002	-0.03	-0.11	-0.40
7	$\beta_5(h^2)$	-3.27	-0.03	-4.60	-0.05	-8.98	-1.30	-0.90	-0.18	-8.00	-0.02	-0.88	-0.009
8	Age			-0.04	-0.01			1.33	0.12			1.75	0.002
9	Age^2			0.0007	0.0005			1.10	0.32			1.07	0.003
10	Female			1.06	2.32			0.75	0.74			-0.91	-0.02
11	Northwestern			-0.27	-0.75			0.12	0.08			-2.78	-0.17
12	Nonmetro			-0.35	-0.56			-0.75	-0.22			1.81	0.01
13	Black			1.99	4.75			1.28	2.55			0.22	0.005
14	Clerical			-0.36	-0.30			-2.43	-0.14			-0.52	-0.01
15	Constant	-0.48	-0.49	0.74	0.27	3.12	3.93	0.95	0.11	3.12	4.53	1.06	0.002
$J \sim \chi^2$			33.92		25.00	33.92		24.99		14.07		-	

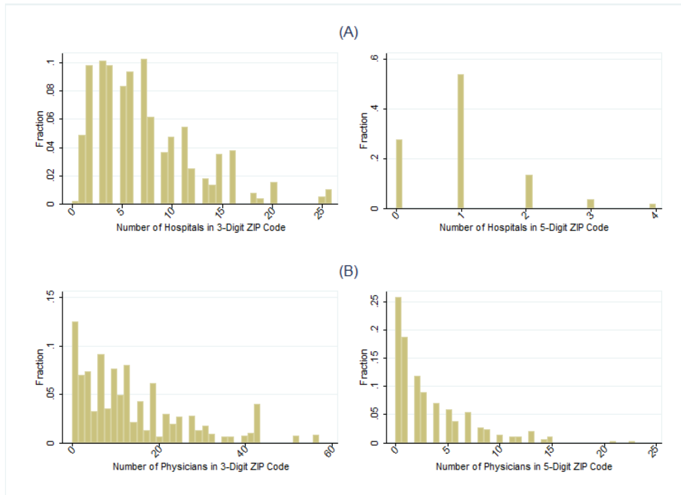
Notes: The first two rows present the estimated standard errors of the private risk signal and error term. The next five rows present the coefficients of the second-order Taylor series approximation of the utility function (with the linear term in M normalized to one). Rows 8 to 15 present the demographics in the function $K(D_i)$, i.e. the deterministic component of the health state. t-statistics are based on a covariance matrix of the estimators computed using numerical gradients.

Appendix B

Appendix for Chapter 2

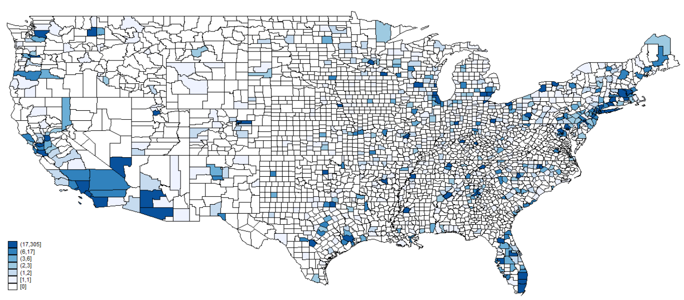
B.1 Figures

Figure B.1
Concentration measures



Source: Area Health Resources Files and SK&A, 2013

Figure B.2
Number of clinical oncologists by geographic location



Source: SK&A, 2013

B.2 Tables

Table B.1
Top 20 Medicare payment categories

All - clinical oncologists (n= 9,528)					
	HCPCS Code	Description	Payments	Location	Cum.
1	J2505	Injection, pegfilgrastim, 6 mg	372,000,000	O	11%
2	J9310	Injection, rituximab, 100 mg	345,000,000	O	11%
3	99214	Established patient office or other outpatient visit, typically 25 minutes	260,000,000	O	8%
4	J9035	Injection, bevacizumab, 10 mg	163,000,000	O	5%
5	96413	Infusion of chemotherapy into a vein up to 1 hour	150,000,000	O	5%
6	J0885	Injection, epoetin alfa, (for non-esrd use), 1000 units	127,000,000	O	4%
7	J0897	Injection, denosumab, 1 mg	122,000,000	O	4%
8	99213	Established patient office or other outpatient visit, typically 15 minutes	118,000,000	O	4%
9	J0881	Injection, darbepoetin alfa, 1 microgram (non-esrd use)	101,000,000	O	3%
10	J2469	Injection, palonosetron hcl, 25 mcg	89,200,000	O	3%
11	99215	Established patient office or other outpatient visit, typically 40 minutes	66,200,000	O	2%
12	99232	Subsequent hospital inpatient care, typically 25 minutes per day	60,400,000	F	2%
13	99214	Established patient office or other outpatient visit, typically 25 minutes	54,800,000	F	2%
14	99233	Subsequent hospital inpatient care, typically 35 minutes per day	51,800,000	F	2%
15	85025	Complete blood cell count (red cells, white blood cell, platelets), automated test	50,600,000	O	2%
16	J9041	Injection, bortezomib, 0.1 mg	48,300,000	O	1%
17	99223	Initial hospital inpatient care, typically 70 minutes per day	45,500,000	F	1%
18	78815	Nuclear medicine study with CT imaging skull base to mid-thigh	41,600,000	O	1%
19	J9305	Injection, pemetrexed, 10 mg	40,300,000	O	1%
20	96367	Infusion into a vein for therapy prevention or diagnosis additional sequential infusion up to 1 hour	39,900,000	O	1%

Source: PUF and SK&A, 2013

Table B.2
Top 10 Medicare facility fee categories

	Description	Facility fee payments
1	Evaluation and Management Services (E&M)	887,000,000
2	Injection, pegfilgrastim, 6 mg	487,000,000
3	Injection, rituximab, 100 mg	450,000,000
4	Infusion of chemotherapy into a vein up to 1 hour	323,000,000
5	Injection, bevacizumab, 10 mg	213,000,000
6	Injection, epoetin alfa, (for non-esrd use), 1000 units	166,000,000
7	Injection, denosumab, 1 mg	160,000,000
8	Injection, darbepoetin alfa, 1 microgram (non-esrd use)	13,2000,000
9	Injection, palonosetron hcl, 25 mcg	117,000,000
10	Infusion into a vein for therapy, prevention, or diagnosis up to 1 hour	83,600,000

Source: PUF and OPPS, 2013

Table B.3

Differences in Medicare payments for E&M services billed as freestanding office-based and as hospital-based

Medicare fee schedule **2012**								
			Service billed as hospital-based					
HCPCS code	Description	Service billed as freestanding office-based*	Physician facility rate*	Outpatient PPS rate (facility fee)**	Total, hospital-based setting rate	Difference in payment (level)	Difference in payment (percentage)
99201	New patient office or other outpatient visit, typically 10 minutes	31.36	20.08	53.79	73.87	42.51	136%
99202	New patient office or other outpatient visit, typically 20 minutes	53.68	37.40	72.12	109.52	55.84	104%
99203	New patient office or other outpatient visit, typically 30 minutes	78.62	57.61	95.12	152.73	74.11	94%
99204	New patient office or other outpatient visit, typically 45 minutes	122.06	97.95	130.41	228.36	106.30	87%
99205	New patient office or other outpatient visit, typically 60 minutes	154.73	127.57	176.51	304.08	149.35	97%
99211	Established patient office or other outpatient visit, typically 5 minutes	14.87	7.10	53.79	60.89	46.01	309%
99212	Established patient office or other outpatient visit, typically 10 minutes	31.70	18.69	72.12	90.81	59.11	186%
99213	Established patient office or other outpatient visit, typically 15 minutes	51.72	36.92	72.12	109.04	57.33	111%
99214	Established patient office or other outpatient visit, typically 25 minutes	77.92	57.87	95.12	152.99	75.07	96%
99215	Established patient office or other outpatient visit, typically 40 minutes	107.12	83.09	130.41	213.50	106.37	99%

Notes: Under the MPFS, some procedures have a separate Medicare fee schedule for physicians' professional services when provided in a facility (hospital-based setting) or in a non-facility (freestanding office-based setting). Generally, Medicare provides additional payments to physicians and to other health care professionals for procedures performed in their freestanding offices because they are responsible for providing clinical staff, supplies, and equipment.

* Paid under the Medicare physician fee schedule

** Paid under the outpatient PPS

Source: PUF and OPPS

Table B.4

Differences in Medicare payments for E&M services billed as freestanding office-based and as hospital-based - cont.

Medicare fee schedule **2013**							
			Service billed as hospital-based				
HCPCS code	Description	Service billed as freestanding office-based*	Physician facility rate*	Outpatient PPS rate (facility fee)**	Total, hospital-based setting rate	Difference in payment (level)	Difference in payment (percentage)
99201	New patient office or other outpatient visit, typically 10 minutes	31.08	19.74	56.77	76.51	45.43	146%
99202	New patient office or other outpatient visit, typically 20 minutes	54.23	36.64	73.68	110.32	56.09	103%
99203	New patient office or other outpatient visit, typically 30 minutes	79.68	56.64	96.96	153.60	73.93	93%
99204	New patient office or other outpatient visit, typically 45 minutes	123.21	97.15	128.48	225.63	102.42	83%
99205	New patient office or other outpatient visit, typically 60 minutes	155.71	126.93	175.79	302.72	147.01	94%
99211	Established patient office or other outpatient visit, typically 5 minutes	15.15	6.62	56.77	63.39	48.23	318%
99212	Established patient office or other outpatient visit, typically 10 minutes	32.22	17.82	73.68	91.50	59.28	184%
99213	Established patient office or other outpatient visit, typically 15 minutes	52.47	36.09	73.68	109.77	57.31	109%
99214	Established patient office or other outpatient visit, typically 25 minutes	78.46	56.91	96.96	153.87	75.41	96%
99215	Established patient office or other outpatient visit, typically 40 minutes	107.60	82.40	128.48	210.88	103.28	96%

Notes: Under the MPFS, some procedures have a separate Medicare fee schedule for physicians' professional services when provided in a facility (hospital-based setting) or in a non-facility (freestanding office-based setting). Generally, Medicare provides additional payments to physicians and to other health care professionals for procedures performed in their freestanding offices because they are responsible for providing clinical staff, supplies, and equipment.

* Paid under the Medicare physician fee schedule

** Paid under the outpatient PPS

Source: PUF and OPPS

Table B.5

Differences in Medicare payments for E&M services billed as freestanding office-based and as hospital-based - cont.

Medicare fee schedule
2014

HCPCS code	Description	Service billed as freestanding office-based*	Service billed as hospital-based: Physician facility rate*	Service billed as hospital-based: Outpatient PPS rate (facility fee)**	Service billed as hospital-based: Total, hospital-based setting rate	Difference in payment (level)	Difference in payment (percentage)
99201	New patient office or other outpatient visit, typically 10 minutes	31.48	20.51	92.53	113.04	81.56	259%
99202	New patient office or other outpatient visit, typically 20 minutes	54.66	38.06	92.53	130.59	75.94	139%
99203	New patient office or other outpatient visit, typically 30 minutes	79.53	57.82	92.53	150.35	70.81	89%
99204	New patient office or other outpatient visit, typically 45 minutes	123.94	99.28	92.53	191.81	67.87	55%
99205	New patient office or other outpatient visit, typically 60 minutes	158.08	130.98	92.53	223.51	65.43	41%
99211	Established patient office or other outpatient visit, typically 5 minutes	14.70	6.95	92.53	99.48	84.78	577%
99212	Established patient office or other outpatient visit, typically 10 minutes	31.89	18.43	92.53	110.96	79.07	248%
99213	Established patient office or other outpatient visit, typically 15 minutes	52.49	37.38	92.53	129.91	77.42	147%
99214	Established patient office or other outpatient visit, typically 25 minutes	79.30	58.79	92.53	151.32	72.02	91%
99215	Established patient office or other outpatient visit, typically 40 minutes	108.91	84.82	92.53	177.35	68.44	63%

Notes: Under the MPFS, some procedures have a separate Medicare fee schedule for physicians' professional services when provided in a facility (hospital-based setting) or in a non-facility (freestanding office-based setting). Generally, Medicare provides additional payments to physicians and to other health care professionals for procedures performed in their freestanding offices because they are responsible for providing clinical staff, supplies, and equipment.

* Paid under the Medicare physician fee schedule

** Paid under the outpatient PPS

Source: PUF and OPPS

Table B.6
Distribution of E&M services by location

HCPCS code	Description	Number of services	Percentage breakdowns: Billed as a freestanding office-based service	Billed as a hospital-based service	Total of E&M billing
99201	New patient office or other outpatient visit, typically 10 minutes	472	25%	75%	0.01%
99202	New patient office or other outpatient visit, typically 20 minutes	3,440	69%	31%	0.04%
99203	New patient office or other outpatient visit, typically 30 minutes	38,815	75%	25%	0.41%
99204	New patient office or other outpatient visit, typically 45 minutes	184,675	78%	22%	1.97%
99205	New patient office or other outpatient visit, typically 60 minutes	311,188	71%	29%	3.31%
99211	Established patient office or other outpatient visit, typically 5 minutes	235,704	95%	5%	2.51%
99212	Established patient office or other outpatient visit, typically 10 minutes	274,056	84%	16%	2.92%
99213	Established patient office or other outpatient visit, typically 15 minutes	2,928,089	79%	21%	31.19%
99214	Established patient office or other outpatient visit, typically 25 minutes	4,442,727	76%	24%	47.33%
99215	Established patient office or other outpatient visit, typically 40 minutes	968,409	66%	34%	10.32%

Source: PUF and SK&A, 2013

Table B.7
Distribution of E&M services by HCPCS code

Integrated - clinical oncologists (n=5,510)

HCPCS code	Description	Number of services in 2012	Percentage breakdowns Total of E&M billings in: 2012	2013	2014	2015	2016	%Δ in payments between 2013-2014
99201	New patient office or other outpatient visit, typically 10 minutes	92	0.08%	0.24%	0.13%	0.09%	0.22%	62.99%
99202	New patient office or other outpatient visit, typically 20 minutes	1,087	0.74%	0.64%	0.63%	0.52%	0.69%	25.58%
99203	New patient office or other outpatient visit, typically 30 minutes	12,802	6.71%	6.40%	6.65%	5.27%	4.95%	-4.57%
99204	New patient office or other outpatient visit, typically 45 minutes	53,534	27.22%	27.57%	29.01%	28.93%	24.47%	-27.98%
99205	New patient office or other outpatient visit, typically 60 minutes	108,553	65.24%	65.14%	63.58%	65.18%	69.67%	-47.36%
99211	Established patient office or other outpatient visit, typically 5 minutes	34,717	0.79%	0.41%	0.37%	0.35%	0.25%	62.99%
99212	Established patient office or other outpatient visit, typically 10 minutes	59,738	1.85%	1.72%	1.62%	1.46%	1.09%	25.58%
99213	Established patient office or other outpatient visit, typically 15 minutes	821,535	29.54%	28.66%	28.86%	25.51%	22.28%	25.58%
99214	Established patient office or other outpatient visit, typically 25 minutes	1,313,705	51.42%	52.54%	52.72%	53.55%	54.28%	-4.57%
99215	Established patient office or other outpatient visit, typically 40 minutes	374,004	16.40%	16.66%	16.43%	19.13%	22.11%	-27.98%

Source: PUF and SK&A

Table B.8
Medicare's facility fee payments for E&M services

		Average annual facility fee payment			
		2012	2013	2014*	%Δ in payments between 2013-2014
HCPCS code	Description				
99201	New patient office or other outpatient visit, typically 10 minutes	53.82	56.77	92.53	62.99%
99202	New patient office or other outpatient visit, typically 20 minutes	72.15	73.68	92.53	25.58%
99203	New patient office or other outpatient visit, typically 30 minutes	95.16	96.96	92.53	-4.57%
99204	New patient office or other outpatient visit, typically 45 minutes	130.47	128.48	92.53	-27.98%
99205	New patient office or other outpatient visit, typically 60 minutes	176.59	175.79	92.53	-47.36%
99211	Established patient office or other outpatient visit, typically 5 minutes	53.82	56.77	92.53	62.99%
99212	Established patient office or other outpatient visit, typically 10 minutes	72.15	73.68	92.53	25.58%
99213	Established patient office or other outpatient visit, typically 15 minutes	72.15	73.68	92.53	25.58%
99214	Established patient office or other outpatient visit, typically 25 minutes	95.16	96.96	92.53	-4.57%
99215	Established patient office or other outpatient visit, typically 40 minutes	130.47	128.48	92.53	-27.98%

Notes: Under the MPFS, some procedures have a separate Medicare fee schedule for physicians' professional services when provided in a facility (hospital-based setting) or in a non-facility (freestanding office-based setting). Generally, Medicare provides additional payments to physicians and to other health care professionals for procedures performed in their freestanding offices because they are responsible for providing clinical staff, supplies, and equipment.
* Effective Jan. 1, 2014, facilities are required to report outpatient clinic visits using a new HCPCS level II code, G0463 (hospital outpatient clinic visit for assessment and management of a patient), rather than using E&M codes 99201-99205 (new patient) and 99211-99215 (established patient). The payment rate for G0463 is based on the mean reimbursement rate of new and established patient clinic visit codes (99201-99205/99211-99215) from the 2012 Outpatient Prospective Payment System (OPPS) claims data.
Source: OPPS

Table B.9
Baseline (Log)

Dependent variable:	Integration indicator								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Facility fees									
IHS(Office)	0.0003	0.0003	0.0006	-0.0001	0.0002	0.0002	0.0000	0.0004	0.0003
	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0008)
IHS(Hospital)	0.0002	0.0001	0.0014	0.0013	0.0014	-0.0003	0.0030	0.0030	0.0009
	(0.0024)	(0.0026)	(0.0029)	(0.0027)	(0.0029)	(0.0032)	(0.0028)	(0.0031)	(0.0034)
Bargaining indexes									
ln(Physician losses)	-0.0183***	-0.0180***	-0.0176***	-0.0237***	-0.0235***	-0.0220***	-0.0214***	-0.0213***	-0.0200***
	(0.0021)	(0.0023)	(0.0024)	(0.0023)	(0.0024)	(0.0026)	(0.0023)	(0.0025)	(0.0027)
ln(Baseline facility fees)	0.0046**	0.0043*	0.0040	0.0018	0.0016	0.0004	0.0009	0.0008	-0.0003
	(0.0023)	(0.0023)	(0.0025)	(0.0024)	(0.0025)	(0.0027)	(0.0024)	(0.0025)	(0.0027)
Concentration indexes									
Number of hospitals 3-ZIP	0.0009	0.0009	0.0008	0.0049***	0.0049***	0.0048***	0.0061***	0.0061***	0.0061***
	(0.0014)	(0.0014)	(0.0014)	(0.0017)	(0.0017)	(0.0017)	(0.0018)	(0.0018)	(0.0018)
Number of physicians 3-ZIP	-0.0008	-0.0008	-0.0008	-0.0018***	-0.0018***	-0.0018***	-0.0026***	-0.0026***	-0.0026***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Indicators									
$Tail^{lower}$		-0.1208	-0.1770		-0.2118	-0.2398		-0.1862	-0.2149
		(0.2554)	(0.1525)		(0.3193)	(0.1673)		(0.3210)	(0.1688)
$Tail^{upper}$		-0.0202	0.0218		0.0126	0.1022		-0.0306	0.0550
		(0.1625)	(0.1201)		(0.1600)	(0.1167)		(0.1662)	(0.1210)
Interactions									
$Tail^{lower}$ * IHS(Office)		-0.0114	-0.0169		-0.0202	-0.0223		-0.0181	-0.0198
		(0.0232)	(0.0143)		(0.0288)	(0.0156)		(0.0290)	(0.0158)
$Tail^{lower}$ * IHS(Hospital)		-0.0174	-0.0222*		-0.0226	-0.0237*		-0.0183	-0.0193
		(0.0207)	(0.0120)		(0.0274)	(0.0136)		(0.0273)	(0.0137)
$Tail^{upper}$ * IHS(Office)		0.0017	-0.0034		-0.0034	-0.0113		0.0001	-0.0069
		(0.0149)	(0.0113)		(0.0147)	(0.0110)		(0.0152)	(0.0114)
$Tail^{upper}$ * IHS(Hospital)		0.0059	0.0007		0.0028	0.0118		0.0043	0.0143*
		(0.0069)	(0.0054)		(0.0074)	(0.0075)		(0.0082)	(0.0081)
Constant	0.3774	0.3856	0.3967*	0.3531	0.3624	1.4216	0.5279*	0.5347*	0.5673*
	(0.3774)	(0.2346)	(0.3967)	(0.3040)	(0.3034)	(0.3048)	(0.3145)	(0.3140)	(0.3156)
Tail		5%	10%		5%	10%		5%	10%
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year 2	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year 3	No	No	No	No	No	No	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,857	3,857	3,857	3,857	3,857	3,857	3,857	3,857	3,857
R-squared	0.1762	0.1769	0.1783	0.2331	0.2338	0.2366	0.2225	0.2231	0.2252

Notes: The dependent variable is a binary indicator taking the value of 1 if a clinical oncologist vertically integrated with a hospital over the course of the sample period or the value 0 if he or she did not. Observations are at the physician level. Robust standard errors are in parentheses.
* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Table B.10
Variable definitions

Variable	Definition
Facility fees	
Office	Constructed index such that it measures the change in facility fees, resulting from the 2014 single payment policy—which could in principle be captured by a hospital integrating with a clinical oncologist if he or she bills all freestanding office-based E&M services as hospital-based E&M services.
Hospital	Constructed index such that it measures the change in facility fees, resulting from the 2014 single payment policy—which could in principle be captured by a hospital integrating with a clinical oncologist that then collects all facility fees from E&M services he or she may have previously performed at other hospitals.
IHS(Office)	Inverse hyperbolic sine of *Office*.
IHS(Hospital)	Inverse hyperbolic sine of *Hospital*.
Bargaining indexes	
Physician losses	Constructed index that measures the upper bound of potential losses to a clinical oncologist when integrating with a hospital then billing all his or her freestanding office-based E&M services as hospital-based E&M services.
ln(Physician losses)	Logarithm of *Physician losses*.
Baseline facility fees	Constructed index that measures the upper bound of potential facility fees an integrating clinical oncologist can generate for a hospital using his or her 2013 billing patterns.
ln(Baseline facility fees)	Logarithm of *Baseline facility fees*.
Concentration indexes	
Number of hospitals 3-ZIP	Number of hospitals in the 3-digit ZIP code of a clinical oncologist.
Number of physicians 3-ZIP	Number of other clinical oncologists in the 3-digit ZIP code of a clinical oncologist.
Indicators	
$Tail^{upper}$	Indicator for if a clinical oncologist is in the 95th to 100th/90th to 100th percentile of those positively affected by the implementation of the 2014 single payment policy.
$Tail^{lower}$	Indicator for if a clinical oncologist is in the 1st to 5th/1st to 10th percentile of those positively affected by the implementation of the 2014 single payment policy.

Year	
Year 1	Integration status is defined using data 1 year after the 2014 single payment policy was implemented.
Year 2	Integration status is defined using data 2 years after the 2014 single payment policy was implemented.
Year 3	Integration status is defined using data 3 years after the 2014 single payment policy was implemented.
Physician characteristics	
Average age	Average age of beneficiaries; beneficiary age is calculated at the end of the calendar year or at the time of death.
Average risk score	Average Hierarchical Condition Category (HCC) risk score of beneficiaries.*
(%) Cancer	Percent of beneficiaries meeting the CCW chronic condition algorithms for cancer. This includes breast cancer, colorectal cancer, lung cancer, and prostate cancer.
(%) Congestive heart failure	Percent of beneficiaries meeting the CCW chronic condition algorithm for heart failure.
(%) Chronic kidney disease	Percent of beneficiaries meeting the CCW chronic condition algorithm for chronic kidney disease.
(%) Chronic obstructive pulmonary disease	Percent of beneficiaries meeting the CCW chronic condition algorithm for chronic obstructive pulmonary disease.
(%) Female	Number of female beneficiaries.
(%) Depression	Percent of beneficiaries meeting the CCW chronic condition algorithm for depression.
(%) Diabetes	Percent of beneficiaries meeting the CCW chronic condition algorithm for diabetes.
(%) Hyperlipidaemia	Percent of beneficiaries meeting the CCW chronic condition algorithm for hyperlipidemia.
(%) Hypertension	Percent of beneficiaries meeting the CCW chronic condition algorithm for hypertension.
(%) Ischemic heart disease	Percent of beneficiaries meeting the CCW chronic condition algorithm for ischemic heart disease.
(%) Rheumatoid arthritis	Percent of beneficiaries meeting the CCW chronic condition algorithm for rheumatoid arthritis/osteoarthritis.

Notes: The data for the Physician and Other Supplier (PUF) are based upon CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service program. The data are available from the CMS Chronic Condition Data Warehouse (CCW)—a database with 100 percent of Medicare enrollment and fee-for-service claims data.

* HCC (hierarchical condition categories): CMS developed a risk-adjustment model that uses HCC (hierarchical condition categories) to assign risk scores. These scores estimate how beneficiaries' FFS spending will compare to the overall average for the entire Medicare population. The average risk score is set at 1.08; beneficiaries with scores greater than that are expected to have above-average spending and vice versa. Risk scores are based on a beneficiary's age, sex, and diagnoses from the previous year. The HCC model was designed for risk adjustment on larger populations such as the enrollees in an MA plan; it generates more accurate results when used to compare groups of beneficiaries rather than individuals. For more information on the HCC risk score, see: https://www.cms.gov/Medicare/HealthPlans/MedicareAdvtgSpecRateStats/Risk-Adjustors.html (accessed January 2, 2019). To protect the privacy of Medicare beneficiaries, the number of beneficiaries fewer than 11 has been suppressed, and the percent of beneficiaries between the 75th percentile and the 100th percentile has been top-coded at the 75th percentile. Information on source data is available from the CMS CCW, http://ccwdata.org/index.php (accessed January 2, 2019).

Source: Medicare Fee-For-Service Provider Utilization and Payment Data Physician and Other Supplier Public Use File: A Methodological Overview https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Downloads/Medicare-Physician-and-Other-Supplier-PUF-Methodology.pdf (accessed January 2, 2019).

Table B.11
Acronym definitions

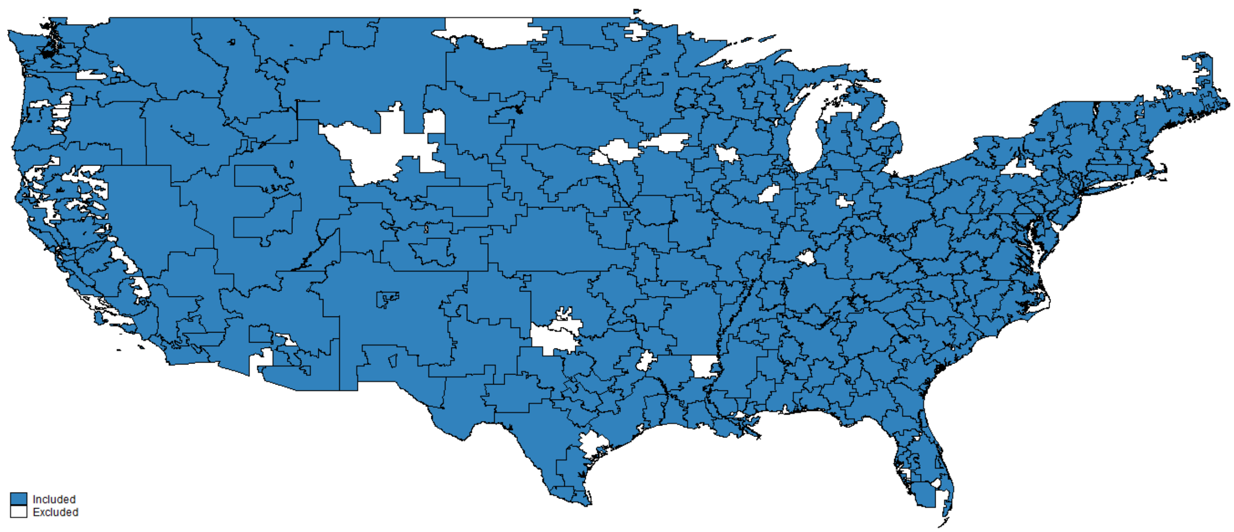
Acronym	Definition
APC	Ambulatory Payment Classification
CMS	Centers for Medicare and Medicaid Services
E&M	Evaluation and Management
FTC	The Federal Trade Commission
HCPCS	Healthcare Common Procedure Coding System
HOPD	Hospital Outpatient Department
MedPAC	The Medicare Payment Advisory Commission
NPI	National Provider Identifier
NPPES	National Plan and Provider Enumeration System
OPPS	Hospital Outpatient Prospective Payment System
PUF	Medicare Fee-For-Service Provider Utilization and Payment Data Physician and Other Supplier Public Use File

Appendix C

Appendix for Chapter 3

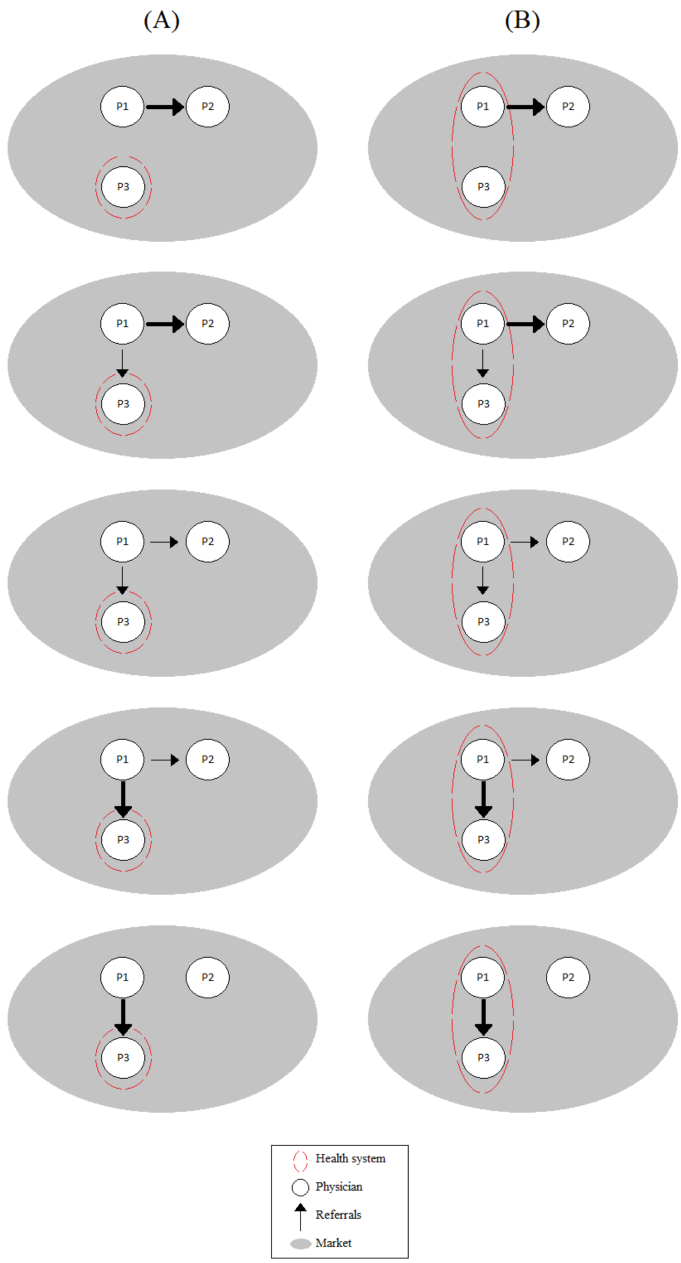
C.1 Figures

Figure C.1
Hospital referral regions (HRR) included in study



Source: SK&A, 2015

Figure C.2
Potential referral impact of hospital-physician integration



Notes: This figure presents a visual representation of all potential impacts of hospital-physician integration on the share of referrals made to oncologists. The figure presents a stylized market with three oncologists and one health system. The arrows represent patients referred from one oncologist to another oncologist, and oncologists encompassed by the red dotted line represent members of a health system. Panel (A) visually demonstrates an all possible referral behavior prior to hospital-physician integration. Panel (B) visually demonstrates an all possible referral behavior post hospital-physician integration.

C.2 Tables

Table C.1

Specialization	Integrated	Independent	Mixed
Clinical oncology	0.47	0.47	0.04
Radiation oncology	0.47	0.42	0.09
Surgical oncology	0.56	0.38	0.05

Notes: This table presents the distribution of the share of integration status of oncologist in the sample by specialization.
Source: SK&A (office level), 2009-2014

Table C.2

	Share of health systems an oncologist is employed by		Share of hospitals an oncologist is employed by	
Clinical oncology				
Number	Integrated	Mixed	Integrated	Mixed
1	0.99	0.99	0.97	0.96
2	0.01	0.01	0.03	0.04
Radiation oncology				
Number	Integrated	Mixed	Integrated	Mixed
1	0.98	0.96	0.96	0.95
2	0.02	0.03	0.04	0.05
Surgical oncology				
Number	Integrated	Mixed	Integrated	Mixed
1	0.98	0.98	0.97	0.95
2	0.02	0.02	0.03	0.05

Notes: This table presents the distribution of: 1) the number of health systems and 2) the number of hospitals oncologists in the sample are employed by over the course of a year.
Source: SK&A (office level), and Hospital Compare, 2009-2015

Table C.3

Number	Frequency	Share
1	318	0.53
2	122	0.21
3	45	0.08
4	37	0.06
5	18	0.03
6-10	44	0.74
11-20	9	0.15
21+	2	0.03

Notes: This table presents descriptive statistics on the number of hospitals in each health system in the sample. Source: SK&A (hospital level), 2015

Table C.4

	Share of offices patients are seen in				Share of patients seen at primary office				Share of patients seen in different settings	
Clinical oncology										
Number	All	Integrated	Independent	Mixed	All	Integrated	Independent	Mixed	Integrated office	Independent office
1	0.74	0.81	0.73		1.00	1.00	1.00			
2	0.21	0.16	0.21	0.71	0.72	0.74	0.69	0.76	0.55	0.45
3	0.04	0.03	0.04	0.22	0.58	0.61	0.55	0.62	0.55	0.45
4	0.01		0.01	0.05	0.49	0.52	0.47	0.52	0.53	0.47
5				0.01	0.45	0.43	0.45	0.46	0.52	0.50
6					0.50	0.43	0.52	0.49	0.54	0.46
7					0.46	0.42	0.48	0.39	0.54	0.46
8					0.38	0.41	0.35	0.46	0.13	0.87
9					0.33	0.30	0.30	0.40	0.16	0.84
10					0.10		0.10			
12					0.08		0.08			
Radiation oncology										
Number	All	Integrated	Independent	Mixed	All	Integrated	Independent	Mixed	Integrated office	Independent office
1	0.68	0.82	0.68		1.00	1.00	1.00			
2	0.22	0.15	0.21	0.65	0.73	0.73	0.72	0.73	0.53	0.47
3	0.06	0.02	0.05	0.24	0.57	0.59	0.55	0.57	0.50	0.50
4	0.02		0.02	0.06	0.49	0.49	0.48	0.50	0.46	0.55
5	0.01		0.01	0.02	0.45	0.36	0.41	0.53	0.33	0.67
6				0.01	0.44	0.28	0.45	0.51	0.27	0.73
7				0.01	0.50		0.51	0.42	0.34	0.66
8				0.01	0.39		0.40	0.36	0.23	0.77
9				0.01	0.37		0.37	0.35	0.21	0.79
10					0.36		0.38	0.32	0.23	0.77
11					0.41		0.41	0.38	0.15	0.85
12					0.36		0.34			
15					0.45		0.45			
16					0.45		0.45			
Surgical oncology										
Number	All	Integrated	Independent	Mixed	All	Integrated	Independent	Mixed	Integrated office	Independent office
1	0.79	0.79	0.89		1.00	1.00	1.00			
2	0.17	0.18	0.09	0.69	0.73	0.71	0.69	0.80	0.59	0.41
3	0.03	0.03	0.01	0.21	0.59	0.57	0.66	0.60	0.60	0.41
4	0.01			0.09	0.50	0.63	0.49	0.44	0.66	0.34
5				0.01	0.44		0.42	0.46	0.52	0.48
6					0.38		0.38			

Notes: This table presents the distribution of: 1) the number of offices oncologists in the sample see patients in over the course of a year, 2) the share of patients seen at an oncologists primary office over the course of a year—conditional on the number of offices an oncologist works in, and 3) the share of patients seen at integrated and independent office settings over the course of a year—conditional on the number of offices a mixed oncologist works in.
Source: SK&A (office level), 2009-2014