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Physicians Treating Physicians: The Relational and Informational Advantages in Treatment and Survival

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Using cancer registry and doctor certificate records, we address unobserved physician quality issues by matching comparable patients with advanced cancer by doctor, hospital, and admission period. Estimates show that physician-patients are less likely to use surgery or radiation, more likely to use targeted drug therapy, spend less on checkups, and enjoy higher long-term survival while paying less on coinsurance than nonphysician-patients. Restricting data to less informed physician-patients, we find that those with stronger professional ties receive less surgical/radiation therapy and have higher survival, though only for 0.5 years. We show that relational and informational advantages appear in healthcare agency problems. JEL: D83, I11, J44. Keywords: physician quality; social ties; communication; information.

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A growing literature in labor economics examines whether complete information or strong social ties can solve agency problems (Bandiera et al., 2009; Jackson and Schneider, 2011). Health economists recently joined this empirical investigation by randomizing doctors' races and incentives for vaccines to patients (Alsan et al., 2018) or exploiting OB/GYN doctors' rotating call schedules' exogenous variation in doctor-patient clinical relationships (Johnson et al., 2016). They find that communication or patients' trust in physicians strongly affects the demand for preventive care (Alsan et al., 2018) or a Cesarean section (Johnson et al., 2016). Both studies use compelling research designs aiming to address the problems with unobserved doctor quality and patient selection.

Besides experimental designs, observational studies have examined whether physician-mothers are more/less likely to have a Cesarean section than nonphysician-mothers.[1] These studies find mixed results. Grytten et al. (2011) find that physician-mothers receive a Cesarean section with higher probability, which they attribute to a closer relationship or better communication with attending doctors. Conversely, Chou et al. (2006) and Johnson and Rehavi (2016) find physician-mothers have a lower probability of receiving a Cesarean section, which they attribute to better information on complications or potential side effects. Irrespective of underuse due to weak social ties or overuse from asymmetric information, the conjectured relational and informational advantages that physician-mothers afford are *empirically inseparable* when restricting the analysis scope to one medical specialty.

[1] Alongside experimental designs, several observational studies have compared self-treatment with treating others to detect healthcare agency problems (Bronnenberg et al., 2015; Carrera and Skipper, 2017); Levitt and Syverson (2008) adopt the same approach to test for agency problems when consumers are experts. However, this comparison might capture the difference in the susceptibility between self-treatments versus treating others, not necessarily reflecting the physician-patients' effect on treatment choice (Ubel, Angot, and Zikmund-Fisher, 2011; Shaban, Guerry, and Quill, 2011). Several earlier studies have avoided the susceptibility bias by comparing physician-patients' healthcare utilization versus other patients' (Bunker and Brown, 1974; Hay and Leahy, 1982).

This paper is the first to evaluate the relative importance of the relational and informational influences in healthcare agency problems by relaxing this restriction. Crucial to our evaluation is a wide range of individually identifiable medical specialists who have attended about 0.3 million patients with advanced cancer, of whom 611 are physician-patients. Using Taiwan's cancer registry, doctor personnel panel records, and universal health insurance administrative data, we have rich controls for both patients' and doctors' attributes. By looking within the matched physician-patients with different specialties attended by the same doctor, we aim to disentangle the relational advantage's impact due to stronger professional ties from the informational advantage's effect driven by being more informed.

Because of no experimental variation, we address unobserved physician quality and patient selection issues using Abadie and Imbens' (2006, 2011) nearest-neighbor matching method, which allows for complex interactions among covariates without linearity assumptions. Our approach is to exploit the *within doctor-hospital* variation across *matched patients* by cancer site, demographics, income level, admission period, previous inpatient cost, and preexisting clinical relationship. This strategy allows us to remove the bias resulting from high-quality doctors with a higher probability of attending physician-patients.

Before evaluating the relational and informational advantages, we follow the literature to compare physician-patients' treatment choice and survival with comparable nonphysicians'. Our matching estimates show that the average physician-patients are less likely to adopt surgical/radiation therapy but more likely to use targeted drug therapy. They also spend less on checkups/coinsurance and enjoy significantly higher long-term survival. These estimates range from 0.2 to 0.4 standard deviations, and all are statistically significant at conventional levels.

These basic results conform to relational and informational mechanisms and other competing explanations, such as the relatively early diagnosis and early treatment of physician-patients. We rule out both competing hypotheses empirically. Using the universal cancer register, we find that doctors are equally likely to detect cancers in the early/advanced stage for physician-patients and nonphysician-patients. Our matching estimates show almost no difference in the diagnosis-to-treatment interval between these two types of patients. The physician-patients in our data are not diagnosed or treated sooner than others. Another model that could generate our basic results showing lower intensive care utilization rates among physician-patients is that nonphysician-patients are more likely to sue. Doctors may use more unnecessary procedures for nonphysician-patients (Currie and MacLeod, 2008). However, Taiwan's tort liability literature shows that most lawsuits are in the ER (Chen et al., 2012), but none of our matched hospital entries appear in the ER. Unequal propensities to sue are an unlikely explanation for our results.

Beyond our basic results, we assess the relative importance of the relational and informational mechanisms by exploiting the specialty composition variation across doctors and physician-patients. We quantify each doctor-patient pair's *relational benefit* (by looking at whether they share the same specialty area) and *informational advantage* (by looking at whether the patient specializes in the area related to her cancer site). When we restrict ourselves to physician-patients with advanced cancer but no informational advantage, we find that the relational benefits increase medication costs and targeted therapy utilization, consistent with the different treatments received by physician-patients versus nonphysician-patients. However, the relational benefits also <u>increase</u> surgery/radiation/palliative care utilization and lead to a higher survival rate, although only in the short term, contrary to the average physician-patient's long-term survival advantage and reduction in these therapies relative to other patients.

These findings show that information advantage <u>reduces</u> intensive care utilization. In contrast, the relational benefit <u>increases</u> intensive care for improving short-term survival. With both advantages, physician-patients have both relational and informational mechanisms working in opposite directions. Eventually, average physician-patients utilize less intensive care in a more advanced stage. All the above results combined suggest the relational mechanism's inability to interpret and the informational mechanism's dominance to explain the treatment differentials between average physician-patients and other patients.[2]

Our assessment of the relational and informational mechanisms contributes to the broad literature on healthcare agency problems. The previous research has focused primarily on doctor-driven channels, including financial incentives and asymmetric information. We freeze both channels by looking within the doctor-hospital variation across physician-patients specializing in areas unrelated to their cancer sites. The matching estimates demonstrate that the doctor-patient relationship matters for cancer treatments and short-term survival at the advanced stage. For both relational and informational mechanisms to work, the theoretical context needs to contain the doctor-driven demand hypothesis in a framework where risk-averse patients undervalue the benefit of intensive care and thus have lower demand. A stronger doctor-patient relationship can overcome the risk aversion via better communications and building trust to induce the demand.

The rest of the paper proceeds as follows. Section 1 describes the data and institutional settings and summarizes our data features. Section 2 discusses our matching scheme of constructing the study sample, reports balance statistics and the core estimates, and implements robustness checks. Section 3 considers alternative explanations for our findings and undertakes an additional analysis of the data to compare the alternatives. Section 4 extends our analysis to distinguish relational effects from informational advantages of treatment intensity and survival rates and explores the possible mechanisms. Section 5 concludes the paper.

[2] Frakes et al. (2019) use data from Military Health System and find that physician-patients received only slightly more medical care. It could be the case that the physician-patient effects potentially contain relational advantages which might have cancelled out the informational premium, leading to a seemingly near-zero effect.

1. Data and Institutional Settings

A. Patient Cost-Sharing and Provider Reimbursement

We use data from Taiwan's National Health Insurance (NHI) database, which is ideal for this study for several reasons. First, the Taiwanese NHI is a single-payer system for all citizens and residents, like Canadian systems, consisting of one uniform comprehensive care benefits package covering drugs, hospitals, and primary care (Hsiao et al., 2016).

Given that participation in the NHI is mandatory, we can eliminate the doubts of adverse selection issues existing in the insurance system. Also, because the NHI database provides data on beneficiaries who have never checked into a hospital and those admitted, we can address patient selection issues.

Furthermore, the NHI administration manages health expenditure inflation via a reimbursement mechanism to providers, rather than charging deductibles or capping out-of-pocket expenses. The reimbursement is on a fee-for-service basis through a nationally uniform fee schedule; thus, providers cannot select or price-discriminate patients. Since hospitals pay doctors also by fees-for-services plus a basic salary that varies across hospitals, doctors' and hospitals' financial incentives are similar.

Moreover, the NHI system imposes a small penalty (only 7 US dollars in 2014) for a hospital visit without first receiving a primary care referral. Consequently, almost all patients choose attending doctors without a primary care referral. Given that patients can freely check into different hospitals or into the same hospital to see various doctors, we analyze doctor-patient relationships by looking into *hospital admissions* data. Hospitals in Taiwan follow a closed-staff structure where the on-staff doctor assumes full responsibility for their medical care. This institutional setting ensures that our patient-physician-matched data well-defines the interactions between doctors and patients during each hospital admission.

B. Data Linkage

Using the NHI Database from 2000 to 2016, we merge administrative data sources by unique scrambled identifiers (IDs) in four steps. First, we link the Cancer Registry to the Death Registry and the Registry of Beneficiaries. This data linkage covers each cancer patient's diagnosis date(s), cancer site(s), and diagnosis stage. It also documents the treatment methods, demographic backgrounds (sex, birthday, income bracket, and registration district), and the death record if the patient was deceased by the end of 2016 whether they received hospital care or not. Approximately 12 percent of the cancer diagnoses resulted in no hospital care.

Second, we identify the physician-patients and obtain their medical specialties by further merging the data with the Registry for Medical Personnel and the Records of Board-Certified Specialists using their IDs. The former covers information about sex, birthday, and the certification date, and the latter records each doctor's medical specialties and practice locations over time.

Third, we compile the above data with Reimbursement Claim Records to obtain inpatient care details per hospital admission one year after a cancer diagnosis. This data set reveals the entire history of the treatments, care volumes, hospital type and location, hospital ID, and attending doctor's ID before and after the diagnosis. Thus, we can calculate total inpatient care costs, coinsurance payment, and spending on medicines, surgery, tube feeding, radiation therapy, and examination for constructing the covariates and outcome variables. Finally, we derive the attending doctor's certified specialty and experience by linking to the Registry for Medical Personnel and the Records of Board-Certified Specialists, again using the attending doctor's ID.

C. Time-Varying Physician Selectivity

Like physician experience, physician selectivity can vary over time. However, unlike experience information that might be known to the general public, the precise knowledge about doctor selectivity is typically unknown, except to expert patients. Using the rich panel data that match patients to their attending doctors, we proxy an expert patient's information about a doctor's selectivity at diagnosis time t using the percentage of hospital admissions made by physician-patients during the past three years before t. For instance, if a doctor has attended 1,000 hospital admissions in the past three years, where only three were physician-patients, the selectivity measure takes the value of 0.3 percent.

Our data shows physician-patients with advanced cancer only see a particular set of doctors who are considerably more selective than other doctors. As we can see in Table 1, inpatient doctors who have never attended to any physician-patient have an average selectivity value of as low as 0.22 percent. In contrast, doctors chosen by physician-patients have a selectivity value at about 0.39 percent, higher than that of nonphysician-patients by more than three quarters (0.17/0.22). The distribution of doctor selectivity is hugely skewed to the right, as most doctors have not seen any physician-patient during the data period. Some doctors' selectivity grows as they become more experienced. As a result, the patients treated earlier are not necessarily comparable to those treated later. The extraordinarily skewed and time-variant doctor selectivity measures are one major challenge of this empirical work. Only a few nonphysician-patients can be compared to physician-patients because we need to fix the attending doctor and the admission time to remove the bias due to patient selection in unobserved doctor quality that might vary over time.

D. Descriptive Statistics

The combined data consist of more than 1.2 million cancer diagnoses among approximately 1 million patients and 1,989 medical doctors. Because Death Registry is available to this study only until December 2016, the N-year survival indicator needs to forgo N years of the combined data. More than 80 percent of cancer patients survive beyond 180 days, and close to 60 percent live more than three years after the first diagnosis. Table A1 summarizes the statistics of cancer diagnosis and patients' attributes and health outcomes. Of all the cancer diagnoses from January 2004 to December 2016, 30 percent are at the advanced stage at the first diagnosis.[3] We began the data period from 2004 January when Taiwan started adopting the AJCC Cancer Staging Manual, the benchmark for classifying patients with cancer, prepared by the American Joint Committee on Cancer. Our analysis covers all the cancer sites, as listed in Table A2's column 3.

One concern is that doctors might have diagnosed physician-patients' advanced cancer earlier than other cancer patients. This sample selection issue would lead this study to overstate physician-patients' treatment and survival advantages. However, Table A1's statistics show otherwise. The first diagnoses for physician-patients are three percentage points more likely to be advanced cancer than those for other cancer patients. This difference further drops to below 0.7 percentage points (with a standard error of 0.009 clustered at patient levels) after holding constant the patient's sex, age, income, region, and spending inpatient care, and diagnosis year. These results suggest that the potential bias due to earlier diagnoses by physician-patients is unlikely in our data.[4]

[3] We identify a hospital admission as "advanced cancer" if the cancer is invasive (the fifth digit of HISTBET = 3), if the patient has multiple cancer sites, or if cells are poorly differentiated anaplastic grade (GRADE = 3 or 4; for colon, rectum, or ovary cancer, any GRADE value except B).

[4] Nine percent of advanced cancer diagnoses did not lead to hospital care, and these statistics are equal between physician- and nonphysician-patients (Table A1). Since no inpatient doctors have attended those patients, we exclude them from our analysis.

We include all the hospital admissions associated with advanced cancer patients at the first diagnosis. Each diagnosis could lead to one or more cancer therapies, including surgery, chemotherapy, radiation therapy, hormone therapy, palliative care, targeted therapy, immunotherapy, stem cell, and Chinese medicine. We exclude the last three from our analysis because less than 9 percent of admissions adopted any of them (Table A1). Namely, only 0.07 percent of admissions adopted Chinese medicine therapy, while no physician-patient uses it.

Table 1 compares hospital admissions between physician- versus nonphysician-patients with advanced cancer, with standard errors clustered at patient levels. Given Taiwanese hospitals' closed-staff structure, each admission matches one attending doctor to one patient. This data covers 1,123,377 admission entries associated with 269,399 nonphysician-patients, where 2,454 entries are associated with 611 physician-patients.

Table 1's statistics show that physician-patients are substantially older, wealthier, more masculine, and have spent less on hospital care before the first cancer diagnosis. Both types of patients are almost equally likely to visit a doctor with a preexisting clinical relationship. However, physician-patients tend to opt for a more experienced male doctor who practices in single locations and specializes in a cancer-related area or practices in a cancer-related department.

On average, there are 123 days from the first diagnosis to inpatient treatment for nonphysician-patients, approximately six days longer than for physician-patients. This difference is at the 90 percent significance level. Nonphysician-patients stay in acute inpatient care units for about eight days, while physician-patients are 10 percent (0.8 days) shorter at the 95 percent significance level.

The unconditional mean difference tests in Table 1 show that physician-patients are less likely to adopt surgery and chemotherapy (5 percent = 0.04/0.8; 8 percent =0.05/0.66) but drastically more likely to use targeted treatment by 44 percent (=0.05/0.11). However, these observed gaps may result from the differences in health or socioeconomic conditions or self-selection into different doctors' practice styles between physician- and nonphysician-patients.

Finally, the bottom part of Table 1 shows that physician-patients with advanced cancer have almost the same 180-day survival rate as other patients. However, their survival rates are substantially higher in longer terms (both one and three years). Physician-patients' survival advantages seem inconsistent for male patients and older patients at a more advanced stage. Those advantages may result from expert patients' selection of doctors, income effects, better communication, closer relationships with the attending doctor, or more cancer-related knowledge.

2. Core Estimates

This section estimates the total effect of a physician-patient on treatment choice and health outcomes. To address patient selection on unobserved doctor quality, we adopt matching methods. We compare hospital admissions by physician-patients and comparable nonphysician-patients attended by the same doctor in the same hospital. To ensure patient comparability, we also match exactly on a comprehensive list of patient types, including cancer sites, income levels, demographics, admission periods, and previous inpatient costs.[5] We choose to use the nearest neighbor matching procedure because it allows complex interactions among those covariates. Since the method nonparametrically matches patient admission periods within doctor-hospital, we can capture any time-varying component in doctor and hospital quality, in addition to any time-invariant variation across doctors and hospitals. In what follows, we report balance statistics, document matching estimates, and present robustness checks using fixed-effect linear regressions.

[5] We control for the following list of "patient types": gender, 17 cancer sites, 2-year age bins, 4-year admission period, six residence regions, hospital spending quintile four years before diagnosis, income quintile in the year before the first diagnosis, and an indicator for a preexisting clinical relationship with the attending three years before diagnosis.

A. Balance Checks

We first leave the attending doctor unmatched and only compare nonphysician-patients to physician-patients with the same patient types in the same hospital. Table 2 shows the balance checks for two matching schemes: scheme-A (left panel) considers the exact match on patient types within hospitals, and scheme-B (right panel) is within doctor-hospital. This initial match (scheme-A) excludes 98 percent of nonphysician-patients and 84 percent of physician-patients due to non-overlap in the covariate cells. As expected, the overlap is rare in matching physician-patients to other patients with advanced cancer because the former is significantly older, healthier, and wealthier, and is composed of more males than the latter. After matching, the total number of admissions is 2,811, consisting of 98 physician-patients (685 admissions) versus 565 matched nonphysician-patients (2,126 admissions).

Although scheme-A drastically narrows down the set of comparable patients, most of them see different attending doctors. As a result, the observed difference in outcomes between physician-patients and other patients might merely reflect physician quality effects. We improve the balance of the matches by further matching attending doctors in scheme-B. This step reduces the sample size to 31 physician-patients (252 admissions) versus 69 nonphysician-patients (300 admissions).

Table 2 compares the balance statistics between matching schemes A and B. We report the p-values of testing the mean difference (t-tests) and the distributional difference (KS-tests) in a set of predetermined doctor attributes and patient health proxies on which the scheme did not match. For the covariates that we have precisely matched, both the t-test and KS-test have p-values equal to 1. The scheme-A statistics show that the patients' pre-diagnosis health conditions, proxied by pre-trend in inpatient cost and prior spending on drugs, are balanced statistically. In contrast, the attending doctors who treated physician-patients have 0.3 SD (standard deviations) more experience than those who treated nonphysician-patients. The distributions of doctor gender, mobility, and the number of specialties also differ significantly between physician-patients and nonphysician-patients.

After further matching patients on their attending doctors in scheme-B, none of these pre-diagnosis characteristics are significantly different from each other, neither in their sample mean nor in their distributions. This result shows that the attending doctor's matching substantially improves the balance on observables, making it plausible that unobserved confounders also balance out.

B. Matching Estimates

Table 3 reports the matching estimates for these two matching schemes: (A) the within-hospital comparison between the 2,811 matched admissions and (B) the within-doctor-hospital comparison between 552 matched entries. In columns (1) and (5), we display the SD in outcomes after removing the matched covariates' variation. Matching additionally on the attending doctor in scheme-B reduces the SD by 15 percent to 75 percent.

Since scheme-A does not match hospital entries according to attending doctors, physician-patients in this scheme tend to see more experienced and selective doctors than nonphysician-patients (Table 2). Suppose that physician-patients are less likely to opt for intensive therapies at a more advanced cancer stage and more capable of identifying highly skilled doctors than other patients. Also, assume that experienced or highly qualified doctors tend to use more intensive care and order more tests.[6] In that case, we will understate the physician-patient's negative impact

[6] The previous literature has suggested that greater intensive care can prolong life. Namely, Balsa and McGuire (2003) and Currie, MacLeod, and Van Parys (2015) show that patients benefit from the aggressive treatment of lung cancer or heart attacks via intensive procedures.

on intensive care utilization and checkup costs if we do not match on attending doctors.

Further matching on the attending doctor, we see scheme-B drastically adjusts the physician-patient's impact upward on surgical/radiation adoption and the costs for examinations as expected. Physician-patients are eight percentage points less likely to undergo surgery and seven percentage points less likely to adopt radiation therapy. These estimates are statistically significant and account for 42 percent and 21 percent of the residual SD, respectively. In contrast, scheme-B adjusts downward the intensive margins on intensive care volume. A physician-patient's impact on the tube-feeding care volume drops from approximately 0.3 log points to 0.03 log points. The effect on radiation volume is also substantially reduced and becomes statistically insignificant.

Our benchmark (scheme-B) shows that physician-patients are significantly less likely to adopt surgery by 0.4 SD (0.083/0.20) and radiation therapy by 0.2 SD (0.071/0.33). As for intensive margins, physician-patients also utilize lower surgical volumes than their counterpart by 0.4 SD (1.159/2.87) while taking approximately the same dose of radiation as other adopters. While using less intensive care, physician-patients with advanced cancer are also less likely to adopt palliative care by 0.2 SD (0.027/0.16). The only item that physician-patients utilize more is prescription medications; they spend 0.4 SD (0.652/1.80) more on drugs relative to other patients.

Physician-patients with advanced cancer spend more on medications could be due to higher quantity, more varieties, or increased prices (e.g., on patent brands) of drugs consumed.[7] However, the NHI administration sets the reimbursement

[7] Bronnenberg et al. (2015) show that more informed patients are around a quintile less likely to buy on-patent brand headache medications than comparable patients. Carrera and Skipper (2017) find physician-patients and nonphysician-patients equally likely to fill prescriptions with generic drug formulations after its patent has expired. However, physician-patients tend to start treatment with on-patent brand drugs earlier than other patients.

price uniformly for each drug and adjusts the price biannually according to a universal formula (Chen and Chuang, 2016). Doctors and hospitals cannot discriminate among patients and charge different fees. This institutional feature leaves the increased drug dose or varieties for physician-patients as likely explanations for the physician-patient's positive impact on NHI drug cost. Given the current data accessibility, this study cannot distinguish the difference in quantity from the difference in varieties.

Finally, we explore whether our basic results derived from nonparametric matching are consistent with the estimates using conventional models. Table 4 shows that the fixed-effect estimates in columns (2) and (3) are strikingly similar to the matching estimates in columns (5) and (6) (derived from Table 3, columns 6−7). However, the fixed-effect results tend to be less precise and suffer from type-II errors. Specifically, the fixed-effect estimator fails to detect a large and significant physician-patient impact on adopting four out of six cancer therapies, including surgery, radiation therapy, targeted therapy, and palliative care.

Unlike fixed-effect models, matching methods are applicable even when the outcome distribution has a mass point at 0 or 1. As 93 percent of our matched sample survive beyond 180 days after the first diagnosis, we follow econometricians' recommendations to use logistic regressions (e.g., Hirano et al., 2000) or quantile regressions. Unfortunately, neither regression model converges for the 180-day survival outcome in our fully matched data.

C. Cost-Effectiveness

We have shown that physician-patients receive less surgery/radiation treatments for advanced-stage cancers than the matched nonphysicians while spending more on drugs and more likely using targeted therapy. According to medical guidelines published by the American Cancer Association, surgery and radiation are more appropriate for early-stage cancers. A more advanced-stage cancer requires treatments to reach the entire body, such as chemotherapy and targeted drug therapy. If the treatments for physician-patients are clinically appropriate, our results indicate that underuse and overuse coexist among nonphysician-patients.

Physician-patients indeed have received different and better care. Table 3 shows the considerable survival benefits of better treatments. Results in columns 5–7 indicate that physician-patients have significantly higher short-term and mid-term survival rates than comparable patients by 2.5 ppts and 9.3 ppts, respectively, at 180-day and 365-day thresholds. The long-term survival is also higher by 7.1 ppts at the 3-year cutoff. All these estimates are statistically significant at the 99 percent level and account for at least one-quarter of the standard deviation.

Besides the survival benefits of better treatments, physician-patients enjoy lower costs than comparable nonphysicians. Our results in columns 6–7 show that physician-patients pay significantly less for coinsurance by 0.226 log points. Overall, physician-patients receive cost-effective care relative to what the matched patients received.

3. Competing Explanations

Several theories could explain our observed reduction in physician-patient intensive care volume and survival advantages. This section examines the possibility that physician-patient relational or informational benefits do not drive our results. We explore four alternative explanations for our observed decrease in intensive care volume for physician-patients: physician-patients are diagnosed earlier with cancer or receive cancer therapies earlier than others; physician-patients exhibit a better health status than nonphysician-patients; physician-patients are more likely to sue for malpractice; finally, physician-patients differ from nonphysician-patients in unobserved ways. We examine each hypothesis below.

A. Physician-Patients Are Diagnosed Earlier or Treated Earlier

Physician relationships and information advantages might have led to earlier diagnosis or earlier treatments than nonphysician-patients, so physician-patients need less intensive care and survive longer than others. Using the universal Cancer Registry, we have failed to accept the hypothesis that the physician-patient status reduces the probability of being diagnosed too late (recall Section 1D).

In Table 3, the matching estimates in panel (B) have shown that physician-patients have almost no impact on the number of days from diagnosis to treatment. Physician-patients have 1.3 days longer waiting times than other patients. This difference is statistically insignificant and accounts for less than 2 percent (1.3/75.6) of standard deviations. Thus, we also cannot accept the hypothesis that physician-patients are treated earlier than nonphysician-patients.

B. Physician-Patients Exhibit Better Health

To ensure our physician- and nonphysician-patient groups are similar in health status, we match patients equally based on their previous hospital spending quintile in the past four years before the first diagnosis of advanced cancer. Nonetheless, it remains possible that physician-patients are healthier than their counterparts in a way not captured in our model. We test this hypothesis by checking the balance on other health variables that we have not matched. In other words, we run placebo tests with these pretreatment variables as outcomes. If physician-patients have better health than comparable nonphysician-patients, then we should observe significantly lower spending on medications or lower growth rates in inpatient costs before diagnosis.

However, the placebo test results in Table 2 show otherwise. The matched physician- and nonphysician-patients do not differ significantly on their previous drug spending or pre-trend hospital cost. These findings are robust, irrespective of scheme A or B (e.g., fixing the attending doctor or not), as long as we have matched admissions by patients' attributes, cancer site, and admission period within hospitals. Based on the above findings, we conclude that our result of decreased surgical or radiation therapy adoption or volumes is not attributable to physician-patients' better health status.

C. Physician-Patients Are Less Likely to Sue for Malpractice

Another possible explanation for our finding of reduced intensive care for physician-patients is that they are less likely than nonphysician-patients to sue for malpractice. From 2004 until 2016, medical doctors in Taiwan were subject to both no-fault liability and joint and severe liability (Chen et al., 2012; Ministry of Health and Welfare, 2018). As Currie and MacLeod (2008) suggest, concerns about potential liability may make doctors carry out more unnecessary procedures, especially for nonphysician-patients in our context. To examine this explanation, we investigate the frequency of possible malpractice lawsuits for the physicians' data. In Taiwan, ER physicians are the most likely to be sued and make the highest median payment (Chen et al., 2012). However, none of our matched physician-patients checked into the ER after being diagnosed with advanced cancer. In the entire cancer registry since 2004, only three entries by physician-patients appear in the ER. These statistics suggest that defensive medicine is unlikely to explain the lower utilization rates of surgical/radiation therapy among physician-patients.

D. Physician-Patients Differ from Other Patients in Unobserved Ways

Despite our best attempts to match hospital admissions according to hospitals, attending doctors, and patient socioeconomic backgrounds, our physician- and nonphysician- patients may differ on dimensions not included in our study, such as education, clinical knowledge, risk aversion level, or trust in their doctors. We directly test whether cancer treatment and care intensity change with informational or relational advantages among matched physician-patients.

All physician-patients have closer professional ties with their attending doctors and greater access to medical information than other patients. Still, both relational and informational advantages vary across the physician-patients' and their doctors' specialty compositions. For example, suppose both the patient and attending doctor specialize in areas unrelated to the patient's cancer site. Compared to other specialty compositions, they are more likely to have a closer professional tie but less likely to have relevant knowledge or clinical experience related to cancer treatments. Using the variation in relational and informational advantages among physician-patients, we can minimize unobserved heterogeneity and address the omitted variable bias. The next section expands on this idea and documents our findings.

4. The Relational versus Information Mechanisms

In this section, we limit our data to physician-patients to probe how the relational and informational mechanisms differ in their impacts on treatment choices and patient survival. By exploiting the variation in their medical specialties and professional ties with their attending doctors, we aim to isolate the effect of having a closer professional connection from being more informed. We extract those parts of the physician-patient effect related to relational advantages, which the previous studies often interpret as an informational effect.

Our matching estimates suggest that physician-patients with a closer professional tie spent substantially more on medication and targeted therapy, which is consistent with the average physician-patient's impact on medication costs. However, physician-patients with relational advantages are *more* likely to utilize surgery/radiation therapy and receive palliative care than other physician-patients. In contrast, the average physician-patients use *fewer* of the same treatments than other patients, as shown in Section 3. This contrast implies that although relational favoritism is at work among physician-patients, the relational mechanism alone cannot explain the differences in therapy choice between the average physician-patients and nonphysician-patients. Other channels—plausibly, the information mechanism—dominate it. We use matching methods to confirm this hypothesis empirically and expand on these findings below.

A. Quantify the Relational and Informational Advantages

To quantify physician-patients' relational and informational advantages, we define two dummy variables. Every physician-patient is somewhat informed. Physician-patients whose medical specialties are related to their cancer sites are defined as *more informed* (indicated by I). Moreover, every physician-patient has some professional connection with the attending doctor. However, specialist-patients who share the attending doctor's specialty are said to have a *robust professional tie* (indicated by R). Such doctor-patient pairs are more strongly connected than other pairs because they are more likely to have met each other on professional occasions before the cancer diagnosis. Because the attending doctor is fully responsible for caring for the patient in each admission under Taiwanese NHI's close staff structure, we can use NHI data to define the professional tie per doctor-patient pair.

Among the 611 physician-patients diagnosed with advanced cancer from 2004 to 2016, we observed 2,453 hospital admissions, of which 19 percent had more-informed physician-patients, and 38 percent had a robust professional tie between the patient and those attending. Despite the homogeneity by occupation and cancer stage, this data still shows differences among physician-patients in their age and male percentage across relational and information advantages (Table A6). On average, more informed physician-patients are five years younger and are at least three percentage points less male than the less knowledgeable physician-patients. Physician-patients with a robust professional tie tend to see doctors with more experience by about half a year than other physician-patients without it. To address patient heterogeneity and self-selection of doctor quality, we continue to use matching methods as detailed below.

B. Exploration of Mechanisms

This subsection explains how we assess the relative importance of the relational and informational advantages among physician-patients. Let β_{IR} denote the total impact of a physician-patient on outcomes, given her relational and informational advantage indicators, I and R. By exploiting the variation in these two indicators across physician-patients, we aim to decompose the total impact into four components:

$$\beta_{IR} = \beta + \eta I + \rho R + \delta I \times R,$$

where β captures the difference in outcomes between nonphysician-patients and physician-patients who have none of these two advantages. The coefficient η is the physician-patient's main benefit from being more informed than other physician-patients while ρ the physician-patient's main benefit from having a robust professional tie. Finally, δ is the effect of having both advantages on outcomes.[8]

Table 5 displays the composition of cancer patients according to their advantages. It also suggests a matching procedure for parameter identification, as illustrated in the bottom and side panels. Using ρ the relational benefit as an example, we first restrict data to less informed physician-patients. By comparing those with a strong

[8] It is noteworthy that the relational and informational components in β remain inseparable like the previous literature. However, we contribute to the literature by assessing the relative importance of relational and information advantages *among physician-patients*, enhancing our understanding of how asymmetric information and relational favoritisms determine the differences in outcome between nonphysician-patients and physician-patients with no relative advantages over other physician-patients.

tie to comparable ones without such a connection, we can identify ρ. Similarly, we can estimate (η−ρ) the difference between relational and informational benefits by limiting the data to physician-patients with I+R=1 (the dark grey areas), who are either more informed or strongly connected with the attending doctor.

To minimize the selection bias in the nonrandom assignment of professional connections, we require exact matches on doctors, hospitals, patient sex, and broadly-defined cancer sites while controlling for patient backgrounds.[9] This empirical strategy means that we consider only inpatient doctors who attend multiple physician-patients of same-sex with the same cancer site, but with different advantages. With these stringent data requirements, we expect to have a low match rate.

Using the nearest-neighbor matching technique, we begin with an identification of ρ the relational advantage. Before matching, we have 597 physician-patients specializing in areas unrelated to their cancer sites (I=0), where approximately one-third of the entries attended by doctors strongly connected to the patient (R=1) and the other two thirds not strongly connected (R=0). We drop 93 percent of these entries from analysis because of no exact match on doctors, hospitals, patient sex, or broadly-defined cancer sites. After matching, the comparison is between 73 entries with professional ties versus 80 entries without it. These 153 cases cover five broadly-categorized cancer sites among 52 physician-patients attended by 11 doctors in 5 hospitals.[10] We derive the exact match rate of 8 percent (=153/(1349+629)). See these statistics in Table A6.

[9] Here we include the following patient backgrounds: two-year age bins, admission periods, income levels, previous inpatient costs tercile, and five-year doctor experience bins. Given 17 cancer sites and 22 medical specialties in NHI data, we simplify our analysis by grouping these sites and specialties into five specialty categories (Table A2). We proxy the specialty area for physicians with no specialty records using their hospital department (Table A3).

[10] Here, we group the 17 cancer sites (see Table A2) into five categories: (1) digestive organs and peritoneum, (2) respiratory system and chest cavity, (3) bones, skin, and connective and other subcutaneous tissues, (4) breast, reproductive, and urinary organs, and (5) others (e.g., eyes, central nerves, endocrine glands, and body parts affected by leukemias)

The first two columns of Table 6 show the balance statistics of predetermined variables not included in this matching procedure. Although we have left doctor time-varying quality measures and patient health proxies and demographics unmatched, these variables do not significantly differ in means or distributions, making it plausible that unobserved doctor qualities or patient characteristics also balance out.

Columns 2 and 3 of Table 7A display the matching estimated effects of the relational mechanism on treatments/outcomes for physician-patients less informed. Perhaps surprisingly, the relational impacts and the average physician-patient effects (columns 8–9) typically go in contrary directions. The relational advantage *increases* surgery, radiation, acute care, and palliative care utilization by over a quarter of SD (on extensive margins). Contrastingly, typical physician patients use these treatments with a significantly *lower* probability. The average physician-patients face substantially *lower* checkup and surgery costs by about 40 percent of SD (on intensive margins). Conversely, our result suggests that the relational advantage has almost no impact on either spending.[11]

These contraries imply that the relational mechanism alone cannot explain why typical physician-patients with advanced cancer spend less on checkups while using surgery/radiation therapy or palliative care with a lower probability. Since we have eliminated competing explanations (Section 3), the *information mechanism's dominance* remains the leading explanation for physician-patients' reduced checkups and surgery and radiation therapies at a more advanced cancer stage.

Contrastingly, the relational mechanism can explain why average physician-patients spend more on drugs and use targeted therapy with a higher probability. In columns 1–3 and 7–9 of Table 7A, the relational impact and the average physician-

[11] We omit hormone therapy from our analysis in this section because it is used to treat prostate and breast cancers. Given patient sex and cancer site, the data show almost no variation in doctor specialty, leaving the parameters of interest unidentified.

patient's effect on medication cost and targeted therapy utilization are significantly positive and large in magnitude, accounting for at least a quarter of SD. These concurrent results suggest the *relational mechanism* can correctly project the differences in treatment decision making, at least for medication costs and target therapy utilization between physician-patients and other patients. This result provides direct evidence of stronger social ties and professional connections impacting treatment. A strong professional relationship with the attending doctor, not a general social relation or status, can lead to higher drug spending and increased target therapy use.

To compare the importance of the relational and information mechanisms for interpreting these two treatment decisions, we estimate ($\eta-\rho$) the difference between relational and informational advantages (by restricting data to physician-patients with I+R=1, who have either the relational or informational advantage but not both). Our results in columns 4–6, in conjunction with the relational advantage's effects on both treatments in columns 1–3, indicate that the information mechanism increases drug spending and targeted therapy utilization *even more*. The difference between the information and relational effects is positive and statistically significant at the 90 percent level or better. These findings confirm the relational mechanism's presence and the information mechanism's dominance, which lead to different treatments.

Moreover, we use the same procedure to estimate η the information's main effect, and ($\eta+\delta$) the information's total impact, where δ is the benefit of the information derived via professional ties. This step requires comparing hospital admissions between more- versus less-informed physician-patients, after restricting data to those with or without a professional connection, R=1 or 0. Although the matched samples are well balanced, the sample size reduces, as Table 7B indicates. Nevertheless, we find evidence of a *shorter* waiting time to treat *more informed* physician-patients by 54.5 days—more than 60 percent of SD (η<0, columns 1–3). This result is contrary to the relational advantage's near-zero impact on waiting time, as Table 7A has indicated.

When more informed physician-patients have stronger professional ties, their network might provide extra knowledge such as authoritative physician opinions.[12] However, network-induced information seeking may prolong the waiting time, leading to a positive δ, which would offset the information's main effect and increase the total medical cost. Table 7B's columns 5–6 limit the data to physician-patients strongly connected with their attending doctors (R=1). We find the information benefit of a shorter waiting time reduces to less than one half (21.3 days) and becomes very imprecise. This extra waiting time is also associated with a substantial increase in the NHI costs and chemotherapy utilization by about 60 percent of SD or more. These estimates show signs of the network-induced information-seeking behavior among highly selective physician-patients.

Finally, although suggestive, the estimates in Table 7B's columns 2–3 show that among physician-patients with no relational advantage, those more informed spend markedly less on checkups than less knowledgeable physician-patients and are more likely to utilize targeted therapy rather than radiation. Even among highly comparable physician-patients, their treatment decisions are still strikingly different because of possessing the most relevant medical knowledge. This pattern is consistent with the average physician-patient's effect on the same treatment choices (columns 8–9). In contrast, the same way does not appear in the less informed physician-patients' relational mechanism. The combination of these results reconfirms the information mechanism's dominant role in treatment decision-making.

[12] Recent narratives of 12 physician-patients diagnosed with cancer describe the information-seeking process. Almost all the cases emphasize that their network's additional information was crucial for their treatment decision-making and better survival outcomes (United Daily News, 2020).

Our matching estimates have revealed the relational mechanism among less informed physician-patients. Their professional ties with the attending substantially increase treatment utilization and drug costs, which drastically improve survival but only for the short term. As shown in Table 7A, columns 2–3, the 180-days survival rate rises by 13.7 ppts, almost two-thirds of SD, while the one-year survival rate remains unchanged. As the relational mechanism cannot explain why average physician-patients reduce surgery/radiation/palliative care utilization, we see the information mechanism as the leading model for treatment decision-making.

5. Conclusion

Agency problems in healthcare play a central role in understanding healthcare inequality. Researchers have found evidence consistent with the hypothesis of doctor-driven demand and the consequence of asymmetric information in treatment. However, much less is known about how the relationship between doctors and patients can mitigate agency problems. While some evidence has shown that social ties might mitigate agency problems in preventive care or Cesarean-section utilization, the role of social relations in mitigating agency problems remain unknown outside of those particular contexts.

In this paper, we first use Taiwan's NHI database over recent decades to establish a benchmark of the physicians treating physicians without separating the relational and information mechanisms. We compare physician-patients' treatments and survival to comparable nonphysicians with the same advanced cancer and attended by the same doctor in the same hospital. In models that exploit within-doctor-hospital variation, we match patients using rich controls to address patient selection and remove unobserved doctor quality. We find that physician-patients receive *less* intensive care, more medication, and more targeted therapy, all of which combined cost less and yield a greater survival rate than comparable nonphysicians.

Physician-patients possess clinical knowledge and professional connections, both of which can contribute to better care and higher survival rates. We assess the relative importance of the relational and information mechanisms by restricting the data to physician-patients with advanced cancer. Across several models that exploit medical-specialty variation among patients and doctors, less-informed patients with stronger professional ties receive *more* intensive care, more medication, and more targeted therapy. Such a highly intensive treatment, induced by a stronger relationship with the attending doctor, improves short-term survival. This evidence reveals the relational mechanism at work. To evaluate which mechanism dominates, we further match physician-patients who either have strong ties or are more informed. We find the information mechanism is the leading explanation for the treatment decisions that lead to better survival in advanced cancers.

Our findings of the relational and information mechanism are consistent with a framework in which risk-averse patients undervalue intensive care's health benefits and thus have low demand for it. A stronger bond between patients and doctors—which builds trust and improves communication—can reduce risk aversion and increase the demand.[13] Doctors can also shift up patient demand to meet their self-interests if patients are less informed, as posited by the classical doctor-driven demand hypothesis.

Although our analytical approach in this paper is novel, our study has two limitations. One is to assume monotonicity of the relational and informational advantages. Namely, the mechanism distinguishing doctor-patient pairs by medical specialties is the same one that can separate physician-patients from nonphysician ones. However, professional ties might differ from nonprofessional connections in affecting treatment decisions. Another limitation of our finding is that our matched

[13] This idea is related to Lopez et al.'s (2020) model on patient-driven demand for malaria treatments, although they assume patients are risk natural while doctors could be averse to risk.

data has a small sample size due to a rare overlap between physician-patients and nonphysicians. Our results shed light on agency problems in healthcare. Relaxing the monotonicity and increasing sample size could be addressed by future work.

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TABLE 1—SUMMARY STATISTICS OF **HOSPITAL ADMISSIONS** FOR END-STAGE CANCER PATIENTS

	End-stage cancer at the first diagnosis		
	Nonphysician	Physicians minus	
Variable	Mean	Nonphysicians	p-value
Patient attributes:			
Male	0.50	0.35	0.000
Age at the first diagnosis	57.76	1.96	0.026
Log income at the first diagnosis	10.05	0.89	0.000
Log previous hospital spending	4.09	-0.72	0.015
Preexisting clinical relationship with attending	0.07	-0.01	0.221
Doctor attributes:			
Male	0.88	0.03	0.049
Experience at admission	12.77	2.06	0.000
Selectivity at first diagnosis	0.0022	0.0017	0.000
Practice in multiple hospitals	0.43	-0.07	0.003
Specialty unrelating to cancer treatments	0.08	-0.02	0.062
Hospital types:			
Teaching	0.21	0.12	0.000
Veteran	0.16	0.13	0.000
Private	0.61	-0.14	0.000
Acute inpatient stays (days)	7.89	-0.81	0.023
Diagnosis-to-treatment interval	122.66	-5.59	0.072
Cancer care and therapy:			
Surgery	0.66	-0.05	0.073
Chemotherapy	0.80	-0.04	0.070
Radiation therapy	0.32	-0.01	0.652
Targeted therapy	0.11	0.05	0.029
Palliative care	0.15	-0.04	0.030
Log spending:			
Total NHI cost	10.50	0.03	0.552
Coinsurance	0.66	0.16	0.010
NHI drugs	8.67	-0.07	0.467
Surgery	2.29	0.06	0.617
Tube feeding	0.56	-0.16	0.003
Radiation therapy	7.10	-0.33	0.001
Examination	6.84	-0.04	0.758
Survival:			
Lived 180 days+	0.93	0.01	0.321
Lived 365 days+	0.81	0.07	0.000
Lived 3 years+	0.55	0.10	0.004

Notes: We include 1,123,377 hospital admissions in the NHI database associated with end-stage cancer diagnoses for first-timers during 2004-2016, where 2,454 admissions are by 611 physician-patients and 1,120,923 entries by 279,399 nonphysician-patients. We cluster standard errors at the patient level in calculating the p-value.

TABLE 2—BALANCE OF A SELECTION OF DOCTOR ATTRIBUTES AND PATIENT CONDITIONS, AFTER MATCHING PATIENT TYPES

	A) Exact match on patient types within hospital			**B) Exact match on patient types within doctor-hospital**		
Predetermined variables		p-value			p-value	
not matched on	Std. mean diff.	t-test	KS-test	Std. mean diff.	t-test	KS-test
Doctor gender	0.14	0.88	0.00	0.00	1.00	1.00
Doctor experience at admission	**0.30**	**0.02**	0.10	-0.04	0.92	1.00
Doctor selectivity at first diagnosis	0.15	0.49	0.67	-0.04	0.90	0.97
Patient's log prior spending on drugs	-0.01	0.87	1.00	-0.01	0.99	1.00
Patient's pre-trend in hospital cost	-0.07	0.55	1.00	-0.01	0.95	1.00
Number/percent of admissions	2811	0.26%		552	0.05%	
Number of physician-patients			98			31
Number of all patients			663			100
Number of hospitals			19			13
Number of attending doctors			441			28
Number of hospital-doctor pairs			443			28
Admission counts by cancer site:						
Otorhinolaryngology			128			45
Digestive organs and peritoneum			1,307			238
Respiratory system and chest cavity			115			23
Bones, skins, and connective and other subcutaneous tissues			472			143
Breast, reproductive, and urinary organs			305			67
Others (e.g., eyes, central nerves, endocrine glands, leukemias)			484			36

Note: We report the p-values of paired t-tests and Kolmogorov-Smirnov KS-tests for the given matching scheme. "Pre-trend in hospital cost" is the 3-years pre-diagnosis trend in inpatient spending. Both matching procedures include a comprehensive list of "patient types," including gender, 17 cancer sites, 2-year age bins, 4-year admission period, six regions of residence, hospital spending quintile four years before diagnosis, income quintile in the year before the first diagnosis, and an indicator for whether having a preexisting clinical relationship with the attending three years before diagnosis. We match admissions precisely by the patient types within hospitals in the scheme-(A) and within doctor-hospital in (B).

TABLE 3—MATCHING ESTIMATED EFFECTS OF A PHYSICIAN-PATIENT ON TREATMENT CHOICE, VOLUME, AND SURVIVAL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Within hospital	(A) Exact match by patient types within hospital			**(B) Exact match by patient types within doctor-hospital**		
	SD	SD	Coef.	SE [Conf. Interval]	SD	Coef.	SE [Conf. Interval]
Acute inpatient stays (days)	12.1	9.6	**-1.94**	0.39	6.2	**-1.5**	0.4
Diagnosis-to-treatment	95.7	89.0	2.7	[-6.5 , 12.0]	75.6	1.3	[-12.5 , 15.2]
Cancer therapy:							
Surgery	0.47	0.26	0.007	[-0.008 , 0.022]	0.20	**-0.083**	0.018
Radiation	0.46	0.40	0.016	[-0.009 , 0.041]	0.33	**-0.071**	0.027
Chemotherapy	0.39	0.28	**0.034**	0.010	0.20	-0.007	[-0.042 , 0.027]
Targeted	0.31	0.27	**0.109**	0.009	0.28	**0.167**	0.024
Palliative care	0.35	0.23	**-0.024**	0.007	0.16	**-0.027**	0.013
Log spending:							
Total NHI cost	1.52	1.91	-0.081	[-0.397 , 0.235]	1.67	-0.055	[-0.405 , 0.296]
Coinsurance	2.20	1.66	-0.193	[-0.414 , 0.029]	1.07	**-0.226**	0.100
NHI drugs	2.15	2.31	0.240	[-0.068 , 0.549]	1.80	**0.652**	0.165
Surgery	4.21	3.89	**-0.712**	0.248	2.87	**-1.159**	0.275
Tube feeding	2.01	1.54	**-0.277**	0.050	0.39	-0.031	[-0.075 , 0.012]
Radiation therapy	2.77	2.58	**-0.307**	0.153	2.00	0.128	[-0.234 , 0.490]
Examination	2.92	2.91	**-0.480**	0.170	2.29	**-0.943**	0.211
Survival:							
Lived 180 days+	0.25	0.18	0.008	[-0.003 , 0.020]	0.11	**0.025**	0.009
Lived 365 days+	0.39	0.31	**0.045**	0.010	0.19	**0.093**	0.015
Lived 1095 days+	0.49	0.39	**0.134**	0.015	0.20	**0.071**	0.021
Number of admissions:	1,100,301	2,811			552		
Lived 180 days+	1,078,870	2,785			531		
Lived 365 days+	1,030,972	2,785			531		
Lived 1095 days+	816,817	1,926			346		

Note: "Pre-trend in hospital cost" is the 3-years pre-diagnosis trend in inpatient spending. Both matching procedures cover a comprehensive list of *patient types*, including gender, 17 cancer sites, 2-year age bins, 4-year admission period, six regions of residence, hospital spending quintile four years before diagnosis, income quintile in the year before the first diagnosis, and an indicator for whether having a preexisting clinical relationship with the attending three years before diagnosis. We match admissions precisely by the patient types within hospitals in the scheme-(A) and within doctor-hospital in (B). The standard deviations (SD) in the first column report information after removing hospital fixed effects. The SD in scheme-A presents information after removing the fixed effects of patient types and 4-year admission periods, in addition to hospital fixed effects. The SD in scheme-B further removes doctor fixed effects. We report the standard error (SE) if the p-value is below 0.05 and the confidence intervals if the p-value equals or exceeds 0.05. Mortality data have fewer observations since we only obtain Death Registry until 2016 December. We cluster standard errors at the patient level.

TABLE 4—COMPARING ESTIMATES USING FIXED-EFFECT VERSUS MATCHING METHODS, USING THE FULLY MATCHED SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)
	Scheme-B: Exact match by patient types within doctor-hospital					
		Fixed-effect model			**Matching method (B)**	
	SD	Coef.	SE [Conf. Interval]	Adj-R2	Coef.	SE [Conf. Interval]
Acute inpatient stays (days)	6.2	**-1.5**	0.5	0.11	**-1.5**	0.4
Diagnosis-to-treatment	75.6	2.8	[-17.2 , 22.8]	0.28	1.3	[-12.5 , 15.2]
Cancer therapy:						
Surgery	0.20	-0.087	[-0.199 , 0.025]	0.78	**-0.083**	0.018
Radiation	0.33	-0.080	[-0.241 , 0.080]	0.53	**-0.071**	0.027
Chemotherapy	0.20	0.005	[-0.083 , 0.093]	0.33	-0.007	[-0.042 , 0.027]
Targeted	0.28	0.147	[-0.013 , 0.308]	0.47	**0.167**	0.024
Palliative care	0.16	-0.019	[-0.088 , 0.050]	0.41	**-0.027**	0.013
Log spending:						
Total NHI cost	1.67	-0.070	[-0.299 , 0.159]	0.48	-0.055	[-0.405 , 0.296]
Coinsurance	1.07	**-0.241**	0.097	0.09	**-0.226**	0.100
NHI drugs	1.80	**0.633**	0.253	0.52	**0.652**	0.165
Surgery	2.87	**-1.259**	0.342	0.27	**-1.159**	0.275
Tube feeding	0.39	-0.024	[-0.087 , 0.038]	0.03	-0.031	[-0.075 , 0.012]
Radiation therapy	2.00	0.165	[-0.234 , 0.565]	0.50	0.128	[-0.234 , 0.490]
Examination	2.29	**-1.043**	0.243	0.50	**-0.943**	0.211
Survival:						
Lived 180 days+	0.11	na		0.07	**0.025**	0.009
Lived 365 days+	0.19	**0.086**	0.039	0.35	**0.093**	0.015
Lived 1095 days+	0.20	0.078	[-0.041 , 0.196]	0.73	**0.071**	0.021

Note: N=552 except for survival outcomes with fewer observations (see table 3). Both matching and fixed-effect models include doctor-hospital fixed effects and *patient types*, including gender, 17 cancer sites, 2-year age bins, 4-year admission period, six regions of residence, hospital spending quintile four years before diagnosis, income quintile in the year before the first diagnosis, and an indicator for whether having a preexisting clinical relationship with the attending three years before diagnosis. The dummy for living 180 days+ has the sample mean of about 7 percent, so we estimate a logistic fixed-effect model but cannot get convergence. The standard deviations (SD) in the first column report the information after removing doctor-hospital fixed effects and patient types. We report the clustered standard errors (SE) at the patient level if the p-value is below 0.05 and the confidence intervals in [.] if the p-value equals or exceeds 0.05.

TABLE 5. THE COMPOSITION OF PHYSICIAN-PATIENTS BY RELATIONAL AND INFORMATIONAL ADVANTAGES

	More informed physician-patient *I = 1*	Less informed Physician-patient *I = 0*	Nonphysician patient	Difference *I = 1 versus I = 0*
With strong ties *R = 1*	β+η+ρ+δ	β+ρ		η+δ
With no strong tie *R = 0*	β+η	β		η
Nonphysician patient			0	
Difference:				
R = 1 versus R = 0	ρ+δ	ρ		

TABLE 6. BALANCE STATISTICS AMONG PHYSICIAN-PATIENTS, P-VALUES

Predetermined variables not matched on	I = 0 Physician-patient specializing in areas unrelated to cancer site Having a strong tie or not t-test	KS-test	I + R = 1 Either with a strong tie or being more informed Being more informed or not t-test	KS-test	R = 1 With a strong tie Being more informed or not t-test	KS-test	R = 0 No strong tie Being more informed or not t-test	KS-test
Patient attributes:								
Age (2-years bins)	0.75	0.46	0.40	0.70	0.92	0.82	1.00	0.52
Log previous inpatient cost	0.85	0.99	0.25	0.70	0.34	0.82	0.84	1.00
Log income 1 year before 1st diagnosis	0.97	0.81	0.49	0.70	0.64	0.82	0.90	0.52
Pre-trend in hospital cost	0.27	0.46	0.26	0.70	0.50	1.00	0.44	1.00
Log prior spending on drugs	0.93	0.99	0.24	0.70	0.14	0.33	0.84	1.00
Doctor attributes:								
Experience at admission	0.24	0.46	0.88	1.00	0.41	0.82	0.61	1.00
Selectivity at first diagnosis	0.60	0.81	0.94	0.70	0.33	0.82	0.71	1.00
Number of specialties	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Number of admissions		153		74		69		44
Exact match rate		8%		9%		7%		3%
Number of physician-patients		52		18		16		12
Number of hospitals		5		4		4		<4
Number of attending doctors		11		4		5		<4
Number of hospital-doctor pairs		11		4		5		<4
Number of admissions by cancer site:								
Digestive organs and peritoneum		58		65				
Respiratory system and chest cavity		18				20		
Breast, reproductive, and urinary organs		44		9		7		
Others (e.g., eyes, central nerves, endocrine glands, leukemias)		33				42		

Note: See the text for I's and R's definitions. All the specifications in this table exactly match on doctor-hospital and cancer sites. Also, we control for 5-year doctor experience bins and patient attributes, including 2-year age bins, 4-year admission period, hospital spending tercile four years before diagnosis, and income tercile in the year before the first diagnosis.

TABLE 7A. MATCHING ESTIMATES: THE RELATIONAL VERSUS THE INFORMATION EFFECTS, USING DATA FROM PHYSICIAN-PATIENTS ONLY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	I = 0			I + R = 1					
		The relational effect (ρ)			Information minus relational effect (η−ρ)			The average physician-patient effect	
Outcome variables:	SD	Coef.	SE [Conf. Interval]	SD	Coef.	SE [Conf. Interval]	SD	Coef.	SE [Conf. Interval]
Acute inpatient stays (days)	8.8	**1.6**	0.0	3.9	-1.9	[-3.8 , 0.1]	6.2	**-1.5**	0.4
Diagnosis-to-treatment	108.1	4.1	[-23.2 , 31.3]	108.2	-12.2	[-59.3 , 35.0]	75.6	1.3	[-12.5 , 15.2]
Treatment choice:									
Surgery	0.50	**0.157**	0.054	0.46	**-0.432**	0.079	0.20	**-0.083**	0.018
Radiation	0.46	**0.150**	0.049	0.50	**-0.689**	0.075	0.33	**-0.071**	0.027
Chemotherapy	0.45	**0.144**	0.062	0.27	**-0.108**	0.036	0.20	-0.007	[-0.042 , 0.027]
Targeted	0.42	**0.183**	0.049	0.45	**0.486**	0.061	0.28	**0.167**	0.024
Palliative	0.40	**0.144**	0.041	0.36	**-0.149**	0.059	0.16	**-0.027**	0.013
Log spending:									
Total NHI cost	2.45	0.269	[-0.437 , 0.975]	0.66	-0.241	[-0.527 , 0.045]	1.67	-0.055	[-0.405 , 0.296]
Coinsurance	2.37	0.318	[-0.441 , 1.078]	2.04	-0.173	[-1.029 , 0.684]	1.07	**-0.226**	0.100
Drugs	2.79	**0.673**	0.290	1.84	0.486	[-0.099 , 1.070]	1.80	**0.652**	0.165
Surgery	4.61	-0.191	[-1.525 , 1.142]	4.59	**-2.561**	1.066	2.87	**-1.159**	0.275
Tube feeding	0.75	-0.078	[-0.429 , 0.273]	0.00	na		0.39	-0.031	[-0.075 , 0.012]
Radiation	3.52	0.011	[-1.140 , 1.162]	2.99	0.930	[-0.242 , 2.103]	2.00	0.128	[-0.234 , 0.490]
Examination	3.14	0.163	[-0.738 , 1.064]	1.54	**-0.915**	0.409	2.29	**-0.943**	0.211
Survival:									
Lived 180 days+	0.21	**0.137**	0.035	0.00	na		0.11	**0.025**	0.009
Lived 365 days+	0.31	0.013	[-0.099 , 0.126]	0.00	na		0.19	**0.093**	0.015
Number of admissions		153			74			552	

Note: See the text for I's and R's definitions. For the two matching schemes in the first six columns, see Table 6 for balance statistics. We precisely match hospital entries on doctors, hospitals, patient sex, and cancer sites while controlling for 5-year doctor experience bins and patient attributes (including 2-year age bins, 4-year admission period, hospital spending tercile four years before diagnosis, and income tercile in the year before the first diagnosis). Columns 7-9 are from Table 3's columns 5-7. SD indicates unconditional standard deviations. We report the clustered standard errors (SE) at the patient level if the p-value is below 0.05 and the confidence intervals in [.] if the p-value equals or exceeds 0.05.

TABLE 7B. MATCHING ESTIMATES: THE INFORMATION EFFECTS, USING DATA FROM PHYSICIAN-PATIENTS ONLY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	R = 0			R = 1					
		Information main effect (η)			Information total effect (η+δ)			The average physician-patient effect	
Outcome variables:	SD	Coef.	SE [Conf. Interval]	SD	Coef.	SE [Conf. Interval]	SD	Coef.	SE [Conf. Interval]
Acute inpatient stays (days)	7.1	**-4.5**	1.6	6.6	**5.9**	2.0	6.2	**-1.5**	0.4
Diagnosis to treatment	90.0	**-54.5**	18.6	81.2	-21.3	[-69.7 , 27.0]	75.6	1.3	[-12.5 , 15.2]
Treatment choice									
Surgery	0.15	0.023	[-0.066 , 0.112]	0.48	-0.058	[-0.135 , 0.019]	0.20	**-0.083**	0.018
Radiation	0.49	**-0.477**	0.106	0.12	-0.014	[-0.051 , 0.022]	0.33	**-0.071**	0.027
Chemotherapy	0.39	-0.045	[-0.149 , 0.058]	0.37	**0.319**	0.069	0.20	-0.007	[-0.042 , 0.027]
Targeted	0.29	**0.318**	0.076	0.50	0.101	[-0.045 , 0.248]	0.28	**0.167**	0.024
Palliative	0.00	na		0.21	0.043	[-0.043 , 0.130]	0.16	**-0.027**	0.013
Log spending									
Total NHI cost	0.94	-0.040	[-0.482 , 0.403]	0.99	**0.584**	0.214	1.67	-0.055	[-0.405 , 0.296]
Coinsurance	1.56	0.497	[-0.530 , 1.524]	1.90	-0.356	[-1.264 , 0.552]	1.07	**-0.226**	0.100
Drugs	1.92	0.355	[-0.558 , 1.269]	2.93	0.927	[-0.710 , 2.565]	1.80	**0.652**	0.165
Surgery	4.95	-0.976	[-3.414 , 1.462]	2.98	1.404	[-0.305 , 3.112]	2.87	**-1.159**	0.275
Tube feeding	0.00	na		0.00	na		0.39	-0.031	[-0.075 , 0.012]
Radiation	3.13	0.002	[-1.180 , 1.185]	1.83	0.210	[-0.879 , 1.299]	2.00	0.128	[-0.234 , 0.490]
Examination	2.04	**-1.793**	0.853	3.55	-0.096	[-1.622 , 1.430]	2.29	**-0.943**	0.211
Survival:									
Lived 180 days+	0.00	na		0.00	na		0.11	**0.025**	0.009
Lived 365 days+	0.00	na		0.00	na		0.19	**0.093**	0.015
Number of admissions		44			69			552	

Note: See the text for R's definition. For the two matching schemes in the first six columns, see Table 6 for balance statistics. We precisely match hospital entries on doctors, hospitals, patient sex, and cancer sites while controlling for 5-year doctor experience bins and patient attributes (including 2-year age bins, 4-year admission period, hospital spending tercile four years before diagnosis, and income tercile in the year before the first diagnosis). Columns 7-9 are from Table 3's columns 5-7. SD indicates unconditional standard deviations. We report the clustered standard errors (SE) at the patient level if the p-value is below 0.05 and the confidence intervals in [.] if the p-value equals or exceeds 0.05.

Appendix

TABLE A1— SUMMARY STATISTICS OF CANCER DIAGNOSIS, PATIENT ATTRIBUTES, TREATMENT CHOICE, AND SURVIVAL, INCLUDING THOSE NON-HOSPITALIZED

	Full sample				End-Stage at first diagnosis sample			
Variable	Nonphysician Mean	Physicians minus Nonphysicians	p-value	Number of diagnoses	Nonphysician Mean	Physicians minus Nonphysicians	p-value	Number of diagnoses
Diagnosis:								
End-stage cancer, at first diagnosis	0.30	**0.03**	0.00	1,216,565				
Patient attributes:								
Male	0.53	**0.35**	0.00	1,216,565	0.56	**0.34**	0.00	364,060
Age at the first diagnosis	61.82	**3.17**	0.00	1,216,565	62.29	**3.56**	0.00	364,060
Log income at the first diagnosis	10.02	**0.74**	0.00	1,216,565	10.02	**0.72**	0.00	364,060
Log previous hospital spending	4.90	**-0.30**	0.01	1,216,565	4.63	**-0.70**	0.00	364,060
Cancer care and therapy:								
Surgery	0.59	**0.04**	0.00	1,216,565	0.59	**-0.04**	0.04	364,060
Chemotherapy	0.39	**-0.08**	0.00	1,216,565	0.54	**-0.07**	0.00	364,060
Radiation	0.24	**-0.05**	0.00	1,216,565	0.26	-0.02	0.24	364,060
Hormone	0.13	0.01	0.16	1,216,565	0.15	**0.05**	0.00	364,060
Palliative care	0.13	**-0.04**	0.00	1,216,565	0.13	**-0.04**	0.00	364,060
No hospital care	0.12	-0.01	0.43	1,216,565	0.09	0.00	0.80	364,060
Targeted	0.05	0.01	0.08	1,216,565	0.07	**0.02**	0.03	364,060
Immunotherapy	0.007	0.001	0.56	1,216,565	0.014	0.005	0.33	364,060
Chinese medicine	0.0005	**-0.0005**	0.00	1,216,565	0.0007	**-0.0007**	0.00	364,060
Stem cell	0.0014	0.0007	0.47	1,216,565	0.0044	0.0007	0.78	364,060
Survival:								
Lived 180 days+	0.84	**0.04**	0.00	1,160,075	0.86	**0.04**	0.00	347,437
Lived 365 days+	0.75	**0.07**	0.00	1,104,203	0.77	**0.08**	0.00	330,819
Lived 3 years+	0.58	**0.10**	0.00	880,428	0.59	**0.12**	0.00	264,977
Died in hospital	0.23	**0.03**	0.00	1,216,565	0.24	**0.04**	0.01	364,060

Notes: After excluding138 patients and 170 diagnoses due to missing income information, we have 1,216,565 cancer diagnoses among the 1,037,216 patients (including 1,987 medical doctors) recorded in Taiwan's NHI database from 2004 to 2016. "Previous hospital spending" is limited to the NHI hospital items used within three years before diagnosis. We identify "end-stage cancer" using one of the following three conditions: (1) the cancer is invasive (i.e., the 5th digit of HISTBET equals 3), (2) the patient has multiple cancer sites, or (3) the cells are poorly differentiated or undifferentiated anaplastic grade (i.e., GRADE equals 3 or 4; for colon, rectum, or ovary cancer, any GRADE value except B). Mortality data have fewer observations since we only obtain Death Registry until 2016 December. We cluster standard errors at the patient level. For the end-stage sample, we include 364,060 cancer diagnoses among the 364,060 patients (including 780 medical doctors) recorded in Taiwan's NHI database during the same data period.

Source: Author calculations using Taiwan's NHI Database.

TABLE A2—DEFINING MORE-INFORMED PHYSICIAN-PATIENTS USING CANCER SITES AND SPECIALTY CERTIFICATE RECORDS

Specialty Category	**Certified specialty**	**Cancer site coding**							
External medicine, relating to cancer treatments	Surgery	C1-C15,	C17						
	OB/GYN	C10							
	Urology	C11	C12						
	Otolaryngology	C01	C02	C03	C05				
	Dermatology	C07	C08						
	Neurosurgery	C14							
	Orthopedics	C06	C07						
	Ophthalmology	C13							
	Plastic Surgery	C01	C02	C03	C06	C08	C09	C13	C15
External medicine, unrelating to cancer treatments	Anesthesiology								
	Emergency								
Internal medicine, relating to cancer treatments	Oncology	C1-C17							
Internal medicine, unrelating to cancer treatments	Neurology								
	Rehabilitation								
	Family Medicine								
	Pediatrics								
	Occupational Medicine								
Examination, unrelating to cancer treatments	Anatomical Pathology								
	Clinical Pathology								
	Nuclear Medicine								
	Diagnostics								
	Medical Imaging								

Note: Following Taiwan's *Cancer Registry Annual Report*s (downloadable from www.hpa.gov.tw), we correspond each cancer site coding to ICD-O-3 codes as below: (1) C00-C14 (lip, oral cavity, or pharynx), except C07-C08 and C11; (2) C07-C08 (salivary gland); (3) C11 (nasopharynx); (4) C15, C26, and C48 (esophagus, intestinal tract, retroperitoneum, or peritoneum); (5) C30-C39 (respiratory and intrathoracic organs); (6) C40-C41 (bone or articular cartilage); (7) C47 and C49 (malignant neoplasm of peripheral nerves and autonomic nervous system, or other connective and soft tissue); (8) C44 (skin); (9) C50 (breast); (10) C51-C58 (female genital organs); (11) C60-C63 (male genital organs); (12) C64-C68 (urinary tract); (13) C69 (eye cancer); (14) C70-C72 (brain/nerves cancer); (15) C74-C75 (adrenal gland, other endocrine glands, or related structure); (16) M95903-M99933, except M99903 (leukemia); (17) C80 (primary site unknown). For doctors without a specialty record, we use their hospital department to identify whether they have cancer-related medical knowledge and whether the knowledge belongs to external or internal medicine. See Table A3.

TABLE A3. USING HOSPITAL DEPARTMENTS TO PROXY ATTENDING DOCTORS' KNOWLEDGE IF NO SPECIALTY RECORDS

Specialty Category	Hospital Department	NHI coding (FUNC_TYPE)
External medicine, relating to cancer treatments	Surgery Department	3
	OB/GYN	5
	Orthopedics	6 or HA
	Neurosurgery	7
	Urology	8
	Otorhinolaryngology	9
	Ophthalmology	10
	Dermatology	11
	Thoracic surgery/critical care	AJ or BC
	Rectal surgery	BA
	Cardiovascular surgery	BB
	Digestive surgery	BD
	Oral and maxillofacial surgery	GA
	Plastic surgery	15
External medicine, unrelating to cancer treatments	Anesthesiology	81
	Emergency medicine	22
Internal medicine, relating to cancer treatments	Internal medicine	2
	Gastroenterology	AA
	Cardiovascular Medicine	AB
	Thoracic medicine	AC
	Nephrology	AD
	Hematology oncology	AF
	Endocrinology	AG
	Radiation oncology	FB
Internal medicine, unrelating to cancer treatments	Neurology	12
	Rehabilitation	14
	Family medicine	0 or 1
	Pediatrics or pediatric surgery	4 or CA
	Occupational medicine	23
	Psychiatry	13
	Tuberculosis	2A
	Dialysis	2B
	Rheumatology	AE
	Geriatrics	AK
	Infectious diseases	AH
	Neonatology	CB
	Pain or hyperbaric oxygen	DA or AI
	Home care	EA
Examination	Radiology Department	FA or 82
	Pathology	83
	Nuclear Medicine	84

TABLE A4—FIXED-EFFECT MODELS: EFFECTS OF A PHYSICIAN-PATIENT ON TREATMENT CHOICE, VOLUME, AND SURVIVAL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Chosen hospitals (N=1,100,301)				Chosen doctors only (N=622,226)			Fully matched sample (N=522)		
	SD	Coef.	SE [Conf. Interval]	Adj-R2	SD	Coef.	SE [Conf. Interval]	Adj-R2	Coef.	SE [Conf. Interval]	Adj-R2
Acute inpatient stays (days)	12.1	**-1.7**	0.3	0.17	11.3	**-1.74**	0.3	0.15	**-1.5**	0.5	0.11
Diagnosis-to-treatment	95.7	**-6.1**	2.9	0.10	94.3	**-5.75**	2.9	0.09	2.8	[-17.2, 22.8]	0.28
Cancer therapy:											
Surgery	0.47	0.012	[-0.027, 0.051]	0.53	0.46	0.012	[-0.027, 0.051]	0.51	-0.087	[-0.199, 0.025]	0.78
Radiation	0.46	0.003	[-0.045, 0.051]	0.26	0.46	0.002	[-0.045, 0.050]	0.25	-0.080	[-0.241, 0.080]	0.53
Chemotherapy	0.39	-0.001	[-0.037, 0.035]	0.33	0.37	0.001	[-0.035, 0.037]	0.31	0.005	[-0.083, 0.093]	0.33
Targeted	0.31	0.037	[-0.003, 0.077]	0.21	0.33	0.036	[-0.003, 0.075]	0.22	0.147	[-0.013, 0.308]	0.47
Palliative care	0.35	**-0.049**	0.018	0.14	0.35	**-0.050**	0.018	0.11	-0.019	[-0.088, 0.050]	0.41
Log spending:											
Total NHI cost	1.52	**-0.125**	0.044	0.34	1.69	**-0.132**	0.044	0.37	-0.070	[-0.299, 0.159]	0.48
Coinsurance	2.20	0.024	[-0.077, 0.124]	0.19	1.95	0.034	[-0.066, 0.134]	0.11	**-0.241**	0.097	0.09
NHI drugs	2.15	-0.155	[-0.315, 0.005]	0.30	2.23	-0.149	[-0.308, 0.011]	0.33	**0.633**	0.253	0.52
Surgery	4.21	-0.097	[-0.294, 0.099]	0.35	4.17	-0.116	[-0.312, 0.080]	0.35	**-1.259**	0.342	0.27
Tube feeding	2.01	**-0.214**	0.047	0.21	1.81	**-0.214**	0.046	0.15	-0.024	[-0.087, 0.038]	0.03
Radiation therapy	2.77	**-0.440**	0.087	0.26	2.72	**-0.438**	0.087	0.29	0.165	[-0.234, 0.565]	0.50
Examination	2.92	**-0.420**	0.108	0.34	3.00	**-0.434**	0.107	0.34	**-1.043**	0.243	0.50
Survival:											
Lived 365 days+	0.39	**0.081**	0.016	0.20	0.38	**0.082**	0.016	0.16	**0.086**	0.039	0.35
Lived 1095 days+	0.49	**0.118**	0.031	0.22	0.49	**0.118**	0.030	0.20	0.078	[-0.041, 0.196]	0.73

Note: The "chosen-hospital" sample includes admissions in hospitals that physician-patients visit. The "chosen-doctor" sample covers entries attended by doctors whom physician-patients see. We derive the "fully matched sample" using matching scheme-B in Table 3. All specifications control for the full set of covariates of the scheme-B (i.e., doctor-hospital fixed effects and patient types, including gender, 17 cancer sites, 2-year age bins, 4-year admission period, six regions of residence, hospital spending quintile four years before diagnosis, income quintile in the year before the first diagnosis, and an indicator for whether having a preexisting clinical relationship with the attending three years before diagnosis). For the first two samples, we add the full set of dummies for 5-year doctor experience bins. The probability of living 180 days+ is about 93 percent, so we estimate a logistic fixed-effect model but cannot reach convergence. We report the clustered standard errors (SE) at the patient level if the p-value is below 0.05 and the confidence intervals in [.] if the p-value equals or exceeds 0.05

TABLE A5. FIXED-EFFECT ESTIMATES USING DATA FROM ADMISSIONS IN HOSPITALS CHOSEN BY PHYSICIAN-PATIENTS

	a) Within doctor-hospital				b) Within doctor, within hospital				c) Within hospital			
	Coef.	SE	p	Adj-R2	Coef.	SE	p	Adj-R2	Coef.	SE	p	Adj-R2
Acute inpatient stays (days)	-1.74	0.33	0.00	0.18	-1.76	0.33	0.00	0.17	-1.81	0.34	0.00	0.08
Diagnosis-to-treatment	-6.09	2.89	0.03	0.10	-5.84	2.89	0.04	0.09	-3.75	2.95	0.20	0.03
Cancer therapy:												
Surgery	0.012	0.020	0.55	0.53	0.012	0.020	0.53	0.53	0.006	0.020	0.77	0.47
Radiation	0.003	0.024	0.92	0.26	0.004	0.024	0.89	0.25	-0.003	0.025	0.91	0.21
Chemotherapy	-0.001	0.018	0.96	0.33	0.000	0.018	0.98	0.32	0.006	0.020	0.76	0.23
Hormone	-0.003	0.014	0.83	0.44	-0.002	0.014	0.86	0.44	-0.007	0.014	0.60	0.42
Targeted	0.038	0.020	0.06	0.21	0.040	0.020	0.05	0.21	0.043	0.020	0.03	0.17
Palliative care	-0.049	0.019	0.01	0.14	-0.045	0.019	0.02	0.13	-0.043	0.019	0.02	0.07
Log spending:												
Total NHI cost	-0.129	0.044	0.00	0.34	-0.130	0.044	0.00	0.34	-0.141	0.048	0.00	0.17
Coinsurance	0.027	0.051	0.60	0.19	0.025	0.051	0.62	0.18	0.025	0.057	0.65	0.05
Drugs	-0.161	0.082	0.05	0.30	-0.162	0.082	0.05	0.30	-0.117	0.088	0.19	0.12
Surgery	-0.095	0.100	0.34	0.35	-0.112	0.102	0.27	0.34	-0.216	0.109	0.05	0.09
Tube feeding	-0.213	0.047	0.00	0.21	-0.214	0.048	0.00	0.21	-0.231	0.051	0.00	0.10
Radiation therapy	-0.445	0.087	0.00	0.26	-0.428	0.087	0.00	0.25	-0.444	0.094	0.00	0.12
Examination	-0.425	0.108	0.00	0.34	-0.418	0.106	0.00	0.34	-0.393	0.122	0.00	0.18
Survival:												
Lived 180 days+	0.015	0.009	0.08	0.12	0.015	0.009	0.08	0.12	0.017	0.009	0.06	0.06
Lived 365 days+	0.082	0.016	0.00	0.20	0.081	0.016	0.00	0.19	0.083	0.017	0.00	0.11
Lived 1095 days+	0.119	0.031	0.00	0.22	0.119	0.031	0.00	0.22	0.117	0.033	0.00	0.15

Note: In all specification, we control for the full set of dummies for 5-year doctor experience bins and the complete set of covariates of the scheme-B (i.e., doctor-hospital fixed effects and patient types, including gender, 17 cancer sites, 2-year age bins, 4-year admission period, six regions of residence, hospital spending quintile four years before diagnosis, income quintile in the year before the first diagnosis, and an indicator for whether having a preexisting clinical relationship with the attending three years before diagnosis). The survival outcomes have fewer observations than other dependent variables (see table). We report the clustered standard errors (SE) at the patient level.

TABLE A6. DOCTOR AND PHYSICIAN-PATIENT ATTRIBUTES, BY THE PATIENT'S RELATIONAL AND INFORMATION ADVANTAGES

	Before matching					After matching on doctor-hospital and cancer site		
	Physician	(R, I)				Data restriction rule		
	patients	(0,0)	(1,0)	(0,1)	(1,1)	I = 0	I + R = 1	R = 1
Physician-patient attributes:								
More informed	0.19	0	0	1	1	0	0.42	0.46
With a closer professional tie with doctor	0.38	0	1	0	1	0.48	0.58	1
Male	0.85	0.85	0.86	0.84	0.84	0.92	1.00	1.00
Age	59.7	60.9	60.4	55.8	55.0	64.92	55.78	57.56
Pre-diagnosis log income	10.9	10.8	11.0	11.3	11.3	10.49	11.21	11.17
Pre-diagnosis log inpatient cost (3 years)	3.4	3.6	3.5	1.3	3.3	3.61	0.72	5.00
Preexisting clinical relationship with attending	0.05	0.06	0.04	0.00	0.08	0.05	0.00	0.30
Doctor attributes:								
Male	0.91	0.91	0.95	0.82	0.88	1.00	1.00	0.87
Experience	14.8	13.8	16.7	15.1	15.7	18.60	17.18	20.17
Selectivity	0.004	0.003	0.005	0.004	0.004	0.008	0.005	0.005
Whether work in multiple hospitals	0.36	0.34	0.36	0.30	0.49	0.45	0.34	0.16
Teaching hospital	0.32	0.31	0.33	0.37	0.34	0.22	0.91	0.16
Veteran hospital	0.29	0.29	0.29	0.28	0.30	0.70	0.09	0.71
Private hospital	0.47	0.45	0.53	0.43	0.45	0.24	0.78	0.29
Exact match rate	100%	55%	26%	7%	12%	8%	9%	7%
Number of hospital admissions	2,453	1,349	629	174	301	153	74	69
Number of physician-patients	610	372	225	59	59	52	18	16
Number of hospitals	107	91	59	26	33	5	4	4
Number of attending doctors	749	479	237	74	81	11	4	5
Number of hospital-doctor pairs	761	483	241	74	84	11	4	5

Note: The information dummy (*I*) indicates the patient whose specialty is related to the cancer site. The relational indicator (*R*) points out the patient who shares the attending doctor's specialty area. In the last four columns, we also control five-year doctor experience bins, in addition to patient attributes, including two-year age bins, four-year admission period, hospital spending tercile four years before diagnosis, income tercile in the year before the first diagnosis.

A. Understanding the Fixed-Effect Estimates

We further explore fixed-effect linear regressions in Table A4 using two expanded samples. One covers all the admissions in hospitals that physician-patients visit ("chosen hospitals"), and the other includes those attended by doctors seen by physician patients ("chosen doctors"). These two samples have a dramatically greater sample size because both include many covariate cells with no overlap between physician-patients and nonphysician-patients. The fixed-effect estimates using the expanded data are strikingly similar but also remarkably different from the matching estimates. Both sets of the fixed-effect estimates suggest nearly-zero effects of physician patients on surgery adoption and medication spending, opposite to what the matching estimates have indicated.

We prefer matching methods because fixed-effect linear models require additional parametric assumptions that are not necessarily valid. See detailed discussion in Angrist and Pischke (2009), Hahn and Kuersteiner (2011), and Ahn, Lee, and Schmidt (2013). Nevertheless, we briefly discuss the doctor-hospital interaction terms from the fixed-effect approach, which are potentially important because 43 percent of doctors practicing in multiple locations (Table 1) might exhibit various propensities across hospitals. However, as no doctors in the fully matched sample practice in multiple hospitals (Table 2), it is not surprising that adding the interaction terms has almost no impact on the results, as we can see in parts (a) and (b) of Table A5.

In contrast, omitting the doctor fixed effect substantially bias the results because of patient selection. Physician-patients are most capable of selecting highly-skilled doctors who operate more advanced surgical therapy and prescribe no unnecessary medication. The estimates in part (c) show that omitting the doctor effect leads to a series of patient selection issues. The estimated impact is biased upward on surgery spending by more than 90 percent (0.216/0.112-1) and downward on drug spending by 28 percent or more (0.117/162-1).

Furthermore, the diagnosis-to-treatment interval effect is also biased downward by 36 percent (3.75/5.84-1). It could be the case that physician-patients have professional relationships with the attending, which might have shortened the waiting time to the treatment (e.g., Johnson et al., 2016). However, our further exploration in Section 4 suggests otherwise. It is only more-informed physician patients who have a shorter waiting time. In contrast, professional ties with the attending have almost no impact on it.