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

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We disentangle relational and informational advantages of physician-patients by exploiting the wide range of specialists treating patients with advanced cancer. We address unobserved doctor quality issues through matching comparable patients by doctor, hospital, and admission period. Physician-patients are less likely to have surgery/radiation/checkups and more likely to receive targeted therapy, spend more on drugs, and enjoy higher long-term survival while paying less on coinsurance than nonphysician-patients. However, stronger professional ties significantly reduce surgical/radiation therapy among relatively less-informed physician-patients and improve survival for only 0.5 years. Both relational and informational mechanisms appear in healthcare agency problems, but an informational one prevails. *Keywords: physician quality; social ties; communication; information. JEL: D83, I11, J44*

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A growing literature in labor economics examines whether complete information or robust 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 vaccine incentives for patients (Alsan et al., 2018) or exploiting the exogenous variation of OB/GYN doctors' rotating call schedules in doctor-patient clinical relationships (Johnson et al., 2016). They found 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 used compelling research designs to address unobserved doctor quality and patient selection problems.

Besides experimental or quasi-experimental designs, observational studies have examined whether physician-mothers are more or less likely to have a Cesarean section than nonphysician-mothers.[1] These studies had mixed results. Grytten et al. (2011) found that physician-mothers receive a Cesarean section with a 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) found that physician-mothers have a lower probability of receiving a Cesarean section. They attribute this lower probability to being better informed on complications or potential side effects. Irrespective of underuse due to weak social ties or overuse due to asymmetric information, the conjectured relational and informational advantages for physician-mothers rely on merely one medical specialty and thus are empirically inseparable.

[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) adopted the same approach to test for agency problems with expert-consumers. However, this comparison might capture the difference in the susceptibility of self-treatment 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 avoided the susceptibility bias by comparing physician-patients to other patients (Bunker and Brown, 1974; Hay and Leahy, 1982; Domenighetti et al., 1993) or expert-consumers to non-experts.

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This paper is the first to evaluate the relative importance of the relational and informational influences in healthcare agency problems by studying a wide range of individually identifiable medical specialists (not only oncologists) who have attended about 0.3 million patients with advanced cancer, including 611 physician-patients. We have rich controls for patients' and doctors' attributes using Taiwan's cancer registry, doctors' personnel panel records, and universal health insurance administrative data. By looking at the matched physician-patients with different specialties attended by the same doctor, we disentangle the relational advantage's impact due to stronger professional ties from the informational advantage's effect because of being more informed.

Because of a lack of experimental variation, we address unobserved physician-quality and patient-selection issues using Abadie and Imbens's (2006, 2011) nearest neighbor matching method, which allows for complex interactions among covariates without linearity assumptions. Our approach exploits 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 choices and survivals with comparable nonphysician-patients. Our matching estimates show that the average physician-patient is less likely to adopt intensive (surgical/radiation) therapy but more likely to use targeted drug therapy than other patients. Physician-patients also spend substantially less on checkups and coinsurance and enjoy significantly higher long-term survival. The magnitudes range from 0.2 to 0.4 standard deviations, all 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 registry data, we find that doctors are equally likely to detect cancers in the early or 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. Thus, the physician-patients in our data are not diagnosed or treated sooner than others.

Another possible scenario 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 unnecessary procedures more frequently to reduce their potential liability (Currie and MacLeod, 2008), particularly for nonphysician-patients in our context. Taiwan's medical liability literature shows that most lawsuits are in neurosurgery, anesthesiology, and the ER (Chen et al., 2012). After removing cancer physician-patients treated by those specialists, our results remain robust, suggesting unequal propensities to sue unlikely drive our results.

Beyond basic results, we assess relational and informational mechanisms' relative importance using specialty variation across attending doctors and within-doctor variation across physician-patients. We quantify each doctor-patient pair's *relational benefit* (whether they share a specialty area) and *informational advantage* (whether the patient's medical specialty is related to her cancer treatment). For example, a physician-patient in leukemia would be more informed if internal medicine were her specialty. If her attending doctor also practices internal medicine, she could benefit from relational and informational advantages. Contrastingly, if the attending doctor practices external medicine, she would have no extra relational benefit, despite her informational advantage.

When we restrict ourselves to physician-patients without informational advantage, 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 increase the utilization of surgery/radiation/palliative care and lead to a higher short-term survival rate, contrary to the average physician-patient's long-term survival advantage and reduction in these therapies relative to other patients.

An information advantage reduces intensive care utilization, while the relational benefit increases it for improving short-term survival. If physician-patients have both edges, they would have relational and informational mechanisms working in opposite directions. Eventually, average physician-patients utilize less intensive care. 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 relational and informational mechanisms assessment contributes to the literature on healthcare agency problems. 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 who specialize in various medical areas. The matching estimates demonstrate that the doctor-patient relationship matters for treatment choice 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 in which *risk-averse* patients undervalue the benefit of intensive care and, thus, have lower demand. A stronger doctor-patient relationship can overcome the risk aversion through better communication and trust-building to induce 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

[2] Frakes et al. (2021) used data from the Military Health System and found that physician-patients received only slightly more medical care. The physician-patient effects potentially had relational advantages that might have canceled out the informational premium, leading to a seemingly near-zero effect.

matching scheme of constructing the study sample, reports balance statistics and the core estimates, and implements robustness checks. Section 3 examines alternative explanations for our findings and undertakes an additional data analysis to compare the alternatives. Section 4 explores the possible mechanisms by extending our research to distinguish relational effects from informational advantages of treatment intensity and survival rates. Section 5 concludes the paper.

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, like Canadian systems, the Taiwanese NHI is a single-payer system for all citizens and residents. It consists 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 doubts about adverse selection issues in the insurance system. Also, we can address patient selection issues because the NHI database includes beneficiaries who have never checked into hospitals and those who have been admitted.

Furthermore, the NHI administration manages health expenditure inflation by reimbursing providers rather than charging deductibles or capping out-of-pocket expenses. The reimbursement is fee-for-service through a nationally uniform fee schedule. Thus, providers cannot select patients or practice price discrimination against them. Also, since hospitals pay doctors by fee-for-service plus a basic salary that varies across hospitals, the financial incentives of doctors and hospitals are similar.

Moreover, the NHI system imposes a minor penalty (only 7 US dollars in 2014) for a hospital visit without first receiving a primary care referral. Consequently, almost all patients choose their attending doctors without a primary care referral. Given that patients can freely check into different hospitals or 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 in which the on-staff doctor assumes full responsibility for a patient's medical care. This institutional setting ensures that matching patients to physicians can precisely describe the interactions between doctors and patients during hospital admission.

B. Data Linkage

In four steps, we merge several administrative data sources in the NHI database from 2000 to 2016 by unique scrambled identifiers (IDs). 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), the death record if the patient was deceased by the end of 2016, and whether they received hospital care or not.

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 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 to construct covariates and outcome variables. Finally, we derive the attending doctor's certified specialty and experience by linking the compiled data to the *Registry for Medical Personnel* and the *Records of Board-Certified Specialists*, again using the attending doctor's ID.

C. Time-Varying Doctor Selectivity

Like physician experience, doctor selectivity can vary over time. We approximate an expert patient's knowledge about a doctor's selectivity at the time of diagnosis using the percentage of hospital admissions made by physician-patients during the three years before the diagnosis. For instance, if a doctor has attended 1,000 hospital admissions in the past three years and only two were with physician-patients, the selectivity measure takes the value of 0.002. However, unlike doctor experiences easily known to the public, doctor selectivity is typically not well known, except to expert patients.

Physician-patients with advanced cancer choose considerably more selective doctors than other patients. As Table 1 shows, the selectivity level is 0.0039 (0.0022+0.0017), almost twice that of other patients. Also, physician-patients select more experienced doctors than those attending nonphysician-patients by two years. These differences in experience and selectivity levels are large in magnitude and significant in statistics at the 95-percent level.

One of the significant challenges of our empirical work is that doctors' selectivity could grow as they become more experienced. As a result, the patients treated earlier are not necessarily comparable to those treated later by the same doctor. To remove this time-varying bias, we fix both the attending doctor and the admission time to make a fair comparison.

D. Descriptive Statistics

The data consists of over 1.2 million cancer diagnoses among approximately one million patients and 1,989 medical doctors. The number of cancer diagnoses exceeds the number of cancer patients because one patient can be diagnosed more than once for recurrence or confirmation. Only 0.01 percent of diagnoses involve multiple cancers. Table A1 compares the cancer diagnoses between physician-patients and nonphysician-patients, including their attributes, inpatient care receipt, and survival outcomes. Of all the cancer diagnoses from January 2004 to December 2016, 30 percent were in the *advanced stage* at first diagnosis.[3] We began the data period from January 2004, when Taiwan started adopting the *American Joint Committee on Cancer's AJCC Cancer Staging Manual*, the benchmark for classifying patients with cancer. Our analysis covers all the cancer sites listed in Table A2.

Table A1 shows that 12 percent of all cancer diagnoses lead to no hospital care. The gap in this statistic between physician- and nonphysician-patients is almost zero. About one-quarter of these diagnoses are in the advanced stage (not shown in the table). After controlling the whole interaction among patient demographics, prior medical spending, and admission year, we found that physician-patients were significantly more likely to receive hospital care by one percentage point (with SE = 0.006; not reported in the table). When we limit the sample to advanced-stage cancer at the first diagnosis, this difference decreases.

Each cancer diagnosis could lead to more cancer therapies, including surgery, chemotherapy, radiation therapy, hormone therapy, palliative care, targeted therapy, immunotherapy, stem cell treatments, and Chinese medicine. We excluded

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

the last three from our analysis because less than one percent of diagnoses have led to adopting any of them (Table A1). Namely, only 0.74 percent and 0.14 percent of diagnoses led to immunotherapy and stem cell treatments, and a mere 0.05 percent resulted in Chinese medicine therapy, though no physician-patient uses it.

Because the Death Registry is available for this study only until December 2016, the N-year survival indicator needs to forgo N years of the combined data. After the first diagnosis, more than 80 percent of cancer patients survive beyond 180 days, and close to 60 percent live more than three years.

Our analysis includes all the hospital admissions associated with patients with advanced cancer at the first diagnosis. One concern is that doctors might have diagnosed physician-patients' advanced cancer earlier than other patients' cancer. This sample-selection issue would lead this study to overstate physician-patients' treatments and survival advantages. However, Table A1's statistics show otherwise. The first diagnoses for physician-patients are roughly three ppts more likely to be advanced cancer than those for other cancer patients. This difference drops below 0.7 ppts (with a standard error of 0.009 clustered at patient levels; not shown in tables) after holding constant the patient's sex, age, income, region, spending on inpatient care, and diagnosis year. These results suggest that the potential bias due to earlier diagnoses by physician-patients is unlikely in our data.

Table 1 compares hospital admissions between physician- and 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 279,399 nonphysician patients and 2,454 associated with 611 physician-patients. Statistics show that physicians are substantially older and wealthier, tend to be male and spend 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 more experienced male doctors practicing in single locations and specializing in a cancer-related area or working in a cancer-related department.

On average, there are 122.66 days from the first diagnosis to inpatient treatment for nonphysician-patients, 5.59 days longer than for physician-patients. This difference is significant at the 90-percent significance level. Additionally, nonphysician-patients stay in acute inpatient care units for about 7.89 days, while physician-patient stays are 10 percent (0.81 days) shorter at the 95-percent significance level.

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

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 for one and three years). Physician-patients' survival advantage seems inconsistent with a population comprising more older male patients at more advanced stages. Those advantages may result from income, better communication, closer relationships with attending doctors, the selection of doctors, or more cancer-related knowledge.

2. Core Estimates

This section estimates the total effect on treatment choice and health outcomes. We adopt matching methods to address patient selection on unobserved doctor quality. We compare hospital admissions by physician-patients and comparable nonphysician-patients attended by the same doctor in the same hospital. We also match precisely according to a comprehensive list of patient types to ensure patient comparability, including cancer sites, income levels, demographics, admission periods, and previous inpatient costs.[4] We choose to use the nearest-neighbor matching procedure because it allows for complex interactions among these covariates. Since the method nonparametrically matches patient admission periods within doctor-hospital, we can capture any time-varying component in doctor and hospital quality, as well as 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.

A. Balance Checks

We first leave the attending doctor unmatched and 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 for patient kinds 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 extremely rare in matching physician-patients to other patients with advanced cancer. The former group is significantly older, healthier, and wealthier and comprises more males than the latter. After matching, the total number of admissions is 2,811, consisting of 685 admissions (for 98 matched physician-patients) versus 2,126 admissions (for 565 matched nonphysician-patients).

Although scheme-A drastically narrows down comparable patients, most see different attending doctors. As a result, the observed difference in outcomes

[4] We control for the following list of patient types: gender, 17 cancer sites, two-year age bins, four-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.

between physician-patients and other patients might merely reflect physician quality effects. We improve the balance of matches by further matching according to attending doctors in scheme-B. This step reduces the sample size to 552 admissions, in which 252 are for 31 physician-patients while 300 are for 69 nonphysician-patients.

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. The t-test and KS-test have p-values equal to one for the precisely matched covariates. The scheme-A statistics show the patients' pre-diagnosis health conditions, proxied by pre-trends in inpatient cost and prior spending on drugs, are balanced statistically. In contrast, the attending doctors who treated physician-patients have 0.3 standard deviations (SD) more experience than those who treated nonphysician-patients. Also, the distributions of doctor gender, mobility, and specialties differ significantly between physician- and nonphysician-patients.

After further matching patients according to 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 of 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 variation of the matched covariates. Further matching those 2,811 admissions to their attending doctors in scheme-B reduces the SD by 15 percent to 75 percent. This reduction suggests that the change in outcomes primarily comes from the variation in attending doctors.

As 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 their nonphysician counterparts (table 2). For example, suppose that physician-patients prefer fewer tests and intensive therapies at a more advanced cancer stage. Also, assume that experienced or highly qualified doctors tend to use more intensive care and order more tests.[5] Because physicians can identify highly skilled doctors more easily than nonphysicians, we will *understate* the physician-patient's negative impact on intensive care utilization and checkup costs if we do not match them according to attending doctors.

Further matching hospital entries according to the attending doctor within the hospital, we see scheme-B drastically *increases* the physician-patient's impact on surgical/radiation adoption and the costs for examinations as expected. Physician-patients are eight ppts less likely to undergo surgery and seven ppts less likely to adopt radiation therapy. These estimates are statistically significant and account for 42 percent and 21 percent of the residual SD (0.083/0.20; 0.071/0.33). In contrast, scheme-B *reduces* 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. These differences in the impacts of physician-patients for the within-hospital and the within-doctor-hospital matched samples suggest that physicians choose better doctors *even within hospitals.*

[5] 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.

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 utilize lower surgical volumes than their counterparts by 0.4 SD (1.159/2.87) while taking approximately the same radiation dose as other adopters. In addition, 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 target drug therapy and prescription medications; they are 60 percent (0.167/0.28) more likely to adopt targeted therapy and spend 0.4 SD (0.652/1.80) more on drugs than other patients.

Physician-patients with advanced cancer spend more on medications, likely due to higher quantity, more varieties, or increased prices (e.g., on patent brands) of drugs consumed.[6] However, the NHI administration sets the reimbursement price uniformly for each drug and adjusts the price according to a universal formula (Chen and Chuang, 2016). Therefore, 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.

B.1 Fixed-Effects versus Matching Estimates

We explore whether our basic results derived from nonparametric matching are consistent with conventional models' estimates. Table 4 shows that the fixed-effect (FE) estimates in columns 2–3 are strikingly similar to the matching estimates in

[6] 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.

columns 5–6 (derived from table 3, columns 6–7). However, the FE results tend to be less precise and suffer from type II errors. Specifically, the FE 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.

Matching estimates show that physician-patients use less intensive care, but FE models cannot detect such reduction in intensive care at the extensive margins because of loss of precision. As for the intensive margins, FE can capture it only if using the fully matched data (tables 4, A3, and A4). Likewise, matching methods show that physician-patients use more drugs and targeted drug therapy. Still, FE models give the same results only if using the fully matched data (the same tables).

Furthermore, Table A4 uses FE models using data that include all the hospitals visited by physician-patients (including chosen and nonchosen doctors). The results show that physician-patients have no impact on intensive care utilization at the external margins, contrary to matching estimates. These FE estimates also show that physician-patients incur lower NHI costs and have no effect on the coinsurance payment, contradicting the matching results. Interestingly, FE models indicate persisting patterns in Tables A3 and A4, regardless of whether we include either doctor FE or doctor-hospital FE. The linearity assumption required by FE models might be unrealistic to ensure conditional independence because physician and nonphysician types have little overlap in the within-hospital or within-doctor-hospital matched samples.[7]

Unlike FE models, matching methods are applicable even when the outcome distribution has a mass point at zero or one. As 93 percent of our matched sample survive beyond 180 days after the first diagnosis, we follow econometricians'

[7] Miller, Shenhav, and Grosz (2021) refer this identification issue with little overlap in fixed-effect models as "selection into identification." They propose reweighting and extrapolation methods for tackling the problem.

recommendations to use logistic regressions (e.g., Hirano et al., 2000) or quantile regressions. Unfortunately, neither the FE nor logistic regression model converges for the 180-day survival outcome in our fully matched data.

C. Cost-Effectiveness

We have shown that physician-patients receive fewer surgery/radiation treatments for advanced-stage cancers than the matched nonphysicians while spending more on drugs and are more likely to use 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 6 and 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 three-year cutoff. 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. 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 physician-patient intensive care volume reduction 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; and 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. However, 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 two percent (1.3/75.6) of standard deviations. Thus, we cannot accept the hypothesis that physician-patients receive treatment 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. We control for the following list of patient types: gender, 17 cancer sites, two-year age bins, four-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.

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 decreased surgical or radiation therapy adoption or volume is not attributable to physician-patients' better health status.

C. Physician-Patients Less Likely Sue for Malpractice than Other Patients

Another possible explanation for our finding of reduced intensive care and examinations for physician-patients is that they are less likely than nonphysician-patients to sue for malpractice. 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 our matched data.

During our data period (2004–2016), medical doctors in Taiwan were subject to no-fault liability or joint-and-several liability (Ministry of Health and Welfare, 2018). According to Taiwan's medical liability literature, ER, neurosurgery, and anesthesiology are the major specialties most likely to get sued and pay the highest payment (Chen et al., 2012). However, in our data, no matched admission appears in the ER, and we find only a handful of neurosurgery or anesthesiology cases. These statistics suggest that very few entries in our matched data have seen doctors in those risky specialties. Thus, defensive medicine is unlikely to explain the lower utilization rates of surgical or radiation therapy among physician-patients with advanced cancer.

Nevertheless, fear of litigation may drive doctors to give different types of procedures to physician-patients and other patients because of their unobserved differences, which we will address next.

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

Despite our best attempts to match hospital admissions according to hospitals, attending doctors, and patients' socioeconomic backgrounds, our physician- and non-physician patients may differ in dimensions not included in our study, such as education, clinical knowledge, risk aversion level, or trust in their doctors. Therefore, 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 to their attending doctors and greater access to medical information than other patients. Still, relational and informational advantages can vary according to physician-patients' and their doctors' specialty compositions. For example, suppose both patient and attending doctor have their first specialty in an area not related directly to cancer cite (e.g., family or emergency medicine). In that case, they are closer professionally, although the patient is not more informed than the average physician-patients. Using the variation in relational and informational advantages among physician-patients treated by the same doctor, we can minimize unobserved heterogeneity and address the omitted variable bias. The following section expands on this idea and documents our findings.

4. The Relational versus Informational Mechanisms

Motivated by Section 3D, we further restrict our data to physician-patients in this section to probe how their relational and informational advantages affect treatment and survival. This exploration is possible because the doctors who have attended physician-patients in our data have a wide range of *first/main* specialties, from OB/GYN to Pediatric Surgery. We explain this data feature in Section 4A. Since maintaining the specialty certification requires annual participation in continuing certification workshops at local and national levels, patients and doctors who share the same specialty tend to have a more robust professional tie.

Since both doctors and physician-patients have a wide range of first specialties, the doctor-patient matched data exhibits diversified specialty compositions and professional connections across the doctor-patient pairs. This variation in professional relationships and the comprehensive data on patient backgrounds allow us to continue applying matching methods to isolate the effect of a closer professional connection from being more informed. Finally, we extract parts of the physician-patient impact related to relational advantages, which previous studies often interpreted as informational.

Our matching estimates suggest that physician-patients with closer professional ties spend substantially more on medication and targeted therapy. This result is consistent with the average physician-patient's impact on medication costs. However, contrary to the average physician-patient's use of fewer intensive treatments, the matched physician-patients with stronger professional ties use *more* than those with weaker connections. This contrast implies that the relational advantages cannot fully explain why average physician-patients use less intensive care than other patients. Instead, other channels — plausibly, the informational mechanism — are the leading explanation for the typical pattern.

By comparing the impact of a change in relational advantages to the effect of a change in informational benefits among matched physician–patients, we confirm that the informational premium is significantly larger than the relational premium. Also, the informational premiums exhibit similar patterns to the premiums received by an average physician-patient. Finally, results show that extra clinical knowledge drastically shortens waiting time for physician-patients with no professional connection. In contrast, *network-induced information* increases waiting time and medical costs for those who have robust professional ties. Overall, the informational mechanism is empirically more critical than the relational mechanism in explaining typical physician-patient treatment patterns and survival premiums. We detail below how we use matching methods to derive these results.

A. Division of Physician Jobs and Specialization

Unlike most doctors in the US who refer all cancer patients out to an oncology subspecialist, organ-specific specialists in Taiwan make most of the diagnoses and removal of cancer via endoscopic procedures. An organ-specific surgeon would remove cancer if operable for patients at the advanced stages. If inoperable, the attending doctor would refer the patient (most likely in the end-stage) to an Oncologist for further chemotherapy or radiation treatment. Consequently, doctors attending stomach cancer patients in our data, for example, could be Gastroenterologists, Gastrointestinal Surgeons, or Radiation Oncologists. This division of physician work is like Japanese systems before 2007 when Japan started certifying oncologist subspecialists (Tamura 2012).

Their *subspecialties* are not directly observed in the NHI database because the government regulates the 23 board certification specialties while leaving subspecialty certifications to medical associations to manage.

This difference in specialization between American and Taiwanese systems results from Taiwan's tight controls over hospital spending under single-payer, global-budgeting systems, which leave little room for hospitals to pay premiums to subspecialists in oncology. Also, the government regulates the board certification for the 24 main specialties,[8] but the law specifies no subspecialties nor rules regarding subspecialty certification. The lack of regulations leaves the subspecialty certification to the discretion of oncology professional associations, typically organized by medical professors and former students in the same first specialty. After finishing two years of residency training, these associations usually require two or more years of training to grant a subspecialty certificate.

Because of these institutional features, the NHI data records each doctor's primary specialty but offers no information about subspecialties. The data source also prohibits further data linking to oncology society member lists. Nevertheless, we infer each doctor's oncology-related subspecialties from the cancer caseload (relative to non-cancer caseload) during the three years before the hospital admission. For physician-patients, we measure their knowledge about their cancer sites using their primary specialty and previous cancer caseloads before being diagnosed with cancer.

[8] The NHI data lists the same 24 medical specialties as in the *Diplomate Specialization of Examination Regulations*. The government enacted the laws in 1988 and amended it several times between 2006 and 2018 (https://law.moj.gov.tw/ENG/LawClass/LawAll.aspx?pcode=L0020028).

B. Mapping Specialists to Knowledge and Social Network

Furthermore, we measure the professional tie between any two doctors using their main specialties because they might have met each other in the

C. Quantify the Relational and Informational Advantages

We define two dummy variables to quantify physician-patients' relational and informational advantages. First, although every physician-patient is somewhat informed, physician-patients whose medical specialties relate directly to cancer sites or treatments are defined as *more informed* (indicated by I). For example, gastroenterologist-patients with advanced stomach cancer are more informed because they specialize in internal medicine, and most cancer treatments involve internal medicine. Urologist-patients with advanced cancer are also considered more informed because urology belongs to external therapy. In contrast, all cancers (except for leukemias) involve organ removal, which is also within the domain of external medicine. However, radiologist-patients with advanced cancer are not more informed because they specialize in examinations that do not relate directly to cancer treatments. We summarize this method of categorization in table A2.[9]

Moreover, every physician-patient has some professional connection with the attending doctor. However, specialist patients who share the attending doctor's

[9] Table A2 shows that all the cancers except the leukemias have a surgical therapy option. Because leukemias are the only cancers that do not permit surgical therapy, we classify physician-patients with non-leukemia cancers whose specialties relate to any cancer treatment as more informed (in the left panel). Leukemia physician-patients who specialize in oncology and several branches of internal medicines are also more informed than other leukemia physician-patients because these specialties relate closely to cancer treatments (in the middle left block). In contrast, physician-patients with non-leukemia cancers who specialize in anesthesiology or emergency medicine are less knowledgeable because neither specialty relates directly to treating cancer (in the top-right block). Leukemia physician-patients who specialize in examinations (in the bottom-right block) or internal medicines that are unrelated to cancer treatment (in the mid-right block) are also relatively less informed than other leukemia physician-patients. According to this classification, a gastroenterologist would know as much about cancer treatments for colon cancer as an oncologist and a bit more than a family medicine specialist would. Finally, if their medical specialties are missing from the NHI database, we use their hospital departments to help determine whether they are more informed than other physician-patients.

specialty area have a *robust professional tie* (indicated by R). Such doctor-patient pairs are more strongly connected than others because they are more likely to have met 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, the professional tie for each doctor-patient pair is well-defined in our NHI data. Additionally, we define a doctor-patient pair as a solid professional link if both in the pair belong to the same cohort (i.e., seven or fewer years apart when they first certified because Taiwan's medical education takes seven years to complete). These pairs might have met in medical school events.

Among the 611 physician-patients diagnosed with advanced cancer from 2004 to 2016, we observed 2,453 hospital admissions, as documented in table A5. Of these admissions, 19 percent were physician-patients with more medical knowledge ((174+301)/2453), and 38 percent had a robust professional tie ((629+301)/2453). Notably, one physician-patient might have multiple admissions for different specialists. As a result, her relational indicators might vary across admissions.

Despite homogeneity by occupation and cancer stage, this data still highlights the age differences among physician-patients and the male attending doctor percentage across relational and information advantages (table A5). On average, more informed physician-patients are five years younger and at least three ppts less likely to seek treatment from a male doctor than less knowledgeable physician-patients. In addition, physician-patients with a robust professional tie tend to see doctors with more experience by about half a year than other physician-patients without. We continue to use matching methods as detailed below to address patient heterogeneity and self-selection of doctor quality.

D. Explorations of Mechanisms

This subsection explains how we assess the relative importance of physician-patients' relational and informational advantages. Let β_{IR} denote our core parameter identified in Section 2 — the total impact of a physician-patient on outcomes given her informational and relational advantage indicators, I and R. We aim to deconstruct the full effect into four components:

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

where β captures the general difference in outcomes between physician-patients and nonphysician-patients, who have neither of those specific advantages. This parameter measures the general superiority in medical knowledge and professional connections any physician-patient would have over other patients. The coefficient η is the physician-patient's main benefit from being more informed than other physician-patients. The parameter ρ measures the physician-patient's main benefit from having a robust professional tie. Finally, δ is the effect of network-induced information or having both advantages on outcomes.[10]

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. Taking the relational benefit (ρ) as an example, we first restrict data to less informed physician-patients. Then, by comparing those with robust ties to comparable ones without such connections, we can identify ρ. Similarly, we can estimate the gap between relational and informational benefits ($\eta - \rho$) by limiting the data to physician-patients with $I + R = 1$ (the dark grey areas), who are either more informed or strongly connected to the attending doctor.

[10] It is noteworthy that the relational and informational components in β remain inseparable as in 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 favoritism determine the differences in treatments and health outcomes.

To minimize the selection bias in the nonrandom assignment of professional connections, we require exact matches for doctors, hospitals, patient sex, and broadly defined cancer sites while controlling for patient backgrounds.[11] This empirical strategy focuses only on inpatient doctors who attend multiple same-sex physician-patients with the same cancer site but different advantages. We expect to have a low match rate with these stringent data requirements.

Our matching schemes 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 were 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 without them. These 153 cases cover five broadly categorized cancer sites among 52 physician-patients treated by 11 doctors in 5 hospitals.[12] Thus, the exact match rate is 8 percent (=153/(1349+629)). See these statistics in table A5.

For identification, our matching strategy requires that patient selection is on observables only. This condition rules out the possibility of reverse causality (e.g., the physician-patient would choose a doctor with a relational advantage that can provide a preferred treatment). As in Section 2A, we test this condition by several placebo tests in table 6. The first two columns prove that the predetermined variables not included in this matching procedure are well balanced between less-

[11] 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 the NHI data, we simplify our analysis by grouping these sites and specialties into five specialty categories. We proxy their specialty areas for physicians with no specialty records using their hospital departments (table A2). We continue using matching methods because fixed-effect models produce less precise results and are more likely to accept a false null hypothesis (Section 2B.1).

[12] 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) other (e.g., eyes, central nerves, endocrine glands, and body parts affected by leukemia).

informed physician-patients with versus without a robust professional tie. Although we have left patient health proxies, demographics, and doctor time-varying quality measures unmatched, these variables do not significantly differ in means or distributions, making it plausible that unobserved patient attributes or doctor qualities also balance out.

Columns (2) and (3) of table 7A display the matching estimated effects of the relational mechanism on treatments/outcomes for relatively less informed physician-patients. Surprisingly, the relational impacts (columns 2–3) and 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, we find no evidence that the relational advantage could significantly affect either expenditure.[13]

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. Also, Section 3 has minimized competing explanations. These results leave the *informational mechanism* as a 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-patient's effect on medication cost and targeted therapy utilization are significantly

[13] We omit hormone therapy from our analysis in this section because hormone therapy treats 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.

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 robust professional relationship with the attending doctor can induce professional and general social interactions and increase drug spending and target therapy use. It is noteworthy that our identification cannot distinguish professional from general social interactions, as doctors in similar specialties interact more for various reasons, not necessarily just for professional reasons.

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

Moreover, we use the same procedure to estimate the information's main effect (η) and the information's total impact ($\eta+\delta$), where δ is the additional information benefit derived from professional ties. This step requires comparing hospital admissions between more- and 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 (54.5/90.0). This result contradicts the relational advantage's near-zero impact on waiting time, as table 7A indicates.

When more informed physician-patients have stronger professional ties, their network might provide extra knowledge, such as authoritative physician opinions.[14] However, network-induced information seeking may prolong waiting times, leading to a positive d that would offset the information's main effect and increase total medical costs. Table 7B's columns 5–6 limit the data to physician-patients strongly connected with their attending doctors (R=1). We find that the informational benefit of a shorter waiting time reduces to less than half (21.3 days) and becomes very imprecise. This extra waiting time is also associated with substantial NHI costs and chemotherapy utilization increases. These estimates show signs of 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 who are more informed spend markedly less on checkups than the less-knowledgeable physician-patients and are more likely to utilize targeted therapy rather than radiation. Thus, even among highly comparable physician-patients, treatment decisions are still strikingly different based on their possession of 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 does not appear in the less-informed physician-patients' relational mechanism. Combining these results reconfirms the information mechanism's dominant role in treatment decision-making.

[14] Recent narratives of 12 physician-patients diagnosed with cancer describe the information-seeking process. Almost all of the cases emphasize that their network's additional information was crucial to 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, drastically improving short-term survival. As shown in table 7A, columns 2–3, the 180-day 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 treatment decision-making model.

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 remains unknown outside of those contexts.

This paper first establishes a benchmark of physicians treating physicians without separating the relational and informational mechanisms. Then we compare physician-patients' and comparable nonphysician-patients' treatments and survival outcomes, given the same advanced cancer and attended by the same doctor in the same hospital. By exploiting the 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 in the case of comparable nonphysician-patients.

Notably, physicians' relatives might receive similar benefits as physician-patients. Because we take those relatives as nonphysician-patients, our results might understate the physician premiums in a broader perspective.

Physician-patients possess clinical knowledge and professional connections, contributing to better care and higher survival rates. We assess the relative importance of the relational and informational 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, medication, and targeted therapy. This highly intensive treatment, induced by a stronger relationship with the attending doctor, improves the short-term survival rate. This evidence reveals the relational mechanism at work. To evaluate which mechanism dominates, we further match physician-patients who have strong ties or are more informed. We find that the informational mechanism is the leading explanation for treatment decisions that result in better survival in advanced cancers.

Our findings on the relational and informational mechanisms are consistent with a framework in which risk-averse patients undervalue the health benefits of intensive care and, thus, have low demand for it. A stronger bond between patients and doctors that builds trust and improves communication can reduce risk aversion and increase demand.[15] Doctors can also increase patient demand to benefit their self-interests if patients are less informed, as posited by the classical doctor-driven demand hypothesis.

These results offer possible lessons for the labor markets of expert services (e.g., real estate agencies, used car dealerships, and initial public offering underwriting). Professional connections bring short-term gains but are incapable of resolving

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

agency issues. Ultimately, relational advantages cannot eliminate conflicting interests. Even for expert consumers, acquiring extra information is more effective than developing business relationships to achieve better outcomes. The key to resolving agency problems is to close the information gap between principals and agents.

Although our analytical approach is novel, our study has three limitations. The first is that it assumes monotonicity of the relational and informational advantages. In other words, the mechanism that distinguishes doctor-patient pairs by medical specialties is the same one that can separate physician-patients from nonphysicians. However, professional ties might differ from nonprofessional connections, affecting treatment decisions and health outcomes. Our second limitation is the assumption that physician-patients' selection in professional relationships can be based entirely upon observables.[16] If the selection is also based on unobservables, we overstate the relational benefits and understate the informational advantages due to reverse causation; physician-patients who prefer intensive care may choose a doctor with whom there is a relational advantage to receive favorable treatments. Third, our matched data has a small sample size due to a rare overlap between physician-patients and nonphysicians. More data support would further enhance our understanding of how networking-induced information affects patient survival. This study sheds light on agency problems in healthcare. Relaxing the monotonicity and increasing sample size could be addressed by future work.

[16] This limitation is the same one faced by Reuter (2006), who attempted to test for favoritism in allocating initial public offering stocks (IPSs) across mutual fund families. He identifies the impact of this favoritism by controlling the level of private information using a proxy that varies across the investor-underwriter relationships. However, the observed favoritism might result from selection issues regarding mutual fund managers' incentive to allocate underpriced IPOs strategically (Gaspar, Massa, and Matos, 2006).

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

	End-stage cancer at the first diagnosis		
Variable	Nonphysician Mean	Physicians minus 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 1095 days+	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

Predetermined variables not matched on	A) Exact match on patient types within hospital: Std. mean diff.	t-test	KS-test	**B) Exact match on patient types within doctor-hospital**: 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
Doctor practice in multiple hospitals	-0.14	0.26	**0.00**	0.00	1.00	1.00
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) Within hospital	(2)	(3)	(4)	(5)	(6)	(7)
		(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 a 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

	Less informed Physician-patient I = 0	More informed physician-patient I = 1	Nonphysician-patient	***Difference:*** I = 1 versus I = 0
With strong ties R = 1	$\beta+\rho$	$\beta+\eta+\rho+\delta$	0	$\eta+\delta$
With no strong tie R = 0	β	$\beta+\eta$	0	η
Nonphysician-patient	0	0	0	
Differences:				
R = 1 versus R = 0	ρ	$\rho+\delta$		

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

	I = 0 Physician-patient specializing in areas unrelated to the cancer site		I + R = 1 Either with a strong tie or being more informed		R = 1 With a strong tie		R = 0 No strong tie	
Predetermined variables	Having a strong tie or not		Being more informed or not		Being more informed or not		Being more informed or not	
not matched on	t-test	KS-test	t-test	KS-test	t-test	KS-test	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		
Bones, skins, and connective and other subcutaneous tissues								
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 according to 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 ($\eta - \rho$)			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 ($\eta+\delta$)			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. 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. For the two matching schemes in the first six columns, see Table 6 for balance statistics. 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				Advanced-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:								
Advanced stage, 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	0.0074	0.0011	0.56	1,216,565	0.0144	0.0048	0.33	364,060
Stem cell	0.0014	0.0007	0.47	1,216,565	0.0044	0.0007	0.78	364,060
Chinese medicine	0.0005	**-0.0005**	0.00	1,216,565	0.0007	**-0.0007**	0.00	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 1095 days+	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 excluding 138 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 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. In 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, CERTIFIED SPECIALTIES, AND HOSPITAL DEPARTMENTS

Specialty Category	**Cancer site coding**	**Relating to cancer treatment, I = 1**		**Unrelating to cancer treatment, I = 0**	
		Certified specialty	**Hospital Department**	**Certified specialty**	**Hospital Department**
Surgery	(1)-(15), (17)	Surgery	Surgery departments	Anesthesiology	Anesthesiology
		OB/GYN	OB/GYN	Emergency	Emergency medicine
		Urology	Urology		
		Otolaryngology	Otorhinolaryngology		
		Dermatology	Dermatology		
		Neurosurgery	Neurosurgery		
		Orthopedics	Orthopedics		
		Ophthalmology	Ophthalmology		
		Plastic surgery	Plastic surgery		
Internal medicine	(1)-(17)	Oncology	Oncology departments	Neurology	Neurology
			Internal medicine	Family medicine	Family medicine
			Gastroenterology	Pediatrics	Pediatrics
			Endocrinology medicine	Rehabilitation	Rehabilitation
			Cardiovascular medicine	Occupational medicine	Occupational medicine
			Thoracic medicine		Others
Examination				Anatomical pathology	Pathology
				Nuclear medicine	Nuclear medicine
				Clinical Pathology	Radiology
				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). If doctors have no specialty record, we use their hospital department to infer their specialties.

TABLE A3—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 the 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 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). In 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 A4. 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 specifications, we control for the complete set of dummies for 5-year doctor experience bins and 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). The survival outcomes have fewer observations than other outcome variables (see table). We report the clustered standard errors (SE) at the patient level.

TABLE A5. 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	611	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) shows 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 A3 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 expanded data’s fixed-effect estimates are strikingly similar but remarkably different from the matching estimates. Both sets of the fixed-effect estimates suggest near-zero effects of physician patients on surgery adoption and medication spending, opposite to what the matching estimates have shown.

We prefer matching methods because fixed-effect linear models require more 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 show 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 A4.

In contrast, omitting the doctor-fixed effect bias the results substantially because of patient selection. Physician-patients are most capable of selecting highly skilled doctors who use 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 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.