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

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We study the role of medical knowledge versus professional networks in treatment choices and patient survival, using medical specialty variation among specialists and physician-patients with advanced cancer. We control unobserved doctor quality by matching comparable patients by attending doctors and admission periods. Compared to nonphysician-patients, physician-patients are less likely to have surgery/radiation/checkups and more likely to receive targeted therapy, spend more on drugs, and enjoy higher survival while spending less on coinsurance. The effect of professional networks explains some but not all patterns, leaving medical knowledge mechanisms to play a key role. Possessing a network equates to medical knowledge reduction for physician-patients with little medical knowledge of their cancers. *Keywords: physician quality; social ties; communication; information. JEL: D83, I11, J44*

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Growing literature in labor economics examines whether complete information or robust social ties can solve agency problems (Bandiera et al., 2009; Jackson & Schneider, 2011). Health economists joined this empirical investigation by randomizing doctors' races and vaccine incentives for patients (Alsan et al., 2019) or exploiting the exogenous variation of OBGYN 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., 2019) 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 more often, attributed to a closer relationship or better communication with their 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 attributed this to more knowledge of complications or potential side effects. Irrespective of underuse due to weak social ties or overuse due to asymmetric information, the relational and informational disadvantages were empirically inseparable because of the absence of data regarding medical specialty variation among the attending doctors.

[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 be capturing the difference in the susceptibility of self-treatment versus treating others, not necessarily reflecting the physician-patients' effect on treatment choice, as noted by Ubel, Angot, and Zikmund-Fisher (2011) and Shaban, Guerry, and Quill (2011). Earlier studies avoided the susceptibility bias by comparing expert consumers to non-expert or physician-patients to other patients (Bunker and Brown, 1974; Hay and Leahy, 1982; Earle et al., 1993).

This paper evaluates the relative importance of the relational and informational influences on healthcare agency issues. We study inpatient doctors in a wide range of first/main specialties in Taiwan who have attended about 0.4 million patients with advanced cancer since 2004, including hundreds of physician-patients. To maintain an oncology subspecialty license, these doctors must regularly attend Taiwan Oncology Society's (TOS) conferences and training courses according to their specialty division. We exploit TOS's taxonomy to define the professional tie between each physician-patient and the attending doctor. Using the universal health insurance data, we include rich controls for patient attributes and quantify each physician-patient's medical knowledge of the diagnosed cancer by calculating the cancer caseload per specialty and hospital department. By looking at matched physician-patients with different specialties attended by the same doctor, we distinguish the effects of relational advantage (due to stronger professional ties) and informational advantage (owing to being more informed).

Because of a lack of experimental variation, we address unobserved physician quality and patient-selection issues through Abadie and Imbens's (2006, 2011) nearest-neighbor matching method, which enables complex interactions among covariates without linearity assumptions. Our approach exploits the *within-doctor-hospital variation* across matched patients treated during the same period, matched by patient types such as gender, cancer sites, and previous inpatient costs. This strategy allows us to minimize the bias 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 survival with comparable nonphysician-patients. Our matching estimates show that the average physician-patient is less likely to adopt surgical/radiation therapies but more likely to use targeted drug therapy than other patients. Physician-patients also spend less on checkups and enjoy significantly higher survival rates from six months to three years. The magnitudes range from 0.2 to 0.4 standard deviations, all statistically significant at conventional levels.

These basic results conform to relational/informational mechanisms and competing explanations, such as the early diagnosis and treatment of physician-patients. We rule out competing hypotheses empirically. Doctors in the universal cancer registry are equally likely to detect cancers in the early or advanced stages for physician and nonphysician patients. Our matching estimates show no difference in the diagnosis-to-treatment interval between these two types of patients. Thus, doctors in our data do not diagnose or treat physician-patients sooner than others.

Another scenario that could lead to our basic results of lower intensive care utilization rates among physician-patients is that nonphysician-patients are more likely to sue. Doctors might prescribe unnecessary procedures to less-informed patients to reduce their potential liability. Taiwan's medical liability literature shows that most lawsuits arise in neurosurgery, anesthesiology, and the ER (Chen et al., 2012). However, our data indicates that almost no patients visited these hospital departments for cancer care, suggesting that unequal propensities to sue are unlikely to drive our results.

We take the basic results to assess the relative importance of relational and informational mechanisms using specialty variation across attending doctors and within-doctor variation in specialties across physician-patients. We measure each physician-patient's medical knowledge of their cancer site using the relative caseload attended by inpatient doctors in their specialty area. Furthermore, we quantify each doctor-patient pair's professional tie by whether their specialties belong to the same TOS specialty taxonomy and division of duties.

By exploiting these proposed measures for network and knowledge, we explore the mechanisms behind the average physician-patient effects. Comparing nonphysician-patients to physician-patients with neither professional ties nor specialist knowledge of the diagnosed cancer site, we find that fundamental physician superiority leads to different treatments but not higher survival. Restricting to physician-patients only, we compare whether they have a professional connection with the attending doctor. While a professional tie does not impact short-term survival, it improves long-term survival by promoting intensive care (i.e., surgical/radiation therapies) at extensive margins. However, neither physician superiority nor professional network explains why typical physician-patients use more targeted therapy and less intensive care at extensive margins while enjoying significantly better short-term survival. This leaves information mechanism as the leading explanation for physician-patients' short-term survival benefits and treatment patterns.

Professional networks and knowledge are exchangeable when physician-patients are less informed. We impose functional form assumptions on comparable physician-patients to quantify their informational exchangeability for a professional tie. For those with knowledge within the bottom quartile, having a network would be equivalent to a reduction of 6 to 18 percentage points (ppts) in specialist knowledge to maintain the same survival level or intensity of treatment. This finding points towards a potential scenario where the attending doctors abuse patient trust and prescribe different procedures than they would to more informed patients. Such a deviation can hurt patient survival. The result indicates the dominant role of information over professional ties in treatment choice and survival, particularly for patients lacking expert knowledge.[2]

Our assessment of relational and informational mechanisms contributes a new dimension to the literature on healthcare agency problems. Previous research has focused primarily on doctor-driven channels, including financial incentives and

[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 near-zero effect.

asymmetric information. We fix both channels by looking within the doctor-hospital variation across physician-patients specializing in various medical areas. Our findings demonstrate that the doctor-patient relationship matters for treatment choice and long-term survival at the advanced cancer stage (since it induces more information for informed patients). We also demonstrate information's dominant role for less informed patients. For both relational and informational mechanisms to work, the theoretical context must include the doctor-driven demand hypothesis via a framework in which *risk-averse* patients undervalue the benefit of intensive care, thus lowering demand. A stronger doctor-patient relationship can overcome risk aversion through better communication and trust-building to induce demand. It can also create a leeway for doctors to abuse their patients' trust and deviate from appropriate care.

The rest of the paper proceeds as follows. Section 1 describes the data and institutional settings and summarizes our data features. Section 2 discusses our matching scheme for constructing the study sample, balance statistics, core estimates, and robustness checks. In Section 3, we examine alternative explanations for our findings. Section 4 explores the possible mechanisms by extending our research to contrast the relational and informational roles of treatment intensity and survival rates. Section 5 concludes the paper.

1. Data and Institutional Settings

A. Patient Cost-Sharing and Provider Reimbursement

Taiwan's National Health Insurance (NHI) database is ideal for this study for several reasons. First, similarly to Canada, 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). Since participation in NHI is mandatory, we can eliminate doubts about adverse selection issues. Furthermore, we can address patient selection issues because the database includes beneficiaries who have never checked into hospitals.

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 via a nationally uniform fee schedule, so providers cannot select patients or impose price discrimination against them. Since hospitals pay doctors via 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 hospital visits without primary care referrals. Consequently, all patients choose their attending doctors without a primary care referral. Since patients can freely check into different hospitals or request different doctors in the same hospital, we analyze doctor-patient relationships by examining *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

We merged several administrative data sources in the NHI database from 2000 to 2018 through four steps using unique scrambled identifiers (IDs). First, we link the *Cancer Registry* to the *Death Registry* and *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 2019, and whether they received hospital care.

Second, we identify the physician-patients and obtain their medical specialties by merging the data with the *Registry for Medical Personnel* and the *Records of Board-Certified Specialists* using their IDs. The former covers 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 the *Reimbursement Claim Records* to obtain inpatient care details per hospital admission one year after a cancer diagnosis. This data reveals the entire history of treatments, care volumes, hospital type and location, hospital ID, and attending doctor's ID, so we can calculate total inpatient care costs, coinsurance payments, 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 *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 three years before 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. 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 more selective doctors than other patients. Table 1 shows that the selectivity level is 0.0039 (0.0022+0.0017), about twice that of other patients. Moreover, physician-patients select more experienced doctors than those attending nonphysician-patients by two years.

These differences are large in magnitude and statistically significant at the 95 percent level.

One significant challenge 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 the attending doctor and the admission time to make a fair comparison.

D. Descriptive Statistics

Table A1 compares the cancer diagnoses between physician-patients and nonphysician-patients, including their attributes, inpatient care receipt, and survival outcomes. The data comprises over 1.2 million cancer diagnoses among approximately 1 million patients and 1,987 medical doctors. The number of cancer diagnoses exceeds that of cancer patients because a single patient can be diagnosed more than once for recurrence or confirmation. Only 0.01 percent of diagnoses involve multiple cancers. 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 in 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 5.

Statistics indicate that 12 percent of all cancer diagnoses lead to no hospital care for all patients. About one-quarter of these diagnoses are in the advanced stage (not shown in the table). After controlling the interaction among patient demographics, prior medical spending, and admission year, we found that physician-patients were

[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).

significantly more likely to receive hospital care by one percentage point (with SE = 0.006; not reported in the table). This difference decreases when limiting the sample to advanced-stage cancer at the first diagnosis.

Each cancer diagnosis possibly led to more cancer therapies, including surgery, chemotherapy, radiation therapy, palliative care, targeted therapy, hormone therapy, immunotherapy, stem cell treatments, and Chinese medicine. We excluded the last three from our analysis because less than one percent of diagnoses led to their adoption (Table A1). Namely, only 0.74 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 chose 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 about 60 percent live more than three years.

One concern about the data is that doctors might have diagnosed physician-patients with advanced cancer earlier than other patients. This sample-selection issue would result in overstating physician-patients' treatments and survival advantages. However, the statistics from Table A1 show no evidence for this. Our analysis includes all the hospital admissions associated with patients with advanced cancer at the first diagnosis. The first diagnoses for physician-patients are about three ppts more likely to be advanced cancer than 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 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. This data covers 1,123,377 admission entries associated with 279,399 nonphysician patients and 2,454 with 611 physician-patients. Given the closed-staff structure of Taiwanese hospitals, each admission matches one attending doctor to one patient. Statistics indicate that physicians are older and wealthier, tend to be male, and spend less on hospital care before the first cancer diagnosis. Both physician- and nonphysician-patients are equally likely to visit a doctor with a preexisting clinical relationship. However, physician-patients tend to opt for male or more experienced doctors practicing in single locations and specializing in a cancer-related area or working in a cancer-related department.

Average nonphysician-patients wait 122 days to receive inpatient treatment after the first diagnosis, which is 5.59 days longer than physician-patients. This difference is significant at the 90-percent 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 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 practice styles of the doctors.

Finally, the bottom part of Table 1 shows that physician-patients with advanced cancer have the same 180-day survival rate as other patients. However, their survival rates for one and three years are higher, which may result from income, better health, better communication, closer relationships with attending doctors, the selection of doctors, or more cancer-related knowledge. The higher survival seems inconsistent for physician-patient comprising mostly older men than other patients with advanced cancer.

2. Core Estimates

This section estimates the total effect on treatment choice and health outcomes. We adopt nearest-neighbor matching methods to address patient selection for unobserved doctor quality by contrasting physician-patients and comparable nonphysician-patients attended by the same doctor in the same hospital. We precisely match patients by their types to ensure patient comparability.[4] Since the method nonparametrically matches admissions by patient types and time components within a doctor-hospital, we capture time-variant and invariant differences in doctor and hospital quality and complex interactions among all these covariates.[5] The following sections present balance statistics and matching estimates.

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) 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. Overlap is extremely rare in matching physician-patients with other patients with advanced cancer. Physician-patients are significantly older, healthier, wealthier, and more masculine. After matching, the total number of

[4] We include 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 doctor three years before diagnosis.

[5] To control for time components, we also precisely match hospital entries according to admission periods and the attending doctor's five-year experience bins at the time of diagnosis.

admissions is 2,811, comprising 685 admissions (for 98 matched physician-patients) versus 2,126 admissions (for 565 matched nonphysician-patients).

Although scheme-A narrows down the comparable patients, most are attended by different doctors. As a result, the observed outcome difference between physician-patients and other patients might 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, of which 252 are for 31 physician-patients while 300 are for 69 nonphysician-patients.

Table 2 tests for balance between matching schemes for variables we did not match. We report the p-values of the mean difference (t-tests) and the distributional difference (KS-tests). Both tests have p-values equal to one for the precisely matched covariates. The scheme-A statistics indicate that the patients' pre-diagnosis health conditions, approximated by pre-trends in inpatient cost and prior drug spending, 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. The distributions of doctor gender, mobility, and specialties differ significantly between physician- and nonphysician-patients.

After matching patients according to their attending doctors in scheme B, none of these pre-diagnosis attributes indicate significant gaps in sample means or distributions. This result strongly suggests 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 the two matching schemes, (A) within-hospital comparison between 2,811 matched admissions and (B) 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 with their attending doctors in scheme B reduces the SD by 15 to 75 percent. This reduction indicates that a large portion of the changes in outcome 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). Suppose physician-patients prefer fewer tests and intensive therapies at the advanced cancer stage, and that experienced or highly qualified doctors tend to use more intensive care and order more tests.[6] 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 and the hospital, we see scheme B drastically *increases* physician-patients' impact on surgical/radiation adoption and 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 statistically significant estimates account for 42 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 tube-feeding care volume drops from approximately 0.3 to 0.03 log points. The effect on radiation volume also substantially decreases and becomes statistically insignificant. These differing impacts of physician-patients on treatments and survival for the within-hospital and within-doctor-hospital matched samples suggest that physicians choose better doctors *even within hospitals*.

[6] The previous literature suggests intensive care can prolong life. Balsa and McGuire (2003) and Currie, MacLeod, and Van Parys (2016) 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 users. In addition, while using less intensive care, physician-patients with advanced cancer are less likely to adopt palliative care by 0.2 SD (0.027/0.16). The only items that physician-patients utilize more are *target drug therapy* (0.167/0.28 = 60 percent more likely) and prescription medications (0.652/1.80 = 0.4 SD greater costs).

Physician-patients with advanced cancer spend more on medications. Given the current data accessibility, we cannot distinguish the sources of the spending hike. The higher spending could be due to higher quantity, more varieties, or increased prices (e.g., on patent brands) of drugs consumed. Given the universally uniform reimbursement prices and adjustments (Chen & Chuang, 2016), doctors/hospitals cannot charge different fees for the same drug. This institutional feature leaves the increased drug dose or variety for physician-patients as a likely explanation for the physician-patient's positive impact on medication cost.[7]

C. Cost-Effectiveness

According to medical guidelines published by the American Cancer Association, surgery/radiation therapies are more appropriate for early-stage cancers. A more advanced-stage cancer requires treatments that reach the entire body, e.g., chemotherapy and targeted drug therapy. We have shown that physician-patients receive fewer surgery/radiation treatments for advanced-stage cancers than the matched nonphysician-patients while spending more on drugs and more likely

[7] An online appendix explores whether our basic results derived from nonparametric matching are consistent with those using conventional fixed-effect models. The matching method provides considerably more precise and robust estimates than fixed-effect models using the same set of controls (Table A2).

using targeted therapy. If physician-patients' treatments are clinically appropriate, our results indicate that underuse and overuse coexist among nonphysician-patients.

Physician-patients have indeed received different and better care. Columns 6-7 of Table 3 show the considerable survival benefits of better treatments. Physician-patients have significantly higher short-term survival than comparable patients by 2.5 ppts (9.3 ppts) at 180-day (365-day) thresholds. Their long-term survival is also higher by 7.1 ppts at the three-year cutoff. These estimates account for at least 0.25 SD. Besides the survival benefits of better treatments, 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. Physician-patient relational or informational benefits might drive our results. We explore three 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; and finally, physician-patients are more likely to sue for malpractice. We examine each hypothesis below.

A. Physician-Patients Are Diagnosed Earlier or Treated Earlier

Physician relationships and information advantages might have led to earlier diagnoses or treatments than nonphysician-patients, resulting in physician-patients needing less intensive care and surviving 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 (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 an SD. Thus, we cannot accept the hypothesis that physician-patients receive treatment earlier than nonphysician-patients.

B. Physician-Patients Exhibit Better Health

To ensure the matched physicians and other patients have similar health conditions, we only compare patients sharing the same quintile for hospital spending in the past three years before being diagnosed with advanced cancer. Nonetheless, it remains possible that physician-patients are healthier than their counterparts in a way not captured by our model. We test this hypothesis by checking the balance of variables excluded from the covariate list. The placebo test results in Table 2 are counter to this hypothesis. The matched patients do not differ significantly in their previous drug spending or pre-trend hospital costs. This pattern is robust, irrespective of scheme A or B (fixing the attending doctor or not) if we limit matched patients in the same hospitals who share the same attributes and cancer sites in the same admission period. These results suggest decreased surgical/radiation use is not attributable to physician-patients' better health status.

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

Another 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. Currie and MacLeod (2008) suggest that 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 malpractice lawsuits for our matched data.

During our data period (2004–2016), medical doctors in Taiwan were subject to no-fault or joint-and-several liability (Ministry of Health and Welfare, 2018). ER doctors, neurosurgeons, and anesthesiologists were the most likely to be sued and pay for non-economic damages (Chen et al., 2012). We investigate our data to see if physician-patients receive exceptionally high premiums in the riskiest departments. However, our matched data shows almost no physician-patients with cancer seeking care in these departments. Consequently, we find no evidence that defensive medicine could explain the lower utilization rates of surgical or radiation therapy among physician-patients with advanced cancer. Nevertheless, fear of litigation may still drive some doctors to prescribe different types of procedures to physician-patients because of unobserved differences, which we will address next.

4. The Informational versus Relational Mechanisms

This section further restricts our data to physician–patients only to probe how professional ties and medical knowledge affect treatment and survival.[8] We aim to extract parts of the physician-patient impact driven by relational advantages, which previous studies often interpreted as informational. This identification is possible because the attending doctors in our data have a wide range of (sub)specialties. We exploit the specialty variation across doctors and the within-doctor variation in physician-patient specialties to separate relational and informational channels.

One data limitation is noteworthy. The government regulates the board certification for 23 specialties, but does not specify any rules for subspecialty

[8] For this section, we include two additional years of NHID data of physician-patients to increase the sample size.

certification. The lack of regulations leaves the subspecialty certification at the discretion of medical associations outside the NHI database's scope. Consequently, we observe each doctor's first/primary specialty, not subspecialties.

Taiwan's specialization structure in cancer care parallels Japan's pre-2007 medical system before enacting the *Cancer Control Act*.[9] Unlike doctors in the US referring cancer patients to oncologists, Taiwanese organ-specific specialists diagnose and remove operable cancer using endoscopic procedures or refer patients to oncologists for chemotherapy or radiation treatment for inoperable cancer. As a result, doctors in Taiwan attending to stomach cancer patients, for example, could be gastroenterologists, gastrointestinal surgeons, or radiation oncologists. We cannot observe whether those specialists have a certified oncology subspecialty.[10]

A. Relational Mechanism: Mapping Specialists to Social Network

As the attending doctor is fully responsible for caring for each admitted patient under Taiwanese NHI's close staff structure, each doctor-patient pair can well-define a professional tie. Physician-patients sharing the doctor's specialty have a stronger tie because they might have met on professional occasions before the diagnosis. Given that subspecialties are unobservable, we infer patient-doctor networks from physician specialties, TOS taxonomy classification, and the doctor's hospital department. We follow the TOS taxonomy to classify networks, allow multiple networks per doctor, and summarize how we map specialists to a social network in Table 4.

TOS covers eight of the top ten cancer-treatment specialties: three belong to the medical oncology network (category I, columns 1–3) and six to the surgical

[9] See Matsuura (2012), Takiguchi et al. (2012), and Tamura (2012).

[10] This difference in specialization between American and Taiwanese medical systems might result from Taiwan's tight controls over hospital spending under single-payer, global-budgeting systems, which leave little room for most hospitals to pay enough premiums to oncology subspecialists.

oncology network (category II, columns 3–8).[11] Although TOS lists pathologists as part of the medical oncology network, we separate them from the medical oncology network if they have no non-pathology specialty or have ever worked in an internal medicine department. Moreover, we follow TOS listing plastic and reconstructive surgeons as part of the surgical oncology network because of the double-dose surgical medicine training requirements for these surgeons to become board-certified surgical oncologists. However, they have zero medical knowledge/caseload of cancer treatment. Finally, dermatologists and ophthalmologists treat most skin/eye cancers, although they are excluded from the TOS taxonomy (columns 9-10). We assume they have separate networks in areas denoted by 'Others,' unrelated to cancer care.

B. Informational Mechanism: Mapping Specialists to Medical Knowledge of a Cancer Site

We approximate each physician-patient's medical knowledge of their cancer site using the caseload per doctor in the same specialty relative to the highest volume. Table A3 illustrates our approximation process using advanced breast cancer. We first calculate the caseload per doctor by specialty and hospital department using 100% inpatient reimbursement data (column 1) and then measure the relative knowledge/caseload of the cancer site per specialty across hospital departments (column 2). The top experts in breast cancer are surgeons in surgery departments because of their highest caseload. Doctors in other departments/specialties account for only a fraction of the top expert caseload.

[11] Since 1990, TOS has certified/renewed medical oncology and surgical oncology subspecialty licenses for eligible doctors. For most events, TOS separates trainees by their specialties (surgical versus medical). Medical oncologists treat cancer primarily using medications (e.g., chemotherapy, immunotherapy, and targeted therapy), whereas surgical oncologists use surgical methods to remove operable cancers. Both categories include the *Taiwan Society for Therapeutic Radiology and Oncology,* so we designate radiation oncologists to both professional networks. The *Taiwan Neurosurgery Society* is on the surgical oncology list. We find no neurosurgeon has treated any cancer physician-patients. Thus, we include neurosurgeons in the surgical oncology network, although we define their knowledge of cancer treatment as zero.

Physician-patients' previous workplaces or hospital departments are unobservable. In column 3, we approximate their knowledge levels of the cancer site given their first specialty by averaging the relative caseloads per specialty across departments, weighted by department shares. Table 4 summarizes the mapping of each cancer site to specialty-specific knowledge. The top experts in treating advanced breast cancer are surgeons in surgery departments, whose knowledge level in this cancer is 0.49, far below one, since most surgeons work in departments rarely treating breast cancer. This data feature appears among other specialists, e.g., radiation oncologists.

We apply this method to all cancer sites. Specialties not listed by the columns have zero relative knowledge, e.g., neurologists, neurosurgeons, and plastic and reconstructive surgeons. The statistics indicate that the top organ-specific cancer experts typically are organ-specific specialists (except for bone cancer). Radiation oncologists have the top expertise in leukemia and stomach cancer treatment. Finally, we standardize physician-patients' knowledge levels given their cancer site.

C. Explorations of Mechanisms

Using the network indicator R and the continuous information measure K constructed in sections 4A and 4B, we evaluate the relative contributions of relational and informational advantages to cancer treatment and patient survival. Let β_{RK} denote the heterogeneous impact of a physician-patient on outcomes given the patient's network R and knowledge K. We aim to deconstruct the full effect into four components:

(1) $\beta_{RK} = \beta + \rho R + e(K) + R\delta(K)$,

where $e(0) = 0 = \delta(0)$. Parameter β captures the difference in outcomes between nonphysician-patients and physician-patients with neither advantage. This parameter measures the *physician status effect,* quantifying the fundamental superiority in general medical knowledge and occupational connections that distinguishes *any* physician-patient from other patients. The network's main effect measures the benefit of having a robust professional tie for patients without superior knowledge of the diagnosed cancer. $e(K)$ is the *knowledge's main effect* if the patient has no professional tie with the attending doctor. $\rho + \delta(K)$ is the *network-induced informational effect* on outcomes.

To evaluate these mechanisms, first, we identify the physician status effect (β) by comparing nonphysicians to comparable physician-patients with neither advantage. Second, we estimate the total impact of a professional tie with the attending doctor ($\beta_{1K} - \beta_{0K}$). This impact includes the *network's main effect* and the *network-induced informational effect,* $\rho + \mathrm{E}[\delta(K)]$, so relational and informational mechanisms are both at work. We cannot separate these two effects using matching methods because of lacking support given continuous medical knowledge.[12] We overcome this challenge in the third step by estimating the value of a network by information percentile upon applying fixed-effect models to matched physician-patients. The following expands each step.

C.1. Physician-patients' general advantage over nonphysician-patients

Using scheme B, we first identify β the physician status effect by matching nonphysician-patients and physician-patients with neither advantage. *Before matching*, physicians with neither advantage tend to be older but healthier males and more likely to seek care from a more experienced doctor than other patients (Table A4, columns 1-2). *After matching* exactly by doctor-hospital and patient types (footnote 4), we obtain a near-perfect balance between nonphysician-patients and physician-patients with no specific advantages. With stringent data

[12] Whenever we group physician-patients by their advantage (e.g., having a knowledge index below versus above the median), the sample shrinks drastically. The matched patients cluster among only one or two specific cancer sites, making it difficult to interpret.

requirements, we have only 5.6 percent of physician-patients (=168/3013) matched to 106 comparable nonphysician-patients treated by 17 doctors in 7 hospitals (not shown in tables).

We document the matching estimates in Table 6 and highlight the coefficients with patterns resembling the average physician-patient effects. Physician-patients with no specific advantage take fewer examinations, use significantly less surgery, and stay shorter in acute inpatient care while significantly spending more on medications than nonphysician-patients (columns 2–3), consistent with the average physician-patients effects (columns 8–9, copied from Table 3). However, unlike average physician-patients, physician-patients with neither advantage receive targeted therapy with a 6.0 ppt *lower* probability but chemotherapy with a 9.4 ppt *higher* probability than nonphysicians. Both estimates are statistically significant and extensive in magnitude, accounting for more than half of the variation in utilization. Nevertheless, such substantially different treatments caused by physician status create no survival advantage (the bottom of columns 2–3).

C.2. The professional network's total impact

To investigate the relative importance of the relational versus informational mechanisms, we must compare the network's main effect (ρ) to the knowledge's main effect ($E[e(K)]$). To this end, we need a balanced sample of physician-patients who have networks but no relevant knowledge versus those who have relevant knowledge but no network. However, this approach requires immense data support and stronger assumptions because the knowledge is continuous. Instead, we estimate $E[\beta_{1K} - \beta_{0K}]$ the professional network's *total impact*, including the network's main effect ρ and the *network-induced informational effect* $E[\delta(K)]$.[13]

[13] A robust professional tie with the attending doctor can induce professional and general social interactions. Our identification cannot distinguish professional networks from general social interactions, as doctors in similar specialties interact for various reasons, not necessarily for professional networking.

We address the selection issues with the nonrandom assignment of professional ties by focusing on inpatient doctors who attend multiple comparable physician-patients with different relational advantages. We precisely match these highly homogeneous patients according to *scheme C* – by doctor-hospital and patient types (gender, cancer sites, and previous hospital spending terciles). Additionally, we control their age, income, prior trends in inpatient spending, and doctor experience in the matching procedure. [14]

If patients select doctors based on their knowledge and characteristics and doctor selectivity and experience, we can remove selection bias by looking within these comparable physician-patients. Because doctor-patient matches are independent decisions made by patients using private information on preference and doctor quality, we can use patient choices to infer these unobservables for bias correction. Thus, our identification relies on the selection on observables and unobservables to rule out the possibility of reverse causality, as confirmed by our placebo tests.

Matching scheme C shows that the total network impact and average physician-patient effects are opposite on intensive care and drug use (columns 5–6 vs. 8–9, Table 6). A network incurs *more* surgery, radiation, and chemotherapy utilization by over 0.25 SD (0.087/0.34) while reducing target therapy utilization by 0.40 SD (0.151/0.38). In contrast, typical physician-patients use intensive care at a lower probability while increasing targeted therapy adoption and medications.[15]

Neither physician status nor a network explains why typical physician-patients tend to replace intensive care with targeted therapy while enjoying better survival in the short term (180 or 365 days; see columns 2-3 vs. 5-6). This puzzle implies

[14] To check whether the network indicator among matched physician-patients is nearly random, we implement placebo tests. Columns 1-3 of Table A5 show a balance between matched physician-patients with versus without a network on those not precisely matched controls (e.g., age). This result confirms the validity of the exogeneity condition. Nevertheless, we include those controls and each physician-patient's knowledge level in this matching scheme.

[15] We omit hormone therapy from our analysis 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.

that the *informational mechanism* is the main driver for intensive care reduction and short-term survival improvement at the advanced stage. On the other hand, the total network effect is consistent with the impact of average physician-patients on coinsurance, palliative care, and three-year survival rates (columns 5-6). A robust professional tie with the attending doctor reduces coinsurance costs and palliative care utilization while enjoying better three-year survival by over 0.28 SD (0.071/0.252). These concurrent results suggest that the *network-related channels* correctly project differences in coinsurance cost, palliative care, and three-year survival between physicians and other patients.

C3. Exchangeability between network and knowledge

Although the average physician-patient effect is consistent with the impact of physician status or network-related mechanisms on some treatments, neither network nor physician status explicates why average physician-patients tend to replace radiation with targeted therapies while enjoying better short-term survival than other patients. This puzzle suggests that information is critical in determining treatment and survival. Using equation 1, we quantify *the value of a network* by information percentiles using the degree of *informational exchangeability for a network,* i.e., how many more medical knowledge percentiles are required to maintain the same survival or treatment intensity if the physician-patient lacks a robust professional tie with the attending doctor. Our parameter of interest is:

$$V_{RK} = -\frac{dK}{\Delta R}\bigg|_{\text{fixing } \beta_{KR}} = \frac{\beta_{1K} - \beta_{0K}}{\partial \beta_{RK} / \partial K} = \frac{\rho + \delta(K)}{e'(K) + R\delta'(K)}$$

The value of a network can vary with the physician-patient's knowledge level ($K \in [0,1]$) and professional connection (R=0 or 1). We note that V_{1K} equals V_{0K} at a knowledge threshold $K = k^*$, where $\delta'(k^*) = 0$.[16] Deviating from the threshold,

[16] To see why, consider $V_{1K} = V_{0K}$ or $\frac{\rho+\delta(K)}{e'(K)+\delta'(K)} = \frac{\rho+\delta(K)}{e'(K)}$ given $K = k^*$. The equality holds if and only if $\delta'(k^*) = 0$.

$\delta(K)$ could be downward or upward sloping or nonlinear in K. To allow a flexible nonlinearity, we assume polynomials with orders (4,4) for $\delta(K)$ and $e(K)$. If using orders (4,3) or (3,4), we find little shifts in the resulting pattern.

Using a matched physician-patient sample, we implement fixed-effect regressions with two causal variables: network and knowledge. To derive sufficient variation in both variables, we combine two balanced samples: one balancing patients with versus without a network (as achieved in columns 1–3 of Table A5 in section C.2) and the other balancing by knowledge above versus below the median (columns 4–6). The balanced data by networks has 277 observations, with 214 overlapping the balanced data by knowledge. The balanced data by knowledge adds 80 extra admissions. Both samples precisely match physician-patients by doctor-hospital and patient types as in scheme C. Table 5 illustrates the data structure, where the shaded areas indicate the included samples.

Using the integrated samples, we estimate the fixed-effect models holding constant the same list covariates as in scheme C. Although the estimated coefficients are imprecise (Tables A6-1 and A6-2), as expected, due to limited support of continuous information, the estimated value of a network shows clear patterns. Figures 1 to 3 sketch the exchangeability given a network (V_{1K}), as the case with no network is (V_{0K}) are too noisy.

We find a strikingly persistent pattern – lacking relevant knowledge of the cancer site makes a network equivalent to knowledge reduction. The value of a network is significantly negative for most outcomes whenever the knowledge level is at the bottom quartile or below. At the bottom quartile, the value of a network is between -11 and -6 ppts. At the bottom 1st percentile, it expands to -18 and -14 ppts. For patients who are professionally connected but less informed, the social tie is equivalent to *losing* 15 to 18 ppts of relevant knowledge of the cancer site for maintaining the same survival or treatment intensity. This result appears in survival rates and spending on examination (Figure 1), use of surgery/radiation therapy at extensive and intensive margins (Figure 2), adoption of target drug therapy, and drug/tube feeding costs (Figure 3). Two exceptions are palliative care and chemotherapy, for which we did not obtain sufficient precision.

In summary, when attending to a physician-patient professionally connected but lacking relevant knowledge, doctors may abuse the patient's trust to deviate from the procedure they would prescribe to a knowledgeable specialist-patient. This abuse could harm patient survival.

5. Conclusion

The agency problem in healthcare plays a leading 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, less is known about how the doctor-patient relationship mitigates agency concerns. Some evidence has shown that social ties lessen agency issues in preventive care or cesarean section utilization. Outside those contexts, the relevance of the doctor-patient relationship in mitigating agency problems remains unknown.

This paper begins with a benchmark of physicians treating physicians without separating the relational and informational mechanisms. We compare treatments and survival outcomes of comparable physician-patients and nonphysician-patients given the same advanced cancer, attending doctor, and hospital. By exploiting the within-doctor-hospital variation, we compare exactly matched patients and use rich controls to address patient selection and remove unobserved doctor quality. We find that physician-patients receive less intensive care, more medication, more targeted therapy, and fewer checkups, all of which cost less and improve survival.[17]

[17] Physicians' family members might receive similar benefits as physician-patients. This paper considers family members as nonphysician-patients, our results might understate the physician premiums from a broader perspective.

Physician-patients possess clinical knowledge and professional connections, potentially contributing to better care and higher survival than other patients. We extend the matching methods to assess the relative importance of the relational and informational advantages by exploiting the medical specialty variation among patients and doctors. With neither advantage, physician status induces attending doctors to prescribe different treatments (e.g., less surgery utilization; spending more on medications and less on tests) to physician-patients but do *not* prolong their lives relative to nonphysician-patients. In the data restricted to physician-patients, a stronger doctor-patient relationship induces more intensive care and improves long-term survival, consistent with the average physician-patients' effects. Nevertheless, neither physician status nor professional tie explains why average physician-patients tend to replace radiation with targeted therapies and enjoy better survival in the short term. This puzzle leaves the informational mechanism as a leading explanation for the result.

To confirm, we estimate the value of a professional tie relative to medical knowledge using more restrictive models. A professional connection equates to a knowledge reduction if physician-patients are less informed. A professional tie tends to lower the physician's survival as they receive treatments differing from those prescribed to specialist patients possessing relevant medical knowledge and experience about their diagnosed cancer.

The revealed mechanisms are consistent with a framework in which doctors can induce demand to benefit their self-interest. A stronger bond between patients and doctors builds trust, which doctors might exploit to induce demand *if patients are less informed*, as posited by the classical doctor-driven demand hypothesis.

These findings offer lessons for the labor markets of expert services (e.g., real estate agencies, used car dealerships, and initial public offering underwriting). The key to resolving agency problems is to close the information gap between principals and agents. Professional connections intensity agency issues if consumers are less informed. Being more informed increases the chance of belonging to a network, which further induces more information. Professional ties can benefit expert consumers, but only long-term when the network provides insider information. Essentially, relational advantages alone cannot eliminate conflicting interests.

Although our analytical approach is novel, our study has three limitations. First, it assumes monotonicity of the relational and informational advantages. In other words, the comparison made by distinguishing doctor-patient pairs by medical specialties is the same as the one by separating physician-patients from nonphysicians. However, professional connections via medical association networks might differ from social ties via occupations in affecting treatment and survival impacts. Second, we assume that observables fully capture physician-patients' selection in professional networks. If the selection is also based on unobservable incentives independent of those observed, 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. [18]

Lastly, the matched sample size is small due to the rare overlap between physician-patients and nonphysicians and among physician-patients by advantage. Given a modest set of controls for patient types (footnote 4), nearest-neighbor matching might not eliminate bias. However, it minimizes bias after precisely matching patients by doctor-hospital. More data availability would enhance our understanding of how networking-induced information impacts patient survival. Our future work aims to increase observations and relax the monotonicity assumption.

[18] This limitation is the same one faced by Reuter (2006), who attempted to evaluate 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 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

Variable	End-stage cancer at the first diagnosis 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 for 611 physician-patients and 1,120,923 entries for 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 for patient types within hospital			B) Exact match for patient types within **doctor**-hospital		
	Std. mean diff.	t-test	KS-test	Std. mean diff.	t-test	KS-test
Doctor gender	**0.14**	0.88	**0.00**	0.00	1.00	1.00
Doctor experience at admission	**0.30**	**0.02**	0.10	-0.04	0.92	1.00
Doctor selectivity at first diagnosis	0.15	0.49	0.67	-0.04	0.90	0.97
Doctor practice in multiple hospitals	-0.14	0.26	**0.00**	0.00	1.00	1.00
Patients 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	2,811	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:						
Lip, oral cavity, or pharynx			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 each matching scheme. "Pre-trend in hospital cost" is the 3-year 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 having a preexisting clinical relationship with the attending doctor three years before diagnosis. We match admissions precisely by the patient types within hospitals in scheme (A) and doctor-hospital in scheme (B).

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

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	
	Within hospital	A) Exact match by patient types within hospital				**B) Exact match by patient types within doctor-hospital**			
	SD	SD	Coef.	Std. Err.		SD	Coef.	Std. Err.	
Acute inpatient stays (days)	12.1	9.6	-1.9	0.4	***	6.2	-1.5	0.4	***
Diagnosis-to-treatment (days)	95.7	89.0	2.7	4.7		75.6	1.3	7.1	
Cancer therapy:									
Surgery	0.47	0.26	0.007	0.008		0.20	-0.083	0.02	***
Radiation therapy	0.46	0.40	0.016	0.013		0.33	-0.071	0.027	***
Chemotherapy	0.39	0.28	0.034	0.010	***	0.20	-0.007	0.018	
Targeted therapy	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	0.161		1.67	-0.055	0.179	
Coinsurance	2.20	1.66	-0.193	0.113	*	1.07	-0.226	0.100	***
NHI drugs	2.15	2.31	0.240	0.157		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	0.022	
Radiation therapy	2.77	2.58	-0.307	0.153	**	2.00	0.128	0.185	
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	0.006		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:	1100301	2811				552			
Lived 180 days+	1078870	2785				531			
Lived 365 days+	1030972	2785				531			
Lived 1095 days+	816817	1926				346			

Note: "Pre-trend in hospital cost" is the 3-year 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 having a preexisting clinical relationship with the attending doctor three years before diagnosis. We match admissions precisely by the patient types within hospitals in scheme (A) and doctor-hospital (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 cluster standard errors at the patient level. * *p<.1, **p<.05, *** p<.01.*

TABLE 4 —MAPPING SPECIALISTS TO MEDICAL KNOWLEDGE AND PROFESSIONAL NETWORKS

ICD-O-3 code	Cancer site	(1) Internal medicine	(2) Nuclear medicine	(3) Radiation oncology	(4) OB/GYN	(5) Surgery	(6) Urology	(7) Orthopedics	(8) Otorhinolaryngology	(9) Dermatology	(10) Ophthalmology
		(I) Medical oncology		*(I) & (II)*	*(II) Surgical oncology*					*Not listed by TOS*	
C74-C75	Adrenal or other endocrine glands	0.033	**0.694**	0.019	0.011	0.103	0.013	0.008	0.084	0.009	0.012
C70-C72, C80	Brain/nerves or unknown	0.118	0.025	**0.273**	0.230	0.208	0.053	0.023	0.131	0.030	0.016
C51-C58	Female genital organs	0.029	0.011	0.091	**0.703**	0.024	0.022	0.010	0.008	0.009	0.007
C50	Breast	0.084	0.004	0.190	0.015	**0.490**	0.008	0.018	0.005	0.006	0.005
C64-C68	Urinary tract	0.073	0.029	0.119	0.023	0.029	**0.883**	0.025	0.013	0.013	0.013
C40-C41	Bone or articular cartilage	**0.552**		0.212	0.112	0.101	0.058	**0.294**	0.106		
C00-C14	Lip/pharynx or oral cavity	0.053	0.005	0.166	0.004	0.033	0.006	0.006	**0.333**	0.005	0.004
C44	Skin	0.115		0.146	0.046	0.220	0.073	0.074	0.129	**0.576**	0.114
C69	Eye	0.328				0.214		0.161	0.277		**1.000**
C60-C63	Male genital organs	0.080		0.134	0.064	0.050	0.916	0.049	0.026	0.058	0.034
C47, C49	Malignant neoplasm of peripheral nerves and autonomic nervous systems or other connective and soft tissues	0.289		0.229	0.170	0.146	0.092	0.234	0.093	0.092	
C30-C39	Respiratory and intrathoracic organs	**0.218**	0.007	0.200	0.014	0.101	0.016	0.016	0.096	0.014	0.007
C15, C16, C48	Esophagus, intestinal tract, retroperitoneum, or peritoneum	0.098	0.015	0.208	0.017	**0.191**	0.015	0.016	0.012	0.004	0.004
*	Leukemia	0.091	0.013	**0.218**	0.006	0.011	0.009	0.007	0.018	0.011	0.008

Specialists attending almost no cancer cases or in charge of pre-treatment diagnosis or post-treatment reconstruction (relative knowledge level = 0):	Pathology	Plastic and reconstruction surgery Neurosurgery	Others
	Diagnostic Radiology		

Note: This table summarizes the taxonomy classification associated with specialists based on their specialties and hospital departments. We derive the knowledge index using the method illustrated in section 4A. Empty cells indicate absolute zeros. Following Taiwan's Cancer Registry Annual Reports (downloadable from www.hpa.gov.tw), we assign each cancer site to ICD-O-3 codes. * Leukemia's coding is M95903-M99933, except M99903. Each doctor might have multiple specialties and work in multiple departments. (1) "Internal medicine" covers internists and doctors working in the following departments: pediatrics, gastroenterology, cardiovascular medicine, thoracic medicine or critical care, nephrology, rheumatology, endocrinology, infectious diseases, geriatrics, home care, tuberculosis, and dialysis. (3) "Radiation oncology" includes radiation oncologists and doctors in hematology-oncology departments. (5) "Surgery" covers general surgeons and doctors in the following departments: pediatric surgery, rectal surgery, cardiovascular surgery, thoracic surgery, digestive surgery, and oral/maxillofacial surgery. "Others" are specialists outside of cancer care, including ER, neurology, anesthesiology, rehabilitation, psychiatry, family medicine, and occupational medicine. Also, we include doctors in neonatology or pain-medicine departments in this category. Our data show no physician-patients who seek cancer treatments from a pathologist, dermatologist, or ophthalmologist. Among data from physician-patients, only three inpatient entries have a professional tie with their attending doctors specializing in "Others."

TABLE 5. CONSTRUCTING THE MATCHED SAMPLE OF PHYSICIAN-PATIENTS FOR ESTIMATING THE INFORMATIONAL EXCHANGEABILITY FOR A NETWORK

		All physician-patients		
		Not matched	Matched subsample for patients with versus without a network	Total
All physician-patients	Not matched	2,656	63	2,719
	Matched subsample for patients with knowledge above versus below the 50th percentile	80	214	294
	Total	2,736	277	3,013

TABLE 6. MATCHING ESTIMATES: THE PHYSICIAN STATUS AND TOTAL RELATIONAL EFFECTS ON OUTCOMES

	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
	Scheme B: Matching nonphysician-patients to physician-patients with no advantage				Scheme C: Matching among physician-patients				Baseline Scheme B:			
		Physician status effect (β)				**Total relational effect** $\rho + E[\delta(K)]$				**The average physician-patient effect** $E[\beta(R,K)]$		
	SD	Coef.	Std. Err.		SD	Coef.	Std. Err.		SD	Coef.	Std. Err.	
Acute inpatient stays (days)	3.7	-1.3	0.5	**	5.8	-2.5	2.2		6.2	-1.5	0.4	***
Diagnosis-to-treatment (days)	65.9	-2.3	11.6		86.7	5.7	11.0		75.6	1.3	7.1	
Cancer therapy:												
Surgery	0.23	-0.088	0.037	**	0.34	0.087	0.043	**	0.20	-0.083	0.018	***
Radiation	0.36	0.011	0.048		0.31	0.194	0.058	***	0.33	-0.071	0.027	***
Chemotherapy	0.16	0.094	0.023	***	0.22	0.253	0.041	***	0.20	-0.007	0.018	
Targeted	0.10	-0.060	0.016	***	0.38	-0.151	0.044	***	0.28	0.167	0.024	***
Palliative care	0.12	0.060	0.016	***	0.19	-0.249	0.026	***	0.16	-0.027	0.013	**
Log spending:												
Total NHI cost	1.67	0.028	0.286		1.32	-0.408	0.269		1.67	-0.055	0.179	
Coinsurance	1.08	-0.165	0.192		1.70	-0.580	0.283	**	1.07	-0.226	0.100	***
NHI drugs	1.73	0.770	0.270	***	1.45	-0.270	0.262		1.80	0.652	0.165	***
Surgery	3.29	-1.512	0.459	***	2.81	-0.379	0.654		2.87	-1.159	0.275	***
Tube feeding	0.00	NA			0.76	-0.323	0.436		0.39	-0.031	0.022	
Radiation therapy	1.81	0.771	0.285	***	2.13	-0.510	0.378		2.00	0.128	0.185	
Examination	2.31	-1.502	0.315	***	2.35	0.057	0.582		2.29	-0.943	0.211	***
Survival:												
Lived 180 days+	+0.00	+0.000	0.000		0.15	0.001	0.029		0.11	0.025	0.009	***
Lived 365 days+	+0.00	+0.000	0.000		0.22	-0.008	0.040		0.19	0.093	0.015	***
Lived 1095 days+	0.20	-0.007	0.034		0.28	0.252	0.077	***	0.20	0.071	0.021	***
The number of admissions:		217				277				552		
Lived 180 days+		180				244				531		
Lived 365 days+		180				237				531		
Lived 1095 days+		146				178				346		

Note: Columns 1–3 use the matched sample where we compare nonphysician-patients to physician-patients without any specific advantages. As in scheme-B of Table 3, we precisely match hospital entries on doctors, hospitals, and 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 having a preexisting clinical relationship with the attending doctor three years before diagnosis). The matched sample exhibits a near-perfect balance similar to panel B of Table 2 but is not shown in the tables. Columns 4–6 use the matched sample to compare physician-patients with versus without a robust professional tie with the attending doctor. Here we precisely match hospital entries on doctors, hospitals, and the patient's sex, cancer site, and hospital spending tercile four years before diagnosis while controlling for the doctor's years of experience and the patient's two-year age bins, inpatient spending growth tercile four years before diagnosis, and income tercile in the year before the first diagnosis. See Table 6 for the balance check result. Columns 7–9 are from Table 3's columns 5–7. The standard deviations (SD) represent information given the matching scheme after removing doctor-hospital fixed effects and patient types. We report the clustered standard errors (SE) at the patient level. * *p<.1, **p<.05, *** p<.01.*

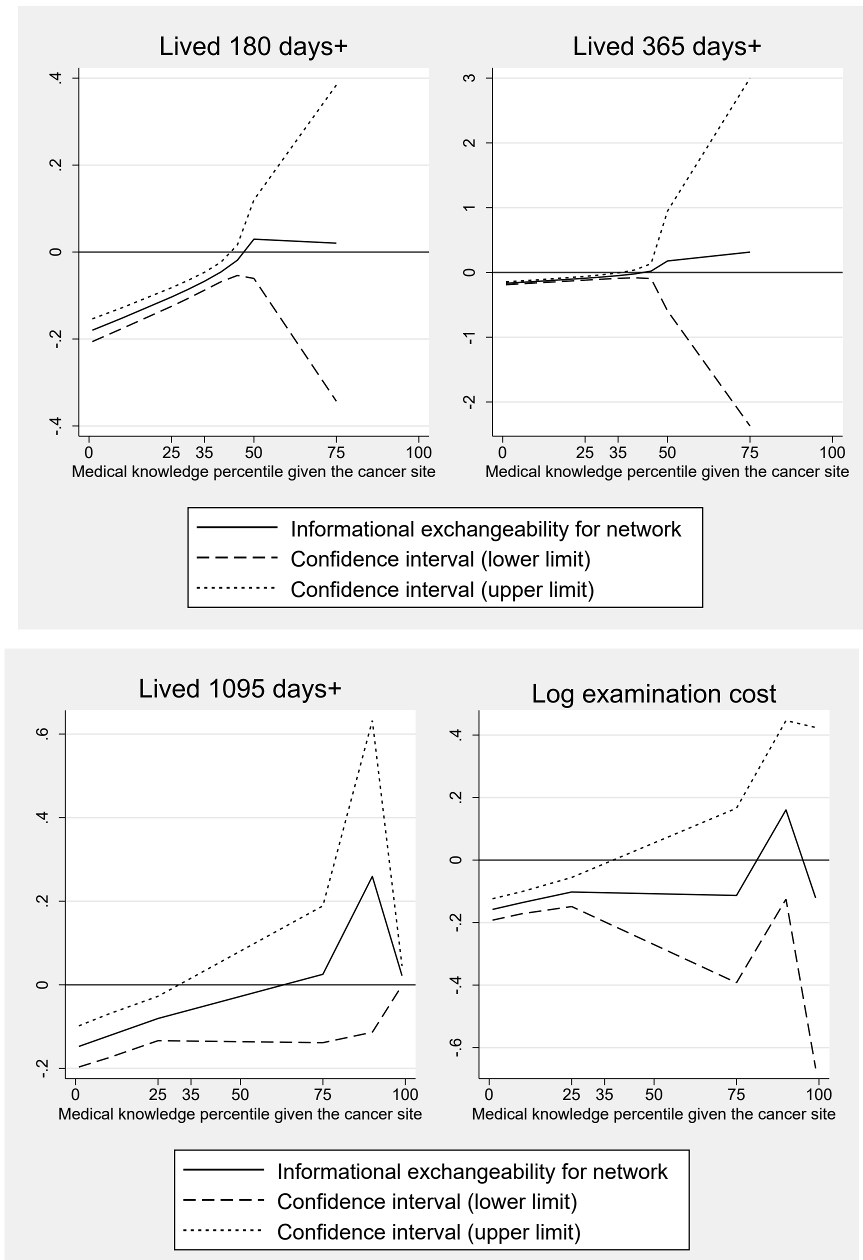

FIGURE 1. INFORMATIONAL EXCHANGEABILITY FOR A SOLID TIE WITH THE ATTENDING DOCTOR, BY PATIENT KNOWLEDGE PERCENTILE – PATIENT SURVIVAL AND EXAMINATION COST

Note: The estimated degrees of exchangeability have wide confidence intervals at the median knowledge for three-year survival and log examination cost, which we omit for ease of exposition. We identify the parameter using the regression results and derive its standard error using Delta methods; see our estimation results in Tables A7-1 to A7-4. We skip the estimates with wide confidence intervals that go off-chart, especially for survival or medical spending outcomes at the upper range of knowledge levels.

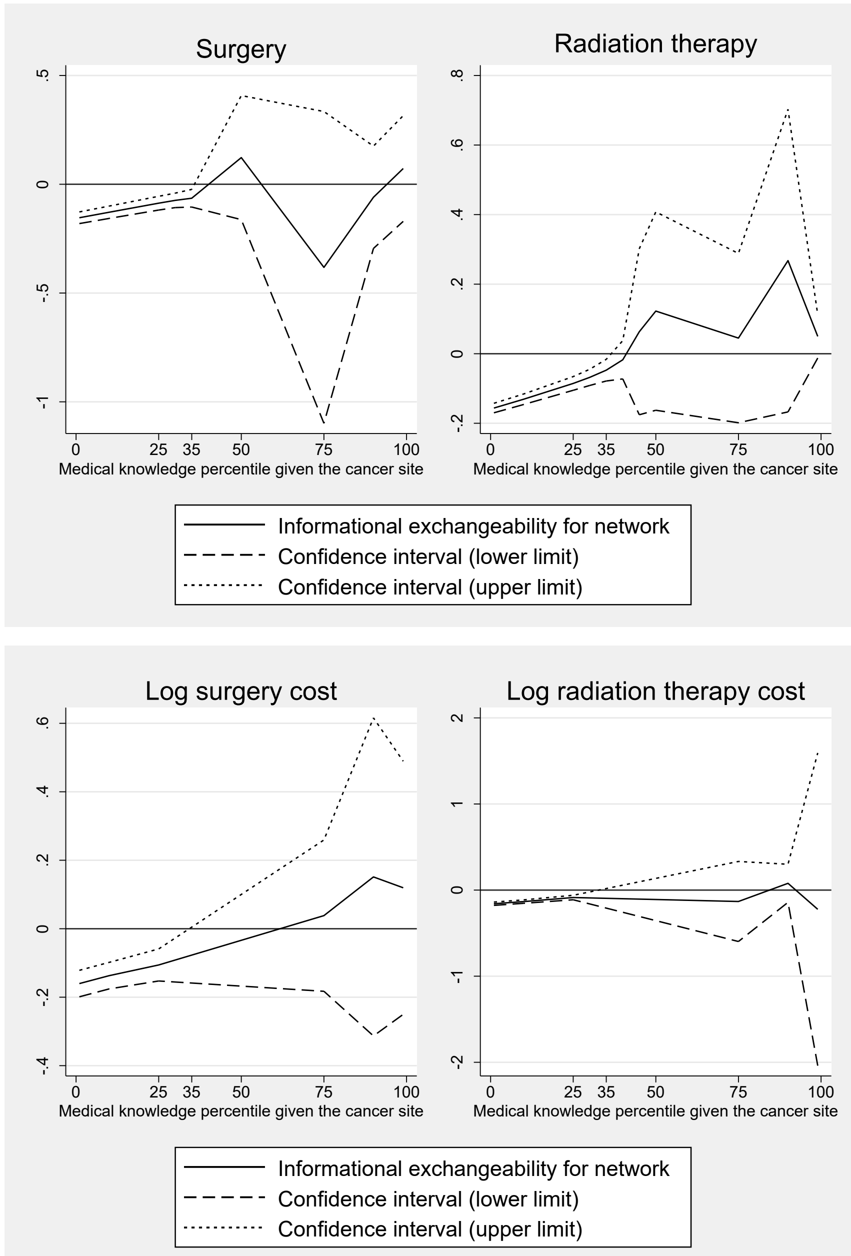

FIGURE 2. INFORMATIONAL EXCHANGEABILITY FOR A SOLID TIE WITH THE ATTENDING DOCTOR, BY PATIENT KNOWLEDGE PERCENTILE – INTENSIVE CARE AT EXTERNAL AND INTERNAL MARGINS

Note: The estimated degree of exchangeability has wide confidence intervals at the median knowledge level for log surgery spending and radiation therapy costs, which we omit for ease of exposition. See the note of figure 1.

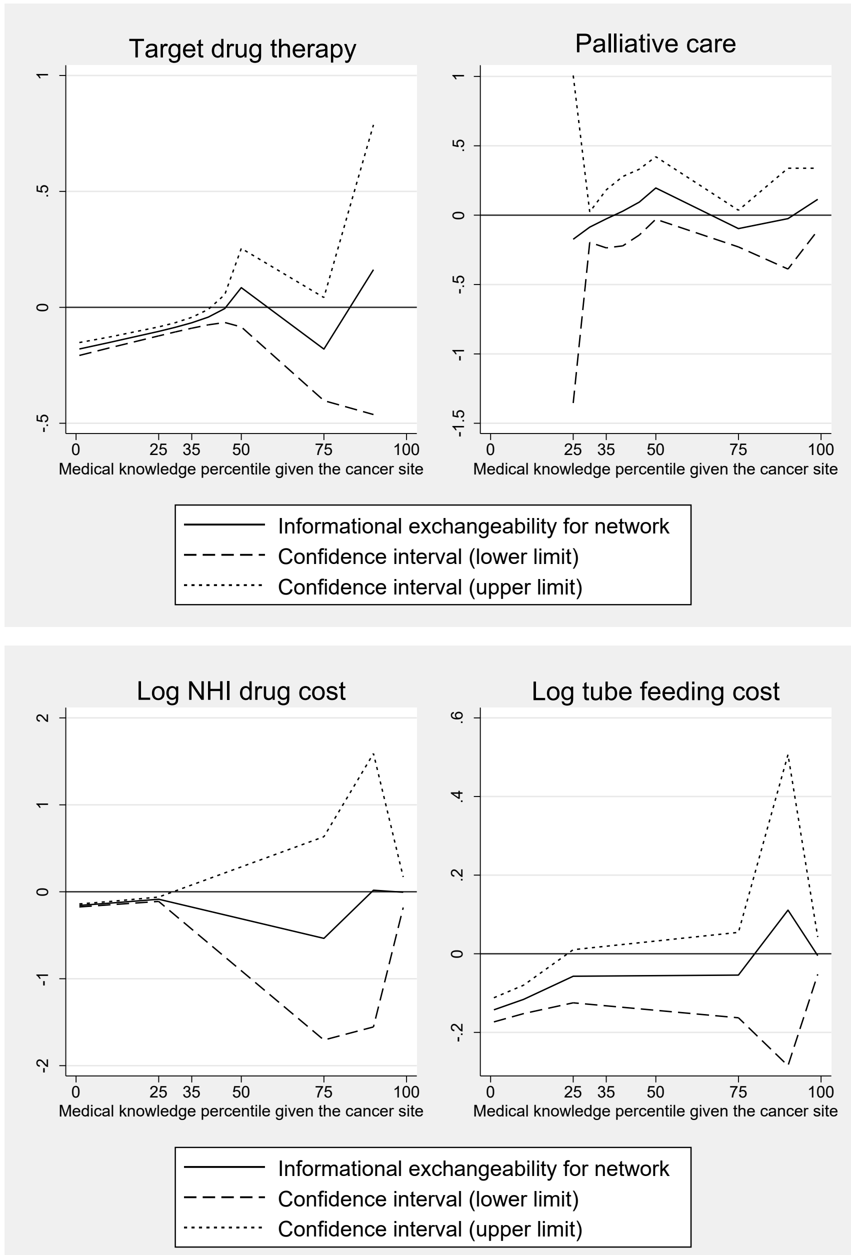

FIGURE 3. INFORMATIONAL EXCHANGEABILITY FOR A SOLID TIE WITH THE ATTENDING DOCTOR, BY PATIENT KNOWLEDGE PERCENTILE – DRUG USE AND OTHER COSTS

Note: The estimated degree of exchangeability has wide confidence intervals at the median knowledge level for log NHI drug and tube feeding costs, which we omit for ease of exposition. See the note of figure 1.

Appendix

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

	Full sample				The 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. 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). "Previous hospital spending" is limited to NHI hospital items used three years before diagnosis. Mortality data have fewer observations since we only obtain Death Registry records up to December 2016. 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—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		
	SD	Coef.	Std. Err.		Adj-R2	Coef.	Std. Err.	
Acute inpatient stays (days)	6.2	-1.5	0.5	***	0.11	-1.5	0.4	***
Diagnosis-to-treatment (days)	75.6	2.8	10.2		0.28	1.3	7.1	
Cancer therapy:								
Surgery	0.20	-0.087	0.057		0.78	-0.083	0.02	***
Radiation	0.33	-0.080	0.082		0.53	-0.071	0.027	***
Chemotherapy	0.20	0.005	0.045		0.33	-0.007	0.018	
Targeted	0.28	0.147	0.082	*	0.47	0.167	0.024	***
Palliative care	0.16	-0.019	0.035		0.41	-0.027	0.013	**
Log spending:								
Total NHI cost	1.67	-0.070	0.117		0.48	-0.055	0.179	
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	0.032		0.03	-0.031	0.022	
Radiation therapy	2.00	0.165	0.204		0.50	0.128	0.185	
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	0.060		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 having a preexisting clinical relationship with the attending doctor 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 column 1 report the information after removing doctor-hospital fixed effects and patient types. We report the clustered standard errors at the patient level. * *p<.1,* ***p<.05,* *** *p<.01.*

TABLE A2-1—FIXED-EFFECT MODELS: EFFECTS OF A PHYSICIAN-PATIENT ON TREATMENT 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		Adj-R2	SD	Coef.	SE		Adj-R2	Coef.	SE		Adj-R2
Acute inpatient stays (days)	12.1	-1.7	0.33	***	0.17	11.3	-1.74	0.33	***	0.15	-1.5	0.51	***	0.11
Diagnosis-to-treatment	95.7	-6.1	2.90	**	0.10	94.3	-5.75	2.87	**	0.09	2.8	10.19		0.28
Cancer therapy:														
Surgery	0.47	0.012	0.020		0.53	0.46	0.012	0.020		0.51	-0.087	0.06		0.78
Radiation	0.46	0.003	0.024		0.26	0.46	0.002	0.024		0.25	-0.080	0.08		0.53
Chemotherapy	0.39	-0.001	0.018		0.33	0.37	0.001	0.018		0.31	0.005	0.04		0.33
Targeted	0.31	0.037	0.020	*	0.21	0.33	0.036	0.020	*	0.22	0.147	0.08	*	0.47
Palliative care	0.35	-0.049	0.018	***	0.14	0.35	-0.050	0.018	***	0.11	-0.019	0.04		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	0.12		0.48
Coinsurance	2.20	0.024	0.051		0.19	1.95	0.034	0.051		0.11	-0.241	0.10	**	0.09
NHI drugs	2.15	-0.155	0.082	*	0.30	2.23	-0.149	0.081	*	0.33	0.633	0.25	**	0.52
Surgery	4.21	-0.097	0.100		0.35	4.17	-0.116	0.100		0.35	-1.259	0.34	***	0.27
Tube feeding	2.01	-0.214	0.047	***	0.21	1.81	-0.214	0.046	***	0.15	-0.024	0.03		0.03
Radiation therapy	2.77	-0.440	0.087	***	0.26	2.72	-0.438	0.087	***	0.29	0.165	0.20		0.50
Examination	2.92	-0.420	0.108	***	0.34	3.00	-0.434	0.107	***	0.34	-1.043	0.24	***	0.50
Survival:														
Lived 365 days+	0.39	0.081	0.016	***	0.20	0.38	0.082	0.016	***	0.16	0.086	0.04	**	0.35
Lived 1095 days+	0.49	0.118	0.031	***	0.22	0.49	0.118	0.030	***	0.20	0.078	0.06		0.73

Note: The "chosen-hospital" sample includes admissions in physician-patients' hospitals. The "chosen-doctor" sample covers entries attended by doctors whom physician-patients see. We derive the "fully matched sample" using the 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 having a preexisting clinical relationship with the attending doctor three years before diagnosis). We add the complete set of dummies for 5-year doctor experience bins in the first two samples. We report the clustered standard errors at the patient level. * $p<.1$, ** $p<.05$, *** $p<.01$. The probability of living 180 days+ is about 93 percent, so we estimate a logistic fixed-effect model but cannot reach convergence.

TABLE A2-2. FIXED-EFFECT ESTIMATES USING DATA FROM ADMISSIONS IN HOSPITALS CHOSEN BY PHYSICIAN-PATIENTS

	a) Within doctor-hospital				b) Within the doctor, within the hospital				c) Within the 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
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 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 having a preexisting clinical relationship with the attending doctor three years before diagnosis). We report the clustered standard errors (SE) at the patient level. The survival outcomes have fewer observations than other outcome variables (see table).

TABLE A3. EXAMPLE OF QUANTIFYING A DOCTOR'S MEDICAL KNOWLEDGE OF A CANCER SITE USING RELATIVE VOLUME BY SPECIALTY AND HOSPITAL DEPARTMENT

ICD-O-Code	Cancer site	First/main specialty	Hospital department	The average number of admissions per doctor (1)	Relative knowledge of the cancer site (2) = (1)/342.3	Average knowledge over departments per specialty (3)
C50	Breast	**Surgery**	Surgery	342.3	1.00	0.490
		Internal medicine	Hematology oncology	329.0	0.96	0.084
		Oncology	Internal medicine	140.8	0.41	0.190
		Surgery	Gastrointestinal surgery	100.8	0.29	
		Surgery	Hematology oncology	80.2	0.23	
		Oncology	Hematology oncology	77.5	0.23	
		OB/GYN	Hematology oncology	70.8	0.21	0.015
		Orthopedics	Surgery	68.0	0.20	
		Internal medicine	Surgery	66.7	0.19	
		Surgery	Internal medicine	57.9	0.17	
		Surgery	Rectal surgery	53.7	0.16	
		Oncology	Radiation oncology	42.6	0.12	
		OB/GYN	Surgery	41.3	0.12	
		Oncology	Radiology	41.0	0.12	
		Oncology	Surgery	36.5	0.11	
		Surgery	Radiation oncology	22.2	0.06	
		Surgery	Plastic surgery	15.2	0.04	
		Urology	Surgery	9.7	0.03	0.008
		Surgery	Radiology	7.7	0.02	
		Internal medicine	Internal medicine	7.1	0.02	
		Orthopedics	Plastic surgery	6.8	0.02	0.018
		OB/GYN	Family medicine	6.8	0.02	
		Surgery	Pulmonary surgery	5.9	0.02	
		Internal medicine	Infectious diseases	5.0	0.01	
		OB/GYN	OB/GYN	4.1	0.01	
		Surgery	Pediatric surgery	4.1	0.01	
		Internal medicine	Thoracic medicine	4.0	0.01	
		Surgery	Cardiovascular surgery	3.5	0.01	
		Surgery	Neurosurgery	3.2	0.01	
		Internal medicine	Radiology	3.0	0.01	
		Internal medicine	Nephrology	2.8	0.01	
		Internal medicine	Family medicine	2.7	0.01	
		Internal medicine	Gastroenterology	2.7	0.01	
		Surgery	OB/GYN	2.7	0.01	
		Orthopedics	Orthopedics	2.5	0.01	

Internal medicine	Cardiovascular medicine	2.4	0.01	
Internal medicine	Rheumatology	2.4	0.01	
Urology	Urology	2.3	0.01	
Surgery	Infectious diseases	2.3	0.01	
Dermatology	Dermatology	2.2	0.01	0.006
Internal medicine	Radiation oncology	2.1	0.01	
Surgery	Urology	2.0	0.01	
Internal medicine	Gastrointestinal surgery	2.0	0.01	
Internal medicine	Endocrinology	2.0	0.01	
Ophthalmology	Ophthalmology	1.8	0.01	0.005
Internal medicine	Neurology	1.8	0.01	
Surgery	Orthopedics	1.8	0.01	
Otorhinolaryngology	Otorhinolaryngology	1.7	0.01	0.005
Surgery	Endocrinology	1.7	0.00	
Surgery	Oral and maxillofacial surgery	1.7	0.00	
Internal medicine	Pulmonary and critical care	1.6	0.00	
Surgery	Family medicine	1.5	0.00	
Internal medicine	Geriatrics	1.5	0.00	
Surgery	Gastroenterology	1.5	0.00	
Nuclear medicine	Nuclear medicine	1.4	0.00	0.004
Urology	Internal medicine	1.3	0.00	
Surgery	Thoracic medicine	1.3	0.00	
Orthopedics	Orthopedics	1.3	0.00	
Orthopedics	Internal medicine	1.3	0.00	
Surgery	Pulmonary and critical care	1.2	0.00	
OB/GYN	Internal medicine	1.1	0.00	
Internal medicine	Tuberculosis	1.1	0.00	

Note: This table illustrates how we qualify a breast cancer physician-patient's medical knowledge given their specialty using inpatient data. First, column (1) derives the average number of hospital admissions per doctor in all specialties and departments treating cancer cases. Assuming that the knowledge on breast cancer treatment is proportional to caseloads, we calculate the *relative knowledge* in column (2) using the average caseload per doctor in their specialty/department relative to the highest per-doctor caseload among all the specialties/departments treating the same cancer. Finally, column (3) computes the weighted average of the relative knowledge over departments per specialty, weighted by caseload share. Specialists or departments not listed in the table have zero relative knowledge/caseload of treating breast cancer.

Source: NHI database 2004-2018.

TABLE A4. DESCRIPTIVE STATISTICS

	(1)	(2)	(3)	(4)	(5)	(6)
	Data for identifying β		All physician-patients			
	Nonphysician-patients	Physician-patients with no advantage, R=0=K		With no network R=0	With network R=1	Physician-patient data included for estimating exchangeability
Patient attributes:						
With a closer professional tie with doctor	0.000	0.000	0.416	0.000	1.000	0.496
Pre-normalized measure for knowledge	0.000	0.000	0.055	0.021	0.102	0.068
Percent knowledge over the raw mean	0.000	0.000	0.324	0.155	0.562	0.420
Male	0.498	0.834	0.868	0.836	0.913	0.944
Age	57.83	62.33	60.18	61.52	58.31	58.10
Log income at diagnosis	10.08	10.75	11.00	10.86	11.18	10.94
Pre-diagnosis log drug cost (4 years)	2.928	2.878	2.492	2.617	2.316	0.657
Pre-diagnosis log inpatient cost (4 years)	4.039	3.939	3.398	3.546	3.189	0.880
Pre-diagnosis trend in inpatient cost	1.069	0.728	0.708	0.417	1.117	0.138
Attending doctor attributes:						
Male	0.850	0.902	0.885	0.888	0.883	0.952
Experience	13.049	14.435	15.149	14.683	15.804	18.686
Number of specialties	1.093	1.121	1.141	1.142	1.139	1.157
Whether work in multiple hospitals	0.481	0.436	0.407	0.408	0.406	0.289
Teaching hospital	0.214	0.337	0.339	0.329	0.353	0.395
Veteran hospital	0.154	0.268	0.285	0.293	0.274	0.431
Private hospital	0.605	0.475	0.464	0.448	0.486	0.364
Number of hospital admissions	1,378,713	1,251	3,013	1,761	1,252	357

TABLE A5. BALANCE STATISTICS AMONG PHYSICIAN-PATIENTS, P-VALUES

	(1)	(2)	(3)	(4)	(5)	(6)
	Scheme C: Having a strong tie or not			Scheme D: Patient knowledge above median or not		
Predetermined variables	Std. mean	p-value		Std. mean	p-value	
not exactly matched on	diff.	t-test	KS-test	diff.	t-test	KS-test
Patient age	-0.12	0.31	0.77	0.21	0.41	0.45
Patient's income tercile at diagnosis	-0.25	0.73	0.96	0.24	0.63	0.73
Patient's prior spending tercile on drugs	-0.09	0.74	1.00	-0.11	1.00	1.00
Patient's pre-trend in hospital cost in tercile	-0.17	0.25	1.00	-0.46	0.16	1.00
Doctor experience at admission	0.01	0.90	0.96	0.28	0.35	0.73
Number of admissions			277			294
Number of physician-patients			71			63
Number of hospitals			7			8
Number of attending doctors			17			17
Number of hospital-doctor pairs			17			17
The number of admissions by cancer site:						
Lip, oral cavity, or pharynx			32			32
Digestive organs and peritoneum			111			129
Respiratory and intrathoracic organs			na			28
Breast, genital, or urinary organs			59			30
Others (e.g., eyes, central nerves, endocrine glands, leukemias)			75			75

Note: We exactly match physician-patients according to doctor-hospital and patient types (sex, cancer sites, and terciles of pre-diagnosis inpatient spending). In the nearest-neighbor matching procedure, we also include two categorical controls (income terciles and pre-trend in hospital cost in tercile) and three continuous controls (2-year age bins, doctor experience at admission in years, and patient knowledge levels) with bias corrections as in Abadie and Imbens (2011). Column 6 of table A5 summarizes the statistics of the integrated sample.

TABLE A6-1. FIXED-EFFECT REGRESSION RESULTS USING MATCHED PHYSICIAN-PATIENTS

			Cancer therapy:				
	Acute inpatient stays	Diagnosis-to-treatment	Surgery	Radiation	Chemotherapy	Targeted	Palliative care
Network	99.5	2438.5	-13.4	-28.9	5.8	22.7	-0.1
	(184.0)	(3551.1)	(11.6)	(14.0)	(9.0)	(16.2)	(9.7)
Normalized knowledge (K)	-13.4	1091.0	-0.4	-0.9	-1.5	3.7	-0.7
	(26.1)	(428.9)	(1.1)	(1.2)	(1.1)	(1.5)	(0.8)
K squared	62.2	-5066.9	2.8	2.8	8.2	-18.8	5.0
	(124.0)	(2200.6)	(5.0)	(6.1)	(5.4)	(7.5)	(4.7)
K power 3	-133.0	7833.6	-5.6	-7.2	-13.9	33.9	-9.6
	(212.0)	(3708.9)	(8.4)	(10.6)	(9.2)	(12.4)	(8.8)
K power 4	82.3	-3882.9	3.2	5.3	7.0	-19.0	5.5
	(115.1)	(1948.8)	(4.5)	(5.9)	(5.1)	(6.6)	(5.0)
Network × K	-580.8	-17597.2	85.9	182.4	-24.1	-128.2	8.6
	(1081.5)	(21206.7)	(70.8)	(83.8)	(55.1)	(97.0)	(57.8)
Network × K squared	1167.8	45768.2	-201.1	-418.5	29.8	264.7	-40.9
	(2326.3)	(46568.1)	(158.0)	(184.7)	(124.0)	(213.3)	(126.4)
Network × K power 3	-978.2	-50564.2	200.7	415.4	-7.8	-241.8	60.0
	(2174.5)	(44547.5)	(153.0)	(177.8)	(121.3)	(203.9)	(120.3)
Network × K power 4	288.8	20093.8	-72.4	-150.9	-3.5	82.9	-27.9
	(747.2)	(15662.2)	(54.3)	(63.0)	(43.5)	(71.4)	(42.2)
N	357	357	357	357	357	357	357
Adjusted R squared	17%	21%	80%	73%	74%	65%	66%

Note: We construct a matched sample by combining two well-balanced data of physician-patients, one balancing patients with versus without a network (as achieved in Table 6) and the other balancing patients with relevant medical knowledge above versus below the median. Both balanced subsamples precisely match physician-patients for their attending doctors, hospitals, and characteristics (e.g., sex, cancer sites, and previous hospital spending terciles). In addition to these control variables, we include dummies for four-year admission periods and five-year age bins in the regressions. Clustered standard errors at patient levels are in parentheses.

TABLE A6-2. FIXED-EFFECT REGRESSION RESULTS USING MATCHED PHYSICIAN-PATIENTS

	Log spending:							Survival:		
	Total NHI cost	Coinsurance	NHI drugs	Surgery	Tube feeding	Radiation therapy	Examination	Lived 180 days+	Lived 365 days+	Lived 1095 days+
Network	-39.0	-142.9	-114.1	-78.4	23.3	101.1	-74.8	8.7	11.9	10.1
	(47.8)	(74.5)	(73.7)	(139.7)	(18.3)	(72.3)	(100.6)	(5.7)	(8.9)	(17.0)
Normalized knowledge (K)	2.7	10.2	0.3	-5.1	-2.1	-13.9	10.2	1.4	1.8	1.5
	(8.5)	(8.0)	(7.8)	(18.6)	(2.9)	(11.3)	(11.5)	(0.6)	(1.0)	(0.8)
K squared	-0.90	-58.8	-1.4	52.5	19.4	59.2	-36.8	-5.7	-6.8	-5.6
	(32.4)	(40.5)	(36.1)	(93.5)	(17.9)	(58.0)	(50.5)	(2.6)	(4.0)	(4.3)
K power 3	-6.4	102.5	12.4	-119.2	-37.9	-93.2	46.3	7.5	8.5	7.0
	(46.6)	(68.6)	(62.0)	(155.2)	(31.5)	(103.2)	(82.5)	(4.0)	(5.9)	(8.5)
K power 4	4.9	-52.8	-12.4	74.1	20.6	47.0	-20.9	-3.1	-3.5	-3.5
	(22.6)	(37.1)	(35.1)	(80.9)	(16.6)	(59.2)	(43.5)	(2.1)	(2.9)	(5.1)
Network × K	226.0	863.4	715.1	486.3	-158.2	-614.1	456.6	-49.1	-71.7	-68.6
	(274.0)	(444.5)	(434.4)	(822.3)	(118.6)	(424.5)	(609.8)	(32.6)	(52.2)	(103.6)
Network × K squared	-492.3	-1866.0	-1618.8	-1151.9	372.1	1329.5	-1032.0	100.3	156.5	172.0
	(579.7)	(975.2)	(937.0)	(1774.7)	(278.3)	(915.3)	(1358.9)	(68.4)	(112.3)	(229.6)
Network × K power 3	470.0	1722.2	1563.3	1205.9	-367.7	-1224.1	1005.3	-88.4	-146.7	-185.7
	(535.9)	(932.7)	(877.5)	(1669.0)	(280.8)	(863.0)	(1316.8)	(62.8)	(104.9)	(219.2)
Network × K power 4	-165.6	-578.3	-545.6	-464.2	130.4	406.0	-353.8	28.4	50.1	72.4
	(182.7)	(328.2)	(301.8)	(578.5)	(102.8)	(302.5)	(467.9)	(21.3)	(36.0)	(76.4)
N	357	357	357	357	357	357	357	331	324	241
Adjusted R squared	49%	16%	56%	38%	15%	42%	51%	75%	75%	93%

Note: We construct a matched sample by combining two well-balanced data of physician-patients, one balancing patients with versus without a network (as achieved in Table 6) and the other balancing patients with relevant medical knowledge above versus below the median. Both balanced subsamples precisely match physician-patients on their attending doctors, hospitals, and characteristics (e.g., sex, cancer sites, and previous hospital spending terciles). In addition to these control variables, we include dummies for four-year admission periods and five-year age bins in the regressions. Clustered standard errors at patient levels are in parentheses.

TABLE A7-1.THE ESTIMATED DEGREE OF INFORMATIONAL EXCHANGEABILITY FOR A NETWORK

		Exchangeability (R=0)		Exchangeability (R=1)	
Percentile	**Outcomes:**	**Coef.**	**SE**	**Coef.**	**SE**
1	Lived 180 days+	6.172	4.011	**-0.180**	0.013
10		9.004	5.766	**-0.152**	0.012
25		-8.378	7.585	**-0.103**	0.011
30		-3.315	2.884	**-0.086**	0.011
35		-1.581	1.485	**-0.067**	0.010
40		-0.727	0.794	**-0.046**	0.012
45		-0.208	0.318	-0.019	0.018
50		0.238	0.746	0.030	0.046
75		0.026	0.220	0.021	0.186
90		-0.064	0.117	0.540	1.723
99		-0.222	0.581	-0.640	4.913
1	Lived 365 days+	6.567	5.770	**-0.167**	0.011
10		8.528	7.168	**-0.139**	0.012
25		-8.982	12.188	**-0.089**	0.015
30		-2.783	3.405	**-0.070**	0.017
35		-1.016	1.368	**-0.049**	0.021
40		-0.254	0.558	-0.022	0.030
45		0.120	0.280	0.021	0.058
50		0.302	0.422	0.178	0.393
75		0.283	0.680	0.315	1.370
90		-0.079	0.422	0.061	0.203
99		0.049	5.435	-0.001	0.047
1	Lived 1095 days+	6.805	12.257	**-0.147**	0.025
10		8.268	15.824	**-0.122**	0.027
25		-5.360	12.779	**-0.081**	0.027
30		-1.625	3.987	**-0.068**	0.025
35		-0.593	1.479	**-0.057**	0.027
40		-0.240	0.494	-0.056	0.079
45		-0.141	0.222	-0.096	0.363
50		-0.139	0.259	-0.285	1.493
75		0.071	0.231	0.025	0.083
90		**0.128**	0.035	0.259	0.190
99		-0.037	0.040	*0.022*	0.012
1	Log exam cost	-7.388	13.437	**-0.158**	0.018
10		-9.171	16.480	**-0.136**	0.018
25		14.336	60.362	**-0.102**	0.024
30		4.123	9.286	**-0.093**	0.031
35		1.774	3.009	-0.089	0.048
40		0.884	1.142	-0.097	0.099
45		0.529	0.519	-0.169	0.390
50		0.433	0.464	1.846	32.982
75		0.344	0.644	-0.113	0.142

90	-0.224	0.428	0.161	0.146
99	-0.184	0.305	-0.121	0.278

TABLE A7-2. THE ESTIMATED DEGREE OF INFORMATIONAL EXCHANGEABILITY FOR A NETWORK

Percentile	Cancer therapy:	Exchangeability (R=0) Coef.	Exchangeability (R=0) SE	Exchangeability (R=1) Coef.	Exchangeability (R=1) SE
1	Surgery	32.994	81.292	**-0.154**	0.014
10		288.006	4480.000	**-0.129**	0.014
25		-12.254	23.846	**-0.087**	0.016
30		-8.866	23.389	**-0.074**	0.017
35		-11.232	71.280	**-0.064**	0.021
40		4.744	26.099	-0.067	0.054
45		0.873	1.857	-0.264	1.428
50		0.569	1.074	0.123	0.145
75		0.933	1.784	-0.382	0.366
90		-0.196	0.631	-0.060	0.120
99		-0.128	0.170	0.072	0.124
1	Radiation	33.783	49.265	**-0.156**	0.007
10		28.879	27.240	**-0.131**	0.008
25		7.048	5.907	**-0.085**	0.010
30		3.135	2.584	**-0.068**	0.012
35		1.102	1.013	**-0.047**	0.016
40		0.175	0.386	-0.017	0.028
45		-0.176	0.177	0.063	0.122
50		*-0.251*	0.154	-0.257	0.468
75		0.926	7.716	0.045	0.124
90		0.077	0.071	0.268	0.222
99		**-0.081**	0.032	0.050	0.032
1	Chemotherapy	-4.070	7.284	*-0.223*	0.136
10		-13.850	25.283	*-0.196*	0.114
25		3.497	4.078	**-0.142**	0.066
30		2.381	2.586	**-0.120**	0.050
35		1.859	2.064	**-0.096**	0.035
40		1.821	2.941	**-0.068**	0.025
45		-6.601	93.780	-0.035	0.024
50		0.053	0.362	0.006	0.036
75		-0.091	0.132	0.110	0.211
90		-1.584	12.608	0.818	0.929
99		0.248	0.942	-0.456	1.937
1	Targeted drug	6.498	4.875	**-0.180**	0.014
10		14.391	11.881	**-0.152**	0.012
25		-6.987	5.914	**-0.104**	0.010
30		-4.667	4.514	**-0.086**	0.010
35		-4.611	7.424	**-0.067**	0.012
40		5.836	27.629	**-0.042**	0.017
45		0.067	0.426	-0.005	0.031
50		-0.247	0.194	0.085	0.086
75		-0.353	0.352	*-0.180*	0.113
90		0.029	0.059	0.162	0.319
99		*-0.041*	0.023	-0.464	2.030

TABLE A7-3.THE ESTIMATED DEGREE OF INFORMATIONAL EXCHANGEABILITY FOR NETWORK

Percentile	Log spending:	Exchangeability (R=0) Coef.	Exchangeability (R=0) SE	Exchangeability (R=1) Coef.	Exchangeability (R=1) SE
1	Surgery cost	18.194	83.149	**-0.160**	0.020
10		-18.623	55.551	**-0.137**	0.020
25		-3.402	8.025	**-0.106**	0.024
30		-3.281	9.482	**-0.101**	0.040
35		-8.008	64.357	-0.102	0.080
40		2.118	5.912	-0.121	0.180
45		0.590	0.654	-0.197	0.531
50		0.292	0.252	-0.820	5.906
75		-0.117	0.355	0.038	0.113
90		0.050	0.080	0.151	0.237
99		-0.049	0.041	0.120	0.189
1	Radiation cost	-7.439	8.106	**-0.158**	0.010
10		-10.999	10.868	**-0.133**	0.010
25		11.690	30.389	**-0.086**	0.013
30		4.523	9.543	**-0.067**	0.017
35		2.005	4.716	-0.042	0.024
40		0.322	2.503	-0.007	0.042
45		7.040	108.576	0.069	0.121
50		1.080	2.298	1.665	16.863
75		-0.146	0.335	-0.132	0.237
90		-0.193	0.690	0.079	0.113
99		-0.128	0.102	-0.223	0.927
1	Total NHI cost	-13.715	44.443	**-0.168**	0.015
10		-8.872	17.297	**-0.146**	0.015
25		-4.820	6.537	**-0.112**	0.018
30		-4.294	7.081	**-0.103**	0.023
35		-4.493	11.278	**-0.097**	0.034
40		-8.992	67.387	-0.099	0.059
45		4.695	26.597	-0.122	0.128
50		1.254	2.532	-0.238	0.454
75		0.444	0.590	-9.782	376.383
90		1.493	17.201	0.339	0.433
99		-0.773	4.718	0.093	0.088
1	Coinsurance	-14.922	15.325	**-0.161**	0.007
10		-58.804	117.672	**-0.136**	0.007
25		5.678	5.493	**-0.089**	0.010
30		3.142	3.329	**-0.070**	0.013
35		1.698	2.271	**-0.046**	0.018
40		0.531	1.816	-0.014	0.031
45		4.389	32.815	0.052	0.083
50		0.811	0.986	0.862	4.064
75		-0.235	0.177	-2.437	15.598
90		2.050	31.214	-0.445	0.691
99		0.145	0.398	0.065	0.073

TABLE A7-4.THE ESTIMATED DEGREE OF INFORMATIONAL EXCHANGEABILITY FOR NETWORK

		Exchangeability (R=0)		Exchangeability (R=1)	
Percentile	**Log spending:**	**Coef.**	**SE**	**Coef.**	**SE**
1	Acute inpatient stay	-7.669	19.551	**-0.165**	0.024
10		-11.206	28.469	**-0.137**	0.025
25		-6.177	23.144	-0.080	0.043
30		-2.002	6.494	-0.054	0.059
35		-0.354	1.946	-0.021	0.084
40		0.187	0.712	0.025	0.127
45		0.327	0.309	0.100	0.211
50		0.325	0.216	0.264	0.492
75		0.094	0.375	-0.302	1.950
90		-0.063	0.142	-0.595	2.890
99		*-0.071*	0.043	-0.190	0.423
1	Diagnosis-to-treatment	2.285	3.359	**-0.144**	0.030
10		3.661	6.389	**-0.114**	0.040
25		-0.870	2.408	-0.060	0.069
30		-0.300	1.205	-0.041	0.088
35		-0.081	0.669	-0.021	0.124
40		-0.004	0.385	-0.003	0.236
45		-0.033	0.268	0.055	0.877
50		-0.410	0.999	0.068	0.132
75		0.072	0.198	-0.055	0.122
90		0.014	0.084	-0.023	0.150
99		**-0.117**	0.055	*0.084*	0.043
1	Palliative care	0.045	16.140	-0.003	1.224
10		4.993	59.682	0.181	5.151
25		0.814	3.687	-0.174	0.602
30		0.553	2.357	-0.086	0.056
35		0.230	1.541	-0.027	0.107
40		-0.387	1.219	0.029	0.128
45		-4.151	23.701	0.094	0.121
50		3.127	11.706	0.196	0.115
75		2.883	25.445	-0.097	0.067
90		-0.012	0.089	-0.025	0.185
99		-0.089	0.051	0.114	0.114
1	Drug cost	-443.000	13000.000	**-0.157**	0.009
10		-183.000	1650.000	**-0.131**	0.010
25		-12.599	23.800	**-0.086**	0.013
30		-5.153	8.292	**-0.069**	0.015
35		-1.884	2.818	**-0.050**	0.019
40		-0.496	0.929	-0.029	0.027
45		-0.002	0.345	0.000	0.063
50		0.046	0.252	-0.047	0.294
75		0.792	1.250	-0.536	0.596
90		-0.002	0.112	0.018	0.802
99		-0.009	0.146	-0.005	0.090
1	Tube feeding cost	-12.488	20.595	**-0.143**	0.016
10		15.377	20.049	**-0.116**	0.018
25		1.015	1.468	-0.057	0.034
30		0.313	0.932	-0.025	0.054
35		-0.268	0.794	0.030	0.112
40		-1.355	2.559	0.199	0.506
45		3.278	9.212	-0.962	4.709

50	0.636	0.417	-0.224	0.216
75	-0.062	0.073	-0.054	0.055
90	-0.164	0.600	0.111	0.202
99	-0.009	0.038	-0.005	0.024

A. Understanding the Fixed-Effect Estimates

We explore fixed-effect linear regressions in Table A2-1 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 across this table but differ remarkably from the matching estimates. Both sets of fixed-effect estimates suggest near-zero effects of physician patients on surgery adoption and medication spending, the opposite to matching estimates.

We prefer matching methods because fixed-effect linear models require more parametric assumptions that are not necessarily valid. See detailed discussions 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 is potentially crucial 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 A2-2.

The estimates in part (c) show that omitting the doctor effect leads to patient selection issues. Omitting the doctor-fixed effect biases 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 estimated impact is biased upward for surgery spending by more than 90 percent (0.216/0.112-1) and downward for 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 is possible that physician-patients have professional relationships with the attending doctor, which might have shortened the waiting time for 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 doctor have almost no impact.