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ABSTRACT

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

We use the medical specialties of physician-patients with advanced cancer to study the role of knowledge versus networks in treatment choices and patient survival by matching comparable patients with doctors and admission periods to control unobserved doctor quality. Physician-patients are less likely to have surgery, radiation, or checkups and more likely to receive targeted therapy, spend more on drugs, enjoy a higher survival rate, and spend less on coinsurance than non-physician-patients. Knowledge mechanisms play a crucial role because the network effect explains some, but not all, patterns. For less informed physician-patients, possessing a network is equivalent to reducing medical knowledge.

JEL Classification: D83, I11, J44

Keywords: physician quality, social ties, communication, information

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A growing body of literature in labor economics is devoted to examining whether complete information or robust social ties can solve agency problems (Bandiera et al., 2009; Jackson & Schneider, 2011). Health economists join 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). Their findings show communication and patients' trust in physicians strongly affect their demand for preventive care (Alsan et al., 2019) or a Cesarean section (Johnson et al., 2016). Both studies addressed unobserved doctor quality and the problem of patient selection using compelling research designs.

Besides experimental or quasi-experimental designs, observational studies have examined whether physician-mothers are more or less likely than non-physician-mothers to undergo a Cesarean section with mixed results.[1] Grytten et al. (2011) found physician-mothers received a Cesarean section more often, perhaps due to a closer relationship or better communication with their attending doctor. Conversely, Chou et al. (2006) and Johnson and Rehavi (2016) found physician-mothers are less likely to undergo a Cesarean section, maybe because they know about the potential complications or side effects. Irrespective of underuse due to weak social ties or overuse due to asymmetric information, the relational and informational disadvantages are empirically inseparable, relying merely on one medical specialty.

The importance of the relational and informational influences on healthcare agency issues is evaluated in this paper by studying Taiwanese inpatient 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 using expert-consumers. However, this comparison may capture the difference in the susceptibility of self-treatment versus treating others, not necessarily reflecting the physician-patients' effect on treatment choice (Ubel, Angot, and Zikmund-Fisher, 2011; Shaban, Guerry, and Quill, 2011). Earlier researchers avoided the susceptibility bias by comparing expert-consumers to non-experts, or physician-patients to other patients (Bunker and Brown, 1974; Hay and Leahy, 1982; Earle et al., 1993).

with a range of first/main specialties who have attended about 0.4 million patients with advanced cancer since 2004, including hundreds of physician-patients. These specialists must regularly attend Taiwan Oncology Society (TOS) conferences and training courses to maintain their oncology subspecialty licenses. We exploit the TOS's taxonomy to identify the professional ties between each physician-patient and attending doctor. Meanwhile, we quantify each physician-patient's medical knowledge of the diagnosed cancer by calculating the cancer caseload given their specialty and hospital department. By matching physician-patients with different specialties treated by the same doctor, we distinguish the effects of relational advantage (due to stronger professional ties) and informational advantage (due to being more informed).

Because of a lack of experimental variation, we address unobserved physician quality and patient selection issues using Abadie and Imbens (2006, 2011)'s nearest-neighbor matching method, which facilitates complex interactions among covariates without linearity assumptions. Our approach exploits the *within-doctor-hospital variation* across patients treated during the same period, matched by factors such as gender, cancer sites, income levels, and previous inpatient costs. This strategy enables us to minimize the bias from high-quality doctors being more likely to attend physician-patients.

Before evaluating relational and informational advantages, we follow the literature to compare physician-patients' treatment choices and survival rates with those of non-physician-patients. Our matching estimates show that the average physician-patient is less likely than others to choose surgical/radiation therapies and more likely to use targeted drug therapy. Physician-patients also spend less on check-ups and enjoy significantly higher survival rates. The magnitude ranges from 0.2 to 0.4 standard deviations, all statistically significant at the conventional level.

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

Another possible reason for the lower intensive care utilization we found among physician-patients is that non-physician-patients are more likely to sue. Doctors may prescribe unnecessary procedures for less informed patients to reduce their potential liability. But Taiwan's medical liability literature shows that most lawsuits arise from neurosurgery, anesthesiology, and the ER (Chen et al., 2012). We found that almost no patients visited these hospital departments for cancer care, suggesting that our results are unlikely to be due to unequal propensity to sue.

Beyond the basic results, we exploit the proposed measures of network and knowledge to explore the mechanisms behind the average physician-patient effects. We compare non-physician-patients to physician-patients with no professional ties or specialist knowledge of the diagnosed cancer site and find physician superiority leads to different treatment but not higher survival rates. When restricted to physician-patients only, we find although a professional tie does not affect short-term survival, it improves long-term survival by promoting intensive care (i.e., surgical/radiation therapies) at extensive margins. However, why typical physician-patients utilize more targeted therapy and less intensive care at extensive margins while enjoying significantly better short-term survival cannot be explained by either physician superiority or professional networks, leaving information mechanism as a likely explanation for physician-patients' short-term survival benefits and treatment patterns.

Our further investigation reveals professional networks and knowledge are interchangeable if physician-patients are less informed. We impose functional form assumptions on comparable physician-patients to quantify their informational interchangeability for professional ties. For those with knowledge in the bottom quartile, 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 treatment intensity. This finding implies a potential scenario where attending doctors abuse patients' trust by prescribing different procedures than they would for more informed patients. Such a deviation can harm patients' survival. This result confirms the dominant role of information over professional ties in treatment choice and survival, particularly for patients who lack expert knowledge.[2]

Our assessment of relational and informational mechanisms contributes a new dimension to the literature on healthcare agency problems. Previous researchers primarily focused on doctor-driven channels, including financial incentives and asymmetric information. Instead, we address both channels by looking within matched sets of physician-patients who specialize in various medical areas and are treated by the same doctor. The findings demonstrate the doctor-patient relationship matters for treatment choice and long-term survival at an advanced cancer stage because it generates more information for informed patients. Also, we demonstrate that information plays a dominant role for less informed patients. For relational and informational mechanisms to work, the theoretical context must include a doctor-driven demand hypothesis via a framework in which *risk-averse* patients undervalue the benefit of intensive care, thereby reducing demand. A stronger doctor-patient relationship can overcome risk aversion with better communication and trust-building to stimulate demand, but it can also give doctors leeway to abuse their patients' trust and deviate from appropriate care.

[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 effect potentially had relational advantages that may have canceled out the informational premium, leading to a near-zero effect. Leuven et al. (2013), Artmann et al. (2022), Chen et al. (2022), and Finkelstein et al. (2022) investigate the information effects by comparing outcomes of physicians' relatives and those of comparable patients.

The remainder of this paper proceeds as follows: Section 1 describes our data sources, institutional settings, and descriptive statistics. Section 2 is our matching scheme to construct the study sample, balance statistics, core estimates, and robustness checks. Alternative explanations for our findings are provided in Section 3, and the possible mechanisms are explored in Section 4 by extending our research to contrast the relational and informational roles of treatment intensity and survival rates. The paper is concluded in Section 5.

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. Firstly, similar to Canada, the Taiwanese NHI is a single-payer system for all citizens and residents consisting of a uniform, comprehensive care benefits package that covers drugs, hospitals, and primary care (Hsiao et al., 2016). Since participation in the 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 been in the hospital.

The NHI administration manages health expenditure inflation by reimbursing providers rather than charging deductibles or capping out-of-pocket expenses. This form of reimbursement is fee-for-service via a uniform national fee schedule to prevent providers from selecting patients or imposing price discrimination on them. Since hospitals pay doctors on a fee-for-service basis 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 US$7 in 2014) on hospital visits without primary care referrals. Consequently, almost all patients choose their attending doctor without a primary care referral. As 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. Taiwanese hospitals work on a closed-staff structure, with the on-staff doctor assuming full responsibility for patient care. This institutional setting ensures that matching patients to physicians can precisely describe the interaction between doctors and patients during hospital admissions.

B. Data Linkage

We merge several administrative data sources in the NHI database from 2000 to 2018 using unique scrambled identifiers (IDs) via four steps. First, we link the *Cancer Registry* to the *Death Registry* and the *Registry of Beneficiaries*. This data link covers cancer patients' diagnosis date(s), cancer site(s), and diagnosis stage. It also documents treatment methods, demographic background (sex, birthday, income bracket, and registration district), death records if patients died 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 *Records of Board-Certified Specialists* using their IDs. The former covers physician gender, birthday, and certification date, and the latter records their medical specialties and practice locations over time. Third, we combine 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 that we can calculate the 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 again use the attending doctor's ID to derive his or her certified specialty and experience by linking the compiled data to the *Registry for Medical Personnel* and *Records of Board-Certified Specialists*.

C. Time-Varying Doctor Selectivity

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

Doctors chosen by physician-patients are twice as selective as those chosen by other patients, with a selectivity level of 0.0039 (0.0022+0.0017), as shown in Table 1. Moreover, physician-patients select more experienced doctors than non-physician-patients by two years. These are large and statistically significant differences at a 95 percent level.

A significant challenge of our empirical work is that doctors could become more selective as they gain experience. As a result, 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 admission time for a fair comparison.

D. Descriptive Statistics

Table A1 compares the characteristics of physician-patients versus non-physician-patients, including their demographics, inpatient care receipt, and survival outcomes. The data comprises over 1.2 million cancer diagnoses, 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. Thirty percent of all cancer first diagnosed from January

2004 to December 2016 was in the *advanced stage*.[3] The data period began in January 2004, when Taiwan began to adopt the *American Joint Committee on Cancer's AJCC Cancer Staging Manual*, the benchmark for classifying cancer patients. Our analysis covers all the cancer sites listed in Table 4.

Notably, statistics indicate that 12 percent of patients diagnosed with cancer need no hospital care. About a quarter of these are in the advanced stage (not shown in the table). After controlling the interaction of patient demographics, prior medical spending, and admission year, we find that physician-patients are significantly more likely to receive hospital care by one percentage point (with SE = 0.006; not reported in the table). This difference was statistically insignificant and decreased when limiting the sample to advanced-stage cancer at the first diagnosis.

Each cancer diagnosis was likely to lead to more cancer therapies, including surgery, chemotherapy, radiation therapy, palliative care, targeted therapy, hormone therapy, immunotherapy, stem cell treatment, and Chinese medicine. We excluded the last three from our main analysis because less than one percent of diagnoses led to their adoption (Table A1).

Because the *Death Registry* for our benchmark study is available until December 2016, the N-year survival indicator needs to forgo N years of the combined data. After the first diagnosis, over 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 may have diagnosed physician-patients with advanced cancer earlier than other patients, which would result in overstating physician-patients' treatment and survival advantages. However, there is no evidence of this in the statistics (Table A1). Our analysis includes all the hospital admissions of first-diagnosis advanced cancer patients. The first diagnosis of

[3] We identify 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).

physician-patients is about three ppts more likely to be advanced than other cancer patients. This drops below 0.7 ppts (with a standard error of 0.009 clustered at patient levels; not shown in the tables) after holding constant the patient's sex, age, income, region, spending on inpatient care, and diagnosis year. These results suggest that our data is unlikely to contain potential bias due to earlier diagnoses by physician-patients.

Hospital admissions of physician- and non-physician-patients with advanced cancer are compared in Table 1, with standard errors clustered at patient levels. This data covers 1,123,377 admissions associated with 279,399 non-physician 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 physician-patients are older and wealthier, tend to be male, and have spent less on hospital care before the first cancer diagnosis. Both physician- and non-physician-patients are equally likely to have a pre-existing clinical relationship with a doctor, but 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.

Non-physician-patients wait an average of 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. Non-physician-patients also stay in acute inpatient care units for about 7.89 days, while physician-patient stays are 10 percent (0.81 days) shorter at a 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 considerably more likely to use targeted treatment by 44 percent (0.05/0.11). However, these gaps may be due to different health or socio-economic conditions or the selection of doctors with different practice styles.

Finally, the bottom part of Table 1 shows that physician-patients have the same 180-day survival rate as other patients. However, their one- and three-year survival rates are higher, possibly due to higher income, better health, better communication, closer relationships with attending doctors, selection of doctors, or more cancer-related knowledge. The higher survival rate of mainly older male physician-patients than other patients with advanced cancer seems inconsistent.

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 non-physician-patients attended by the same doctor in the same hospital. Patients are precisely matched by type to ensure patient comparability.[4] Since the method non-parametrically matches admissions by patient types and time components within doctor-hospital, both time-variant and invariant differences are captured in doctor and hospital quality and complex interactions among these covariates.[5] Balanced statistics and matching estimates are presented in the next sections.

A. Balance Checks

Firstly, the attending doctor is left unmatched, and non-physician-patients and physician-patients of the same patient type in the same hospital are compared. 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

[4] The following patient types are included: 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 of a pre-existing clinical relationship with the attending doctor three years before diagnosis.

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

panel) looks at those within doctor-hospital. Scheme A excludes 98 percent of non-physician-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 because physician-patients are significantly older, healthier, wealthier, and more masculine. After matching, the total number of admissions is 2,811, comprising 685 admissions (for 98 matched physician-patients) versus 2,126 admissions (for 565 matched non-physician-patients).

Although scheme A narrows down comparable patients, these patients are mostly attended by different doctors; hence, the varied outcomes observed between physician-patients and other patients may be due to physician quality. We improve the balance of matches by further matching attending doctors in scheme B, which reduces the sample size to 552 admissions. Of these admissions, 252 are for 31 physician-patients and 300 are for 69 non-physician-patients.

The balance tests for variables we did not match are shown in Table 2, in which the p-values of the mean difference (t-tests) and distributional difference (KS-tests) are reported. Both tests have p-values equal to one for the precisely matched covariates. Scheme A statistics indicate that patients' pre-diagnosis health conditions, estimated by pre-trends in inpatient costs and prior drug spending, are balanced statistically. In contrast, doctors who treated physician-patients have 0.3 standard deviation (SD) more experience than those who treated non-physician-patients. The distribution of the doctor's gender, mobility, and specialties differs significantly between physician- and non-physician-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 matching attending doctors 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. The SD in outcomes is displayed in columns 1 and 5 after removing the variation of the matched covariates. Further matching those 2,811 admissions with attending doctors in scheme B reduces the SD by 15–75 percent. This indicates that many of the changes in outcome are due to the variation in attending doctors.

As scheme A does not match the hospital entries according to attending doctors, physician-patients tend to see more experienced and selective doctors than their non-physician counterparts in this scheme (Table 2). Suppose that physician-patients prefer fewer tests and fewer intensive therapies at the advanced cancer stage and that experienced or highly qualified doctors tend to choose more intensive types of care and order more tests.[6] As physicians can more easily identify highly skilled doctors than non-physicians, we *understate* physician-patients' negative impact on intensive care utilization and checkup costs if we do not match them according to their attending doctors.

Matching hospital entries according to attending doctors and hospitals in scheme B dramatically *increases* physician-patients' 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 choose 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 margins of intensive care. Physician-patients' tube-feeding care drops from approximately 0.3 to 0.03 ppts. The effect of radiation also substantially decreases and becomes statistically

[6] Previous researchers suggest that intensive care can prolong life. Balsa and McGuire (2003) and Currie, MacLeod, and Van Parys (2016) show that lung cancer or heart attack patients benefit from aggressive treatment via intensive procedures.

insignificant. These impacts of different treatments on physician-patients' survival within-hospital and within-doctor-hospital matched samples suggest that physician-patients pick better doctors, *even within hospitals.*

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 surgery less frequently than their counterparts by 0.4 SD (1.159/2.87) while taking approximately the same radiation dose. 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 physician-patients utilize more are *targeted drug therapy* (0.167/0.28 = 60 percent more likely) and *prescription medication* (0.652/1.80 = 0.4 SD greater costs).

Physician-patients with advanced cancer spend more on medication, but the source of the spending rise cannot be determined from the currently available data. The higher spending could be due to greater quantities, more varieties, or increased drug prices (e.g., on patented brands). Doctors/hospitals cannot charge different prices for the same drugs due to universally uniform reimbursement prices and adjustments (Chen & Chuang, 2016). This institutional feature leaves physician-patients' increased drug dose or variety as the likely explanation for their increased medication cost.[7]

C. Cost-Effectiveness

According to the American Cancer Association's published medical guidelines, surgery/radiation therapies are more appropriate for early-stage cancers. More advanced cancer requires treatment that reaches the entire body (e.g., chemotherapy

[7] Whether our basic results derived from non-parametric matching are consistent with those using conventional fixed-effect models is explored in an online appendix. The matching method provides considerably more precise and robust estimates than fixed-effect models using the same set of controls (Table A2).

and targeted drug therapy). We have shown that physician-patients receive less surgery/radiation treatment for advanced cancer than the matched non-physician-patients while spending more on drugs and being more likely to use targeted therapy. If physician-patients' treatment is clinically suitable, our results indicate that underuse and overuse coexist among non-physician-patients.

Physician-patients receive different and better treatment, significantly increasing their chances of short-term survival compared to other patients by 2.5 ppts (9.3 ppts) at 180- and 365-day thresholds, as shown in Columns 6–7 of Table 3. Their long-term survival is also higher by 7.1 ppts at the three-year cut-off. These estimates account for at least 0.25 SD. Besides the survival benefit of better treatment, physician-patients pay significantly less for coinsurance by 0.226 log points. Overall, physician-patients receive cost-effective care relative to that given to matched patients.

3. Competing Explanations

Several theories could explain physician-patients' intensive care decline and their increased chances of survival, which may be driven by physician-patient relational or informational benefits. Three alternative explanations for the observed decline in physician-patients' intensive care volume may be that they are diagnosed with cancer earlier or receive cancer therapies earlier than others, that they exhibit better health than non-physician-patients, or that they are more likely to sue for malpractice. Each explanation is examined below.

A. Physician-Patients Are Diagnosed Earlier or Treated Earlier

Physician-patient relationships and informational advantages may lead to earlier diagnoses or treatment than non-physician-patients, resulting in the former needing less intensive care and surviving longer. However, the hypothesis that the physician-patient status reduces the likelihood of being diagnosed too late cannot be accepted according to data from the universal cancer registry (Section 1D).

The matching estimates in panel B of Table 3 show that physician-patients wait 1.3 days longer than other patients between diagnosis and treatment. This difference is statistically insignificant and accounts for less than two percent (1.3/75.6) of an SD. Hence, the hypothesis that physician-patients receive treatment earlier than non-physician-patients cannot be accepted.

B. Physician-Patients Exhibit Better Health

To ensure that the matched physicians and other patients have similar health conditions, we only compare patients in the same quintile for hospital spending in the three years before being diagnosed with advanced cancer. However, 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 contrary to this hypothesis. The matched patients' previous drug spending and pre-trend hospital costs are not significantly different. This pattern is robust, irrespective of scheme A or B (accounting for the attending doctor or not) if limited to matched patients in the same hospitals who share the same attributes and cancer sites during the same admission period. This result suggests that physician-patients' better health is not due to reduced surgical/radiation treatment before diagnosis.

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

Another explanation for our finding of physician-patients' reduced intensive care and examinations is they are less likely than non-physician-patients to sue for malpractice. Currie and MacLeod (2008) suggest that potential liability concerns may induce doctors to perform more unnecessary procedures, especially for non-physician-patients in our context. We examine this explanation by investigating 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 most likely to be sued and pay non-economic damages (Chen et al., 2012). On investigating our matched data to see if physician-patients in the riskiest departments receive exceptionally high premiums, we found almost no physician-patients with cancer seeking care in these departments. As a result, there is no evidence that the lower utilization rates of surgical or radiation therapy of physician-patients with advanced cancer could be explained by defensive medicine. Nevertheless, fear of litigation may still drive some doctors to prescribe different types of procedures to physician-patients than non-physician-patients due to unobserved differences, which we will address next.

4. Informational versus Relational Mechanisms

In this section, we further restrict our data to physician-patients only to probe the effect of professional ties and medical knowledge on treatment and survival.[8] We aim to extract parts of the physician-patient impact driven by relational advantages that previous researchers have often interpreted as informational. This task is possible because the attending doctors in our data have a wide range of (sub)specialties. We examine various specialties among doctors and physician-patient to distinguish between the relational and informational channels.

One noteworthy data limitation is in Taiwan, the government regulates board certification for 23 specialties, but it does not specify any rules for subspecialty certification. The absence of regulation leaves subspecialty certification at the

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

discretion of medical associations outside the NHI database scope. Consequently, we observe doctors' first/primary specialty, not their subspecialties.

Taiwan's cancer care specialization structure parallels Japan's pre-2007 medical system before Japan enacted the *Cancer Control Act*.[9] While doctors in the US refer cancer patients to oncologists, Taiwanese organ-specific specialists diagnose and remove operable cancer using endoscopic procedures or refer inoperable cancer patients to oncologists for chemotherapy or radiation treatment. Thus, doctors in Taiwan attending to stomach cancer patients could be gastroenterologists, gastrointestinal surgeons, or radiation oncologists, and we cannot determine if these specialists have a certified oncology subspecialty.[10]

A. Relational Mechanism: Mapping Specialists to Social Networks

As the attending doctor is fully responsible for caring for each admitted patient under Taiwanese NHI's closed staff structure, each doctor-patient pair has a well-defined professional connection. Physician-patients who share the doctor's specialty have a stronger tie because they may have met professionally before the diagnosis. Since subspecialties are unobservable in our data, we can infer patient-doctor networks from physician specialties, TOS taxonomy classification, and the doctor's hospital department. We follow the TOS taxonomy to classify networks, allowing one doctor to have multiple networks, and summarize how we map specialists according to a social network in Table 4.

TOS covers eight of the top ten cancer treatment specialties: three from the medical oncology network (category I, columns 1–3) and six from the surgical oncology network (category II, columns 3–8), with radiation oncology belonging

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

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

to both networks (column 3).[11] Although TOS lists pathologists as part of the medical oncology network, we separate from the medical oncology network those without another specialty and those who have never worked in internal medicine departments. However, despite having no medical knowledge of or caseload involving cancer treatment, TOS-listed plastic and reconstructive surgeons are included as part of the surgical oncology network due to the double-dose surgical training required for them to become board-certified surgical oncologists. Finally, although dermatologists and ophthalmologists who treat most skin/eye cancers are excluded from the TOS taxonomy (columns 9–10), we assume they have separate networks unrelated to cancer care in areas denoted by "Others."

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

We estimate physician-patients' medical knowledge of their cancer site using the caseload per doctor in the same specialty relative to the highest volume. Table A3 illustrates our estimation process for advanced breast cancer. First, we calculate the caseload per doctor by specialty and hospital department using 100% inpatient reimbursement data (column 1); then we measure the relative knowledge/caseload of the cancer site per specialty across hospital departments (column 2). The top breast cancer experts are surgeons in surgery departments with the highest caseload, while 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. It separates trainees by their specialties (surgical versus medical) for most events. As medical oncologists primarily treat cancer using medication (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,* we designate radiation oncologists to both professional networks. Although the *Taiwan Neurosurgery Society* is on the surgical oncology list, we cannot find a neurosurgeon who has treated a cancer physician-patient. Hence, we include neurosurgeons from the surgical oncology network, although we emphasize their zero knowledge of cancer treatment.

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

We apply this method to all cancer sites. Surgeons with specialties not listed in the columns have zero relative knowledge/caseload (e.g., neurologists, neurosurgeons, and plastic and reconstructive surgeons). The statistics show the top cancer experts are typically organ-specific specialists (except for bone cancer), and radiation oncologists are the top leukemia and stomach cancer treatment experts. Finally, we standardize physician-patients' knowledge levels of their cancer site.

C. Exploration of Mechanisms

Using the network indicator R and 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 physician-patients' heterogeneous impact on outcomes given their network R and knowledge K. We assume the full effect can be broken into four components:

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

where $e(0) = 0 = \delta(0)$. The *physician status effect* (β) captures the different outcomes when neither non-physician-patients nor physician-patients have an advantage. This parameter quantifies the fundamental superior general medical knowledge and occupational connections that distinguish *any* physician-patient from other patients. The *network's main effect* (ρ) measures the benefit of a robust professional tie for patients without superior knowledge of the diagnosed cancer. The *knowledge's main effect* is $e(K)$ if the patient has no professional tie with the attending doctor. The *network-induced informational effect* on the outcome is $\delta(K)$.

To evaluate these mechanisms, we first identify the physician status effect (β) by comparing non-physician-patients and physician-patients with no advantage. Secondly, we estimate the total impact of a professional tie with the attending doctor ($\beta_{1K} - \beta_{0K}$), including the *network's main effect* and *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 due to the lack of support of continuous medical knowledge.[12] We overcome this challenge in the third step by estimating the value of a network by information percentile when applying fixed-effect models to matched physician-patients. Each step is expanded, as shown below.

C.1. Physician-patients' general advantage over non-physician-patients

Using scheme B's procedure, we first identify β, the physician status effect, by matching non-physician-patients and physician-patients *with no advantage*. *Before matching*, physicians with no advantage tend to be older but healthier males and are more likely to seek care from a more experienced doctor than other patients (Table A4, columns 1–2). *After matching* by doctor-hospital and patient types (footnote 4), we obtain a near-perfect balance between non-physician-patients and physician-patients with no specific advantage. With these stringent data requirements, only 5.6 percent of physician-patients (=168/3013) are matched to

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

106 comparable non-physician-patients treated by 17 doctors in 7 hospitals (not shown in the tables).

The matching estimates are presented in Table 6, and the coefficients are highlighted with patterns resembling the average physician-patient effect. Physician-patients with no advantage have fewer examinations, significantly less surgery, and shorter stays in acute inpatient care while spending much more than non-physician-patients on medication (columns 2–3), consistent with the average physician-patient effect (columns 8–9, copied from Table 3). However, unlike average physician-patients, physician-patients with no advantage have a probability of targeted therapy 6.0 ppts *lower* but a probability of chemotherapy 9.4 ppts *higher* than non-physician-patients. Both estimates are highly statistically significant, representing more than half of the variation in utilization. Surprisingly, this substantially different treatment due to physician status shows no survival advantage (bottom of columns 2–3).

C.2. Total impact of professional network

The network's main effect (ρ) must be compared to the knowledge's main effect ($E[e(K)]$) to determine the relative importance of relational versus informational mechanisms. This task requires a balanced sample of physician-patients with networks but no relevant knowledge versus those with relevant knowledge but no networks. However, as this approach requires immense data support and stronger assumptions because the knowledge is continuous, instead, we estimate $E[\beta_{1K} - \beta_{0K}]$ the *total impact* of the professional network, including its 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 issue with a non-random assignment of professional ties by focusing on inpatient doctors who attend multiple comparable physician-patients with different relational advantages. We match these highly homogeneous patients precisely according to *scheme C,* by doctor-hospital and patient types (gender, cancer sites, and previous hospital spending terciles). Furthermore, we also control their age, income, prior trends of inpatient spending, and doctor experience in the matching procedure.[14]

If patients select doctors based on doctor quality and patient attributes and preferences, we can minimize selection bias by looking at these precisely matched physician-patients. As doctor-patient matches are independent decisions patients make using private information on preference and doctor quality, we can use patient choices to infer these unobservables for bias correction. Hence, our identification relies on assuming self-selection upon observables and unobservables to minimize the possibility of reverse causality, as confirmed by our placebo tests.

The total networking impact and average physician-patient effect are shown to be opposite for intensive care and drug use in matching scheme C (columns 5–6 vs. 8–9, Table 6). Networking induces over 0.25 SD (0.087/0.34) *more* surgery, radiation, and chemotherapy utilization while reducing target therapy by 0.40 SD (0.151/0.38). In contrast, typical physician-patients are *less* likely to receive intensive care but use increased targeted therapy and medication instead.[15]

Neither physician status nor networking explains why typical physician-patients tend to replace intensive care with targeted therapy while enjoying better short-term survival rates (180 or 365 days; see columns 2–3 vs. 5–6). On the one hand, this

[14] We implement placebo tests to check if the network indicator among matched physician-patients is nearly random. A balance between matched physician-patients with versus without a network on those not precisely matched controls (e.g., age) is shown in Columns 1-3 of Table A5. This 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 it 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.

implies the *informational mechanism* is the main driver of <u>intensive care reduction and short-term survival improvement</u> at the advanced stage; on the other, 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 strong professional tie with the attending doctor reduces coinsurance costs and the need for palliative care, with a chance of three years' survival over 0.28 SD (0.071/0.252). These concurrent results suggest the *network-related channels* correctly project the different <u>coinsurance costs, palliative care, and three-year survival rates</u> of physician-patients and non-physician-patients.

C3. Interchangeability between network and knowledge

Although the average physician-patient effect on some treatments is consistent with the impact of physician status or network-related mechanisms, neither of these elements explains why average physician-patients tend to replace radiation with targeted therapies while enjoying better short-term survival than non-physician-patients. This suggests that this information is crucial in determining treatment and survival. Using equation (1), we quantify *the value of a network* by information percentiles using the degree of *informational interchangeability 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:

$$(2)\ V_{RK} = -\frac{dK}{\Delta R}\Big|_{\text{fixing } \beta_{KR}} = \frac{\beta_{1K} - \beta_{0K}}{\partial\beta_{RK}/\partial K} = \frac{\rho + \delta(K)}{e'(K) + R\delta'(K.)}$$

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

[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 $\delta'(k^*) = 0$.

threshold, $\delta(K)$ could be downward or upward sloping or nonlinear in K. To allow flexible non-linearity, 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.

We perform fixed-effect regressions with two causal variables, network and knowledge, by combining two balanced samples to derive sufficient variation: one balancing patients with versus without a network (as shown in columns 1–3 of Table A5 in section C.2), and the other balancing knowledge above versus below the median (columns 4–6). We illustrate the data structure in Table 5. The shaded areas indicate the samples included. The data balanced by networks has 277 observations, which overlaps the data balanced by knowledge in 214 cases. The data balanced by knowledge adds 80 extra admissions that are not balanced by network(s).

Using this integrated sample, we estimate that the fixed-effect model holds the same list of covariates constant as in scheme C of section C1. Although the estimated coefficients are imprecise (Tables A6-1 and A6-2) due to the limited support of continuous information, there are clear patterns in the estimated value of networks. We sketch the interchangeability of a given network (V_{1K}) in Figures 1 to 3, as the case with no network (V_{0K}) is too noisy.

We find a strikingly persistent pattern. Lacking relevant knowledge of the cancer site makes networking equivalent to knowledge reduction. The value of networking for most outcomes, when the knowledge level is at or below the bottom quartile, is significantly negative, between -11 and -6 ppts. It further expands to -18 and -14 ppts at the bottom 1st percentile. For professionally connected but less informed patients, the social tie is equivalent to *losing* 15 to 18 ppts of relevant knowledge of the cancer site to maintain the same survival or treatment intensity. This result affects survival rates, examination costs (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). Palliative care and chemotherapy are exceptions for which we obtained insufficient precision.

In summary, when doctors attend to professionally connected physician-patients with no relevant knowledge, they may abuse the trust of these patients by deviating from the treatment they would prescribe to a knowledgeable specialist-patient, harming their chance of survival.

5. Conclusions

The agency problem 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, but the relevance of the doctor-patient relationship in mitigating agency issues remains unknown outside those contexts.

This paper began with a benchmark of physicians treating physicians without separating relational and informational mechanisms. We compared treatments and survival outcomes of physician-patients and non-physician-patients with the same advanced cancer, attending doctor, and hospital. We exploited the within-doctor-hospital variation to compare exactly matched patients. Using rich controls, we addressed patient selection and unobserved doctor quality. The results show that physician-patients require less intensive care and receive more medication, more targeted therapy, and fewer checkups, all of which cost less and improve survival.[17]

Physician-patients have clinical knowledge and professional connections, which potentially contribute to better care and higher survival rates than non-physician-

[17] Physicians' relatives may receive benefits similar to physician-patients. As relatives are considered as non-physician-patients in this paper, our results may understate the physician premiums.

patients. We extended the matching method to evaluate the importance of relational and informational advantages by exploiting various medical specialties among physician-patients and their attending doctors. Physician-patients who possess neither advantage induce the attending doctor to prescribe different treatments (e.g., less surgery, more medication, and fewer tests), which do *not* prolong their lives relative to non-physician-patients. In data restricted to physician-patients, a stronger doctor-patient relationship induces more intensive care and improves long-term survival, consistent with the average physician-patient effect. Nevertheless, neither physician status nor professional tie explains why average physician-patients tend to replace radiation with targeted therapies and enjoy a better short-term survival rate. This leaves the informational mechanism as the leading explanation for the result.

To confirm, we estimated 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, and this tends to lower their chance of survival as they receive treatment different from that prescribed to specialist patients who possess relevant medical knowledge and experience of their diagnosed cancer.

The revealed mechanisms are consistent with a framework in which doctors can induce demand to benefit their self-interest. A stronger patient-doctor bond builds trust, which the latter may exploit to induce demand *if patients are less informed*, as posited by the classic 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 intensify agency issues if consumers are less informed. Better information increases the chance of belonging to a network, which generates more information. Professional ties can only benefit expert consumers in the long term when networking 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 that relational and informational advantages are monotonic. In other words, the comparison made by distinguishing doctor-patient pairs by medical specialties is the same as separating physician-patients from non-physician-patients. However, professional connections via medical association networks may differ from social ties via occupations in affecting treatment and survival rates. Second, we assume that physician-patients' choice of professional networks is fully captured by observables. If their choice is also based on unobservable incentives independent of those observed, we have overstated the relational benefits and understated the informational advantages due to reverse causation. Physician-patients who prefer intensive care may choose a doctor with whom they have a relational advantage to receive favorable treatment.[18]

Finally, the matched sample size is small because of the rare overlap between physician-patients and non-physician-patients and among physician-patients by advantage. Nearest-neighbor matching may not fully eliminate bias given a modest set of controls for patient types (footnote 4), although precisely matching patients by doctor-hospital substantially reduces it. Our understanding of the impact of networking-induced information on patient survival would be significantly enhanced by more available data. We aim to increase our observations and relax the monotonicity assumption in future research.

[18] This limitation is the same as that 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 may be due to selection issues related to mutual fund managers' incentive to strategically allocate underpriced IPOs (Gaspar, Massa, and Matos, 2006).

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

	End-stage cancer at the first diagnosis		
Variable	Non-physicians Mean	Physicians minus Non-physicians	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
Pre-existing 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 unrelated to cancer treatment	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 non-physician-patients. We cluster standard errors at the patient level to calculate the p-value.

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

Predetermined variables not matched on	Scheme A) Exact match on patient types within hospital			**Scheme B) Exact match on 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
Work in multiple hospitals	-0.14	0.26	**0.00**	0.00	1.00	1.00
Patient's log prior spending on drugs	-0.01	0.87	1.00	-0.01	0.99	1.00
Patient's pre-trend in hospital cost	-0.07	0.55	1.00	-0.01	0.95	1.00
Number/percent of admissions	2811	0.26%		552	0.05%	
Number of physician-patients			98			31
Number of non-physician-patients			565			69
Number of admissions by physician-patients			685			252
Number of admissions by nonphysician-patients			2126			300
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 of a pre-existing clinical relationship with the attending doctor three years before diagnosis. We match admissions precisely by 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) Within hospital	(2) A) Exact match by patient types within hospital	(3)	(4)		(5) **B) Exact match by patient types within doctor-hospital**	(6)	(7)	
	SD	SD	Coef.	SE		SD	Coef.	SE	
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 of 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 of a pre-existing 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 show the data 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 (SE) 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: The taxonomy classification associated with specialists based on their specialties and hospital departments are summarized in this table. We derive the knowledge index using the method illustrated in section 4A. Empty cells indicate absolute zeros. We assign each cancer site to ICD-O-3 codes following Taiwan's Cancer Registry Annual Reports (downloadable from www.hpa.gov.tw). * Leukemia's coding is M95903-M99933, except for M99903. Each doctor may have multiple specialties and work in multiple departments. (1) "Internal medicine" covers interns 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 cancer care, including ER, neurology, anesthesiology, rehabilitation, psychiatry, family medicine, and occupational medicine. We also include doctors in neonatology or pain-medicine departments in this category. Our data show no physician-patients who seek cancer treatment from a pathologist, dermatologist, or ophthalmologist. Only three inpatient entries of the physician-patient data have a professional tie with their attending doctor specializing in "Others."

TABLE 5. CONSTRUCTING THE MATCHED SAMPLE OF PHYSICIAN-PATIENTS TO ESTIMATE THE INFORMATIONAL INTERCHANGEABILITY OF 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: PHYSICIAN STATUS AND TOTAL RELATIONAL EFFECTS ON OUTCOMES

	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
	Scheme B: Matching non-physician-patients to physician-patients with no advantage				Scheme C: Matching of physician-patients				Baseline Scheme B:			
		Physician status effect (β)				**Total relational effect** ρ + E[δ(K)]				**Average physician-patient effect** E[β(R,K)]		
	SD	Coef.	SE		SD	Coef.	SE		SD	Coef.	SE	
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 non-physician-patients to physician-patients without any specific advantages. As in scheme-B in Table 3, we precisely match hospital entries to 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 of a pre-existing clinical relationship with the attending doctor three years before diagnosis). The matched sample exhibits a near-perfect balance, which is 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 strong professional tie with the attending doctor. Here, we precisely match hospital entries to doctors, hospitals, 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.*

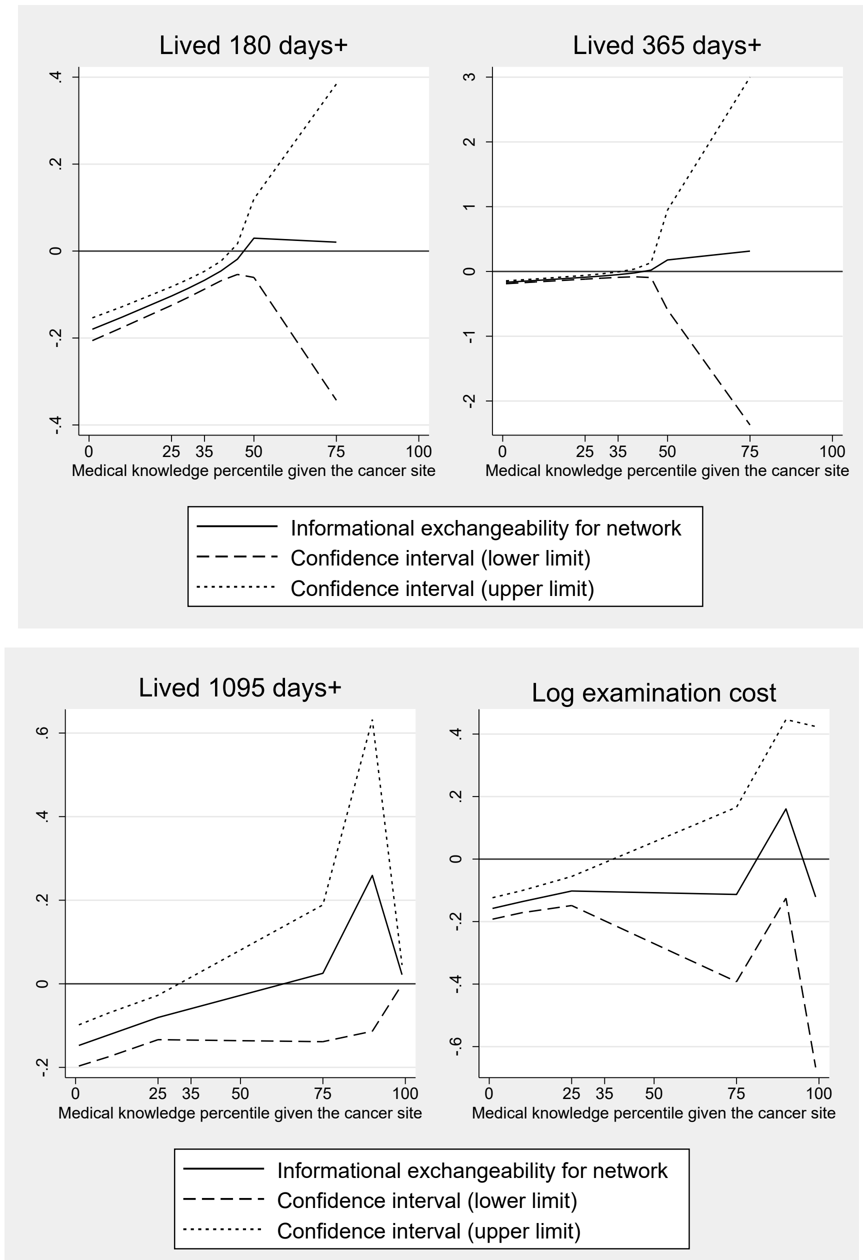
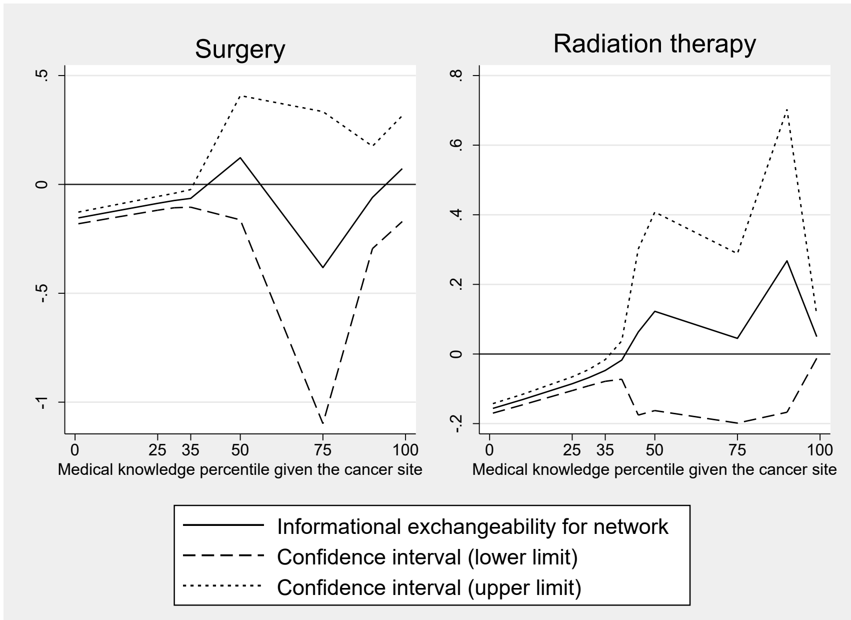


FIGURE 1. INFORMATIONAL EXCHANGEABILITY FOR A SOLID TIE WITH THE ATTENDING DOCTOR BY PATIENT KNOWLEDGE PERCENTILE – PATIENT SURVIVAL AND EXAMINATION COST

Note: The estimated degree of exchangeability has 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 estimated results in Tables A7-1 to A7-4. We omit the estimates with wide confidence intervals that go off-chart, especially for survival or medical spending outcomes at the upper range of knowledge levels.



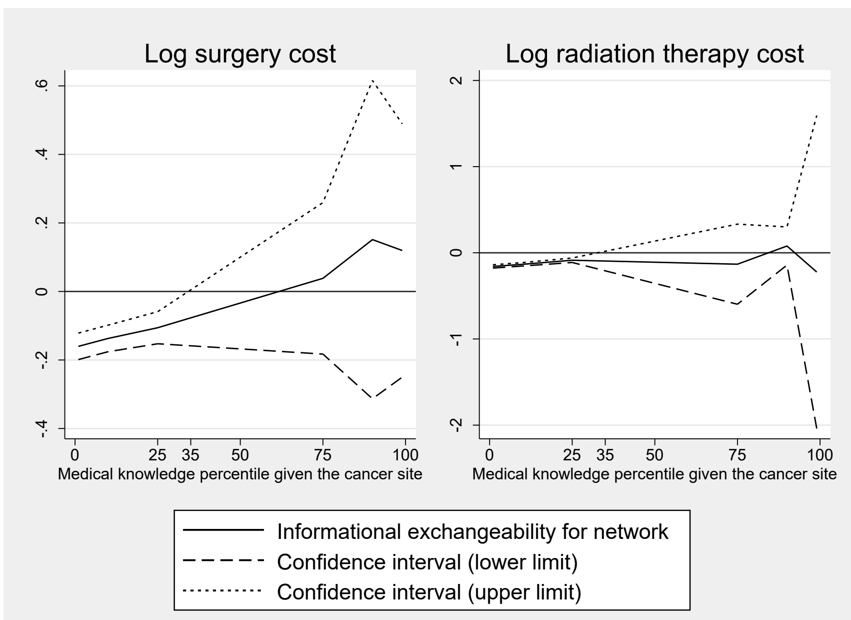


FIGURE 2. INFORMATIONAL EXCHANGEABILITY FOR A SOLID TIE WITH ATTENDING DOCTOR, BY PATIENT KNOWLEDGE PERCENTILE – INTENSIVE CARE AT EXTERNAL AND INTERNAL MARGINS

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.

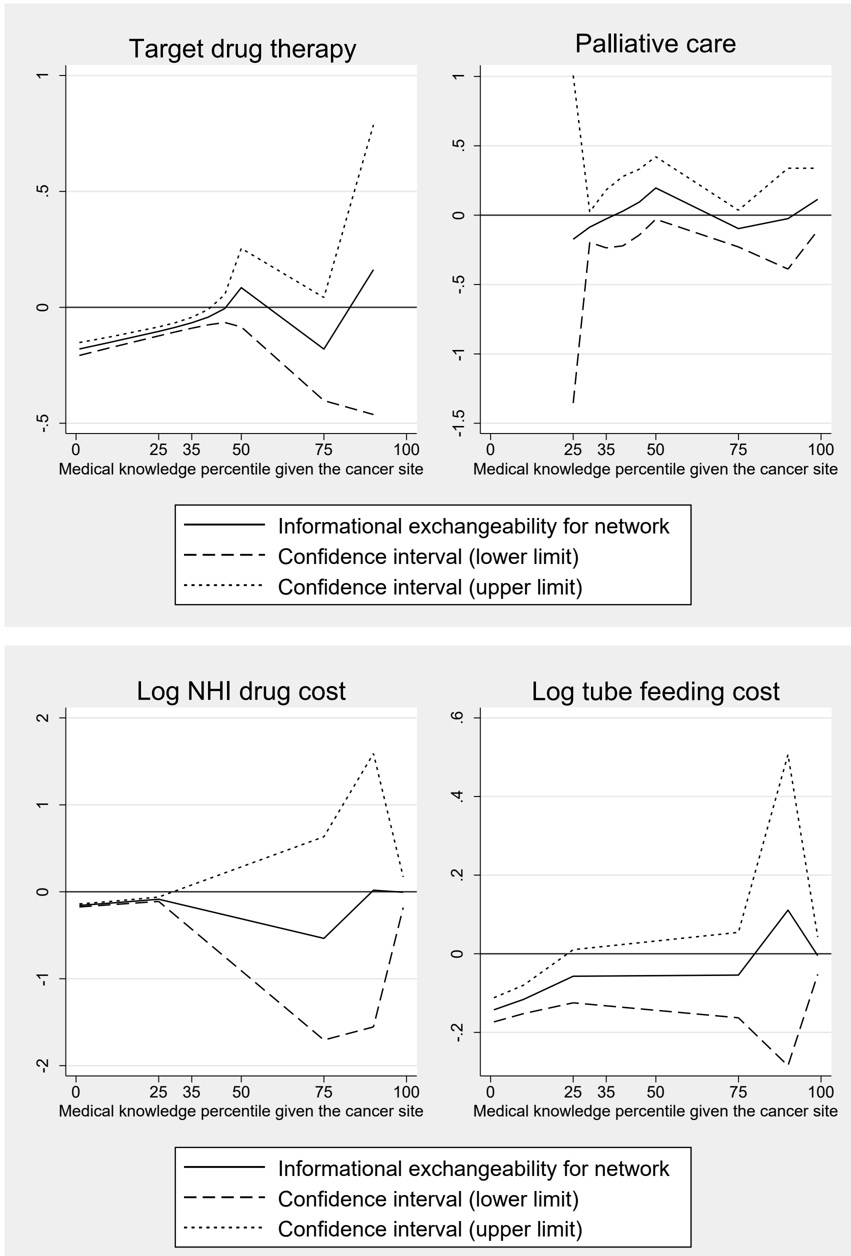


FIGURE 3. INFORMATIONAL EXCHANGEABILITY FOR A SOLID TIE WITH ATTENDING DOCTOR BY PATIENT KNOWLEDGE PERCENTILE – DRUG USE AND OTHER COSTS

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.