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Hospital Readmission after Post-acute Care at Different Settings: Estimation using the Propensity Score Matching Method

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Abstract

Objective: This study examines the relative risk of hospital readmission for patients receiving post-acute care (PAC) at different health care settings by utilizing an innovative big-data approach.

Study design: The electronic health records of 124, 127 patients from a large-scale health care system are extracted to allow for propensity score (PS) matching. The PS method is able to put patients into matched pairs, which became the unit of analysis in computing the odds ratios (OR) of hospital readmission for patients having received PAC at 5 different settings-home, home health agency (HHA), skilled nursing facility (SNF), inpatient rehabilitation facility (IRF), and long term care hospital (LTCH). The PS matching method controlled the effects of a large number of confounding variables, and computed the odd ratios of hospital readmission for patients at different PAC settings.

Results: We obtained mixed results regarding the odds ratios of hospital readmission for PAC settings in comparison with home care. While PAC patients at IRF and LTCH had a lower OR of hospital readmission than home care (0.77 and 0.76, respectively), PAC patients at HHA and SNF had a higher OR of hospital readmission (1.26 and 1.25, respectively). These results are statistically significant at $p<0.05$.

Conclusions: This research demonstrates an innovate approach to utilize EHR data for improving population health. Our findings call for rigorous techniques to improve care coordination specifically for PAC patients at institutional settings. Improved PAC coordination is able to reduce health care cost, and improve quality of health care delivery.

Keywords: Post-acute care; Hospital readmission; Electronic health records; Propensity score

Introduction

Electronic health records (EHRs) have enabled health providers to improve health care coordination in ways that were impossible in the past. Among other things, the vast amount of data made available by EHRs—some researchers call them "big data" [1]—allow health providers to offer evidence-based optimal care for patients with different medical conditions and severity [2]. In this paper, we focus on what has been called "post-acute care" (PAC) in the literature [3]. PAC refers to medical care services in support of an individual patient's continuous recovery from any acute or chronic illness (including disability) that necessitates admission to a hospital [3].

Yet, several analytic challenges must be overcome to utilize EHR data: First, EHR database can have a complex structure. Health providers typically know little about the extraction, manipulation and analysis of EHR data [4]. Accessing the data itself is often an insurmountable task. The data might be stored in non-traditional formats and cannot be made available conveniently. Besides, even after data have been extracted and converted, the researcher/health provider team must be able to identify appropriate statistical techniques that can handle and take advantage of the vast amount of EHR data [4]. Given the newness of EHR data, few research frameworks exist in the literature that can be borrowed to address PAC-related issues or other important questions in health care.

This study seeks to improve PAC by analyzing a large EHR database. Our team consists of experts in health informatics, health care management, as well as experienced practitioners. Having secured access to a very large EHR database, we explore optimal PAC by initiating an innovative approach. Specifically, we derive estimates of hospital readmission—a prior hospitalization followed by another hospital admission within thirty days—for patients receiving PAC at different settings. Our general design was to treat home care ("going home" after hospital discharge) as the "baseline", and then we analyzed whether patients of other PAC settings—home health agency (HHA), skilled nursing facility (SNF), inpatient rehabilitation facility (IRF), and long term care hospital (LTCH)—were more or less likely to be readmitted to a hospital within 30 days. These PAC settings represent different levels of service intensity, and financial costs. They are the most common types in the PAC sector. A long-term care hospital (LTCH) is normally regarded as providing the most intensive level of combined clinical services than other settings in our list. LTCH is followed by IRF, SNF, HHA and home care (in that order) in terms of intensity of clinical services [5,6].

The findings reported in this paper come from a larger research project that has been taking place in the past few years. In this paper, we focus on a specific quantitative method called the propensity score (PS) matching method, which provides a basis to evaluate the relative risk of hospital readmission for patients receiving PAC at different settings mentioned above.

Hospital readmission and post-acute care settings

The physician's decision to admit a patient to the hospital, sometimes called hospitalization, indicates that acute care is needed for the patient. The general expectation is that a period of acute care provided in the hospital would facilitate the patient to recover from illness. Since hospitalization involves a high cost, patients cannot expect to stay in a hospital more than what is necessary [7]. Traditionally, physicians alone had to determine when a patient should be discharged, whether the patient needs additional, "post-acute" care (PAC) and, if so, where PAC should be delivered. In recent years, there has been an increased emphasis on team-base care, and patient-centeredness in health care [8]. A care team can consist of physicians, care managers, specialists, and patients [9]. Care managers, in particular, can provide useful advice to patients to become more active in determining their PAC treatment. Care managers also assist patients in acquiring health knowledge, increasing self-management skills, and readiness to make changes in health behaviors [9]. Research has shown that the benefits of team-based care for older patients are very significant [10].

Regardless of who determines the choice of PAC, the clinical effectiveness of PAC might be evaluated by one or more quantitative indicators. One such indicator is hospital readmission [11]. While PAC is assigned after a patient is discharged from a prior hospitalization, it is reasonable to expect that the patient would recover sufficiently such that "going back" to the hospital within a reasonably short time would not happen. Nonetheless, some patients do get readmitted to the hospital in reality. In the PAC sector, the event of hospital readmission has been deployed as an indicator to represent the clinical effectiveness of the PAC services [12]. By extension, it is reasonable to measure how many patients get readmitted to the hospital (i.e., the hospital readmission rate) for a PAC facility, and interpret the readmission rate as an indicator of the PAC's clinical effectiveness. Hospital readmission is also associated with a recent policy enacted with the Accountable Care Act (ACA). Based on this policy, hospitals would be penalized by the Center for Medicare and Medicaid Services (CMS) if a "high-than-average" number of patients is readmitted to the hospital within 30 days [13]. The 30-day window has thus given readmission a specific numerical value as a reference point. In research, the 30-day hospital readmission has been used as a "dependent variable" to evaluate the quality of PAC settings [14].

Because each form of PAC offers a unique set of services with varying levels of clinician availability and oversight, it can be difficult to compare them without any statistical control or adjustment. HHA provides in-home nursing care for patients with less acute conditions such as wound care; SNF provides care for conditions needing longer nursing hours and direct physician supervision such as dialysis; IRF delivers intensive physical and occupational therapy on patients that need functional recovery; LTCH provides care akin to an acute care hospital, typically for a small set of patients who really need continuous and intensive medical attention. In the literature, researchers tended to focus on a single type of PAC settings and even specific medical conditions, such as pancreatectomy [15]. The PS approach enabled us to make appropriate statistical control and adjustment.

Practically, there are desirable reasons to compare the clinical quality of different PAC settings. An appropriate choice of PAC would ensure good transitions of care [14]. The choice of PAC may be particularly difficult for patients who do not show a clear need to go to one setting rather than another [16]. Choosing an inappropriate setting can have long-term negative consequences. For instance, because of psychological stress and exposure to hospital infection [17], older patients being assigned to an inappropriate PAC setting could experience functional declines and increased mortality rates [18].

Methods

Data

For this research, we used patient-level clinical data collected through the electronic health records (EHR) from the Advocate Health Care ("Advocate" hereafter). Advocate is a large health care system composed of eight hospitals—all of them are primarily located in the urban Chicago area. Since Advocate manages a number of PAC facilities including HHA, SNF, IRF and LTCH, there were sufficient data to undertake a comparative analysis to reveal their relative clinical effectiveness. It is also noteworthy that Advocate's EHR are managed by the Cerner Corporation [19]. The two organizations collaborated and agreed (based on an open letter signed April 11, 2012) to utilize EHR data for research purposes in compliance with the Health Insurance Portability and Accountability Act (HIPAA) regulations. All data extraction and analysis performed in this study was conducted by HIPAA certified analysts in accordance with standards and regulations to protect patient confidentiality.

The sample used in this study included all inpatients aged 18 or above that had a hospital stay but not expired/deceased in the hospital from March 1, 2011 to July 31, 2012, in any one of the eight hospitals within the Advocate Health Care system. We used a twelve-month look-back period prior to March 1, 2011 to obtain historical information for each patient (e.g., previous hospital utilization, comorbid conditions and medication history, etc.). Data for the month of August 2012 was used to track possible 30-day readmissions for patients in July 2012. Through these criteria, we obtained an initial cohort of 124,127 patients. We excluded patients who: (a) left the hospital against medical advice (N = 1,351); (b) were labeled as still an impatient (N = 210); (c) were transferred to psychiatric hospitals (N = 1,196); (d) were transferred to hospice (N = 1,562); and (e) were transferred to an unknown type of healthcare facility (N = 72). Upon these exclusions, the final sample contained 119,736 patients. All of these patients received PAC at different settings.

Propensity score method

To utilize these "big data", our analysis included two distinctive features: First, we applied the propensity score (PS) method to match comparable patients [20]. The PS method offers a feasible alternative to the randomized clinical trials (RCT) method [21]. Conducting randomized clinical trials (RCT) for PAC patients is challenging because, for ethical and logistical reasons, the provider or researcher is typically unable to randomly assign comparable patients into two (or more) different PACs and examine their relative clinical effectiveness. The PS approach enables researchers to match patients on a retrospective basis. This approach has been extensively validated in the literature, and its utility is increasingly recognized [21].

Our analysis evaluated all individual patients by computing each of their propensity score for entering different PAC settings. This analytical approach is based on an influential review in the propensity score literature [22]. To create "matched pairs" based on the patients' propensity score, we borrowed what is called the "greedy-matching" algorithm to match subjects using calipers that were defined to have a maximum width of 0.2 standard deviations of the logit of the estimated propensity score [22]. The matching can be assessed by t-tests, McNemar's test, the mean of each covariate, and other standardized differences between treated and untreated patients [23]. Those who could not find a match would be removed from further analysis.

Each individual patient in a matched pair was supposed to have the same clinical need but they could enter different PAC settings. For example, two individual patients that have the propensity score—each patient's score is computed by combining all available individual-level variables in the EHR dataset—turned out to receive home care and enter a skilled-nursing facility respectively. We could then examine whether their hospital readmission differed or not. By replicating this step, we would have a sufficient number of matched pairs in various PAC settings in our sample, so that we could computer the odds ratios (OR) of hospital readmission for patients at different PAC settings. In essence, this procedure enabled us to simulate the RCT process on a retrospective basis. More specifically, we fitted a logistic regression model and derive the effects of PAC settings on hospital readmission. The model can be estimated using generalized estimating equation (GEE) methods [22].

Another distinctive feature in the analysis was concerned with confounding effects that came from a large number of variables simultaneously. Our EHR data consisted of many variables, including the patient's demographic profiles, medical histories, insurance status, and the like. In total, we had more than 400 variables. We were able to control for the confounding effects of all these variables in the PS method, and singled out the main effect of PAC services on hospital readmission. That is, our analysis revealed the "independent effect" of PAC type, per se, on our outcome of interest—hospital readmission. The details of our statistical control procedures are complex, and out of the scope of this paper. We plan to discuss them in another publication.

Results

Descriptive statistics

Our sample contained patients with diversified demographic characteristics across PAC settings (Table 1). With respect to age, SNF had the oldest population. The mean age of patients receiving PAC in SNF sample was 75.5, followed by HHA (67.9), LTCH (66.4), IRF (65.6), and home (51.8). Gender distribution was almost even in IRF (49.5% males vs. 50.5% females), LTCH (48.2% males vs. 51.8% females), and HHA (44.0% males vs. 56.0% females). Yet, in both SNF and home care, there were much less male than female patients (only 38.6% males in home care and 37.6% males in SNF). Racial distribution was quite consistent across PAC settings: Around 60% were Caucasian patients, between 22% and 32% were African American patients, and the rest were Hispanics and patients of other races. For home care patients, the majority of them (56.0%) had commercial insurance, and only 27.1% of home care patients had Medicare. Compared with other PAC settings, SNF had the highest proportion of Medicare insurance beneficiaries (72.8%), followed by LTCH (56.5%), HHA (54.4%), IRF (53.5%) and home care (27.1%). Close to 10% of LTCH patients had Medicaid, followed by IRF (8.7%), home care (7.9%), HHA (5.5%) and SNF (3.9%). 9% of home care patients' insurance was "self-pay and others". Less than 4% of all other PAC patients used this type of insurance.

The comorbidity index was an indicator of the level of clinical needs required by PAC patients. The higher the index the higher the need was. The scores for HHA (2.7), SNF (2.8) and LTCH (2.8) were similar, and they were regarded as high in terms of comorbidity [20]. The scores for home care and IRF were lower, 1.4 and 1.7, respectively. Another indicator of clinical needs was functional status score. A higher functional status score indicates a higher clinical need. The scores for the sample patients ranged between 0.00 and 0.09, and the direction of them was consistent with the comorbidity index for different PAC patients. Finally, Table 1 showed the readmission rate for different PAC settings. This variable was measured by an incidence of a 30-day unplanned or non-elective, all-cause readmission to the hospital for each patient. Among PAC settings, the readmission rate of SNF was the highest (13.95). This means that about 14% of patients in this PAC setting could expect to be readmitted to the hospital within 30 days after the discharge from a prior hospitalization. SNF's hospital readmission rate was followed by HHA (11.7), LTCH (8.03), IRF (7.24) and home care (4.99). Our finding was consistent with similar research in the literature [5,24].

Relative clinical effectiveness

Using the readmission rates in Table 1 to represent the relative clinical effectiveness of PAC settings is imprecise, because the risk profile of patients discharged to each setting could be quite different. A more precise comparison is derivable by focusing on similar patients across PAC settings, and controlling for confounding variables. As mentioned, the PS method enabled us to match individuals by computing a score based on all characteristics of individual patients. Our subsequent analysis of the relative clinical effectiveness of different PAC settings can then focus on "matched pairs" of patients (with the same propensity score) as the unit of analysis, and dropped cases that could not be matched. The odds ratios that we computed after controlling for confounding variables such as medical histories, admission dates and the like also had increased validity.

		Post-acute care settings				
		Home (N=80,329)	HHA (N=15,813)	SNF (N=17,557)	IRF (N=2,913)	LTCH (N=3,124)
Age (in years)	Mean	51.8	67.9	75.5	65.6	66.4
Gender (column %)	Male	38.6	44.0	37.6	49.5	48.2

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	Female	61.4	56.0	62.4	50.5	51.8
Race (column %)	Caucasian	59.2	62.4	69.2	65.4	55.3
	African American	22.3	24.8	22.1	20.9	32.4
	Hispanic	10.8	7.8	4.3	6.8	6.3
	Others	7.7	5.0	4.5	6.8	6.0
Insurance (column %)	Commercial	56.0	36.5	22.4	34.2	31.6
	Medicare	27.1	54.4	72.8	53.5	56.5
	Medicaid	7.9	5.5	3.9	8.7	9.5
	Self-pay and others	9.0	3.7	1.0	3.6	2.3
Comorbidity Index	Mean	1.4	2.7	2.8	1.7	2.8
Functional status score*	Mean	0.00	0.04	0.09	0.02	0.09
Readmission rate (%)		4.99	11.70	13.95	7.24	8.03

Table 1: Descriptive statistics of PAC settings.

In Table 2, we present the relative clinical effectiveness of PAC settings in terms of odds ratios (OR). An OR greater than 1 indicates that, relative to the baseline group, there was an increased likelihood of hospital readmission for patients of the focal PAC setting; whereas an OR less than 1 indicates that, relative to the baseline group, there was a reduced likelihood of hospital readmission for patients of the focal PAC setting. The upper panel of Table 2 presents ORs of hospital readmission for all PAC settings with reference to a common baseline category (home care); the lower panel of Table 2 presents ORs of hospital readmission between two adjacent severity levels of PAC settings (e.g., between LTCH and IRF or between HHA and home care).

	Home	**HHA**	**SNF**	**IRF**	**LTCH**
Home Care as Baseline					
Odds Ratios	1	1.26	1.25	0.77	0.76
(95% CI)		(1.16, 1.37)	(1.12, 1.39)	(0.62, 0.97)	(0.62, 0.93)
Lower Adjacent Level as Baseline					
Odds Ratios	1	1.26	0.99	0.62	0.98
(95% CI)		(1.16, 1.37)	(0.86, 1.13)	(0.48, 0.80)	(0.73, 1.33)

Table 2: Estimated treatment effects of post-acute settings.

Using home care as the baseline, patients of HHA and SNF had an odds ratio of more than 1 (1.26 and 1.25, respectively). Substantively, this statistics suggested that PAC patients of HHA and SNF had more than 25% of increased likelihood than PAC patients of home care to be readmitted to the hospital within 30 days. As shown in Table 2, we computed a 95% confidence interval (95% CI) to examine if the statistics was significant at the $p < 0.05$ level. IRF and LTCH had an odds ratio of less than 1 (0.77 and 0.76, respectively). This suggested that PAC patients of IRF and LTCH had between 23% and 24% of reduced likelihood than PAC patients of home care to be readmitted to the hospital within 30 days.

The lower panel presents another set of interesting comparison. As mentioned, we used the PS method to match patients that could go to either one of two comparative PAC settings to analyze their relative clinical effectiveness. Our findings showed that sending patients to a PAC setting of high clinical severity might or might not reduce the likelihood of hospital readmission. For example, there was a higher OR of hospital readmission for patients who received PAC from HHA than home (OR = 1.26). The difference between HHA and SNF was not statistically significant. Yet, between SNF and IRF, patients had a reduced likelihood of hospital readmission if they received PAC in IRF rather than SNF (0.62 vs. 0.99). Finally, between LTCH and IRF, patients had an increased likelihood of hospital readmission if they received PAC in LTCH rather than IRF (0.98 and 0.62).

This study has presented an innovative approach to utilize the big data of EHR. We have expended great effort to extract, clean and manipulate data to convert them into an analyzable manner. Our analysis increased the evidence base regarding the relative clinical effectiveness of PAC settings in terms of hospital readmission, and we recognize that there may be other possibilities to utilize EHR data.

Consistent with the literature, our findings suggested that HHA and SNF patients had a higher risk of hospital readmission than PAC patients having received home care. Research has consistently shown that SNF to have the highest readmission rates among all PAC settings [5,25,26]. While previous research has identified patient-level and organizational factors, such as the fact that sicker patients are often more frequently discharged to a SNF than other PAC settings [18], our analysis has already controlled for a large number of factors.

However, we were not able to control for facility ownership, staff quality and staff ratio, and these factors might be responsible for the higher readmission rate of SNF. In fact, these factors have received increasing attention in the literature: First, ownership of the facility, whether the PAC is privately owned or part of a corporate chain and whether it is linked to an acute care hospital, can significantly affect the availability of resources needed to manage acute illness [7]. Additionally, staffing mix (how many RNs and licensed practitioner nurses) and staff-to-residence ratio directly impact the quality and availability of services at SNFs [7].

To investigate these factors, we had conducted a small number of interviews with care managers and clinicians to obtain preliminary data. Interviewees had several specific concerns about the SNF environment. Most importantly, there were concerns that SNF imposes a higher risk of infection to patients compared to home. Also, SNF patients might become accustomed to "being taken care of" in a facility and not exercise enough and/or take medications on schedule. That is, there might be a "delayed return to independence" among SNF patients [27]. The reasons for the high readmission rates from HHA are well known. However, research suggested that certain medical conditions such as pancreatectomy were common in HHA, and there might be a high risk for patients of this and other medical conditions to be readmitted to the hospital [13]. Besides, HHA had been underfunded in recent years. Staffs of HHA had to provide fewer home health visits for patients, leading to undesirable recovery after the patient's discharge from the hospital [28]. Further research can examine this issue more systematically.

Our results have significant implications for PAC care management. Among other things, the results can become useful knowledge for physicians, care managers, specialists and patients to work together more closely so that the patient can receive the best PAC. With this knowledge, patients can be more proactive—and with more confidence—in their recovery process. For example, while residing in a SNF, patients should strive to restore independence instead of relying on nurses to "take care" of their needs. It does not mean that patients cannot seek help when they need it. But it means that patients' determination has the most critical role to play in recovery. Similarly, patients also should not feel being deprived of good care if a PAC decision of "going home" is made. Home care can be very effective in PAC, and the ability to go home can actually indicate that the patient has a great prospect of smooth and successful recovery from acute care.

While our analysis was unable to capture all possible factors that can impact hospital readmission for PAC patients, the quantitative approach that we applied adds useful value to the literature. Combining the propensity score matching method and other techniques such as logistic regression, we were able to utilize EHR data and quantify the relative clinical effectiveness of PAC settings succinctly. Our findings can be utilized to recommend optimal PAC settings for patients to minimize the risk of hospital readmission. Moreover, our findings identify potential areas for further research, and we have laid the groundwork already. We are particularly interested in building a mathematical model that can be more readily used by physicians to determine the appropriate PAC setting for patients discharged from a prior hospital stay. We plan to report the details in a separate paper. By increasing the rigor of analytic techniques as such, our analysis is able to improve care coordination for PAC patients. In the longer run, improved PAC coordination is able to reduce health care cost, and improve quality of health care delivery [29,30].

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