What Drives Readmission? A New Perspective from Hidden Markov Model Analysis

Completed Research Paper

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Abstract
We investigate the effect of unobserved patient health status on patient readmission rates and the impact of telehealth on patient health status. We develop a hidden Markov model to capture the evolving latent health status of a patient to model its impact on readmissions. We obtained a large, inpatient panel dataset of Congestive Heart Failure patient visits along with the American Hospital Association IT Supplement data. We find that telehealth exerts a positive impact only on patients in less healthy states, while this impact diminishes as patients' health improves. Our results also show that less healthy patients tend to incur significantly higher readmission rates compared with healthier patients. These results suggest nonclinical factors such as patients' latent health status can impact readmission significantly. Focusing solely on hospital readmission rates may yield myopic policies.

Keywords: Readmission, telehealth, latent health status, hidden Markov model

Introduction
High hospital readmission rates, defined as patient admission within 30-days of being discharged from the same or another hospital (CMS 2014) for the same principal diagnosis, have recently become the focus of clinicians, healthcare leaders and policy makers, due to their high cost burden on the United States healthcare system (McCarthy et al. 2013). The Centers for Medicare and Medicaid Services (CMS) has promoted the use of 30-day readmission rate as a quality metric to measure hospital performance (Weissman et al. 1999), and starting in 2013 with the Hospital Readmission Reduction Program (HRRP), has started penalizing hospitals with high 30-day readmission rates for several chronic diseases including heart attack (AMI), congestive heart failure, and pneumonia. Two-thirds of hospitals were issued a 1%
reduction in Medicare reimbursements in 2013 for a total of $280 million. CMS has increased this penalty to 2% in 2014, and 3% in 2015 (Joynt and Jha 2013). Considering the fact that hospitals operate on an aggregate margin of 4%-5% (American Hospital Association [AHA] 2013), the financial penalty imposed by CMS hospital readmission reduction program is substantial.

Recently, researchers and healthcare providers have questioned the validity of using readmission rates as the sole measure of a hospital’s quality of care (Tsai et al. 2013), and have argued that readmissions may be caused by factors that are unrelated to the quality of hospital care delivery (Barnett et al. 2015). For instance, Kangovi and Grande (2011) suggested that hospital readmission rates should be treated as a function of the quality of care delivery, but may be determined by several factors including patient health status, access to health services, and availability of socio-economic resources. U.S. Senators Joseph Manchin and Roger Wicker went further and argued that “the readmission policy has been flawed from the beginning”¹. They maintained that hospitals should not be penalized simply because of the social-economic characteristics of their patients. In 2014, they introduced a bill that called for consideration of patient-specific socio-economic factors when calculating hospital readmissions. Their bill suggests that HRRP has unfairly targeted many hospitals, which serve high-risk and vulnerable populations, for high readmission rates. The bill was introduced to help protect hospitals by requiring CMS to use practical and impartial data to determine readmission rates going forward. This issue serves as our motivation, as our research aims to use objective data to re-calculate the readmission rate attributable to quality of care provided.

Specifically, the objectives of this study are threefold. First, we study the role of non-clinical factors and whether they can explain potential risks of future readmissions among patients. We collectively refer to these non-clinical factors as the latent health status of patients (after discharge from the hospital). Second, we develop a hidden Markov model (HMM) to estimate the extent to which readmissions can be attributed to clinical versus non-clinical factors. Our method provides a viable method to determine appropriate readmission penalties for hospitals and address the concerns associated with the current HRRP. Third, we study the change in patient health status via utilization of telehealth services between providers and patients, and examine whether telehealth adoption is associated with reduction in future readmissions.

Patient health status may depend on personal factors such as unhealthy lifestyle, alcohol or drug abuse, medical factors such as lack of access to outpatient facilities and primary care providers, or social support, such as lack of support from family and friends. Often, their health status is neither controllable nor modifiable by hospitals. Most of time, they are not observable to hospitals, but may change over time. We accordingly include “patient health status” as a latent, time-variant variable in our model. It is reasonable to expect that patients with poor latent health status are more likely to incur readmissions.

We are interested in the interventions that care providers and policy maker can undertake to ameliorate patients’ latent health status. Of particular interest to us is the use of telehealth. Patient health status can be monitored by the adoption of telehealth technologies outside healthcare settings, or during transitions between healthcare facilities (Overby et al. 2010). Healthcare policy experts have observed that unnecessary readmissions can be reduced if care delivery across inpatient and outpatient settings are better coordinated, so that patients receive timely follow-up care after discharge (Hernandez et al. 2010; Orszag and Emanuel 2010). Interventions like nurse or pharmacist visits after discharge can help improve patients’ health status by optimizing medication management and identifying early clinical deterioration (Stewart et al. 1999). Since these visits are resource-intensive in terms of staff and time (Campion 1997), telehealth technologies can offer complementary capabilities to overcome such logistical challenges (Wakefield et al. 2008). The use of telehealth enables communication and coordination between providers and patients, informs patients about their diagnoses, tests, and follow-up care. Prior research suggests that telehealth can improve care delivery for chronically ill patients by sending early warning messages about changes in their health status (Whitten et al. 2009), which can potentially reduce the cost

of readmissions (Gorst et al. 2014). Accountable care organizations (ACOs) advocate using telehealth to enhance post-discharge care and post-surgical follow-up (Modahl and Meinke 2014).

Our research contributes to the debate over whether hospital readmission rates represent a valid measure of the quality of care delivery at hospitals; or whether, other non-clinical factors, such as patients’ health status, should also be taken into account in terms of their role as determinants of readmissions. Further, our research provides a better understanding of the role of new types of health IT applications, such as telehealth, in terms of their impact on reducing the disparities in care delivery across healthcare settings and as an enabler of better care coordination.

To test our hypotheses on the relationship between telehealth and health status, and study its impact on readmission, we relied on data from two data sources: (1) Dallas Fort Worth Hospital Council (DFWHC) Research Foundation, and (2) American Hospital Association (AHA) IT Supplement database. The DFWHC database provides a comprehensive inpatient panel dataset of Congestive Heart Failure (CHF) patient visits across 68 hospitals in North Texas, for a seven-year period from 2005 to 2011. The AHA IT Supplement database provides data on hospital usage of health IT between 2008 and 2013. We model unobserved patient health conditions (status) as a latent state, via a hidden Markov modeling (HMM) approach.

Our HMM estimation results indicate that there is a substantial difference in readmission rates among patients in different health states. Specifically, we find that patients in poor health states exhibit significantly higher readmission rates compared to patients in good health states. In addition, we observe a stronger impact of telehealth adoption on readmissions among patients in poor health states, while its impact diminishes as patients’ health improves. This research sheds light on the growing debate over the use of readmission rate as a sole quality metric of hospital performance, and lends support for proposals which argue that the non-clinical factors, such as patient health state and socio-economic status, may be likely causes of disparities in readmission rates. We provide evidence which suggest that policy makers should consider factors that impact patients’ readmission propensity after hospital discharge, along with clinical factors. Our findings suggest that hospitals are not the only source of disparities in terms of readmission rates, since post-discharge planning and follow-up care coordination must be supported by payers and a network of care providers.

Background

Prior readmission studies have reported results based on a wide variety of patient populations, locations, settings, designs and conditions (Bardhan et al. 2015; Vest et al. 2010). According to McCarthy et al. (2013), patient recovery or health deterioration is subject to a complex interplay of personal, medical, social, and financial factors. Within the context of our study, we analyze the impact of patient health status (a non-clinical factor) on future readmission, and assess the role of telehealth in coordinating patient care delivery and improving patient health, which can result in reduced readmission rates.

Health Status and Readmission

When studying the determinants of patient readmissions, it is important to consider patients’ health status prior to a new hospitalization. Readmission can occur due to deteriorated health or inability to cope with health conditions, outside the hospital or after a patient has been discharged. Therefore, patients’ health condition following their discharge from their previous hospital visit is an important determinant that might lead to future readmissions.

A unique aspect of this study is the treatment of health status as an unobserved attribute of patient admissions. Although some patient health conditions are observable and often recorded during a patient’s visit, such as severity level and identified comorbidities, many health conditions that can critically affect a patient’s recovery process (and thus future readmission risk) are often unobservable (e.g., physique, fitness, emotional/mental and spiritual strength) to healthcare providers and researchers. Other socio-demographic factors, such as family lifestyle, marital status, and income levels, are often not captured by providers, as part of the patient’s electronic health records. Wolfe and Behrman (1984, p. 696) reported that “..... True health status is not directly observable. The indicators of health status that have been used in empirical studies are anthropometric measures, number of sick days, self-reported or clinical disease
records, and inputs such as nutrients ....” Harris and Remler (1998) further argued that unmanaged heterogeneity in the variance of patient outcomes in prior studies caused biased estimates and further strengthened the likelihood that any statistically significant findings were in fact due to patients’ unobserved health status.

**Telehealth and Health Status**

The US Department of Health and Human Services defines telehealth as “the use of technology to deliver health care, health information, or health education at a distance including tele-radiology, continuing professional education, and home monitoring” (HRSA.gov, 2014). Telehealth has changed the way doctors and patients interact with each other. In 2014 alone, it is estimated that there were 75 million e-visits in the US and Canada that can be attributed to telehealth (Modahl and Meinke 2014). Electronic healthcare systems facilitate patients’ current and long-term health outside hospitals by providing access to clinicians in a post-discharge care setting (Venkatesh et al. 2011). Overby et al. (2010) demonstrated the usefulness of telehealth wherein a traditionally physical process, such as an office visit, has been replaced with a virtual process. Benefits accrued from the virtualization of medical processes can range from reduced readmission rates to lower healthcare costs (AHA 2015). Compared to physical processes, telehealth can result in better outcomes for patients with chronic illnesses that require frequent follow-ups (Dellifraine and Dansky 2008). This is achieved by expanding physician access to patients in remote regions and wider range of patients at distant locations (Miscione 2007). With a projected $1.9 billion market for telehealth in the US in 2018, telehealth adoption rates have shown a steady growth over the years between 2007 and 2014, surpassing 60% in 2014 (AHA 2015).

The three core technology modalities for telehealth are: a) Real-time, a two-way interaction between a patient and a healthcare provider using audiovisual technologies to consult, diagnose, and treat patients, b) Store-and-forward that transmits patient’s health data (e.g., X-rays, images, etc.), and c) Remote-monitoring that allow providers to track patients’ health progression after discharge. For instance, by recording clinical indicators of patient health data, medication administration support, and scheduling self-measurements via wireless weight scales and blood pressure cuffs, telehealth can help patients develop self-care skills in decision-making and monitor their own conditions which can improve their overall health status and quality of life (Riley et al. 2013). In this research, we analyze the impact of telehealth on changes in patients’ health state via better care coordination, and their overall impact on patient readmission rates.

Given these enhanced features of telehealth technologies, researchers and policy makers have argued that healthcare quality and outcomes can be expected to improve with greater adoption of telehealth; indeed, ACOs have made telehealth a cornerstone to enable improvements in care coordination across providers and transitions of care. For example, by recording clinical indicators of patient health, medication administration support, and scheduling self-measurements via wireless weight scales and blood pressure cuffs, telehealth can help patients develop self-care skills in monitoring their own conditions which ultimately help improve their overall health status (Rahimpour et al. 2008). Remote-monitoring and real-time video capabilities of telehealth can replace nurse home visits by avoiding the inconvenience of travel and waiting for clinic rooms (Wakefield et al. 2008). Hence, adoption of telehealth can provide a virtual experience of a physical nurse visit or physician consultation, thereby improving patient care delivery (Gorst et al. 2014).

**Hypotheses**

**Patient Health Status**

Once patients are discharged from a hospital (or other inpatient facility), and transition to a different facility (home, rehab center, or tertiary care facility), their health status is subject to various exogenous factors that are beyond the control of the discharging hospital and its care providers. Specifically, personal and social factors may alter the way how a patient’s recovery proceeds post-discharge (McCarthy et al.

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2 Telehealth may not constitute a purely virtual process, but may instead be a hybrid process since it augments the physical services provided and some of the physical activities, such as home visits by nurses.
Telehealth, Patient Health, and Readmissions

2013), and this phenomenon can create unobserved heterogeneity across the patient population (Harris and Remler 1998). In the labor economics literature, the treatment of health status poses a significant problem since it is not directly observable and subject to mis-specification error (Dwyer and Mitchell 1999). Thus, we first have to reveal the factors impacting patient health status—an unobservable artifact for the researcher and an un-controllable artifact for care providers. Developing a better understanding of these factors is critical in order to effectively treat chronic diseases that are characterized by high readmission rates, significant deterioration in functioning, reduction in quality of life, and increased dependence on caregivers (Wolinsky et al. 1997).

Socio-economic factors, such as disparities in patients’ access to care and discharge destinations, play a role in determining patient health status. Patients may utilize a combination of inpatient or outpatient facilities to access health services (Kangovi and Grande 2011). When a patient has good access to inpatient care, but has poor access to outpatient/preventive care, their readmission risk increases (Kangovi and Grande 2011). However, in the event of lack of access to outpatient care, such as nursing homes, general physician practices, or specialty clinics, patients may not be able to receive timely treatment, which may aggravate their current health condition (Ferrer 2007) and eventually lead to their readmission as an inpatient (Starfield et al. 2005). With respect to discharge destinations, patients may be sent to skilled nursing facilities, tertiary care facilities, or home-based care. Nursing homes may provide better care opportunities for patients in terms of treatment and support compared to home care, especially if the patient lacks social support at home. Prior research suggests that patients with chronic obstructive pulmonary disease or dementia experience a lower likelihood of readmission within 30 days, if they are discharged to nursing homes, rather than to their homes (Camberg et al. 1997). Depending on the deterioration of their health conditions after being discharged, as a result of socio-economic factors, patients may seek care elsewhere, and eventually need to be readmitted as inpatients.

Social support represents another important factor that impact patients’ health conditions. A patient’s inability to comply with discharge recommendations and medication regimen, as well as lack of transportation and social support, have often been cited as important determinants of health deterioration and readmission risk (Kangovi et al. 2013). After discharge, patients begin to experience difficulties adhering to discharge recommendations because of various personal and social issues, such as a sense of abandonment, dysfunctional social networks, misaligned discharge goal-setting, lack of family support, lack of transportation resources and meals that meet diet restrictions, inability to check weight, non-compliance with medication, and lack of exercise (Kangovi et al. 2013). Accordingly, patient health status will deteriorate if their personal and social factors are detrimental to patient health and increase their readmission risk.

The lack of visibility into disparities in patients’ health status (after discharge) introduces unobserved heterogeneity. Therefore, it becomes essential to reveal unobserved patient health status to assess its differential impact on health outcomes. Furthermore, we posit that unobserved heterogeneity has a bearing on health outcomes to the extent that patients in a poor health state will experience higher readmission risk, compared to patients in a better health state. We argue that the health state of such patients will deteriorate over time, due to the negative impacts of socio-economic, personal and social factors. We hypothesize that,

Hypothesis 1: Patient readmission rates are significantly associated with changes in the unobserved patient health status.

Telehealth

Patients’ health conditions are prone to the influence of various non-clinical factors, after discharge from hospitals. In such cases, frequent follow up and monitoring of patients can help improve their health status and quality of life (Anker et al. 2011; Wakefield et al. 2008). Historically, patient follow up was primarily conducted either through phone calls established between nurse and patients or outpatient clinic visits to their primary care physician’s office (Bashshur et al. 2014). With advancements of digital

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3 Generally, outpatient facilities include medical offices, ambulatory care facilities (labs, surgery, imaging centers), or hospital emergency departments that do not require an over-night stay (Emedicine Health 2014).
Telehealth, Patient Health, and Readmissions

Technologies, new modes of service delivery through virtualization have emerged. Medical monitoring processes can now be provided electronically to distant and remote locations and to a wider swath of patients (Miscione 2007). Telehealth technologies enable these types of care coordination process by efficiently managing patient's self-care by connecting patients to providers in a coordinated system of care.

Telehealth can impact patients’ health status by improving access to care for patients living in rural and isolated areas who face limited medical resources within reasonable driving distance/time (Bashshur et al. 2014). By promoting self-care management and increased communication between patients and their primary or specialist providers, telehealth reduces disparities in terms of access to care. This eases the limitation of traditional models of care where follow up visits are scheduled at deterministic time points (Woolliscroft and Koelling 2004), which may not accommodate arbitrary visit requests of patients when illness exacerbates or other needs arise. Darkins et al. (2008) show that veterans, who joined home telehealth programs, experienced significant reductions in healthcare resource utilization with reductions of 29.1% for veterans in urban, 17% in rural, and 50.1% in highly rural locations, demonstrating telehealth's positive impact on access to care.

Home telemonitoring is a component of telehealth in which patients assume greater responsibility in managing their health by utilizing audio, video, and other telecommunication technologies that help monitor their status remotely (Paré et al. 2007). With telemonitoring, clinical data can be instantly shared by healthcare providers that is in line with the goal of providing “appropriate care at the appropriate time and place in the most appropriate manner” (Woolliscroft and Koelling 2004). In addition, patient educational resources and reminders related to proper diet, smoking cessation, and exercise are other artifacts of telemonitoring, that can help improve patient’s health. For instance, Rahimpour et al. (2008) find that the perceived usefulness of the system improves as a result of its ability to inform patients about their health status, e.g., warning patients at an early stage of health deterioration and creating interventions by providing feedback from the system.

Telehealth can also offer solutions to address the mental and other physical challenges of patients with chronic illnesses that are caused due to complexities in required lifestyle changes. For instance, Rutledge et al. (2006) estimate depression prevalence rate of 21.6% among CHF patients that is 2 to 3 times the rate of the general population. It has been found that patients, who receive telehealth services, experience 50% lower depression scores and use significantly fewer emergency department visits with clinical decision support, reinforced self-efficacy, and depression counseling (Gellis et al. 2014).

In the light of these findings, we argue that patients who receive telehealth services will be healthier after they are discharged from hospitals, and the effect of telehealth will be more pronounced for patients in poor health state, compared to patients who in better health state. Accordingly, we posit that,

**Hypothesis 2:** Telehealth services will have a positive effect on patient health status and as their health status improves, the strength of the relationship between telehealth and health status will decrease.

**Research Methodology**

**Data**

We test our hypotheses using two data sources: (a) Dallas-Fort Worth Hospital Council (DFWHC) Research Foundation database, and (2) American Hospital Association (AHA) IT Supplement database. Data obtained from DFWHC is based on admission-level, administrative claims that records each patient’s admissions (including those to other hospitals) in the North Texas region starting from 2005 to 2011. In total there are 68 non-Federal hospitals across 26 different health systems. Since CHF is one of the four conditions that are part of the CMS Hospital Readmission Reduction Program, it represents an

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4 Some other novel applications use GSM, Bluetooth, and GPRS to monitor health (Whitten et al. 2009).

5 CMS considered acute myocardial infarction, heart failure, pneumonia in FY 2012, included chronic obstructive pulmonary disease, total hip arthroplasty, total knee arthroplasty and coronary artery bypass graft surgery in FY 2015, and expanded to aspiration pneumonia and sepsis pneumonia in FY 2016.
important diagnosis for in-depth studies by researchers and policy makers (Ross et al. 2008). Our study focuses on inpatient admissions with CHF as the principal diagnosis, i.e., admissions with ICD-9 code of “428.xx”.

Because the AHA IT database only reports hospital IT information starting from 2008, we used admissions that occurred between 2008 and 2011 from DFWHC dataset. In order to calculate the (future) 30-day readmission risk, each patient in our dataset is required to have at least two admissions. Accordingly we obtained 10061 patients with 19469 observations in total, not including the last admission of patients since these final observations did not contain any future readmission risk information. We derive and calculate several variables at the admission, patient, and hospital level.

The Readmission variable was calculated as a binary 30-day readmission risk where: Readmission = 1 if patient will be admitted to a hospital within 30 days following a discharge; and zero otherwise. The average readmission rate was 29% at the admission level, after the last observation for each patient was removed. We also controlled for length of stay (LOS), number of diagnoses (NumDiag), risk mortality (RiskMortality), discharge destinations (DischargeNursingFac and DischargeHomeCare), patient demographics, and hospital characteristics (Bardhan et al. 2015; Mudge et al. 2011). The average LOS was 5.23 days, average NumDiag was 14.56. RiskMortality is defined as a scale ranging from 1 (minor) to 4 (extreme) and average was 2.39. For discharge destinations, DischargeNursingFac and DischargeHomeCare constituted 10% and 14% of admissions in our dataset, respectively. We were also able to extract patient gender (female or male) – PtFemale, age – PtAge and race (white or non-white) – PtWhite information. Our data shows that 48% of patients are female; average age is 67.46 and 62% of patients are of white origin.

To operationalize our model and telehealth construct, we extracted information from the AHA IT database regarding the telehealth activities of hospitals. We observe that 9% of patient admissions were associated with hospitals utilizing Telehealth services. For other hospital information, we use CMS provided information and classify hospitals according to their teaching status – HsTeaching and geographic locations (urban vs rural) – HsUrban, hospital case mix index (CMI) – HsCMI. Based on our sample statistics, 47% of hospitals are teaching hospitals, 93% of hospitals located in urban areas, and the average hospital CMI was 1.65. We provide definitions and descriptive statistics of our model variables in Table 1.

### Model Specification

We model unobserved patient health status, as a latent state, via a Hidden Markov Model (HMM). HMM depicts the relationship between two stochastic processes: (1) an observed process and (2) an underlying “hidden” or unobserved process (MacKay Altman 2004). HMM assumes a mixture distribution for the marginal distribution of its observed outcomes, suggesting the existence of hidden discrete states that generate these outcomes (Visser 2011). HMM models specify latent states as a Markov chain evolving over time, creating serially dependent observations. The Markov property simplifies the serially dependency, where observations form a conditionally independent sequence, given the state of the Markov chain at the time of the observation (Ephraim and Merhav 2002). In our study, health status represents the latent states and constitutes a stochastic process since patients’ health status can change over time. Transitions among states may happen at any discrete time interval (Rabiner 1989). The observable outcomes, which depend on the latent health states, are defined by the patient’s readmission process. In our model, these observed outcomes will reveal the latent health condition of patients.

For a given patient, our model captures the dependency among patient health state and readmission. Transitions among health states is explained by time-varying covariates, such as the level of care provided to a patient on the previous admission, as well as covariates specific to the admitting hospital. This stochastic transition process is then transformed into an observed patient readmission process in a probabilistic manner. By making the current admission event dependent on the previous admission, correlations among admission events will be captured by our model. Unlike previous studies in the literature, which use HMM as their research model (Netzer et al. 2008; Singh et al. 2011), our model considers a feedback loop between the previous time period’s outcome variable and the current period’s unobserved state, suggesting that patient’s health status depends on the previous period’s readmission event. The conceptual view of our research model is depicted in Figure 1.
### Table 1. Descriptive Statistics of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Dimen.</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Readmission</td>
<td>30-day Readmission event</td>
<td>Binary</td>
<td>0.29</td>
<td>0.45</td>
</tr>
<tr>
<td>DischargeNursingFac</td>
<td>1 = if discharged to nursing facility</td>
<td>Binary</td>
<td>0.10</td>
<td>0.30</td>
</tr>
<tr>
<td>DischargeHomeCare</td>
<td>1 = if discharged to home care</td>
<td>Binary</td>
<td>0.14</td>
<td>0.32</td>
</tr>
<tr>
<td>RiskMortality</td>
<td>Risk mortality increases from 1 to 4</td>
<td>(1, 4)</td>
<td>2.39</td>
<td>0.81</td>
</tr>
<tr>
<td>LOS</td>
<td>Length of stay</td>
<td>Cont's</td>
<td>5.23</td>
<td>4.68</td>
</tr>
<tr>
<td>NumDiag</td>
<td>Number of diagnoses</td>
<td>Count</td>
<td>14.56</td>
<td>5.37</td>
</tr>
<tr>
<td>Telehealth</td>
<td>1 = if telehealth is present</td>
<td>Binary</td>
<td>0.09</td>
<td>0.29</td>
</tr>
<tr>
<td>HsCMI</td>
<td>Case mix index</td>
<td>Cont's</td>
<td>1.65</td>
<td>0.28</td>
</tr>
<tr>
<td>HsTeaching</td>
<td>1 = if it is a teaching hospital</td>
<td>Binary</td>
<td>0.47</td>
<td>0.50</td>
</tr>
<tr>
<td>HsUrban</td>
<td>1 = if it is an urban hospital</td>
<td>Binary</td>
<td>0.93</td>
<td>0.26</td>
</tr>
<tr>
<td>InsuranceMedicare</td>
<td>1 = if patient was on Medicare</td>
<td>Binary</td>
<td>0.56</td>
<td>0.50</td>
</tr>
<tr>
<td>InsuranceMedicaid</td>
<td>1 = if patient was on Medicaid</td>
<td>Binary</td>
<td>0.09</td>
<td>0.29</td>
</tr>
<tr>
<td>InsuranceSelfpay</td>
<td>1 = if patient was Selfpay</td>
<td>Binary</td>
<td>0.08</td>
<td>0.28</td>
</tr>
<tr>
<td>InsurancePrivate</td>
<td>1 = if patient had Private insurance</td>
<td>Binary</td>
<td>0.03</td>
<td>0.17</td>
</tr>
<tr>
<td>InsuranceOther</td>
<td>1 = if patient had any other insurance</td>
<td>Binary</td>
<td>0.24</td>
<td>0.42</td>
</tr>
<tr>
<td>PtAge</td>
<td>Patient age</td>
<td>Cont's</td>
<td>67.46</td>
<td>15.47</td>
</tr>
<tr>
<td>PtWhite</td>
<td>1 = if race is white</td>
<td>Binary</td>
<td>0.62</td>
<td>0.49</td>
</tr>
<tr>
<td>PtFemale</td>
<td>1 = if gender is female</td>
<td>Binary</td>
<td>0.48</td>
<td>0.50</td>
</tr>
</tbody>
</table>

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Figure 1. A Hidden Markov Model of the patient readmission process

In the figure, the hidden health states are represented by dark circles, while readmission states are represented by squares. A hidden health state takes a value from the discrete set \( \{1, 2, \ldots, N_S\} \), each value representing an unobserved state such as good, bad or other conditions, where the optimal number of states is determined by the model. Readmission takes a value of either zero for no readmission, and one if a readmission occurs. Straight lines among different type of states represent the transition processes, i.e., health state transition, whereas the dotted lines represent the dependence among various types of states. In our model, we define the health state sequence of a patient \( p \) as \( S = \{s_0, s_1, s_2, \ldots, s_T\} \) and the readmission sequence as \( R = \{r_0, r_1, r_2, r_3, \ldots, r_T\} \) for a total duration of \( T \) periods. Hence, health state sequence \( S \) and \( R \) constitute an HMM process. In addition, we define \( R^t \) as a readmission history of patient \( p \) from time 1 up to time \( t \), and similarly for the unobserved health state \( S^t \). To analyze the patient readmission process, we model \( Pr_p(R^T) \) for each patient \( p \) and maximize the likelihood of observing \( R^t \) for patient \( p \) as \( L^t_p = Pr_p(R^t) = \sum_{S^t} Pr_p(R^T, S^t) \). Analyzing the directed graph in Figure 1, under the first order Markov property by examining the parents of each node (dependencies), we write \( L^t_p \) with conditional probabilities as:

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As can be inferred from the likelihood function, HMM model requires us to specify three components: i) Initial state distributions at time t=1, \( \Pr_p(S_1) \), ii) The transition probabilities, for example \( \Pr_p(S_t|S_{t-1}, R_{t-1}) \), and iii) State dependent outcome probabilities, i.e., \( \Pr_p(R_t|S_t) \). Next, we define the initial state distribution- the probability that patient \( p \) is in state \( s \) at \( t=1 \) is \( \Pr_p(S_1 = s) = \pi_p(s) \), where \( s \in \{1, ..., n\} \).

The health state transition probability of patient \( p \), where the patient is in state \( s \) at time \( t=1 \), and is switching to state \( s' \) at time \( t \) can be represented as \( \Pr_p(S_t = s'|S_{t-1} = s, R_{t-1} = r_{t-1}) = q_{p,s}^{s,s'} \) for \( s, s' \in \{1, ..., S\} \). The care received in hospital \( h \) at time \( t=1 \) should be strong enough to transition the patient to another health state. Therefore, this transition can be modeled as an ordered multinomial logit model where \( F(\alpha_{s,s'}) = \frac{\exp(\alpha_{s,s'} - X_{pt}q_{s})}{1 + \exp(\alpha_{s,s'} - X_{pt}q_{s})} \) with \( q_{p,s}^{s,s'} = F(\alpha_{s,s'}) - F(\alpha_{s,s'-1}) \) (for \( s \to s' \)) and \( q_{p,s}^{s,s} = 1 - F(\alpha_{s,s-1}) \) (for \( s \to S \)).

Here, \( X_{pt} \) is the time varying covariate vector for patient \( p \), \( \beta_s \) is a vector of parameters capturing the impact of care received for the propensity to transition from the health state \( s \). In addition, \( \alpha_{s,s'} \) represents the ordered logit threshold between states \( s \) and \( s' \) + 1, given that the current state is \( s \), where \( s \in \{1, ..., S\} \) and \( s' \in \{1, ..., S - 1\} \). For a given state \( s \), \( \alpha_{s,1} \leq \alpha_{s,2} \leq \cdots \leq \alpha_{s,S-1} \). The covariates \( X_{pt} \) for hidden state transition probabilities may contain variables associated with patient’s health. As discussed previously, these covariates might be related to medical, personal and social factors. Hence, we include \( \text{Telehealth}, \text{DischargeNursingFac}, \text{DischargeHomeCare}, \text{Readmission}_{t-1}, \text{RiskMortality}, \text{logNumDiag}, \text{logLOS}^6 \) hospital and patient characteristics.

The probability of a patient readmission is modeled as a logit model assuming readmissions are conditionally independent, given the patient’s health state \( s \). \( \Pr_p(R_t = 1 | S_t = s) = \rho_p^{s} = \frac{\exp(\delta_0sY_{pt} \delta_2)}{1 + \exp(\delta_0sY_{pt} \delta_2)} \)

Then, \( \Pr_p(R_t | S_t = s) = \tilde{\rho}_p^{s} = \rho_p^{s}(1 - \rho_p^{s})^{1-r_t} \). Here, \( Y_{pt} \) represents the time varying covariates for patient \( p \). \( \delta_0s \) is a vector of state specific parameters and \( \delta_0S \) is the state specific constant. Furthermore, we ensured the identification of the states by restring the readmission probabilities to be nonincreasing in the relationship states. We mean-centered the continuous \( Y_{pt} \) variables and then were able to impose the restriction \( \delta_{0,1} \geq \delta_{0,2} \geq \cdots \geq \delta_{0,S-1} \geq \delta_{0,S} \) by \( \delta_{0,S} = \rho_p^{s} + \sum_{i=1}^{S-1} \exp(\delta_{0,i}) \) for \( s = 1 ... S - 1 \) and \( \delta_{0,S} = \delta_{0,S} \). In our framework, \( Y_{pt} \) contains \( \text{RiskMortality}, \text{logNumDiag}, \text{logLOS} \), hospital and patient characteristics. Finally, we can write the likelihood for patient \( p \) as:

\[
L_p^T = \sum_{s_1, s_2, ..., s_T} \pi_p(s_1) \prod_{t=2}^{T} \tilde{\rho}_p^{s_t} q_{p,t}^{s_t s_{t-1}} \tag{1}
\]

One complication about this equation is that it has \( NS^T \) elements which are computationally intractable for even modest values of \( T \) (Netzer et al. 2008). To simplify computation, we rewrite equation (1) in a matrix product form, as suggested by MacDonald and Zucchini (1997):

\[ L_p^T = \sum_{s_1, s_2, ..., s_T} \pi_p(s_1) \prod_{t=2}^{T} \tilde{\rho}_p^{s_t} q_{p,t}^{s_t s_{t-1}} \]

6 These variables may also include zipcode-specific, social-economic metrics such as unemployment rate, median household income, number of ambulatory care organizations (outpatient clinics within a specified radius).
\[ L_p^T = \pi_p \tilde{\beta}_p,1 Q_{p,1} \cdots 2 \tilde{\beta}_p,2 Q_{p,2} \cdots 3 \tilde{\beta}_p,t-1 \cdots \tilde{\beta}_p,T \]  

where \( \tilde{\beta}_p,t \) is a \( NS \times NS \) diagonal matrix with the elements of \( \tilde{\beta}_{p,t}^{st} \) on the diagonal, \( Q_{p,t-1-t} \) being a transition matrix containing the probabilities of \( q_{p,t}^{st-1} \) for a patient \( p \) from time \( t-1 \) to \( t \), and \( 1 \) is a \( NS \times 1 \) vector of 1s.

In HMM, the number of latent states \( NS \) is not explicitly given or modeled. To select the number of states, scenarios with different number of states are estimated and each scenario’s model fit is calculated for further comparison. We use the common Bayesian Information Criterion (BIC) to compare the models (Greene and Hensher 2003). With respect to our model parameters \( (nVars) \) and the number of observations \( (nPatiots) \), BIC is calculated with the formula

\[ BIC = -2lnL + nVars * ln(nPatients) \]

where, \( L \) is the maximum likelihood of the model, \( nVars \) is the number of total parameters being estimated, and \( nPatients \) is the number of patients in our model.

### Results

To initiate our HMM estimation, the initial latent health state distribution has to be provided. We apply the latent class regression to our model in SAS (Lanza et al. 2007) and used the expected latent class membership rates as the initial health state distribution in HMM. Then, the maximum likelihood estimation (MLE) method is used to estimate the HMM parameters with the BFGS Newton-Raphson algorithm (Whittaker and Robinson 1967).

We first select the number of states using BIC. We report the results of HMM scenarios with different number of states in Table 2. The two-state HMM outperforms others with respect to the BIC. Therefore, we select and continue with the two-state HMM estimation results. It is important to note that, although the log-likelihood increases with the number of states and variables, the model complexity doubles when \( NS = 2 \) is compared to \( NS = 4 \), with respect to the number of variables being estimated.

<table>
<thead>
<tr>
<th>Number of States</th>
<th>Log-Likelihood</th>
<th>BIC</th>
<th>Number of Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-11604.8</td>
<td>-23495.4</td>
<td>31</td>
</tr>
<tr>
<td>2</td>
<td>-11305.3</td>
<td>-23200.5</td>
<td>64</td>
</tr>
<tr>
<td>3</td>
<td>-11249.6</td>
<td>-23411.6</td>
<td>99</td>
</tr>
<tr>
<td>4</td>
<td>-11181.1</td>
<td>-23615.6</td>
<td>136</td>
</tr>
</tbody>
</table>

After incorporating the initial state distribution from latent class regression, the HMM estimation results obtained from MLE are reported in Tables 3 through 6, where the corresponding standard errors are shown in parentheses. The interpretation of the two states is determined by the state-specific intrinsic propensity of a patient to be readmitted at the mean of covariates. Accordingly, the propensity to be readmitted, given state 1, is 34.4% and is equal to 8.1%, given state 2. We label these two states as “bad” and “good” health states, respectively.

### HMM Results

For any given time period, we can reveal the health state a patient is most likely to observe. The filtering approach (Hamilton 1989) is one of the commonly used methods in recovering the hidden states of subjects in HMM studies (Netzer et al. 2008; Singh et al. 2011). The filtering approach uses the information based on the history of the subject up to time \( t \) to unravel the subject’s hidden state at time \( t \). Probability of being in state \( s \) conditioned on the subject’s history of readmissions is calculated as:

\[ Pr_p (S_t = s | R_1, R_2, ..., R_t) = \pi_p \tilde{\beta}_p,1 Q_{p,1} \cdots 2 \tilde{\beta}_p,2 Q_{p,2} \cdots 3 \tilde{\beta}_p,t-1 \cdots \tilde{\beta}_p,T | L_p^T \]  

where \( Q_{p,t-1-t} \) is the \( st \) column of the transition matrix \( Q_{p,t-1-t} \) and \( L_p^T \) is the likelihood of the observed sequence of readmissions up to time \( t \).

After each patient’s hidden state is recovered using equation (4), we compare the mean readmission rates at each health state, bad and good. Results of this comparison are used to test Hypothesis 1, which states...
that readmission rates should differ across health states. In other words, health states impose unobserved heterogeneity on patient readmissions to hospitals. We present the mean and standard deviation of readmissions per each state in Table 3. Accordingly, we observe that the difference between the readmission rates of latent states is statistically significant with \( p < 0.001 \), supporting hypothesis 1.

<table>
<thead>
<tr>
<th>Readmission / Health State</th>
<th>Bad (N = 9743)</th>
<th>Good (N = 9726)</th>
<th>Difference (Bad – Good)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.570</td>
<td>0.007</td>
<td>0.563</td>
</tr>
<tr>
<td>Std. Error</td>
<td>0.005</td>
<td>0.0008</td>
<td>0.005 with ( t = 110.5 )</td>
</tr>
</tbody>
</table>

**HMM Results of Health State Transitions**

Hypothesis 2 suggests that telehealth services will have a positive impact on patient health status. We report the health state transition parameter estimates in Table 4, where the third column shows the difference in parameter estimates across bad and good health states. We observed that telehealth’s impact is only positive for patients who are in unhealthy (bad) state. Next, Hypothesis 2 further posits that the impact of telehealth on health status will decrease as patients become healthier. Table 4 shows that the impact of telehealth, while positive for patients in unhealthy state (5.481 with \( p < 0.01 \)), becomes insignificant when patients are in good health state. This decline from 5.481 to 0.234 is significant, based on the Wald test with a statistic of 20.569 \( (\chi^2_{0.01}(1) = 6.635) \). Hence, our results support H2 with respect to the impact of telehealth on latent health status.

We also observe other notable results in Table 4. Having a previous readmission (Readmission\(_{-1}\)) for a patient in the bad health state lowers the utility obtained in the current admission (−1.390, \( p < 0.01 \)), i.e., worsens the health of a patient. However, we do not observe a worsening effect of having a prior readmission for patients in good health status. For patients in poor health state, being discharged to nursing home care improves their health state on their next admission (1.904, \( p < 0.01 \)); whereas patients discharged to home care do not show any significant change in their health state. Staying longer in hospitals (i.e., higher LOS) helps patients in the bad health state improve their health (2.833, \( p < 0.01 \)), whereas this is not the case for patients in good health. In addition, patient risk mortality is associated with significant reductions in patient health status for patients both in poor (−0.459, \( p < 0.01 \)) and good health status (−0.325, \( p < 0.01 \)). Poor health state patients admitted to hospitals with teaching status and higher CMI tend to improve their health status on their next admission (8.785, \( p < 0.01 \) and 4.944, \( p < 0.01 \)), while this is not the case for patients in good health state. On the other hand, patients who are in poor health state and admitted to hospitals in urban locations experience lowered health status in their next admission (−12.725, \( p < 0.01 \)).

Among patient specific covariates, we observe that Caucasian and older patients tend to improve their health status if they are admitted when they are in a poor health status (5.254, \( p < 0.01 \) and 1.624, \( p < 0.01 \)). These results hold if we compare them to their counterparts in good health status (5.728, \( p < 0.01 \) and 1.675, \( p < 0.01 \)). However, female patients who are in poor health status lower their health status (−7.968, \( p < 0.01 \)), as supposed to male patients who in good health (−8.307, \( p < 0.01 \)). Compared to Medicare patients, Medicaid patients did not show any significant differences in their health status, while self-pay patients tend to improve their health status regardless of health state. We also find that privately insured patients in poor health experience reductions in their health status compared to Medicare patients (−11.383, \( p < 0.01 \)).

We also calculate the matrix of the intrinsic propensities to transition, which is shown in the second and third columns of Table 5, under the heading “No Covariates”. Based on this result, we can deduce that patients are highly sticky to their health states if they are in bad health state. We observe that staying in good health state is accomplished 60.4% of the time, whereas staying in bad health state is accomplished 99% of the time. Once patients are discharged from hospitals, their health status might either worsen (by 39.6%) or improve (by 1%) at the base rate.

Though we present the parameter estimates of the covariates affecting HMM health state transition probabilities in Table 4, more meaningful insights can be gleaned when we estimate the transition matrix using the estimated values of each variable one at a time. We included the matrices derived by variables which had a substantial impact on the base transition matrix, as shown in Table 5. To generate the transition matrices given in Table 5, we plugged in the values of two focal variables, (i.e. Telehealth, and...
logNumDiags), one at a time, and calculate the transition propensity for each observation of a patient, while the values of the other variables are set at zero.

In Table 5, the two columns under the heading “Base Transition Matrix with Telehealth” show the transition matrix when a patient’s hospital used telehealth services at time $t-1$. If a patient is in bad health state at time $t-1$ and the hospital utilized telehealth services, then the patient’s likelihood of transitioning into a good health state increases significantly from 1% to 7% at time $t$.

The effect of logNumDiags on the base transition matrix is provided under the heading “Base Transition Matrix with logNumDiags” in Table 5. If a patient is in bad health state and had a high number of diagnoses at time $t-1$, then their likelihood of transitioning into a good health state significantly decreases from 1% to 0% at time $t$. Similarly, if a patient is in good health state and had a high number of diagnoses at time $t-1$, then their likelihood of transitioning into a good health state decreases from 60.4% to 42.5% at time $t$. Hence, patients who undergo multiple diagnoses tend to have reduced health states on their next admission.

Table 4. HMM Parameter Estimates for Health State Transition

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Health State 1 (Bad)</th>
<th>Health State 2 (Good)</th>
<th>Difference (Bad – Good)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Telehealth</td>
<td>5.181*** (1.024)</td>
<td>-0.234 (0.372)</td>
<td>5.415*** (1.194) W=20.569</td>
</tr>
<tr>
<td>NursingHomeCare$_t$</td>
<td>1.904** (0.778)</td>
<td>-0.871 (0.647)</td>
<td>2.775** (1.12) W=6.135</td>
</tr>
<tr>
<td>HomeCare$_t$</td>
<td>-0.064 (0.600)</td>
<td>0.698 (0.464)</td>
<td>-0.762 (0.951) W=0.641</td>
</tr>
<tr>
<td>Readmission$_t$</td>
<td>-1.390*** (0.444)</td>
<td>0.855 (0.767)</td>
<td>-2.245*** (0.871) W=6.646</td>
</tr>
<tr>
<td>RiskMortality$_t$</td>
<td>-0.459*** (0.185)</td>
<td>-0.325*** (0.160)</td>
<td>-0.134 (0.266) W=0.255</td>
</tr>
<tr>
<td>LogNumDiagnoses$_t$</td>
<td>-2.082*** (0.488)</td>
<td>-0.274 (0.198)</td>
<td>-1.806*** (0.433) W=17.414</td>
</tr>
<tr>
<td>LogLOS$_t$</td>
<td>2.833*** (0.342)</td>
<td>-0.162 (0.213)</td>
<td>2.995*** (0.472) W=40.227</td>
</tr>
<tr>
<td>HsTeaching$_t$</td>
<td>8.785*** (0.744)</td>
<td>-0.276 (0.255)</td>
<td>9.061*** (0.821) W=121.884</td>
</tr>
<tr>
<td>HsCMI$_t$</td>
<td>4.944*** (0.964)</td>
<td>-0.973*** (0.120)</td>
<td>5.917*** (0.97) W=37.195</td>
</tr>
<tr>
<td>HsUrban$_t$</td>
<td>-12.725*** (1.230)</td>
<td>0.353 (0.554)</td>
<td>-13.078*** (1.261) W=107.57</td>
</tr>
<tr>
<td>PtWhite$_t$</td>
<td>5.254*** (0.645)</td>
<td>-0.475*** (0.146)</td>
<td>5.728** (0.654) W=76.625</td>
</tr>
<tr>
<td>PtFemale$_t$</td>
<td>-7.968*** (1.024)</td>
<td>0.339 (0.252)</td>
<td>-8.307*** (1.195) W=48.325</td>
</tr>
<tr>
<td>LogPtAge$_t$</td>
<td>1.624*** (0.396)</td>
<td>-0.051 (0.197)</td>
<td>1.675*** (0.403) W=17.287</td>
</tr>
<tr>
<td>InsuranceMedicaid$_t$</td>
<td>0.007 (0.333)</td>
<td>0.158 (0.279)</td>
<td>-0.151 (0.431) W=0.123</td>
</tr>
<tr>
<td>InsuranceSelfpay$_t$</td>
<td>1.406*** (0.444)</td>
<td>0.472* (0.250)</td>
<td>0.935* (0.509) W=3.371</td>
</tr>
<tr>
<td>InsurancePrivate$_t$</td>
<td>-11.383*** (1.374)</td>
<td>-0.394 (0.598)</td>
<td>-11.079*** (1.471) W=56.791</td>
</tr>
<tr>
<td>InsuranceOther$_t$</td>
<td>1.749*** (0.440)</td>
<td>0.545*** (0.149)</td>
<td>1.205*** (0.448) W=7.244</td>
</tr>
</tbody>
</table>

Thresholds $\alpha_{bad\rightarrow good} = 4.601*** (0.108)$ $\alpha_{good\rightarrow bad} = -0.424*** (0.587)$

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Wald test statistics are shown for the difference of coefficients.

Continuous variables are mean 0 centered to reduce the collinearity among variables.

Table 5. HMM Estimation Transition Matrices

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Base Transition Matrix (No Covariates)</th>
<th>Base Transition Matrix with Telehealth$_t$</th>
<th>Base Transition Matrix with logNumDiags$_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-1 $\rightarrow$ t</td>
<td>Bad$_t$, Good$_t$</td>
<td>Bad$_t$, Good$_t$</td>
<td>Bad$_t$, Good$_t$</td>
</tr>
<tr>
<td>Bad$_{t-1}$</td>
<td>99.0%</td>
<td>93.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Good$_{t-1}$</td>
<td>93.0%</td>
<td>7.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

HMM Results of State Dependent Readmission

We present the estimated parameters and their marginal impact on the odds ratio (OR) to be readmitted for the state dependent readmission process in Table 6. The variation in the coefficients of a variable across states indicates that a change in the health state causes a change in the readmission propensity. Among the admission related covariates, risk mortality has a significant and positive impact on the readmission risk for patients, in bad and good health states; and this effect is higher for patients in the good health state, with the odds of being readmitted increase from 13.4% to 91.9%. The number of
diagnoses significantly increases the readmission risk only for the good health status and more diagnoses are associated with significantly higher readmission risk for patients in the good health state (+70.6% in OR), compared to patients in bad health state (+2.3% in OR). LOS is associated with an increase in the readmission propensity if a patient is in a good health state (+22.3% in OR), but we do not find a significant impact on the readmission propensity when a patient is already in a poor health state.

Among hospital specific covariates, teaching hospitals exhibit lower readmission risks as patients become healthier (+14.4% in OR). Older patients in the bad health state tend to experience lower readmission risk (+16.2% in OR and +18.8 in OR). Female patients in the bad health state tend to have a higher readmission risk when they are admitted to hospitals in urban locations (+21.9%).

Among patient demographics, Caucasian patients in the poor and good health states incur greater readmission risks as patients become healthier (+13.2% in bad to 739% in good state), which may be attributed to the likelihood that patients with more serious complications (in bad state) may be admitted to teaching hospitals due to their access to greater resources. The hospital CMI index is associated with substantially lower readmission risk for patients in the bad health state (-29.8%) compared to patients in the good health state (+55.9%). Further, patients in the bad health state tend to experience higher readmission risk when they are admitted to hospitals in urban locations (+21.9%).

Among patient demographics, Caucasian patients in the poor and good health states incur greater readmission risk (+16.2% in OR and +18.8 in OR). Female patients in the bad health state tend to have lower readmission risks (+37.9% in OR in bad vs 7100% in good). We also included variables for payer type using dummy variables for Medicaid, selfpay, private and other insurance types with Medicare as the reference category. Accordingly, admissions with Medicaid insurance experience lower readmission propensity if a patient is in a good health state (+22.3% in OR), but we do not find a significant impact on the readmission propensity if a patient is in a good health state (+22.3% in OR), but we do not find a

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Health State 1 (Bad)</th>
<th>Health State 2 (Good)</th>
<th>Difference (Bad – Good)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.575*** [77.7%] (0.085)</td>
<td>-2.423*** [-91.1%] (0.035)</td>
<td>2.997*** (0.095) W=997.841</td>
</tr>
<tr>
<td>RiskMortality_t</td>
<td>0.126** [13.4%] (0.055)</td>
<td>0.652*** [91.9%] (0.047)</td>
<td>-0.526*** (0.074) W=50.92</td>
</tr>
<tr>
<td>LogNumDiagnoses_t</td>
<td>0.023 [2.3%] (0.044)</td>
<td>0.534*** [70.6%] (0.051)</td>
<td>-0.511*** (0.059) W=75.493</td>
</tr>
<tr>
<td>LogLOS_t</td>
<td>-0.022 [-2.2%] (0.047)</td>
<td>0.201** [22.3%] (0.081)</td>
<td>-0.222** (0.088) W=6.419</td>
</tr>
<tr>
<td>HsTeaching_t</td>
<td>0.124 [13.2%] (0.076)</td>
<td>-0.495*** [-39%] (0.072)</td>
<td>0.619*** (0.085) W=52.816</td>
</tr>
<tr>
<td>HsCMI_t</td>
<td>-0.354*** [-29.8%] (0.100)</td>
<td>0.444*** [55.9%] (0.050)</td>
<td>-0.798*** (0.128) W=38.784</td>
</tr>
<tr>
<td>HsUrban_t</td>
<td>0.198 [21.6%] (0.077)</td>
<td>-0.652*** [-47.9%] (0.082)</td>
<td>0.857*** (0.099) W=73.379</td>
</tr>
<tr>
<td>PtWhite_t</td>
<td>0.150*** [16.2%] (0.041)</td>
<td>0.172* [18.8%] (0.068)</td>
<td>-0.023 (0.086) W=0.069</td>
</tr>
<tr>
<td>PtFemale_t</td>
<td>-0.156*** [-14.4%] (0.031)</td>
<td>0.043 [4.4%] (0.049)</td>
<td>-0.199*** (0.062) W=10.235</td>
</tr>
<tr>
<td>LogPtAge_t</td>
<td>-0.488*** [-38.6%] (0.039)</td>
<td>3.231*** [2430.5%] (0.200)</td>
<td>-3.718*** (0.216) W=295.445</td>
</tr>
<tr>
<td>InsuranceMedicaid_t</td>
<td>0.321*** [37.9%] (0.115)</td>
<td>-9.209*** [-100%] (0.684)</td>
<td>9.53*** (0.726) W=172.338</td>
</tr>
<tr>
<td>InsuranceSelfpay_t</td>
<td>0.193 [21.3%] (0.153)</td>
<td>0.898*** [145.5%] (0.142)</td>
<td>-0.705*** (0.236) W=8.938</td>
</tr>
<tr>
<td>InsurancePrivate_t</td>
<td>0.143 [15.4%] (0.179)</td>
<td>1.138*** [212.1%] (0.191)</td>
<td>-0.996** (0.297) W=11.254</td>
</tr>
<tr>
<td>InsuranceOther_t</td>
<td>0.061* [6.3%] (0.028)</td>
<td>0.261*** [29.8%] (0.078)</td>
<td>-0.2*** (0.073) W=7.556</td>
</tr>
</tbody>
</table>

We address several econometric concerns to ensure unbiased and consistent estimation of our HMM parameters. We incorporated patient random effects in the health status transition process to account for additional individual unobserved heterogeneity. We follow a nonparametric approach to estimate the HMM by incorporating support points and associated mass probabilities as model parameters (Heckman and Singer 1984) and set the boundary for random effects to be between zero and one with an additional rescaling parameter (Yan and Tan, 2014). Our estimation yields similar results and can be summarized as: (a) The optimal number of states was two, (b) readmission propensity significantly differed across two states, 41.5% for bad and 1.1% for good health state and (c) the impact of telehealth is lower for patients in the good health state (0.530, p<0.01).

Robustness Checks

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It is common not to include the random effects in the state dependent outcome (i.e. readmission) process (Netzer et al. 2008), so as not to lose the ability to classify patients into different health states.
We also checked for the presence of multi-collinearity among our explanatory variables by calculating the correlation matrix and the Variance Inflation Factors (VIFs). The highest correlation was -0.624, which was between *InsuranceOther* and *InsuranceMedicare* with a VIF value of 3.84 and 2.92, respectively. All VIF values were less than 10, suggesting that there was no severe multi-collinearity problem.

One may also argue that the telehealth and patient health status constructs may be subject to endogeneity concerns. First, we analyze if the readmission process is prone to endogeneity issues. Although endogeneity arising from omitted variable bias is controlled by revealing the latent health status of patients, we test whether different health states can explain readmission risk even after the confounding effects are expunged from the model. To do this, we adopt a propensity score matching technique and matched patients in bad health state to patients in good health state using the algorithm developed by Rosenbaum (1989). We adopted a one-to-one matching strategy using the SAS macro developed by Mayo Clinic (Bergstrahl and Kosanke 1995), and include all the patient, admission, and hospital attributes, as matching covariates\(^8\). Once matching is complete, we calculated the average readmission rate across bad and good health state patients that also revealed a significant association of health states to readmission rates\(^9\).

Next, *Telehealth* is used as an independent variable in the health state transition process of patients; however, hospitals admitting sicker patients may adopt telehealth services by choice which may raise endogeneity concerns. Since we observed *Telehealth* across multiple time periods for each patient, a quasi-natural experiment setting is available naturally and the *Telehealth* coefficient can be used as a difference-in-difference (DID) estimate because it is a binary variable. In a quasi-experiment setting, the group of subjects that receive intervention (treatment group) is compared against the control group, where the intervention effect is measured against a control group in the pre- and post-intervention periods. With this specification, the potential confounding effects of unobserved factors and time-invariant features from intervention effects are addressed (Meyer 1995). We matched hospitals who did not implement *Telehealth* (control) to hospitals who implemented *Telehealth* at some point in time (treatment). We applied the same matching algorithm described earlier. DID coefficient for the percent of admissions with good health state status was calculated as 0.11, suggesting that after *Telehealth* implementation hospitals observe 11% more good health state admissions compared to hospitals who do not implement. We further repeated this analysis by incorporating all the control variables into the model. Our results were consistent and DID coefficient suggested an increase of 8.1% in good health state admissions to the treatment hospitals. Although these resulting DID coefficients were free of patient-, visit-, and provider-level effects, one could still argue that Telehealth might be subject to potential endogeneity. To address this concern, we adopted control function estimation approach which disintegrates the correlation between endogenous explanatory variables and unobservables affecting the outcome using additional regressors that do not appear in the structural equation (Wooldridge 2010). Our results suggested an increase of 8.2% in the rate of good health status admissions to the treatment hospitals after Telehealth is implemented. These various approaches control for endogeneity that may be due to the simultaneity in our HMM specification. Our analyses yield consistent results where telehealth remains to exert significant impact on health status.

**Discussion**

In this study, we analyze the determinants of readmission risk by developing a novel conceptual framework. We study the role of non-clinical factors, unobserved patient health status coupled with telehealth utilization, and their impact on readmission risk. Our study establishes a relationship between unobserved patient health status, telehealth, and readmission risk, a link that has not been addressed in prior studies (Tsai et al. 2013). We contribute to the healthcare and information systems literatures, as well as to the current health policy debate on whether hospital readmission rates should serve as a valid

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\(^8\) We classify patients as being in good health status if their average revealed health status across their admissions is higher than 0.5, since good health status is coded as 1, and zero otherwise. Accordingly, we matched 4129 patients in bad health to 4129 patients in good health status. All the robustness check results are available upon request.

\(^9\) Average \(_{Readmission}^{good}\) = 0.01 and Average \(_{Readmission}^{bad}\) = 0.60 with t statistics of 104.8 for the difference in the average values across the two health states.
measure of the level of quality of care. Our results suggest that (1) patient health condition may worsen after discharge due to medical, personal and social factors, which in turn, may induce patients to re-visit hospitals and increase readmissions, (2) telehealth as an emerging technology can help patients improve their health status after discharge.

Our results reveal that non-clinical factors represent an important dimension in the current policy debate on the role of care coordination and transition across care settings in terms of their impact on readmission risk. Since hospitals are responsible for their patients’ readmission rates, under the newly established ACA policies, and are penalized by CMS for high readmission rates, we argue that it is important for providers and policy makers to carefully consider the importance of non-clinical factors and their association with readmission risk. In addition, digitization of healthcare services through emerging telehealth technologies can address some of the disparities in the quality of healthcare services that exist today.

**Policy Implications**

The key contribution of this paper is the development of a viable approach for policy makers to re-adjust the readmission rate by taking into account the impact of non-clinical factors. Our model shows that latent health status accounts for 37.9% of variation (in terms of pseudo-$R^2$) in the readmission process. Specifically, our pseudo-$R^2$ calculations for each hospital (aggregated over 2008-2011) showed that latent health state due to non-clinical factors explained between 1.0% and 75.0% of readmission rate of hospitals in our sample. This alarmingly large impact necessitates the adjustment of readmission rate of hospitals. We argue that our proposed adjusted readmission rate better reflects the liable portion of readmissions of a hospital and can potentially serve as a better benchmark to assess the quality of care across hospitals.

ACOs have been proposed as a potential solution to address the fragmented nature of the US healthcare system. Under the Medicare Shared Savings program, providers as part of an ACO will assume the responsibility for the quality and cost of care delivered to a population of patients. These providers may consist of integrated delivery systems, primary care medical groups, hospital-based systems, and virtual networks of physicians, which are jointly held accountable for achieving quality improvements and reductions in the rate of spending growth. We believe that our results lend support for ACO types of healthcare delivery models, in order to achieve reduction in patient readmission rates, by enabling better care coordination through the use of telehealth technologies. Crosson (2011) suggests that ACOs can encourage healthy behaviors in patients by preventing and detecting diseases early where possible, and by aggressively managing costly chronic illnesses that would lead to better care quality and lower cost.

Our study reports that while a patient’s health status is unobservable to healthcare providers, it might lead to an increase in patient readmission rate if their health deteriorates after discharge from the hospital. Further, our analyses suggests that telehealth technologies can improve the health status of patients who are comparably in an unhealthier state. Therefore, adoption of telehealth technologies have the potential to coordinate and monitor patient care by various stakeholders in the care continuum. With telehealth, patients can receive education on self-care management initiatives, obtain timely appointments, visit ambulatory facilities if needed, receive preventive care, and receive timely support and preventive care, before an unplanned hospital visit, all of which can reduce the readmission rate. In addition, current policies acknowledge poor performance as a consequence of the lack of individual accountability, rather than flawed systems (Fisher and Shortell 2010). Hence, telehealth technologies can establish a platform, where various types of providers and patients can coordinate patient care and delivery, thereby reducing the wide disparities in the quality of patient outcomes across socio-economic barriers.

**Conclusions**

In this study, we propose a novel framework to jointly study the clinical and non-clinical factors associated with readmission. We argued that readmissions arise not only as a consequence of hospital-based clinical factors, but also as a result of non-clinical factors, such as patient health status. We found that patient-specific, unobservable health status may deteriorate upon discharge, due to personal and social factors. In our study, we also investigate whether telehealth usage can help patients become healthier after hospital discharge. These factors are neither directly controllable nor observable by
hospitals, which leads to a reduction in patient health status and consequently results in a higher rate of future readmissions. Taken together, our study provides evidence that readmission are not a purely, hospital-driven quality metric. Rather, unobserved patient health status represents an important non-clinical factor that may affect patient readmission risk. Unless there are technologies in place to facilitate care coordination, such as telehealth, readmission risk of patients will always be subject to factors beyond the reach of healthcare providers.

Our study is subject to a few limitations. First, we study patients whose principal diagnoses are CHF. For a more comprehensive analysis, myocardial infarction and pneumonia patients should also be included in this type of analysis, in which different disease related effects can be studied comprehensively. Second, the size of our data set could have been increased by obtaining information from other geographic regions. However, it was not possible for us to achieve this since the DFWHC gathers discharge claims data only from North Texas region hospitals. Third, although we examined the HMM with telehealth information gathered from AHA IT database, we need access to more granular, observational data on telehealth utilization by patients, in order to generalize the findings of our study. Fourth, the sequence of events taking place after discharge could be modeled if we had more detailed data, e.g., information on discharging patients to nursing home then transferring to home care etc. Future directions can include the examination of moderation effect of Telehealth with discharge location, e.g., nursing home or home care as well as incorporating patient zip code level health data. Nevertheless, we believe that this study represents a first start to explore an important phenomenon dealing with patient health status, and the role of telehealth in determining readmission rates.

References


