THE IMPACT OF PATIENT HEALTH INSURANCE COVERAGE AND LATENT HEALTH STATUS ON HOSPITAL READMISSIONS

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ABSTRACT

Hospital readmission rate is adopted as a key hospital quality metric by the Centers for Medicare and Medicaid Services (CMS). In 2012, CMS began penalizing 2200 hospitals with excess readmission rates for a total about $280 million in Medicare payments. However, readmission rate may not be an appropriate quality metric because it may be driven by factors other than the care given at hospitals. In this research, rather than treating readmission as a consequence of a mere inpatient care quality, we investigate several other important factors that may lead to readmission, such as insurance coverage and patient's unobserved health status outside hospitals. We posit that generous insurance coverage may result in higher readmission rates; and deteriorated health status, which is unobservable most of the time, may result in higher readmission rates. We utilize a comprehensive inpatient panel dataset of Congestive Heart Failure patient visits across 68 hospitals in North Texas from 2005 to 2011. We apply a quasi-experimental approach to investigate the impact of switching to Medicare plan on increasing readmission rate and develop a Hidden Markov Model (HMM) to capture the unobservable health status and its impact on the readmission rate. Our quasi-experimental results demonstrate that privately insured or self-pay patients face higher readmission propensity after they enroll in Medicare. HMM estimation results indicate that there is a substantial difference in the readmission rates among different health states (e.g., less healthy had significantly higher readmission rates compared to healthier), all of which reveals the association between level of unobserved health status and readmission rate. This research sheds light onto debate over readmission rate as a sole quality metric and tries to explain that unobservable health status and financial risk borne by patients are likely causes of readmission.

1 INTRODUCTION

High hospital readmission rates, defined as patient's admission to a hospital within 30-days of being discharged from the same or another hospital (CMS 2014), have recently become the focus of clinicians, healthcare leaders and policy makers, due to its prevalence and high cost on the United States (US) healthcare system (McCarthy et al. 2013). Hospital Readmission Reduction Program (HRRP), established by the Centers for Medicare and Medicaid Services (CMS) has set its initiative on reducing the frequency of Medicare readmissions. In spite of recent improvements, the US still has the highest readmission rates compared to other developed countries (Dorland Health 2014; Joynt and Jha 2013; Kociol et al. 2012). While these findings suggest that readmission rates in the US are excessive and reducible, according to Sommers and Cunningham (2011), until wide-spread efforts are made to prevent readmission, the US healthcare system will shoulder a $16 billion burden.

In addition to severe financial implications, high readmission rates are also perceived to be a sign of low hospital care quality (Benbassat and Taragin 2000). CMS has been promoting to use the reducible readmission rate to assess the quality of care given in hospitals (Weissman et al. 1999). In 2013, CMS began implementing a regulatory policy of the HRRP, which was developed and adopted by the Payment Advisory Commission (PAC) in 2011, the goals of which are reduce, and ultimately prevent readmissions (Medicare Payment Advisory Commission 2011). To that end, CMS will penalize hospitals with high 30-day readmission rates for heart attack, heart failure, and pneumonia patients by reducing or withholding reimbursements for services. Accordingly, two thirds of hospitals were issued a 1% reduction in Medicare reimbursements in 2013, which resulted in a savings of 280 million dollars. Going forward, CMS will increase this penalty to 2% in 2014, and to 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 will have a substantial impact on hospitals.

Recently, researchers and healthcare providers, e.g., Tsai et al. (2013), started questioning the validity of using readmission rates as the sole measure of a hospital's quality of care: readmission reduction may need to go beyond factors associated to hospital care quality, such as patients receiving substandard care during their index hospitalizations. Kangovi and Grande (2011) suggested that rates of readmission alone do not even constitute a valid metric of quality, yet it is more of a measure of health service use, which is a function of quality of care, patients' health status, access to health services, and socio-economic resources.

In this study our objective was to explore non-clinical factors that are not related to hospital quality of care but explain potential risks to readmission. Mainly, we are interested in two non-clinical factors that might be affecting the readmission process: (a) health status of patients outside the hospital, and (b) patients' insurance coverage. First, patients' health status might 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 supports such as lack of family and friend attention. We assert that patients with worsened health state outside the hospital will require readmission following a discharge. In addition, health status is incorporated as an unobservable variant in our model, because neither can providers track nor do hospitals include the health status of patients in discharge claim files. Second, socio-economic factors such as financial factors and the resultant insurance coverage might impact the patient's decision of re-hospitalization. When a patient realizes his or her insurance coverage increases and their financial liability decreases, a patient may decide to visit the hospital for previously undertreated health conditions, which comes with an increased risk of readmission. Hence, we posit that lowered financial liability increases the readmission propensity of patients as patients will be less reluctant to visit hospitals. This necessitates us to analyze the impact of the change of insurance plans on the propensity of readmission rather than the aggregated impact of individual insurance plans on readmissions. Overall, these two factors, health status and insurance coverage, are neither controllable nor modifiable by hospitals. Thus, our research contributes to settle the debate over whether readmission rates are really a valid measure of the level of quality of care given at hospitals; or whether other non-clinical factors, such as health status and insurance coverage can also explain readmission rates.

To test our hypotheses on the impact of health status and insurance policy change, as they relate to readmission, we utilized a comprehensive inpatient panel dataset of Congestive Heart Failure (CHF) patient visits across 68 hospitals in North Texas from 2005 to 2011. We extracted observations of patients with given payer information as either private, or self-pay, or Medicare and created two full datasets consisting of: (a) 828 observations for 305 privately insured and/or Medicare patients and (b) 1978 observations for 636 self-pay and/or Medicare patients. We apply a quasi-experiment approach to investigate the impact of insurance policy change on readmission rate and model unobserved patient health status as a latent state via a HMM approach. Our results demonstrate that privately insured or self-pay patients face higher readmission propensity after they enroll in Medicare. HMM estimation results indicate that there is a substantial difference in the readmission rates among different health states (e.g., less healthy had significantly higher readmission rates compared to healthier), all of which reveals the association between level of unobserved health status and readmission rate. This research sheds light on the growing debate over readmission rate as a sole quality metric and explains that two non-clinical factors—health status and financial risk borne by patients—are likely causes of readmission. Therefore, it is arguable that policy makers should consider factors impacting patients' readmission propensity outside the hospital, along with clinical factors related to hospital quality of care. As these findings suggest, hospitals alone do not seem to be the only source of accountability when analyzing the health outcomes of patients.

2 HYPOTHESES

In this section, we develop our hypotheses to investigate the implications of insurance policy change and patient's health status and their association to readmission event over the course of patient's admission history.

2.1 Insurance Policy Change

Literature on healthcare economics has studied the healthcare utilization with respect to various insurance plans. Rand Corporation in 1970s conducted a randomized evaluation of healthcare utilization and found that insurance type has a substantial effect on healthcare use and plans with lower co-insurance rate showed greater expenditures (Manning and Marquis 1996). Doyle Jr (2005) finds that crash victims without insurance have about 15% shorter hospital stays and facility charges, and 40% higher mortality rates than those with private insurance suggesting that lack of insurance coverage causes discrepancies in the density and quality of care. Massachusetts has been implementing a healthcare reform to achieve near universal health insurance coverage since 2006 (Long and Masi 2009). Accordingly, it has been reported that readmission rates has significantly increased from 14.3% to 14.5%, while other states have witnessed a decrease of readmission from 19% to 17.9% in the meantime, as the reform unfolds and the number of uninsured decreased (Lasser et al. 2014). Overall, Agency for Healthcare Research and Quality (AHRQ) reports that Medicare patients have higher 30-day readmission rates (24%) compared to both uninsured (13%) and privately insured patients (11%) in 2008 throughout the 15 states (Wier et al. 2011). All these findings suggest that with a better health insurance plan, i.e., Medicare, patients will incur higher readmission risks compared to patients who are privately insured or uninsured given that these types of patients would face higher financial hardships if they were to visit hospitals.

The above literature suggests that different insurance plans may lead to different quality of care at the aggregated level. Though, we are interested to examine how changes in insurance plans have a bearing on the quality of care outcomes, i.e., readmission, because better access to insurance plans has impact on the access to care and subsequently the health care resource utilization. In addition, the recent policy--Affordable Care Act (ACA) requires patients to switch insurance plans, and become either privately insured or covered by Medicaid. McWilliams et al. (2003) examine the changes in health care services in two different groups of patients: people who had held health insurance coverage before reaching age 65 and patients who are uninsured throughout the study period. Accordingly, McWilliams et al. (2003) conclude that the rate of medical screening procedure use increases after age 65 for the uninsured group. In another study on healthcare utilization, Lichtenberg (2002) shows that utilization of healthcare resources, e.g., inpatient care, increases abruptly at the age of 65 once patients become eligible for Medicare. As pointed out previously, Medicare beneficiaries are entitled to Medicare benefits conditional on survival to age 65.

Hence, better coverage and potential improved health in old age might induce individuals in younger ages to take better care of themselves before 65. On the other hand, this better coverage after age 65 might induce elderly to participate in activities that reduces health quality and increases mortality risk, i.e., starting smoking, eating unhealthy food (Khwaja 2010). Therefore, after the age of 65, elderly patients might start using healthcare resources more because of the increased coverage and access to care. According to the "Coverage Matters" report by the Institute of Medicine (2001), people without insurance are less likely to see a doctor within a given year, have fewer visits annually and are less likely to have a regular source of medical care. Thus once these underinsured patients enroll in Medicare, they might experience higher number of visits to hospitals to reduce the health risks already accumulated up until the age of 65 (Card et al. 2007; McWilliams et al. 2007). Therefore, we hypothesize that previously uninsured or privately insured patients would face higher number of readmissions after they enroll in Medicare due to reduced financial risks and increased coverage.

Hypothesis 1a: *Patients who were privately insured previously and switch to Medicare are more likely to exhibit higher readmission rate.*

Hypothesis 1b: *Patients who were uninsured previously and switch to Medicare exhibit higher readmission rate.*

2.2 Patient Health Status

One main reason why patients come back to hospitals and are readmitted in a short amount of time is the need of care to improve their worsened health condition outside hospitals. Once patients are discharged from hospitals, patients' health status will be subject to various factors that providers might not have any control on. Specifically, medical, personal and social disturbances alter the way how recovery of patient proceeds outside hospitals (McCarthy et al. 2013). Unless health status is self-reported, it is unobservable to care providers and researchers, or at least difficult to measure (Wolfe and Behrman 1984). Harris and Remler (1998) suggest that patients are heterogeneous in terms of unobservable factors, in which health status is one of them. In labor economics literature, health status has been investigated as a determinant of retirement decisions extensively, where the treatment of health status constituted one big problem since it was not directly observable (Dwyer and Mitchell 1999). People's self-reported health statuses were only a subjective measure because people used to mis-specify their health statuses in order to justify their early retirement decisions (Dwyer and Mitchell 1999). Thus either in healthcare or labor economics, health status is a complex measure, which is not directly observable. In our case, to analyze the impact of patient health status on readmission, we first have to reveal the factors impacting patient's health status—an unobservable artifact for the researcher and an un-controllable artifact for the care providers.

One of the medical factors impacting patient's recovery and health status is the level of access to care. Patient's health status, which could be negatively affected by his inability to receive treatment at outpatient settings, is one important link that should not be excluded in readmission analyzes. In the case of lack of outpatient clinics, such as nursing homes, general physician practices, or home care, patient will not be able to receive timely treatment, which will aggravate a patient's current health condition (Ferrer 2007) and eventually lead to the patient's readmission to an inpatient setting. Goodman et al. (1994) find that pediatric medical hospitalizations are positively associated to regions with high bed supply and negatively associated to regions with high number of ambulatory care facilities—suggesting that supply of inpatient and outpatient care are important factors in explaining pediatric medical hospitalizations. Another medical factor that might have an impact on patient's health status is the discharge destination. For instance, patients can be discharged to either home care or nursing home. Nursing homes have better care opportunities for patients in terms of treatment and support compared to home care. It has been found that patients with chronic obstructive pulmonary disease or dementia experience lower likelihood of readmission within 30 days if they are discharged to nursing homes rather than to personal homes (Camberg et al. 1997). In addition, educational interventions and post-discharge follow-up care, i.e., RN telephoning the patient or visiting at home, are found to have reducing effects on the readmission risk of CHF patients (Gwadry-Sridhar et al. 2004), all of which can be considered as medical factors.

Another important group of factors impacting patient's health condition is related to personal or social factors. Patient's inability to comply with discharge recommendation and medication regimen, lack of transportation and social support have been cited as important determinants of health deterioration and readmission risk (Annema et al. 2009; Kangovi et al. 2013a; Kangovi et al. 2013b; Retrum et al. 2013). After discharge, patients begin to experience difficulties of performing discharge recommendations because of various personal issues, such as sense of abandonment, dysfunctional emotional supportive social networks, misaligned discharge goal-setting, external constraints and lack of family support (Kangovi et al. 2013a). Retrum et al. (2013) also cites that inadequate support or lack of resources, such as transportation to medical appointments, lack of meals meeting diet restrictions, and self-care issues, such as inability to check weight, non-compliance with medication and lack of exercise, were among the main issues CHF patients self-reported after discharge from index hospitalization. Accordingly, patient's health status will deteriorate if the explained personal and social factors are detrimental for patient. As a consequence, patient will need to be readmitted to hospital to improve his health, which will be achieved by using the resources available in hospitals that are not available to patient otherwise.

Patients experience various factors and obstacles after discharge from hospitals, which affect patients' health condition and introduce heterogeneity among patients. Depending on the level of impact, patients' health statuses deteriorate over time and become impossible to measure for care providers and researchers unless patients self-report in an ideal managed-care scenario. Though, Deb and Trivedi (2002) argue that even these self-perceived health statuses may not fully capture population heterogeneity from the source. Therefore, it becomes essential to reveal patient unobserved health status to assess its differential impact on health outcomes.

We posit that the 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, in which patients' health will deteriorate over time due to negative impacts of medical, personal and social factors.

Hypothesis 2: *Patient readmission rates are significantly associated with changes in patient health status.*

Based on these hypotheses, we depict our conceptual research model in Figure 1.

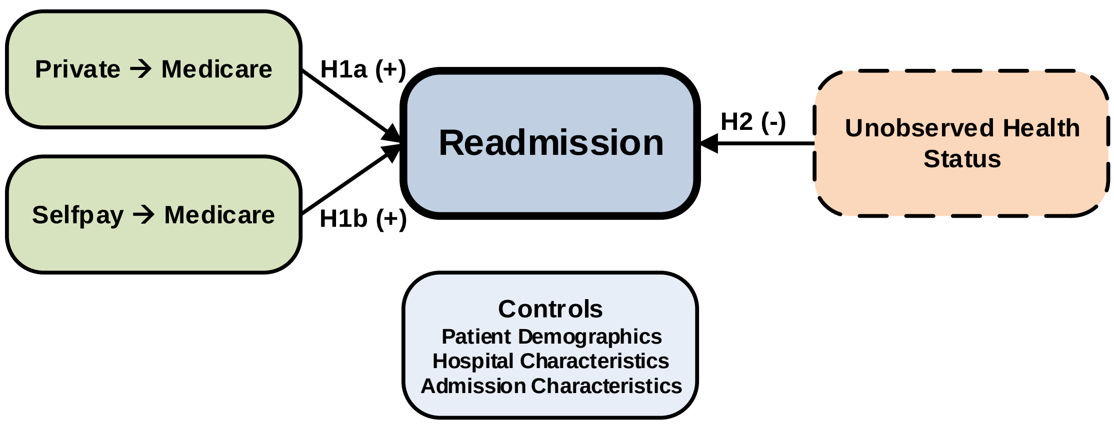

Figure 1 Conceptual Research Model

3 RESEARCH METHODOLOGY

Our conceptual research model given in Figure 1 is tested using the data obtained from Dallas-Fort Worth Hospital Council (DFWHC) Research Foundation. We first explain the data and variables that we use to set up our conceptual research model and test our research hypotheses H1a, H1b and H2.

3.1 Data

Data obtained from DFWHC is based on admission-level administrative claims in which each patient might have multiple admissions to different hospitals in the North Texas region starting from 2005 to 2011. Each patient is given a unique patient identifier number-- the regional master patient index (REMPI) by DFWHC Foundation (Bardhan et al. 2011). With REMPI, each patient can be tracked over time and across all hospitals in the region allowing us to obtain the patient's entire visit and diagnosis history. In total there are 68 non-Federal hospitals with 26 different health systems that these hospitals belong to. Since CHF is one of the three conditions with which CMS has been penalizing hospitals on according to the rate of readmission these hospitals possess, CHF has constituted an important study area for researchers and policy makers (Ross et al. 2008). Therefore, in this study we focus on inpatient admissions with CHF as the principal diagnosis, i.e., patient admissions with ICD-9 code of “428.xx”. Focusing only on their principal diagnosis alleviates possible patient heterogeneity arising from disease related treatment variations.

According to our conceptual model (Figure 1), we need to focus on patients with at least three admissions[1]. We then drop the last admission of patients since it does not have any 30-day readmission risk information for itself. Finally, we created two datasets; one dataset for private & Medicare (P&M) patients and one dataset for selfpay & Medicare (S&M) patients. After the last admissions were dropped, we ended up with two datasets having 828 observations (305 patients) and 1978 observations (676 patients) for private & Medicare and selfpay & Medicare patients, respectively.

In observational studies, when it is impossible to randomly assign subjects into treatment and control groups due to ethical or practical reasons, matching strategy is recommended[2] (Rosenbaum 1989). Rather than applying greedy algorithms, such as propensity score matching in the statistics literature, Rosenbaum (1989) find that optimal matching algorithm based on network flow analysis gives closer and more tolerable matches. Accordingly, we follow the algorithm developed by Rosenbaum (1989), and also suggested by Cram et al 2009, to match patients from treatment to control groups. To match patients, we used the SAS macro developed by Mayo Clinic (Bergstralh and Kosanke 1995) and included patient age, sex, race, risk mortality and severity level as matching covariates.

3.2 Variables

We derive and calculate several variables using the DFWHC Foundation claims dataset at the admission, patient, physician and hospital level. Our main variables of interest are readmission risk, insurance policy change, operating physician experience and specialization, hospital congestion, comorbidities. We report the definitions and the statistics of these variables in Table 1.[3]

[1] (i) We need at least two admissions per patient in order to calculate the insurance policy change variable with respect to the prior visit information, (ii) We again need at least two admissions per patient to calculate the (future) 30-day readmission risk with respect to the future visit information. Therefore, at least three admissions per patient would suffice us to fully develop insurance policy change and 30-day readmission risk variables together for one patient.

[2] Conducting a quasi-experiment to test the change of insurance policy and its associated effect on readmission risk required us to assign patients into treatment and control groups with respect to their insurance policy history. Patient who had stayed on the same insurance policy, such as private or selfpay, constituted the control group for two datasets, P&M and S&M respectively, whereas patients who had changed their insurance policy from private to Medicare or selfpay to Medicare constituted the treatment group for two datasets, P&M and S&M respectively.

[3] Due to space limitation, we skip the explanation of these variables and we report them in Table 1.

Table 1 Descriptive Statistics of Variables

Variable	Definition	Dimen.	***P&M (Private → Medicare) N = 828***		***S&M (Selfpay → Medicare) N = 1978***	
			Mean	**Std Dev**	**Mean**	**Std Dev**
Admission Characteristics						
Readmission	30-day Readmission event	Binary	**0.31**	0.46	**0.31**	0.46
ComorbidityIndex	Normalized comorbidity intensity index out of 9 comorbidities	[0, 1]	**0.31**	0.15	**0.28**	0.14
SourcePersPhys	1 = if patient is referred from his personal physician	Binary	**0.39**	0.49	**0.25**	0.43
DischargeNursingFac	1 = if patient is discharged to nursing facility	Binary	**0.05**	0.22	**0.01**	0.07
DischargeHomeCare	1 = if patient is discharged to home care	Binary	**0.11**	0.32	**0.02**	0.15
AdmissionEmergency	1 = if it is an emergency admission	Binary	**0.74**	0.44	**0.93**	0.25
RiskMortality	Risk mortality increases from 0 to 4	(0,..,4)	**2.19**	0.79	**1.94**	0.82
LOS	Length of stay	Cont's	**4.87**	4.58	**4.64**	3.91
NumProc	Number of procedures	Count	**0.86**	1.54	**0.76**	1.56
NumDiag	Number of diagnoses	Count	**12.12**	5.15	**11.65**	4.96
Physician Characteristics						
OprPhysExperience	Number of patients seen so far	Cont's	**81.54**	75.68	**90.36**	78.92
OprPhysSpecialization	Herfindahl Index wrt to performed procedures	[0, 1]	**0.23**	0.11	**0.24**	0.11
Hospital Characteristics						
HospitalCongestion	Number of patients / Max patients in the hospital	Cont's	**0.5**	0.2	**0.52**	0.19
HsCMI	Case mix index	Cont's	**1.63**	0.28	**1.66**	0.23
HsTeaching	1= if it is a teaching hospital	Binary	**0.34**	0.47	**0.6**	0.49
HsUrban	1= if it is an urban hospital	Binary	**0.92**	0.28	**0.95**	0.22
HsBedSize	Hospital bed size	Cont's	**362.35**	277.53	**483.98**	322.68
Patient Demographics						
Treatment	1 = If patient switches from Private (Selfpay) to Medicare	Binary	**0.33**	0.47	**0.25**	0.43
Control	1 = If patient stays on Private (Selfpay)	Binary	**0.67**	0.47	**0.75**	0.43
PtAge	Patient age	Cont's	**62.76**	14.6	**51.14**	9.78
PtWhite	1 = if race is white	Binary	**0.61**	0.49	**0.41**	0.49
PtFemale	1 = if gender is female	Binary	**0.39**	0.49	**0.33**	0.47

4 MODEL SPECIFICATION

4.1 Quasi Experimental Setup

To examine if changing insurance policy is associated to a change in the patient outcomes, we utilize a difference-in-difference (DID) specification which is extensively used in healthcare and management literatures (Card et al. 2007; Currie and Gruber 1996; Kumar and Telang 2012; Lichtenberg 2002; McWilliams et al. 2003; Meyer 1995). In our analysis, we run our experiment on two different datasets, P&M and S&M, mainly focusing on patients whose insurance type changes from Private to Medicare in P&M and Selfpay to Medicare in S&M (We refer to the first experiment as P→M and the second experiment as S→M). For that reason our treatment group for the first dataset comprised of patients whose insurance policy has changed from Private to Medicare. On the contrary, the Control group for the first dataset comprised of patients whose insurance policy was Private for the full analysis period. Patients are assigned to Treatment and Control groups following the matching strategy explained in the previous section. Matching allowed us to create a binary variable $Treatment_i$ specifying which group each patient belongs to[4].

In our quasi-natural experiment, we also incorporated the variables associated to our hypotheses, such as physician (*OprPhysExperience* and *OprPhysSpecialization*) and hospital related factors (*HospitalCongestion*). We also control for admission, patient and hospital specific factors. Accordingly, we estimate the following DID model for $Readmission_{it+1}$ for both datasets P→M and S→M. For $Readmission_{it+1}$ variable, since it is a binary variable, we follow a logistic regression and specify Eq1 with respect to the effects of covariates on the log of odds of readmission. Logistic regression for $Readmission_{it+1}$ (Eq1) is defined as follows:

$$
\begin{aligned}
Logit(Readmission_{it+1}\,) &= \alpha_0 + \alpha_1 Treatment_i + \alpha_2 Post_{it} + \alpha_3 Treatment * Post_{it} \\
&+ \alpha_4 OprPsyExperience_{it} + \alpha_5 OprPsySpecialization_{it} + \alpha_6 HospitalCongestion_{it} \\
&+ Controls * \alpha_c \quad (\mathbf{Eq1})
\end{aligned}
$$

where *i* denotes a patient and *t* denotes admission time index. $Treatment_i$ equals one if patient *i* changes his insurance policy from Private to Medicare (or Selfpay to Medicare) throughout his full admission history. $Post_{it}$ equals one if patient *i*'s admission time *t* is after the time of insurance change. The coefficient estimate of α_3 for $Treatment * Post_{it}$ is of our primary interest since it captures the change in the quality outcome (either readmission risk or duration till the next admission) for patients whose insurance type changes relative to patients whose does not. We also account for admission characteristics (emergency

[4] After matching is complete, we synchronize the time of insurance change for a patient in a control group with the time when his match in the treatment group changes his insurance. This allowed us to create the pre- and post-treatment binary variable Postit for patients in the control group.

admission, length of stay, risk mortality), patient characteristics (patient age, gender, race) and hospital characteristics (hospital CMI, teaching status, location of being urban vs suburban, bedsize) in our DID estimation approach.

4.2 Hidden Markov Model Approach

We model unobserved patient health state 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 its observed outcomes' marginal distribution—suggesting the existence of hidden discrete states that generate these outcomes (Visser 2011). HMM models latent states as a Markov chain evolving over time and creating serially dependent observations. With Markov property, serially dependent observations become conditionally independent observation sequence given the state of the Markov chain at the time of the observation (Ephraim and Merhav 2002). In our study, health states represent the latent states and constitute a stochastic process since patients' health states can change over time. Transitions among states may happen at any discrete time interval (Rabiner 1989). The observable outcomes that depend on the latent health states are defined by a readmission process of a patient. In our HMM, these observed outcomes as time dependent sequences will reveal the latent health condition of patients.

Specifically, for a given patient, our model captures the dependence among health states of patients, and readmission. Transitions among health states is explained by time-varying covariates such as the level of care given to the patient in the previous admission as well as covariates specific to the hospital that the patient was admitted to. This stochastic transition process is then transformed into the 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. Different from previous studies in the Management literature using 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 generic view of our model is depicted in Figure 2.

In the figure, the hidden health states are represented with darkened circles, readmission states are represented with squares. A hidden health state takes a value from the set $\{1, 2, \ldots, NS\}$, each value representing an unobserved state such as good, bad or other conditions where the optimal number of states will be determined by the model. Readmission takes a value of either 0-no readmission, 1-readmission. Straight links among different type of states represent the transition processes, i.e., health state transition, whereas the dashed links represent the dependence among various types of states. In our model, we define the health state sequence of a patient – p as $S = \{s_0, \dots, s_{t-1}, s_t, s_{t+1}, \dots, s_T\}$ and the readmission sequence as $R = \{r_0, \dots, r_{t-1}, r_t, r_{t+1}, \dots, r_T\}$ for a total duration of T periods. Here, health state sequence S, and R

constitute an HMM process. In addition, we define $\boldsymbol{R}^t$ as a readmission history of patient *p* from time 1 up to time *t*, and similarly for the unobserved health state $\boldsymbol{S}^t$. To analyze the patient readmission problem, we have to model $\Pr_{\mathrm{p}}(\boldsymbol{R}^T)$ for each patient *p* and maximize the likelihood of observing $\boldsymbol{R}^T$ for patient *p* as:

$$L_p^T = \Pr_{\mathrm{p}}(\boldsymbol{R}^T) = \sum_{\boldsymbol{S}^T} \Pr_{\mathrm{p}}(\boldsymbol{R}^T, \boldsymbol{S}^T)$$

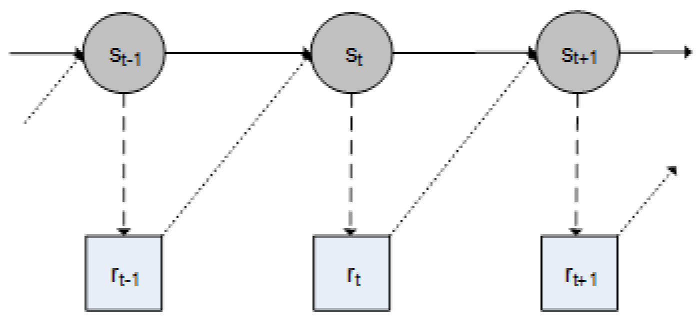

Figure 2 HMM of the Readmission Process

Analyzing the directed graph in Figure 2 under the *first order Markov property* by checking the parents of each node (dependencies), we can write L_p^T with conditional probabilities as:

$$L_p^T = \sum_{\boldsymbol{S}^T} \Pr_{\mathrm{p}}(\boldsymbol{R}^T | \boldsymbol{S}^T) \Pr_{\mathrm{p}}(\boldsymbol{S}^T | \boldsymbol{S}^{T-1}, \boldsymbol{R}^{T-1})$$

$$L_p^T = \sum_{s_1, s_2, \ldots, s_T} \Pr_{\mathrm{p}}(\mathrm{S}_1 = s_1) \prod_{\mathrm{t}=2}^{\mathrm{T}} \Pr_{\mathrm{p}}(\mathrm{R}_{\mathrm{t}} = r_t | \mathrm{S}_{\mathrm{t}} = s_t) \Pr_{\mathrm{p}}(\mathrm{S}_{\mathrm{t}} = s_t | \mathrm{S}_{\mathrm{t}-1} = s_{t-1}, \mathrm{R}_{\mathrm{t}-1} = r_{t-1})$$

As can be inferred from the likelihood function, HMM model requires specifying three types of components: i) Initial state distributions at time t=1, $\Pr_{\mathrm{p}}(\mathrm{S}_1)$, ii) The transition probabilities for example $\Pr_{\mathrm{p}}(\mathrm{S}_{\mathrm{t}} | \mathrm{S}_{\mathrm{t}-1}, \mathrm{R}_{\mathrm{t}-1})$, iii) State dependent outcome probabilities, i.e., $\Pr_{\mathrm{p}}(\mathrm{R}_{\mathrm{t}} | \mathrm{S}_{\mathrm{t}})$.

Now define the initial state distribution- the probability that patient p is in state s at t=1:

$$\Pr_{\mathrm{p}}(\mathrm{S}_1 = \mathrm{s}) = \pi_p(s), \text{ where } s \in \{1, \ldots, n\}$$

The health state transition probability of patient p, where patient is in state s at time t-1, and switching to state s’ at time t can be represented as:

$$\Pr_{\mathrm{p}}\left(\mathrm{S}_{\mathrm{t}} = \mathrm{s} \middle| \mathrm{S}_{\mathrm{t}-1} = \mathrm{s}', \mathrm{R}_{\mathrm{t}-1} = r_{t-1}\right) = \mathrm{q}_{\mathrm{p,t}}^{\mathrm{s,s}'} \text{ for } s, s' \in \{1, \ldots, S\}$$

To move from one state to another, 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:

$$\text{for } s \rightarrow 1, \qquad q_{p,t}^{s,1} = \frac{\exp(\alpha_{s,1} - \mathbf{X}_{pt}\beta_s)}{1 + \exp(\alpha_{s,1} - \mathbf{X}_{pt}\beta_s)}$$

$$\text{for } s \rightarrow s', \qquad q_{p,t}^{s,s'} = \frac{\exp(\alpha_{s,s'} - \mathbf{X}_{pt}\beta_s)}{1 + \exp(\alpha_{s,s'} - \mathbf{X}_{pt}\beta_s)} - \frac{\exp(\alpha_{s,s'-1} - \mathbf{X}_{pt}\beta_s)}{1 + \exp(\alpha_{s,s'-1} - \mathbf{X}_{pt}\beta_s)}$$

$$\text{for } s \rightarrow S, \qquad q_{p,t}^{s,S} = 1 - \frac{\exp(\alpha_{s,S-1} - \mathbf{X}_{pt}\beta_s)}{1 + \exp(\alpha_{s,S-1} - \mathbf{X}_{pt}\beta_s)}$$

Here, $\mathbf{X}_{pt}$ is the time varying covariate vector for patient p and β_s is a vector of parameters capturing the impact of care being received for the propensity to transition from the health state s. In addition, $\alpha_{s,s'}$ represents the s' ordered logit threshold for being in state $s \in \{1, \ldots, S\}$ with $s' \in \{1, \ldots, S-1\}$. $\mathbf{X}_{pt}$ for hidden state transition probabilities may contain variables associated to patient's health. As discussed previously, these covariates might be related to medical, personal and social factors. Hence, we include $SourcePersPhys_t$, $DischargeNursingFac_t$, $DischargeHomeCare_t$, $Readmission_{t-1}$, LOS_t, $ComorbidityIndex_t$, $InsuranceMedicare_t$, and hospital and patient characteristics[5].

Next is the state dependent outcome which is the readmission event of a patient. The probability that a readmission of a patient will be modeled as a logit model assuming readmission events of a patient are conditionally independent given the patient's health state *s*.

$$\Pr_p(R_t = 1 \mid S_t = s) = \rho_{p,t}^{s} = \frac{\exp(\boldsymbol{Y}_{pt}\delta_s)}{1 + \exp(\boldsymbol{Y}_{pt}\delta_s)}$$

Then;

$$\Pr_p(R_t \mid S_t = s) = \tilde{\rho}_{p,t}^{s} = {\rho_{p,t}^{s}}^{r_t}(1 - \rho_{p,t}^{s})^{1-r_t}$$

Here, $\boldsymbol{Y}_{pt}$ represents the time varying covariates for patient p associated to the readmission event. δ_s is a vector of state specific parameters. In our framework, $\mathbf{Y}_{pt}$ contains $RiskMortality_t$, $NumProc_t$, $NumDiag_t$, LOS_t, $ComorbidityIndex_t$, $InsuranceMedicare_t$, and hospital and patient characteristics. Since readmission event might suggest how severe the patient's condition is, related variables such as risk mortality, number of procedures and diagnoses are included to differentiate readmission process from hidden state transition process.

Finally, we can write the likelihood for patient p as:

$$L_p^T = \sum_{s_1, s_2, \ldots, s_T} \pi_p(s_1) \prod_{t=2}^{T} \tilde{\rho}_{p,t}^{s_t} \, q_{p,t}^{s_t, s_{t-1}} \quad \textbf{(Eq2)}$$

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[5] These variables could also include zipcode based unemployment rate, median household income, number of ambulatory care organizations (outpatient clinics within a specified radius). However, due to a possibility of collinearity among these variables with patient's insurance and demographics information, we did not include these variables as covariates.

One complication about Eq3 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 Eq3 in a matrix products form as suggested by MacDonald and Zucchini (1997):

$$L_p^T = \pi_p \tilde{\rho}_{p,1} Q_{\mathrm{p},1\to2} \tilde{\rho}_{p,2} Q_{\mathrm{p},2\to3} \dots Q_{\mathrm{p,T-1\to T}} \tilde{\rho}_{p,T} 1' \quad \textbf{(Eq3)}$$

where $\tilde{\rho}_{p,t}$ is a $NS \times NS$ diagonal matrix with the elements of $\tilde{\rho}_{p,t}^{s_t}$ on the diagonal, $Q_{\mathrm{p,t-1\to t}}$ is a transition matrix containing the probabilities of $\mathrm{q}_{\mathrm{p,t}}^{\mathrm{s_t,s_{t-1}}}$ for a patient *p* from time *t-1* to *t*, and $1'$ is a $NS \times 1$ vector of 1s.

In developing HMM, number of latent states *NS* is not explicitly given or modeled. To select the number of states, HMM scenarios with different number of states are estimated and each scenario's model fit is calculated for further comparison. There are various model criterions developed to compare the model fit values, e.g., BIC, AIC (Zucchini 2000), each of which should be carefully implemented depending on the model and data structure. Among these, Corrected Akaike Information Criterion (AICc) was first introduced by Hurvich and Tsai (1989) as an alternative selection criterion, which was a version of general Akaike Information Criterion (AIC). AICc was able to correct for small sample bias and shown to perform well in shorter univariate time series, nonlinear regression and autoregression models (Costa and De Angelis 2010; Hurvich et al. 1990). AICc also penalizes greater complexity, i.e., over-fitting, caused by the increased number of parameters and hence values parsimonious models (Bebbington 2007). Lower values of AICc are preferred in model selection. With respect to our model parameters (*nVars*) and number of observations (*nPatients*), AICc is calculated as follows:

$$AICc = -2lnL + 2\frac{nVars * nPatients}{nPatients - nVars - 1}$$

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.

5 RESULTS

We now present our results for Eq1 with the quasi-experimental approach. The Logistic regression estimation results for Eq1 are shown in the second and fourth columns of Table 2 for P&M and S&M datasets respectively.

5.1 DID Results to Test Hypothesis 1a and 1b

We start by explaining the DID results obtained for P&M datasets to test Hypothesis 1a, in which we explore the impact of changing insurance policy from Private to Medicare. Then we continue by showing the DID results obtained for S&M dataset to test Hypothesis 1b, in which we analyze the impact of changing insurance policy from Selfpay to Medicare.

Hypothesis 1a: From Private to Medicare

DID results for the impact of change of insurance from Private to Medicare on Readmission are reported in the second column of Table 2. The coefficient for the interaction term ($Treatment * Post_{it}$) is positive and significant ($\alpha_3 = 0.584, p < 0.10$) suggesting a 79% increase in the odds of readmission for patients switching to Medicare from a private insurance compared to patients who stay on their current private insurance policies. On the other hand, when just the treatment (patients whose insurance types change) and the control (patients whose insurance types stay as private) group of patients are compared, the propensity to be readmitted is significantly lower for the treatment group ($\alpha_1 = -0.746, p < 0.05$). However, pre and post-treatment periods for the whole data sample do not reveal any significant difference with respect to the propensity to be readmitted. In addition, as the operating physician's specialization increases, i.e., different types of procedures performed reduces, patient's readmission risk increases significantly ($\alpha_5 = 1.697, p < 0.05$). Neither operating physician experience nor hospital congestion show a significant association to the propensity of readmission.

The estimates of the interaction term, *Treatment*Post*, obtained from logistic regression suggest that when patients change their insurance policies from private to Medicare, the propensity of readmission increases significantly—supporting Hypothesis 1a.

Hypothesis 1b: From Selfpay to Medicare

The fourth column of Table 2 shows the results of DID estimation for the impact of change of insurance from Selfpay to Medicare on readmission. Accordingly, the coefficient for the interaction term ($Treatment * Post_{it}$) is positive and significant ($\alpha_3 = 0.677, p < 0.10$) suggesting a 97% increase in the odds of readmission for patients switching to Medicare from being a Selfpay patient compared to patients who stay as Selfpay patients. On the other hand, when just the treatment (patients whose insurance types change) and the control (patients whose insurance types stay as Selfpay) group of patients are compared, the propensity to be readmitted is significantly lower for the treatment group ($\alpha_1 = -0.964, p < 0.001$). However, pre and post-treatment periods for the whole data sample do not reveal any significant difference for the propensity to be readmitted. In addition, as the operating physician's specialization increases, i.e., different types of procedures performed reduces, patient's readmission risk increases significantly ($\alpha_5 = 0.848, p < 0.10$). Neither operating physician experience nor hospital congestion shows a significant association to the propensity of readmission. Among control variables, risk mortality is associated to a significant and increasing impact on the readmission propensity, while hospitals with high number of beds are associated to a decreasing effect on the readmission propensity.

The estimates of the interaction term, *Treatment*Post*, obtained from logistic regression suggest that when previously uninsured patients switch to Medicare, the propensity of readmission increases significantly—supporting Hypothesis 1b.

Robustness Check: Survival Analysis

We also wanted to analyze readmission event with a different model set up. Survival analysis has been widely used in biostatistics and management literature due to its effectiveness in leveraging censored data (Fisher and Lin 1999; Helsen and Schmittlein 1993)[6]. Basically, survival analysis models the time it takes for an event to occur, which is going to be the readmission event in our case. Since survival can also be depicted according to the hazard rate, we refer hazard rate, h(t), as the readmission rate of a patient per unit of time in our case, where $h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t<T<t+\Delta t \mid T>t)}{\Delta t}$. Mainly, h(t) models the instantaneous readmission rate that a patient, who is not readmitted by time t, will be readmitted during the infinitesimally small time interval, (t, t+Δt) (Bardhan et al. 2014). We apply one of the most commonly used survival model Cox Proportional-Hazards model to examine the hazard rate of a readmission event (Cox 1972). In a Cox model, where the effects of covariates on hazard rate are present, these effects multiply the hazard rate by a function of the explanatory covariates. If ratio of two observations' hazard rates is calculated, the constant time varying effect diminishes. Therefore, the only effect left to explain the ratio of hazard rates is the one associated to explanatory covariates' (Fisher and Lin 1999). Accordingly, we specify a Cox Proportional-Hazards model to analyze the relationship of $DurationTillNext_{it}$ (time to readmission) to the covariates in Eq2:

$$\log \mathrm{h}_i(t) = \theta(t) + \theta_1 Treatment_i + \theta_2 Post_{it} + \theta_3 Treatment * Post_{it} + \theta_4 OprPsyExperience_{it} + \theta_5 OprPsySpecialization_{it} + \theta_6 HospitalCongestion_{it} + Controls * \theta_c \quad (\mathbf{Eq4})$$

$\mathrm{h}_i(t)$ in Eq2 represents the hazard function of readmission (t as time to readmission or $DurationTillNext_{it}$). $\theta(t)$ represents the baseline hazard rate that depends on time but cancels out during estimation and hence need not be specified functionally.

DID results for the Cox Proportional-Hazard model involving the impact of change of insurance from Private to Medicare on the duration to next admission are reported in the third column of Table 2. The coefficient for the interaction term ($Treatment * Post_{it}$) is positive and significant ($\theta_3 = 1.976, p < 0.001$) suggesting an increase of more than 700% in the hazard rate after patients switch to Medicare from a private insurance compared to patients who stay on their current private insurance policies. For S&M dataset, the coefficient for the interaction term ($Treatment * Post_{it}$) is again positive and significant ($\theta_3 = 1.52, p < 0.01$) suggesting an increase of more than 450% in the hazard rate to be admitted after patients switch to Medicare rather than staying as Selfpay patients. Cox Proportional-Hazard model results for both

[6] Since survival analysis can handle right censored data, just for our case, we don't have to exclude the last admissions of patients due to unavailability of the readmission information. That also means that we can now include patients with at least two observations, rather than three, and keep the last admissions of each patient. As can be seen in Table 2, for survival analysis, we have 691 patients with 1916 observations for the P&M dataset, and 1236 patients with 3908 observations for the S&M dataset.

P&M and S&M present similar results to our logistic regression results and provide evidence to support Hypothesis 1a and 1b.

5.2 HMM Estimation

In this section, we use the P&M dataset to estimate the parameters of HMM, in which we create a new variable to indicate whether patients are privately insured or Medicare beneficiaries (e.g., *InsuranceMedicare* = 1 if patient is a Medicare beneficiary, 0 if privately insured). To start our HMM estimation, initial latent health state distribution has to be provided. We apply 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)[7].

In developing HMM, we didn't specify an exact value for the number of latent health states *NS*. To select the number of states, we simulate HMM scenarios with different number of states and calculate a selection criterion—AICc for each scenario. We report the results of HMM scenarios with different number of states in Table 3. Accordingly, in Table 3, two-state HMM outperforms others with respect to the AICc. 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 hence with the number of variables, the model complexity increases more than twice when NS = 2 is compared to NS = 4 with respect to the number of variables being estimated.

After incorporating the initial state distribution from latent class regression (0.383 and 0.617 for two-states), the HMM estimation results obtained from MLE are reported in Table 4, Table 5, Table 6, and Table 7 where the corresponding standard errors are shown in parentheses. The interpretation of the two states is determined by the state-specific intrinsic propensity to be readmitted at the mean of covariates. Accordingly, the propensity to be readmitted given state 1 is 100% and given state 2 is 0%. We label these two states as "bad" and "good" health states, respectively.

[7] We also run our model including two correlated patient random effects using a non-parametric estimation approach (Singh et al. 2011); one for readmission process, and one for the transition process. However, in each case when the model fit values, AICs, are compared, no-random-effect models gave better results so we continued without expressing random effects. Interested readers can contact authors to obtain the results of random effects model.

Table 2 DID Insurance Policy Change Results

Dataset	**P&M**			**S&M**		
Model	**Eq1**	**Eq2**		**Eq1**	**Eq2**	
Estimation	**Logistic**	**Cox PHR**		**Logistic**	**Cox PHR**	
Dependent Variable	**Readmission**	**Duration**		**Readmission**	**Duration**	
Parameters	**Est (StdErr)**	**Est (StdErr)**	**[Hazard Ratio]**	**Est (StdErr)**	**Est (StdErr)**	**[Hazard Ratio]**
Intercept	-0.213 (1.445)	-	-	-1.835 (1.455)	-	-
Treatment (1 = if P→M or S→M)	-0.746** (0.293)	-0.563*** (0.08)	[0.569]	-0.964*** (0.301)	-0.336*** (0.059)	[0.715]
Post	-0.125 (0.179)	-2.791*** (0.113)	[0.061]	-0.155 (0.114)	-1.98*** (0.06)	[0.138]
Treatment * Post	0.584* (0.324)	1.976*** (0.141)	[7.215]	0.677* (0.4)	1.52*** (0.091)	[4.57]
OprPhysExperience	-0.026 (0.112)	0.087*** (0.031)	[1.091]	-0.048 (0.061)	0.083*** (0.022)	[1.086]
OprPhysSpecialization	1.697** (0.711)	0.504** (0.245)	[1.655]	0.848* (0.47)	0.19 (0.168)	[1.209]
HospitalCongestion	0.367 (0.418)	0.263* (0.15)	[1.301]	-0.191 (0.278)	-0.127 (0.1)	[0.881]
EmergencyAdmission	-0.03 (0.208)	-0.102 (0.074)	[0.903]	0.004 (0.223)	-0.194** (0.081)	[0.823]
RiskMortality	0.189* (0.1)	0.06 (0.039)	[1.062]	0.275*** (0.07)	0.073*** (0.025)	[1.076]
LOS	-0.054 (0.163)	0.028 (0.054)	[1.028]	0.017 (0.115)	-0.003 (0.04)	[0.997]
PtAge	-0.244 (0.386)	0.002 (0.143)	[1.002]	-0.398 (0.289)	-0.097 (0.11)	[0.907]
PtWhite	0.168 (0.261)	0.159 (0.1)	[1.172]	0.135 (0.182)	0.164*** (0.061)	[1.178]
PtFemale	0.172 (0.314)	0.094 (0.112)	[1.098]	0.218 (0.295)	0.07 (0.094)	[1.072]
HsCMI	0.038 (0.146)	-0.024 (0.049)	[0.976]	-0.082 (0.118)	-0.084** (0.038)	[0.92]
HsTeaching	-0.366 (0.276)	-0.166* (0.089)	[0.847]	0.422 (0.32)	-0.075 (0.089)	[0.928]
HsUrban	0.231 (0.17)	-0.173*** (0.063)	[0.841]	-0.185 (0.134)	-0.09** (0.042)	[0.914]
HsBedSize	0.203 (0.179)	0.023 (0.059)	[1.023]	-0.306** (0.13)	-0.021 (0.041)	[0.98]
N obs / N patients	**828 / 305**	**1916 / 691**		**1978 / 636**	**3908 / 1236**	
QIC / -2LogL for PHR	**1038.12**	**16038.56**		**2448.85**	**39137.25**	
QICu / AIC for PHR	**1034.44**	**16070.56**		**2438.53**	**39169.25**	

Standard errors in parentheses.
Hazard ratios are reported inside the brackets for Eq2 estimation
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 HMM Scenario Comparison

Number of States	Log-Likelihood	AICc	Number of Variables
1	-1347.00	2746.428	24
2	**-1300.58**	**2721.976**	**50**
3	-1263.53	2739.853	78
4	-1201.59	2745.084	108

5.3 HMM Results

For any given time period, we can reveal the health state a patient is most likely to observe. 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). 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* condition on the subject's history of readmissions is calculated as:

$$\mathrm{Pr_p}(\mathrm{S_t} = \mathrm{s}|\mathrm{R_1}, \mathrm{R_2}, \dots, \mathrm{R_t}) = \pi_p \tilde{\rho}_{p,1} Q_{\mathrm{p},1\to 2} \tilde{\rho}_{p,2} Q_{\mathrm{p},2\to 3} \dots Q_{\mathrm{p,t-1\to t|s}} \tilde{\rho}^{s}_{p,t} / L^t_p \quad \textbf{(Eq5)}$$

where $Q_{\mathrm{p,t-1\to t|s}}$ is the s[th] column of the transition matrix $Q_{\mathrm{p,t-1\to t}}$ and L^t_p is the likelihood of the observed sequence of readmissions up to time *t*.

After each patient's hidden state is recovered using Eq5, we made a comparison on the mean readmission rates at each health state—bad and good. Results of this comparison are used to test our Hypothesis 2, which stated that readmission rates should differ across health states. In other words, health states impose unobserved heterogeneity in the readmission of patients to hospitals. We present the mean, standard deviation of readmissions per each state in Table 4. Accordingly, difference between the readmission rates of latent states is statistically significant with $p < 0.001$—supporting our hypothesis 2.

Table 4 T-Test for the Readmission-by-State Mean Difference

State	**Bad**	**Good**	*Mean*(Bad – Good) = 0.270 *StdErr*(Bad - Good) = 0.033 $t = 8.28$ with $p < 0.001$
Mean Readmission	0.502	0.232	
StdDev Readmission	0.501	0.423	
N	313	509	

5.4 HMM Results of State Dependent Readmission

Table 5 presents the estimated parameters for the state dependent readmission process. 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. Accordingly, patients in bad health state with high risk mortality (-79.717, p<0.01) have lower readmission propensity in the next admission compared to patients in good health state (129.156, p<0.01), suggesting that risk mortality starts increasing readmission risk as patient's health condition improves from bad to good. Similarly, number of procedures is effective in reducing the readmission propensity if patient is in a bad health state rather than a good health state (-26.628, $p<0.01$ in bad vs 26.822, $p<0.01$ in good). Again, as a patient becomes sicker, i.e., patient's health deteriorates, number of diagnoses starts reducing the readmission propensity (-32.509, $p<0.01$ in bad vs 38.164, $p<0.01$ in good). Therefore the number of procedures and diagnoses help patient to receive better care during hospitalization, which results in reduced readmission risk of the patient. Conversely, LOS increases the readmission propensity if a patient is in bad health state (17.696, $p<0.01$) whereas it reduces the readmission propensity if a patient is in a good health state (-37.044, $p<0.01$). One explanation could be that LOS might increase the probability of hospital-acquired adverse events (Bueno et al. 2010) and might lead to an increase in the readmission rates of patients in bad health state. Yet, patients in good health state might benefit from staying longer in the hospital to have further diagnoses and treatments as well as receive social support from providers that will not be possible after discharge if these patients are unable to reach their family and friends. As a patient becomes sicker and admitted, the known comorbidities are found to increase patient's readmission risk in the next admission (37.613, $p<0.01$ in bad vs -91.511, $p<0.01$ in good). Patients admitted to teaching hospitals with bad health status will have higher propensity to be readmitted in the next admission compared to patients admitted to teaching hospitals with good health status (57.775, $p<0.01$ in bad and -62.479, $p<0.01$ in good). High number of bed size is associated with lower readmission risk if the patient is in a bad health state compared to being in a good health state (-77.935, $p<0.01$). Among patient demographics, being white, female and old comes with an increasing effect on the readmission propensity if patient is in a good health state. In our dataset we only used Medicare and private insurance admissions. To compare the impact of these two insurance types, we check the coefficient of the *InsuranceMedicare* variable. Accordingly, admissions with Medicare insurance type have higher propensity to be readmitted if the patient is in bad health state (96.128, $p<0.01$) relative to patients in good health state. Thus as patients move to a better health state, impact of Medicare insurance on readmission risk reduces.

Table 5 HMM State Dependent Readmission Parameter Estimates

Parameters	Health State 1 (Bad)	Health State 2 (Good)
Constant	68.840*** (18.561)	-159.628*** (43.527)
RiskMortality$_t$	-79.717*** (21.380)	129.156*** (35.191)
NumProc$_t$	-26.628*** (7.130)	26.822*** (7.212)
NumDiag$_t$	-32.509*** (8.394)	38.164*** (10.314)
LOS$_t$	17.696*** (4.453)	-37.044*** (9.630)
ComorbidityIndex$_t$	37.613*** (10.077)	-91.511*** (24.876)
HsTeaching$_t$	57.775*** (14.925)	-62.479*** (17.244)
HsBedSize$_t$	-77.935*** (20.132)	48.481*** (13.476)
PtWhite$_t$	-50.575*** (13.805)	51.973*** (14.033)
PtFemale$_t$	-60.038*** (15.880)	41.221*** (11.453)
PtAge$_t$	-107.926*** (28.722)	121.377*** (32.981)
InsuranceMedicare$_t$	96.128*** (25.565)	-153.923*** (41.669)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All variables are mean 0 centered to reduce the collinearity among variables

5.5 HMM Results of Health State Transitions

Thresholds reported in Table 6 provide the intrinsic propensity to transition from one state to another. Since our model allows patient's health status to move from one state to another, these thresholds guarantee that moving is not free and patients have to incur (or gain) some utility to pass these boundaries. The matrix corresponding to intrinsic propensity to transition is shown in the second and third columns of Table 6 under the heading "No Covariates". Based on this result, we can deduce that patients are moderately stable in their health states, such as staying in good health state is accomplished by 60% of the time whereas staying in bad health state is accomplished by 52.4% of the time. Therefore, once patients are discharged from hospitals, care they receive outside hospital might either worsen (by 40% chance) or improve (by 47.6% chance) their health condition.

Though we present the parameter estimates of the covariates affecting HMM health state transition probabilities in Table A1 in the Appendix, more meaningful insights can be obtained 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—intrinsic propensity to transition matrix in Table 6, heading "Base Transition Matrix". To generate the transition matrices given in Table 6, we plugged in the values of two focal variables, e.g., $Readmission_{t-1}$ and LOS_t, 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. Hence, we were able to calculate the 95% confidence intervals for transition probabilities overall for all of the sample points in our dataset.

Columns four and five of Table 7 under the heading "Base Transition Matrix with Readmissiont-1" show the transition matrix after the previous period's readmission information, $Readmission_{t-1}$, is incorporated into the base transition matrix. If a patient is in bad health state at time t-1 and had a readmission in the previous period then his likelihood of getting into a good health state increases from 47.6% to 48.3% significantly at time t. Similarly, if a patient is in good health state at time t-1 and was readmitted in the previous period then his likelihood of getting into a good health state significantly increases from 60% to 64.5% at time t. Therefore, these results suggest that readmission in the previous period helps patients move to a better health state in the current period, maybe through better inpatient care if outpatient resources and personal capabilities are not sufficient.

We also look at the impact of LOS on the health state transition probabilities. The effect of LOS on the base transition matrix is provided under the heading "Base Transition Matrix with LOS_t" in Table 7. If a patient is in bad health state and had a long LOS at time t-1 then his likelihood of getting into a good health state significantly decreases from 47.6% to 47.3% at time t. Similarly, if a patient is in good health state and had a long LOS at time t-1 then his likelihood of getting into a good health state significantly reduces from 60% to 58.9% at time t. Hence, patients who stay for an excess period of time as an inpatient will tend to have reduced health condition in the next admission. Healthcare literature also suggest that patients with excess LOS are prone to acquiring infections and experiencing injuries during their hospitalizations—posing threats to health condition of the patients (Pittet et al. 1994; Zhan and Miller 2003), which might, of course, come at a cost of readmission.

Table 6 HMM Health State Transition Thresholds—α's

	Health State 1 (Bad)	**Health State 2 (Good)**
Health State 1 (Bad)	0.000	0.097 (0.227)
Health State 2 (Good)	-0.407* (0.237)	0.000

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 HMM Estimation Transition Matrices

	Base Transition Matrix (No Covariates)		Base Transition Matrix with Readmission$_{t-1}$		Base Transition Matrix with LOS$_t$	
t-1 → t	**Bad$_t$**	**Good$_t$**	**Bad$_t$**	**Good$_t$**	**Bad$_t$**	**Good$_t$**
Bad$_{t-1}$	52.4%	47.6%	51.7% [51.6% - 51.8%]	48.3% [48.2% - 48.4%]	52.7% [52.5% - 52.8%]	47.3% [47.2% - 47.5%]
Good$_{t-1}$	40.0%	60.0%	35.5% [34.9% - 36.1%]	64.5% [63.9% - 65.1%]	41.1% [40.5% - 41.7%]	58.9% [58.3% - 59.5%]

95% Confidence interval values are inside the brackets

6 DISCUSSION AND CONCLUSION

In this study, we analyzed the determinants of readmission risk by following a novel conceptual framework. Mainly, we looked into the impact of two non-clinical factors—change of patient's insurance policy and unobserved patient health status— on the readmission risk. These non-clinical factors were discussed in prior studies, however, as of yet, their causal link to readmission has not been established empirically. Thus, we contribute to the overall healthcare literature, as well as the policy debates on whether readmission rates are really a valid measure of the level of quality of care given at hospitals by suggesting that: (1) once a patient's financial liability reduces through a change in patient's insurance policy, patient's readmission risk increases, (2) patient's health condition might worsen after discharge due to medical, personal and social factors which might induce patient to re-visit hospital and possibly increasing patient's readmission.

Our results show that when patients change their insurance policies from private to Medicare, the odds of readmission increases by 79% compared to patients who stay on private insurances. Similarly, patients who switch from selfpay to Medicare experience 97% increase in the odds of readmission relative to patients who are selfpay throughout their admission history. Our robustness check with survival analysis also gave similar results. Accordingly, we find a 700% increase in the hazard rate of admission when patients change their insurance policy from private to Medicare while this increase was 450% for patients switching from selfpay to Medicare. Therefore, this increase in the hazard rate of admission would eventually lead to an increase in the readmission rate. Second part of our study showed that the best model fit was given by a two-state HMM rather than a one-state HMM—no heterogeneity case. We labeled these two hidden states as bad and good health status states. After recovering each patient's health status states, the comparison of the mean readmission rates revealed that patients in bad health status are readmitted significantly higher than patients in good health status. Our result suggested the presence of unobserved patient heterogeneity due to varying levels of health status.

Our main results suggest that there are factors which cannot be controllable or modifiable by the index hospitals after patients are discharged. Hospitals inadvertently admitting patients that soon to be changing their insurance policies or admitting patients that lack medical, personal, and social support outside hospitals would have higher risk of readmitting these patients within 30-days. These hospitals would be penalized by CMS if they had higher than national-average readmission rates. Therefore, it is arguable that policy makers should consider non-clinical factors causally linking to patients' readmission risk, as these findings suggest, hospitals alone do not seem to be the only source of accountability when analyzing the health outcomes of patients.

6.1 Policy Implications

Affordable Care Act (ACA)

The full implementation of ACA has started in the beginning of 2014. ACA will impact various parts of US healthcare system and nation as a whole. Among various implications of ACA, Medicaid expansion will be the most likely to be of importance for both patients and hospitals in the short run (Rosenbaum 2011). With the implementation of ACA, people having incomes at or below 138% of Federal Poverty Level (FPL) will be eligible to enroll in Medicaid, which would then decrease the uninsured population by 16-17 million (Congressional Budget Office [CBO] 2012). In literature and practice, there is lack of evidence on how providers and patients would be affected from this significant increase in the Medicaid population. Nevertheless, our study results on the insurance policy change for patients switching to Medicare, who were uninsured (self-pay) previously, indicate that patients facing with less obstacles in financial eligibility would start using healthcare resources immediately, which is evident from increased readmission rates. Medicaid population expansion due to ACA would also result in higher readmission rates for previously underserved population—uninsured citizens. Therefore, unless necessary precautions are taken, overall healthcare cost and resource utilization would increase in the US in which hospitals would be penalized for uncontrollable readmissions due to patient-specific factors, i.e., lowered financial liabilities.

Accountable Care Organizations (ACO)

ACOs are proposed as a solution to the fragmented nature of the US healthcare system (Berwick 2011). Under the Medicare Shared Savings program, which was established through the Section 3022 of the ACA, providers as part of an ACO will assume the responsibility for the quality and cost of care delivered to a population of patients (Berenson 2010). 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 measured quality improvements and reductions in the rate of spending growth (McClellan et al. 2010). Although there is a big skepticism on the premises of ACOs, i.e., healthcare cost reduction (Crosson 2011; Devers 2009; Fisher and Shortell 2010), we believe that our HMM results reveal supports for an ACO-like-system to achieve reduction in the unnecessary cost through reduced readmission rates. Second part of our study found that a patient's health status is unobservable to the providers, which might lead to an increase in the readmission rate if patient's health was subject to deterioration outside the hospital. Crosson (2011) commented that ACO would encourage healthy behaviors in its patients by preventing and detecting diseases early where possible, and by aggressively managing costly chronic illnesses that would lead to better quality and lower cost. Therefore, if there was a possibility to coordinate and monitor patient's care by various stakeholders in continuum, patient could get timely appointments, visit ambulatory facilities if needed, receive preventive care, and get support before an urge to re-visit an inpatient setting had aroused, which would reduce the readmission rate eventually. In addition, current policies, e.g., CMS's HRRP, acknowledge poor performance as a consequence of individual failure, rather than flawed systems (Fisher and Shortell 2010). Hence, ACOs would establish the platform, where hospitals and various other types of providers would have to share the accountability of care all together. That would also help resolve the uncertainties about whether readmission is a hospital quality metric.

Health Information Technologies (HITs)

Following the non-clinical factors that might be impacting the readmission rate, one other aspect is to understand how coordinated care could leverage the continuum of care of patients and lead to improved quality outcomes, i.e., reduction in readmission rates. In doing so, the dependency of coordinated care on the use of HITs should not be left out. HITs are not only embedded into clinical and diagnostic equipment, but they are also developed to capture, store, process, and communicate timely information to providers with the goal of coordinating the whole healthcare system together with providers and patients (Fichman et al. 2011). For instance, Venkatesh et al. (2011) suggest that e-healthcare systems help patients envision their current and long-term health outside the hospital setting by enabling the communication between providers and patients, and informing patients about diagnoses, tests, and follow-up care. In that regard, Telehealth and/or Telemedicine would resort an important HIT application through establishing communication between patients and providers at a distance. As the U.S. Department of Health and Human Services defines; Telehealth is the use of technology to deliver health care, health information or health education at a distance including teleradiology, continuing professional education and home monitoring. Although there is still a need to empirically reveal the true potential of Telehealth and Telemedicine in terms of their impact on patient's health and quality outcomes at the patient level, some studies suggest that Telehealth may improve care delivered to chronically ill patients, e.g., CHF and COPD, by sending early warning messages of health status deterioration (LaFramboise et al. 2009; Rahimpour et al. 2008; Whitten et al. 2009) and may reduce the rate and cost of readmissions (Finkelstein et al. 2006; Gorst et al. 2014; Myers et al. 2006; Sorknæs et al. 2011). However, Anker et al. (2011) argue that revealing the potential of Telehealth in managing patients with CHF is challenging because of the varying capabilities of Telehealth approaches, as well as varying needs of CHF patients. Hence, the profile of patients, who can potentially benefit from telemedicine, is unknown, and more research is required to uncover the true impact of

Telehealth on patient outcomes (Anker et al. 2011). Although we haven't tested yet, the impact of Telemedicine on patient's health status and readmission is left for future research. We comment that Telemedicine would reduce the readmission risk of patients in bad health status and we would like to reveal this association in the extension of this study.

6.2 Limitations and Future Directions

Our study is subject to a few limitations. First, we studied the patients whose principal diagnoses were 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 should also be controlled for. Second, dataset size could have been increased by obtaining information on private, selfpay and Medicare patients from other geographic regions. However, it was impossible for us to achieve this since DFWHC gathers discharge claims data only from North Texas region hospitals. Third, although we examined the HMM with two patient random effects, we couldn't find an improvement in our model fit measures compared to no random effect case. Future research should incorporate patient random effects.

In future, we would like to assess the importance of using HITs in our HMM framework. Mainly, we would like to observe how telemedicine would impact patient's unobserved health status and subsequently the readmission risk. We believe that telemedicine would have an improving impact on patient's health outside hospitals and therefore would reduce the preventable readmission rates. We are planning on getting hospital level data from HIMSS Analytics on telemedicine. This database is one of the most widely used data sources with respect to the adoption and usage of HIT systems in US hospitals.

7 REFERENCES

American Hospital Association [AHA]. 2013. "Trendwatch Chartbook 2013: Trends in Hospital Financing," AHA.

Anderson, M.A., Clarke, M.M., Helms, L.B., and Foreman, M.D. 2005. "Hospital Readmission from Home Health Care before and after Prospective Payment," *Journal of Nursing Scholarship* (37:1), pp. 73-79.

Anker, S.D., Koehler, F., and Abraham, W.T. 2011. "Telemedicine and Remote Management of Patients with Heart Failure," The Lancet (378:9792), pp. 731-739.

Annema, C., Luttik, M.-L., and Jaarsma, T. 2009. "Reasons for Readmission in Heart Failure: Perspectives of Patients, Caregivers, Cardiologists, and Heart Failure Nurses," *Heart & Lung: The Journal of Acute and Critical Care* (38:5), pp. 427-434.

Arbaje, A.I., Wolff, J.L., Yu, Q., Powe, N.R., Anderson, G.F., and Boult, C. 2008. "Postdischarge Environmental and Socioeconomic Factors and the Likelihood of Early Hospital Readmission among Community-Dwelling Medicare Beneficiaries," *The Gerontologist* (48:4), pp. 495-504.

Bardhan, I.R., Kirksey, K., Oh, J.-h., and Zheng, Z. 2014. "A Predictive Model for Readmission of Patients with Congestive Heart Failure: A Multi-Hospital Perspective," *Information Systems Research* (Fortcoming).

Bebbington, M.S. 2007. "Identifying Volcanic Regimes Using Hidden Markov Models," *Geophysical Journal International* (171:2), pp. 921-942.

Benbassat, J., and Taragin, M. 2000. "Hospital Readmissions as a Measure of Quality of Health Care: Advantages and Limitations," *Archives of Internal Medicine* (160:8), pp. 1074-1081.

Berenson, R. 2010. "Shared Savings Program for Accountable Care Organizations: A Bridge to Nowhere?," *The American journal of managed care* (16:10), p. 721.

Bergstralh, E.J., and Kosanke, J.L. 1995. "Computerized Matching of Cases to Controls," *Mayo Clinic*.

Berwick, D.M. 2011. "Launching Accountable Care Organizations—the Proposed Rule for the Medicare Shared Savings Program," *New England Journal of Medicine* (364:16).

Bindman, A.B., Grumbach, K., Osmond, D., Komaromy, M., Vranizan, K., Lurie, N., Billings, J., and Stewart, A. 1995. "Preventable Hospitalizations and Access to Health Care," *Jama* (274:4), pp. 305-311.

Blomström, M. 1986. "Foreign Investment and Productive Efficiency: The Case of Mexico," *The Journal of Industrial Economics*), pp. 97-110.

Bueno, H., Ross, J.S., Wang, Y., Chen, J., Vidán, M.T., Normand, S.-L.T., Curtis, J.P., Drye, E.E., Lichtman, J.H., and Keenan, P.S. 2010. "Trends in Length of Stay and Short-Term Outcomes among Medicare Patients Hospitalized for Heart Failure, 1993-2006," *Jama* (303:21), pp. 2141-2147.

Camberg, L.C., Smith, N.E., Beaudet, M., Daley, J., Cagan, M., and Thibault, G. 1997. "Discharge Destination and Repeat Hospitalizations," *Medical care* (35:8), pp. 756-767.

Card, D.E., Dobkin, C., and Maestas, N. 2007. *The Impact of Health Insurance Status on Treatment Intensity and Health Outcomes*. RAND.

CMS. 2014. "Readmissions Reduction Program." Retrieved 05/15/2014, 2014, from http://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.html

Congressional Budget Office [CBO]. 2012. "Updated Estimates for the Insurance Coverage Provisions of the Affordable Care Act." Retrieved 11/23/2013, from http://www.cbo.gov/sites/default/files/cbofiles/attachments/03-13-Coverage%20Estimates.pdf

Corrigan, J.M., and Martin, J.B. 1992. "Identification of Factors Associated with Hospital Readmission and Development of a Predictive Model," *Health Services Research* (27:1), p. 81.

Costa, M., and De Angelis, L. 2010. "Model Selection in Hidden Markov Models: A Simulation Study,").

Cox, D.R. 1972. "Regression Models and Life Tables," *JR stat soc B* (34:2), pp. 187-220.

Crosson, F.J. 2011. "The Accountable Care Organization: Whatever Its Growing Pains, the Concept Is Too Vitally Important to Fail," *Health Affairs* (30:7), pp. 1250-1255.

Currie, J., and Gruber, J. 1996. "Health Insurance Eligibility, Utilization of Medical Care, and Child Health," *The Quarterly Journal of Economics* (111:2), pp. 431-466.

Davis, K., Schoen, C., Doty, M., and Tenney, K. 2002. "Medicare Versus Private Insurance: Rhetoric and Reality," *HEALTH AFFAIRS-MILLWOOD VA THEN BETHESDA MA-* (21:6), pp. 11-11.

Deb, P., and Trivedi, P.K. 2002. "The Structure of Demand for Health Care: Latent Class Versus Two-Part Models," *Journal of health economics* (21:4), pp. 601-625.

Devers, K.J. 2009. "Can Accountable Care Organizations Improve the Value of Health Care by Solving the Cost and Quality Quandaries?,").

Donzé, J., Lipsitz, S., Bates, D.W., and Schnipper, J.L. 2013. "Causes and Patterns of Readmissions in Patients with Common Comorbidities: Retrospective Cohort Study," *BMJ: British Medical Journal* (347).

Dorland Health. 2014. "U.S. Readmission Rates Dwarf Foreign Countries, Says Jama." Retrieved 05/15/2014, 2014, from http://www.dorlandhealth.com/dorland-health-articles/u-s-readmission-rates-dwarf-foreign-countries-says-jama

Doyle Jr, J.J. 2005. "Health Insurance, Treatment and Outcomes: Using Auto Accidents as Health Shocks," *Review of Economics and Statistics* (87:2), pp. 256-270.

Dwyer, D.S., and Mitchell, O.S. 1999. "Health Problems as Determinants of Retirement: Are Self-Rated Measures Endogenous?," *Journal of health economics* (18:2), pp. 173-193.

Elixhauser, A., Steiner, C., Harris, D.R., and Coffey, R.M. 1998. "Comorbidity Measures for Use with Administrative Data," *Medical care* (36:1), pp. 8-27.

Emedicine Health. 2014. "Types of Outpatient Services." Retrieved 06.01.2014, 2014, from http://www.emedicinehealth.com/outpatient_services-health/page2_em.htm#Types of Outpatient Services

Ephraim, Y., and Merhav, N. 2002. "Hidden Markov Processes," *Information Theory, IEEE Transactions on* (48:6), pp. 1518-1569.

Ferrer, R.L. 2007. "Pursuing Equity: Contact with Primary Care and Specialist Clinicians by Demographics, Insurance, and Health Status," *The Annals of Family Medicine* (5:6), pp. 492-502.

Fichman, R.G., Kohli, R., and Krishnan, R. 2011. "Editorial Overview-the Role of Information Systems in Healthcare: Current Research and Future Trends," Information Systems Research (22:3), pp. 419-428.

Finkelstein, S.M., Speedie, S.M., and Potthoff, S. 2006. "Home Telehealth Improves Clinical Outcomes at Lower Cost for Home Healthcare," Telemedicine Journal & e-Health (12:2), pp. 128-136.

Fisher, E.S., and Shortell, S.M. 2010. "Accountable Care Organizations: Accountable for What, to Whom, and How," *JAMA* (304:15), pp. 1715-1716.

Fisher, L.D., and Lin, D.Y. 1999. "Time-Dependent Covariates in the Cox Proportional-Hazards Regression Model," *Annual review of public health* (20:1), pp. 145-157.

Forster, A.J., Stiell, I., Wells, G., Lee, A.J., and Van Walraven, C. 2003. "The Effect of Hospital Occupancy on Emergency Department Length of Stay and Patient Disposition," *Academic Emergency Medicine* (10:2), pp. 127-133.

Friedman, B., and Basu, J. 2004. "The Rate and Cost of Hospital Readmissions for Preventable Conditions," *Medical Care Research and Review* (61:2), pp. 225-240.

Fuller, R.L., Atkinson, G., McCullough, E.C., and Hughes, J.S. 2013. "Hospital Readmission Rates: The Impacts of Age, Payer, and Mental Health Diagnoses," *The Journal of ambulatory care management* (36:2), pp. 147-155.

Goodman, D.C., Fisher, E.S., Gittelsohn, A., Chang, C.-H., and Fleming, C. 1994. "Why Are Children Hospitalized? The Role of Non-Clinical Factors in Pediatric Hospitalizations," *Pediatrics* (93:6), pp. 896-902.

Gorst, S.L., Armitage, C.J., Brownsell, S., and Hawley, M.S. 2014. "Home Telehealth Uptake and Continued Use among Heart Failure and Chronic Obstructive Pulmonary Disease Patients: A Systematic Review," Annals of Behavioral Medicine), pp. 1-14.

Gwadry-Sridhar, F.H., Flintoft, V., Lee, D.S., Lee, H., and Guyatt, G.H. 2004. "A Systematic Review and Meta-Analysis of Studies Comparing Readmission Rates and Mortality Rates in Patients with Heart Failure," *Archives of Internal Medicine* (164:21), pp. 2315-2320.

Hamilton, J.D. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica: Journal of the Econometric Society*), pp. 357-384.

Handel, B.R., and Kolstad, J.T. 2013. "Health Insurance for “Humans”: Information Frictions, Plan Choice, and Consumer Welfare," National Bureau of Economic Research.

Hannan, E.L., Racz, M.J., Walford, G., Ryan, T.J., Isom, O.W., Bennett, E., and Jones, R.H. 2003. "Predictors of Readmission for Complications of Coronary Artery Bypass Graft Surgery," *Jama* (290:6), pp. 773-780.

Harris, K.M., and Remler, D.K. 1998. "Who Is the Marginal Patient? Understanding Instrumental Variables Estimates of Treatment Effects," *Health services research* (33:5 Pt 1), p. 1337.

Hasan, O., Meltzer, D.O., Shaykevich, S.A., Bell, C.M., Kaboli, P.J., Auerbach, A.D., Wetterneck, T.B., Arora, V.M., Zhang, J., and Schnipper, J.L. 2010. "Hospital Readmission in General Medicine Patients: A Prediction Model," *Journal of general internal medicine* (25:3), pp. 211-219.

Helsen, K., and Schmittlein, D.C. 1993. "Analyzing Duration Times in Marketing: Evidence for the Effectiveness of Hazard Rate Models," *Marketing Science* (12:4), pp. 395-414.

Hurvich, C.M., Shumway, R., and Tsai, C.-L. 1990. "Improved Estimators of Kullback–Leibler Information for Autoregressive Model Selection in Small Samples," *Biometrika* (77:4), pp. 709-719.

Hurvich, C.M., and Tsai, C.-L. 1989. "Regression and Time Series Model Selection in Small Samples," *Biometrika* (76:2), pp. 297-307.

Joynt, K.E., and Jha, A.K. 2013. "A Path Forward on Medicare Readmissions," *New England Journal of Medicine* (368:13), pp. 1175-1177.

Kangovi, S., Barg, F.K., Carter, T., Levy, K., Sellman, J., Long, J.A., and Grande, D. 2013a. "Challenges Faced by Patients with Low Socioeconomic Status During the Post-Hospital Transition," *Journal of general internal medicine*), pp. 1-7.

Kangovi, S., Barg, F.K., Carter, T., Long, J.A., Shannon, R., and Grande, D. 2013b. "Understanding Why Patients of Low Socioeconomic Status Prefer Hospitals over Ambulatory Care," *Health Affairs* (32:7), pp. 1196-1203.

Kangovi, S., and Grande, D. 2011. "Hospital Readmissions—Not Just a Measure of Quality," *Jama* (306:16), pp. 1796-1797.

Khwaja, A. 2010. "Estimating Willingness to Pay for Medicare Using a Dynamic Life-Cycle Model of Demand for Health Insurance," *Journal of Econometrics* (156:1), pp. 130-147.

Kociol, R.D., Lopes, R.D., Clare, R., Thomas, L., Mehta, R.H., Kaul, P., Pieper, K.S., Hochman, J.S., Weaver, W.D., and Armstrong, P.W. 2012. "International Variation in and Factors Associated with Hospital Readmission after Myocardial Infarction," *JAMA* (307:1), pp. 66-74.

Kumar, A., and Telang, R. 2012. "Does the Web Reduce Customer Service Cost? Empirical Evidence from a Call Center," *Information Systems Research* (23:3-part-1), pp. 721-737.

LaFramboise, L.M., Woster, J., Yager, A., and Yates, B.C. 2009. "A Technological Life Buoy: Patient Perceptions of the Health Buddy," Journal of Cardiovascular Nursing (24:3), pp. 216-224.

Lanza, S.T., Collins, L.M., Lemmon, D.R., and Schafer, J.L. 2007. "Proc Lca: A Sas Procedure for Latent Class Analysis," *Structural Equation Modeling* (14:4), pp. 671-694.

Lasser, K.E., Hanchate, A.D., McCormick, D., Manze, M.G., Chu, C., and Kressin, N.R. 2014. "The Effect of Massachusetts Health Reform on 30 Day Hospital Readmissions: Retrospective Analysis of Hospital Episode Statistics," *BMJ: British Medical Journal* (348).

Levy, H., and Meltzer, D. 2004. "What Do We Really Know About Whether Health Insurance Affects Health," *Health policy and the uninsured*), pp. 179-204.

Lichtenberg, F.R. 2002. "The Effects of Medicare on Health Care Utilization and Outcomes," *Frontiers in health policy research* (5:3).

Long, S.K., and Masi, P.B. 2009. "Access and Affordability: An Update on Health Reform in Massachusetts, Fall 2008," *Health Affairs* (28:4), pp. w578-w587.

MacDonald, I.L., and Zucchini, W. 1997. *Hidden Markov and Other Models for Discrete-Valued Time Series*. CRC Press.

MacKay Altman, R. 2004. "Assessing the Goodness- of- Fit of Hidden Markov Models," *Biometrics* (60:2), pp. 444-450.

Manning, W.G., and Marquis, M.S. 1996. "Health Insurance: The Tradeoff between Risk Pooling and Moral Hazard," *Journal of health economics* (15:5), pp. 609-639.

McCarthy, D., Johnson, M.B., and Audet, A.-M. 2013. "Recasting Readmissions by Placing the Hospital Role in Community Context," *JAMA* (309:4), pp. 351-352.

McClellan, M., McKethan, A.N., Lewis, J.L., Roski, J., and Fisher, E.S. 2010. "A National Strategy to Put Accountable Care into Practice," *Health Affairs* (29:5), pp. 982-990.

McWilliams, J.M., Meara, E., Zaslavsky, A.M., and Ayanian, J.Z. 2007. "Use of Health Services by Previously Uninsured Medicare Beneficiaries," *New England Journal of Medicine* (357:2), pp. 143-153.

McWilliams, J.M., Zaslavsky, A.M., Meara, E., and Ayanian, J.Z. 2003. "Impact of Medicare Coverage on Basic Clinical Services for Previously Uninsured Adults," *JAMA* (290:6), pp. 757-764.

Medicare Payment Advisory Commission. 2011. "Report to the Congress: Medicare Payment Policy," Washington, D.C.

Meltzer, D., Manning, W.G., Morrison, J., Shah, M.N., Jin, L., Guth, T., and Levinson, W. 2002. "Effects of Physician Experience on Costs and Outcomes on an Academic General Medicine Service: Results of a Trial of Hospitalists," *Annals of Internal Medicine* (137:11), pp. 866-874.

Meyer, B.D. 1995. "Natural and Quasi-Experiments in Economics," *Journal of business & economic statistics* (13:2), pp. 151-161.

Mudge, A.M., Kasper, K., Clair, A., Redfern, H., Bell, J.J., Barras, M.A., Dip, G., and Pachana, N.A. 2011. "Recurrent Readmissions in Medical Patients: A Prospective Study," *Journal of Hospital Medicine* (6:2), pp. 61-67.

Myers, S., Grant, R.W., Lugn, N.E., Holbert, B., and Kvedar, J.C. 2006. "Impact of Home-Based Monitoring on the Care of Patients with Congestive Heart Failure," Home Health Care Management & Practice (18:6), pp. 444-451.

Netzer, O., Lattin, J.M., and Srinivasan, V. 2008. "A Hidden Markov Model of Customer Relationship Dynamics," *Marketing Science* (27:2), pp. 185-204.

Novotny, N.L., and Anderson, M.A. 2008. "Prediction of Early Readmission in Medical Inpatients Using the Probability of Repeated Admission Instrument," *Nursing research* (57:6), pp. 406-415.

Parker, J.P., McCombs, J.S., and Graddy, E.A. 2003. "Can Pharmacy Data Improve Prediction of Hospital Outcomes?: Comparisons with a Diagnosis-Based Comorbidity Measure," *Medical care* (41:3), pp. 407-419.

Pittet, D., Tarara, D., and Wenzel, R.P. 1994. "Nosocomial Bloodstream Infection in Critically Iii Patientsexcess Length of Stay, Extra Costs, and Attributable Mortality," *Jama* (271:20), pp. 1598-1601.

Rabiner, L.R. 1989. "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," *Proceedings of the IEEE* (77:2), pp. 257-286.

Rahimpour, M., Lovell, N.H., Celler, B.G., and McCormick, J. 2008. "Patients' Perceptions of a Home Telecare System," International journal of medical informatics (77:7), pp. 486-498.

Retrum, J.H., Boggs, J., Hersh, A., Wright, L., Main, D.S., Magid, D.J., and Allen, L.A. 2013. "Patient-Identified Factors Related to Heart Failure Readmissions," *Circulation: Cardiovascular Quality and Outcomes* (6:2), pp. 171-177.

Rosenbaum, P.R. 1989. "Optimal Matching for Observational Studies," *Journal of the American Statistical Association* (84:408), pp. 1024-1032.

Rosenbaum, S. 2011. "The Patient Protection and Affordable Care Act: Implications for Public Health Policy and Practice," *Public Health Reports* (126:1), p. 130.

Ross, J.S., Mulvey, G.K., Stauffer, B., Patlolla, V., Bernheim, S.M., Keenan, P.S., and Krumholz, H.M. 2008. "Statistical Models and Patient Predictors of Readmission for Heart Failure: A Systematic Review," *Archives of internal medicine* (168:13), pp. 1371-1386.

Shea, S., Misra, D., Ehrlich, M.H., Field, L., and Francis, C.K. 1992. "Predisposing Factors for Severe, Uncontrolled Hypertension in an Inner-City Minority Population," *New England journal of medicine* (327:11), pp. 776-781.

Silverstein, M.D., Qin, H., Mercer, S.Q., Fong, J., and Haydar, Z. 2008. "Risk Factors for 30-Day Hospital Readmission in Patients≥ 65 Years of Age," *Proceedings (Baylor University. Medical Center)* (21:4), p. 363.

Singh, P.V., Tan, Y., and Youn, N. 2011. "A Hidden Markov Model of Developer Learning Dynamics in Open Source Software Projects," *Information Systems Research* (22:4), pp. 790-807.

Sommers, A., and Cunningham, P.J. 2011. "Physician Visits after Hospital Discharge: Implications for Reducing Readmissions," *National Institute for Health Care Reform, Research Brief*:6).

Sorknæs, A.D., Madsen, H., Hallas, J., Jest, P., and Hansen-Nord, M. 2011. "Nurse Tele-Consultations with Discharged Copd Patients Reduce Early Readmissions–an Interventional Study," The clinical respiratory journal (5:1), pp. 26-34.

Starfield, B., Shi, L., and Macinko, J. 2005. "Contribution of Primary Care to Health Systems and Health," *Milbank quarterly* (83:3), pp. 457-502.

Strauss, M.J., LoGerfo, J.P., Yeltatzie, J.A., Temkin, N., and Hudson, L.D. 1986. "Rationing of Intensive Care Unit Services: An Everyday Occurrence," *Jama* (255:9), pp. 1143-1146.

Thalken, M.K. 2014. "4 Steps to Maintaining Communication after Discharge." Retrieved 6/14/2014, from http://www.healthcareitnews.com/blog/4-steps-maintaining-communication-after-discharge

Timms, J., Parker, V.G., Fallat, E.H., and Johnson, W.H. 2002. "Documentation of Characteristics of Early Hospital Readmission of Elderly Patients: A Challenge for Inservice Educators," *Journal for Nurses in Professional Development* (18:3), pp. 136-143.

Tsai, T.C., Joynt, K.E., Orav, E.J., Gawande, A.A., and Jha, A.K. 2013. "Variation in Surgical-Readmission Rates and Quality of Hospital Care," *New England Journal of Medicine* (369:12), pp. 1134-1142.

Venkatesh, V., Zhang, X., and Sykes, T.A. 2011. "“Doctors Do Too Little Technology”: A Longitudinal Field Study of an Electronic Healthcare System Implementation," Information Systems Research (22:3), pp. 523-546.

Vest, J.R., Gamm, L.D., Oxford, B.A., Gonzalez, M.I., and Slawson, K.M. 2010. "Determinants of Preventable Readmissions in the United States: A Systematic Review," *Implementation Science* (5:1), p. 88.

Visser, I. 2011. "Seven Things to Remember About Hidden Markov Models: A Tutorial on Markovian Models for Time Series," *Journal of Mathematical Psychology* (55:6), pp. 403-415.

Weeks, W.B., Lee, R.E., Wallace, A.E., West, A.N., and Bagian, J.P. 2009. "Do Older Rural and Urban Veterans Experience Different Rates of Unplanned Readmission to Va and Non- Va Hospitals?," *The Journal of Rural Health* (25:1), pp. 62-69.

Weissman, J.S., Ayanian, J.Z., Chasan-Taber, S., Sherwood, M.J., Roth, C., and Epstein, A.M. 1999. "Hospital Readmissions and Quality of Care," *Medical care* (37:5), pp. 490-501.

Whittaker, E.T., and Robinson, G. 1967. *The Calculus of Observations: An Introduction to Numerical Analysis*. Dover Publications.

Whitten, P., Bergman, A., Meese, M.A., Bridwell, K., and Jule, K. 2009. "St. Vincent’s Home Telehealth for Congestive Heart Failure Patients," Telemedicine and e-Health (15:2), pp. 148-153.

Wier, L.M., Barrett, M., Steiner, C., and Jiang, H.J. 2011. "All-Cause Readmissions by Payer and Age, 2008,").

Wolfe, B.L., and Behrman, J.R. 1984. "Determinants of Women's Health Status and Health-Care Utilization in a Developing Country: A Latent Variable Approach," *The Review of Economics and Statistics*), pp. 696-703.
Wolinsky, F.D., Overhage, J.M., Stump, T.E., Lubitz, R.M., and Smith, D.M. 1997. "The Risk of Hospitalization for Congestive Heart Failure among Older Adults," *Medical care* (35:10), pp. 1031-1043.
Zekry, D., Loures Valle, B.H., Graf, C., Michel, J.-P., Gold, G., Krause, K.-H., and Herrmann, F.R. 2012. "Prospective Comparison of 6 Comorbidity Indices as Predictors of 1-Year Post-Hospital Discharge Institutionalization, Readmission, and Mortality in Elderly Individuals," *Journal of the American Medical Directors Association* (13:3), pp. 272-278.
Zhan, C., and Miller, M.R. 2003. "Excess Length of Stay, Charges, and Mortality Attributable to Medical Injuries During Hospitalization," *Jama* (290:14), pp. 1868-1874.
Zucchini, W. 2000. "An Introduction to Model Selection," *Journal of Mathematical Psychology* (44:1), pp. 41-61.

APPENDIX

Table A 1 HMM Health State Transition Parameter Estimates

Parameters	Health State 1 (Bad)	Health State 2 (Good)
$SourcePersPhys_t$	-0.192 (0.187)	0.087 (0.260)
$DischargeNursingFac_{t-1}$	-0.091 (0.329)	-0.031 (1.301)
$DischargeHomeCare_{t-1}$	-0.035 (0.707)	-0.090 (0.137)
$Readmission_{t-1}$	0.146 (0.867)	1.140*** (0.390)
LOS_t	-0.126 (0.167)	-0.613*** (0.232)
$ComorbidityIndex_t$	-0.132 (0.132)	0.102 (0.750)
$HsTeaching_t$	-0.162 (0.207)	0.217 (0.766)
$HsBedSize_t$	-0.125 (0.507)	-0.529 (0.546)
$PtWhite_t$	-0.133 (0.151)	-0.640** (0.262)
$PtFemale_t$	0.186 (0.472)	-0.026 (0.511)
$PtAge_t$	0.124 (0.222)	-0.344** (0.159)
$InsuranceMedicare_t$	0.141 (0.706)	0.455* (0.273)

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All variables are mean 0 centered to reduce the collinearity among variables