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Using Administrative Data to Characterize Patterns of End-of-Life Care in Diverse Settings

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Using Administrative Data to Characterize Patterns of End-of-Life Care in Diverse Settings

A dissertation submitted in partial satisfaction of the

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in Health Services

by

Yan Kim

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ABSTRACT OF THE DISSERTATION

Using Administrative Data to Characterize Patterns of End-of-Life Care in Diverse Settings

by

Yan Kim

Doctor of Philosophy in Health Services

University of California, Los Angeles, 2015

Professor Jack Needleman, Chair

End-of-life (EOL) care in the United States is costly, highly fragmented, and uncoordinated. Despite devoting almost one third of all Medicare expenditures to caring for patients during their last year of life, studies have repeatedly shown that the overall quality of care and quality of life at the EOL is poor. In order to provide better quality care at the EOL, it is crucial that we have a solid understanding of how EOL care is provided under our current healthcare system.

This dissertation uses two large administrative datasets to explore and explain variations and patterns in the care patients receive at the EOL and contains three papers. Paper one explores the variations in the use of life-sustaining treatments before death. Paper two examines the impact the organization of our healthcare system has on the use and underuse of hospice services among patients in long-term care hospitals with chronic critical illness. Paper three explores the power of financial incentives in the form of Medicare reimbursements in influencing providers' decision on discharging patients from long-term care hospitals.

In this work, we showed that patterns of care near the EOL are highly variable across subgroups of patients, provider institutions, and geographic regions; and are heavily influenced by financial incentives as well as the supply of healthcare providers. More importantly, this dissertation illustrates the urgent need to develop new and expand on existing data sources with the relevant information required to gain a more in-depth understanding of what is driving the differences in care in order to deliver true patient-centered and family-oriented care near the EOL.

The dissertation of Yan Kim is approved.

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University of California, Los Angeles

2015

DEDICATION

To Ben and Gabriel – the two boys I love more than anything in this world…

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2012 **YS Kim**, I Susanto, CA Lazar, A Zarrinpar, P Eshaghian, MI Smith, R Busuttil, TS Wang. Pneumothorax Ex-vacuo or "trapped lung" in the setting of hepatic hydrothorax. *BMC Pulm Med*. 2012 Dec 17;12(1):78.

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CHAPTER 1

Introduction

In our national debate on raising healthcare costs, no other topic is as controversial, intense, and emotional as the cost near the end-of-life (EOL); largely because death is a deeply personal experience that evokes strong emotions and reactions, but also because the costs of care for the dying consume a disproportionate share of our healthcare expenditures.

Much has been written about the high cost of care during the last year of life: Medicare spends one third of its entire budget on the 5-7% of beneficiaries that die each year; the cost of care during the last year of life accounts for approximately 30% of our total healthcare expenditure; and the average per capita spending for decedents is roughly six times higher than survivors. As a result of the aging population and advances in chronic disease management, these alarming figures are expected to continue to grow and place increasing burdens on the financing of EOL care.

However, despite devoting almost one third of all Medicare expenditures to caring for patients during their last year of life, studies have repeatedly shown that the overall quality of care and quality of life at the EOL is poor. More often than not, patients suffer from pain and other symptoms such as depression and isolation at the EOL; and a significant portion of patients receive overly aggressive treatments that are discordant to their preferences. Furthermore, high intensity treatment at the EOL has not been proven to prolong survival, to improve quality of life, or result in satisfaction for the patients or their families. Finally, there is significant geographic variation in the cost of care near death that is primarily attributed to practice differences and not patient preferences.

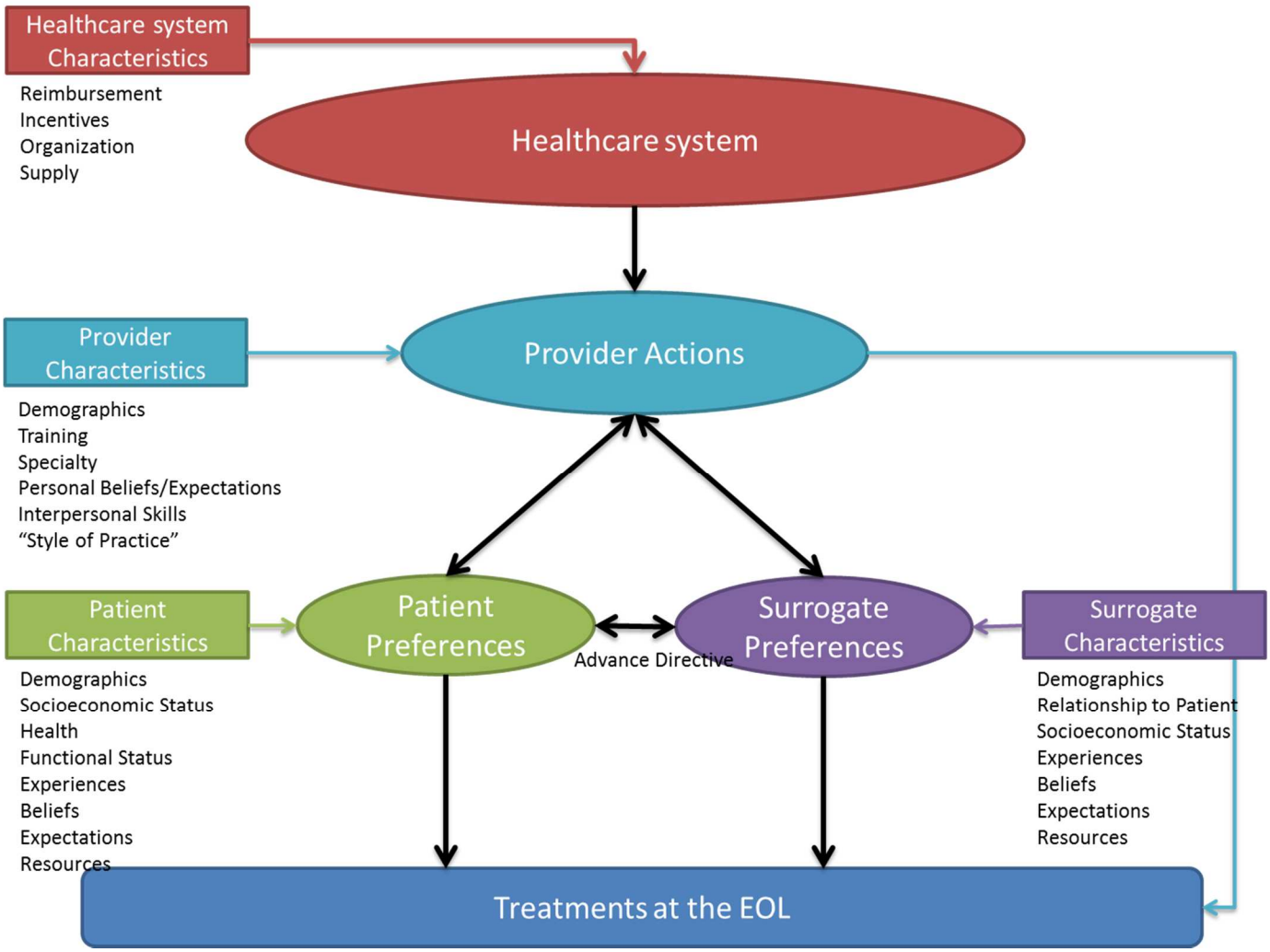
The need to deliver patient-centered and family-oriented care at the EOL is therefore urgent. However, barriers such as structural differences related to the delivery system and misaligned incentives continue to pose great challenges to providing high quality of care near the EOL. The objective of this dissertation is to use administrative data to characterize patterns of care at the EOL in diverse settings in the United States. Through a series of three papers, we aim to show that in addition to the individual patient, much of the care patients receive near the EOL also depends very much on the interaction between the healthcare system, providers, and patients. Therefore, any meaningful improvements in EOL care delivery will require changes to occur on a multitude of levels and stakeholders involved in making and implementing decisions about patient care and in structuring the healthcare environment.

CHAPTER 2

Conceptual Framework

Figure 1 illustrates the conceptual framework on the factors central to the delivery of care at the EOL. The key constructs in this model include patients, patients' surrogate decision-makers, providers, and the healthcare system.

Figure 1. Conceptual Framework on the determinants of treatments patients receive at the end-of-life.



Patients:

Central to the model is patients and their preferences. As the EOL approaches, patients often have to make decisions seeking to balance the desire to avoid death and the trade-offs one is willing to make in order to avoid death. Such preferences are based on specific personal characteristics including demographics, socioeconomic status, health conditions, functional status, social support, availability of resources, understanding of prognosis, expectations, and prior experiences. Patients can leave advance directives to help communicate their preferences through a surrogate decision-maker in the even that they lose decision-making capacity.

Surrogate Decision-makers:

Because many patients are not able to participate in medical decision-making at the EOL, treatment decisions are often deferred to and decided by their surrogate decision-makers. Therefore, although surrogates are asked to make decisions primarily based on their understanding of the patients' values and preferences, preferences of the surrogate are likely to direct impact the treatments patients receive at the EOL. Surrogates' preferences for treatment may also be very different from the patients' preferences and be influenced by the relationship between the surrogate and the patient, responsibilities the surrogate feels towards the patient, the surrogates' understanding of the patients' preferences, the surrogates' own expectations and understanding of the prognosis, and the surrogates' characteristics as well as their own experiences.

Providers and the Healthcare system:

Providers play critical roles in diagnosis, communication, guidance and direction, treatment, negotiation, and advocacy for patients and families/surrogate decision-makers.

Therefore, the actions of the provider can be essential in shaping patients' and their surrogates' expectations and influence the EOL choices they ultimately make. Provider characteristics such as level of training, specialty, communication skills, expectations, and local practice styles are important to consider because they often help shape the way prognosis is communicated and options are presented to patients and their families. Furthermore, providers and their actions can be influenced by various incentives, the environment in which they practice, and the supply of healthcare resources available to them.

Interactions:

Significant interactions between these four key players exist and are depicted using bidirectional arrows in the model. First of all, patients and families/surrogate decision-makers are likely to influence each other's preferences because of the proximity of their relationship to one another. On the next level, the interaction between patients/surrogate decision-makers can influence the providers' actions and recommendations. For example, if the patient had communicated clearly with the provider about his wishes to forgo life-sustaining treatments, the provider may take a stronger stance on recommending palliation. Furthermore, patient and surrogate characteristics may interact with provider actions to influence treatment decisions at the EOL. Finally, the way providers respond to the external pressures (i.e. financial incentives, peer pressure related to local practice norms, and the availability of certain services) can have profound implications on the care patients receive.

The decisions and treatments patients make and receive at the EOL is an extremely complex process and the relationships illustrated by this model are by no means exhaustive. What this model does is to highlight the most significant factors that affect EOL care to provide

a roadmap not only for this dissertation, but for future research to better understand the relationships among these key domains and their impact in our efforts to improve the quality of care patients receive at the EOL.

Structure of the Dissertation:

In this dissertation, we used two unique administrative data sources to examine patterns of care at the EOL. Using Medicare claims data linked to a large, nationally representative survey, Chapter 1 sought to characterize the patterns of life-sustaining treatment (LST) use prior to death and to understand how patients' characteristics (demographics, preferences, and health conditions) might be associated with these patterns of LST use. Chapter 2 uses Medicare claims data alone to examine provider- and regional-level variations in the use of hospice services among patients discharged from long-term care hospitals and conclude that although to better understand the influences providers and the local healthcare environment might have, independent of patient-level factors, on the transition from long-term care hospital to hospice. Chapter 3 also uses Medicare claims data to investigate the power of incentives on dictating practice patterns at long-term care hospitals and show that reimbursement policies indeed have significant influences over how providers practice and the care patients receive.

CHAPTER 3

Trajectories of Life-sustaining Treatment Use during the Last 3 Months of Life

Introduction

Healthcare costs near the end-of-life (EOL) consume a disproportionate share of our total healthcare expenditures,[1-3] and much of it has been attributed to the use of aggressive, high-cost intensive treatments that have not been shown to improve mortality, quality of care, or patients' and bereaved family members' satisfaction. Worse, studies have also suggested that such use of intensive treatments are often inconsistent with patients' goals, values, and stated preferences.[4-7]

Prior research has shown that approximately one quarter of the Medicare decedents receive intensive care unit (ICU) care during the last 6 months of life and among hospitalized older adults, the majority received one or more life-sustaining treatment before they died. However, there is very little population based information regarding the patterns of life-sustaining treatment (LST) use at the EOL. Because preference for the use of LST is a central part of advance care planning, a detailed understanding of how and among whom LST is being used prior to death will provide useful information to help guide patients, families, and providers in making difficult EOL decisions.

In order to better understand the provisions and transitions in the use of LST prior to death, we conducted a study to identify distinct patterns in the use of LST during the last year of life using group-based trajectory modeling, to characterize the patient factors associated with these patterns, and to determine how these patterns might be associated with symptoms at the EOL and cost of care.

METHODS

Patient Sample:

We used data from the Health and Retirement Study (HRS) for participants who died between years of 2002 and 2008. The HRS is a nationally representative longitudinal survey with biennial interview of over 25,000 older adults in the United States.[15] The survey data is linked to Medicare claims for participants who provided their Medicare number and consented to the release of their claims for research purposes. Because Medicare claims are only available for fee-for-service (FFS) enrollees, we excluded patients who were not continuously enrolled in FFS Medicare during the last five years of life. We used data on participants who died through 2008 because those were the most recently available data with Medicare claims linkage.

Life-Sustaining Treatment

We identified the use of LST using *International Classification of Diseases, Ninth Revision, Clinical Modification* procedure (ICD-9) codes from Medicare claims using methodology that has been previously used and validated as measures of treatment intensity at the EOL.[16] These included: intubation and mechanical ventilation (ICD-9 codes 96.04, 96.05, 96.7x), tracheostomy (ICD-9 codes 31.1, 31.21, 31.29), gastrostomy tube insertion (ICD-9 codes 43.2, 43.11, 43.19, 43.2, 44.32), hemodialysis (ICD-9 code 39.95), enteral or parenteral nutrition (ICD-9 codes 96.6 and 99.15), and cardiopulmonary resuscitation (CPR, ICD-9 codes 99.60, 99.63). We calculated the time of LST use to death for each LST procedure by subtracting the start date of the Medicare claim for each LST procedure from the date of death. We counted the number of LST procedures for each patient on a weekly basis during the last 3 months of life (we chose to focus on the last 3 months of life because the data showed that the majority of LST

episodes were initiated during this time). For claims that spanned across multiple weeks, we only used the start date of the claim to calculate the time to death. We assumed that each LST episode ended when the claim episode ended and there were no future claims for the same procedure.

Patient-level Factors Associated with LST use:

Patient-level covariates included: age at time of death (65-74, ≥75-84, and ≥85 years), gender, race (White and non-White), education (<12 years and ≥12 years), marital status (single, married, and widowed), and the presence of an advance directive (AD) or durable power of attorney (DPOA). To understand the impact of medical conditions on the use of LST, we controlled for both a number of pre-existing (diagnosed 1 month prior to death) and newly diagnosed (diagnosed within 1 month of death) medical conditions indicative of major organ system dysfunction by collapsing ICD9 codes from each patient's claims into the following categories: cardiovascular (a composite measure for acute myocardial infarction, congestive heart failure, ischemic heart disease, and atrial fibrillation), respiratory, chronic kidney disease, stroke, dementia, cancer, and hip fracture. We distinguished chronic conditions from newly diagnosed conditions because both have the potential to influence treatment decisions. For example, a previously healthy patient with a new diagnosis of cancer during the last month of life may be more likely to choose aggressive care (including LST) compared to a patient who has been living with cancer and failed curative treatment.

Because it is well documented that there is significant geographic variation in practice patterns, we mapped each patient's zip code at the time of death to hospital referral regions (HRRs). We classified each patient as living in a low-, average-, or high-spending region by

using the average Medicare spending per decedent in the last 6 months of life for each HRR reported by the Dartmouth Atlas of Health Care averaged across the years 2003 to 2007 divided into tertiles.

Cost of Care

We aggregated Medicare payments from individual claims for each patient into monthly and weekly intervals during the last 12 months of life. We converted all payments to 2008 dollars using the consumer price index to account for inflation.

Symptoms at the EOL

We obtained symptoms at the EOL using the exit interviews, which are conducted with the patient's next of kin after the death of the patient. The outcomes of interests were proxy-reported pain (yes/no) and dyspnea (yes/no) during the last year of life.

Statistical Analysis

Group-based Trajectory Modeling:

We used group-based trajectory modeling (GBTM) to identify distinct patterns of LST use during the last year of life using the number of LST procedures on a weekly basis among patients with any LST use during the last year of life. We did not include patients without any LST use in the trajectory analysis to maximize efficiency and the ability of the model to pick up patterns of LST use.

GBTM, while initially developed to predict trajectories of future criminal convictions among adolescents, has gained traction in field such as psychology, sociology, and clinical research over the last decade.[17,18] Instead of assuming that the study population is composed of two or more subgroups, GBTM uses the data to approximate the unknown distribution of patterns and trajectories across the entire study population.[18] Furthermore, GBTM does not consider membership assignment to be absolute but instead determines each individual's probability of belonging to each group simultaneously and assigns membership based on the highest probability.[19] In this study, the number of LST procedure for each participant was modeled as a zero-inflated Poisson distribution using a STATA Plugin developed by Jones and Nagin.[20] We used the Bayesian information criterion (BIC) to test the number of patterns and to determine the best fit for each pattern by varying the number and the order (intercept only, linear, quadratic, or cubic) of each model until the BIC was maximized, according to the specifications and instructions from the model developers.[20,21] Each patient was assigned a probability of belonging to each specific pattern. A probability of 0.9 or higher was considered an excellent fit and a probability of 0.7 or lower was considered a poor fit.[19,22] We chose not to adjust these patterns with any covariates because we wanted the patterns to emerge from the data itself without imposing any assumptions on the specific patient characteristics that could be associated with the different patterns. A more detailed description of the GBTM as it was applied in this study can be found in the technical appendix.

Multivariate Regression:

We used multivariate logistic regression models to evaluate the association between patient-level factors and the likelihood of LST use. Because we wanted to first explore the

differences between those who used LST and those who did not, the dependent variable for our first model was LST use vs. no LST use during the last 3 months of life. We then carried out a secondary multinomial model where the outcome was the four patterns of LST use: early-discontinuation of LST; late discontinuation of LST; terminal LST use; and persistent LST use.

To evaluate the association between the cost of care and the patterns of LST use, we used a generalized linear model with a logit link and Gaussian family to accommodate the skew of cost data. The outcomes of interest were: cumulative costs of care during the last year of life, last 6 months of life, last 3 months of life, and last month of life. Because we wanted to understand the relationship between cost and the initiation and discontinuation of LST, we further broke down the cost data into weekly intervals and modeled the cost during each of the week for the last three months of life as a function of LST pattern, controlling for patient-level differences and geographic variation.

Finally, to understand how each of the patterns of LST use might be associated with symptoms at the EOL, we used multivariate logistic regression to model the differences in proxy-reported pain, the severity of proxy-reported pain, and the presence of dyspnea associated with the patterns of LST use.

Continuous data are summarized using mean (standard deviation) or median (interquartile range) and categorical data as number (%). We conducted all analyses using STATA/SE version 13 (StataCorp; College Station, TX) and considered a p-value ≤ 0.05 to be significant.

RESULTS

Our final sample contained a total of 2,633 respondents from the 2002-2008 HRS who died between the years of 2003 and 2008 with Medicare claims linkage. During the last 12

weeks of life, 450 (17.1%) underwent at least one LST procedure and we identified 4 distinct patterns of LST use (**Figure 1**): early discontinuation of LST (n=60; 13.3%), late discontinuation of LST (n=120; 26.7%), terminal use of LST (n=161; 35.8%), and persistent use of LST (n=109; 24.2%).

The total Medicare payment during the last year of life for this decedent cohort was approximately $106 million. While patients with any LST use during the last 12 weeks accounted for only 18% of the $106 million, the average per-patient spending for patients with any LST use ($66,109 +/- $56,469) was approximately twice the spending compared to patients without LST much higher ($35,152 +/- $35,194) (all in 2008 dollars).

Table 1 contains selected patient characteristics, LST procedures in detail, and place of death associated with each of the patterns of LST use during the last 12 weeks of life. Patients were older in the no LST and early termination of LST groups. Non-White patients were underrepresented in the no LST group. The early LST discontinuation group had the lowest proportion of males. The distribution of other demographics did not differ significantly across groups. Patients with no LST use were more likely to have had an advance directive (AD). Half of the patients in the LST group died in a high-spending region and less than 1 in 5 patients in the terminal LST group died in a low-region. Patients without LST use were least likely to die in the inpatient setting and most likely to die in hospice. However approximate 1 in 7 patients with LST use also died in hospice, including 1 in 4 patients with persistent LST use.

Table 2 shows the distribution of medical conditions by pattern of LST use. Overall, over half of the decedents had at least 3 or more pre-existing medical conditions, regardless of LST use. Patients in the terminal LST group had the highest percentage of patients without any

pre-existing conditions (11.6%). Cardiac, CKD, and stroke were the most common diagnoses during the last month of life among patients with LST use.

Table 3 presents the adjusted odds ratio associated with the use of LST and the discontinuation of LST among those with LST initiated. Increasing age was associated with lower odds of LST use (OR 0.96 for each one year increase in age, 95% CI: 0.94-0.97) and higher odds of discontinuing LST use prior to death (OR 1.03, 95% CI: 1.00-1.05). Being male was associated with higher odds of using LST and discontinuing LST. White race, having an advance directive, and dying in a region with high levels of EOL spending were associated with lower odds of using LST but were not significant predictors in LST discontinuation. Pre-existing cardiac diagnoses, CKD, and stroke were associated with higher odds of LST use; while dementia and cancer were associated with lower odds of LST use. New diagnoses of cardiac conditions, CKD, hip fracture, and stroke had significantly higher odds of LST use. Only the new diagnosis of respiratory conditions was associated with significantly higher odds of LST discontinuation (OR 3.46; 95% CI: 1.26-9.60). Having new diagnoses of CKD and COPD tended to be associated with higher odds of LST discontinuation but failed to reach statistical significance. The remainder conditions (pre-existing and newly diagnosed) did not significantly impact the odds of LST discontinuation.

Table 4 contains the adjusted relative risk ratios associated with each of the patterns of LST use, relative to those without any LST use prior to death. While advance directive was significantly associated with lower odds of LST use, it only appeared to be significant among those with terminal LST use (RRR 0.60, 95% CI: 0.42-0.87). Similarly, dying in a high-spending HRR was only significantly associated with a higher risk of terminal LST use, comparing to dying in a low-spending HRR (RRR 1.80, 95% CI: 1.12-2.87). Newly diagnosed

CKD was associated with higher risk of LST use, regardless of the pattern. Having pre-existing cancer and dementia were associated with lower risk of undergoing terminal LST use.

Figure 2 shows the regression-adjusted predicted total per patient Medicare cost of care during the last year, last 6 months, last 3 months, last 6 weeks, last 1 month, and last 7 days of life by pattern of LST use. The differences in predicted cumulative Medicare expenditures across the patterns of LST use differed significantly depending on the time interval chose. For example, while predicted cumulative Medicare expenditures during the last year of life were similar for patients without any LST use ($35497 +/- 1439) and those with terminal LST use ($35943 +/- 4597); patients with terminal LST use started to having significantly higher costs compared to the no LST group starting at the last 3 months of life, and the difference became larger as time to death decreased, reflecting the fact that most of the difference was driven by the use of LST during the last week of life. Similarly, although patients in the early, late, and persistent LST groups had very different cumulative last year expenditures, their costs started to become more and more similar as death approached.

Table 5 shows the association between the patterns of LST use and proxy-reported symptoms at the EOL. After adjusting for demographics, region, advance directive, and health conditions, proxies of patients in the early discontinuation group were almost twice as likely to report that the patient had experienced pain during the last year of his/her life (OR 1.93, 95% CI: 1.07-3.48), compared to proxies of patients who did not have any LST use. There were no differences in proxy-reported pain for the remainder of the LST patterns and no differences in proxy-reported dyspnea for any of the LST patterns.

DISCUSSION

In this study of decedents from a nationally representative sample, we found that the majority of the patients died without any LST use. Among those who used LST prior to death, we identified 4 distinct patterns: patients who discontinued LST at more than two weeks before death (early discontinuation), patients who discontinued LST at least one week prior to death (late discontinuation), patients who remained on LST throughout the EOL period (persistent LST), and patients who had LST initiated during the last week of life (terminal LST).

Our findings are consistent with prior studies in that younger age, male sex, living a region with high-level of EOL spending, cardiac diagnoses, CKD, and stroke were significantly associated with higher odds of LST use during the last three months of life; while White race, the presence of an AD, preexisting dementia and cancer significantly decreased the odds of LST use. Once LST was initiated, however, only older age, male sex, and being diagnosed with COPD during the last month of life continued to be significant predictors of LST discontinuation. However, the explanatory power of our model to predict LST discontinuation was much reduced, indicating that the process of LST discontinuation, in addition to patient demographics and medical diagnoses, involves complex interactions of patient/surrogate preferences, demographics, and communication between patients and providers regarding prognosis – variables that are not available in large administrative data sources, even with the ability to link to survey information.

More importantly, our study reveals several novel insights with respect to using administrative data to characterize LST utilization and cost at the EOL. First, using trajectory analysis, we were able to describe distinct patterns of LST use at the end of life, while prior studies have primarily focused on examining the differences between patients who used and did not use LST or between patients who had LST initiated then withdrawn. By examining the data

in much smaller time intervals, we showed that it is possible to use administrative data to characterize patterns of LST use in much greater detail than what had been done previously. Moreover, these patterns indicate that not all LST use nearing the EOL is the same, and collapsing all LST use into one category to compare to patients without LST use may lead to inferences that may not hold true for important subgroups or populations. For example, one study using the same data source as ours found that having an advance directive is associated with a 30% reduction in the odds of use LST during the last 6 months of life, which we were able to confirm by grouping all LST use into one category. However, once we took the different patterns of LST use into consideration, the presence of an AD was only significantly associated with reduced use of LST in the terminal LST group – preciously what one would expect because ADs as they exist today primarily focus on whether to resuscitate or intubate. The purpose of this study is not to discredit the importance of ADs or previous research findings, but to highlight the complexity surrounding LST use before death and to encourage investigators to consider different patterns of LST use when characterizing care at the EOL and not simply focus on whether LST was or was not used.

Second, we found that the cost of care on an individual patient level remained relatively stable until the last three months or less of life was reached, the period when the majority of last year's expenses became concentrated, regardless of LST use. This was especially true among the terminal LST group, where the cost was comparable with the group without any LST use until the last week of life when LST was initiated, suggesting that the use of LST in the terminal group was likely precipitated by an unexpected catastrophic event that resulted in death shortly after, in which case the initiation of LST at the time of the catastrophic event was likely entirely appropriate. This level of insight would not have emerged had we not dissected the cost data

down to weekly intervals and is important for two reasons: 1) Cost, especially cumulative cost over an arbitrarily defined time interval prior to death, is not always predictive of treatment intensity. Despite the high cost associated with the use of LST, last year costs are similar among patients with no LST use and terminal LST use and among patients with early and late discontinuation of LST – because cumulative expenditures do not differentiate cost prior to LST initiation from cost during LST use and cost after LST discontinuation; and 2) Intensive and aggressive treatments that occur prior to death are not always inappropriate, and therefore inferences about the value of LST at the EOL need to be put into the context of both the clinical situation and patient preferences.

Third, from the HRS linkage with administrative data, we showed that proxies of patients who had LST discontinued early were more likely to report that patients had suffered from pain during the last year of his or her life. Because the model was not able to determine cause and effect, we were unclear as to whether pain was what had prompted the discontinuation of LST or whether patients who had LST discontinued subsequently failed to receive adequate palliation – neither of which is acceptable. This is a crucial and important finding because adequately addressing and effectively relieving pain should be a top priority for any EOL population, regardless of LST use.

LIMITATIONS

Our study includes several important limitations. One, we relied on the dates provided by Medicare claim to determine the timing of LST use with respect to death and did not have detailed day to day accounting of LST use during the length of the claim. Because there are no ICD9 codes to document LST discontinuation, we assumed that LST ended when the claim

episode ended and when future claims no longer contained any LST procedure codes. Therefore, we could have under-estimated the discontinuation of LST, especially with those who were initiated on LST during the last week of life. Second, we were only able to study patients with continuous enrollment in FFS Medicare and thus our findings are not generalizable to patients enrolled into Medicare Advantage plans. Studies have shown that patients enrolled in Medicare Advantage plans tend to use fewer intensive services at the EOL.[38] Third, although HRS contains detailed survey information, it was only conducted every 2 years and not always reflective of the patients' functional or health status immediately prior to death; therefore we were not able to utilize many of the survey items such as functional or health status to examine their association with the four patterns of LST use beyond basic demographic information, geographic location, and a list of medical conditions and diagnoses.

CONCLUSION

Our study showed that more careful examination of administrative can yield much more useful and clinically relevant information in characterizing the patterns of care at the EOL. After dissecting the data into weekly intervals, we were able to detect four different patterns of LST use – early discontinuation, late discontinuation, terminal, and persistent LST use – details that were not previously described using administrative data. In addition to determining the important patient-level factors associated with these patterns, we found that proxy-reported EOL symptoms differ significantly across different patterns of LST use, although we were not able to show whether the choices patients and their families made regarding LST use were the cause or result of LST use – an important quality of care distinction. Our findings both illustrate the power and the limitation of administrative datasets to understand patterns of LST use at the EOL.

Future efforts should be invested to develop data sources that combine rich clinical information with informative patient-level data to allow investigators to achieve a more concrete understanding of the associations between subject characteristics and patterns of care in order to improve the delivery of patient-centered and family-oriented care at the EOL that honors patients' and their families' preferences.

Figure 1. Patterns of life-sustaining treatment (LST) use during the last 12 weeks of life in weekly intervals. Dotted lines represent 95% confidence intervals for each of the patterns. Patients without any LST use were omitted from this graph.

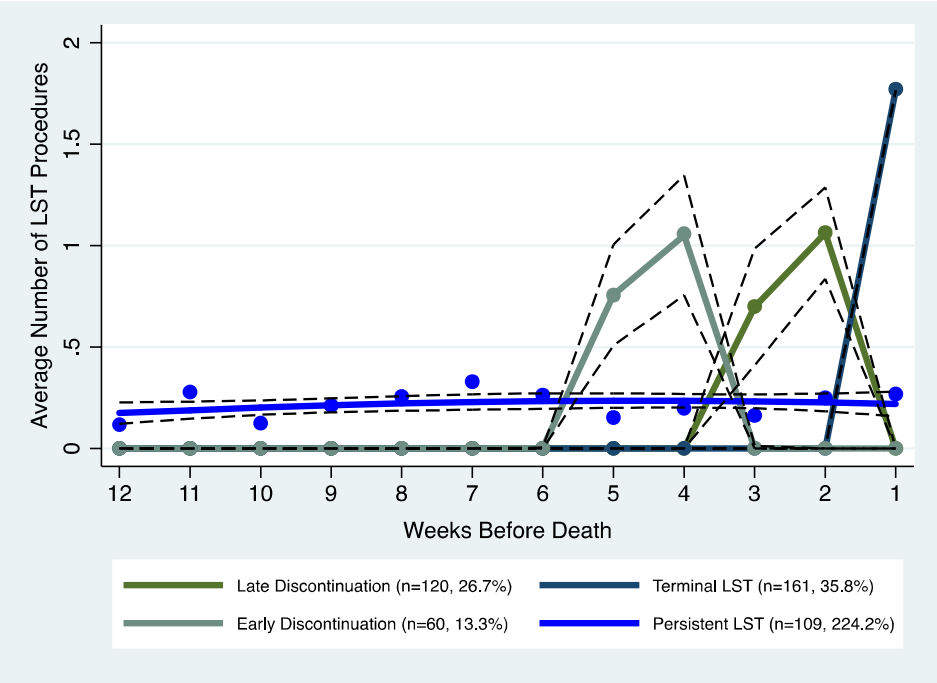


Table 1. Selected patient characteristics and end-of-life (EOL) use by pattern of life-sustaining treatment use.

	No LST	LST			
		Early Discontinuation	Late Discontinuation	Terminal	Persistent
N	2183	60	120	161	109
Age at death*^	83 ±9.2	83 ±9.1	79 ±9.4	79 ±8.8	78 ±9.6
Male*^	1014 (46.5%)	15 (25.0%)	46 (38.3%)	63 (39.1%)	47 (43.1%)
Nonwhite*^	373 (17.1%)	22 (36.7%)	44 (36.7%)	48 (29.8%)	46 (42.2%)
<12yrs education^	889 (40.7%)	28 (46.7%)	61 (50.8%)	67 (41.6%)	50 (45.9%)
Married at time of death^	765 (35.0%)	17 (28.3%)	50 (41.7%)	58 (36.0%)	38 (34.9%)
Widowed^	961 (44.0%)	31 (51.7%)	47 (39.2%)	62 (38.5%)	45 (41.3%)
Not Married or Widowed^	457 (20.9%)	12 (20.0%)	23 (19.2%)	41 (25.5%)	26 (23.9%)
Have Children^	1975 (90.5%	59 (96.7%)	116 (92.6%)	159 (93.0%)	109 (94.0%)
Advance Directive^	1434 (65.7%)	30 (50%)	66 (53.2%)	70 (43.5%)	52 (47.7%)
Region by EOL spending Level*					
Low	595 (27.3%)	14 (23.3%)	26 (21.7%)	28 (17.4%)	22 (20.2%)
Average	774 (35.5%)	22 (36.7%)	42 (35.0%)	63 (39.1%)	30 (27.5%)
High	814 (37.3%)	24 (40.0%)	52 (43.3%)	70 (43.5%)	57 (53.3%)
Place of Death					
Inpatient	747 (34.2%)	36 (60.0%)	86 (71.8%)	157 (97.5%)	67 (61.5%)
Hospice	822 (37.7%)	12 (20.0%)	26 (21.7%)	2 (1.2%)	29 (26.6%)
SNF	187 (8.6%)	11 (18.3%)	6 (5.0%)	0 (0.0%)	14 (12.8%)
LST Use					
Intubation/MV	-	25 (41.7%)	74 (61.7%)	132 (82.0%)	49 (45.0%)
Tracheostomy	-	4 (6.7%)	5 (4.2%)	0 (0%)	15 (13.7%)
Hemodialysis	-	9 (15.0%)	22 (18.3%)	14 (8.7%)	48 (44.0%)
CPR	-	2 (3.3%)	11 (9.2%)	41 (25.5%)	6 (5.5%)
Artificial Nutrition	-	18 (30.0%)	22 (18.3%)	8 (5.0%)	23 (21.1%)
Total Count of LST	-	1.73 +/- 0.9	1.75 +/- 0.9	1.75 +/- 0.7	2.9 +/- 2.0

*p<0.05 across all groups

^ Variables derived from the Health and Retirement Survey

LST: Life-Sustaining Treatment; DPOA: Durable Power of Attorney; AD: Advance Directive; SNF: Skilled Nursing Facility.

Table 2. Medical conditions by pattern of life-sustaining treatment use.

	No LST	LST			
		Early Discontinuation	Late Discontinuation	Terminal	Persistent
N	2183	60	120	161	109
Pre-existing Conditions					
Cardiac	1639 (75.1%)	46 (76.7%)	76 (63.3%)	114 (70.8%)	94 (86.2%)
Dementia	911 (41.7%)	23 (38.3%)	39 (32.5%)	43 (26.7%)	45 (41.3%)
CKD	691 (31.7%)	26 (43.3%)	59 (49.2%)	52 (32.3%)	76 (69.7%)
Respiratory	1011 (46.3%)	32 (53.3%)	61 (50.8%)	66 (41.0%)	66 (60.6%)
Hip Fracture	266 (12.2%)	6 (10.0%)	15 (12.5%)	14 (8.7%)	16 (14.7%)
Depression	881 (40.4%)	24 (40.0%)	48 (40.0%)	63 (39.1%)	49 (45%)
Stroke	759 (34.8%)	19 (31.7%)	42 (35.0%)	56 (34.8%)	56 (51.4%)
Cancer	540 (24.7%)	12 (20.0%)	20 (16.7%)	22 (13.7%)	22 (20.2%)
Total Count of Pre-existing Conditions					
0	113 (5.2%)	0 (0%)	5 (4.2%)	17 (11.6%)	0 (0%)
1 to 2	681 (31.2%)	25 (41.7%)	443 (35.8%)	61 (37.9%)	12 (11.0%)
≥3	1389 (63.6%)	35 (58.3%)	72 (60.0%)	83 (51.6%)	97 (80.0%)
Conditions Diagnosed within Last Month of Life					
Cardiac	221 (10.1%)	8 (13.3%)	34 (28.3%)	29 (18.1%)	14 (12.8%)
Dementia	62 (2.8%)	5 (8.3%)	3 (2.5%)	8 (5.0%)	3 (2.8%)
CKD	160 (7.3%)	12 (20.0%)	23 (19.2%)	27 (16.8%)	12 (11.0%)
Respiratory	58 (2.7%)	6 (10.0%)	8 (6.7%)	4 (2.5%)	3 (2.8%)
Hip Fracture	30 (1.4%)	1 (1.7%)	7 (5.8%)	2 (1.2%)	3 (2.8%)
Depression	35 (1.6%)	2 (3.3%)	1 (0.8%)	3 (1.9%)	0 (0%)
Stroke	70 (3.2%)	8 (13.3%)	11 (9.2%)	19 (11.8%)	5 (4.6%)
Cancer	46 (2.1%)	2 (3.3%)	5 (4.2%)	2 (1.2%)	1 (0.9%)
Total Count of Conditions Diagnosed During Last Month of Life					
0	1677 (76.8%)	28 (46.7%)	61 (50.8%)	91 (56.5%)	78 (71.6%)
1 to 2	490 (22.5%)	32 (53.3%)	54 (45.0%)	67 (41.6%)	30 (27.5%)
≥3	16 (0.73%)	0 (0%)	5 (4.2%)	3 (1.9%)	1 (0.9%)

*$p<0.05$

LST: Life-Sustaining Treatment; CKD: Chronic Kidney Disease.

Table 3. Adjusted odds ratios associated with LST use and LST discontinuation (among those with any LST use).

	LST Use			LST Discontinuation		
	OR	95% CI	p-value	OR	95% CI	p-value
Age	0.96	0.94-0.97	<0.001	1.03	1.00-1.05	0.05
Male	1.84	1.44-2.36	<0.001	1.80	1.13-2.86	0.01
White	0.5	0.38-0.66	<0.001	0.82	0.50-1.35	0.44
Advance Directive	0.77	0.61-0.98	0.04	1.20	0.77-1.86	0.42
Have Children	1.4	0.89-2.12	0.16	1.57	0.66-3.74	0.31
<12 years Education	0.99	0.78-1.26	0.96	1.25	0.79-1.95	0.34
Marital Status						
Married	reference					
Widowed	0.87	0.65-1.16	0.35	0.69	0.40-1.18	0.17
Not Married	0.79	0.58-1.08	0.14	0.61	0.33-1.12	0.11
HRR (by EOL spending Level)						
Low	reference					
Average	1.24	0.92-1.68	0.16	1.06	0.60-1.87	0.84
High	1.5	1.12-2.01	0.01	0.83	0.49-1.42	0.50
New Conditions Diagnosed During Last Month of Life						
Cardiac	2.42	1.52-3.87	<0.001	1.03	0.44-2.43	0.94
Dementia	1.30	0.72-2.33	0.38	0.96	0.34-2.73	0.94
CKD	3.52	2.49-4.98	<0.001	1.65	0.89-3.06	0.11
Respiratory	1.66	0.93-2.96	0.09	3.46	1.26-9.49	0.02
Hip Fracture	3.01	1.47-6.16	0.003	2.83	0.83-9.60	0.10
Stroke	3.67	2.33-5.77	<0.001	1.21	0.59-2.50	0.60
Cancer	0.88	0.42-1.84	0.74	3.09	0.73-13.04	0.12
Chronic Conditions						
Cardiac	1.56	1.04-2.34	0.03	0.60	0.27-1.33	0.21
Dementia	0.71	0.55-0.92	0.01	1.14	0.71-1.83	0.59
CKD	2.38	1.86-3.04	<0.001	1.53	0.94-2.47	0.08
Respiratory	1.20	0.95-1.51	0.12	1.44	0.94-2.21	0.09
Hip Fracture	1.27	0.89-1.81	0.19	0.93	0.48-1.77	0.82
Stroke	1.34	1.05-1.71	0.02	0.75	0.48-1.18	0.22
Cancer	0.69	0.51-0.91	0.01	1.06	0.61-1.84	0.83

LST: Life-Sustaining Treatment; CKD: Chronic Kidney Disease.

Table 4. Relative risk ratios associated with the patterns of LST use, compared to patients with no LST use.

	Early Discontinuation			Late Discontinuation			Terminal			Persistent		
	RRR	95% CI	p-value	RRR	95% CI	p-value	RRR	95% CI	p-value	RRR	95% CI	p-value
Age	1.00	0.96-1.03	0.80	0.96	0.94-0.98	<0.001	0.96	0.94-0.97	0	0.93	0.91-0.95	0.00
Male	3.45	1.79-6.64	0.00	2.18	1.41-3.37	<0.001	1.73	1.19-2.50	0.00	1.32	0.85-2.07	0.22
White	0.41	0.21-0.78	0.01	0.46	0.29-0.73	<0.001	0.67	0.44-1.02	0.06	0.41	0.25-0.66	0.00
Advance Directive	0.80	0.45-1.45	0.47	0.93	0.61-1.42	0.74	0.60	0.42-0.87	0.01	0.94	0.60-1.47	0.80
Children	4.25	0.97-18.6	0.06	1.23	0.56-2.68	0.61	1.23	0.65-2.31	0.53	1.18	0.52-2.68	0.69
<12 years Education	0.93	0.52-1.66	0.80	1.28	0.84-1.95	0.24	0.90	0.63-1.30	0.58	0.90	0.58-1.41	0.66
Marital Status												
Married	ref			ref			ref			ref		
Widowed	0.90	0.45-1.81	0.77	0.61	0.37-1.01	0.06	0.95	0.61-1.48	0.82	1.05	0.62-1.80	0.85
Not Married	0.78	0.35-1.73	0.54	0.52	0.30-0.90	0.02	0.96	0.61-1.51	0.86	0.88	0.50-1.54	0.65
HRR by EOL Spending Level												
Low	ref			ref			ref			ref		
Average	1.10	0.54-2.22	0.79	1.15	0.68-1.93	0.61	1.64	1.02-2.63	0.04	0.93	0.52-1.67	0.81
High	1.04	0.51-2.09	0.92	1.39	0.83-2.32	0.21	1.80	1.12-2.87	0.01	1.57	0.92-2.67	0.10
New Conditions Diagnosed During Last Month of Life												
Cardiac	1.11	0.36-3.49	0.85	3.23	1.49-7.00	0.00	1.95	1.01-3.74	0.05	12.03	1.53-94.55	0.02
Dementia	2.70	0.94-7.78	0.07	0.66	0.19-2.26	0.51	1.47	0.66-3.29	0.35	0.98	0.28-3.48	0.98
CKD	4.15	1.95-8.85	0.00	4.62	2.59-8.25	<0.001	2.70	1.65-4.43	0.00	4.24	2.00-9.00	0.00
Respiratory	5.92	2.15-16.33	0.00	2.20	0.92-5.28	0.08	0.67	0.23-1.96	0.47	1.41	0.40-5.00	0.60
Hip Fracture	1.39	0.18-11.00	0.75	6.27	2.45-16.0	<0.001	1.24	0.28-5.39	0.78	4.27	1.17-15.5	0.03
Stroke	4.93	2.10-11.59	0.00	3.09	1.47-6.50	<0.001	3.82	2.12-6.90	0.00	2.53	0.92-6.93	0.07
Cancer	1.26	0.28-5.77	0.76	1.57	0.58-4.29	0.38	0.52	0.12-2.20	0.37	0.42	0.05-3.20	0.40
Chronic Conditions												
Cardiac	1.17	0.46-3.00	0.74	1.14	0.55-4.29	0.08	1.50	0.87-2.62	0.15	10.11	1.37-74.67	0.02
Dementia	0.91	0.49-1.67	0.75	0.67	0.42-1.05	<0.001	0.56	0.37-0.84	0.01	0.91	0.56-1.45	0.70
CKD	2.34	1.28-4.30	0.01	3.20	2.03-5.03	0.14	1.21	0.83-1.77	0.33	5.11	3.06-8.53	0.00
Respiratory	1.88	1.05-3.36	0.04	1.36	0.90-2.05	0.18	0.82	0.58-1.16	0.26	1.54	1.00-2.63	0.05
Hip Fracture	0.78	0.32-1.91	0.59	1.53	0.83-2.81	0.45	0.96	0.53-1.74	0.89	1.93	1.05-3.53	0.03
Stroke	0.88	0.48-1.62	0.69	1.18	0.77-1.82	0.15	1.36	0.93-1.98	0.11	1.80	1.17-2.79	0.01
Cancer	0.91	0.46-1.79	0.79	0.68	0.41-1.15	0.54	0.51	0.32-0.82	0.01	0.90	0.54-1.50	0.68

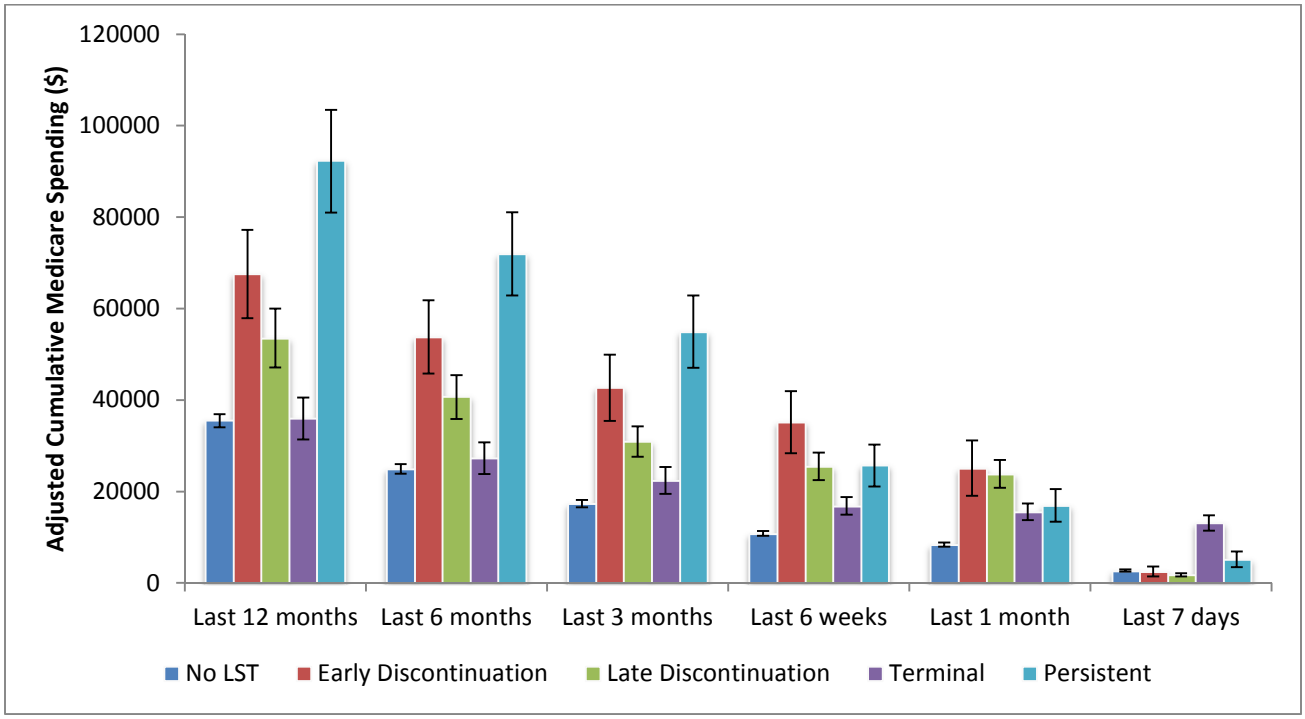
RRR: Relative Risk Ratio; LST: Life-Sustaining Treatment; CKD: Chronic Kidney Disease.

Table 5. The association between patterns of LST use and pain and dyspnea .

	Pain			Dyspnea		
	OR	95% CI	p-value	OR	95% CI	p-value
No LST	*ref*			*ref*		
Early Discontinuation	1.93	1.07-3.48	0.03	0.73	0.42-1.28	0.27
Late Discontinuation	1.26	0.84-1.87	0.27	1.17	0.78-1.73	0.45
Terminal	1.00	0.72-1.41	0.98	0.75	0.53-1.06	0.10
Persistent	1.42	0.92-2.20	0.11	1.33	0.86-2.04	0.20

LST: Life-sustaining Treatment; OR: Odds Ratio; CI: Confidence Interval.
Models adjusted for demographics, geographic region, advance directive, and health conditions.

Figure 2. Regression-adjusted cumulative Medicare spending during different time intervals prior to death (error bars represent 95% confidence interval of the predicted spending).



CHAPTER 3 APPENDIX

Technical Appendix for Group-Based Trajectory Modeling[19]

The Basic Model Concept

Group-based trajectory modeling is an application of a finite mixture models with the conceptual aim of the analysis being able to identify clusters of individuals with similar trajectories or patterns using maximum likelihood estimation (MLE), which are consistent and asymptotically distributed.

In this analysis, the longitudinal sequence of LST procedures for individual i over T periods can be denoted as: $Y_i=\{y_{i1}, y_{i2}, \ldots y_{iT}\}$; and the probability of Y_i is specified as the Poisson distribution for count data. The objective of the model is to estimate a set of parameters, Ω, that maximizes the probability of Y_i, or $P(Y_i)$. GBTM assumes that individual differences in trajectories can be summarized by a finite set of different polynomial functions of time.

Because group membership is not observed, the proportion of the population making up each group j – π_j – is used to form the unconditional probability of the data:

$$P(Yi) = \sum_{j}^{J} \pi_i P^j(Yi)$$

In such that $P(Y_i)$ -- the unconditional probability of observing individual i's longitudinal sequence of LST procedures – equals the sum across the J groups of the probability of Y_i given I's membership in group j weighted by the probability of membership in group j.

Because the number of LST procedures is an example of count data, the model uses the Poisson distribution to model the data. So, for each group j:

$$p^j = \frac{\lambda_{jt}^{y_{it}} e^{-\lambda_{jit}}}{y_{it}!} (y_{it} = 0, 1, 2, \dots)$$

Hence, the probability assigned to each possible outcome depends on the mean rate of occurrence of the event (LST procedures, in this case) in a given group j at each time period t, where the rate is denoted by λ_{jt}. In other words, $\boldsymbol{\lambda_{jt}}$ measures the expected number of LST procedures for each time interval (monthly or weekly), for all individuals belonging to group j at time t. A link function is required to connect the LST trajectory with time and is accomplished by assuming that λ_{jt} varies with time in the following form:

$$\ln(\lambda_t^i) = \beta_0^j + \beta_1^j Time_{it} + \beta_2^j Time_{it}^2 + \beta_3^j Time_{it}^3$$

Model Estimation

The model in the manuscript was estimated using a STATA Plugin, also available as a SAS-based procedure called Proc Traj. Parameters from the link function $\beta_0^j,\ \beta_1^j,\ \beta_2^j, and\ \beta_3^j$ determine the shape of the trajectory or pattern for each group j. Because a separate set of parameters is estimated for each group j, the model allows the shapes of trajectories to vary freely across groups, depending on the values of the βs. For example, when β1 and β2 both equal to zero, the resultant shape is a flat line. When both β1 and β2 are positive, the resultant shape is one that steadily increases over the entire time period. The model allows for the inclusion of intercept-only, linear, quadratic, and cubic terms to specify the shape of each trajectory.

Model Selection

The objective of GBTM is to identify groups of individuals with distinctive individual-level trajectories. Because it uses the finite mixture modeling framework, in fitting such a model, one must first determine the optimal number of such groups to include in the model, and then the shape of each group's trajectory.

The first challenge is to determine how many group to include in this finite mixture model and making valid statistical comparisons about the chosen number of groups. In other words, how can we determine whether J group is superior to J+1 groups? In the context of GBTM, the Bayesian Information Criterion (BIC) is used and the model with the largest BIC is selected. The BIC is calculated as:

$$BIC = \log(L) - 0.5k \log(N)$$

Where L is the value of the model's maximized likelihood; N is the sample size; and k is the number of parameters in the model, which is defined by the order of the polynomial used to model each trajectory and the number of groups. The first component measures the improvement in model fit that is gained by generalizing the model to include more parameters; and the second component of the BIC acts to counteract the gain by placing a penalty for the addition of more parameters. Therefore, the addition of another trajectory group is only desirable if the improvement in fit exceeds the penalty for adding more parameters.

One possibility in GBTM is to try every combination with respect to the number of groups and the shapes for each trajectory group and compare their BICs to choose the one that has the

largest BIC. This strategy can be exhausting because for a 5-group model, there can be 3^5=243 different combinations from order zero (flat) to 2 (quadratic). Therefore, Nagin suggested a 2-step approach when one first chooses the number of groups to include in the model using the same order of the polynomial for each group's trajectory (i.e. all quadratic). Once the optimal number of groups is determined, one can turn to selecting the preferred order of the polynomial that determines the shape of each trajectory.

Using Nagin's recommendations, we fitted the model with 2 to 5 groups and used BIC to select the model with 4 groups. The BICs and the probability of being the correct model for each selected number of groups can be found in **Appendix Table 3**, where the probability that a model with j groups is the correct model from a set of J different models is approximated by:

$$\frac{e^{BIC_j - BIC_{max}}}{\sum_j e^{BIC_j - BIC_{max}}}$$

Once the optimal number of groups is determined, we relied on both substantive theory from clinical experience and BIC to select the final model. While clinical experience suggests using a zero-order polynomial to model a stable chronic trajectory among those with persistent LST use, the actual inclusion of a zero order polynomial caused model to fail. The final model chosen was a 4-group model with quadratic order for each of the groups.

Determining Model Fit

The posterior probabilities are used to both create profiles of the trajectory group members and to assess the quality of the model's fit to the data. The posterior probability is different from the probability of group membership, in such that the probability of membership is the probability

that a randomly chosen individual follows group j's trajectory and this is the basis of how GBTM assigns group membership. The posterior probability of membership is the probability that an individual with a specific profile belongs to a specific trajectory group j. Therefore, the posterior probability can provide an objective basis for assigning individuals to the trajectory group that best matches their profile and the average posterior probability (APP) of assignment for each trajectory group can be used to determine model fit. In the ideal situation, the assignment probability for each individual is 1 and the APP also equals 1. As the certainly of the group assignment based on posterior probability declines, APP also declines. Nagin recommends that APP should be at least 0.7 for all groups; and the higher the APP, the better the model fit. **Appendix Table 4** lists the APP, standard deviation, and range for each trajectory group.

Appendix Table 3. The results of using BIC to select the number of groups to include in the weekly LST model .

Number of Groups	BIC	Probability of Being the Correct Model
2	-2455.58	0.0000%
3	-2351.09	0.0000%
4	-2299.14	99.9999%
5	-2313.27	0.0001%

Appendix Table 4. Average posterior probabilities, standard deviation, and range according to group assignment. A probability of 0.9 or above means excellent fit into that particular group and a probability of 0.7 or below means poor fit.

Assigned Group	APP	Standard Deviation	Min	Max
Early Discontinuation	0.850	0.100	0.730	1.000
Late Discontinuation	0.930	0.049	0.850	1.000
Terminal LST	0.980	0.018	0.960	1.000
Persistent LST	0.999	0.001	0.990	1.000

APP: Average Posterior Probability of assignment; LST: Life-Sustaining Treatment.

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CHAPTER 4

Variations in the Transition from Long-term Care Hospital to Hospice

Introduction:

Long-term acute care hospitals (LTCHs) specialize in caring for medically complex patients with substantial risk of mortality.[1] Most LTCH patients are chronically critically ill, and require mechanical ventilation (MV), prolonged intravenous medications, and/or extensive wound care treatment.[2,3] The number of LTCHs increased from 192 in 1997 to 408 in 2006, reflecting an annual growth of 12%. The total cost of LTCH care spent by Medicare soared from $398 million in 1993 to $5.6 billion in 2011.[2-4] The prognosis of patients admitted to LTCHs is extremely poor, with a one-year mortality of 69.1% for those with MV and 46.2% for those without.[2] Among survivors, many live with severe functional limitations with frequent transitions across care settings.[5,6]

Consideration for how to integrate hospice and palliative care services into LTCHs is urgently needed, given that such care has been shown to improve patient-centered outcomes, help with symptom management at the end-of-life (EOL), and reduce health care spending for America's sickest and most costly patient populations.[7-10] In the LTCH setting, where the majority of the patients die despite the use of aggressive life-sustaining interventions and the cost of care is high,[4,11] hospice and palliative care may be especially valuable because of their focus on the provision of symptom management and facilitation of discussion related to goals of care.[12] Although hospice use in general has increased over time, nothing is known regarding the use of hospice in the LTCH population.[12] We aimed to fill this gap by characterizing patient-related factors and variations at the facility and regional level associated with the transition from LTCH to hospice using data from Medicare.

Methods:

We conducted retrospective, cross-sectional analyses using data from the LTCH Expanded Modified Medicare Provider Analysis and Review (LTCH-MedPAR) files from the years 2008 to 2010. We supplemented the files with the Health Cost Report Information System (HCRIS) for LTCH-specific information such as location, ownership, and size. We used the Dartmouth Atlas (http://www.dartmouthatlas.org) and the Healthcare Indicator Warehouse (http://healthindicators.gov) to obtain the supply of various healthcare providers in each hospital referral region (HRR).

Patient Population

We included all patients discharged from non-government owned LTCHs over the age of 65 and with an identifiable discharge location. We excluded patients under the age of 65 because such patients reflect a very different population based on their eligibility compared to those aged into Medicare and patients from government-owned LTCHs because patients in government-owned LTCHs only represent 10% of all LTCH patients and are very different in terms of diagnoses, characteristics, and prognosis compared to patients admitted to for-profit and nonprofit LTCHs.

Outcome

The primary outcome was discharge to hospice (including both home- and facility-based hospices), compared to other destinations including acute-care hospital, home, skilled nursing facilities (SNF), and death.

Variable Selection

To examine the variations related to the transition from LTCH to hospice, we included patient-, LTCH-, and regional-level variables in the random-effects model. On the patient-level, we included nonclinical factors such as age (65 to 74, 75 to 84, and ≥ 85), sex, and race (White and Non-white) that have been shown to be associated with the use of hospice.[13,14] To control for case-mix and disease severity, we included both the patients' diagnosis-related group (DRG), whether the patient had used any life-sustaining treatment (LST) at the LTCH, and their major comorbidities. Because LTCH patients are heterogeneous in terms of their DRGs, we categorized the DRGs into respiratory failure with MV, respiratory failure without MV, sepsis, skin ulcers, cardiac, renal failure, rehabilitation, and other. We identified the use of LST using *International Classification of Diseases, Ninth Revision, Clinical Modification* procedure (ICD-9) codes from Medicare claims using methodology that has been previously used and validated as measures of treatment intensity at the EOL.[15] These included: intubation and mechanical ventilation (ICD-9 codes 96.04, 96.05, 96.7x), tracheostomy (ICD-9p codes 31.1, 31.21, 31.29), gastrostomy tube insertion (ICD-9p codes 43.2, 43.11, 43.19, 43.2, 44.32), hemodialysis (ICD-9p code 39.95), enteral or parenteral nutrition (ICD-9p codes 96.6 and 99.15), and cardiopulmonary resuscitation (CPR, ICD-9p codes 99.60, 99.63). Because MV can be used in patients outside of DRGs that specify the use of MV, we combined DRG and ICD9 procedure codes containing MV into one variable to indicate the use of MV. Finally, we used ICD9 codes to determine major comorbidities for each patient. These included acute myocardial infarction (AMI), congestive heart failure (CHF), stroke, dementia, chronic obstructive pulmonary disease (COPD), diabetes, liver failure, renal failure, and cancer.

On the LTCH-level, we included ownership (for-profit chain, for-profit non-chain, and nonprofit), census region (Northeast, Midwest, South, and West), location (urban and rural), number of LTCH beds standardized to per 1,000 Medicare decedents in the HRR divided into tertiles (small, medium, large), and market share (percentage of total LTCH beds held by each LTCH in its HRR) in quartiles. On the regional-level, we included the number of ICU beds, non-ICU hospital beds, SNF beds, and number of hospice providers, all standardized to per 1,000 Medicare decedents in the HRR. Finally, we included year dummy variables to account for changes over time.

Statistical Analysis

Because patients are clustered within LTCHs, we used a multivariate logistic regression with random-effects at the LTCH level to model the variations in the probability of being discharged to hospice from LTCH among different LTCHs and regions. We performed a sensitivity analysis by restricting the analysis to patients with cancer diagnoses and without any use of LST who died or were discharged to hospice. We chose the sample of cancer patients without LST use because hospice enrollment is more widely accepted among patients with cancer and patients with LST might be too complex for hospice to properly manage. Assuming that patients discharged to hospice were expected to die but chose to die in a different setting than those who died in LTCHs, this sensitivity analysis allowed us to examine predictors associated with dying in hospice compared to dying in LTCH in a patient population where hospice enrollment is more widely accepted and the barrier of LST was a non-issue. All analyses were performed using STATA 12SE (StataCorp, College Station, TX). The institutional review board at the University of California, Los Angeles approved the study.

Results:

Our final sample included a total of 322,102 LTCHs discharges from 435 LTCHs. Discharged to hospice accounted for 3.6%, compared to 27.3% to home, 40.5% to SNF, 11.8% to acute care hospital, and 16.8% due to death.

Table 1 presents the patient-level characteristics of LTCH patients by discharge location. Overall, patients discharged to hospice were older (30.4% were ≥85), more likely to be White (80%), and more likely to have cancer (16.2%). One quarter of the patients discharged to hospice were admitted to LTCH for respiratory failure without requiring MV. Patients discharged to hospice had a median LTCH LOS of 23 days (interquartile range: 15-34 days) and underwent 2.3 ± 2.1 procedures during their LTCH stay. More than one third of LTCH patients discharged to hospice required at least one type of LST, compared to 17.8%, 32.8%, 45%, and 53.6% among those discharged to home, SNF, acute-care hospital, and died, respectively.

Table 2 shows the patient-level predictors of being discharged to hospice compared to other locations. After controlling for differences at the LTCH- and regional-level, older age (OR 2.12, 95% CI: 2.01-2.23 for patients ≥ age 85 compared to age 65-74) and White race (OR 1.32, 95% CI: 1.25-1.38 compared to nonwhite) remained significant predictors of hospice enrollment upon LTCH discharge. The association between LST use and hospice enrollment at LTCH discharged was mixed: patients requiring HD (OR 1.34, 95% CI: 1.24-1.45) and artificial nutrition (OR 1.42, 95% CI: 1.37-1.54) were significantly associated with hospice enrollment while CPR was not (OR 0.35, 95% CI: 0.27-0.45). MV was not a significant predictor in either direction. Finally, patients with cancer (OR 2.67, 95% CI: 2.52-2.82), stroke (OR 1.17, 95% CI: 1.10-1.24), dementia (OR 1.31, 95% CI: 1.10-1.57), and chronic kidney disease (OR 1.08, 95% CI: 1.01-1.14) were significant predictors of hospice enrollment upon LTCH discharge. Being

admitted to LTCH for rehabilitation (OR 0.82, 95% CI: 0.68-0.99), having COPD (OR 0.89, 95% CI: 0.85-0.93), and diabetes (OR 0.70, 95% CI: 0.66-0.74) were associated with significantly lower odds of being discharged to hospice.

Table 3 shows the LTCH- and regional-level predictors of being discharged to hospice for the entire sample. Patients at for-profit chain LTCHs had 1.24 times the odds (95% CI: 1.01-1.54) of being discharged to hospice compared to patients at nonprofit LTCHs, controlling for everything else in the model. Additionally, patients at LTCHs located in the South (OR 2.31, 95% CI: 1.73-3.09) and the Midwest (OR 1.74, 95% CI: 1.25-2.42) were significantly more likely to transition to hospice compared to patients in LTCHs located in the West. Patients in the largest LTCHs and LTCHs with higher occupancy were significantly less likely to be discharged to hospice. On the regional-level, patients were less likely to be discharged to hospice when there is greater availability of hospital beds and SNF beds in the area.

Table 4 shows the results of the sensitivity analyses on the probability of being discharged to hospice compared to dying in LTCH among patients with cancer and no LST use. In this model, patients at for-profit chain LTCHs were no longer more likely to be discharged to hospice compared to nonprofit LTCHs (OR 1.19, 95% CI: 0.86-1.65). However, we continued to observe similar differences with respect to geographic region and the supply of acute care hospital beds in the area.

Discussion:

Using LTCH-MedPAR data, we found that the rate of transition from LTCH to hospice is only 3.6% with significant variation with respect to LTCH ownership, geographic location, and the supply of alternative providers in the local healthcare market.

To our knowledge, this is the first study to characterize the transition from LTCH to hospice. LTCH patients are among the sickest of the sick in our healthcare system, many of whom die within one year of their initial LTCH admission. The high rate of mortality despite the use of aggressive treatments in this patient population makes providing quality EOL care an important priority to ensure that symptoms are properly managed, patients and their families are supported, and goals of care are clearly communicated between patients and providers.

The results of our study point to several important questions that warrant future investigation. First is how to interpret the 3.6% LTCH to hospice transition rate – is it too low, about right, or high? Examination of data from Healthcare Cost and Utilization Project (HCUP) shows that the rate of hospice discharge from acute care hospitals for patients with similar DRGs as LTCHs are around 2-3% (data not shown), suggesting that a similar proportion of LTCH like patients are discharged to hospice from both LTCHs and acute care hospitals. Although the Medicare Hospice Benefit were designed to ensure that patients in the last 6 months of life have access to high-quality palliative and supportive care, there is evidence to suggest that the current hospice eligibility criteria – the requirement to forgo curative and life-sustaining treatments and the availability of families/caregivers who are comfortable with managing symptoms at home under the supervision of an on-call nurse or physician – may be excluding patients with the greatest need for better EOL care.[16,17] Furthermore, hospices may not be willing or able to provide care to patients with LTCH-level complexity.[18] Patients in LTCHs, due to their poor prognosis and high illness burden, are especially vulnerable. Future studies with more granular patient-level data are needed to better understand and meet the EOL needs of LTCH patients.

Second, several factors may explain the large variations with respect to LTCH ownership and location. Part of this difference related to ownership is likely due to residual confounding,

because after we restricted the sample to patients who went to hospice or died in the LTCH with cancer diagnoses but without the use of LST (the population most likely to enroll into and be accepted to hospice), the difference between for-profit chain and nonprofit LTCHs was no longer significant. In other words, the initial difference between for-profit chain and nonprofit LTCHs may be due to unobserved patient-level differences in such a way that patients admitted to for-profit LTCHs in general may be better hospice candidates compared to patients admitted to nonprofit LTCHs. However, this difference by ownership may also be due to differences in organization or the way providers practice. Future studies are needed to better understand the provision of palliative care in the LTCH setting to ensure that LTCHs are properly incentivized to provide high quality EOL care.

Third, we found that patients admitted to LTCHs in the South and the Midwest had significantly higher odds of being discharged to hospice coincides with areas with the fastest growth of hospice providers,[19] suggesting that access may be a contributing factor in explaining the large variations in hospice enrollment upon discharge from LTCHs. Alternatively, this difference may also be related to differences in regional hospice operations and enrollment criteria, as hospices in the South have the least restrictive enrollment criteria.[18] Although our model was not able to show a significant association between the number of hospice providers in the region and the probability of being discharged to hospice, the relationship between LTCHs and hospice providers is worth further studying, especially when the same parent corporation own or operate both hospices and LTCHs.

Finally, an increase in the availability or higher abundance of hospital and SNF beds in the area were less likely to be discharged from LTCH to hospice. While this may be a spurious finding indicating different EOL practice norms in areas with higher number of healthcare

providers, there is also evidence in the literature supporting that healthcare use is heavily influenced by the availability of providers. Thus, LTCHs may have an easier time with discharging their patients in areas with more hospital and SNF beds and therefore be less motivated to discuss alternatives such as hospice in patients with poor prognosis.

Limitations:

Our study has a number of limitations. First, we used Medicare data and were limited in our ability to adjust for patient-level characteristics and did not have information on patient preferences or social support. Although age, race/ethnicity, and having cancer have been shown to predict hospice use, they only serve as crude proxies. Thus, the variation in hospice use observed among LTCHs could be explained in part by preferences or the lack of caregivers to take care of patients after discharge to hospice. Second, we relied on the discharge location coding to identify patients discharged to hospice and did not have a way to validate hospice enrollment independently using hospice claims because the LTCH data is de-identified and does not allow for linkage with other Medicare data. Third and most important, hospice discharge by itself is not fully indicative of EOL practices at LTCHs. Because many LTCH patients are dependent on life support and extremely complex medically, they may not be able to be discharged to hospice despite preferences for comfort care. Such patients may receive high-quality palliative care and yet be indistinguishable from those who die while receiving aggressive care. Therefore, the results of our study should not be used to compare EOL care performance at LTCHs.

Conclusions:

We found that less than 4% of all LTCH patients transitioned to hospice on LTCH discharge, a number that is low in comparison to the general population but may be in part due to the barriers to enrollment under the current hospice eligibility criteria. We also found substantial variation in being discharged from LTCH to hospice by LTCH ownership, size, occupancy, and geographic location. High quality EOL care can be extremely valuable for LTCH patients in improving symptom control, providing emotional support, and facilitating goals of care discussions to minimize potentially inappropriate care when prognosis remains poor despite maximum medical intervention. Future studies are needed to better understand the preferences and needs of LTCH patients; to examine barriers in accessing and hospice services; and to explore incentives for patients, LTCHs, other acute and post-acute care providers, and hospices to work together to improve EOL care for this patient population.

Table 1. Selected characteristics of LTCH patients by discharge location.

	Hospice	Home	SNF	Acute Care Hospital	Died
N	11681	87880	130387	38049	54105
Age					
65 to 74	3479 (29.7%)	41662 (47.4%)	48336 (37.1%)	17610 (46.3%)	16769 (31.0%)
75 to 84	4656 (39.9%)	31917 (36.3%)	51235 (39.3%)	14709 (38.7%)	21841 (40.4%)
≥ 85	3555 (30.4%)	14301 (16.3%)	30816 (23.6%)	5730 (15.1%)	15495 (28.6%)
Male	5384 (46.1%)	39997 (45.5%)	58117 (44.6%)	19215 (50.5%)	26871 (49.7%)
White	9341 (80.0%)	66505 (75.7%)	97634 (74.9)	28948 (76.1%)	40278 (74.4%)
Clinical Characteristics					
LTCH DRG					
Respiratory Failure with MV	1610 (13.8%)	4544 (5.2%)	19710 (15.1%)	8114 (21.3%)	15264 (28.2%)
Respiratory Failure without MV	2891 (24.8%)	21776 (24.8%)	27113 (20.8%)	6583 (17.3%)	12088 (22.3%)
Sepsis	988 (8.5%)	4964 (5.7%)	9879 (7.6%)	2252 (5.9%)	4839 (8.9%)
Cardiac	758 (6.5%)	8490 (9.7%)	7973 (6.1%)	2738 (7.2%)	2914 (5.4%)
Skin Ulcers	1022 (8.8%)	4735 (5.4%)	10092 (7.7%)	2005 (5.3%)	2718 (5.0%)
Renal Failure	248 (2.1%)	1763 (2.0%)	2418 (1.9%)	815 (2.1%)	965 (1.8%)
Rehab	119 (1.0%)	1474 (1.7%)	1920 (1.5%)	457 (1.2%)	343 (0.6%)
Comorbidities					
Acute MI	514 (4.4%)	4205 (4.8%)	5848 (4.5%)	2281 (6.0%)	3324 (6.1%)
CHF	2510 (21.5%)	21666 (24.7%)	27658 (21.2%)	8198 (21.6%)	12614 (23.3%)
Stroke	1237 (10.6%)	6502 (7.4%)	17300 (13.3%)	3445 (9.1%)	4845 (9.0%)
Dementia	137 (1.2%)	706 (0.8%)	1885 (1.5%)	262 (0.7%)	395 (0.7%)
COPD	2544 (21.8%)	27079 (30.8%)	28545 (21.9%)	7949 (20.9%)	12999 (24.0%)
Diabetes	1617 (13.8%)	22829 (26.0%)	25952 (19.9%)	7342 (19.3%)	7459 (13.8%)
Chronic Kidney Disease	1910 (16.4%)	14813 (16.9%)	19024 (14.6%)	7771 (20.4%)	9768 (18.1%)
Cancer	1892 (16.2%)	7066 (8.0%)	7217 (5.5%)	3273 (8.6%)	8442 (15.6%)
Liver Failure	195 (1.7%)	572 (0.7%)	832 (0.6%)	385 (1.0%)	924 (1.7%)
Charlson Comorbidity Index	1.9 ± 2.1	1.7 ± 1.6	1.5 ± 1.5	1.7 ± 1.6	2.0 ± 2.2
Utilization					
LOS	23 (15-34)	23 (18-29)	28 (22-37)	18 (8-30)	17 (8-30)
Number of Procedures	2.3 ± 2.1	1.6 ± 1.8	2.1 ± 2.0	2.3 ±2.1	2.5 ± 2.1
Types of Procedures					
Any LST	4179 (35.8%)	15652 (17.8%)	42758 (32.8%)	17105 (45.0%)	29024 (53.6%)
CPR	60 (0.5%)	70 (0.1%)	304 (0.2%)	807 (2.1%)	3290 (6.1%)
MV	2033 (17.4%)	5248 (6.0%)	23908 (18.3%)	10595 (27.9%)	21369 (39.5%)
Hemodialysis	1113 (9.5%)	5962 (6.8%)	9692 (7.4%)	4622 (12.2%)	6240 (11.5%)
Artificial Nutrition	1945 (16.7%)	6465 (7.4%)	18139 (13.9%)	6421 (16.9%)	8868 (16.4%)
Other Procedures					
Venous Catheterization	3602 (30.8%)	15934 (18.1%)	31836 (24.4%)	8137 (21.4%)	15675 (29.0%)
Wound Debridement	1080 (9.3%)	6772 (7.7%)	12704 (9.7%)	3118 (8.2%)	3580 (6.6%)

All p-values across all groups <0.05

SNF: Skilled Nursing Facility; LTCH: Long-term Care Hospital; DRG: Diagnosis-Related Group; MV: Mechanical Ventilation; CHF: Congestive Heart Failure; COPD: Chronic Obstructive Pulmonary Disease; LOS: Length of Stay; LST: Life-sustaining treatment; CPR: Cardiopulmonary Resuscitation; HD: Hemodialysis

Table 2. Patient-level predictors associated with being discharged to hospice from LTCH.

	OR	95% CI	p-value
Age			
65-74	*reference*		
75-84	1.45	1.38-1.52	0.00
≥ 85	2.12	2.01-2.23	0.00
Male	0.99	0.95-1.03	0.65
White	1.32	1.25-1.38	0.00
DRGs			
Respiratory Failure without MV	1.32	1.25-1.38	0.00
Cardiac	1.11	1.03-1.21	0.01
Skin Ulcers	1.49	1.38-1.60	0.00
Renal Failure	1.17	1.02-1.21	0.03
Sepsis	1.27	1.18-1.37	0.00
Rehabilitation	0.82	0.68-0.99	0.04
Life-Sustaining Treatment Use			
MV	0.98	0.92-1.03	0.39
CPR	0.35	0.27-0.45	0.00
HD	1.34	1.24-1.45	0.00
Artificial Nutrition	1.45	1.37-1.54	0.00
Comorbidiites			
AMI	0.92	0.84-1.01	0.08
CHF	0.95	0.90-1.00	0.04
Stroke	1.17	1.10-1.24	0.00
Dementia	1.31	1.09-1.57	0.01
COPD	0.89	0.85-0.93	0.00
Diabetes	0.70	0.66-0.74	0.00
Cancer	2.67	2.52-2.82	0.00
Chronic Kidney Disease	1.08	1.01-1.14	0.02

LTCH: Long-term Care Hospital; DRG: Diagnosis-Related Group; MV: Mechanical Ventilation; CPR: Cardiopulmonary Resuscitation; HD: Hemodialysis.

Table 3. Facility- and regional-level predictors associated with being discharged to hospice.

	Adjusted OR	95% CI	p-value
Ownership			
Nonprofit	reference	-	-
For profit Chain	1.24	1.01-1.54	0.05
For profit non-chain	0.85	0.72-1.02	0.08
Geographic Region			
West	reference	-	-
Northeast	0.85	0.56-1.28	0.43
Midwest	1.74	1.25-2.42	0.00
South	2.31	1.72-3.09	<0.001
LTCH size*			
Small	reference	-	-
Average	0.97	1.80-1.17	0.72
Large	0.77	0.61-0.99	0.04
LTCH Market Share			
Quartile 1 (Most Competition)	reference	-	-
Quartile 2	1.05	0.92-1.20	0.45
Quartile 3	1.08	0.92-1.27	0.33
Quartile 4 (Least Competition)	0.89	0.73-1.09	0.26
Regional Supply of Healthcare Resources*			
Supply of ICU beds	1.01	1.00-1.02	0.19
Supply of non-ICU Hospital beds	0.98	0.97-1.00	0.05
Supply of SNF beds	0.98	0.98-0.99	0.00
Supply of Hospice Providers	1.00	1.00-1.00	0.97

* Standardized to per 1,000 Medicare decedents in the Hospital Referral Region.
ICU: Intensive Care Unit; SNF: Skilled Nursing Facility.

Table 4. Facility- and regional-level predictors associated with being discharged to hospice among patients with cancer and without any use of life-sustaining treatments.

	Adjusted OR	95% CI	p-value
Ownership			
Nonprofit	reference	-	-
For profit Chain	1.19	0.86-1.65	0.29
For profit non-chain	0.86	0.64-1.16	0.33
Geographic Region			
West	reference	-	-
Northeast	1.03	0.56-1.90	0.92
Midwest	1.68	1.03-2.73	0.04
South	1.77	1.17-2.68	0.01
LTCH size*			
Small	reference	-	-
Average	0.82	0.62-1.08	0.16
Large	0.83	0.59-1.17	0.29
LTCH Market Share			
Quartile 1 (Most Competition)	reference	-	-
Quartile 2	0.91	0.65-1.28	0.58
Quartile 3	1.06	0.72-1.57	0.76
Quartile 4 (Least Competition)	0.88	0.56-1.39	0.59
Regional Supply of Healthcare Resources*			
Supply of ICU beds	0.98	0.96-0.99	0.02
Supply of non-ICU Hospital beds	0.94	0.92-0.96	<0.001
Supply of SNF beds	0.99	0.98-1.00	0.16
Supply of Hospice Providers	1.00	0.99-1.01	0.48

* Standardized to per 1,000 Medicare decedents in the Hospital Referral Region.
ICU: Intensive Care Unit; SNF: Skilled Nursing Facility.

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CHAPTER 5

The Impact of Medicare Payment Policy on Lengths of Stay in Long-term Care Hospitals

Introduction

Long-term care hospitals are post-acute care facilities that specialize in caring for medically complex patients requiring extended hospital-level care. These patients often require prolonged mechanical ventilation, the administration of multiple and long-term intravenous medications, and/or complex wound care treatments.(1, 2) To be classified and paid as a long-term care hospital under Medicare regulations, these facilities must have an average length of stay of 25 days or greater.(3)

Long-term care hospitals first emerged in the 1980s as a cost-effective alternative for patients who would otherwise require extended care in short-term acute care hospitals.(3) Over time, they have become the fastest growing and highest paid post-acute providers in the Medicare program.(4) From 1993 to 2011, the number of long-term care hospitals increased from 192 to 424, and Medicare expenditures on long-term care hospitals soared from $398 million to $5.6 billion.(1, 5) The rapid growth in volume and cost has attracted much attention from policymakers and resulted in a number of attempts to reform the long-term care hospital payment system. Initially, the growth was attributed to the implementation of Medicare's inpatient prospective payment system, which exempted long-term care hospitals and was believed to have created incentives for short-term acute care hospitals to increase discharges to long-term care hospitals.(6, 7) In 2002, to remedy the situation, the long-term care hospital prospective payment system was implemented.(8) Under this system, payments to long-term care hospitals became set by diagnosis-related group (DRG). Furthermore, because long-term care hospitals were designed to care for patients requiring extended hospital-level care, a short-stay

outlier policy was created to discourage short stays and unnecessary transfers between short-term acute care and long-term care hospitals by reducing payments for long-term care hospital patients who were discharged prior to a DRG-specific short-stay threshold.(9-11) Short-stay outliers are reimbursed at a much lower rate compared to patients whose lengths of stay exceed the threshold, even if the difference in lengths of stay is only one day. For example, while the full long-term care hospital payment for patients with respiratory diagnosis with prolonged mechanical ventilation for 2014 is $80,098, the short-stay outlier payment may only be $30,480.(12)

The Medicare Payment Advisory Commission (MedPAC) have repeatedly expressed concerns that the financial incentives created by the short-stay policy may be influencing long-term care hospitals to base their discharge decisions on whether patients' lengths of stay have exceeded their short-stay threshold, rather than on actual clinical need.(5, 12) This concern was based in part on the observation that the majority of patients with the top two most common DRGs were discharged on or a few days after the short-stay threshold. However, the MedPAC Reports did not take discharge patterns prior to the introduction of the short-stay policy, case-mix, discharge location, or facility-level differences into consideration.

Using Medicare data from before and after the implementation of the short-stay payment policy, we extended the MedPAC analysis to better understand to what degree long-term care hospitals are responding to the financial incentives by keeping patients until after their lengths of stay have exceeded the short-stay threshold. In this paper, we focus on patients with respiratory system diagnosis with prolonged mechanical ventilation (DRG 207) – the most common and one of the most expensive conditions served by long-term care hospitals. To assess long-term care hospitals' responses to the incentives among patients requiring prolonged mechanical ventilation

under DRG 207, we: 1) Compare the distribution of lengths of stay before and after the introduction of the short-stay policy; 2) Examine the strength of the financial incentives of the short-stay threshold by comparing the Medicare reimbursement-to-charge ratios for patients discharged just before and after the threshold; and 3) Examine whether the pattern of waiting to discharge patients differed by discharge destination or long-term care hospital ownership.

We hypothesized that the short-stay policy would have differential impact on lengths of stay by discharge location. Because discharges to home are least likely to be impacted by constraints outside of the discharge facility's control (e.g. the availability of beds on the receiving end for those discharged to skilled nursing facilities or the acuity of the patients for those who need to go back to the short-term acute care hospital); we postulated that the lengths of stay for patients discharged to home would be most likely to be impacted by the short-stay threshold.

We also hypothesized that for-profit long-term care hospitals would be more likely to be influenced by the financial incentives associated with the short-stay threshold compared to nonprofit facilities.

Methods

Data Sources

We used the LTCH PPS Expanded Modified MedPAR files from year 2002 (before short-stay policy) and years 2005-2010 (after short-stay policy). Data from 2003 was not available from the Centers for Medicare and Medicaid Services (CMS) and we excluded 2004 as a transition year. The MedPAR files provide the patient's demographic characteristics, length of stay, charges, Medicare reimbursement, discharge location and status, DRG, and International

Classification of Diseases, Ninth Edition (ICD-9) codes for chronic conditions. We supplemented the MedPAR files with the Health Cost Report Information System (HCRIS), Provider of Service Files, Long-term care Hospital Historical Impact Files, and DRG files to obtain facility-specific information such as ownership and the short-stay threshold for each case.

Patient Sample

Because long-term care hospital patients are heterogeneous in terms of medical need and diagnoses, we limited our sample to patients with respiratory system diagnosis with prolonged mechanical ventilation (DRG 207 for years 2006-2010 and DRG 75 for years 2002 and 2005). We chose this DRG because it is persistently the most common and highest reimbursed DRG.(4, 5) The short-stay threshold for DRG was 29 days for years 2005-2010, so any stays shorter than 29 days would be subject to payment penalties. We excluded: 1) Cases with other/unspecified discharge locations; 3) Cases from government-owned facilities because they operate in a different context compared to other long-term care hospitals; 4) Influential outliers such as those with lengths of stay >95th percentile for DRG 207 (60 days); 5) Cases under age 65; 6) Cases ineligible for Medicare reimbursement; and 7) Cases with any missing data.

From 2002 and 2005-2010, a total of 949,196 cases were discharged from 499 LTCHs, and 100,417 (11 percent) belonged to DRG 207. After applying our exclusion criteria, our final sample contained 55,840 discharges from 444 LTCHs. Thirty-three percent of the discharges were due to death, followed by discharges to skilled nursing facility (32 percent), short-term acute care hospital (24 percent), and home (11 percent). Details on sample determination are in Appendix Exhibit A1.(13)

Statistical Analysis

We first graphed the distribution of length of stay by discharge location and by year. To show the relative change in Medicare reimbursement with respect to charges to ensure that the changes in reimbursements were not related to simultaneous increases in expenses, we constructed a Medicare reimbursement-to-charge ratio by dividing the Medicare reimbursement amount by Medicare covered charges for each case and graphed the average reimbursement-to-charge ratio for each length of stay by year.

To model the relationship between reimbursement-to-charge ratios and whether the discharge occurred before, on, or after the short-stay threshold, we used multivariate linear regression and applied fixed effects to control for unobserved heterogeneity at the facility level. We estimated separate models for discharges that occurred before the short-stay policy and those that occurred after to compare the change in reimbursement-to-charge ratios as a result of the short-stay policy. The models were also stratified by discharge location.

To model the differences in discharge timing with respect to the short-stay threshold, we used a multinomial logistic regression model. The outcome was a categorical variable indicating when the discharge took place with respect to the short-stay threshold. This variable consists of 9 categories – starting from discharges during the week before the threshold, to discharges on the day of the threshold, followed by discharges that happened on day 1, 2, 3, 4, 5, 6, and 7 after the threshold. This model thus estimates the relative risk ratio of the risk associated with being discharged on the day of the threshold and on each day after the threshold (up to day 36) to the risk associated with being discharged before the threshold, among patients with prolonged mechanical ventilation discharged after implementation of the short-stay policy relative to before. More details about the regression models and the full model outputs are provided in the appendix.(13)

We limited the sample to patients with lengths of stay of 22-36 days (one week before and after the threshold) in both regression models because discharges within this window are believed to best represent those that could reasonably have taken place either before or on/after the threshold. The models were adjusted for patient-level differences including age (65-74, 75-84, and ≥85); sex; race (White and nonwhite); and comorbidities (stroke, cancer, lung disease, heart failure, liver disease, renal disease, and diabetes). Incorporating fixed-effects prevented the inclusion of other facility-specific information in the model on reimbursement-to-charge ratio. Because fixed-effects cannot be performed with multinomial logistic models, we controlled for facility-level differences including size (small, average, and large), geographic region (Northeast, Midwest, South, and West), and ownership (for-profit and nonprofit) in the timing of discharge model.

Finally, we estimated the cost to Medicare associated with delaying discharges among patients with prolonged mechanical ventilation discharged between days 22 and 36. We first estimated the percent of expected charges by assuming that discharges otherwise would be evenly distributed by lengths of stay, then subtracted the percent expected from the percent of observed discharges, and multiplied it by the total number of patients to obtain the number affected. The excess cost was obtained by multiplying the number of patients affected by the average reimbursement differential associated with crossing the threshold. More details are provided in Section A6 of the Appendix.(13)

We conducted two sensitivity analyses. One, we performed the same detailed analyses for patients admitted with skin ulcers (DRGs 592 and 593). We chose skin ulcers because they are among the top most common DRGs but with a much lower average DRG price tag ($32,434) compared to patients requiring prolonged mechanical ventilation ($73,289) to test whether the

financial incentives created by the short-stay policy extended beyond the highest reimbursed DRGs.(14) Second, we graphed the distribution in lengths of stay for all patients across all DRGs to visually confirm the concentration of discharges on and immediately after the short-stay threshold applied to all long-term care hospital discharges after the short-stay payment policy went into effect. Further details regarding our sensitivity analyses are provided in Section A5 of the Appendix.(13) We used STATA/12SE (StataCorp, College Station, TX) for all statistical analysis.

Limitations

Our study has several limitations. First, while we controlled for age, sex, race, and comorbidity burden, the differences in the timing of discharge could have resulted in part from unobserved factors such as patient preferences and medical needs that we were not able to capture using administrative data. Second, although we examined the impact of the short-stay policy by ownership, because the existing data did not allow us to distinguish freestanding long-term care hospitals from facilities that are co-located within short-stay acute care hospitals (hospital within hospital), we could not examine whether variations in the response to the short-stay payment incentives existed across these two different facility structures unique to long-term care hospital providers. Third, we limited our primary analysis to one single DRG. However, our sensitivity analyses using a second DRG and across all DRGs show that the results were comparable.

Results

Exhibit 1 shows the lengths of stay distribution for patients requiring prolonged mechanical ventilation before and after the short-stay policy was introduced. The vertical axis crosses at the short-stay threshold of 29 days. In 2002, before the short-stay policy, the lengths of stay were evenly distributed evenly without any noticeable spikes. In 2005-2010, we noticed a significant shift in lengths of stay in such that very few cases were discharged before the short-stay threshold and a substantial increase in the percent of discharges was seen on and immediately following the threshold. When graphed by discharge location (Appendix Exhibit A2)(13), discharges to home, skilled nursing facility, and short-term acute care hospital all showed a significant increase in the percent of discharges on or immediately after the threshold was met, whereas discharges due to death did not.

Exhibit 2 shows the average per case Medicare reimbursement-to-charge ratio by length of stay for patients requiring prolonged mechanical ventilation before and after the short-stay policy. The vertical line crosses at the short-stay threshold of 29 days. A sharp and large increase in reimbursement-to-charge ratio was seen on the day of the threshold and slowly declined as length of stay lengthened.

Exhibit 3 shows the adjusted average predicted Medicare reimbursement-to-charge ratios for patients requiring prolonged mechanical ventilation for discharges during the week before, on, and during the week after the short-stay threshold. Before the short-stay policy, reimbursement-to-charge ratios were similar across these three different discharge periods. After the short-stay policy was introduced, the reimbursement-to-charge ratios became significantly higher for discharges occurring on the day of and during the week following the short-stay threshold, compared to discharges during the week before the threshold.

Exhibit 4 presents the adjusted relative risk ratios of the risk of being discharged on each day starting from the day of the threshold up to 7 days after the threshold over the risk of being discharged before the threshold, after the short-stay policy relative to before, among patients requiring prolonged mechanical ventilation. For all discharges except deaths, there was a substantial increase in the risk of being discharged on and immediately after the threshold. The relatively flat line hovering around a relative risk ratio of one for discharges due to death indicates that the short-stay threshold did not impact the lengths of stay for patients who died.

Compared to the expected percent of discharges, discharges among patients with prolonged mechanical ventilation to home, skilled nursing facility, and acute care hospital had an excess of 24 percent, 35 percent, and 16 percent, respectively, of discharges that took place on or after the threshold. This translated into an excess of $164 million in Medicare reimbursements to long-term care hospitals for DRG 207 alone. Impacts of similar magnitudes are seen among patients with skin ulcers, with $60 million in excess reimbursements. Details on these calculations and assumptions are provided in Section A6 of the Appendix.(13)

Discussion

Using Medicare data, we found evidence that the timing of discharge for long-term care hospital patients requiring prolonged mechanical ventilation is strongly influenced by financial incentives brought on by the short-stay payment policy, at a high cost to Medicare. After the short-stay payment policy went into effect, discharges swiftly became heavily concentrated on and immediately after the day of the short-stay threshold, corresponding to the period when the reimbursements are highest and the reimbursement-to-charge ratio is the most favorable.

Our findings confirm and amplify the original MedPAC analysis by showing that changes in lengths of stay and discharge patterns for patients requiring prolonged mechanical ventilation are directly related to implementation of the short-stay policy under the long-term care hospital prospective payment system and the large financial implications created by the short-stay threshold, and not as a result of patient-level differences (Appendix Exhibit A4).(13)

Furthermore, by examining lengths of stay by discharge location and by ownership, with a different DRG (Appendix Exhibit A5-A8)(13), and across all DRGs (Appendix Exhibit A9)(13), we showed that the responses to the incentives are similar across all long-term care hospitals regardless of ownership (Appendix Exhibit A3)(13) and for all patients discharged alive, even after accounting for patient- and facility-level differences.(13)

The fact that we did not see any increases in discharges on or after the short-stay threshold for patients who died provides some reassurances that long-term care hospitals are not basing their end-of-life care decisions such as the timing of discontinuation of life-support based on financial gains.

Policy Implications

Our findings have significant and timely implications for policymakers in the era of post-acute care payment reform as alternative ways of structuring long-term care hospital payments are being considered to ensure that treatment and discharge decisions reflect the medical needs of patients.

First, they raise concerns about recent decisions to create additional short-stay payment disincentives. In December of 2012, CMS implemented a very short-stay policy in addition to the current short-stay policy, which added another threshold on which to base payments.(5)

Currently, MedPAC estimates that close to half of all short-stay outliers are also very short-stay outliers and therefore subject to the additional payment penalty. From our results showing how quickly, effectively, and universally long-term care hospitals were able to shift their lengths of stay following the introduction of the short-stay policy, we predict that there will likely be a similar response to this new policy by shifting the lengths of stay of such patients to just beyond the very short-stay threshold.

Second, these results speak to the need to examine how best to incentivize discharge decisions to reflect actual patient need. MedPAC in its 2014 Report proposed a new formula that would reduce the payment penalty for patients discharged prior to the short-stay threshold by basing payments for short-stay outliers on a base-rate plus a per diem adjustment until the full standard pay rate is reached.(12) Although this new formula would eliminate the steep payment cliff associated with failing to cross the short-stay threshold and therefore make discharges prior to the threshold less financially unappealing; the short-stay outlier payment concept remains unchanged as full payments would continue to be conditional on surpassing the short-stay threshold. Given our results showing how responsive long-term care hospitals are to payment incentives, its ultimate success would depend on how well the payments match providers' costs. What remains unclear is the level of profit margin it would require for long-term care hospitals to overlook the large gains associated with crossing the short-stay threshold.

Finally, our findings caution the inclusion of any variations of lengths of stay requirements in future payment reform efforts, such as those passed under the Pathway for Sustainable Growth Rate (SGR) Reform Act of 2013.(12) Under this law, long-term care hospitals will only continue to receive current payment levels for patients who stay at least 3 days in an intensive care unit of an acute care hospital prior to being admitted to a long-term care

hospital or patients requiring prolonged mechanical ventilation for more than 96 hours at the long-term care hospital. The estimated payment differential for patients not meeting the above criteria is significant at approximately $30,000 (from $40,000 to $12,000).(12) While this change was intended to discourage long-term care hospitals from admitting patients with lower levels of severity; our findings suggest that such incentives and requirements could result in longer intensive care unit stays for acute care hospitals and longer duration of mechanical ventilation as long-term care hospitals seek to quality for higher payments.

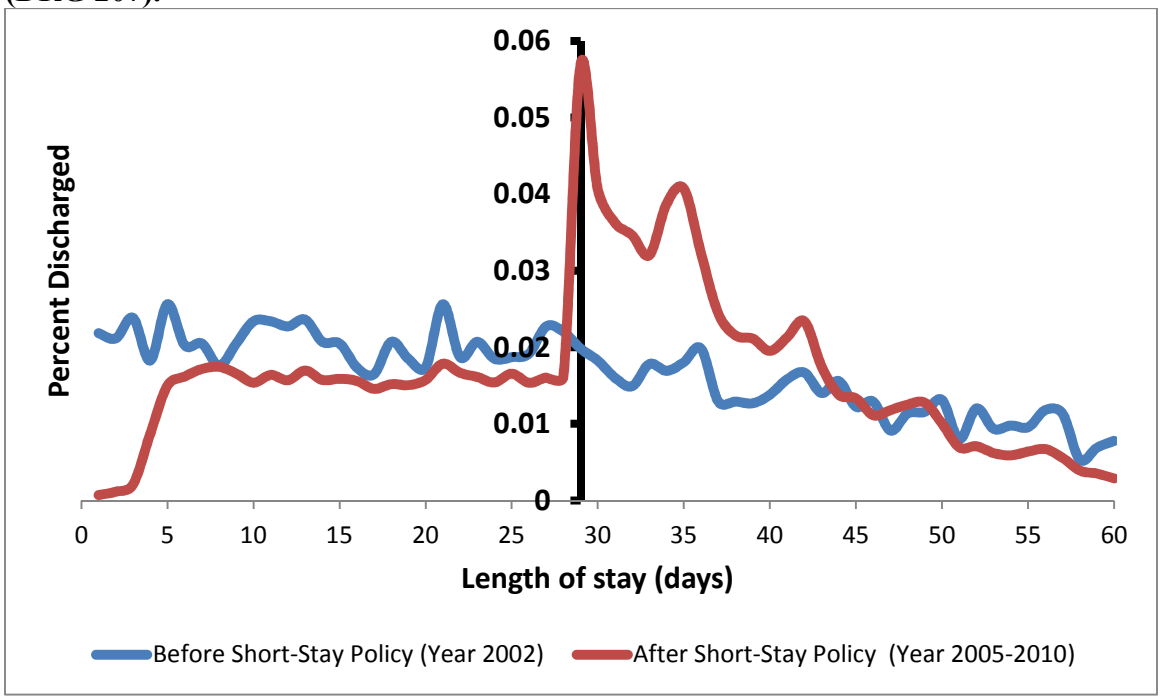
One potential option to address these disincentives associated with basing payments on various lengths of stay requirements is to bundle acute and post-acute payment, which would help align incentives for providers of all levels to partner together to improve patient care.(15-17) However, because they are the most expensive post-acute care providers, long-term care hospitals might be most disadvantaged by bundled payment arrangements, as those managing patients at the acute care hospital level sought to contract with and send their patients to the least-costly post-acute care setting, to start their own post-acute care units, or to keep the patients in the hospital longer.(18) To date, long-term care hospitals have not been major participants in CMS payment bundling demonstrations; and when long-term care hospitals have participated, they have often done so for only a limited number of DRGs.(19) The reluctance in participation and in testing a wide variety of DRGs among long-term care hospitals indicate that significant challenges and barriers exist in engaging this important stakeholder in payment reform.

Conclusions

Long-term care hospitals were created to fulfill a special role in caring for the medically complex patients who would otherwise remain for extended periods of time in short-term acute

care hospitals. The short-stay outlier policy within the prospective payment system established for long-term care hospitals, with its sharp differentiation of payment levels between early discharges and discharges after meeting a DRG-specific threshold, has created strong incentives for these hospitals to delay discharges until the threshold has been met. In this work, we observe how strongly long-term care hospitals have responded to these incentives and the distortion of patient discharges in response to these incentives. Our findings suggest an urgent need to reexamine and restructure the payment system for long-term care hospitals and to clarify the expected and actual role of long-term care hospitals in the care continuum to ensure that the incentives are properly aligned with providing care that is in the best interest of the patients and best reflects the level of resources needed to provide such care.

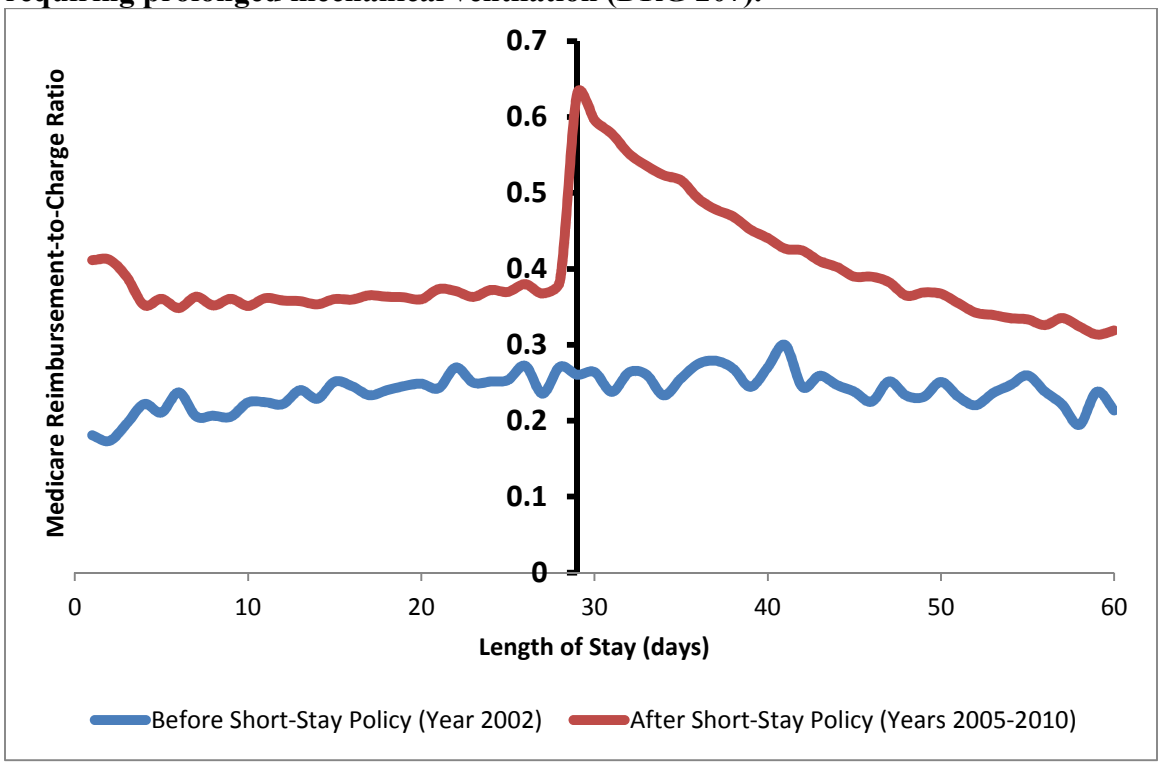
Exhibit 1. The distribution in patients' lengths of stay before and after implementation of the short-stay outlier policy under the long-term care hospital prospective payment system for patients with respiratory system diagnosis requiring prolonged mechanical ventilation (DRG 207).



SOURCE: Authors' analysis using LTCH MedPAR data from years 2002 and 2005-2010.

Notes: Dashed vertical line indicates the short-stay threshold of 29 days for DRG 207. DRG: Diagnosis-related group.

Exhibit 2. Average per discharge Medicare reimbursement-to-charge ratios by lengths of stay, before and after implementation of the short-stay outlier policy under the long-term care hospital prospective payment system for patients with respiratory system diagnosis requiring prolonged mechanical ventilation (DRG 207).



SOURCE: Authors' analysis using LTCH MedPAR data from years 2002 and 2005-2010.

Notes: Dashed vertical line indicates the short-stay threshold of 29 days. DRG: Diagnosis-related group.

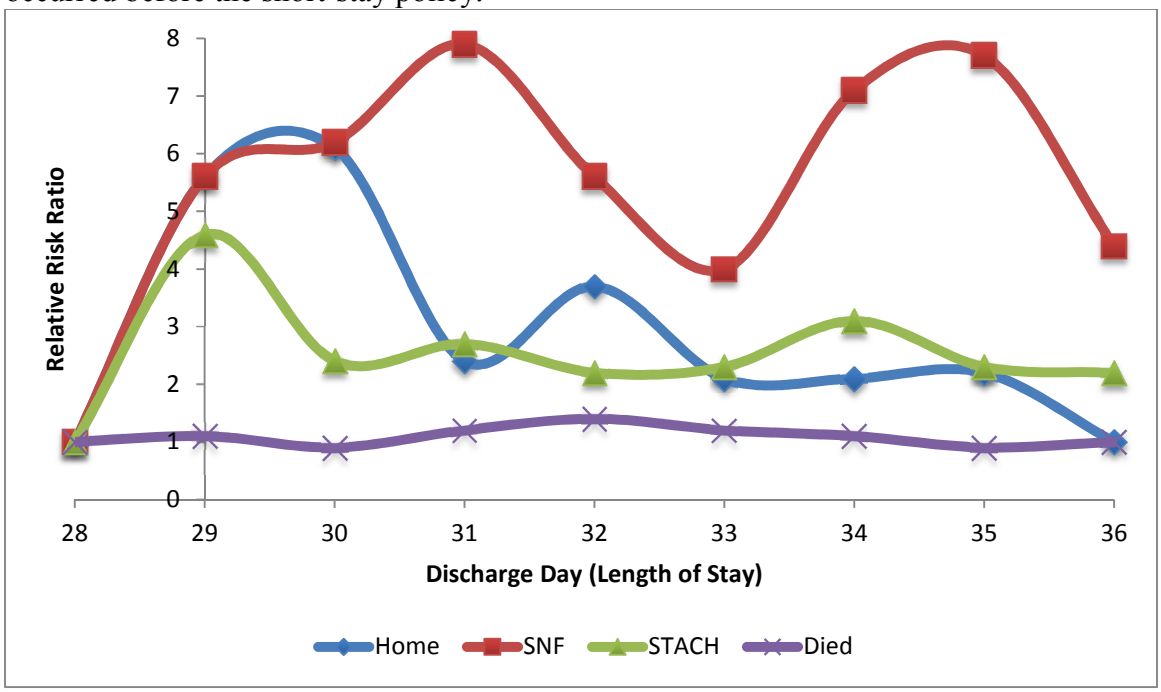
Exhibit 3. Predicted average Medicare reimbursement-to-charge ratio for long-term care hospital patients with respiratory system diagnosis requiring prolonged mechanical ventilation (DRG 207) discharged before, on, and after the short-stay threshold by discharge location and year.

	Before short-stay policy			**After short-stay policy**		
	Discharge Occurred			Discharge Occurred		
Discharge Location	Before threshold	On threshold	After threshold	Before threshold	On threshold	After threshold
Home	0.34	0.32	0.31	0.40	0.71	0.62
SNF	0.31	0.32	0.30	0.37	0.64	0.55
STACH	0.26	0.25	0.25	0.38	0.63	0.54
Died	0.22	0.21	0.21	0.35	0.52	0.46
Overall	0.26	0.26	0.25	0.37	0.64	0.54

SOURCE: Authors' analysis of LTCH MedPAR files.

Notes: Regressions were stratified by discharge location and performed separately for year 2002 (before short-stay outlier policy) and for years 2005-2010 (after short-stay outlier policy). All models controlled for age, sex, race, and comorbidities and included fixed effects at the facility-level. SNF: skilled nursing facility; STACH: Short-term acute care hospital.

EXHIBIT 4. Relative risk ratio of the risk associated with being discharged on the day of the threshold and on each day after the threshold to the risk associated with being discharged before the threshold, for patients with respiratory diagnosis requiring prolonged mechanical ventilation (DRG 207) discharged after implementation of the short-stay policy relative to discharges that occurred before the short-stay policy.



SOURCE: Authors' analysis of LTCH MedPAR files.

Exhibit 4. Relative risk ratio of the risk associated with being discharged on the day of the threshold and on each day after the threshold (up to day 36) to the risk associated with being discharged before the threshold, by discharge location for patients with respiratory diagnosis requiring prolonged mechanical ventilation (DRG 207) discharged after implementation of the short-stay policy relative to discharges that occurred before the short-stay policy.

CHAPTER 5 APPENDIX

Section A1: Sample size determination

We used the LTCH PPS Expanded Modified MedPAR files from year 2002 (before short-stay policy) and years 2005-2010 (after short-stay policy). Data from 2003 was not available from the Centers for Medicare and Medicaid Services (CMS) and we excluded 2004 as a transition year.

We further limited our sample to patients with respiratory system diagnosis with prolonged mechanical ventilation (DRG 207 for years 2006-2010 and DRG 75 for years 2002 and 2005). We applied the following exclusion criteria to our initial sample: 1) Cases with other/unspecified discharge locations; 3) Cases from government-owned facilities because they operate in a different context compared to other long-term care hospitals; 4) Influential outlier cases such as those with lengths of stay greater than the 95th percentile for DRG 207 or 60 days; 5) Cases under age 65; 6) Cases ineligible for Medicare reimbursement; and 7) Cases with missing data. Details on the number and percent of patients excluded by exclusion criteria are presented in Appendix Exhibit A1.

Appendix Exhibit A1. Analytical sample size determination**.**

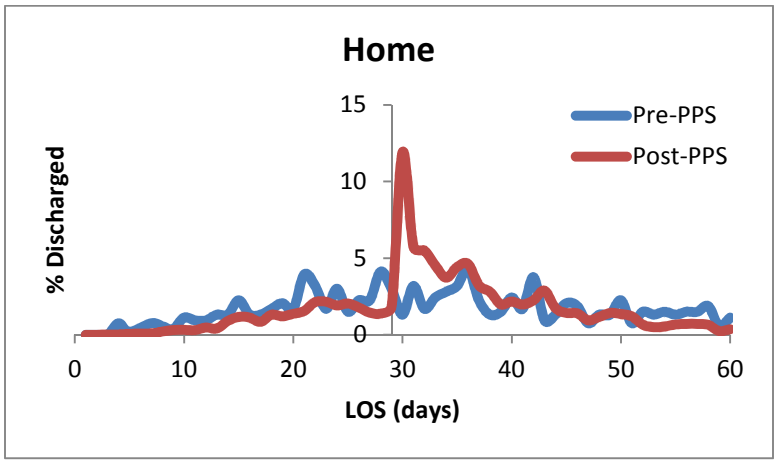
	N	%
Initial Sample (All DRGs)	**949,196**	
DRG 207	**100,417**	**11%**
Excluded:		
Age <65	20,799	21%
Government owned LTCHs	2,123	2%
Unknown/other discharge destination	2,858	3%
High cost outlier	11,803	12%
Not eligible for Medicare reimbursement	3,907	4%
Long stay outliers	2,893	3%
Missing data	194	0%
FINAL SAMPLE DRG 207	**55,840**	56%
Final Sample DRG 207 limited to LOS 22-36	21,342	38%

Source: Authors' analysis using LTCH MedPAR data from years 2002 and 2005-2010.
NOTES: DRG: Diagnosis-related group; LTCH: Long-term care hospital; LOS: length of stay.

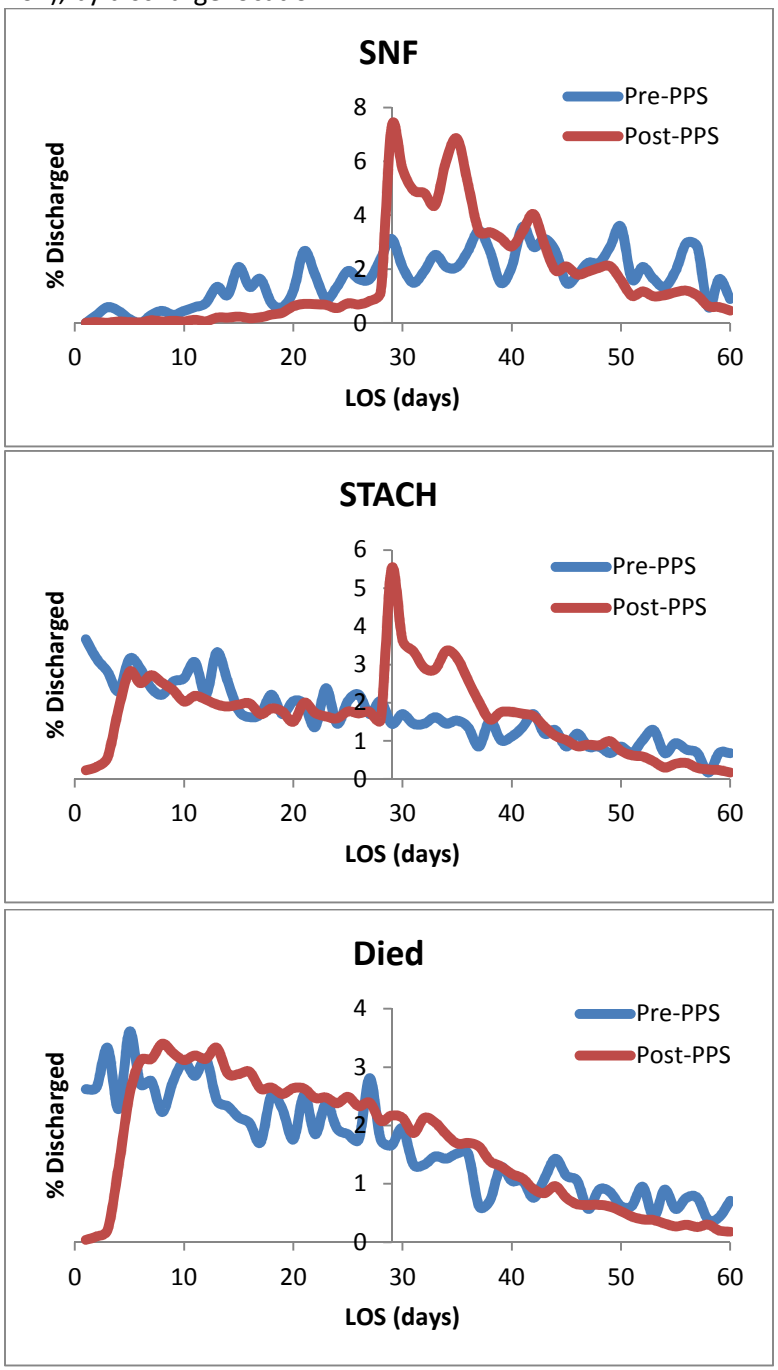
Section A2: The differential impact of the short-stay outlier policy by discharge location

In order to examine whether there was differential impact of the short-stay policy by discharge location, we graphed the distribution in patients' lengths of stay before and after implementation of the short-stay outlier policy under the long-term care hospital prospective payment system for patients with respiratory system diagnosis requiring prolonged mechanical ventilation or DRG 207 (Appendix Exhibit A2). The discharge locations included: home, skilled nursing facility (SNF), short-term acute care hospital, and patients who died on discharge. We found that there was a significant increase in the percent of patients discharged on and immediately after the short-stay threshold after payments became tied to crossing the threshold for patients discharged to home, to SNF, and to short-term acute care hospital; but not due to death.

Appendix Exhibit A2. The distribution in patients' lengths of stay before and after implementation of the short-stay outlier policy under the long-term care hospital prospective payment system for patients with respiratory system diagnosis requiring prolonged mechanical ventilation (DRG 207), by discharge location.



Appendix Exhibit A2 (continue). The distribution in patients' lengths of stay before and after implementation of the short-stay outlier policy under the long-term care hospital prospective payment system for patients with respiratory system diagnosis requiring prolonged mechanical ventilation (DRG 207), by discharge location.



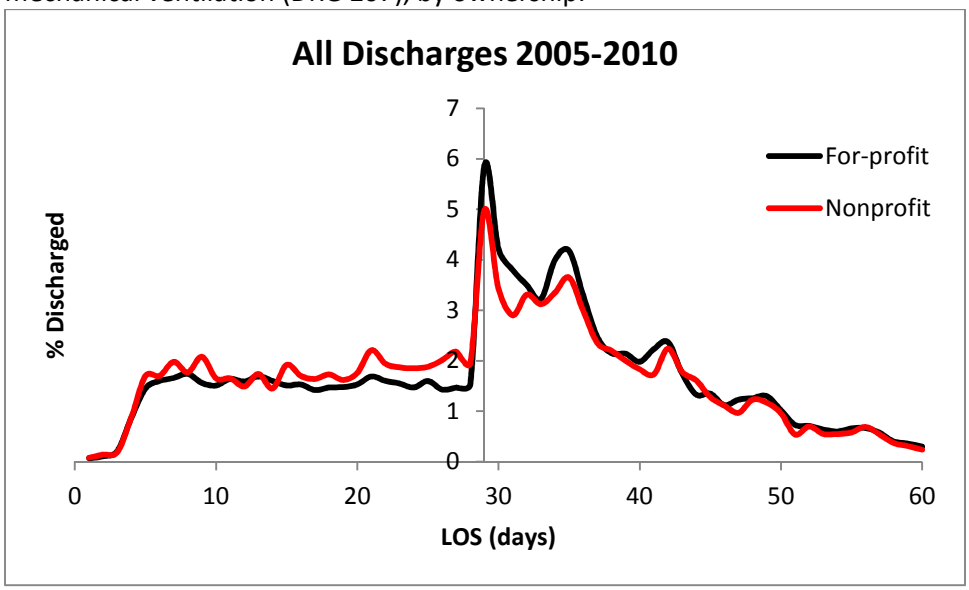
SOURCE: Authors' analysis using LTCH MedPAR data.

NOTES: Dashed vertical line indicates the short-stay threshold of 29 days for DRG 207. DRG: Diagnosis-related group; PPS: prospective payment system; LOS: length of stay; SNF: skilled nursing facility; STACH: short-term acute care hospital.

Section A3: No differential impact of the short-stay policy by LTCH ownership

To understand whether there was differential impact of the financial incentives brought on by the short-stay policy by LTCH ownership, we graphed distribution of discharges occurring on each day after implementation of the short-stay policy by facility ownership (Appendix Exhibit A3) and found a similar spike in the percent of discharges occurring on and immediately after the short-stay threshold among for profit and nonprofit LTCHs.

Appendix Exhibit A3. The distribution of discharges (to all locations including patients who died) occurring on each day after implementation of the short-stay threshold for patients requiring prolonged mechanical ventilation (DRG 207), by ownership.



SOURCE: Authors' analysis using LTCH MedPAR data from years 2005-2010.

NOTES: Dashed vertical line indicates the short-stay threshold of 29 days for DRG 207. DRG: Diagnosis-related group; LOS: length of stay.

Section A4: Patients discharged before, on, and after the threshold are similar with respect to patient demographics and chronic illness burden

Appendix Exhibit A4 compares selected patient characteristics and comorbidities for patients requiring prolonged mechanical ventilation who were discharged 1-7 days before the threshold, on the day of the threshold, and 1-7 days after the threshold for years 2005-2010. The Elixhauser Score and the Charlson Comorbidity Index are commonly used summary comorbidity scores to measure overall disease burden. Overall, there were very few differences in demographics and comorbidities burden across patients discharged before, on, and after the threshold.

Appendix Exhibit A4. Selected patient characteristics and comorbidities for patients requiring mechanical ventilation discharged before, on, and after the short-stay threshold by discharge location, years 2005-2010.

	Home			SNF			STACH			Died		
	Before SST	On SST	After SST	Before SST	On SST	After SST	Before SST	On SST	After SST	Before SST	On SST	After SST
N	669	636	1694	914	1251	6511	1451	345	2702	2745	359	2211
Age (%)												
65 to 74	68	66	58	48	45	42	49	50	50	35	41	36
75 to 84	28	29	34	37	43	43	39	41	41	56	41	45
≥85	4	6	8	15	12	15	12	9	9	19	19	18
Male (%)	50	49	45	45	45	44	52	49	51	51	51	50
White (%)	84	83	77	75	76	73	78	83	82	77	81	77
Conditions (%)												
Cancer	6	5	6	5	3	4	4	5	4	9	10	8
CHF	39	36	35	35	34	33	24	29	33	39	40	38
COPD	53	46	44	39	35	34	34	35	33	37	35	35
Liver	1	0	1	1	1	1	1	0	1	2	1	2
Renal	9	10	9	9	11	10	18	10	13	18	16	17
Diabetes	24	18	16	18	17	15	13	15	14	10	9	9
Summary Comorbidity Measures (mean)												
ES	2.7	2.5	2.4	2.4	2.3	2.2	2.2	2.2	2.2	2.3	2.2	2.2
CCI	1.8	1.5	1.6	1.5	1.5	1.4	1.5	1.4	1.4	1.7	1.6	1.7

SOURCE: Authors' analysis of LTCH MedPAR files.

NOTES: Before SST: patients discharged during the week prior to reaching the short-stay threshold; On SST: patients discharged on the day of the short-stay threshold; After SST: patients discharged during the one week after reaching the short-stay threshold. SNF: Skilled nursing facility; STACH: Short-term acute care hospital; SST: Short-stay threshold; CHF: Congestive heart failure; COPD: Chronic obstructive pulmonary disease; ES: Elixhauser score; and CCI: Charlson Comorbidity Index.

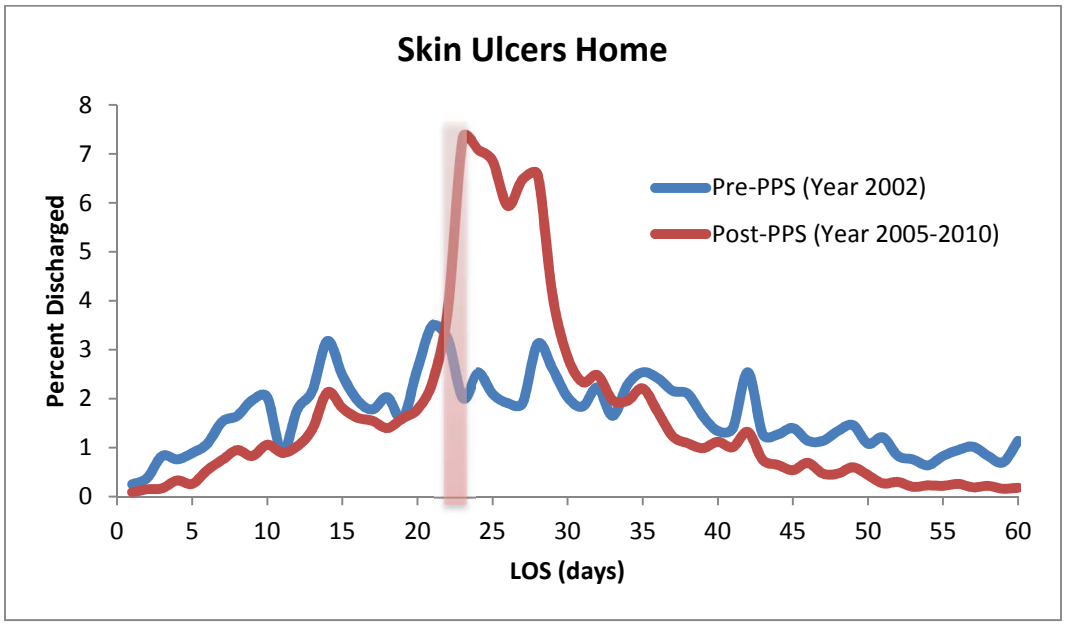
Section A5: Sensitivity analyses show that similar findings extend to other DRGs and to all DRGs

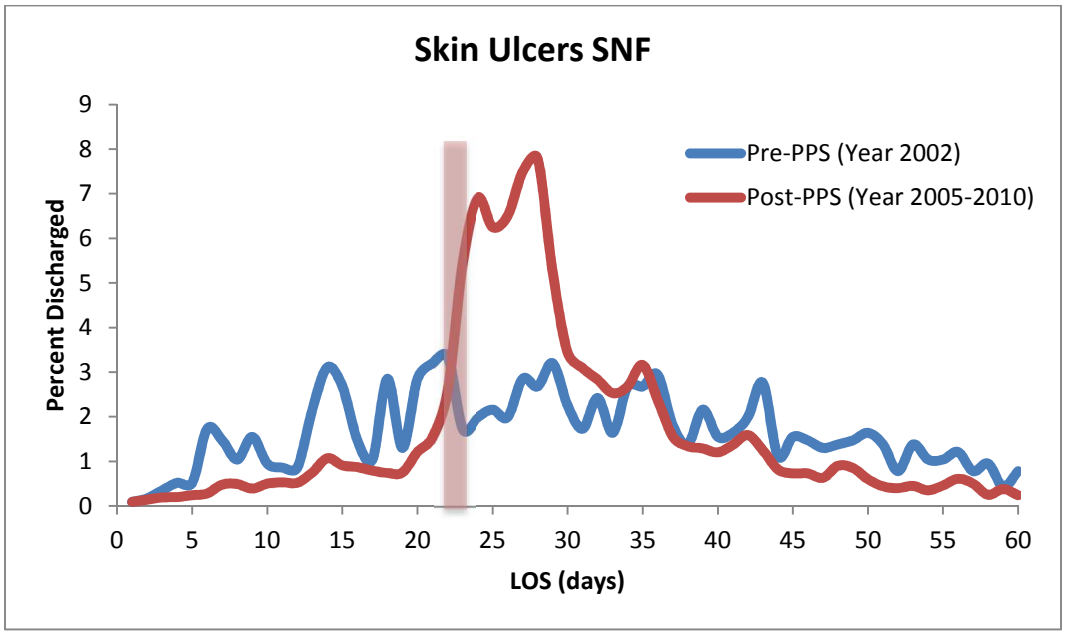
We conducted two sensitivity analyses to ensure that our results were robust and extend beyond long-term care hospital patients with respiratory diagnosis requiring prolonged mechanical ventilation.

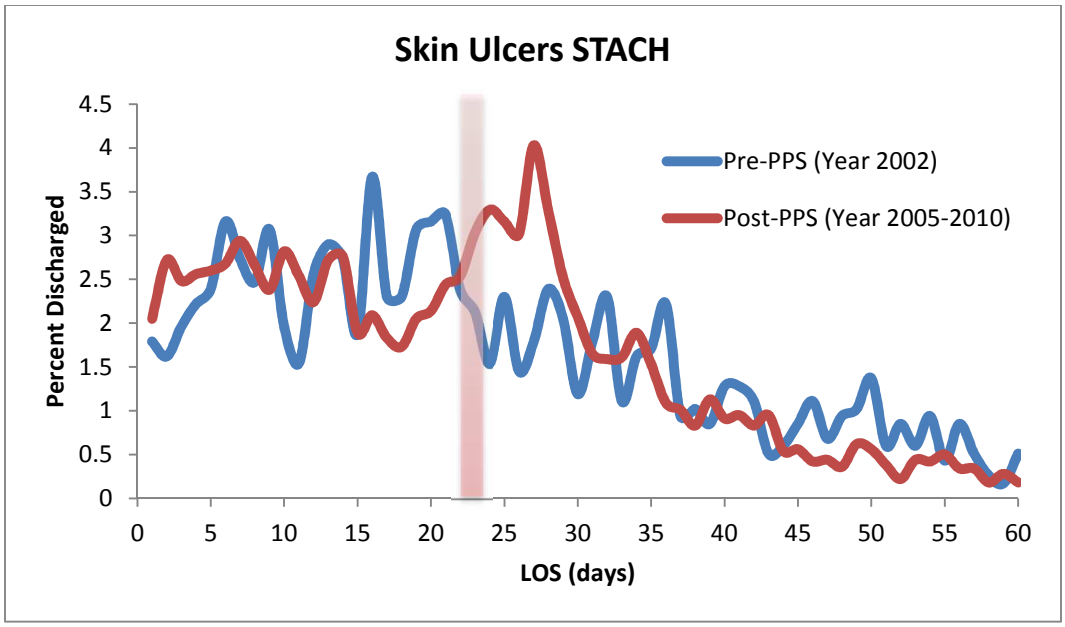
First, we performed the same detailed analyses for patients admitted with skin ulcers (DRGs 592 and 593). We chose skin ulcers because they are among the top most common DRGs but with a much lower average DRG price tag ($32,434) compared to patients requiring prolonged mechanical ventilation ($73,289). This tests whether the financial incentives created by the short-stay policy extended beyond the highest reimbursed DRGs. The results of the first sensitivity analysis are summarized in Appendix Exhibits A5-A8.

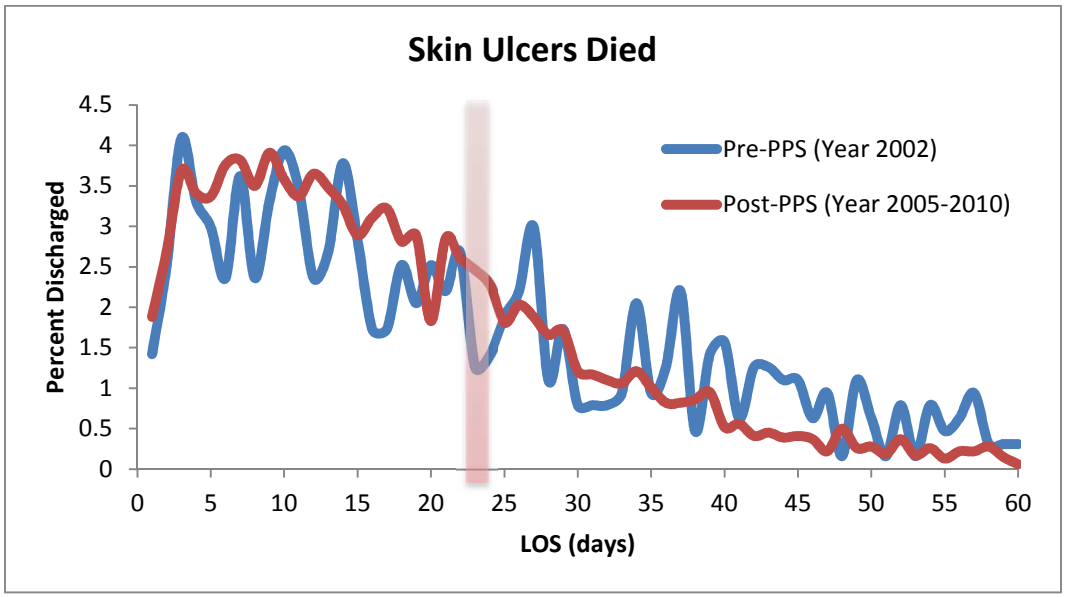
Second, we graphed the distribution in patients' lengths of stay with respect to the short-stay threshold for all DRGs to visually confirm the results for DRG 207 were representative of total long-term care hospital cases. These are summarized in Appendix Exhibits A9.

Appendix Exhibit A5. Distribution of discharges by length of stay for patients treated at long-term care hospitals for skin ulcers (DRG 592 and 593) before and after implementation of the short-stay policy under long-term care hospital prospective payment system, by discharge location. Red vertical line indicates the short-stay threshold range of 22-24 days (short-stay threshold was given in a range because it fluctuated between years 2005-2010).





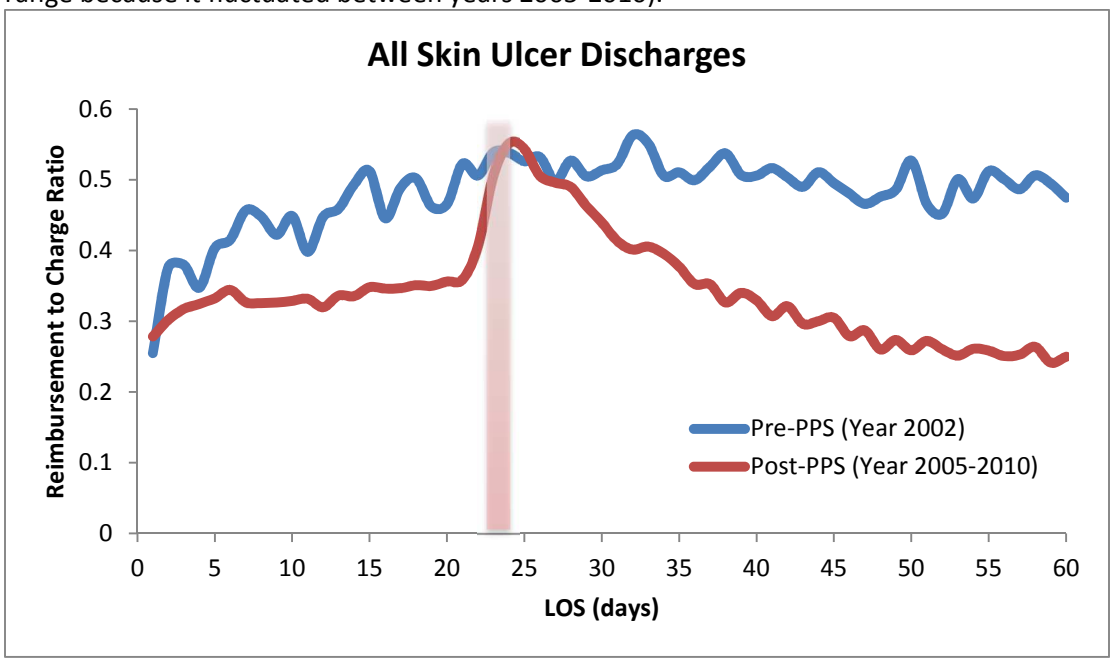




SOURCE: Authors' analysis of LTCH MedPAR files.

NOTES: LOS: length of stay; PPS: prospective payment system; SNF: Skilled nursing facility; and STACH: Short-term acute care hospital.

Appendix Exhibit A6. Average per case Medicare reimbursement-to-charge ratio by length of stay for all patients treated at long-term care hospitals for skin ulcers (DRG 592 and DRT 593), before and after implementation of the short-stay policy under long-term care hospital prospective payment system. Red vertical line indicates the short-stay threshold of 22-24 days (short-stay threshold was given in a range because it fluctuated between years 2005-2010).



SOURCE: Authors' analysis of LTCH MedPAR files.

NOTES: LOS: length of stay; and PPS: prospective payment system.

Appendix Exhibit A7. Adjusted predicted Medicare reimbursement-to-charge ratio for patients treated for skin ulcers and discharged 1-7 days before the short-stay threshold, on the day of the short-stay threshold, and 1-7 days after the short-stay threshold, by discharge location for years 2005-2010. All results adjusted for age, sex, race/ethnicity, year, and Charlson Comorbidity Index using fixed-effects at the LTCH level. We were unable to model year 2002 because of insufficient number of observations.

Discharge location	1-7 days before crossing short-stay threshold	On short-stay threshold	1-7 days after crossing short-stay threshold
Home	0.39	0.59	0.52
SNF	0.37	0.56	0.48
STACH	0.36	0.52	0.46
Died	0.34	0.43	0.38
Overall	0.37	0.56	0.49

All p-values <0.001.

SOURCE: Authors' analysis of LTCH MedPAR files.

NOTES: All results adjusted for age, sex, race/ethnicity, year, and Charlson Comorbidity Index using fixed-effects at the LTCH level. SNF: skilled nursing facility; and STACH: short-term acute care hospital.

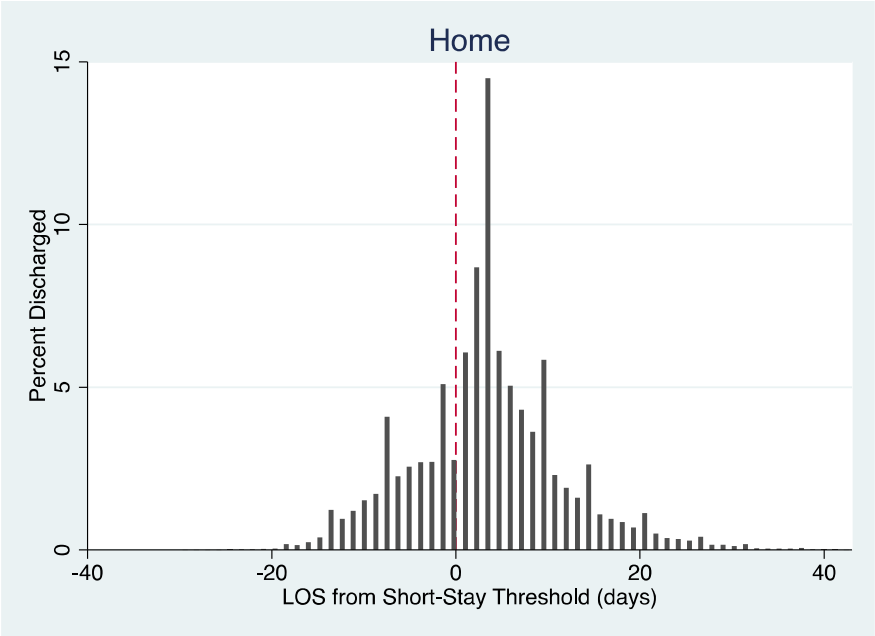
Appendix Exhibit A8. Adjusted relative risk ratio and 95% confidence intervals of the risk of being discharged on and during 1-7 days after the short-stay threshold compared to the risk of being discharged during 1-7 days before the threshold, after implementation of the short-stay policy relative to before, by discharge location.

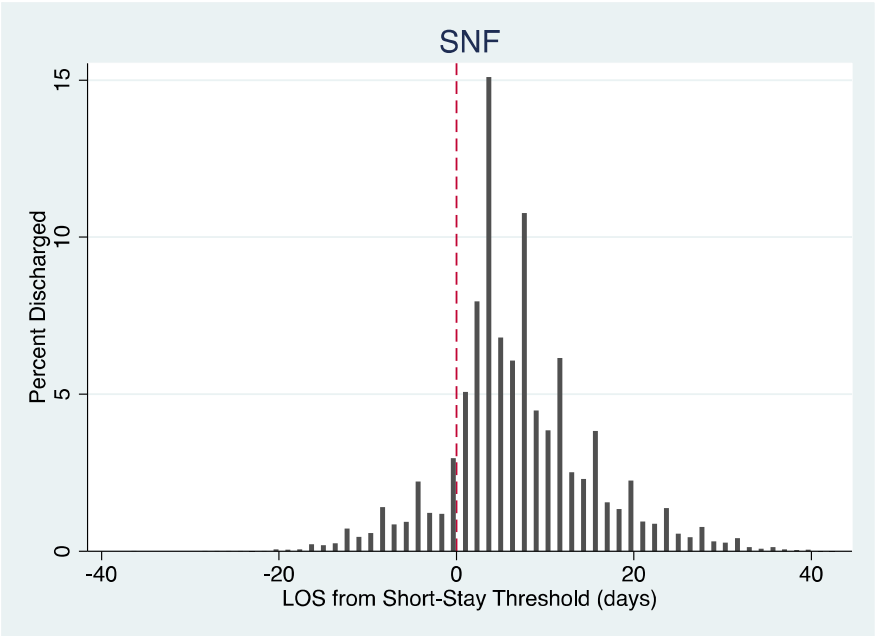
Discharge location	Discharged 1-7 days before short-stay threshold	Discharged on day of short-stay threshold	Discharged 1-7 days after short-stay threshold
Home	reference	4.7 (3.3-6.6)	4.4 (3.7-5.3)
SNF	reference	7.8 (5.0-12.1)	7.6 (6.2-9.3)
STACH	reference	3.4 (2.0-5.6)	2.8 (2.3-3.5)
Died	reference	1.4 (0.7-2.9)	1.1 (0.8-1.5)
Overall	reference	4.8 (3.9-6.1)	4.5 (4.1-5.0)

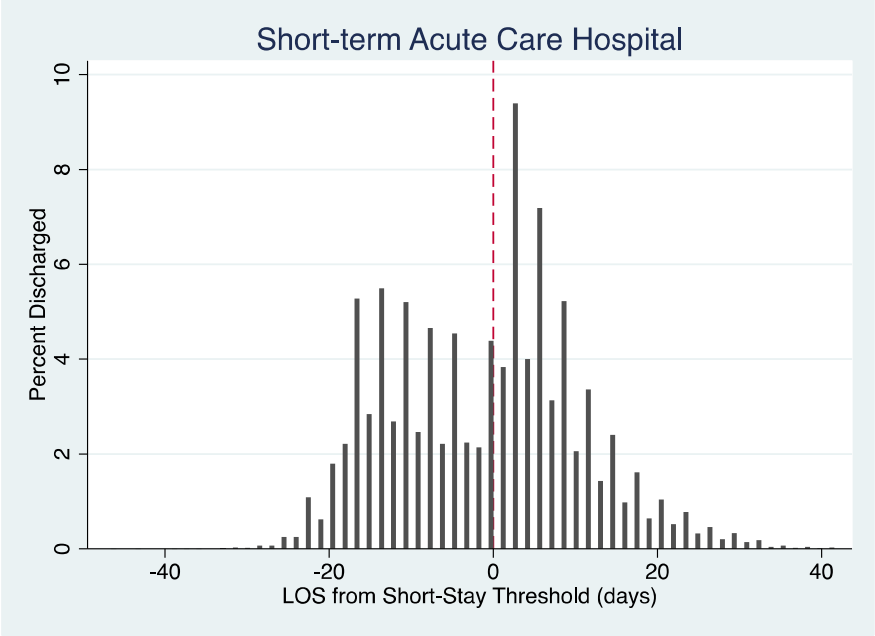
SOURCE: Authors' analysis of LTCH MedPAR files.

NOTES: All results adjusted for age, sex, race/ethnicity, and Charlson Comorbidity Index at the patient level; plus ownership, size, and geographic location of the long-term care hospital. SNF: skilled nursing facility; and STACH: short-term acute care hospital.

Appendix Exhibit A9. The distribution in patients' lengths of stay for all DRGs discharged from long-term care hospitals in years 2005-2010, by discharge location. The red dashed line denotes the short-stay threshold. Because the short-stay threshold is different for each DRG, we calculated the number of days from the day of discharge to the short-stay threshold by subtracting the short-stay threshold from the patient's length of stay. Therefore, zero on the x-axis (location of the red dashed line) represents discharges on the day of the threshold. Patients discharged before the threshold are to the left of the red dashed line because their lengths of stay were shorter than the short-stay threshold. Patients discharged after the threshold are to the right of the red dashed line because their lengths of stay exceed the short-stay threshold.







SOURCE: Authors' analysis of LTCH MedPAR files.

NOTES: LOS: length of stay; and SNF: skilled nursing facility.

Section A6: How much does waiting until after the threshold to discharge patients cost Medicare?

To estimate the cost to Medicare associated with waiting until after the threshold to discharge patients, we employed the following assumptions and calculations. This analysis was performed for DRG 207 and repeated for DRG 592/593.

1. We assumed that if discharges were to occur randomly, the percentage of patients discharged on each day would not be significantly different. Therefore, within a 15day window spanning from one week before to one week after the short-stay threshold, we would expect 8/15=54% of the patients to be discharged on or after the threshold. This is the percent of expected discharges and remains at 54% regardless of discharge location.

2. We obtained the percent of patients actually discharged on the threshold and during the one week after crossing the threshold by discharge location for years 2005-2010. This is the percent of observed discharges. Since only discharges to home, skilled nursing facility, and acute care hospitals appear to be affected by the threshold, we limited the analysis to these three locations.

3. We subtracted the percent expected from the percent observed for each discharge location. This is the percent of excess discharges that occurred on or after the threshold as a result of the short-stay policy.

4. We then obtained the total number of patients discharged to each discharge location.

5. We multiplied the percent of excess discharges to the total number of patients to calculate the number of patients affected.

6. We determined the differences in Medicare reimbursement using the data by subtracting the average reimbursement amount (unadjusted) for patients discharged before the threshold from the average reimbursement amount (unadjusted) for patients discharged on the threshold for each discharge location.

7. We multiplied the number of patients affected for each location by the differences in Medicare reimbursement from step 6 for each discharge location. This is the amount of excess reimbursement paid by Medicare assuming that all of these discharges could have been discharged before the threshold.

8. We summed the excess reimbursements by discharge location. This is the estimated total excess cost to Medicare.

9. We then calculated the total cost to Medicare by adding up the amount of Medicare reimbursement for every discharged that occurred within the 15day window.

10. Finally, we divided the estimated total excess cost to Medicare by the total amount Medicare reimbursed from step 9. This is the percentage of Medicare reimbursement that is attributable to waiting until after the threshold to discharge patients.

Exhibit A10: Detailed calculations to determine the financial impacts to Medicare as a result of waiting until after the threshold to discharge patients.

Prolonged Mechanical Ventilation Patients (DRG 207)							
	Observed %	**Expected %**	**Excess %**	**N Total**	**N Affected**	**Reimbursement Differential**	**Excess Reimbursement**
Home	78%	54%	24%	2999	720	$37,023	$26,647,674.48
SNF	89%	54%	35%	8676	3037	$37,134	$112,761,104.40
Acute Care	70%	54%	16%	4833	773	$31,632	$24,460,392.96
Total Excess Reimbursement							$163,869,171.84
Total Medicare Reimbursement							$1,450,000,000.00
% Total excess/Total Medicare reimbursement							11.3%

Skin Ulcer Patients (DRG 592/593)							
	Observed %	**Expected %**	**Excess %**	**N Total**	**N affected**	**Reimbursement Differential**	**Excess Reimbursement**
Home	78%	54%	24%	7218	1732.32	$11,997	$20,782,643.04
SNF	87%	54%	33%	9160	3022.8	$12,202	$36,884,205.60
Acute Care	62%	54%	8%	2153	172.24	$10,734	$1,848,824.16
Total Excess Reimbursement							$59,515,672.80
Total Medicare Reimbursement							$566,000,000.00
% Total excess/Total Medicare reimbursement							10.5%

Section A7: Technical appendix on regression models

I. Medicare reimbursement-to-charge ratio analysis (Exhibit 3)

The Medicare reimbursement-to-charge ratio was modeled using multivariate linear regression with fixed-effects at the facility-level. The regressions were stratified by discharge location with one model for each discharge location. After the model was estimated, we used the "margins" command to predict the average reimbursement-to-charge ratio while holding all covariates at their mean values. The full model output is summarized in Appendix Exhibit A11 (before implementation of the short-stay policy) and A12 (after implementation of the short-stay policy).

- Outcome (continuous): Reimbursement-to-Charge ratio, constructed by dividing the amount of Medicare reimbursement by covered charges

- Primary regressor of interest: The timing of discharge in relation to the short-stay threshold (1-7 days before the threshold, on the day of the threshold; and 1-7 days after the threshold). Reference category was 1-7 days before the threshold.

- Covariates:
    - Age: 65 to 74 (reference), 75-84, ≥85
    - Sex: female (reference), male
    - Race/ethnicity: white, nonwhite (reference)
    - Comorbidities (dichotomous 0/1 indicator for each of the following conditions based on ICD-9 codes):
        - Stroke
        - Cancer
        - Heart failure
        - Chronic obstructive pulmonary disease
        - Renal failure
        - Liver disease
        - Diabetes

Appendix Exhibit A11. Full regression model output summary for reimbursement-to-charge ratio (stratified by discharge location) for long-term care hospital patients requiring prolonged mechanical ventilation, before implementation of the short-stay policy (year 2002):

	Home		SNF		STACH		Died	
N	213		199		296		559	
Groups	111		97		116		143	
R-squared:								
within	0.233		0.0721		0.1758		0.0809	
between	0.0017		0.0103		0.0042		0	
overall	0.0328		0.0082		0.037		0.0059	
Model Results:								
	Coefficient	SE	**Coefficient**	SE	**Coefficient**	SE	**Coefficient**	SE
Primary regressor of interest								
Before Threshold	**reference**		**reference**		**reference**		**reference**	
On Threshold	**-0.009**	0.03	**0.016**	0.026	**-0.003**	0.020	**-0.006**	0.012
After Threshold	**-0.034**	0.01	**-0.009**	0.017	**-0.005**	0.010	**-0.007**	0.006
Covariates								
Age 65 to 74	**reference**		**reference**		**reference**		**reference**	
age75to85	**0.006**	0.02	**-0.007**	0.020	**0.006**	0.010	**0.009**	0.007
age85	**0.007**	0.03	**-0.042**	0.025	**0.028**	0.021	**0.023**	0.009
male	**-0.011**	0.01	**-0.010**	0.015	**-0.018**	0.011	**-0.001**	0.006
white	**-0.003**	0.02	**-0.016**	0.020	**-0.040**	0.015	**-0.014**	0.008
stroke	**0.222**	0.08	**0.015**	0.029	**0.040**	0.016	**0.041**	0.013
heart	**-0.015**	0.01	**-0.011**	0.019	**-0.024**	0.012	**-0.006**	0.006
lung	**0.008**	0.01	**-0.004**	0.018	**-0.004**	0.010	**0.011**	0.006
diabetes	**0.024**	0.02	**-0.009**	0.019	**0.007**	0.014	**-0.012**	0.008
liver	**0.042**	0.08	**0.000**		**0.006**	0.070	**0.002**	0.024
renal	**-0.066**	0.03	**-0.037**	0.045	**-0.038**	0.016	**-0.020**	0.008
cancer	**0.014**	0.02	**0.010**	0.045	**-0.003**	0.018	**0.011**	0.011
_cons	**0.342**	0.02	**0.340**	0.026	**0.308**	0.017	**0.220**	0.009
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sigma_u	**0.116**		**0.113**		**0.116**		**0.115**	
sigma_e	**0.066**		**0.075**		**0.064**		**0.059**	
rho	**0.756**		**0.696**		**0.767**		**0.792**	
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F	4.23		4.42		6.37		11.02	

SOURCE: Authors' analysis of LTCH MedPAR files.

Notes: SNF: skilled nursing home; STACH: short-term acute care hospital; SE: standard error.

Appendix Exhibit A12. Full regression model output summary for reimbursement-to-charge ratio (stratified by discharge location) for long-term care hospital patients requiring prolonged mechanical ventilation, after implementation of the short-stay policy (year 2005):

	Home		SNF		STACH		Died	
N	2999		8676		4833		5313	
Groups	392		409		403		403	
R-squared:								
within	0.3458		0.2089		0.3123		0.2916	
between	0.0871		0.0351		0.0575		0.0732	
overall	0.1857		0.1053		0.1788		0.1594	
Model Results:								
	Coefficient	SE	**Coefficient**	SE	**Coefficient**	SE	**Coefficient**	SE
Primary Regressor of Interest								
Before Threshold	**reference**		**reference**		**reference**		**reference**	
On Threshold	**0.310**	0.009	**0.268**	0.006	**0.247**	0.007	**0.169**	0.006
After Threshold	**0.217**	0.007	**0.179**	0.005	**0.159**	0.005	**0.109**	0.003
Covariates								
Age 65 to 74	**reference**		**reference**		**reference**		**reference**	
age75to85	**0.012**	0.006	**0.014**	0.003	**0.007**	0.004	**0.010**	0.003
age85	**0.035**	0.012	**0.028**	0.004	**0.006**	0.007	**0.027**	0.004
male	**-0.009**	0.006	**-0.009**	0.003	**-0.014**	0.004	**-0.001**	0.003
white	**0.000**	0.008	**0.002**	0.004	**0.001**	0.005	**-0.004**	0.004
stroke	**0.017**	0.013	**0.034**	0.005	**0.047**	0.007	**0.006**	0.006
heart	**0.002**	0.006	**0.006**	0.003	**0.011**	0.004	**0.016**	0.003
lung	**0.016**	0.006	**0.014**	0.003	**0.021**	0.004	**0.027**	0.003
diabetes	**0.012**	0.008	**0.030**	0.004	**0.034**	0.006	**0.021**	0.005
liver	**0.033**	0.031	**0.037**	0.014	**-0.003**	0.019	**-0.002**	0.011
renal	**-0.010**	0.010	**-0.018**	0.005	**-0.029**	0.006	**-0.017**	0.004
cancer	**0.002**	0.012	**-0.004**	0.007	**-0.015**	0.010	**0.006**	0.005
_cons	**0.387**	0.011	**0.351**	0.006	**0.373**	0.007	**0.330**	0.005
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sigma_u	**0.195**		**0.176**		**0.147**		**0.136**	
sigma_e	**0.145**		**0.131**		**0.131**		**0.099**	
rho	**0.643**		**0.644**		**0.560**		**0.654**	
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F	**10.33**		**24.11**		**12.29**		**16.46**	

SOURCE: Authors' analysis of LTCH MedPAR files.

Notes: SNF: skilled nursing home; STACH: short-term acute care hospital; SE: standard error.

II. Timing of discharge analysis (Exhibit 4)

We used multinomial logistic regression to model the ratio of the risk associated with being discharged on the day of the threshold and on each day after the threshold to the risk associated with being discharged before the threshold for patients requiring prolonged mechanical ventilation discharged after implementation of the short-stay policy relative to discharges that occurred before the short-stay policy. The models were stratified by discharge location. The key components of the model are defined as follows and the full model output for each discharge location can be found in Appendix Exhibit A13-A16.

- Outcome is a categorical variable coded as:
    - 1 if discharge occurred before day 29 (base outcome)
    - 2 if discharge occurred on day 29 (threshold day)
    - 3 if discharge occurred on day 30 (threshold + 1)
    - 4 if discharge occurred on day 31 (threshold + 2)
    - 5 if discharge occurred on day 32 (threshold + 3)
    - 6 if discharge occurred on day 33 (threshold + 4)
    - 7 if discharge occurred on day 34 (threshold + 5)
    - 8 if discharge occurred on day 35 (threshold + 6)
    - 9 if discharge occurred on day 36 (threshold + 7)

- Primary regressor of interest: 0/1 indicator of whether discharge occurred before=0 or after implementation of the short-stay policy=1.

- Covariates:
    - Age: 65 to 74 (reference), 75-84, ≥85
    - Sex: female (reference), male
    - Race/ethnicity: white, nonwhite (reference)
    - Comorbidities (0/1 indicator of the following conditions):
        - Cancer
        - Stroke
        - Heart failure
        - Lung disease
        - Renal failure
        - Liver disease
        - Diabetes
    - LTCH size (divided into tertiles by number of beds): small (reference), average, and large

- LTCH ownership: for-profit (reference), and nonprofit
- LTCH location: Northeast (reference), Midwest, South, and West

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CHAPTER 6

Conclusions

The use of administrative data has been an important source of information to study patterns of care. The objective of this dissertation was to use administrative data to characterize and understand the patterns of care at the EOL. Using two different data sources from Medicare with one linked to patient-level survey information, we showed that significant variations exist on multiple levels with respect to the provision of care at the EOL.

In Chapter 3, we showed that the pattern of life-sustaining treatment use varies by many patient level factors including age, race, advance directives, and diagnoses such as cancer, dementia, and chronic kidney disease. We further showed that the pattern of life-sustaining use is closely related to the cost of care and the symptoms patients felt as reported by their family members. In Chapter 4, we found that the transition from long-term care hospital to hospice varied wildly by provider-level factors such as hospital ownership and size, as well as the supply of alternative healthcare providers in the region, after controlling for patient-level differences. In Chapter 5, we showed that the lengths of stay among patients in long-term care hospitals are heavily influenced by reimbursement incentives, even after controlling for case-mix and facility-level differences.

In this work, we have clearly demonstrated that treatments patients receive depend not only on patients and their families but are the results of how our healthcare system is organized and reimbursed. However, our ability to explain the observed variations was limited by the lack of detailed information in these large administrative datasets. Despite the rich information on healthcare utilization, their generalizability, and the ability to track utilization longitudinally;

without good measurements of quality of life, severity of illness, prognosis, and especially patient-reported preferences, we could not conclude whether the observed differences and variations were due to differences in preference or disparities in care – a distinction that is vital to the delivery of quality patient-centered care.

Much of the research on care at the end-of-life has relied on and will continue to rely on administrative data to identify utilization patterns, variations, and differences. However, because the treatment and decisions at the EOL involve a complex set of processes and interactions of patient/surrogate preferences, demographics, health and functional status, past experiences, expectations, and communication between patients and providers, etc.; the next frontier in EOL and palliative care research should focus on expanding our toolkit by developing data sources that contain the relevant information required to gain a more in-depth understanding of what is driving the differences in care.