Predictors of Nursing Home Residents' Time to Hospitalization

Citation	O'Malley, Alistair James, Daryl J. Caudry, and David C. Grabowski. 2011. Predictors of nursing home residents' time to hospitalization. Health Services Research 46(1 Pt 1): 82-104.
Published Version	doi:10.1111/j.1475-6773.2010.01170.x
Accessed	February 19, 2015 11:56:26 AM EST
Citable Link	http://nrs.harvard.edu/urn-3:HUL.InstRepos:10612550
Terms of Use	This article was downloaded from Harvard University's DASH repository, and is made available under the terms and conditions applicable to Other Posted Material, as set forth at http://nrs.harvard.edu/urn-3:HUL.InstRepos:dash.current.terms-of-use#LAA

(Article begins on next page)

HSR Health Services Research

DOI: 10.1111/j.1475-6773.2010.01170.x
RESEARCH ARTICLE

Nursing Homes

Predictors of Nursing Home Residents' Time to Hospitalization

A. James O'Malley, Daryl J. Caudry, and David C. Grabowski

Objectives. To model the predictors of the time to first acute hospitalization for nursing home residents, and accounting for previous hospitalizations, model the predictors of time between subsequent hospitalizations.
Data Sources. Merged file from New York State for the period 1998–2004 consisting of nursing home information from the minimum dataset and hospitalization information from the Statewide Planning and Research Cooperative System.
Study Design. Accelerated failure time models were used to estimate the model parameters and predict survival times. The models were fit to observations from 50 percent of the nursing homes and validated on the remaining observations.
Principal Findings. Pressure ulcers and facility-level deficiencies were associated with a decreased time to first hospitalization, while the presence of advance directives and facility staffing was associated with an increased time. These predictors of the time to first hospitalization model had effects of similar magnitude in predicting the time between subsequent hospitalizations.
Conclusions. This study provides novel evidence suggesting modifiable patient and nursing home characteristics are associated with the time to first hospitalization and time to subsequent hospitalizations for nursing home residents.

Key Words. Accelerated failure time model, hospitalizations, Medicare, Medicaid, nursing homes, time between hospitalizations

The hospitalization of nursing home residents has recently emerged as an important area of interest for policy makers. These hospitalizations are known to be frequent (Intrator et al. 2007), costly (Grabowski, O'Malley, and Barhydt 2007), often preventable (Saliba et al. 2000), and potentially associated with negative health outcomes (Ouslander, Weinberg, and Phillips 2000). Reducing avoidable hospitalizations has been proposed as a performance measure in the planned Medicare nursing home value-based purchasing (NHVBP) demonstration. In conjunction with other quality dimensions, nursing homes with lower avoidable hospitalization rates will be rewarded with higher incentive-based payments. By law, the demonstration must be budget neutral. For example, Medicare demonstration bonus pool payments to nursing homes with lower hospitalization rates would be balanced against the savings to Medicare from reduced hospitalizations.

If policy makers are going to use hospitalizations to reward "good" behavior and also generate savings, it is important that the resident and facility characteristics associated with these hospitalizations are known. In a recent review of the literature, Grabowski and colleagues (2008) identified 59 published studies between 1980 and 2006 examining predictors of acute hospitalization for nursing home residents. Based on these studies, resident-level factors associated with hospitalization included sociodemographic factors, health characteristics, and the presence of advance directives. The facility-level factors correlated with hospitalizations included physician and nurse staffing, presence of ancillary services, use of hospice, and ownership status of the facility.

A potentially important source of bias and statistical inefficiency in the existing literature is the manner in which hospitalizations from nursing homes have been modeled. The standard approach has been to estimate the likelihood of any hospitalization over some fixed interval of time such as a quarter year (Carter 2003), half year (Intrator, Castle, and Mor 1999), or full year (Freiman and Murtaugh 1993). On policy, clinical, and statistical grounds, we assert that the more appropriate approach is to model the time to first hospitalization and more generally the time between subsequent hospitalizations. From a policy perspective, the incentives to hospitalize may vary based on the generosity of nursing home reimbursement (Intrator et al. 2007). If a qualifying hospital stay preceded entry into the nursing home, services are covered in part by Medicare for up to 100 days. After the Medicare benefit is exhausted, care is generally covered by Medicaid or privately out of pocket. Moreover, many private-pay nursing home residents eventually "spend down" their assets over the course of their stay and qualify for Medicaid. Given that Medicare payment rates and private out-of-pocket prices are considerably more generous relative to Medicaid payment rates (Troyer 2002), these shifts in payer status may introduce variation in the incentive to hospitalize over a fixed interval of time.

From a clinical and statistical perspective, modeling time to (or rate of) hospitalization is preferred because the risk of hospitalization is not constant

Address correspondence to A. James O'Malley, Ph.D., Department of Health Care Policy, Harvard Medical School, 180 Longwood Avenue, Boston, MA 02115-5899; e-mail: omalley@hcp.med.harvard.edu. Daryl J. Caudry, S.M., and David C. Grabowski, Ph.D., are with the Department of Health Care Policy, Harvard Medical School, Boston, MA.

over time. For example, health status may deteriorate quite rapidly for disabled nursing home residents. Moreover, a time to event approach avoids the problem of having to designate a particular hospitalization—typically the initial hospitalization—as more important than others that occur during a fixed interval of time. The Medicare Payment Advisory Commission (MedPAC) heard testimony at its October 2008 public meeting related to the frequent cycling of individuals between the nursing home and hospital. The standard approach used in the literature—modeling any hospitalization over some fixed time interval—will not account for multiple hospitalizations over a given period.

The only previous survival analyses of hospitalization of nursing home residents reported in the literature used Cox-proportional hazards (Murtaugh and Freiman 1995). This model facilitates an estimate of the relative risk of hospitalization, but it applies only to the first hospitalization and requires additional modeling to estimate the time until hospitalization or, equivalently, the probability that hospitalization occurs during a given time interval. We offer a novel approach to estimating the predictors of hospitalization using accelerated failure time (AFT) models for time to first hospitalization and time between subsequent hospitalizations, extending the AFT model to handle repeated measures data with time-varying covariates. Relative to previous research on hospitalizations for nursing home residents, these models have the advantage of modeling all hospitalizations, accounting for changes over time in the value of predictor variables including summary measures of the number of past hospitalizations, accounting for censoring, and generating interpretable outputs such as the probability that the next hospitalization occurs within a certain time.

Conceptual Framework

We assume a basic model in which the decision to hospitalize a resident is made by the nursing home via a physician order (Freiman and Murtaugh 1993). The facility's decision function incorporates several arguments including the *resident's welfare*, the *resident's preferences*, and the *financial implications* of hospitalization. The resident's welfare relates to sociodemographics and health characteristics. For example, certain health conditions will necessitate hospitalization, while others can be treated safely in the nursing home environment (depending on resources available at the nursing home). The resident's welfare will also be affected by how safely the individual can be cared for in the nursing home given the number of physician and nurse staff and also the availability of ancillary services and hospice. Nursing homes with greater resources will be less likely to hospitalize residents. The resident's preferences for hospitalization will be reflected, for example, in the presence of advance directives.

From a financial perspective, several factors might impact the facility's decision to hospitalize a resident including the nursing home payment rate and the average daily cost of resident care, the additional costs and payments for treating residents with an acute illness potentially necessitating hospitalization, and the additional costs and revenues associated with hospitalization. The ownership status of the facility (e.g., profit-status, chain affiliation) will impact how the facility weighs objectives such as the resident's welfare with the financial implications of hospital transfers. Several changes were made to the way nursing homes were paid by Medicare and Medicaid during the study period (e.g., the prospective payment system, the balanced budget refinement act). However, because this study was based only on New York State, all of the changes occurred uniformly across all facilities in the state.

METHODS

Data

Longitudinal observations are available for each resident admitted from the community to a nursing home in New York State over a 7-year period (1998–2004). Snapshots of each resident's health status in the nursing home are provided at time of admission and then (approximately) quarterly thereafter via minimum dataset (MDS) assessments. MDS assessments are also performed within a week following readmission from hospital. We organized the analytic file around these assessments, because they are made on all residents regardless of hospitalization. Thus, the dataset is a sequence of intervals with predictors evaluated using the MDS collected on the first day of the interval. If a resident is hospitalized, the end date is the hospitalization date; otherwise the end date is the day of the next MDS assessment. After each MDS assessment, a new interval with updated values of any time-varying covariates is added to the sequence. The survival time accumulates across time intervals until the resident is hospitalized or the MDS indicates a discharge to somewhere other than the hospital, in which case the observation of the resident is considered concluded (i.e., censored). If the patient reenters the nursing home from the hospital, a new at-risk period and associated survival time begins. If the patient is discharged to the community (i.e., other than to hospital), the patient's record is terminated for the purposes of our study and the individual must subsequently reenter the nursing home and have an MDS assessment before they would once again be eligible for hospitalization. Right censoring due to death is treated the same as if a resident was discharged to the community.

Information about hospitalizations, including detailed information about the resident's condition and stay, is obtained from the New York Statewide Planning and Research Cooperative System (SPARCS). We use the SPARCS admission field to assist with any measurement issues with the discharge field in the MDS. Specific rules for cleaning the data are listed in Appendix SA2.

We augment the resident-level data with nursing home–level characteristics obtained from the annual online survey certification and reporting (OSCAR) system and the New York Medicaid cost reports (e.g., counts of bed days available and in use). These data are appended to all intervals that occur between the date of the current OSCAR survey or cost report and the next one. By design, some variables in the MDS are only measured in a "full" assessment, which is conducted at admission and then annually thereafter. These and any other variables in the MDS not measured at a particular survey are carried forward until they are next measured. To ensure that all variables are defined homogeneously across residents, the data are restricted to those residents who first enter the nursing home during the study period.

Dependent Variable

The dependent variable is the time from when the MDS indicates a resident enters the nursing home from the community or reenters the nursing home from hospital until the resident's next hospitalization. The time to first hospitalization is the resident's first hospital admission date minus the date of intake MDS assessment at the nursing home (performed within a week of actual admission). If a resident reenters the nursing home following hospitalization, he or she is at risk for another hospitalization and the dependent variable is the time of next hospitalization minus the resident's readmission date.

A compelling motivation for modeling time to first and time between hospitalizations, as opposed to binary regression models of any hospitalization over a fixed time interval, is that the data are a sequence of intervals of differing lengths separated by hospitalizations or occasions when a resident's covariates are observed to have changed. By modeling the time to hospitalization and treating changes in covariate and end of follow-up as right-censoring events, we account for both differential time at risk and time-varying covariates and thus enable all the information in the data to bear on our analysis.

Predictors

The predictors are divided into those affecting the resident's welfare, the resident's preferences, financial implications of the hospitalization, and history of hospitalization variables (see Table 1 for a complete list). Resident's welfare includes sociodemographics, health characteristics, and resident care practices along with facility resources such as the number of physician and nurse staff and the availability of ancillary services and hospice. Sociodemographics include gender, race, age at the start of follow-up, and residence (upstate versus not). Living (or comfort level) variables include, for example, physical functioning, cognitive functioning, presence of physical restraints, and presence of a feeding tube. Chronic conditions include, for example, chronic obstructive pulmonary disease (COPD) and congestive heart failure (CHF). Changes in physical-self or care needs/treatment include variables such as weight loss, more or less self-sufficient, and use of new medications. Medical symptoms include measures such as a problem with swallowing or diarrhea. Acute conditions include accidental hip fracture and an acute episode or flare-up of a chronic problem.

We hypothesized that any change related to deterioration in the residents' health status, including medical symptoms and acute conditions, would be associated with shorter times to hospitalization. In terms of resident preferences, advance directives for resuscitation and hospitalization reflect residents' attitude toward medical intervention; these were expected to be associated with longer times to hospitalization.

At the facility level, we hypothesized that the total number of beds, percentage of beds occupied, nurse staffing, availability of other medical personnel (e.g., presence of a mental health specialist, physician extender), availability of other resources (e.g., pharmacy resident, oxygen), and the overall severity of residents in the facility (as measured by the annual average Resource Utilization Groups case mix index [CMI] across all MDS assessments) would impact time to hospitalization.

Payment method (Medicaid, Medicare, other) is a key financial predictor because it not only encompasses insurance status but also serves as a proxy for socioeconomic status. Another key financial predictor is postacute versus chronic care resident. Following previous research (Gillen et al. 1996; Grabowski, O'Malley, and Barhydt 2007; Intrator et al. 2007), we used length of stay to identify these two populations. The threshold for defining a resident as a chronic care recipient was presence in the nursing home for a total of 100 days, the length of time covered by Medicare for a postacute stay. Upon entry

Table 1: Descriptive Statistics of Predictors by Hospitalization Status of At-Risk Period

	First Observation		*Subsequent Observations*	
	Hospitalized N = 217,697	*Not Hospitalized N = 2,178,622*	*Hospitalized N = 190,837*	*Not Hospitalized N = 789,920*
Term	*Mean ± Standard Deviation (for Nonbinary Variables)*			
Resident level				
Personal characteristics				
Male	0.37	0.30	0.38	0.32
African American	0.15	0.13	0.21	0.15
Not white or African American	0.08	0.06	0.10	0.07
Married	0.25	0.21	0.21	0.19
Daily life				
Severe physical functioning	0.79	0.75	0.85	0.84
Moderate physical functioning	0.14	0.17	0.10	0.11
Severe cognitive functioning	0.22	0.21	0.35	0.32
Moderate cognitive functioning	0.38	0.39	0.36	0.40
Bladder incontinent	0.45	0.44	0.58	0.59
Bowel incontinent	0.40	0.35	0.58	0.53
Restrained by bedrails	0.56	0.56	0.52	0.54
Has trunk, limb, or chair restraints	0.01	0.01	0.02	0.02
Restrained by bedrails and either trunk, limb, or chair restraints	0.04	0.04	0.05	0.06
Special treatment, procedures, and programs	0.58	0.51	0.62	0.55
Nutritional approaches: Feeding tube use	0.10	0.06	0.23	0.13
Nutritional approaches: Parenteral IV	0.01	0.01	0.02	0.02
Medication count	9.2 ± 4.3	8.2 ± 4.1	9.5 ± 4.3	8.8 ± 4.2
Chronic conditions				
Edema	0.18	0.16	0.15	0.15
Stage 1 pressure ulcer	0.04	0.04	0.03	0.04
Stage 2 + pressure ulcer	0.23	0.14	0.28	0.19
Unstable condition	0.28	0.22	0.29	0.27
Alzheimer's or dementia	0.36	0.40	0.45	0.49
Anemia	0.24	0.21	0.30	0.27
Cancer	0.12	0.10	0.10	0.09
Congestive heart failure	0.25	0.19	0.31	0.28

continued

Table 1. *Continued*

	First Observation		*Subsequent Observations*	
	Hospitalized N= 217,697	*Not Hospitalized N= 2,178,622*	*Hospitalized N= 190,837*	*Not Hospitalized N= 789,920*
Term	*Mean ± Standard Deviation (for Nonbinary Variables)*			
Chronic obstructive pulmonary disease	0.18	0.14	0.22	0.19
Daily pain	0.19	0.17	0.16	0.15
Diabetes mellitus	0.31	0.24	0.37	0.30
Dysrhythmia	0.15	0.13	0.15	0.16
Internal bleeding	0.01	0.01	0.01	0.01
Neurological disease	0.35	0.34	0.44	0.42
Other cardiology disease	0.74	0.70	0.76	0.75
Changes since last assessment				
Weight loss	0.13	0.10	0.19	0.17
New medication	0.71	0.65	0.68	0.64
Number of days physician ordered changes to care needs	0.78	0.70	0.75	0.69
Abnormal lab result	0.73	0.69	0.78	0.74
More self-sufficient (less support)	0.11	0.13	0.04	0.05
Less self-sufficient (more support)	0.18	0.14	0.16	0.15
Mood status deteriorated	0.06	0.05	0.06	0.06
Symptoms				
Problem swallowing	0.16	0.12	0.27	0.22
Diarrhea	0.04	0.03	0.03	0.03
Shortness of breath	0.10	0.06	0.11	0.09
Vomiting	0.02	0.02	0.02	0.02
Acute conditions currently affecting activities of daily living				
Accident: Fall	0.29	0.28	0.26	0.27
Accident: Nonhip fracture	0.04	0.05	0.02	0.03
Accident: Hip fracture	0.04	0.05	0.03	0.05
Acute episode or flare-up of chronic problem	0.11	0.09	0.14	0.12
Infection	0.26	0.20	0.31	0.27
Pneumonia	0.05	0.03	0.08	0.07
Resident preferences				
Do-not-hospitalize directive	0.00	0.01	0.00	0.02
Do-not-resuscitate directive	0.34	0.40	0.41	0.52
Discharge from nursing home planned	0.21	0.23	0.05	0.05

continued

Table 1. *Continued*

	First Observation		*Subsequent Observations*	
	Hospitalized N= 217,697	*Not Hospitalized N= 2,178,622*	*Hospitalized N= 190,837*	*Not Hospitalized N= 789,920*
Term	*Mean ± Standard Deviation (for Nonbinary Variables)*			
Financial implications				
Current length of stay > 100 straight days	0.42	0.51	0.83	0.85
Medicare payer	0.51	0.52	0.53	0.55
Medicaid payer	0.21	0.22	0.30	0.27
Nursing home level				
Resident welfare				
Total number of deficiencies (in 10 s)	0.41 ± 0.41	0.42 ± 0.41	0.43 ± 0.41	0.45 ± 0.43
Yearly case mix index	0.99 ± 0.11	0.98 ± 0.11	1.00 ± 0.10	0.99 ± 0.10
Total number of beds at home	262 ± 156	255 ± 160	256 ± 159	256 ± 163
FTE direct care RN staff per bed (in 10 s)	0.55 ± 0.43	0.57 ± 0.43	0.62 ± 0.50	0.63 ± 0.48
Financial implications				
Government-owned nursing home	0.10	0.11	0.10	0.12
Not-for-profit nursing home	0.42	0.45	0.37	0.40
Inpatient days paid for by Medicaid per resident (in 100 s)	0.83 ± 1.00	0.80 ± 0.89	0.87 ± 1.75	0.83 ± 1.56
Percent Medicare patients (annual)	0.52 ± 0.21	0.51 ± 0.21	0.55 ± 0.21	0.54 ± 0.21
Percent Medicaid patients (annual)	0.24 ± 0.18	0.24 ± 0.19	0.25 ± 0.18	0.24 ± 0.17

Notes. First observation refers to the time period up to and (if applicable) including a resident's first hospitalization. Subsequent observations are from the time period following the first hospitalization. FTE, full-time equivalent; RN, registered nurse.

to the nursing home, all residents were designated as short-stay residents; if they have spent 100 days or more in the nursing home (accumulative over hospitalizations), then they were reclassified as long-stay residents (thus, the short-stay/long-stay variable is a time-varying predictor). At the facility level, the ownership status of the nursing home (i.e., for-profit, government-owned, nonprofit) may also influence the financial incentives to hospitalize residents. Dummies for calendar year account for changes in the way nursing homes were paid by Medicare and Medicaid during the study period.

Statistical Models

Previous analyses have generally modeled hospitalization of nursing home residents over some fixed interval of time. Modeling time to hospitalization is preferred because the risk of hospitalization is not constant over time due to various policy and clinical factors. Moreover, this approach allows us to model multiple hospitalizations for a given individual.

Models generated by multiplicative error structures (i.e., log-linear models) or that satisfy the proportional hazards assumption (e.g., Cox-proportional hazards model) are the most common forms of survival models. In this paper, we use the AFT model (Klein and Moeschberger 1997), a special case of the highly flexible log-linear family of models. An appropriate AFT model for modeling time to hospitalization is

$$\log(t_{ij}) = \theta_i + x_{ij}^T \beta + \varepsilon_{ij} \tag{1}$$

where t_{ij}, x_{ij}, and ε_{ij} denote the survival time, a vector of covariates, and the error term for resident j at nursing home i; θ_i is the coefficient of the dummy variable for nursing home i, and β is a vector of parameters measuring the association of each element of x_{ij} with time to hospitalization. Although the predictors may change in continuous time, we only observed them at the discrete observation times and so do not express them as a function of time (t). The presence of θ_i ensures that any time-invariant home-level confounding variables do not bias results.

To account for heterogeneity in the shape of the survival curves between nursing homes, we introduce a nursing home–specific shape parameter λ_i such that $S(t^*; \lambda_i, x_{ij}) = S(t^*; x_{ij})^{\lambda_i}$, where $S(t^*; \lambda_i, x_{ij})$ is the probability that the jth resident at nursing home i is not hospitalized before time t^*. We treat λ_i as a random effect, commonly referred to as a frailty in the survival analysis literature, to account for the correlation of hospitalization times for residents at the same nursing home. In all of our analyses, frailties are assumed to have gamma distributions.

Time to First Hospitalization

Although due to changes in time-varying covariates each resident's time at risk for first hospitalization may be split into multiple at-risk periods (time intervals), there is still only a single observation per resident. Therefore, equation (1) in conjunction with the frailty λ_i is an appropriate model. The variance of λ_i quantifies the amount of unexplained between-nursing home heterogeneity in the shape of the survival distribution for time to hospitalization after accounting for the effects of home and resident-level predictors on expected time to hospitalization.

Time between Hospitalizations

The time to first hospitalization model is extended to allow the effects of predictors to change with (or be modified by) the number of past hospitalizations and to account for correlation between the multiple survival times for a resident who reenters the same nursing home following hospitalization. Specifically, we introduce a subscript h for hospitalization number, add predictors variables involving h alone and the products of these with elements of x_{ij}, and let the random effect λ_{ij} denote the frailty for the jth resident in the ith home. Ideally, we would also include the nursing home frailty λ_i to distinguish variation between nursing homes from variation between residents within homes. However, software limitations restrict us to a single frailty.

Parametric Modeling

For several reasons, we chose to model the survival times parametrically, basing inferences on a probability distribution for ε_{ij}. The specification of a full probability model enables evaluation of the probability that a resident with certain characteristics is hospitalized and the expected number of hospitalizations within a given time. It also avoids the computational difficulties faced by semi-parametric models when there are a large numbers of residents or a large number of time-varying predictors. We compared model fit for the Weibull, gamma, log-normal, and log-logistic distributions before settling on the log-normal as our distribution of choice.

Estimation

The Stata module "*streg*" (StataCorp 2005) was used to compute maximum likelihood inferences (see Appendix SA2) and evaluate predictions from the fitted model. The "random" option was used to specify nursing home and resident frailties in the time to first hospitalization and time between hospitalizations models, respectively.

Model Validation

We used a 50 percent random sample of nursing homes to fit the models (the "training" sample) and saved the remaining data (the "test" sample) for model validation. After selecting our preferred model using the training sample (see Appendix SA2), we refitted the model on the test sample and compared the two sets of estimated regression coefficients and variance parameters. Similar values imply the absence of predictors that by fluke explained purely random variation in the training sample (D'Agostino et al. 2001). We quantified the magnitude of the differences using a statistic that sums the squared between sample standardized differences of the estimated parameters (see Appendix SA2). As a further test, we replicated the entire model-building process on the validation sample and confirmed that the predictor variables retained in the final models were the same as for the test sample.

Based on the above and in the interest of model parsimony, we excluded predictors (e.g., physician extenders) from our final model with p-values in excess of the removal threshold ($p > .0005$), although this did not qualitatively change our findings in regard to the remaining predictors in the model.

RESULTS

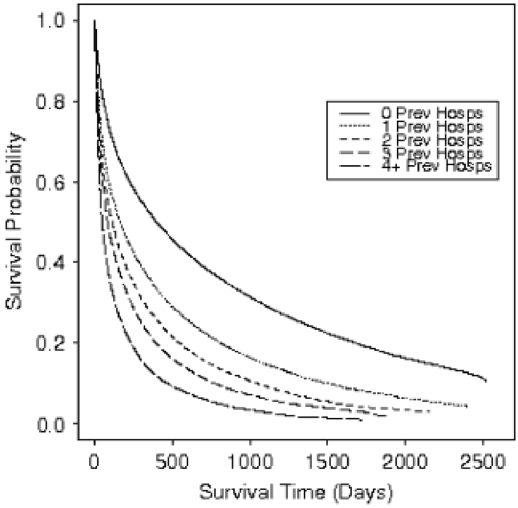
There were 687,956 new admissions across 677 nursing homes over the 1998–2004 study period. These new admissions experienced 408,534 hospitalizations, of which 217,697 were first-time hospitalizations. The total number of distinct at-risk periods for hospitalization was 3,377,076 and the total number before or including the first hospitalization was 2,396,319. The proportions of residents who died in a hospital and in a nursing home were 8.27 percent and 17.52 percent, respectively; thus, 25.79 percent of residents died during the study period. Table 1 shows the unadjusted means and standard deviations (for nonbinary variables) of the predictors for the four categories of at-risk periods corresponding to whether the first hospitalization had yet to occur at the start of the period and whether hospitalization terminated the period.

The Kaplan–Meier survival function (unadjusted for covariates) is displayed in Figure 1 as a function of the number of past hospitalizations. The average time until next hospitalization decreases markedly with the number of previous hospitalizations; the biggest drop is between the first and second hospitalizations; thereafter the decrements are smaller but of consistent magnitude. These observations are consistent with the use of a binary indicator of a past hospitalization from the nursing home both as a main and interaction effect predictor and the log of the number of past hospitalizations (if any) just as a main effect predictor in the time between hospitalization model.

Time to First Hospitalization

The models in Tables 2 and 3 were fit to the 50 percent training sample. A positive (negative) regression coefficient implies a longer (shorter) time to hospitalization. Male and married residents had shorter times to first hospitalization (Table 2). Of the daily life variables, medication count and receipt of

Figure 1: Kaplan–Meier Curves of Time to Hospitalization by the Number of Past Hospitalizations



Note. The curves do not cross.

a special treatment had the strongest associations with shorter time to hospitalization. Bladder incontinence was protective against hospitalization, while severe physical or cognitive functioning and use of a feeding tube or intravenous drip for nutrition were associated with less time to hospitalization.

Table 2: Effects on Time to First Hospitalization

	Statistic		
Term	*Coefficient*	*z*	*p*> |*z*|
Resident level			
Personal characteristics			
Male	– 0.21	– 27.8	0
African American	– 0.01	– 0.4	.66
Not white or African American	0.05	3.5	.001
Married	– 0.07	– 8.9	0
Daily life			
Severe physical functioning	– 0.16	– 10.8	0
Moderate physical functioning	– 0.06	– 3.5	0

continued

Table 2. *Continued*

Term	*Coefficient*	*z*	*p>|z|*
	Statistic		
Severe cognitive functioning	– 0.11	– 8.4	0
Moderate cognitive functioning	– 0.02	– 2.8	.006
Bladder incontinent	0.07	7.2	0
Bowel incontinent	– 0.11	– 10.9	0
Restrained by bedrails	– 0.01	– 1.1	.26
Has trunk, limb, or chair restraints	– 0.07	– 2.1	.034
Restrained by bedrails and either trunk, limb, or chair restraints	0.03	1.5	.127
Special treatment, procedures, and programs	– 0.20	– 22.5	0
Nutritional approaches: Feeding tube use	– 0.14	– 8.9	0
Nutritional approaches: Parenteral IV	– 0.22	– 7.2	0
Medication count	– 0.04	– 39.8	0
Chronic conditions			
Edema	– 0.10	– 10.8	0
Stage 1 pressure ulcer	– 0.11	– 6.7	0
Stage 2 + pressure ulcer	– 0.25	– 28.7	0
Unstable condition	– 0.17	– 19.6	0
Alzheimer's or dementia	0.10	11.8	0
Anemia	– 0.09	– 11.0	0
Cancer	– 0.18	– 17.0	0
Congestive heart failure	– 0.18	– 21.5	0
Chronic obstructive pulmonry disease	– 0.10	– 10.7	0
Daily pain	– 0.09	– 9.9	0
Diabetes mellitus	– 0.11	– 14.4	0
Dysrhythmia	– 0.10	– 10.7	0
Internal bleeding	– 0.23	– 6.2	0
Neurological disease	0.07	9.3	0
Other cardiology disease	– 0.04	– 5.2	0
Changes since last assessment			
Weight loss	– 0.13	– 12.3	0
New medication	– 0.07	– 7.7	0
Number of days physician ordered changes to care needs	– 0.21	– 21.3	0
Abnormal lab result	– 0.08	– 9.2	0
More self-sufficient (less support)	0.13	11.6	0
Less self-sufficient (more support)	– 0.09	– 9.9	0
Mood status deteriorated	– 0.12	– 8.0	0
Symptoms			
Problem swallowing	– 0.10	– 8.7	0
Diarrhea	– 0.17	– 9.7	0
Shortness of breath	– 0.28	– 22.3	0
Vomiting	– 0.25	– 11.4	0

continued

Table 2. *Continued*

	Statistic		
Term	*Coefficient*	*z*	*p*> |*z*|
Acute conditions currently affecting activities of daily living			
Accident: Fall	– 0.04	– 5.0	0
Accident: Nonhip fracture	0.13	8.0	0
Accident: Hip fracture	0.21	13.2	0
Acute episode or flare-up of chronic problem	– 0.16	– 13.5	0
Infection	– 0.11	– 13.0	0
Pneumonia	– 0.06	– 3.4	.001
Resident preferences			
Do-not-hospitalize directive	0.83	16.9	0
Do-not-resuscitate directive	0.12	14.7	0
Discharge from nursing home planned	– 0.08	– 7.7	0
Financial implications			
Current length of stay > 100 straight days	0.86	84.2	0
Medicare payer	– 0.10	– 11.6	0
Medicaid payer	0.09	7.4	0
Constants			
Intercept	8.58	28.4	0
1999 year	– 0.05	– 3.6	0
2000 year	– 0.06	– 4.0	0
2001 year	– 0.06	– 3.9	0
2002 year	– 0.06	– 3.7	0
2003 year	– 0.07	– 3.6	0
2004 year	– 0.12	– 5.0	0
Variance (within nursing homes)	1.88	57.0	0
Nursing home level			
Resident welfare			
Total number of deficiencies (in 10 s)	– 0.06	– 5.3	0
Yearly case mix index	– 0.31	– 3.2	.002
Total number of beds at home	0.00	0.0	.991
FTE direct care RN staff per bed	0.11	1.6	.102
Financial implications			
Government-owned nursing home	– 0.30	– 4.7	0
Not-for-profit nursing home	– 0.05	– 1.4	.175
Inpatient days paid for by Medicaid per resident	– 0.71	– 3.0	.003
Percent Medicare patients (annual)	0.02	0.5	.635
Percent Medicaid patients (annual)	0.01	0.2	.864
Variance (between nursing homes)	2.03	5.8	0

Notes. As described in the Appendix, the model resulted from a comprehensive model-building strategy. For instance, among the staffing variables there were many candidate predictors (e.g., full-time direct care nurse staff effort per bed) that were not retained in the final model because they were dominated by the nurse staff effort per bed variable. Random frailty effects were included for each nursing home to account for correlation between times to first hospitalization for residents in the same nursing home. FTE, full-time equivalent; RN, registered nurse.

Table 3: Effects on Time between Hospitalizations

Term	*Statistic* *Coefficient*	*z*	*p>|z|*
Resident level			
Personal characteristics			
Male	– 0.20	– 30.1	0
African American	– 0.01	– 0.6	.55
Not white or African American	0.05	3.9	0
Married	– 0.06	– 8.1	0
Daily life			
Severe physical functioning	– 0.16	– 12.1	0
Moderate physical functioning	– 0.06	– 3.9	0
Severe cognitive functioning	– 0.13	– 11.4	0
Moderate cognitive functioning	– 0.03	– 3.6	0
Bladder incontinent	0.06	6.6	0
Bowel incontinent	– 0.10	– 10.7	0
Restrained by bedrails	– 0.02	– 2.0	.048
Has trunk, limb, or chair restraints	– 0.04	– 1.5	.132
Restrained by bedrails and either trunk, limb, or chair restraints	0.05	2.7	.008
Special treatment, procedures, and programs	– 0.22	– 28.6	0
Nutritional approaches: Feeding tube use	– 0.16	– 12.2	0
Nutritional approaches: Parenteral IV	– 0.14	– 5.4	0
Medication count	– 0.04	– 44.3	0
Chronic conditions			
Edema	– 0.09	– 11.5	0
Stage 1 ulcer	– 0.09	– 6.7	0
Stage 2 + ulcer	– 0.24	– 30.2	0
Unstable condition	– 0.18	– 22.4	0
Alzheimer's or dementia	0.10	12.7	0
Anemia	– 0.08	– 11.1	0
Cancer	– 0.18	– 18.2	0
Congestive heart failure	– 0.18	– 23.1	0
Chronic obstructive pulmonry disease	– 0.10	– 11.7	0
Daily pain	– 0.10	– 13.2	0
Diabetes mellitus	– 0.10	– 15.3	0
Dysrhythmia	– 0.08	– 9.9	0
Internal bleeding	– 0.19	– 6.2	0
Neurological disease	0.07	10.0	0
Other cardiology disease	– 0.03	– 4.0	0
Changes since last assessment			
Weight loss	– 0.10	– 11.0	0
New medication	– 0.05	– 6.2	0
Number of days physician ordered changes to care needs	– 0.26	– 28.1	0
Abnormal lab result	– 0.08	– 10.3	0

continued

Table 3. *Continued*

Term	*Statistic* *Coefficient*	*z*	*p*> |*z*|
More self-sufficient (less support)	0.08	8.2	0
Less self-sufficient (more support)	– 0.15	– 17.7	0
Mood status deteriorated	– 0.11	– 8.3	0
Symptoms			
Problem swallowing	– 0.10	– 10.1	0
Diarrhea	– 0.15	– 9.8	0
Shortness of breath	– 0.30	– 25.2	0
Vomiting	– 0.27	– 13.8	0
Acute conditions currently affecting activities of daily living			
Accident: Fall	– 0.02	– 3.1	.002
Accident: Nonhip fracture	0.14	9.8	0
Accident: Hip fracture	0.21	15.9	0
Acute episode or flare-up of chronic problem	– 0.17	– 16.4	0
Infection	– 0.10	– 13.7	0
Pneumonia	– 0.03	– 2.4	.017
Resident preferences			
Do-not-hospitalize directive	0.90	23.0	0
Do-not-resuscitate directive	0.13	17.9	0
Discharge from nursing home planned	– 0.09	– 10.4	0
Financial implications			
Current length of stay >100 straight days	0.86	97.2	0
Medicare payer	– 0.11	– 14.3	0
Medicaid payer	0.04	4.0	0
Past hospitalizations			
At least one previous hospitalization	– 0.54	– 18.7	0
Log no past hospitalizations if >0	– 2.67	– 88.8	0
Interactions			
Past hospitalization × Number of days care-needs orders changed	0.19	8.8	0
Past hospitalization × More self-sufficient	– 0.29	– 13.2	0
Past hospitalization × Less self-sufficient	0.02	0.7	.502
Past hospitalization × Unstable condition	0.15	7.7	0
Past hospitalization × Cancer	0.12	4.3	0
Past hospitalization × Congestive heart failure	0.10	5.2	0
Past hospitalization × Shortness of breadth	0.16	5.6	0
Constants			
Intercept	6.65	55.4	0
1999 year	– 0.06	– 4.5	0
2000 year	– 0.09	– 6.6	0
2001 year	– 0.09	– 6.6	0
2002 year	– 0.09	– 6.5	0
2003 year	– 0.11	– 6.5	0
2004 year	– 0.18	– 8.4	0
Variance (within residents)	1.35	116.4	0

continued

Table 3. *Continued*

Term	*Statistic* *Coefficient*	*z*	$p > \|z\|$
Nursing home level			
Resident welfare			
Total number of deficiencies (in 10 s)	– 0.06	– 5.7	0
Yearly case mix index	– 0.21	– 2.5	.014
Total number of beds at home	0.00	0.1	.954
FTE direct care RN staff per bed	0.03	0.4	.669
Financial implications			
Government-owned nursing home	– 0.31	– 5.7	0
Not-for-profit nursing home	– 0.04	– 1.2	.243
Inpatient days paid for by Medicaid per resident	– 0.67	– 3.2	.002
Percent Medicare patients (annual)	0.03	0.9	.389
Percent Medicaid patients (annual)	0.06	1.3	.197
Variance (between residents)	0.05	47.10	0

Notes. Random frailty effects were included for each resident to account for correlation between repeated observations of time to hospitalization made on the same resident.

Partial restraint (bedrails alone or trunk, limb, and chair alone) was associated with a shorter time to hospitalization. Chronic conditions such as stage 2+ (pressure) ulcer, CHF, diabetes, unstable conditions, and cancer were also associated with shorter time to hospitalization. Interestingly, the only two chronic conditions that were protective against hospitalization, Alzheimer's/dementia and neurological disease, were both mental health conditions.

In terms of measures of changes in a resident's health status, the number of days physicians changed care needs orders and weight loss were associated with shorter times to hospitalization, while, as expected, residents more self-sufficient (i.e., with improved care needs) than at their last MDS assessment were associated with longer times to hospitalization. Residents less self-sufficient (i.e., having greater care needs) were hospitalized more frequently. Shortness of breath and vomiting were the symptoms associated with greatest risk of hospitalization. Recent fractures (especially hip) were generally protective against hospitalization, which may reflect the increased rehabilitative care and limited mobility following a fracture. An acute episode related to a chronic problem and infection had the strongest associations with shorter time to hospitalization among the acute condition predictors. Pneumonia was only moderately associated with time to hospitalization, although many cases of pneumonia (and other acute illnesses) are likely missed in the regular MDS assessment due to their sudden onset.

In terms of resident preferences, the presence of advance directives (in particular the "do-not-hospitalize" directive) was strongly protective of hospitalization. Among the financial predictors, residence in the nursing home for 100 days or more and payment by Medicaid (relative to private pay) were protective of hospitalization. Payment by Medicare was also associated with shorter times to hospitalization relative to private-pay status.

There was modest evidence that residents in nursing homes with more registered nurses per bed had a longer time to hospitalization ($p = .10$), while residents in nursing homes with greater deficiencies had shorter time to hospitalization. Higher facility-level CMI scores (indicating that patients are on average in worse health status) were associated with shorter times to hospitalization and the percentage of Medicare and Medicaid residents were associated with longer times to hospitalization, respectively. The hospitalization rates at government-owned facilities were much higher than at for-profit facilities, while the rates at nonprofit and for-profit facilities were similar.

Time between Hospitalizations Model

The predictors in the time to first hospitalization model had similar effects in the time to next hospitalization model (Table 3). Thus, to avoid redundancy, in this section we focus on the results for the main effects of past hospitalization and the log of the number of past hospitalizations (see Appendix SA2 for precise definition) and the interaction effect of other predictors with past hospitalization. The fact that the significant interactions are only with the binary indicator of any past hospitalization and not the log of the number of past hospitalizations reveals that although the effects of some predictors change substantially after first reentry to the nursing home from hospital, there is little additional modification thereafter.

The main effects of past hospitalization, -0.54, and the log of the number of the number of past hospitalizations, -2.67, are highly significant, implying that the time between hospitalizations decreases substantially after a resident has been hospitalized. The slope of the combined effect of these variables has a steep downward trajectory that flattens as the number of hospitalizations increases, consistent with the nonoverlapping Kaplan–Meier survival functions displayed in Figure 1.

With the exception of more self-sufficient (i.e., resident has fewer care needs), all of the interaction effects with past hospitalization are positive, whereas their main effects are negative. In the case of more self-sufficient, the interaction effect is larger than the main effect; thus, more self-sufficient is a risk factor for further hospitalization among readmitted residents. The overall effect of number of days a physician changed a resident's orders, unstable condition, cancer, CHF, and shortness of breath were negative but closer to zero than their main effects.

Model Validation

The signs of all statistically significant effects in both models were generally the same across the training and test samples and cohered with our intuition. There was minimal evidence of overfitting or lack of face validity. In particular, given that one of the major contributions of this paper is to account for the effect of past hospitalizations on the time to next hospitalization, it is reassuring that the estimated interaction effects in the time between hospitalization model were among the most similar effects across samples.

Discussion

Providers, policy makers, and researchers have a strong interest in identifying the major determinants of hospitalization among nursing home residents. Given that our study is the first to implement an alternative modeling strategy, it is useful to compare our results against those obtained by previous studies; see Grabowski et al. (2008) for a comprehensive literature review. Of particular interest are those factors that may be candidates for interventions by nursing homes or policy makers to reduce hospitalizations.

Similar to the earlier literature, we observed that residents with pressure ulcers or a feeding tube in place were more likely to be hospitalized, while advance directives were protective of hospitalization. Our findings also supported earlier research suggesting nursing homes with more full-time registered nurses had fewer hospital transfers. One key area of departure between our findings and those of the earlier studies relates to nursing home ownership. We found no statistically significant association between for-profit ownership and time to hospitalization, while just over half (12 out of 20) of the earlier studies report that for-profit ownership is positively correlated with hospitalization (Grabowski et al. 2008). One possible explanation for this discrepancy is our focus on New York State, which has a regulation prohibiting large out-of-state chains from owning and operating nursing homes in the state. As such, New York has a much higher proportion of nonprofit nursing homes relative to other states, which may suggest different intersectoral competition between nonprofits and for-profits. For example, Grabowski and Hirth (2003) have found that an increase in nonprofit market share improves the quality of for-profit nursing homes.

An issue that plagues both our paper and earlier studies in this literature is how to properly risk-adjust hospitalizations from the nursing home setting to distinguish avoidable and unavoidable hospitalizations. Using a model of the clinical necessity of hospitalization (O'Malley et al. 2007), we found that the predicted proportion of potentially preventable hospitalizations (those with a low predicted necessity of hospitalization) for a nursing home had little predictive power and we consequently excluded it from the models.

Although we have pursued a rigorous analytic approach, one issue that we have not dealt with is informative censoring due to death (or any other reason). It is possible that individuals who die and the hospitalization decisions made about them differ in systematic ways from those who do not die. If true, this could bias the coefficients of the associated effects. Informative censoring can be explicitly modeled by fitting a bivariate survival model in which correlation between time until hospitalization and time until death is modeled using a resident-specific latent variable (Lancaster and Intrator 1998; Fleming and Lin 2000; Ghosh and Lin 2003). However, specialized software is required to fit such a model. In lieu of this approach, we used sensitivity analyses to gauge the robustness of our results to informative censoring by death. This involved truncating each resident's record 12 months before their death or last censoring time. By only considering periods of observations that are at least 12 months before death, we hoped to remove the impact of informative censoring due to death from observed predictors (this does not, however, control for unmeasured confounding variables). Thus, the analyses of the remaining observations are expected to be less sensitive to informative censoring by death. The results were similar to those from the analysis of the full 50 percent training sample, implying that censoring by death is most likely noninformative. An alternative approach would have been to model the three-level variable (no event, hospitalization, death) as in Intrator et al. (2007). Because this form of analysis ignores the natural time to event structure of the data, it is not applicable to our analysis.

In summary, this study offered a novel approach to estimating the predictors of hospitalization using AFT models for time to first hospitalization and time between subsequent hospitalizations. Modifiable patient and nursing home factors were found to be predictive of the time to hospitalization, suggesting nursing homes can be responsive to payment incentives directed at discouraging acute hospitalizations among residents.

ACKNOWLEDGMENTS

Joint Acknowledgment/Disclosure Statement: This work was supported by a grant from The Commonwealth Fund on Using Incentives to Reduce Hospitalizations of Nursing Home Residents in New York State. The authors also acknowledge and thank Nancy Barhydt, Suzanne Broderick, Anna Colello, Matthew Leary, Michael Lindsay, and Dawn Maynus at the New York State Department of Health for their assistance with this study. Any errors are our own.

Disclosures: None.

Disclaimers: None.

REFERENCES

Carter, M. W. 2003. "Variations in Hospitalization Rates among Nursing Home Residents: The Role of Discretionary Hospitalizations." *Health Services Research* 38 (4): 1177–206.

D'Agostino, R. Sr., S. Grundy, L. M. Sullivan, and P. Wilson. 2001. "Validation of the Framingham Coronary Heart Disease Prediction Scores: Results of a Multiple Ethnic Groups Investigation." *Journal of the American Medical Association* 286: 180–7.

Fleming, T. R., and D. Y. Lin. 2000. "Survival Analysis in Clinical Trials: Past Developments and Future Directions." *Biometrics* 56: 971–83.

Freiman, M. P., and C. M. Murtaugh. 1993. "The Determinants of the Hospitalization of Nursing Home Residents." *Journal of Health Economics* 12 (3): 349–59.

Ghosh, D., and D. Y. Lin. 2003. "Semiparametric Analysis of Recurrent Events Data in the Presence of Dependent Censoring." *Biometrics* 59: 877–85.

Gillen, P., D. Spore, V. Mor, and W. Freiberger. 1996. "Functional and Residential Status Transitions among Nursing Home Residents." *Journals of Gerontology: Medical Sciences* 51 (1): M29–36.

Grabowski, D. C., and R. A. Hirth. 2003. "Competitive Spillovers across Non-Profit and For-Profit Nursing Homes." *Journal of Health Economics* 22 (1): 1–22.

Grabowski, D. C., A. J. O'Malley, and N. R. Barhydt. 2007. "The Costs and Potential Savings Associated with Nursing Home Hospitalizations." *Health Affairs (Millwood)* 26 (6): 1753–61.

Grabowski, D. C., K. A. Stewart, S. M. Broderick, and L. A. Coots. 2008. "Predictors of Nursing Home Hospitalization: A Review of the Literature." *Medical Care Research and Review* 65 (1): 3–39.

Intrator, O., N. G. Castle, and V. Mor. 1999. "Facility Characteristics Associated with Hospitalization of Nursing Home Residents: Results of a National Study." *Medical Care* 37 (3): 228–37.

Intrator, O., D. C. Grabowski, J. Zinn, M. Schleinitz, Z. Feng, S. Miller, and V. Mor. 2007. "Hospitalization of Nursing Home Residents: The Effects of States' Medicaid Payment and Bed-Hold Policies." *Health Services Research* 42 (4): 1651–71.

Klein, J., and M. Moeschberger. 1997. *Survival Analysis: Techniques for Censored and Truncated Data*. New York: Springer.
Lancaster, T., and O. Intrator. 1998. "Panel Data with Survival: Hospitalization of HIV-Positive Patients." *Journal of the American Statistical Association* 93: 46–53.
Murtaugh, C. M., and M. P. Freiman. 1995. "Nursing Home Residents at Risk of Hospitalization and the Characteristics of Their Hospital Stays." *Gerontologist* 35 (1): 35–43.
O'Malley, A. J., E. R. Marcantonio, R. L. Murkofsky, D. J. Caudry, and J. L. Buchannan. 2007. "Deriving a Model of the Necessity to Hospitalize Nursing Home Residents." *Research on Aging* 29: 606–25.
Ouslander, J. G., A. D. Weinberg, and V. Phillips. 2000. "Inappropriate Hospitalization of Nursing Facility Residents: A Symptom of a Sick System of Care for Frail Older People." *Journal of the American Geriatric Society* 48 (2): 230–1.
Saliba, D., R. Kington, J. Buchanan, R. Bell, M. Wang, M. Lee, M. Herbst, D. Lee, D. Sur, and L. Rubenstein. 2000. "Appropriateness of the Decision to Transfer Nursing Facility Residents to the Hospital." *Journal of the American Geriatric Society* 48 (2): 154–63.
StataCorp. 2005. *Stata Statistical Software: Release 9*. College Station, TX: StataCorp LP.
Troyer, J. 2002. "Cross-Subsidization in Nursing Homes: Explaining Rate Differentials among Payer Types." *Southern Economic Journal* 68 (4): 750–73.

Supporting Information

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.
Appendix SA2: Detail of Methodology.

Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting materials supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.