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ORIGINAL PAPER

Inpatient length of stay: a finite mixture modeling analysis

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Abstract Length of stay (LOS) in hospital for inpatient treatment is a measure of crucial recovery time. Using nationwide data on inpatient healthcare in India, a three-component finite mixture negative binomial model was found to provide a reasonable fit to the heterogeneous LOS distribution. Associated risk factors for short-stay, medium-stay and long-stay subgroups were identified from the respective negative binomial components. In addition, significant heterogeneities within each group were also found.

Keywords Finite mixture modeling · Inpatient length of stay · Heterogeneity

JEL Classification C5

Introduction

Hospitalization in most cases is for curative treatment of ailments, and length of stay (LOS) in hospital is a sensitive indicator of patient recovery time. In addition, inpatient LOS is often used as a measure of hospital performance and is considered a proxy of hospital resource consumption [1, 2]. In view of the structural adjustment in the Indian health care sector in the early 1990s [3], and the near absence of health insurance in India, a comprehensive understanding of LOS in hospital is vital for meeting the demand for curative treatment.

At present, the health care system in India is characterized by the co-existence of the public and private sectors. According to the Indian Constitution, the primary responsibility for public health care rests with state government, which consists of three tiers: central, state and local government. Hospitalization and treatment charges in the public sector are subsidized. However, the public sector is under pressure to cope with the ever increasing demand for healthcare, and the quality of services offered is coming under scrutiny. Structural adjustments in the healthcare system to ease the pressure on the public sector has led to a mushrooming of the private health sector run by corporations. Hospitalization and treatment charges in private healthcare facilities are exorbitant. However, hospitals in the private sector provide specialized modern treatment. But, unlike the public sector, there is no statutory regulation requiring standardized hospitalization and treatment charges in the private sector. As such, out-of-pocket expenditure for hospitalization in the public and private sectors differs significantly. Nevertheless, patients seeking specialized and quality healthcare opt for the private sector. Against this background, this paper attempts to identify risk factors for short-stay, medium-stay and long-stay subgroups of patients, and analyzes LOS as an indicator of the pressure on inpatient treatment, with a view to enhancing standardization of the curative healthcare delivery system in India. From both the physical and mental health perspectives of patients, the shorter the recovery time (in terms of shorter LOS), the more effective is the curative treatment [4–6].

It is assumed that, in many hospitals, LOS outliers have different resource consumption patterns from those with normal LOS. Indeed, in one such study, it was found that

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many hospital case-mix schemes such as diagnosis related groups (DRG)—a patient classification scheme that provides a clinically meaningful way of relating the type of patients treated to the resources required by the hospital—are based on this assumption. As such, outliers are funded differently by state health authorities [7]. DRG classification categorizes acute admitted patient episodes according to diagnostic information and clinical details recorded in the hospital morbidity data system [8]. Previous retrospective and claims-based studies have demonstrated widespread variations in LOS for a variety of medical conditions, including community-acquired pneumonia [9, 10].

To prepare for meeting the ever increasing demand for inpatient treatment from a service management perspective as well as from the point of view of users of a health facility, it is imperative to assess the relative performance of service providers by modeling the distribution of LOS. The time elapsed since admission as an inpatient can be described by a two-term mixed exponential distribution reflecting two different types of patient [11]. Such models have also been used successfully by manpower planners to describe LOS in jobs where there are short- and long-stay employees [12]. In a recent study, McClean and Millard [13] fitted a two-term mixed exponential distribution using death/discharge and transfer as the two components of the mixture. Accounting for distributional characteristics should assist in the preparation of prescriptive policies for more efficient utilization of resources, but heterogeneity of LOS within latent groups introduces a problem into the statistical analysis [14]. The application of finite mixture models dealing with latent groups has been discussed extensively in the literature [15]. Each individual in an underlying sub-population differs in socio-economic and demographic characteristics, which results in heterogeneity of the observed outcomes, as discussed extensively by several scholars [16–18], particularly in the context of health care utilization. Inpatient LOS is a readily available indicator of hospital activity. It is also a reasonably good proxy of resource consumption [19, 20].

As stated above, in many hospitals case-mix schemes such as DRG are based on the assumption that long-stay patients have different resource consumption patterns than those of short-stay patients. Therefore, the heterogeneous LOS observations can be modeled by a two-component model, with components corresponding to the short-stay sub-population and the long-stay sub-population [21, 22].

Due to the correlated nature of observations collected from the same hospital and from the same patient, the analysis of patient outcomes pertaining to LOS is complex. The dependence of clustered data (patients nested within hospitals) may sometimes lead to spurious associations and misleading inference. A recent work by Leung et al. [23] accounted for such dependency after arbitrarily trimming extreme LOS observations under the framework of a linear mixed effect model. The aim of this study is to differentiate inpatients in terms of LOS by fitting a finite mixture model (FMM) accounting for both inherent correlations and heterogeneity.

Methods

The Ministry of Statistics and Programme Implementations of the Government of India collected data on morbidity and health care in India from a national representative sample of 73,868 households in the 60th Round of National Sample Survey Organization (NSSO) during the period January–June 2004. The data includes out-of-pocket expenditure, type of ailment, length of hospitalization and health sector of service utilization, together with individual and household socio-economic backgrounds. The sample design is a two-stage stratified design with census villages and urban blocks as the first-stage units for rural and urban areas, respectively, and households as the second stage unit. The rural and urban sub-samples of first-stage units are drawn independently in the form of two sub-samples and equal numbers of first-stage units of each sub-sample are allocated to the two sub-rounds.

We considered hospitalized cases only and design weight was adjusted accordingly. A person was considered hospitalized for treatment if he/she had availed themselves of medical services as an inpatients in any hospital. Hospital, for the purpose of the survey, referred to any medical institution having provision for admission of sick persons as inpatients for treatment. Once admitted as an inpatient for treatment, an individual was always considered as a hospitalized case irrespective of the LOS in hospital. It should also be noted that release from hospital does not necessarily mean total recovery. The survey was retrospective in nature and the reference period for hospitalized cases was 365 days. The outcome variable LOS was defined as the number of (whole) days from admission to discharge in any type of hospital whether public or private during the 365 days prior to the survey date. The present study is based on a total of 6,726 hospitalized cases pertaining to five different types of ailments, namely diarrheal disease, heart disease, tuberculosis, urinary disease and gynecological disorders.

Among methods commonly used for the analysis of LOS are hurdle models, zero-inflated models, etc. Deb and Trivedi [24] proposed the use of FMMs as an alternative to hurdle models in the empirical modeling of health care utilization. In a more recent paper [25], the same authors pointed out that “a more tenable distinction for typical cross-sectional data may be between an ‘infrequent user’ and a ‘frequent user’ of medical care, the difference being determined by health status, attitudes to health risk, and choice of lifestyle". They argue that this is a better framework than the hurdle model in distinguishing between users and non-users of care.

In an FMM, the population is assumed to be made up of C distinct sub-populations in proportions $\pi_1,\ldots, \pi_c$, where $\sum_{j=1}^{c} \pi_j = 1,\ 0 < \pi_j < 1 (j = 1, \ldots, c)$. The C-point finite mixture model is given by

$$f(y_i/\Theta) = \sum_{j=1}^{c} \pi_j f_j(y_i/\theta_j) \quad (1)$$

where the mixing probabilities π_j are estimated along with all other parameters, denoted as Θ. Also, $\pi_c = 1 - \sum_{j=1}^{c-1} \pi_j$.

The component distributions in a C-point finite mixture negative binomial (FMNB) model are defined as

$$f_j(y_i) = \frac{\Gamma(y_i + \Psi_{j,i})}{\Gamma(\Psi_{j,i})(y_i + 1)} \left(\frac{\Psi_{j,i}}{\lambda_{j,i} + \Psi_{j,i}}\right)^{\Psi_{j,i}} \left(\frac{\lambda_{j,i}}{\lambda_{j,i} + \Psi_{j,i}}\right)^{y_i} \quad (2)$$

where, $j = 1,\ldots,c$ are the latent classes, $\lambda_{j,i} = \exp(x_i'\beta_j)$ and $\Psi_{j,i} = (1/\alpha_j)\lambda_{j,i}^{k}$.Inserting the value of $\Psi_{j,i}$ in Eq. 2 implies

$$f_j(y_i/x_i) = \frac{\Gamma\left(y_i + \left(\lambda_{j,i}^{k}/\alpha_j\right)\right)}{\Gamma\left(\lambda_{j,i}^{k}/\alpha_j\right)\Gamma(y_i + 1)} \left(\alpha_j \lambda_{j,i}^{1-k} + 1\right)^{-\lambda_{j,i}^{k}/\alpha_j} \times \left(1 + \frac{\lambda_{j,i}^{k-1}}{\alpha_j}\right)^{-y_i} \quad (3)$$

In general specification, all the elements of parameter vector β_j as well as the overdispersion parameters α_j are allowed to vary across the latent classes.

Yau et al. [16], made an attempt to fit a two-component mixture that accounts for correlation and heterogeneity inherited from unobserved covariates of LOS outcomes. They introduced simultaneous random effects in the mixture probability and the component distributions. In this study, we attempted to fit a finite mixture negative binomial (FMNB) model by taking inpatient duration of stay in hospital as the count variable. We estimated models with $c = 2$ and 3. Regarding the distribution of component densities, we chose the most usual densities applied to model count data, i.e., Poisson, negative binomial I and II [21, 24–26]. We estimate several FMMs, which were compared using Bayesian information criterion (BIC) and Akaike information criterion (AIC) measures [27]. Maximization problems are solved by the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm.

Results

For policy and planning purposes, an understanding of the different groups of patients utilizing hospital resources as inpatients for short as well as for longer periods is essential. Identification of pertinent factors responsible for variation in inpatient LOS is required in order to provide important information for health care planning and resource allocation.

The empirical distribution of the dependent variable, i.e., LOS for inpatients treated for five conditions (diarrhea, heart disease, tuberculosis, urinary disease, and gynecological disorders) is shown in Table 1. The maximum relative frequency (12.85) was found to be concentrated on a LOS of 2 days. The count variable, which is the LOS as an inpatient during last 365 days, ranges from a minimum of 1 day to a maximum of 365 days.

The covariates used in this study were those determinants found to be pertinent for LOS in other studies [16, 28]. Table 2 shows the definitions and coding categories of covariates used to fit the negative binomial FMM, and which are also likely to be associated with LOS for inpatients considered in this study. The covariates are grouped into three categories, encompassing socioeconomic, health status and hospital characteristics according to the information available from the present data set. In the first group/category, variables such as 'sex', 'age', 'education', 'place of residence' and a variable 'monthly per capita expenditure' (here a proxy for household economic status), are included.

The second category includes the type of ailment, which is a proxy for health status. The third category considers the type of hospital, type of hospital ward and the patient's past treatment history. Hospitalization in the public sector is treated as the reference category for comparison with LOS for hospitalization in the private sector. The type of inpatient wards available in hospitals in India are general wards, the reference category for comparison in which lodging is either free or highly subsidized, and special paying wards where inpatients can stay upon payment of higher charges. All other variables are self-explanatory. We now discuss the model selection procedure used to select the preferred FMM in terms of the number of classes and component distributions.

Models $c = 1$ and 2 are nested, so it is possible to use likelihood ratio (LR) tests to choose among them [26, 28]. Models with $c = 1$ were rejected, leaving the comparison of $c = 2$ or 3. Table 3 shows the values of BIC and AIC for different FMM with $c = 2$ and 3, along with Poisson, negative binomial I and II component distributions.

Based on the entire sample for the study, both BIC and AIC indicators/measures support the three-component negative binomial I finite mixture model (FMNB-I). In other words, for the present data set, FMNB-I is the best fit. Thus, all further interpretation is based on the results of the FMNB-I model with three latent classes.

Table 1 Empirical frequency distribution of the length of stay (LOS) in hospital

Count	Frequency	Relative frequency	Count	Frequency	Relative frequency	Count	Frequency	Relative frequency
1	476	7.08	25	40	0.59	70	3	0.04
2	864	12.85	26	8	0.12	74	1	0.01
3	821	12.21	27	12	0.18	75	1	0.01
4	609	9.05	28	22	0.33	80	2	0.03
5	541	8.04	29	3	0.04	90	22	0.33
6	293	4.36	30	153	2.27	93	1	0.01
7	584	8.68	32	3	0.04	100	2	0.03
8	442	6.57	33	1	0.01	105	2	0.03
9	126	1.87	34	3	0.04	120	6	0.09
10	523	7.78	35	7	0.10	125	1	0.01
11	78	1.16	37	1	0.01	130	1	0.01
12	168	2.50	38	2	0.03	135	1	0.01
13	64	0.95	39	2	0.03	138	1	0.01
14	65	0.97	40	11	0.16	148	1	0.01
15	393	5.84	42	1	0.01	150	2	0.03
16	26	0.39	44	1	0.01	155	1	0.01
17	22	0.33	45	29	0.43	180	5	0.07
18	27	0.40	48	1	0.01	190	1	0.01
19	9	0.13	50	3	0.04	210	1	0.01
20	109	1.62	59	1	0.01	225	1	0.01
21	24	0.36	60	30	0.45	240	1	0.01
22	38	0.56	61	1	0.01	245	1	0.01
23	12	0.18	64	1	0.01	320	2	0.03
24	13	0.19	68	1	0.01	365	2	0.03

Table 2 Variable definitions and coding structure ($n = 6{,}726$)

Variable	Definition	Variable	Definition
Stays	Number of days in the hospital in the last year	Health status	
Socioeconomic			=0 if heart disease inpatient
Age	Age in years		=1 if diarrhea inpatient
Sex	=1 if female		=2 if tuberculosis inpatient
Education			=3 if urinary inpatient
	=0 if illiterate		=4 if gynecology inpatient
	=1 if at most middle education	Hospital characteristics	
	=2 if secondary education and above	Health sector	=1 if private hospital
Place	=1 if urban	Hospital ward	=1 if paying special ward
lnmpce	Log of monthly per capita expenditure [in Rupees (Rs)]	Treatment history	=1 if treated in the past

Table 4 highlights the sample average of estimates of the fitted mean for different latent classes along with some other summary statistics. Short-stay patients comprise 64% of the population, with an average LOS of 4.9 days annually; medium-stay patients constitute 31% of the population with 12.0 days per year and the remaining 5% are long-stay patients, requiring an annual stay of 37.6 days, i.e., around 3 days per month.

It is evident that, for the whole sample, mean LOS estimated from the model is 8.8 days, with a minimum of 3.26 and a maximum of 18.36 days. However, there are large variations in the mean LOS between latent classes; minimum–maximum LOS as an inpatient are 2.49–8.01, 3.53–24.99 and 8.56–125.62 days for short-stay, medium-stay and long-stay patients, respectively. Looking at the percentile values, it can be seen that, for the entire sample,

Table 3 Bayesian information criterion (BIC) and Akaike information criterion (AIC) for possible models among non-nested models

Model	Class-2 finite mixture		Class-3 finite mixture	
	BIC	AIC	BIC	AIC
Poisson	45,485.54	44,165.29	44,489.55	43,167.29
Negative binomial-I	42,930.03	42,739.24	40,485.54	40,165.29[a]
Negative binomial-II	40,545.74	40,334.52	40,609.85	40,323.68

[a] Preferred model

Table 4 Distribution of fitted mean values by latent classes

Statistic	Class-I Short-stay	Class-II Medium-stay	Class-III Long-stay	Population
Mean	4.92	11.98	37.62	8.80
Minimum	2.49	3.53	8.56	3.26
Maximum	8.01	24.99	125.62	18.36
Percentile				
10	3.19	4.55	17.38	4.37
30	4.20	10.21	24.59	6.86
50	5.07	13.29	32.48	9.12
70	5.74	14.93	41.85	10.41
90	6.41	17.82	65.74	12.78

the 10–90 percentile value range is 4.37–12.78, whereas the respective values for the three latent classes are 3.19–6.41, 4.55–17.82 and 17.38–65.74. In summary, we found variations in LOS between the latent classes, i.e., classification of latent groups of patients utilizing hospital resources is necessary as far as the five types of ailments considered here are concerned. The empirical and fitted three-component negative binomial mixture distributions are plotted in Fig. 1.

The three-component mixture appears to fit the empirical data reasonably well, with approximately 5% of the patients identified as having relatively long LOS.

Table 5 shows the parameter estimates, average marginal effects (AME) and z-values of covariates included in the three-component FMM. A look at the table shows that the majority of the covariates included in the analysis have a statistically significant bearing on LOS, particularly in component-I. It can also be seen that the effects of some of the covariates as measured by AME varies across the latent classes corresponding to both short-stay and medium-stay groups of patients, with a statistically significant impact. LOS is expected to vary with patient age as the human immune system tends to better support younger patients to speedy recovery. For short-stay patients, age was found to have a significant positive association with LOS. Although the magnitude of association of age with LOS is nominal, it was incorporated in the analysis as a control for confounders of LOS. As regards gender differential, females tended to have shorter LOS as inpatients compared to males in the short-stay and medium-stay latent groups of patients, possibly due to biological superiority or the type of ailments associated with women. Considering the fact that educational attainment makes patients more knowledgeable regarding preventive and curative health care, inpatient educational level was included in this study. Although inpatients with more education tended to have shorter LOS, this relationship was by and large not statistically significant. This suggests that inpatient hospital-based healthcare in India is accessible to all patients regardless of educational status. Urban-based inpatients have shorter LOS compared to rural inpatients, and this is significant for short-stay and medium-stay inpatients. This is an indication of the concentration of better and more

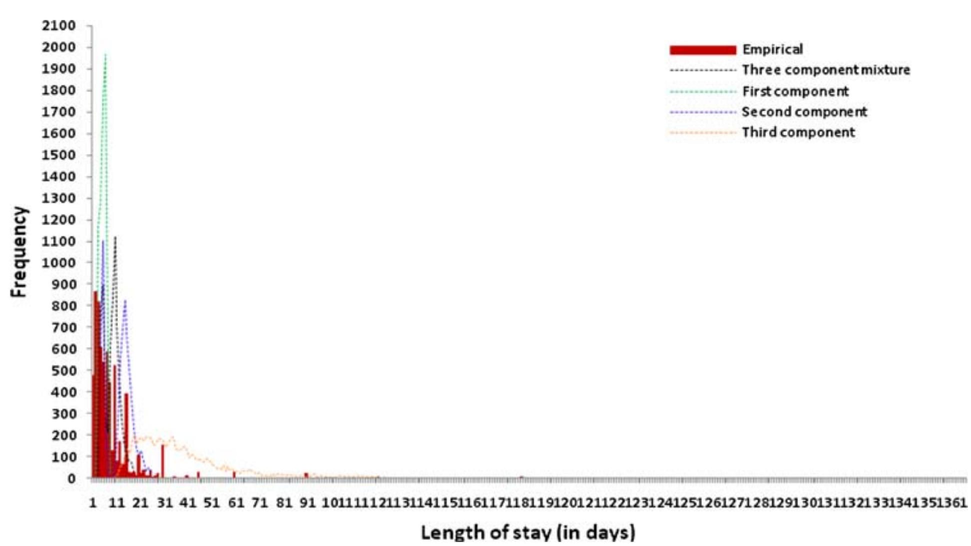

Fig. 1 Empirical distribution of inpatient length of stay (LOS) and fitted three-component negative binomial mixture model (FMNB-I)

Table 5 Parameter estimates and average marginal effects (AME) for the three-component negative binomial-I finite mixture model (FMNB-I)

	Latent class-I		Latent class-II		Latent class-III	
	Short-stay: average (4.9)		Medium-stay: average (12.0)		Long-stay: average (37.6)	
	(64%)		(31%)		(5%)	
	β	AME	β	AME	β	AME
π	0.639*	–	0.309*	–	0.052*	–
Constant	1.437*	–	2.850*	–	4.793*	–
α	0.537*	–	1.736*	–	28.569*	–
Socioeconomic						
Age	0.003	0.013*	0.002	0.018**	0.000	0.003
Female	−0.063	−0.303*	−0.105	−1.120*	0.012	0.389
At most middle	−0.042	−0.197	−0.106	−1.111*	−0.172	−5.584
Secondary+	−0.066	−0.306*	−0.064	−0.664	0.044	1.486
Urban	−0.116	−0.547*	−0.075	−0.785*	−0.086	−2.792
Lnmpce	0.020	0.093	−0.015	−0.158	−0.131	−4.311
Health status						
Diarrhea	−0.330	−1.476*	−1.073	−9.563*	−0.848	−24.236*
Tuberculosis	0.008	0.037	0.216	2.502*	0.461	18.426*
Urinary	0.085	0.418*	0.019	0.207	−0.063	−2.036
Gynecology	0.088	0.432*	−0.061	−0.632	−0.392	−11.680*
Hospital characteristics						
Private	−0.112	−0.542*	−0.157	−1.687*	−0.321	−10.927*
Paying special ward	−0.001	−0.002	0.078	0.847	−0.147	−4.591
Past history	0.220	1.030*	0.112	1.178*	0.224	7.266*
Log likelihood	−20,035.646					
N	6,726					

* $P < 0.05$; ** $P < 0.01$

modern inpatient hospital care facilities in urban than in rural areas. The monthly per capita expenditure, which is used as a proxy for measuring the economic status of patients, was found to have a negative effect on LOS. The elasticity of LOS relative to monthly per capita expenditure was negative in both medium- and long-stay patients, whereas it was positive in the short-stay group; however, association is statistically not significant for any of the latent groups. This insignificant association of a proxy measure of economic status and LOS is an indication that hospitals in India are accessible for inpatient treatment regardless of the economic well-being of the patient.

Considering the types of ailments, much variation was found in the effects of covariates on LOS between the latent classes. Compared to inpatients with heart disease, patients suffering from diarrhea have a negative significant impact on the utilization of hospital resources in terms of LOS in all latent classes. The reverse is true for tuberculosis patients, i.e., they have a positive impact in all classes compared to heart disease inpatients but the effect is significant only in medium-stay and long-stay patients. Patients with urinary diseases have a higher probability of belonging to short-stay and medium-stay groups but a lower chance of being in the long-stay group. Hospitalization related to gynecological problems tends to be for slightly longer in the short-stay class, but accounts for shorter periods in the long-stay group in comparison to inpatients with heart disease in the corresponding latent classes. This effect is statistically significant for both short and long-stay groups.

As regards differentials in LOS in the public and private sectors, it was observed that those patients hospitalized in private hospitals tend to stay in hospital for a shorter time irrespective of latent class; this association was statistically significant. This could indicate that the delivery system in privately managed hospitals is better than that in government-managed hospitals, possibly because of the more advanced and modern healthcare facilities available in private hospitals. Irrespective of hospital ownership, it is evident that those in paying special wards have a negative effect on LOS in all latent classes except for the medium-stay group. This is due to the fact that, for medium-stay patients, the amount to be paid for treatment can balance the LOS. It can be inferred that LOS does not differ within the same hospital whether lodging in a subsidized ward or in a ward with a higher tariff. There is no doubt that patients having undergone medical treatment in the past would have longer LOS irrespective of ailment type compared to inpatients with no medical treatment history. Finally, significant hospital variation in LOS for all classes was evident as shown by the corresponding variance (α) component estimate. Again, a Chi-square value of 209.26 (not shown) indicates a significant difference in the covariates included in the model across latent classes.

From the results of this analysis, it is clear that the different latent classes possess different socio-economic and hospital characteristics, and thus unobserved characteristics influencing LOS that are not captured by the present data must be taken into account .

Concluding remarks

The present study is an attempt to explore LOS as inpatients in hospitals in the Indian context in terms of identifying the associated risk factors of latent short-stay, medium-stay and long-stay patient groups fitting a three-component negative binomial finite mixture regression model. The short-stay latent group of patients constitutes 64% of all inpatients with an average LOS of 5 days, while 31% belongs to the medium-stay group with an average LOS of 12 days. The remaining 5% of inpatients come under the long-stay group, staying on average 38 days in hospital. Such skewness induced overdispersion in LOS values, as evident from the figure of dispersion measure of the three-component FMNB-I model. An encouraging feature of the health care system in India emerging from the findings of this study is that inpatient care in hospitals is accessible to patients regardless of economic and educational status. This finding is important in view of the near absence of health insurance and the fact that healthcare expenditure is borne by patients. Inpatient hospital-based healthcare facilities seem to be biased towards urban settings in terms of concentration of modern facilities and efficiency of treatment. Taking this into account, it is desirable that the public health care system in India is expanded from its present status to meet the curative health care needs of the larger rural masses, through a network of outreach service providers. Incentives such as exemption from specified taxes and fees can be given to private hospitals set up in rural areas.

For all the three groups of patients treated in private hospitals, LOS was significantly shorter compared to the corresponding groups of inpatients treated in public hospitals. It should be noted that, in India, private hospitals are run by corporations, and charges levied are much higher than the subsidized charges of public hospitals. However, specialized treatment is more often provided by private hospitals, and management is also more professional. From the point of view of providing affordable and accessible curative healthcare, it would be rewarding to modernize public health care in India in terms of delivery systems and sophistication. To overcome the budgetary constraints which accompany modernization and sophistication, service charges could be enhanced on a moderate scale over time. At the same time, the Constitution of India needs to be amended to regulate hospitalization and service charges of private hospitals to ensure equity in healthcare. As mentioned earlier, in both public and private hospitals there are two types of wards to which inpatients can be admitted: general wards, which can be used either free of charge or at a subsidized rate; and paying special wards available on the basis of higher user fee payment. It is encouraging to note that, according to the results of this study, within the same category of hospital, public or private, LOS has no association with type of ward.

The foregoing discussion on the results of this study and their interpretation are subject to the limitations of the data used. The present data on LOS come not from hospital administrative records of admitted inpatients, but from a nationally representative survey of households designed to collect data on morbidity and health care of individual members in the sampled households. As such, data on LOS analyzed in this paper are subject to recall bias and digit preference. For this reason, the results and interpretations are influenced to some extent by reporting bias. Nevertheless, this study not only fills a research gap in understanding LOS as inpatients in the Indian context, but also initiates discussion on the need to streamline the health care system in India, focusing on the matters of concern highlighted above.

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