The applicability of Lee-Carter method to forecast health services use in Brazil

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1. Introduction

Recent changes in health care systems, like technological advances, strengthening of primary health care and supply control mechanisms have led to substantial variations in health services utilization (WHO, 2008; Neto et al, 2008; Paris et al, 2010). At the same time, the recognition of rapidly changing demographic composition of population and its consequences to health care system has led to an increase of studies that attempt to forecast health services uses and spending around the world (Lee and Miller, 2002; Reinhardt, 2003; Chan, Li and Fong, 2004; Brockmann and Gampe, 2005; Busse, Krauth and Schwartz, 2007).

The usual way to forecast is to consider constant rates for the last period of data available, and estimate only demographic changes (Finlayson et al, 2004; Schulz et al, 2004; Tate et al, 2004; Strunk et al, 2006). This is of particular interest when assessing the need of future health care supply for which the age structure of a population over many decades is crucial. Despite the importance of this kind of estimation, health care forecasting is necessary as inputs for health services planning. Therefore the methods should also incorporate trends in health services utilization to provide a realistic picture of the future.

In recent years, health care planners and scholars have tried to accurately forecast the use of health care services based on time series data. A number of approaches have been tried. Approaches based on simple trend extrapolation (Evans et al, 2001; Finlayson et al, 2004) have used time series analysis to forecast future utilization rates which are allowed to fluctuate only deterministically over time. The scenario framework (Dormont, Grignon and Huber, 2006) has also been used and includes expert opinion about the future of the rates. Other methods use cross sectional data and include regression analysis with a trend term to identify the factors that influence the utilization (Tate et al, 2004) and counterfactual simulation based on changes in regressions' coefficients and in policies (Hancock et al, 2003).

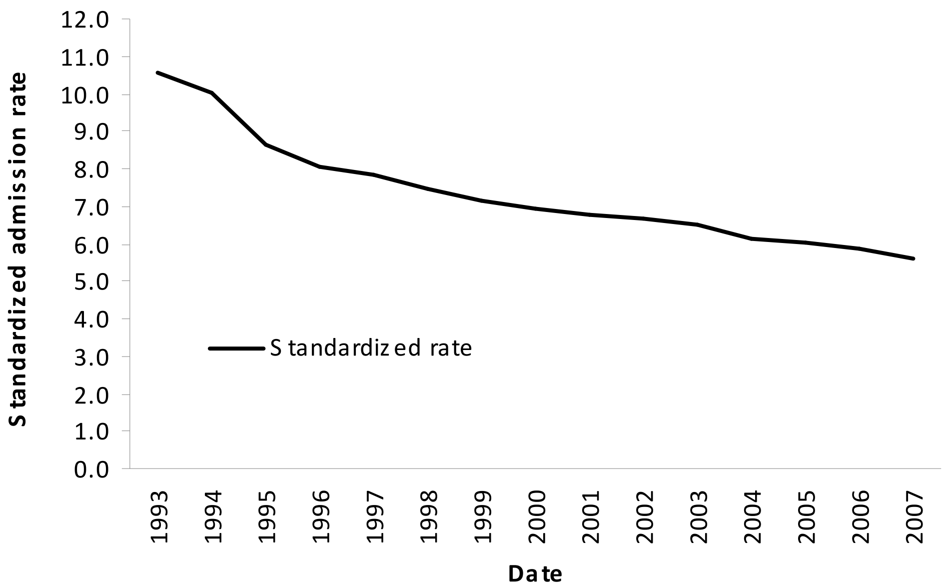
These methods, especially those that use time series data, offer plausible estimates of the utilization in the future, but they depend not only on the historical time series but the additional assumptions about the future of the main components that affect the rates. It's a way to quantify uncertainty, but lacks probabilistic meaning (Goldstein, 2004). As health services utilization depends on many forces, as political and economic performance, health status, age pattern, and so on, the rates are not so reliable predictable over long periods as population are. So specialists in forecasting have a responsibility to indicate the degree of uncertainty their forecasts may be.

In this paper, we use an innovative forecasting method in the field of health services research that takes into account changes in utilization rates using a stochastic approach. Specifically, we adapt the Lee-Carter method (Lee and Carter, 1992) - originally created to forecast life expectancy - to forecast public hospital admission rates in Brazil with probabilistic confidence intervals. We first discuss our general approach of stochastic forecasting. We then describe the traditional approach to forecast health services that consider simple trend extrapolation of data, but we develop a new way of modeling the rates using the Brass logit transformation. Finally, we compare the results and discuss the performance of both methods to the specific case of the Brazilian public health care system. The application of the methods was given to the State of Minas Gerais, one of the most populous states in Brazil, located at Southeast Region.

Trends in admission rates

Figure 1 shows trends of standardized admission rates for 1993 to 2007 in Minas Gerais. There is a sharp decline in admission rates in Minas Gerais at an average of about 4.7 percent a year, but more pronounced from 1993 to 1996. In general, rates of admission are measured as discharges from hospital, and most heath service information systems collect data about episodes rather than about people. So, variation in rates over time may reflect both differences in number of people treated or variation in multiple admissions per individual.

Figure 1: Total admission rates – Minas Gerais, 1993 to 2007



Source: SIH/SUS and National Household Sample Survey (PNAD) – 1993 to 2007.

There are two main hypotheses to explain the reasons for reducing admission rates in Brazil. The first hypothesis is related to changes in the institutional framework of the health system, like regulatory mechanisms of assistance and the incentives given to primary health care programs. These mechanisms can help reducing the need for hospitalization over time. There are evidences, both in Brazil as in many countries, that government have introduced barriers to entry such as budget cuts, limits on the establishment of health professionals or direct control over the supply of health services, especially hospital beds (Paris et al, 2010).

In Brazil, a way to contain the expenditures growth of hospital services was the adoption of quotas for admission (Neto et al, 2008). Until 1993 the hospital expenses were paid without the establishment of budgetary limits or in the number of procedures performed in hospital. From 1994 it was established that the amount of quotas authorized at each location depend on a fixed proportion according to population size. The quotas were then fixed at 10 percent of the population in 1994, but they are decreasing over time.

Besides that, the priority given by primary health care, as Family Health Program in Brazil, can help to prevent injuries and promote the health of population (Paim, 2008).

Some papers discuss the importance of expanding and consolidating the Family Health Program in order to reduce the incidence of hospital admissions, especially for those that could be avoided by an ambulatory care quality (Perpétuo and Wong, 2006; Oliveira, 2007; Alfradique et al, 2009).

The second hypothesis is based on improving the health status of the population, resulting in reduced demand for hospital services. The changes in the population health and its effects on reducing admission rates may result from several factors. One of them, as addressed earlier, refers to the improvement of primary prevention programs and sanitary conditions that act as inhibiting factor for hospital admissions (Francisco et al, 2004). Evidences for Minas Gerais, in Brazil, show that admissions for causes linked do sanitary conditions, like diarrhea, were greatly reduced in recent years (Perpétuo and Wong, 2006). Another factor may be related to the reduction of risk factors in the population, such as alcohol consumption, smoking, physical inactivity and obesity, with decreased likelihood of disease (Barata, 2008).

2. Data and methods

We used data about hospital admissions from *Sistema de Informações Hospitalares do Sistema Único de Saúde* – SIH/SUS (Hospital System Information from Unified Health System), an administrative record from federal government about all the public hospitalizations in Brazil. We built hospital admission rates from 1993 to 2007, the only available period of time with information about age and sex of the patients. The hospital admission rates were forecasted from 2008 until the year 2020.

Let the hospital admission of age x to x+n at time t be ${}_nU_x(t)$, for t=0,1,2….T, and x=0,1,2,3,…..w. The stochastic method is an application of the traditional Lee-Carter method (Lee and Carter, 1992) to health services data. This method first applies the singular value-decomposition (SVD) on log of a historical rates matrix of ${}_nU_x(t)$ to obtain:

$$\ln({}_nU_{x,t}) = {}_na_x + {}_nb_x . k_t + {}_n\varepsilon_{x,t} \tag{1}$$

where ${}_na_x$ is calculated as the average of $\ln({}_nU_{x,t})$ over time, so the average pattern of hospital admissions by age across years; ${}_nb_x$ is the relative proportional rates of change of hospital admissions by age; k_t represents an index of the level of admissions at time t. Both ${}_na_x$ and ${}_nb_x$ are fixed over time, and k_t is treated as a random variable and projected by ARIMA (0,1,0), generating probability distributions for age specific hospital admissions. The model is given by $k_t = c + k_{t-1} + u_t$, where c is average annual change in k_t. The uncertainty resulting from imperfect fit of the model or from parameters estimates are also incorporated.

In order to compare the LC model with the traditional models of forecasting health services utilization which use simple trends extrapolation (Evans et al, 2001; Finlayson et al, 2004), we applied what we call deterministic method, expressed as follows:

$$\frac{1}{2}\ln\left(\frac{1-{}_nU_x^z}{{}_nU_x^z}\right)=\frac{1}{2}\ln\left(\frac{1-{}_nU_x^i}{{}_nU_x^i}\right)*\left[1+{}_nw_x*(t^z-t^i)\right] \tag{2}$$

where z and i are the superscripts to final and initial year of forecasting, respectively, and ${}_nw_x$ is the average of annual variation observed in the rates by 5-year age groups between period t and $t+n$, being the initial (t) and final ($t+n$) period of the historic trend of data.

We developed an approach to model the admission rate in the deterministic method that is based upon a logit transformation, as developed by Brass (1968). The arithmetic advantage of this transformation is that as the admission rate can be considered a kind of probability that ranges from 0 to 1, the logit of ${}_nU_x$ takes all the values between $-\infty$ and $+\infty$. As the ${}_nw_x$ and the forecasted rates are calculated on this basis, the anti-logit of ${}_nU_x$ by the expression $\frac{\exp(2*{}_nU_x)}{1+\exp(2*{}_nU_x)}$ will map into a value between 0 and 1. In the limit, the rate will be 0, but never negative.

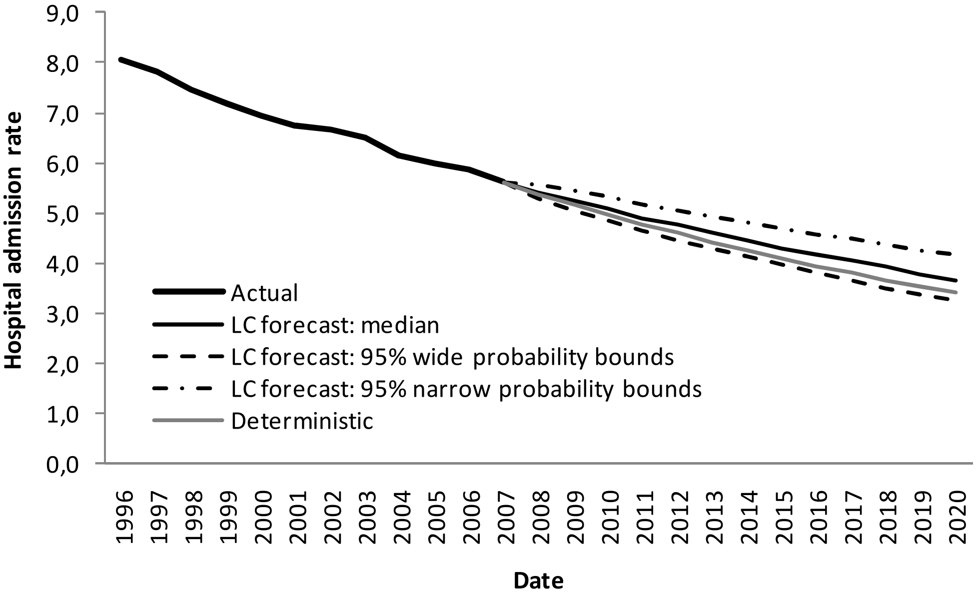
As the forecast is made over a short time horizon in both methods, it's appropriate to minimize the variance in the series, assuming structural similarity of the process (Li et al, 2002). To test for structural changes we applied the Chow Predictive Test (Greene, 2000), that analyses if there was a break in the historical trend stability of the series. Using a regression model to several sub periods from 1993 to 2007 and comparing the parameters from the critical period and the whole period, this test showed the year from 1996 to 2007 was the best period to use as time series to forecast. The great advantage of this test is that it gives a more robust choice of what is the relevant historical period to use as time series.

In order to perform a goodness-of-fit test we retrocede the forecasting to the historical data from the period among 2003 to 2007 and compared it to the actual admission rates in this period. The application of the methods was given to the State of Minas Gerais, one of the most populous states in Brazil, located at Southeast Region. From 1996 to 2007 there was a decrease in number and rate of hospital admissions in this state by the order of 14,5% and 27%, respectively, with the amount of admissions in 2007 of 1.144.850, and a rate of 5,8 admissions per 100 population.

3. **Results**

Figure 2 plots actual admission rates from the years 1996 to 2007 and the forecast values from 2008 to 2020. Admission rates have shown a decreasing trend over time. The wide bound of the 95% probability intervals of Lee-Carter method incorporates a sharp decline in admissions, while the narrow bound considers a more conservative trend of admission rates declines. The 95% narrow bound of Lee-Carter method resembles the deterministic method that takes into account a constant variation in admission rates from the historical average from 1996 to 2007. In LC median forecast and deterministic method, we find admission rates are 35 and 39 percent lower in 2020 in comparison to 2007, respectively.

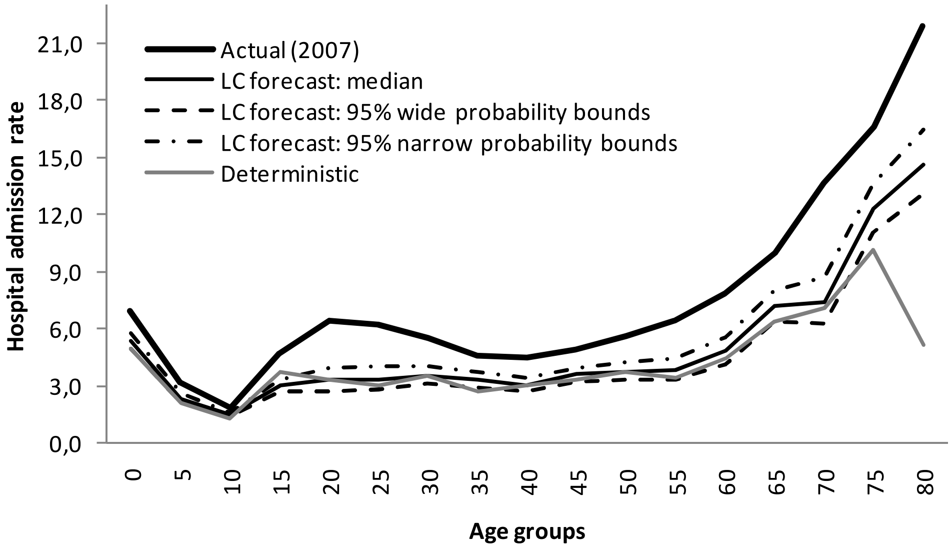
Figure 2: Actual admission rates and forecasts – Minas Gerais, 1996 to 2020



Source: SIH/SUS and National Household Sample Survey (PNAD) – 1996 to 2007.

The actual admission rates in 2007 and forecasts to 2020 by age groups are shown in Figure 3. The decrease in admission rates between 1996 and 2007 was accompanied by more dramatic decline in admission rates at some ages than at others. The most striking decline was seen to older age groups, especially to the open age group 80 and over. It seems to be a feature of the data and logit Brass model, since admission rates for this group fluctuate systematically over time (data not shown). However, we cannot tell this group is numerically less expressive, since the proportion of admissions in this group can match the proportion found in numerically higher age groups as the younger ones.

Figure 3: Actual admission rates (2007) and forecasts (2020) by age groups – Minas Gerais



Source: SIH/SUS and National Household Sample Survey (PNAD) – 1996 to 2007.

This is reflected at very different forecasting rates in deterministic method than what was seen to LC method. Moreover, a possible explanation for this difference is that the LC variation in a group is dependent on the other (Lee and Carter, 1992), which is not the case with deterministic, where the variation in each group age is considered independent in the forecasting. However, even in LC method, the variance explained by the model in this age group was 49 percent, the lowest in comparison with all other groups. The lowest proportion of variance in this age group explained by the model is probably linked to the error in estimating the parameter that measures the change in rates over the period (*bx*), since the estimation for this parameter covers the period from 1996 to 1998, when occurred a sharp drop in admission rates in this group.

Table 1: Proportion of variance accounted by Lee-Carter model, by age groups - Minas Gerais, 1996 a 2007

Age groups	Variance* (%)
0 a 4	95,5
5 a 9	93,9
10 a 14	79,9
15 a 19	82,4
20 a 24	90,3
25 a 29	92,0
30 a 34	96,4
35 a 39	88,5
40 a 44	97,9
45 a 49	95,1
50 a 54	97,5
55 a 59	97,2
60 a 64	99,2
65 a 69	91,4
70 a 74	91,1
75 a 79	84,0
80 e mais	49,3

Source: SIH/SUS and National Household Sample Survey (PNAD) – 1996 to 2007.

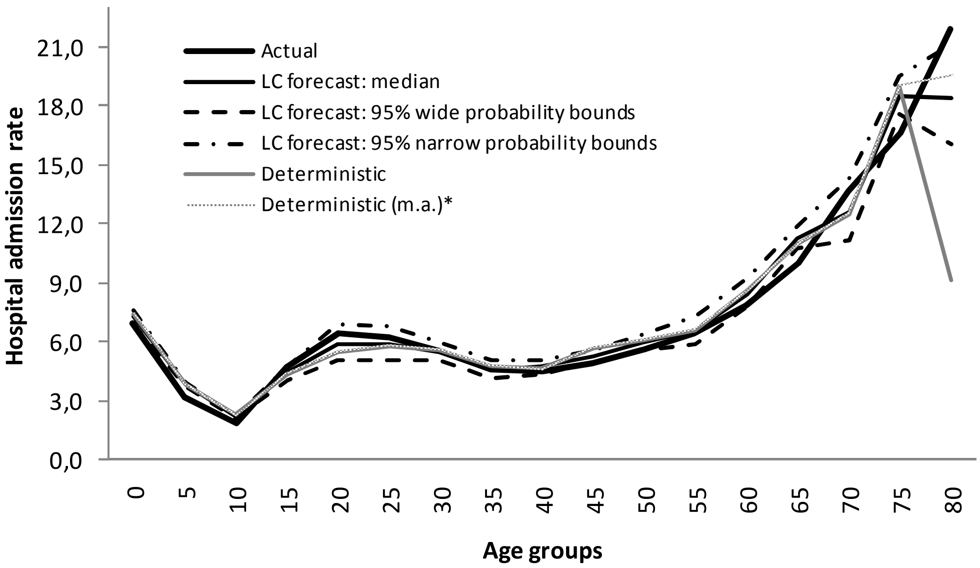
Note: * The proportion of variance is expressed by $\frac{\left({}_{n}s_{x} - {}_{n}\hat{s}_{x}\right)}{{}_{n}s_{x}} - 1$, where S_x is the variance of the rate observed in age group x to x+n at the historical período of available data and ${}_{n}\hat{S}_{x}$ is the variance of estimated rate by the model in the same age group and time t (Lee & Carter, 1992).

Validation of the methods

To evaluate the performance of the methods, we estimate admission rates for the period between 2003 and 2007 and compared with the actual data in this period. We adjust the available data from 1996 to 2002 as the historic time series used to forecast the rates from 2003 to 2007. We focus on short-term forecast accuracy because of the availability of data. The results for age groups in 2007 are shown in Figure 4.

We find that forecasted admissions were similar to observed data, especially in the first age groups, with de median LC and deterministic method the best fitted. For the age group 80+ there was an underestimation of the forecasting, indicating that the decrease in actual admission rates between 2003 and 2007 were lower than those projected for this period by the average 1996 to 2002.

Figure 4: Actual admission rates and forecasts by age groups – Minas Gerais, 2007



Source: SIH/SUS and National Household Sample Survey (PNAD) – 1996 to 2007.
Note: * (m.a.): moving average of rates for age group 80 and over.

The adjustment for age groups that show a very different pattern from actual, as the age group 80 and over, could be solved with smoothing techniques. These nonparametric techniques are applied in order to minimize the irregularities presented in reported data or in estimates obtained from them (United Nations, 1983). In our study this was caused by the small number of events in older age groups. One way of smoothing would be plot logit transformation of admission rates against some standard, like in Brass relational model of two parameters, but this would imply an arbitrary judgment of future rates.

We applied a simple technique of smoothing, based on moving average from three adjacent years. This was applied only for rates from aged 80 and over, which presented the high variance over time. The result is presented at Figure 4. The average rate of change in the admission rates for this group decreased using this smoothing procedure, and made the error associated to forecasting about 82% lower than what was estimated without this technique.

4. **Conclusion**

In general, methods of forecasting health care services are concerned with the level of utilization in the future (Barer et al, 1995; Zweifel et al, 1999; 2004; Finlayson et al, 2004; Schulz et al, 2004; Tate et al, 2004; U.S. Department of Health and Human Resources, 2006). The studies with this approach usually assume a fixed shape of utilization by age group, and the level of utilization by age is determined by multiplying this fixed schedule by a shifting age composition. However, in the context of changes in health care utilization, it is advisable to consider trends in the utilization rates mainly if the changes are not homogeneous across age groups (Evans et al, 2001).

The main contribution of this article is to quantify uncertainty in health services utilization through a stochastic approach. Methods of stochastic forecasting in the field health services research are relatively new and largely unexplored. Partially, these methods are limited by the availability of reliable data and long time series for health care services. The specific use of Lee-Carter method in this field was first made by Lee and Miller (2002) to forecast Medicare expenditures from the year 2020 to 2075. The authors used 30 years as historical data and a fixed age schedule between age and time until death, a proxy for health status.

In our study, age is considered a proxy for health status, and we let total admission rates by age follow a random path, based on past trends in actual admissions. The method was evaluated by comparing forecast admission rates with actual admission rates from 2002 to 2007. The results suggest the best fitted model was LC method, but the performance may be different if different period of data is used because accuracy depends on the particular trends (Booth, 2006). Probably the gain in accuracy would be largest if the fitting period was longer or if age-specific admission rates moved slowly over time, which is not the case for aged 80 and over. However, simple smoothing techniques, which do not require complex statistical procedures, also can minimize the variance of the rates and make more reliable estimates.

Despite of the shortcoming to use a short time-series to estimate future health care utilization rates, especially when applying the Lee-Carter method, the procedures seem to work well with the data. We have shown that useful forecasting of health services utilization can be derived, both from the Lee-Carter method and also using the traditional deterministic model.

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