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Day Hospital versus Ordinary Hospitalization:
factors in treatment discrimination

Luca Grassetti
Department of Statistical Sciences
University of Padua
Italy

Michela Battauz
Department of Statistical Sciences
University of Padua
Italy

Abstract: The aim of this article is to highlight one possible use of administrative archives in decision making processes. The phenomenon we want to analyse is the carpal tunnel syndrome surgery treatment. Nowadays, from an operative point of view, two different ways coexist in treating the problem: the day hospital (DH) and the ordinary hospitalization (OH) surgery. Causes of this dichotomy are not so clear. In particular, because of the simplicity of the intervention we can hypothesize that, given the effects of some observed factors, no other significant differences should be observed between different hospitals. We extract 16431 observations from the administrative archive of Region Lombardia. Data used for this analysis refer to year 2002. The observations are clustered in 128 hospitals. The binary response variable, the hospitalization regimen, is modelled with a logistic regression. Fixed all the other observed variables (referred both at hospital and at patient level), we identify by a random coefficient a significant hospitals effect. Day hospital treatment presents lower costs for the national health service. The suspect of the administration is that DRG reinboursement system can create the premise for acting opportunistically. Administrations of hospitals are induced to choice OH instead of DH in order to obtain majour reinboursement. The identification of hospitals presenting higher probability (resulting from the random effect values) in deciding for a OH instead of the more common DH could be useful for the administrative control system. Maximum likelihood results will be presented and diffent methods of estimation of random effects will be compared.

Keywords: administrative archive, bayesian approach, binary data, carpal tunnel syndrome, generalized mixed models, maximum likelihood.

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Department of Statistical Sciences
University of Padua
Italy

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Contents

1 Introduction **1**

2 Data **2**

3 Model Specification: Mixed Models for Binary Data **4**

4 Estimation Results **6**

5 Random Effects Analysis **7**

6 Conclusion **9**

Department of Statistical Sciences
Via Cesare Battisti, 241
35121 Padova
Italy

tel: +39 049 8274168
fax: +39 049 8274170
http://www.stat.unipd.it

Corresponding author:
Luca Grassetti
tel: +39 049 827 4168
grassetti@unipd.it
http://www.stat.unipd.it/~grassetti

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1 Introduction

Nowadays the carpal tunnel syndrome and the consequent surgery treatment are very common in the population. For this common disorder several surgical treatment options are available, with no consensus on the most affective method of treatment. Several studies have been conducted in order to determine the best treatment in terms of a set of standard outcome measures. Nevertheless there's no strong evidence supporting a particular way of treating. Several studies have been conducted also in order to identify factors affecting the carpal tunnel post treatment status (Mondelli *et al.*, 2004, see e.g.), but also in this case no significant factors have been found. Given these evidences (as for example in Scholten *et al.*, 2002; Chung *et al.*, 1999), we concluded that there is no need to collect data on patient status in order to study the phenomenon. The carpal tunnel treatment can be studied considering only the data collected for an administrative use.

In particular the phenomenon we want to analyse is the carpal tunnel syndrome surgery treatment. Nowadays, from an operative point of view, two different ways coexist in treating the problem: the day hospital (DH) and the ordinary hospitalization (OH) surgery. Because of the simplicity of the intervention, causes of this dichotomy are not so clear. We can hypothesize that, given the effects of some observed factors, no other significant differences may be observed between various cases and, in particular, between different hospitals. The paper is organized as follows. The second paragraph give an overview of the data extraction process and of the descriptive data analysis. The third paragraph present the generalized linear mixed model specification and, in particular, the problem of inference about the random effects. Different methods of estimation are available for this kind of model specification. In the fourth section we present the principal results of our analysis, focusing on the comparison of results obtained with different sample selection. Finally we discuss the opportunity of considering the obtained results in administrative decision processes, showing a comparison between different approaches to random effects estimation, in order to explore the stability of the estimates.

2 Data

All the variables included in the analysis are collected for administrative aims. This represents both the strength and the weakness of our study. Sample size could reach very large dimensions with very low costs, but the reliability of the archives is partially unknown.

The data are collected from the administrative discharge database (SDO) of Region Lombardia (Italy) referred to the year 2002. From this huge archive we select the carpal tunnel sindrome cases and we obtain a sample of 16431 units. This observations are clustered in 128 hospitals. In order to avoid the problem of correlation between observations, we used only patient having a single hospitalization during the considered period. As just said, given the simplicity of the considered phenomenon, we are able to continue the analysis without any additional information on the impatient clinical status. The omission of the repeated hospitalizations helps us in maintaining this hypothesis.

Because of the presence of some not available values (NAs) in the sample, we decided to omit from our study all observations presenting at least one NA value. We assume that this operation respects the hypothesis that observation presenting NA values are selected randomly from the sample. In this case the resample operation probably does not affect the model estimation. Table 1 presents a comparison between the final sample (16248 units) and the omitted observations (183). Variables presenting NA values are not considered in the comparison and they are identified with an NA value in the column regarding the omitted units summary statistics.

Table 1 summarizes the main characteristics of the patient and of the hospitalization. In the third section of the table we present:

- for the continuous variables the t-test for difference in mean of two samples;
- for the binary variables the χ^2-test for independence in a two way table (where all variables are considered in contrast with dropped/not dropped dummy variable).

The reported test statistics indicate that the dropped sample respect a pattern similar to the residual dataset. Indeed, we can also conclude that the remaining 16248 observations are representative of the population at least as well as the starting sample.

	Complete Sample (16248)		Omitted Units (183)		Test Statistics	
Variable	Mean	Std.Err.	Mean	Std.Err.	t-test	p-value
Age	55.37	14.59	54.75	15.56	-0.537	0.592
Number of Diagnoses	1.15	0.43	1.14	0.45	-0.370	0.712
Number of Intervention	1.24	0.59	0.73	0.63	-10.926	<0.001
	Proportion		Proportion		χ^2-test	p-value
Administrative Regimen	0.036		0.033		<0.001	0.991
Nationality	0.989		NA		-	-
Work	0.523		0.530		0.011	0.915
Married	0.712		NA		-	-
Trauma	0.070		0.038		2.336	0.126
Primary Diagnoses	0.989		0.984		0.076	0.783
Primary Intervention	0.992		NA		-	-
Ordinary Discharge	0.999		1.000		0.349	0.554
Sex (Female)	0.780		0.749		0.876	0.349

Table 1: Comparative study of final sample and units dropped from the analysis (given the presence of NA values). Test statistics are respectively the t-test for mean in two samples and the χ^2-test of independence in a two way table.

The largest difference is observed in the number of treatments, but this variable will be finally excluded from the model specification.

It is useful to describe the variables considered in the following.

- Number of Diagnoses: the total number of diagnoses (primary and secondary) attributed to the patient during the hospitalization - in some sense a proxy of the subject health condition.
- Number of Interventions: the total number of treatments (primary and secondary) endured by patients.
- Administrative Regimen: this dummy identifies the ordinary hospitalizations (the cases subordinated to different financing treatment): 1 - ordinary hospitalization; 0 - day hospital cases.
- Nationality: 1 - Italian; 0 - other nationality.
- Work: 1 - workers; 0 - all other positions (not working, ex-workers, etc.).
- Married: the civil status of patient: 1 - married; 0 - other classes (not married, widow/er, etc.).
- Trauma: 1 - the patient endured a traumatic event; 0 - no trauma observed.
- Primary Diagnoses: 1 - the primary diagnosis is coherent with the DARG; 0 - otherwise.
- Primary Intervention: 1 - the primary treatment is coherent with the DRG; 0 - otherwise.
- Ordinary Discharge: this variable identifies the cases ended with ordinary discharge: 1 - ordinary discharge; 0 - otherwise (voluntary discharge, transfer to different hospital/ward, etc.).
- Sex: 1 - female; 0 - male.

All dummies regarding the hospitalization are in some sense proxies of patient status. For example, the fact that primary intervention is coherent with DRG classification identify a normal treatment procedure; the presence of trauma can be a signal of worse starting patient conditions, etc.

3 Model Specification: Mixed Models for Binary Data

The model formulated for the probability of registering an ordinary hospitalisation is a mixed logit model with random intercepts (see McCulloch and Searle, 2001). Let y_{ij} denote the jth observation (j in $1, \ldots, n_i$) on the ith cluster (i in $1, \ldots, m$). We assume the model

$$y_{ij}|\mathbf{u} \overset{ind.}{\sim} \text{Bernoulli}(\pi_{ij})$$

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \mathbf{x}_{ij}\boldsymbol{\beta} + u_i$$

$$u_i \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_u^2)$$

so that the log likelihood is

$$
\begin{aligned}
l(\mathbf{y}|\mathbf{u},\sigma_u^2,\boldsymbol{\beta}) &= \log\Bigg[\prod_{i=1}^{m}\int_{-\infty}^{\infty}\prod_{j=1}^{n_i}\left\{\frac{\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{y_{ij}}\times \\
&\qquad \left\{\frac{1}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{1-y_{ij}}\frac{1}{\sqrt{\pi}\sigma_u}\exp\left(-\frac{1}{2}\frac{u_i^2}{\sigma_u^2}\right)du_i\Bigg] \\
&= \log\left\{\prod_{i=1}^{m}L_i(\mathbf{y}_i|\sigma_u^2,\boldsymbol{\beta})\right\},
\end{aligned}
$$

where

$$
\begin{aligned}
L_i(\mathbf{y}_i|\sigma_u^2,\boldsymbol{\beta}) = & \int_{-\infty}^{\infty}\prod_{j=1}^{n_i}\left\{\frac{\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{y_{ij}}\times\left\{\frac{1}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{1-y_{ij}} \\
& \frac{1}{\sqrt{\pi}\sigma_u}\exp\left(-\frac{1}{2}\frac{u_i^2}{\sigma_u^2}\right)du_i.
\end{aligned}
$$

The estimation of this model can be faced by different methods and approaches. Results presented in Table 2 are the maximum likelihood estimates obtained by both Gauss-Hermite and adaptive quadrature (see Rabe-Hesketh *et al.*, 2002, for more details).

One of the methods used in our work for conducting inference about random effects is the one proposed in Booth and Hobert (1998). This approach consist of obtaining standard errors of the random effects as conditional mean squared error of prediction, using the Laplace's approximation for integrals. Some other methods can be applied in order to obtain standard errors for point estimates (as for example suggested in McCulloch, 1997).

In our case, the conditional distribution of the random effects $\mathbf{u}$, given the data $\mathbf{y}$, is

$$
\begin{aligned}
f(u_i|\mathbf{y}_i;\sigma_u^2,\boldsymbol{\beta}) &= \frac{f(\mathbf{y}_i|u_i,\boldsymbol{\beta})f(u_i|\sigma_u^2)}{f(\mathbf{y}_i|\sigma_u^2,\boldsymbol{\beta})} \\
&= \frac{1}{L_i(\mathbf{y}_i|\sigma_u^2,\boldsymbol{\beta})}\prod_{j=1}^{n_i}\Bigg[\left\{\frac{\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{y_{ij}}\times \\
&\qquad \left\{\frac{1}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{1-y_{ij}}\Bigg]\frac{1}{\sqrt{\pi}\sigma_u}\exp\left(-\frac{1}{2}\frac{u_i^2}{\sigma_u^2}\right) \\
&= L_i^{-1}(\mathbf{y}_i|\sigma_u^2,\boldsymbol{\beta})\exp\left\{l_i(u_i)\right\},
\end{aligned}
$$

where

$$
\begin{aligned}
l_i(u_i) = & \log\Bigg[\prod_{j=1}^{n_i}\left[\left\{\frac{\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{y_{ij}}\left\{\frac{1}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}^{1-y_{ij}}\right]\times \\
& \frac{1}{\sqrt{\pi}\sigma_u}\exp\left(-\frac{1}{2}\frac{u_i^2}{\sigma_u^2}\right)\Bigg].
\end{aligned}
$$

Following Booth and Hobert (1998)

$$
Var(u_i|\mathbf{y}_i)\approx -l_i^{(2)}(\tilde{u}_i)^{-1},
$$

where $\tilde{u}_i$ denote the maximizer of $l_i(u_i|\hat{\beta},\hat{\sigma}_u^2)$ and $l_i^{(r)}(u_i)=\partial^r l_i(u_i)/\partial u_i^r$.

In our case

$$
\begin{array}{rcl}
l_i^{(2)}(\tilde{u}_i) & = & -\sum_{j=1}^{n_i}\left\{\frac{\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}\left\{\frac{1}{1+\exp(\mathbf{x}_{ij}\boldsymbol{\beta}+u_i)}\right\}-\frac{1}{\sigma_u^2} \\
 & = & -\sum_{j=1}^{n_i} p_{ij}(1-p_{ij})-\frac{1}{\sigma_u^2}
\end{array}
$$

then

$$
Var(u_i|\mathbf{y}_i)\approx\left\{\sum_{j=1}^{n_i}\hat{p}_{ij}(1-\hat{p}_{ij})-\frac{1}{\sigma_u^2}\right\}^{-1}.
$$

Turning our attention to model specification and estimation we are principally interested in obtaining robust and reliable results. In order to examine the plausibility of the estimated models we conducted a comparative study of different estimation techniques. Results of this step are omitted in order to focus on the interpretation of the fixed and random effects estimates. We used different software (`R`, `Stata` and `SAS`) and, also within the same software, we consider different algorithms (Penalized Quasi Likelihood and Maximum Likelihood estimated both with adaptive quadrature or Laplace approximation methods). The principal feature of this comparison is a good stability of the estimations.

4 Estimation Results

In the final model specification we considered a set of 8 covariates. The significant variables related to individual characteristics are nationality, marriage status and age of patient. The variables connected to hospitalization features are number of diagnoses, and some dummies for trauma presence, coherence of primary diagnosis and treatment, and ordinary discharge.

Some hospitals (49) present no variation in the considered phenomenon (all observed cases are DH). From a computational point of view these units represent a serious problem. As one can see from figure 1 d) the random effects standard error estimates are strongly affected by this subset, while point estimates present a high rank correlation (see figure 1 b)). In our analysis we avoid this problem considering a restricted set of data (we drop the observed macro units having none ordinary hospitalization) but, as clearly explained in Carlin *et al.* (2001), this kind of datasets can be treated by mixed effects models considering a discrete mixture model.

As one can see from Table 2 we estimate the model on the complete sample and the sample considering only hospitals presenting both DH and OH. Table 2 summarise the estimated values for the complete sample and the reduced sample.

From an interpretative point of view we can notice that there are not great differences between the two estimated models. The only parameters presenting a significant change passing from the complete dataset to the reduced one are the intercept and the variance of 2^{nd} level random effects. This result highlights a strong robustness of the model to the sample selection. The variance coefficient and intercept reductions are due to the exclusion of macro units concentrated in the lower tail of distribution presented in figure 1 a). Anyway the omitted units are not interesting in our analysis presenting negative values of random effects and large confidence intervals (C.I.). These effects are not statistically different from

	1^{st} level units 16248 2^{nd} level units 128 log-likelihood -1597.767			1^{st} level units 10558 2^{nd} level units 79 log-likelihood -1547.305		
Variable	Est.Coef.	Std.Err.	p-value	Est.Coef.	Std.Err.	p-value
Intercept	-3.55482	0.929	<0.001	-1.57945	0.859	0.066
Age	0.02294	0.004	<0.001	0.02273	0.004	<0.001
Number of Diagnoses	1.40806	0.083	<0.001	1.38049	0.084	<0.001
Nationality	-1.04275	0.360	0.004	-1.02108	0.359	0.004
Conjugated	0.45024	0.108	<0.001	-0.44432	0.108	<0.001
Trauma	2.21324	0.203	<0.001	2.25567	0.202	<0.001
Primary Diagnosis	-1.24164	0.284	<0.001	-1.18404	0.283	<0.001
Primary Intervention	-1.35358	0.294	<0.001	-1.29750	0.292	<0.001
Ordinary Discharge	-1.71772	0.679	0.011	-1.62292	0.691	0.019
Total Equipment	0.01051	0.003	0.003	-	-	-
Squared of Total Equipment	-0.00001	<0.001	0.025	-	-	-
σ_u^2	3.29048	0.656		1.82063	0.371	

Table 2: Comparative analysis of models parameters estimated by `Stata-gllamm`. This procedure is based on likelihood maximization obtained by adaptive quadrature iterative algorithm.

0 (as one can see in figure 1a)). The dataset truncation reduces the unexplained variance connected to hospital characteristics. The two coefficients related to the hospital dimensions are not still significant after sample reduction so we omit them from model specification.

In the following we consider the results of the reduced model. The estimated coefficient enlight a positive effect of age, number of diagnoses and trauma. These variable affect positively the probability of ordinary hospitalization. All other variables have a negative effect on this probability.

5 Random Effects Analysis

In this paragraph we present the estimated random effects and we give an interpretation of their values. The random effects can be used in order to construct a ranking of the macro units. In particular these values allow to identify the hospitals with a higher probability of treating the carpal tunnel sindrome by ordinary hospitalization instead of the cheaper (for the public health administration) day hospital procedure. These units have no explicit reason to act in non common way. For this reason we propose the use the random effects as an indicator of unwanted heterogeneity between the considered hospitals.

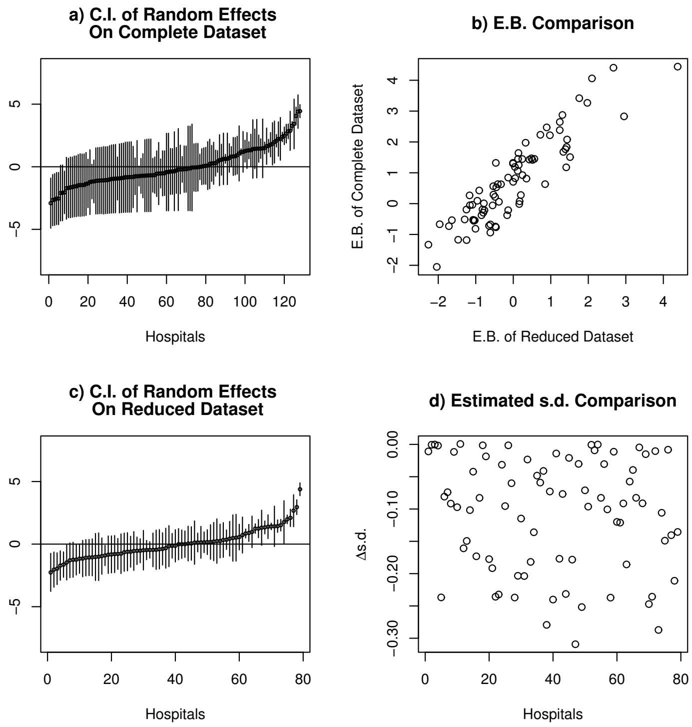

Figure 1: Random Coefficients Analysis. This figure illustrate: a) the random effects and the C.I. calculated using the completed dataset; b) the comparison between the random effects estimated with the two samples (the complete - y - and the reduced one - x); c) the random effects and the C.I. calculated using the reduced dataset; d) the plot of differences between standard errors estimated using the two samples.

Given the importance of the decision connected to the analysis of the random coefficients, we also consider different estimating methods for both the random effects and their standard deviations.

The statistical software we used in model estimation - `Stata` - gives us both these quantities. Starting from the point estimates of second level effects we propose the results for standard deviations given in Booth and Hobert (1998). Finally, we propose a bayesian estimation for the specified model (see e.g. Natarajan and Kass, 2000). Starting from a set of non informative diffuse prior distribution we obtained a logit multilevel model specification with `WinBugs` (Spiegelhalter *et al.*, 2003). Given the non informative characterization of the priors and the huge sample size, the estimation results are very similar to the ML ones. The point estimates for random effects are also very similar to the Empirical Bayes (E.B.). Using this approach we also obtain the empirical confidence intervals.

In figure 2 we present a comparison of the three principal results. Given the substantial convergence of the results of `Stata - gllamm` (see Rabe-Hesketh *et al.*, 2001), of the procedure described in the paragraph about model specification and, finally, of the Bayesian approach, we can conclude that the proposed instrument is reliable.

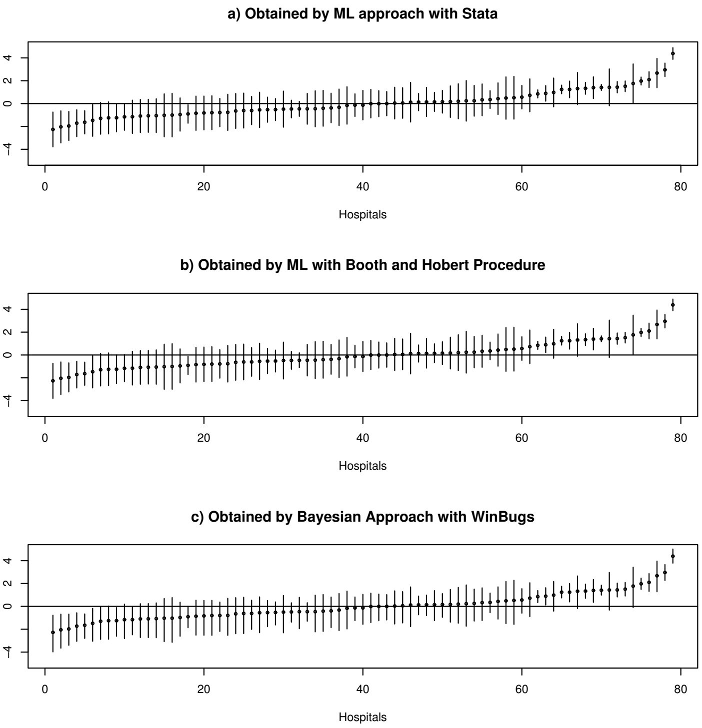

Figure 2: Estimated random coefficients and relative standard deviations: This figure illustrate the estimated values of random effects and their relative standard deviations obtained with three different methods.

6 Conclusion

The principal aim of this work is to investigate the factors in treatment discrimination. In particular we focus on random effects capturing the unobserved variability at hospital level. Given the simplicity of the considered surgical practice this variability should not be connected to hospital decision so we conclude that positive hospital random effects highlight uncommon operating conditions, maybe opportunistic behaviors. We remember here that ordinary hospitalizations correspond to higher National Health System financing. With the obtained rankings we are able to identify the suspect units.

Our approach to "outlier" treatment (the exclusion) is only a starting point for the analysis of complete dataset. A possible extension of this work can follow the idea suggested in Carlin *et al.* (2001). The authors consider a discrete mixture model in order to control for outlier macro units.

A positive aspect of our analysis is the strong stability of point estimates both with respect to model specification and considered sample. This stability regards both the fixed and the random effects and, consequently we consider the obtained estimates reliable for an administrative use.

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