Comparing Rules for Truncating Hospital Length of Stay

Christiane Ruffieux, Mathematician, Fred Paccaud, MD, Alfio Marazzi, PhD

Institute of Social and Preventive Medicine, School of Medicine, University of Lausanne, Switzerland

Correspondence and reprint address

Christiane Ruffieux
Institute of Social and Preventive Medicine
Rue du Bugnon 17, CH-1005 Lausanne
Tel +41.21.314.7247
Fax +41.21.314.7373
email Christiane.Ruffieux@inst.hospvd.ch

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Abstract

Most distributions of hospital length of stay are asymmetric, with a long right tail and some very large observations (outliers). These features vitiate the reliability of many statistical summaries, such as the arithmetic mean, and comparisons based on them.

A common remedy is to truncate (i.e., remove) values outside some limits and take the arithmetic mean of the remaining values. In general, the limits are based on a position measure (e.g., mean, median, quartiles) and a scale measure (e.g., standard deviation, median absolute deviation, interquartile range). In addition, a scale transformation (usually the logarithm) is frequently used.

Using a data base with almost five millions hospital stays from five European countries, this paper explores the performance of five common truncation rules combining various options on transformation, position and scale. These rules are compared with a new one called « approximated quartile based truncated mean » or AQTM. The AQTM is based on a parametric model which takes into account the shape of the data distribution.

This paper shows that the usual truncation rules produce very different estimates, and that most of the usual rules are biased with respect to the AQTM. There is one exception based on symmetric truncation beyond the interquartile range on the logarithmic scale. Since the AQTM is computationally as simple as the usual rules, but has a better foundation, it is preferred.

Introduction

Length of stay (LOS) is used as an indicator of hospital activity for various purposes[1 2 3 4 5 6 7 8 9 10 11 12 13 14]. Unfortunately, LOS distributions are usually strongly skewed toward high values and contain outliers. Such asymmetry limits the use of inference techniques based on the normality assumption, e.g. estimation, confidence intervals and tests for comparing means. Outliers - i.e., values markedly different from most others - have a substantial impact on the sample mean and other common statistics. Since the values and the frequency of outliers typically fluctuate from sample to sample, the mean and the related inferences are very unstable.

A common remedy is to remove outliers from the statistics. An informal approach to identify « obvious » outliers is based on visual data inspection. However, more formal procedures are required in practice. These procedures are based on two steps : (a) determination of two boundaries (upper and lower) according to some predefined rules (« truncation rules ») ; (b) computation of the arithmetic mean of the values within the boundaries. Truncation rules have the practical advantage of objectivity and simplicity ; they suffer however from the lack of a sound theoretical foundation and most of them appear to be unsuitable for many common distribution models. This makes their application questionable[15 16].

In order to fill this gap, a mathematical framework for deriving boundaries from statistical principles has been developed[17] and easy to use approximations to the theoretically exact boundaries have been described [18]. This paper considers one of these procedures, the *approximated quartile based truncated mean* (AQTM), and compare it to five of the most usual rules.

Data

A database described elsewhere [16] has been used. This database contains 4,758,347 hospital stays from five European countries - Belgium (BE), the Swiss Canton Vaud (CH), Ireland (EI), the Italian region Lombardia (LB), and the United Kingdom (UK) - and three calendar years: 1988, 1989, and 1990. The following abbreviations are used: BE88 denotes the Belgian data of year 1988, CH89 the Swiss data of year 1989, etc. With this notation, the database includes nine country/year data sets: BE88, CH88, CH89, CH90, EI90, LB89, LB90, UK88, UK90.

Stays are classified into 478 Diagnosis Related Groups (DRG). Each DRG/country/year data set is called a sample here. 4085 samples have been analyzed in this paper.

Methods

Truncated means. A truncated mean is defined as the arithmetic mean of the data contained between two boundaries. In general, the computation of the boundaries is based on three numbers : a measure of position, a measure of scale, and a factor. The boundaries are set at a certain distance from the position, the distance being the product of the scale times the factor. Moreover, the boundaries are computed on the original scale or on some transformed (usually logarithmic) scale. A sample truncated mean is an estimate of the population truncated mean defined in the same way. The term *trimmed mean* is often used in the literature about LOS to denote a truncated mean. In the statistical literature, however, a trimmed mean denotes a slightly different procedure (i.e., the mean of the data contained between two empirical percentiles) [19]. We use the statistical terminology.

Usual truncation rules. This paper considers five truncation rules that are widely used in practice. Their characteristics are summarized in Table 1. The abbreviated names of these rules and the corresponding boundaries t_1 and t_2 are :

Tiqr	$t_1 = q_1 - 1.7[q_3 - q_1]$	$t_2 = q_3 + 1.7[q_3 - q_1]$
TLmr	$\ln(t_1) = \ln(q_2) - 1.5[\ln(q_3) - \ln(q_1)]$	$\ln(t_2) = \ln(q_2) + 1.5[\ln(q_3) - \ln(q_1)]$
TLqr	$\ln(t_1) = \ln(q_1) - 1.15[\ln(q_3) - \ln(q_1)]$	$\ln(t_2) = \ln(q_3) + 1.15[\ln(q_3) - \ln(q_1)]$
TLmm	$\ln(t_1) = \ln(q_2) - 3\,\mathrm{mad}\{\ln(x)\}$	$\ln(t_2) = \ln(q_2) + 3\,\mathrm{mad}\{\ln(x)\}$
Tlas	$\ln(t_1) = \mathrm{ave}\{\ln(x)\} - 3\,\mathrm{sd}\{\ln(x)\}$	$\ln(t_2) = \mathrm{ave}\{\ln(x)\} + 3\,\mathrm{sd}\{\ln(x)\}$

where q_1 and q_3 denote the first and the third empirical quartiles, q_2 the median, $\mathrm{mad}\{\cdot\}$ the median absolute deviation, $\mathrm{ave}\{\cdot\}$ the arithmetic mean, $\mathrm{sd}\{\cdot\}$ the standard deviation, and x a particular LOS.

Table 1 about here

The approximated quartile based truncated mean. The AQTM is a particular truncated mean [18]. A major feature of the AQTM is to take into account the distribution pattern of the sample to which it is applied. More precisely, it assumes that the sample distribution is the mixture of a « regular distribution » - that includes rare but expected long stays - and a « contaminating distribution » that describes the irregular, exceptional and unexpected stays. (This contamination might be due to any kind of accidents, ranging from errors in the codification process to catastrophic medical situations[13]). In addition, the regular distribution is described with the help of a parametric model. The AQTM is aimed at estimating the mean of the regular distribution, after removal of extreme cases that are likely to belong to the contaminating distribution. This procedure is a flexible approach to the management of both a variety of distribution patterns and proportions of outliers [16].

Since most LOS distributions can be fitted by the Lognormal, the Weibull, or the Gamma models [16], AQTMs have been defined for each one of these models. To fix the boundaries (see appendix 1), two factors k_1 and k_2 are used as follows :

AQTM : $\ln(t_1) = \ln(q_2) - k_1[\ln(q_3) - \ln(q_1)]$, $\ln(t_2) = \ln(q_2) + k_2[\ln(q_3) - \ln(q_1)]$,

where

$k_1 = 3.26 - 1.36s + 0.20s^2$ and $k_2 = 1.20$ in the Weibull case,

$k_1 = 1.718 + 0.167s - 0.153s^2 + 0.024s^3$ and $k_2 = 1.710 - 0.437s - 0.071s^2$ in the Gamma case,

$k_1 = 1.72 - 0.55s$ and $k_2 = 1.725$ in the Lognormal case,

and $s = \ln(q_3) - \ln(q_1)$.

Model selection. Since the AQTM requires a model to be selected, a simple and automated selection criterion, called the « average trimmed absolute residual », has been proposed [16]. This criterion quantifies the difference between the sample and the expected quantiles (according to the model) for the middle part of the distribution. For the analyses reported in this paper, however, the models selected in a previous work [16] have been used for all samples with more than 20 stays (whereas samples with less than 20 stays have been arbitrarily fitted with the Weibull distribution).

Case-Mix Weighted Trimmed Mean (CMWTM). For a specific country/year *c*, we assume that the population is grouped into g DRGs and that truncated means $\hat{m}_j^c(\text{TM})$ ($j = 1, \cdots, g$) are computed for each group according to a given rule TM (e.g., one of the rules defined above). The CMWTM $\hat{M}^c(\text{TM})$ is the weighted mean defined by

$$\hat{M}^c(\text{TM}) = \frac{\left\{ \sum_{j=1}^{g} n_j^c \hat{m}_j^c(\text{TM}) \right\}}{N^c},$$

where n_j^c is the number of cases in group *j*, and $N^c = \sum n_j^c$ is the total number of stays in country/year *c*.

Bias with respect to AQTM. In order to quantify the bias of a given truncation rule due to disregard of the distribution pattern, the AQTM has been chosen as a « gold standard » (since it is ideally based on an accurately selected model fitted to the data). A procedure TM is considered as unbiased with respect to the AQTM, if the casemix mean $\hat{M}^c(\text{AQTM})$ belongs to the symmetric 99%-percentile interval of the bootstrap distribution of $\hat{M}^c(\text{TM})$ (based on 250 simulated samples). (This interval may be interpreted as an approximate 99%-confidence interval for the population value $M^c(\text{TM})$ of $\hat{M}^c(\text{TM})$ [20 21]).

Results

Three examples. Three samples, also described elsewhere[18], have been selected to give typical examples of the performances of the truncated means defined above. They illustrate the two most frequent pattern of distribution[16] : DRG35/CH88 and DRG14/BE88, are well fitted by a Weibull model, whereas DRG127/EI90 can be described with the help of a Lognormal model.

Table 2 shows, for each sample, the truncated and non-truncated means, the lower and upper boundaries (t_1 and t_2), and the proportions (p_1 and p_2) of stays beyond the boundaries. We observe that :

- There is a substantial variation between the means according to the truncation rule. For DRG 35 (Table 2, panel a), Tiqr is close to AQTM, whereas TLas moves away. On the contrary, for DRG 127, TLas provides the closest estimation with respect to AQTM, and Tiqr the most distant. The (non-truncated) classical mean is usually larger than the truncated means. However, this is not the case for DRG14 (Table 2, panel b) : in this example, TLqr is larger than the arithmetic mean.
- The lower boundary (t_1) of Tiqr is negative (i.e., meaningless) in the three examples.
- There is a strong variability in the upper limits (t_2); furthermore, some of the upper limits are larger than the maximal observed LOS.
- The truncated means depend not only on the upper limit (t_2), but also on the lower bound (t_1): for DRG 35, despite a smaller upper limit , TLqr is larger than TLmm: this is due to the exclusion of some of the smallest stays (see p_1). The same can be observed for DRG 14, where TLqr is larger than the classical mean.

Table 2 about here.

Comparing DRG truncated means. The truncated means of the 25 most frequent DRGs (see Appendix 2) were computed according to the rules mentioned above. In Figure 1, the means for Ireland are plotted by DRG (sorted according to AQTM). For some DRGs, the differences are substantial (up to 7 days for DRG 014). Similar patterns (not shown here) were observed for the other countries. The ranking of the values is quite stable across the samples : in most samples, the smallest average is provided by Tiqr, while the largest one is given by TLas. The AQTMs are located somewhere between the other rules.

Figure 1 about here.

Comparing Case-Mix Weighted Means. Figure 2 shows the CMWTMs by country/year. Variations due to the use of different truncation rules range from 1 day (CH90) to more than 3 days (UK90). The ranking is rather stable across country/years. TLas is usually close to the classical mean except for UK90. TLqr, TLmm, and TLmr provide estimations which are close one another, and close to AQTM.

Figure 2 about here.

Bias with respect to AQTM. Results for three countries (Belgium, Switzerland and Ireland) and for the 25 most frequent DRGs are given in Table 3. Two rules, Tiqr and TLas, are biased with respect to AQTM. Tiqr is systematically smaller than AQTM, while TLas is systematically larger. TLmr and TLmm provide varying results. TLqr is the single unbiased rule with respect to AQTM.

Table 3 about here.

Discussion

This paper contributes to the development of statistical methods for the analysis of LOS. It compares five truncation rules commonly used in practice and a new procedure, called the AQTM. The results show that the usual rules produces very different results. Moreover, these usual rules (with one exception) are biased with respect to AQTM. Since the AQTM is computationally as simple as the usual rules, but theoretically more satisfactory, it is preferred.

In the area of LOS analysis, the need of outliers resistant procedures has long been recognized (as in early papers by Gustafson [22] and others [23 24]). The identification and removal of outliers has been based on various procedures [1 4 12 14 25 26 27 28 29 30 31 32] ; the most common one has been implemented by the Medicare administration [26 33]. Unfortunately, these procedures do not rely upon a solid theoretical background [13 15 16]. In addition - as shown in Figure 1 for the 25 most frequent DRGs and in Figure 2 for the CMWTM - they provide very discrepant values for the same data set. This variability (also reported by others [13]) is a source of troubles when comparing and pooling results from different studies [34]. It is obviously related to the boundary definition and to the capability to adapt boundaries to the distribution pattern [15 16]; this latter capability is missing in the usual rules.

The AQTM is a new rule whose boundaries are based on a distribution model fitted to the data. It turns out that a variety of models is usually necessary to conveniently describe a mixture (case-mix) of LOS distributions. Thus, if the model is accurately selected, the AQTM is a superior procedure. Moreover, thanks to its theoretical foundation, the AQTM allows derivation of statistical inference procedures for comparing truncated means of two or several groups. Inference procedures based on usual rules[13] are more confused, although improper use (including multivariate analysis [31]) is widely disseminated [29 35].

The AQTM is not computationally more complex than usual truncated means. Moreover, an automated procedure to select the required distribution model has been suggested. The procedures described in this paper are made available at our Internet site[36]. The AQTM is therefore an attractive choice as a new standard rule. Note however that, for various reasons, one might prefer to use a single model for all groups of an entire case-mix; for example, for the purpose of estimating the CMWTM, a single model (e.g., Gamma) usually provides a satisfactory description[15 16]. The TLqr is the single usual procedure that performs like the AQTM. This procedure, which combines a lognormal transformation with a symmetric truncation rule based on the interquartile range, can be considered as the best choice among the five usual rules considered in this paper.

The use of DRGs (or other classification systems) has became common to adjust comparisons of LOS and other variables (like costs [28 34 37] or inpatient mortality [26 38 39]) among mixtures of groups of patients. It is therefore crucial to cope with the problems of skewness and outliers in this area. Though this study has been designed for LOS , the general approach can be used for any skewed variable [40].

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Appendix 1: definition of lower and upper boundaries of the AQTM.

The AQTM is based on the assumption that the data can be described by means of a parametric model $F_{\alpha,\sigma}$, where α is a shape parameter and σ a scale parameter. Let $F_{n,y}$ denote the sample distribution, $m(F)$ and $s(F)$ the median and the range interquartile of a distribution F, and $\hat{\alpha},\hat{\sigma}$ the solutions of the equations $\hat{\sigma}m(F_{\hat{\alpha},1}) = m(F_{n,y})$ and $\hat{\sigma}s(F_{\hat{\alpha},1}) = s(F_{n,y})$. Let u=.99, t_u be the u-quantile of $F_{\hat{\alpha},\hat{\sigma}}$, and t_l be the solution of

$$\frac{1}{u - F_{\hat{\alpha},\hat{\sigma}}(t_l)} \int_{t_l}^{t_u} x dF_{\hat{\alpha},\hat{\sigma}}(x) dx = \int_{0}^{\infty} x dF_{\hat{\alpha},\hat{\sigma}}(x) dx$$

The boundaries of the AQTM are defined as polynomial approximations (in s) of t_l and t_u.

A similar definition can be given when the data are described with a location and scale model.

Appendix 2: the 25 most frequent DRGs as used in this study

014	Specific cerebrovascular disorders except TIA
032	Concussion age >17 w/o cc
060	Tonsillectomy &/or adenoidectomy only, age 0-17
089	Simple pneumonia & pleurisy age >17 w cc
119	Vein ligation & stripping
127	Heart failure & shock
162	Inguinal & femoral hernia procedures, age >17 w/o cc
167	Appendectomy w/o complicated principal diag w/o cc
182	Esophagitis, gastroent & misc digest disord age >17 w cc
183	Esophagitis, gastroent & misc digest disord age >17 w/o cc
184	Esophagitis, gastroent & misc digest disord age 0-17
209	Major joint & limb reattachment procedures
219	Lower extrem & humer proc exc hip, foot, femur age >17 w/o cc
222	Knee procedures w/o cc
225	Foot procedures
227	Soft tissue procedures w/o cc
231	Local excision & removal of int fix devices exc hip & femur
243	Medical back problems
281	Trauma to the skin, subcut tiss & breast age >17 w/o cc
324	Urinary stones w/o cc
355	Uterine, adnexa proc for non-ovarian/adnexal malignancy w/o cc
369	Menstrual & other female reproductive system disorders
371	Cesarean section w/o cc
373	Vaginal delivery w/o complicating diagnoses
381	Abortion w d&c, aspiration curettage or hysterotomy

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Table 1. Characteristics of truncation rules**.**

Rule		*Transformation*	*Position*	*Scale s*	*Factor* k_1	*Factor* k_2
« usual » truncation rule	*Tiqr*	identity	quartiles	interquartile range	1.7	1.7
	TLmr	logarithmic	median	interquartile range	1.5	1.5
	TLmm	logarithmic	median	median absolute deviation	3.0	3.0
	TLqr	logarithmic	quartiles	interquartile range	1.15	1.15
	TLas	logarithmic	mean	standard error	3.0	3.0
« new » truncation rule	*AQTM weibull*	logarithmic	median	interquartile range	$3.26-1.36s+.2s^2$	1.2
	AQTM gamma	logarithmic	median	interquartile range	$1.718+.167s-.153s^2+.024s^3$	$1.71-.437s+.071s^2$
	AQTM lognormal	logarithmic	median	interquartile range	$1.72-.55s$	1.725

Table 2. Estimates provided by various rules : three examples. (t_1 and t_2 are the lower and upper boundaries; p_1 is the proportion of stays shorter than t_1, p_2 is the proportion of stays shorter than t_2)

(a) DRG 35 (Disorders of nervous system), Switzerland, 1988 - Weibull model

	Classical	*Tiqr*	*TLmr*	*TLmm*	*TLqr*	*TLas*	*AQTM*
mean (day)	**25.47**	**4.00**	**4.23**	**4.41**	**4.67**	**14.23**	**4.00**
t_1 (day)	1	-3.2	1.15	.94	1.04	.09	.61
p_1 (%)	-	*.0*	*6.3*	*.0*	*6.3*	*.0*	*.0*
t_2 (day)	374	12.2	14.0	17.0	16.3	298.4	10.9
p_2 (%)	-	*12.5*	*12.5*	*9.4*	*9.4*	*3.1*	*12.5*

(b) DRG 14 (Specific cerebrovascular disorders except TIA), Belgium, 1988 - Weibull model

	Classical	*Tiqr*	*TLmr*	*TLmm*	*TLqr*	*TLas*	*AQTM*
mean (day)	**19.46**	**16.4**	**19.42**	**19.21**	**20.02**	**19.46**	**18.23**
t_1 (day)	1	-26.3	1.65	1.95	1.16	0.43	1.19
p_1 (%)	-	*.0*	*6.27*	*6.27*	*6.27*	*.0*	*6.27*
t_2 (day)	204	57.3	119.1	100.4	129.0	321.2	77.6
p_2 (%)	-	*3.93*	*.96*	*1.17*	*.43*	*.0*	*2.24*

(c) DRG127 (Heart failure and shock), Ireland, 1990 - Lognormal model

	Classical	*Tiqr*	*TLmr*	*TLmm*	*TLqr*	*TLas*	*AQTM*
mean (day)	**11.58**	**9.21**	**10.26**	**10.03**	**10.75**	**11.34**	**11.27**
t_1 (day)	1	-10.3	1.71	1.86	1.53	.60	2.44
p_1 (%)	-	*.0*	*4.2*	*4.2*	*4.2*	*.0*	*8.8*
t_2 (day)	221	29.3	37.5	34.3	45.8	106.6	47.3
p_2 (%)	-	*6.2*	*3.6*	*4.4*	*2.1*	*.17*	*2.0*

Table 3. Case-mix adjusted means (M^c) and 99%-percentile intervals (*PI*) in three countries, according to various rules

		Classical	*Usual truncation rules*					*New rule*
		mean	*Tiqr*	*TLmr*	*TLmm*	*TLqr*	*TLas*	*AQTM*
Belgium	M^c	8.53	7.43	7.92	7.92	8.03	8.34	8.02
	PI	8.35-8.70	7.29-7.59	7.75-8.14	7.75-8.12	7.85-8.27	8.18-8.52	
Switzerland	M^c	8.74	7.99	8.42	8.47	8.48	8.61	8.39
	CI	8.57-8.93	7.82-8.17	8.25-8.61	8.27-8.63	8.30-8.67	8.44-8.79	
Ireland	M^c	5.57	4.28	4.92	4.95	5.05	5.31	5.06
	CI	5.43-5.74	4.18-4.37	4.76-5.04	4.78-5.06	4.93-5.18	5.20-5.47	

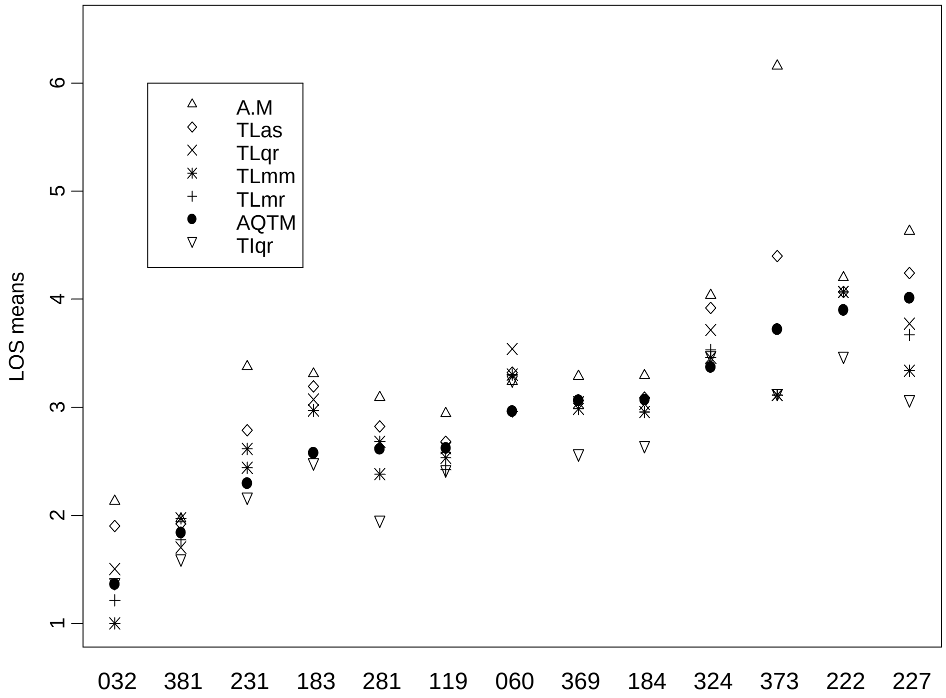

Figure 1a : Usual and new truncated means for the shorter frequent DRG-s in Ireland

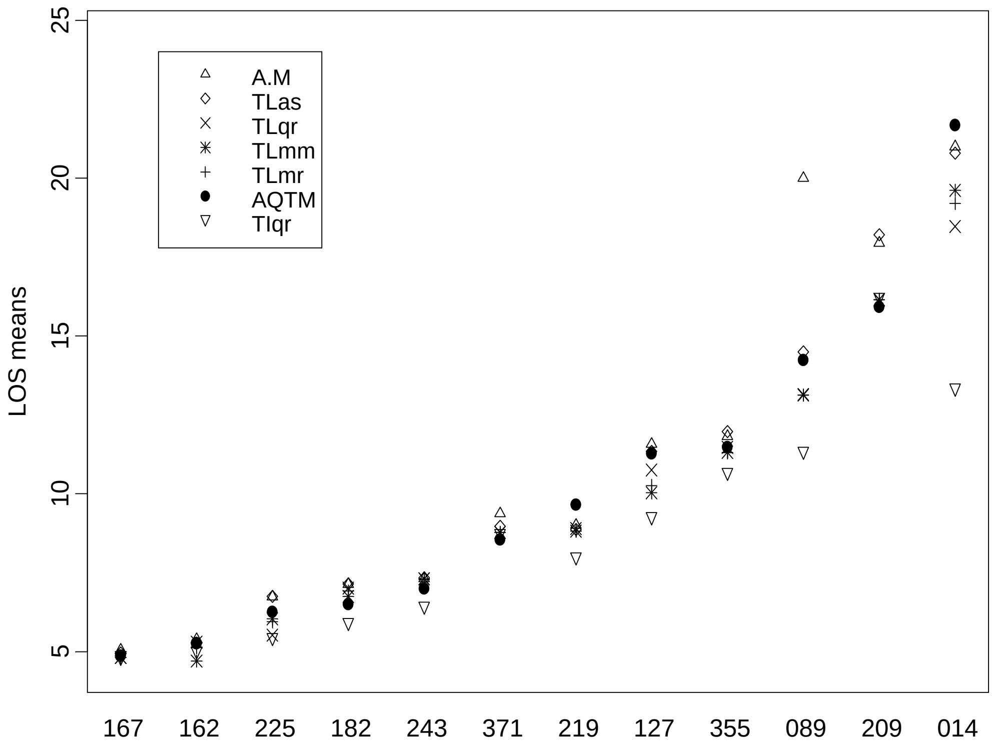

Figure 1b : Usual and new truncated means for the larger frequent DRG-s in Ireland

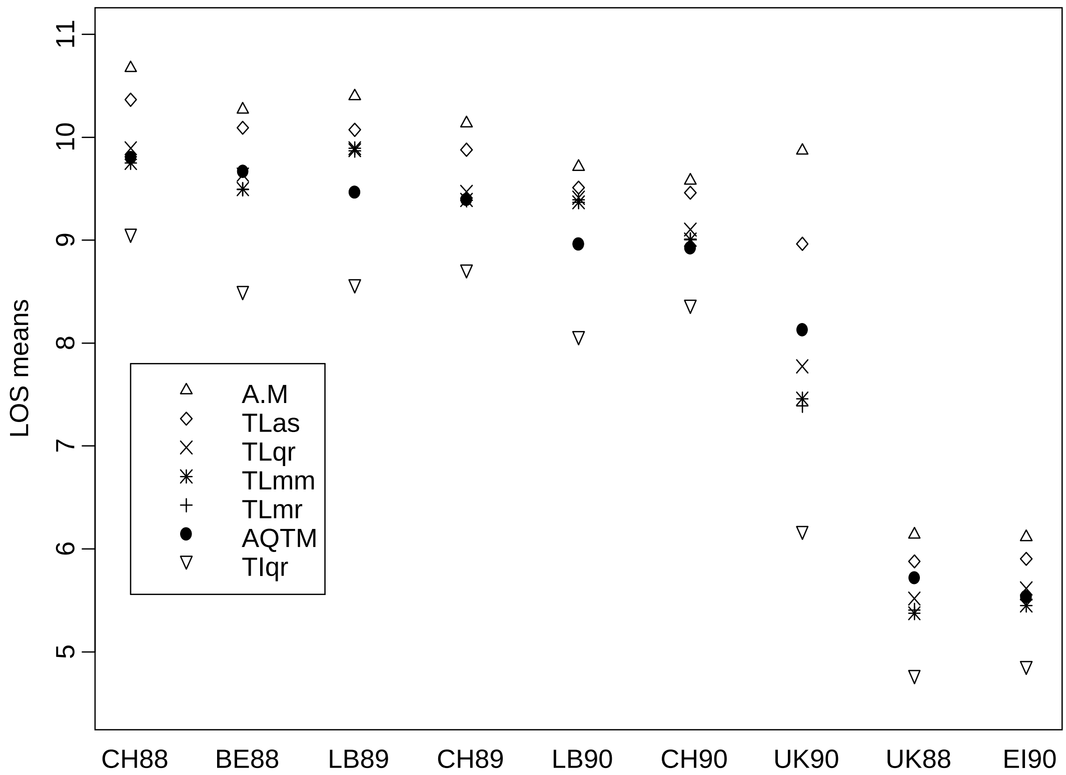

Figure 2 : Estimations of Case-Mix Weighted Truncated Means by country/year, provided by usual and new rules