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Introduction

Hospitals show differences in terms of quality of care (McConnell et al. 2013; Lenzi et al., 2016). Past research has investigated extensively how to implement risk-adjustments based on inputs, case-mix or other patients' characteristics to limit potential biases when benchmarking hospital performance (Wallmann et al. 2013; Lingsma et al., 2018). Despite the undoubted value of these contributions, three intertwined limitations still puzzle our understanding of how to provide regulators and hospital managers with evidence-based guidelines about how to improve quality of care. First, past contributions underemphasized the role of management practices, privileging patients-related covariates (Au et al. 2012; Wallmann et al. 2013) or hospital resources (Häkkinena et al. 2013). Recent studies–for a review refer to Lega et al. 2013–claim that management practices affect hospital quality of care. Grounding on this emerging evidence, Lega et al. (2013) argued that "empirical efforts of researchers must extend our understanding of the relationship between management practices and performance" (pg. S50). Second, past studies that investigated the relationship between management practices and quality of care proved it through either self-reported surveys or expert opinion. In this view, regulators and hospital managers pointed out that current evidence about the existence of this relationship is not enough robust as studies on hospital performance based on administrative data (e.g., Bottle, Sanders, et al. 2013; Murdoch & Detsky 2013; Cook & Collins 2015)–even if limited to patient-related covariates. Regulators and hospital managers need more conclusive evidence about which managerial practices affect the quality of care to implement improvement strategies (Park et al., 2014). Third, 30-day mortality and 30-day unplanned readmission are competing outcomes (Di Tano et al. 2015). While the mainstream approach is to analyze them as a single outcome (Au et al. 2012), an increasing number of scholars (Krumholz et al. 2006; Wallmann et al. 2013) analyzed them separately to better understand what explains different quality of care and the role played by different managerial alternatives (Bonow 2008; Glance et al., 2017).

With this study, we aim at narrowing these limitations and shedding new light on the role that management practices might have to determine the quality of care. We developed and empirically tested, through administrative data, an original hierarchical logistic model that combines individual-level covariates about patients' characteristics with hospital-level ones about management practices to gather more robust evidence about the role that management practices play. Data comes from the hospital discharge abstracts for Heart Failure (HF) patients in the Lombardy Region (Northern Italy). As indicators of hospital quality of care, we considered the well-established measures of quality of treatment on short-term outcomes for Heart Failure (HF) patients (Bonow 2008; Bottle, Middleton, et al. 2013): 30-day mortality and 30-day unplanned readmission. A significant body of evidence shows that HF patients have a high risk of mortality (Frigerio et al. 2017; Krumholz et al. 2006) and a high probability of incurring multiple urgent admissions (Au et al. 2012; Keenan et al. 2008; Robertson et al., 2012). These indicators can be measured reliably through administrative data (Bottle, Sanders, et al. 2013). Finally, since reimbursement is based on tariffs that are independent of hospital performance, treatment costs have not been considered in this study.

Methods

Measurement of Quality of Care

In this study, we refer to 30-day mortality as the number of deaths for any cause within 30 days after the incident HF admission and 30-day unplanned readmission as the number of non-programmed hospitalizations for any cause within 30 days after the incident HF admission. With incident admission, we mean for any patient the first ever admission in a hospital for HF. While 30-day mortality was measured considering intra-hospital and out–of–hospital mortality for all causes, using the Lombardy Region's registries about deaths; 30-day unplanned readmissions were measured excluding the cases of a patient being transferred from one hospital to another, planned readmissions, and readmissions occurred more than 30 days after discharge. Additionally, patients died during the incident admission or within 7 days from discharge were excluded to evaluate non-programmed readmissions. The latter choice was made to exclude patients who have decided, for personal reasons, to die at home rather than in hospital. Finally, hospitals located outside the Lombardy Region or with less than 100 HF hospitalizations were excluded.

Data

Our analysis was based on administrative data from hospital discharge abstracts and death statistics with respect to the Lombardy Region. Data from death statistics allowed us to evaluate mortality outside the hospital. Other data (e.g., the percentage of surgical DRGs) were collected from regional reports on hospitals' activity. In Lombardy, hospital discharge abstracts contain information on patient characteristics (e.g., sex and age) and hospital admission (e.g., date of admission, date of discharge, principal diagnosis and comorbidities (from secondary diagnoses), procedures, admission ward, etc.).

Our study focused on Heart Failure (HF) to identify the most relevant covariates recommended by past studies. HF is the leading cause of hospitalization for citizens 65+ in all the most developed Countries (Joynt et al. 2011) that absorbs significant financial resources. Although the focus of our study is HF patients, we claim that our methods to generate evidence–by means of hierarchical logistic regressions and funnel plots–are generalizable to other typologies of patients as well as to other Regions/Countries that collect administrative data. Respectively, we considered incident hospitalizations for HF–i.e. the first hospitalization for HF–since 2010 to 2012 occurred in hospitals located in the Lombardy Region limited to patients who are residents in the same Region. Hospitalizations for HF were identified according to the ICD-9-CM codes proposed by the Agency for Healthcare Research and Quality in their quality indicator of intra-hospital mortality due to HF (AHRQ, 2015) and those proposed by the Center for Medicare and Medicaid Services (CMS) in their risk adjustment model for capitation payments. In particular, as recommended by Evans et al. 2011, the category HCC80 have been used consecutively (CMS-HCC80, version 12th). The codes were searched in any diagnosis position (up to six) of the hospital discharge abstracts. A hospitalization for HF was defined as the incident one for the patient if there was a previous period of at least five years without other hospitalizations due to HF. Respectively, extracting these data we were able to evaluate 1) Hospital re-admissions for any cause after the incident HF hospitalization, 2) Number of admissions occurred for any cause within the 6 months before the incident HF hospitalization, and 3) Patients' comorbidities at the incident hospitalization, using the algorithm proposed by Gagne et al. 2011. With respect to this point, we followed the recommendations by Sharabiani et al. 2012 and thus we searched for codes of comorbidities in the previous hospitalizations of the patient. We adopted look-back period one year before the incident HF; when chronic comorbidities were detected, they were assumed affecting the patient also in the subsequent hospitalizations.

Statistical Models

Our research strategy combined two-level hierarchical logistic regressions and funnel plots to identify hospitals with divergent performance (outliers) and isolate management practices (i.e., covariates at the hospital-level) that explain the differences between best and worst performers. Funnel plots were used to visualize outlier hospitals for both mortality and readmission and have been built on the ratio between the number of observed and the expected number of deaths (or readmissions), as stated in the formula (1):

$$Y = \frac{\sum_{i=1}^{n_j} y_{ij}^{obs}}{\sum_{i=1}^{n_j} \widehat{p_{ij}}} = \frac{O_j}{E_j} \tag{1}$$

where y_{ij}^{obs} is the observed outcome for patient ‘i’ treated in the hospital ‘j’, n_j is the number of patients treated in hospital ‘j’ and $p_{ij}$is the corresponding expected value for patient ‘i’ treated in hospital ‘j’. The expected value was evaluated through a regression model and is described as follow. The upper and lower control limits, defined as 90% and 95% confidence intervals, were calculated as recommended by Ieva & Paganoni 2015 in absence of over-dispersion (according to our data) and were used to identify outlier hospitals. To estimate correctly the expected values of mortality and readmissions, we developed a multilevel logistic regression model, adjusting for different characteristics of patients and hospitals (Diez-Roux 2000). Therefore, we introduced covariates at the patient- (first level of our hierarchical model) and hospital-level (second level of our model) to take into account possible heterogeneity in patients’ or hospitals’ management practices. The explanatory variables for estimating mortality and readmission, at both levels, have been selected based on past contributions (Gruneir et al. 2011; Au et al. 2012; Sasaki et al. 2013; Wallmann et al. 2013) and available data. As recommended for hierarchical models, we started testing the “null” model and evaluating the Interclass Correlation Coefficient (ICC). Then, we introduced the first level (i.e. about patients) variables and subsequently the second level (i.e. about hospitals) variables. Variables were included in our final statistical model through a backward selection method. Patient-level variables are age, sex, length of stay (LOS), comorbidities weight, number of admissions in the previous six months and type of admission ward. The latter variable had three levels to distinguish patients directly admitted in cardiologic wards, in Intensive Care Units or in other wards. We assumed this variable as a proxy for the correct placement of the patient at hospital admission.

The investigation of management practices through administrative data required the identification of those covariates that are included in the discharge forms and can be assumed as a proxy for managerial practices. The limitations–as well as the opportunities–of this approach compared to traditional surveys or expert opinion elicitation will be discussed in the “Limitations” section. We considered these variables: number of inpatient cases, average LOS, the percentage of surgical DRGs, type of hospital, attractiveness from local Health Districts (HDs) others than where the hospital is located, attractiveness from other Italian Regions or from abroad. At the time of this study, in the Lombardy Region, there were 15 HDs, including hospitals and outpatient services providers. The number of admissions, being related to the volume of patients, is a proxy of the hospital relevance and size; this characteristic is also explained by the attractiveness of patients from other HDs, other Regions and abroad. The percentage of surgical DRGs characterizes hospitals as it represents synthetically the frequency of the surgical procedures carried out by a hospital. The typology of a hospital–we considered three types: non-research public hospitals, non-research private hospitals, research hospitals (both public and private)–may echo different types of governance and processes. Data management and statistical analysis were performed using SAS 9.4.

Results

Considering the timespan 2010-2012, 78,907 residents in the Lombardy Region and aged at least 18 were hospitalized for HF for the first time. Applying the exclusion criteria described in the 'Methods' section, we identified 72,083 patients admitted to 117 hospitals eligible for evaluating mortality and 60,771 patients admitted to 116 hospitals at risk for unplanned 30-day readmissions.

Regarding 30-day mortality ratio, out of 72,083 patients, 9,480 (13.15%) died within 30 days from the incident event. The ICC of the 'null' model is 4.85%, confirming the hierarchical structure of data. All patient-related variables (first level variables in our model) were correlated significantly with the outcome; therefore, all of them were included in our final model. Among the hospital-related variables second level variables in our model), only some of them were correlated significantly to the outcome; they were the percentage of surgical DRGs and the type of hospital (non-research public hospitals/non-research private hospitals/research hospitals). All the other second-level variables were removed from our final model with the backward selection method. Parameter estimates and odds ratios (ORs) for fixed effects in the definitive model are in Table 1.

[Table_1]

Except two, all covariates have a positive association with 30-day mortality. Results are reported in terms of Odd Ratios and confidence intervals (CI). As expected, age (OR=1.070; CI (1.067-1.073)) and comorbidity weight (OR=1.190; CI (1.172-1.209)) positively affect the probability of death. The number of previous admissions, as a proxy of patient worsening condition, is also positively related to the probability of death (OR=1.323; CI (1.281-1.367)). Being male increases the risk of death (OR=1.323; CI (1.112-1.223)). The type of admission ward shows a strong association with 30-day mortality. As expected, patients admitted in Intensive Care Units show higher probabilities of death than those admitted in cardiac wards (OR=3.108; CI (2.801-3.448)); being admitted to non-cardiac wards is strongly associated to higher mortality than being admitted in cardiac wards (OR=2.890; CI (2.655-3.145)). As "protective" factor, i.e. covariates associated with lower probability of death, the LOS indicates that the longer the stay the lower the probability of death (OR=0.997; CI (0.994-1.000)). However, although the significant p-value, the confidence interval suggests a moderate effect. At last, only the percentage of surgical DRGs–as variable at the hospital level–is positively associated with mortality (OR=1.007; CI (1.003-1.011)). Admissions in research hospitals and non-research private hospitals are associated with a lower mortality than in non-research public hospitals (respectively OR=0.624; CI (0.485-0.803) and OR=0.746; CI (0.626-0.889)). Finally, we calculated the total observed mortality for each hospital and we evaluated the expected deaths of patients admitted to the hospital to define the observed/expected ratio and to build the funnel plot, as shown in Figure 1.

[Figure_1]

The funnel plot on 30-day mortality shows that all 117 hospitals are 'in-control' because none of them is over the upper limit (worst performers) or below the lower limit (best performers). This happens also considering the less restrictive 90% confidence interval. In addition, hospitals that manage a smaller number of HF patients (left side of the funnel plot) do not show performance that is over the upper limit.

Respecting to 30-day unplanned readmission ratio, out of 60,771 patients, 5,363 (8.82%) were readmitted within 30-days from the discharge of the incident hospitalization. The ICC of the 'null' model is 0.66%; such value is quite low. However, the ratio between the estimated variance (0.022) associated with the random effect, i.e. hospitals, and the associated standard error (0.007) is greater than 1.96 and, therefore, significantly different from zero. This suggests that a multilevel model has to be preferred (Alexandrescu et al. 2011). Unlike what we found for mortality, the effect of patients' sex was not significant (p=0.1757) and this variable was therefore removed from the model. Among the second-level explanatory variables, the hospital average LOS was the only one with a significant effect ($p<.0001$) on readmissions and was therefore included in the final model. Parameter estimates and odds ratios for fixed effects in the definitive model are in Table 2. As expected, except for hospital mean LOS, all the other covariates had a positive association with the probability of readmission. As it happened for mortality, age (OR=1.011; CI (1.009-1.014)) and comorbidity weight (OR=1.094; CI (1.072-1.117)) are associated with higher probability of readmission. The number of previous admissions was also associated with an increased probability of readmission (OR=1.272; CI (1.221-1.325)).

[Table_2]

As for mortality, this variable is a proxy of the worsening condition of the patient, who has needed several hospitalizations. The effect of the admission ward on readmissions was similar to what we found about mortality but with a weaker effect. Being admitted to an ICU (OR=1.510; CI (1.358-1.679)) or in other wards (OR=1.378; CI (1.272-1.493)) implies an increased probability of subsequent readmission compared to being admitted in a cardiac ward. Contrary to mortality, longer hospitalizations are associated with a higher probability of readmission (OR=1.023; CI (1.019-1.026)). Therefore, as for mortality, the association is probably due to the worse condition of patients admitted for prolonged periods. At hospital-level, only the average LOS shows a significant effect on readmission. In particular, hospitals with lower mean duration of hospitalization expose patients to a higher probability of readmission (OR=0.961; CI (0.945-0.977)). As done for mortality, we calculated for each hospital the number of observed and expected readmissions to define the observed/expected ratio and build the funnel plot, as shown in Figure 2.

[Figure_2]

Considering the 95% confidence interval, four hospitals were located outside the control limits: among them, three hospitals were below the lower limit (best performers) and one hospital was over the upper limit (worst performers). If we consider the 90% confidence interval, eight hospitals are found as ‘outliers’: while five hospitals perform better than all the others do yet, three of them can be identified as worst performers.

Mortality vs. Readmission

Table 3 shows our results in terms of variables (both at the individual- and at the hospital-level) that have been confirmed to affect 30-day mortality and 30-day readmissions. These results are relevant for our discussion because, as claimed by (Keenan et al. 2008), the two performance indicators explain individually different dimensions of the “quality of care” but if analyzed together they allow understanding the potential trade-offs between these concurrent outcomes.

[Table_3]

Focusing on patient-related variables, our results show that age, the weight of comorbidities and number of previous admissions are significantly associated with an increased probability of 30-day mortality or 30-day unplanned readmission. These variables all-together capture the severity of the disease and the complexity of the clinical case that hospital professional have to cope with. Type of ward at the entrance shows a similar effect on both mortality and readmission, even if with a higher effect on mortality rather than on readmission. According to our results, being admitted in non-cardiac wards increases the risk of death and readmission. This is an interesting result because, despite it is a patient-level variable, the type of ward at admission can be associated with the organizational procedures and patient pathways put in place in the specific hospital. The same considerations can be done for the patient’s LOS, whose duration is determined by a combination of patients’ characteristics and hospital choices. However, LOS has an opposite effect on the two indicators. While a longer LOS is associated with a lower probability of 30-day death, a longer LOS is associated with a higher probability of unplanned readmission.

Moving to the hospital-level variables, mortality and readmission have been found associated with different variables. On the one hand, higher readmission rates are associated with lower mean hospital LOS. This indicates that, after controlling for hospital case-mix and patients’ characteristics, hospital policies on LOS affect the probability of subsequent unplanned hospitalizations. This result is significant for both hospital managers and policy-makers who, while deciding for reducing LOS to save costs, might fail to see the future costs due to unplanned re-hospitalizations. On the other hand, higher percentages of surgical DRGs are associated with higher probability of death. This association captures, on the one hand, that surgery has higher risks rather than other kinds of treatments, and, on the other hand, that the hospital is accepting patients with more complex conditions. In this regard, it is worth to note once again that administrative data do not include detailed clinical information. Finally, the type of hospital has an impact on mortality. Public, non-research hospitals show higher mortality and readmission rates than private, non-research hospitals and research hospitals (private and public) does.

Discussion

Our results show management practices affect hospital quality of care despite patients' peculiar characteristics. In this view, the discussion will deal with two main issues. First, we will discuss the role played by management practices and their implication for theory advancement and practice improvement. Second, we will discuss administrative database as a source of evidence for grounding decision-making and the implementation of performance improvement strategies.

Our results show that hospital managers have the opportunity to improve quality of care by adopting effective management practices being a performance not driven just by patients' characteristics. Leveraging on different configurations of governance, processes, and practices, hospital managers can actually improve quality of care. With respect to HF patients, the "isolation" of this effect on performance refers to four practices: the choice of the admission ward at the first hospitalization (intensive care unit vs. cardiac unit vs. non-cardiac unit), the average LOS, the percentage of surgical DRGs, and the type of hospital (research vs. private, non-research vs. public, non-research). These results suggest two directions of discussion. First, the former three variables echo hospital managers and professionals' capability to organize clinical pathways that are effective and safe. The choice of the ward at admission is mainly led by clinical motivations; however, it can be affected by the existence of skills and protocols that guarantee a correct triage of patients and the identification of the adequate treatment for them. Leaving the patients wandering through different wards has the twofold effect of decreasing the quality of care–and thus increasing the probability of death or readmission–and absorbing more costs for ineffective–when not harmful–care. Similar reasoning deals with the choice of the adequate LOS. Reducing the average LOS while might contribute to increase the hospital profitability in both the short-term (because reimbursements are decided based on tariffs regardless of the days actually spent by the patients in the hospital) and the mid/long-term (because of repeated hospitalizations), could harm the patient. In this view, hospital managers and professionals have the responsibility to manage this trade-off balancing ethics and sustainability over time. Similar implications can be argued with respect to the percentage of surgical DRGs. On the one hand, surgery is characterized by superior risks rather than other treatments and thus professionals should define appropriate protocols to select those patients who might actually benefit from this risk-increasing procedure. On the other hand, surgery treatments should be concentrated in specialized hospitals that, by performing a significant number of surgical procedures per year, would develop superior skills to minimize the risk of death or side effects.

Second, the significance of the type of hospital points out the relevance of innovation and change. Research hospitals, regardless of their ownership, have been found to outperform the others. Their continuous tension to innovation, improvement, and learning paves the way for the systematic updating of governance configurations and clinical pathways, aligning them to best available evidence. Considering non-research hospitals, private hospitals have been found to outperform public ones. Because we are not fully able with administrative data to control for patients' clinical condition, part of the explanation might be related, as found in previous studies (Berta et al. 2010), to the fact that private hospitals are more likely to select patients with a lower case-mix (i.e., treated patients have a better general condition and facilitate the achievement of positive performance). Another explanation grounds on the superior capability of private hospitals to design and implement changes aimed at improving performance; in particular, private hospitals implement such changes rapidly and with limited resistance from healthcare professionals.

The second issue is the role that administrative data might play in helping policy-makers and hospital managers and professionals to isolate the effect that management practices play in shaping the quality of care and generate reliable evidence to support decision-making and improvement strategies. Our multilevel statistical model allowed us to identify those hospitals achieving "out of control" performance in terms of 30-day mortality or readmissions and, more than this, to disentangle explanatory patient-related variables from hospital-related ones. Our results, despite the specific case of HF patients, confirmed that administrative data are a valuable source of evidence to benchmarking hospital performance and provide decision-makers at different levels with relevant and reliable insights about performance and their determinants. Our results should encourage policy-makers and hospital managers to crystallize best practices and virtuous behaviors from best performers to translate them to the poor performers (Dover & Schopflocher 2011). Although the value stored in administrative data, particular attention should be paid to the interpretation of the results. The main concern is the lack of detailed clinical information, which could better guide researchers in unfolding the specific characteristics of the treated patients and avoid biases in the comparison.

Additionally, the weight of comorbidities and of case-mix could provide first-hand information about the clinical status of patients, but more detailed clinical information is necessary to risk-adjust the performance achieved by different hospitals. For instance, the correlation between the LOS and 30-day mortality could be biased by fact that some hospitals treat more complex patients who actually die after the very first days because of their severe conditions that did not leave possibilities to professionals. We controlled for age, sex, previous admissions, comorbidities score etc. but these factors, the only available in administrative datasets, could not be enough to capture all the variance connected to the severity of the clinical condition of patients. In this regards, two actions should be taken to improve the richness of the available data. On the one hand, administrative data should be complemented with clinical information stored in clinical registries and hospital medical records. On the other hand, different administrative data should be integrated to provide researchers with all available information. For instance, administrative data from discharge abstracts should be complemented with data from the Emergency Departments and about drug prescriptions.

Despite the limitations described above, our results show that the combination of multilevel statistical models and funnel plots offers policy-makers and regulators the opportunity to monitor and control the performance achieved by the regional healthcare system with respect to different pathologies. For instance, the fact that there are not outliers for 30-day mortality means that the system as a whole is achieving satisfying performance and guarantees patients about the safeness and effectiveness of the services received. In this regard, further research should monitor such results with a longitudinal perspective aimed at understanding if (i) the delivery system is improving as a whole; (ii) specific improvement strategies (e.g., the sharing of best practices, the design of more severe accreditation parameters, the increased frequency of audits and inspections, etc.) are or not producing the expected benefits; and (iii) hospitals have or not the capability to improve performance over time, understanding both the time required to change and improve (thus testing our argument that private hospitals are faster in implementing change and in reacting to poor performance) as well as the factors that might facilitate/inhibit such changes.

Conclusions

This study offers original insights on the use of administrative data to investigate the effect that management practices have on the quality of care. Administrative data can provide policy-makers and hospital managers with the opportunity to design evidence-based improvement strategies by understanding the management practices that explain the difference, in terms of quality of care, between best and worst performers. By applying hierarchical statistical models, researchers can manage the nested structure of these data to compare significant performance such as 30-day mortality and readmission. In this regard, funnel plots offer an evidence-grounded identification of "out of control" hospitals and an easy-to-get interpretation of results also to those decision-makers who might not familiar with sophisticated statistical analyses (Ieva & Paganoni 2015).

The identification of variables significantly associated with death and readmission as well as of characteristics that differentiate best vs. worst performers. This identification offers original and evidence-based insights to further the discussion about patient pathways within and outside the hospital, hospitals' policies on LOS, the implications of public vs. private ownership and of research vs. non-research orientation, volumes of treated cases and the need of minimum scales of activities. Coherently, we expect administrative data will receive an increasing interest from scholars of health services research as well as from policy-makers and practitioners, aimed at implementing improvement strategies by unfolding the evidence stored in routinely collected data (Taylor et al., 2015).

Despite the contributions offered, our results must be interpreted under the light of the limitations of our study, that pave the way for further research. First, our analysis dealt with HF patients treated in Lombardy Region hospitals. Although we argue that our approach could be generalized to other pathologies and other Countries that have access to administrative data, further research should confirm or disconfirm such claim. Second, the information available in administrative data to characterized hospitals is limited to the variables explored in our analysis. Other variables that might be explanatory of different variables such as senior managers' and senior physicians' leadership styles, technological excellence, tension to innovation measured by publication impact factors or patents were not easily available and thus overlooked in this study. Further research should collect such information from other accessible sources (e.g., hospitals' website, official documents, etc.) to extend our comprehension.Regulators should evaluate the systematic collection of this data from hospitals to enable longitudinal studies.

Third, the patient hospitalized for HF may be transferred from a hospital to another one to receive treatment or procedures unavailable in the previous one. The 30-day mortality and readmission rates developed in the model assigns the responsibility for results to hospitals in which patients were originally admitted. This approach places in the hands of the sending hospital responsibility to transfer patients appropriately, establishing properly timing and health facility. If the receiving hospital is not able to provide high-quality care, then the first hospital should consider other options (Krumholz et al. 2006). However, a future development could be done attributing the outcome to all the hospitals that treated the patient, in the perspective of sharing responsibilities on the patient outcome. Fourth, further analysis should take a longitudinal approach to gather evidence about the capability of the system and of each hospital in the system to improve.

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List of abbreviations

1. ....HF Heart Failure
2. ....LOS .length of stay
3. ....ICD-CM International Classification of Diseases, Clinical Modification
4. ....DRGS Diagnosis Related Groups
5. ....OR Odds Ratio
6. ....CI Control Intervals
7. ....ICC Interclass Correlation Coefficient
8. ....HDs .Health Districts

Index of Tables and Figures

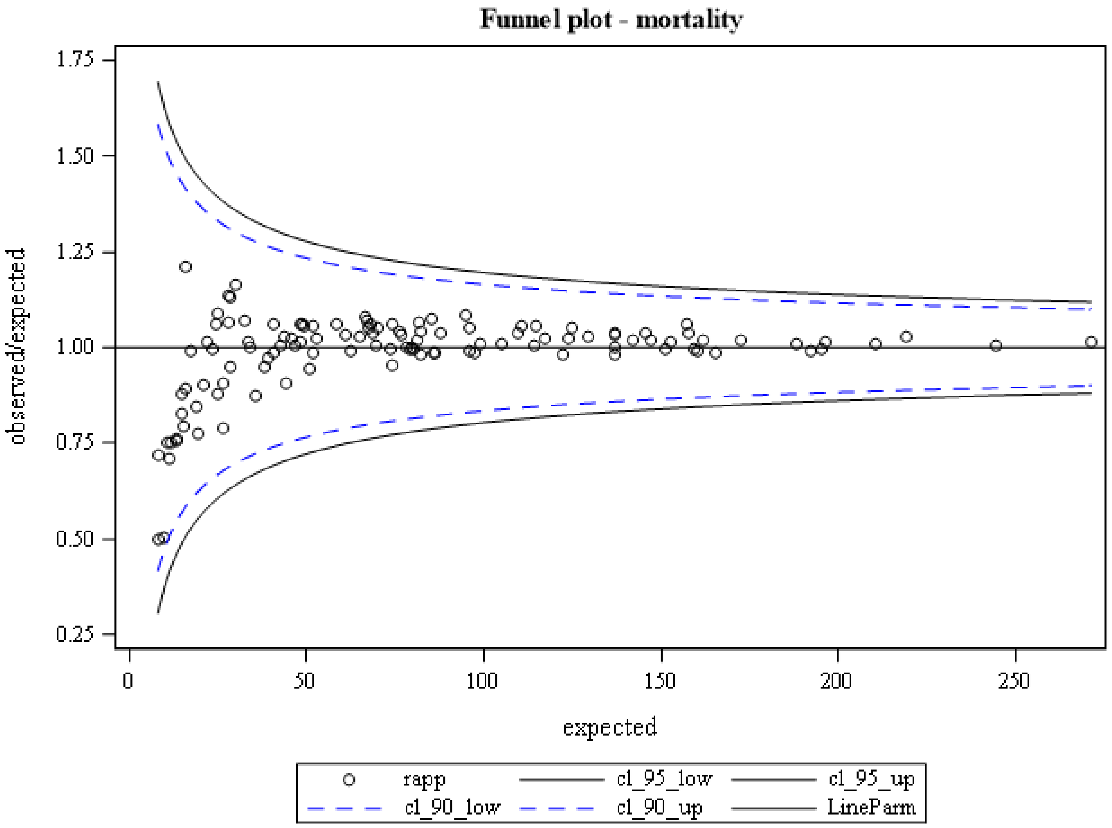

Figure 1. Funnel plot for mortality of the 117 hospitals studied (dots); 90% (dashed line) and 95% (continuous line) confidence limits

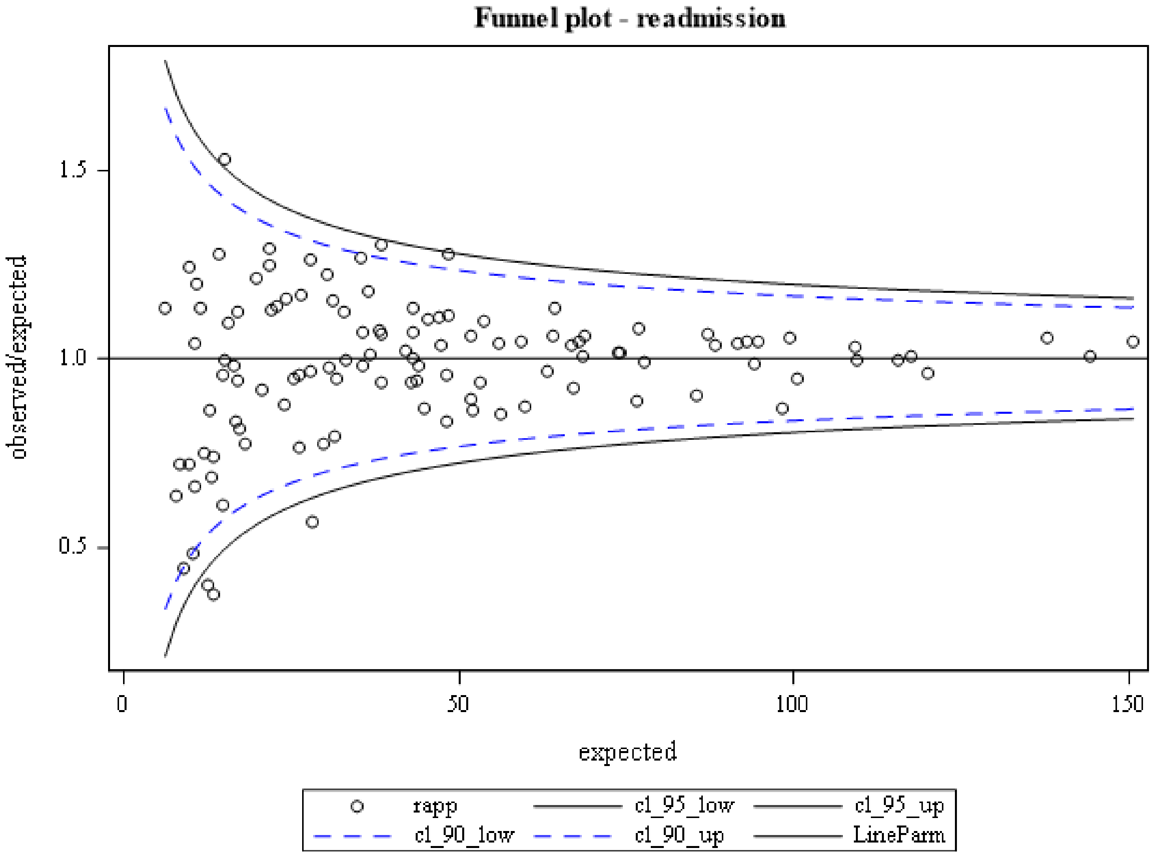

Figure 2. Funnel plot for readmission of 116 hospitals studied (dots) with 90% (dashed line) and 95% (continuous line) confidence limits

Table 1. Hierarchical logistic model for 30-day mortality

Variable	Estimate	Standard Error	P-value	Odds Ratio	95% Confidence
Intercept	-2.12	.08	<.0001	-	-
Age	.07	.001	<.0001	1.070	1.067-1.073
Sex (*male vs. female*)	-.15	.02	<.0001	1.166	1.112-1.223
Length of Stay	-.003	.001	.0299	.997	.994-1.000
Comorbidity weight	.17	.008	<.0001	1.190	1.172-1.209
Number of previous admissions	.28	.02	<.0001	1.323	1.281-1.367
% of surgical DRGs*	.01	.002	.0003	1.007	1.003-1.011
Admission ward					
• *IC or CIC vs. cardiac**	-1.06	.04	<.0001	3.108	2.801-3.448
• *Other vs. cardiac*	.07	.04	<.0001	2.890	2.655-3.145
Type of structure					
• *Research hospitals vs. non-research public hospitals*	.29	.09	<.0001	.624	.485-.803
• *Non-research private hospitals vs. non-research hospitals*	-.18	.14	<.0001	.746	.626-.889

*IC= Intensive Care, CIC= Cardiac Intensive Care, DRG= Diagnosis Related Group

Table 2. Hierarchical logistic model for 30-day readmissions

Variable	Estimate	Standard Error	P-value	Odds Ratio	95% Confidence
Intercept	-2.33	.02	<.0001	-	-
Age	.01	.001	<.0001	1.011	1.009-1.014
Length of Stay	.02	.002	<.0001	1.023	1.019-1.026

Comorbidity weight	.09	.01	<.0001	1.094	1.072-1.117
Number of previous admissions	.24	.02	<.0001	1.272	1.221-1.325
Admission ward					
• *IC or CIC vs. cardiac**	-.32	.04	<.0001	1.510	1.358-1.679
• *Other vs. cardiac*	-.02	.05	<.0001	1.378	1.272-1.493
Hospital mean length of stay	-.04	.01	<.0001	.961	.945-.977

*IC= Intensive Care, CIC= Cardiac Intensive Care

Table 3. Results for mortality vs. readmission

	Variables	30-day Mortality	30-day Readmission
Individual-level variables	Age	+	+
	Sex (male vs female)	+	
	Length of Stay	(-)	+
	Comorbidity Weight	+	+
	Number of Previous Admissions	+	+
	Ward Admission	+	+
Hospital-level variables	Mean Number of Admissions		
	Mean Length Of Stay (LOS)		(-)
	% Surgical Hospitalizations	+	
	Type of Hospital	+	
	% Patients from other Local Health Agencies		
	% Patients from other Regions		

(‘+’ means positive correlation, ‘**(-)**’ means negative (i.e. protective) correlation)