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Predicting Hospital's Costs to Treat Emergency Patient

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Abstract

The Accident and Emergency Departments (A&EDs) are responsible for a large share of overall hospitalization, diagnostic activity, and ultimately health care expenditure. Most health care systems use retrospective reimbursement systems to finance A&E departments, but this system may not be efficient. Prospective payments systems would have the advantage to reduce uncertainty both for the purchaser and the provider. In Italy some Regions are starting to use prospective payments systems using triage codes to define the output. In this article we use a unique dataset that allows determining the cost of each patient going through an A&ED to determine whether triage codes can be used for this purpose

Keywords*: emergency department, quality, efficiency*
Jel Classification*: I110, I120, C000*

1. Introduction

The Accident and Emergency Departments (A&EDs) are responsible for a large share of overall hospitalization, diagnostic activity, and ultimately health care expenditure.

In spite of their crucial role, very little is known about their efficiency in treating patients and in the use of the resources. Most health care systems use retrospective reimbursement systems, but they may not be efficient. The reimbursement of their activity is however still an open issue. Cost reimbursement has several drawbacks: it does not allow predicting or controlling the cost of A&E departments and it may allow hospitals to pay strategically. In a context where hospitals are paid using prospective payments based on DRG's it is possible to shift some costs from the provider to the purchaser by strategically timing the admission of the patient from A&E to the ward. Patients may be kept longer in A&ED in order to do diagnostic tests that should be routinely done after the admission to a ward and in this case they would be reimbursed through the DRG code. For this reason, some authors have proposed to use DRG based payment systems also for Emergency Departments. The high level of uncertainty and volatility in the level of resources that are needed to treat each patients is however a serious hurdle to the use of Prospective Payment System (PPS) to reimburse A&E Departments.

The use of triage codes as any other indicators is not supported by any empirical evidence on which indicators can be considered good predictors of the cost per patient treated. These codes are in fact designed to determine priorities in the treatment of patients and they might not be a good indicator of the cost incurred by the hospital. The issue is very important since the difference in the weight given to each triage code is quite different.

The aim of this study is to provide a first effort in determining the actual cost the hospital will incur when treating patients in the A&ED and to propose a reimbursement system for this important part of hospital activity

The main component is the salary of medical and no medical staff (which represents the 70% of total costs) whereas other variable costs account for just 6% of the total (Cremonesi et al. 2010).

Given the importance of this component it is necessary to allocate this cost across patients using some verifiable indicators. The information, available in the patient file is not sufficient; for this reason a collaboration between the University of Genova and the E.O. Ospedali Galliera of Genoa has made it possible to collect for a sample week data on the time devoted by the medical staff to each patient, on the diagnostic tests that have been prescribed to treat each case, and on their cost. This additional information has been matched up with patients' files and other relevant accounting and economic information to estimate the cost incurred by the A&E department to treat each patient.

This information can be used to determine the variance in the cost observed for each patient and to try to answer to the question of which is the best system to reimburse emergency care. In our analysis we will focus on the predictive power of triage codes for the cost of treating patients.

Triage codes are a system of priority setting in the A&E department and should be related to patients' severity. They are quite easy to be observed and cannot be manipulated. However, their use for pricing A&E care is an open issue. These codes are in fact related to the critical condition of the patient rather than to its need for care. Red codes must be attended immediately, for yellow and green codes some waiting is possible while white codes should indicate inappropriate use of the Department .

The aim of our analysis is to answer this question:

- can triage codes be used to define a DRG-based prospective payment system?

- which alternative indicators can be used to define a prospective payment system if triage codes cannot be used?

To answer these questions we will first determine the cost for each patient and we will show the relationship between costs and triage codes.

We will then use cluster analysis and multinomial logit regressions methods to determine the relationship between codes and costs.

This preliminary analysis shows that crude triage codes cannot be used to reimburse A&EDs. Red and yellow codes are not distinguishable from a cost point of view, hence they can be merged together. This merged group is certainly different from white codes, but the tails of the distribution of green codes do not allow discriminating between white and green and green and yellow/red.

2. Material and methods

Reimbursing A&E departments is a very important topic in health care. Most systems use cost reimbursement, but it would be more efficient to move towards prospective payments systems. This would allow purchasers and providers to be more efficient. In order to set up a payment system is it necessary to determine the cost for each patient. As noted above a considerable portion of the cost of the Department relates to fixed cost that needs to be distributed among patients using a robust criterion. The second important aspect is related to the variance in the need for patients in A&E which may make prospective payment systems quite unreliable unless an observable index related to the patient or the use of the resource exists that allows to reduce this variance.

The first important consideration is that the data on the patients file are not sufficient to allow defining a set of indicators to define the cost for each patient treated. The information retrieved for each patient is a set of records, provided by the electronic data processing centre of the A&ED, pertaining both to the patient himself and his clinical pathway. In particular data refers to:

(i) Date and time of arrival; (ii) Medical attendant (that is the identification code of the accepting medical staff); (iii) Triage entrance code; (iv) Patient's personal information (in particular: gender and date of birth); (v) Date and hour of first visit; (vi) Number of Laboratory and non-laboratory prescriptions; (vii) Patient outcome; (viii) Attending Physician; (ix) Date and hour of discharging (it refers to the patient report closing time).

This information is however not adequate to allocate all kind of costs. For instance the medical and staff cost, which represent a large component of total cost, should be distributed according to actual time devoted to each patients by physicians (Cremonesi et al. 2010, 2012), but this latter variable is unavailable.

The time elapsing between the arrival at A&ED and discharge is not a good indicator of the time required to treat the patient because of the two-level system to access and treatment. At the first level the patient is seen by the nursing staff which assigns each patient a specific triage code from white (inappropriate access) to red (emergency). The triage code determines the priority in being attended by the medical staff. For this reason, white and green codes may be left waiting for a long time, especially when the medical staff has to treat very severe cases. On the other hand, given that the cases are not severe, most white and green codes are discharged after a visit by the medical staff. The time between the first visit and discharge may be a better indicator of the use of resources, provided it is strictly correlated with the actual time the staff devotes to each patient, which is usually unknown.

To overcome these problem, during the week Thursday 9th December 2010, 8:00 pm until Thursday 16th December 2010, 8:00 pm 6 researchers joined the A&E team. During this week medical doctors were asked to report the actual time they devoted to each patient and to detail all the tests and other treatments they prescribe to patient. This information is essential to estimate the actual cost of laboratory, non laboratory and x-ray tests. Patients' file in fact simply record the number of laboratory and non-laboratory prescriptions for each patients which are not good proxies for the level of care of each patients.

For non laboratory prescriptions a one to one correspondence exists between prescriptions and test (one prescription for each diagnostic test). For laboratory prescriptions (cfr. Table 1) this correspondence does not exist: a prescription may be used for a variable number of tests whose costs may vary significantly. The data collected during this week made it possible to match patients with diagnostic tests and to determine their cost.

3. Results

During the week of observation 1011 patients went through the Department. About 65% of them had a green triage code and the most important characteristics of the dataset are presented in table 1.

The age of the patients increases with the triage code and there seems to be a small prevalence of women in the white code. The time between the visit and discharge is increasing as expected for the first three codes: red codes do not seem to require more time than green codes. This result may be explained in several ways: red codes are usually very critical patients that may be hospitalized more quickly to other Departments within the hospitals; yellow codes may contain patients that need to be monitored for a longer period than red codes. This intuition seems to be confirmed by the last part of the table where the time that the medical staff has devoted to each patient is recorded. Time is increasing with patients' severity as one might expect, and the same reasoning applies also for laboratory and non-laboratory examinations and for the time medical doctors devoted to patients. It is interesting to note the difference between the number of laboratory prescriptions and the number of laboratory tests. In other words one might observe that the former would be a very biased proxy of the latter.

Table 1: Sample dataset - descriptive statistics

		Triage Code White	Green	Yellow	Red	All
	Obs	81	689	219	22	1011
Variable						
Age	*Mean*	***37,82716***	***45,63861***	***64,12785***	***76,18182***	***49,68249***
	Std. Err.	1,96676	0,777855	1,463293	3,761641	0,702863
	[95% Conf.Interval]	33,91318	44,11135	61,24384	68,35906	48,30325
		41,74114	47,16586	67,01187	84,00458	51,06173
Gender (female)	*Mean*	***0,641975***	***0,496372***	***0,520548***	***0,454546***	***0,512364***
	Std. Err.	0,053601	0,019062	0,033836	0,108657	0,015728
	[95% Conf.Interval]	0,535307	0,458945	0,453861	0,228581	0,481501
		0,748644	0,533798	0,587235	0,68051	0,543228
time elapsing between 1st ex-am.and exit	*Mean*	***0,518107***	***1,898041***	***4,487215***	***2,176515***	***2,354402***
	Std. Err.	0,278603	0,10085	0,371261	0,301205	0,114385
	[95% Conf.Interval]	-0,03633	1,70003	3,755494	1,550124	2,129942
		1,072544	2,096052	5,218935	2,802906	2,578862
n. of non-lab. Presc	*Mean*	***1,901235***	***3,13643***	***5,077626***	***6,954545***	***3,541048***
	Std. Err.	0,067139	0,061573	0,180049	0,476628	0,066995
	[95% Conf.Interval]	1,767623	3,015536	4,722766	5,963343	3,409584
		2,034846	3,257323	5,432485	7,945748	3,672513
n.of lab.prescr.	Mean	**0,08642**	**0,381713**	**1,141553**	**1,136364**	**0,53907**
	Std. Err.	0,035994	0,02568	0,058001	0,074887	0,024345
	[95% Conf.Interval]	0,01479	0,331292	1,027237	0,980628	0,491297
		0,158049	0,432134	1,255868	1,292099	0,586843
n. of lab tests	*Mean*	***0,493827***	***3,4209***	***11,87671***	***13,36364***	***5,234421***
	Std. Err.	0,267662	0,228415	0,447384	1,031003	0,222267
	[95% Conf.Interval]	-0,03884	2,972425	10,99496	11,21955	4,798264
		1,026492	3,869375	12,75846	15,50772	5,670579
time devoted to patients	*Mean*	***3,962963***	***7,844477***	***14,49315***	***19,22727***	***9,222772***
	Std. Err.	0,692875	0,229092	0,626097	3,8308	0,253027
	[95% Conf.Interval]	2,584098	7,394673	13,25917	11,26069	8,726253
		5,341828	8,29428	15,72713	27,19386	9,719292

Data reported in next Table 2 have been computed using the procedure described in Ameri et al. (2011b) and Cremonesi et al. (2012).

Table 2: Cost per triage code

		Total cost	Medical Doctors	Nurses-Other Personnel- Adm Staff.	Mortgages, Kitchen & Laundry, Cleaning and other expenses	Health Services, Surg. & Med. devices, Drugs	X-ray	Non-Lab tests	Lab tests
White	Mean	87,83	21.02	19.16699	1.45	.42	8.26	33.61	1.14
	Min	53,38	9.05	8.176112	0	0	0	15.49	0
	Max	409.59	36.97	34.35328	57.15	7.92	238.41	77.47	35.2
	std.dev.	48.61	5.76	5.356368	6.64	1.34	35.94	12.45	5.35
	Interq.range (75-25)	20.88	9.45	8.539142	.04	.03	0	0	0
Green	Mean	189,38	35.00	32.89114	5.66	3.07	50.77	34.41	8.02
	Min	42,94	14.19	12.82174	0	0	0	15.49	0
	Max	673,51	71.00	66.82436	57.35	16.51	369.12	139.95	65.27
	std.dev.	98.84	10.22	9.80417	7.26	2.66	62.98	18.09	13.92
	Interq.range (75-25)	127.48	11.69	11.2017	4.97	3.06	73.97	20.66	15.06
Yellow	Mean	340,54	59.14	55.4617	12.86	4.93	97.90	50.60	28.27
	Min	71,79	29.41	26.5799	.04	.03	0	15.49	0
	Max	1074.72	99.920	93.44545	63.13	47.48	696.18	154.16	83.66
	std.dev.	147.922	11.94	11.22563	14.55	3.67	110.90	26.17	16.38
	Interq.range (75-25)	164.74	13.82	13.10275	6.45	2.85	101.13	39.25	15.88
Red	Mean	407,39	68.80	63.95808	6.69	4.38	4.38	99.01	32.85
	Min	184,86	47.70	45.17806	1.23	.81	0	15.49	0
	Max	680,05	89.43	83.25746	21.43	14.03	369.13	258.23	73.23
	std.dev.	128.50	9.17	8.620408	4.34	2.84	108.81	53.42	12.30
	Interq.range (75-25)	215.5	8.62	7.115616	3.94	2.57	80.9	46.22	7.07
All	Mean	218,73	39.84	37.35679	6.91	3.29	58.72	39.26	12.40
	Min	42,94	9.05	8.176112	0	0	0	15.49	0
	Max	1074.72	99.92	93.44545	63.13	47.48	696.18	258.23	83.66
	std.dev.	133.65	15.80	14.93725	6.24	3.06	79.56	23.80	16.80
	Interq.range (75-25)	173.33	22.48	21.3552	9.83	3.56	78.59	30.21	27.62

Costs are increasing with the triage code, as one might expect, but the variance for each triage code is quite important. Furthermore, if we observe the minimum value for each subsequent triage code and we compare it with the maximum value for the previous triage code we note that there is a considerable overlapping. Red and yellow codes do not appear to be significantly different, especially when the personnel cost are considered. The first column of Table 3 can be used to compute the "DRG equivalent" weights; in table five we compare them with what proposed by Region Lazio and Region Liguria

Table 3: triage cost's weight

Triage Code	Weights[1]		
	Sample week	**Liguria[2]**	**Lazio[3]**
White	1,0	1,0	1,0
Green	2,2	3,0	3,8
Yellow	3,9	8,0	7,6
Red	4,6	10,0	25,1

Both Regions overestimate the weights of the triage codes; this is especially true for Lazio and for yellow and red codes. An incorrect cost reimbursement might cause dramatic results both in terms of health care level and efficiency, and it may also induce hospitals to strategically assign patients to triage codes that are more generous from the point of view of the reimbursement. This well known problem that the literature on DRG payment system refers to "up-coding" is potentially more important for A&ED.

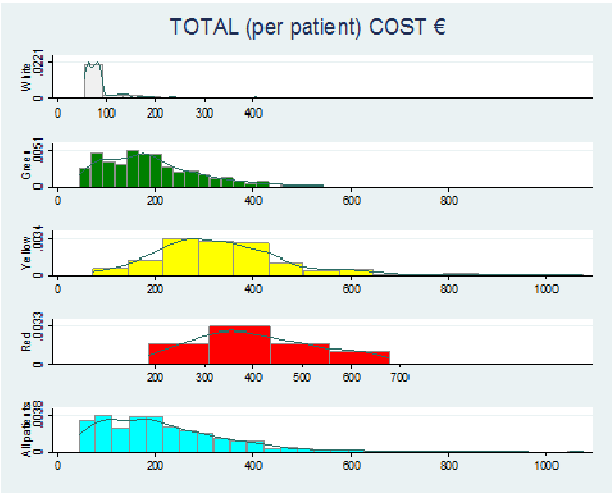
[1] Weights have been obtained by a normalization procedure

[2] DGR 5 agosto 2005, n. 935 "Quadro delle risorse finanziarie del Fondo sanitario regionale e finanziamento delle Aziende Sanitarie - anno 2005"

[3] Regione Lazio DGR 22 marzo 2006, n. 143 "Ripartizione nei livelli di assistenza del fondo sanitario regionale 2006"

To design a prospective payment system two set of instruments are essential: an observable variable, possible outside the provider's control that may allow to define homogeneous groups of patients from the point of view of the cost and a set of variables on which the purchaser may refrain providers' strategic behaviour.
Let us now examine if the triage code satisfies the first requirement. If it was a good indicator, costs per triage code should have a relative small variance within each group while the mean of the cost of each triage code should be significantly different. Several tests can be performed to check for these characteristics, but they usually imply that the distribution of the observations is not significantly different from a normal distribution. Figure 1 below provides the cost density distribution by triage code.

Figure 1: total cost (triage)



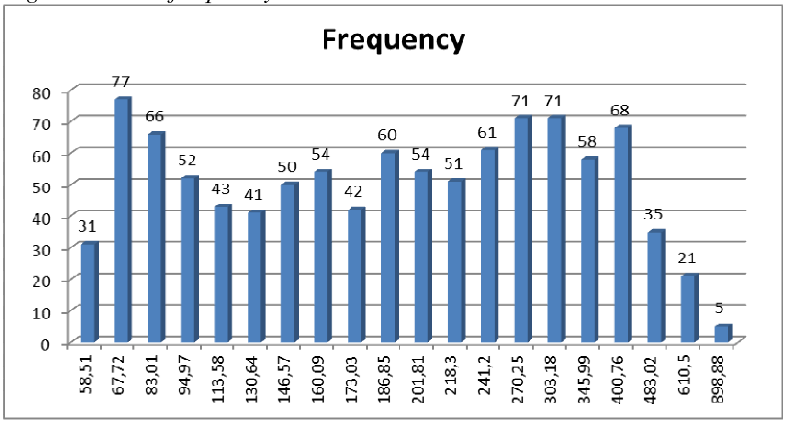
Total costs present a large variability "within" each triage colour which means that the triage code may not be a good proxy of the cost of each patient, especially if the purchaser wants to use it as the main indicator for a prospective payment system. The second interesting result is that the most expensive patients are not red codes as one might expect, but they are the yellow ones. Therefore it is possible to state that triage code classification is not suitable in representing the patient cost variability. In other words the triage code classification is a biased proxy of cost: costs are not naturally clustered by triage code and that yellow and red codes are indistinguishable from a cost perspective.

4. Cluster analysis

The distribution of costs by triage code shows that, although the average cost per each triage code is increasing, the variance within each code is too high; furthermore some triage codes may be similar from a cost point of view and could well be merged into a single category. In order to get more insights in the relationship between costs and triage code we have clustered patients by k-means procedure identifying 20 different classes of total cost. This technique allows identifying 20 cost classes that are quite homogeneous from the point of view of the cost. We expect triage codes to be good cost predictors if their presence in each class is clustered around a rather small number of contiguous classes and there is a one to one correspondence between higher triage code and higher class.

Table 4 provides per each class the mean, the number of observation, the minimum and the maximum value (in Euro) while Figure 2: class frequency shows the composition of each cluster by triage code.

Figure 2: class frequency



Class	Mean of total cost	N.of Obs	Min	Max
1	58,51	31	42,94	62,7
2	67,72	77	63,16	74,7
3	83,01	66	75,89	88,77
4	94,97	52	89,15	103,32
5	113,58	43	105,08	121,31
6	130,64	41	122,44	137,98
7	146,57	50	138,62	152,55
8	160,10	54	153,56	166,28
9	173,03	42	166,61	179,26
10	186,85	60	180,14	193,98
11	201,81	54	194,34	209,56
12	218,30	51	210,4	229,11
13	241,20	61	230,21	255,39
14	270,25	71	256,3	286,31
15	303,18	71	286,78	322,59
16	345,99	58	325,4	370,4
17	400,76	68	374,62	436,03
18	483,02	35	442,96	543,93
19	610,50	21	546,98	720,8
20	898,89	5	794,83	1074,7

Table 1: classes for total cost

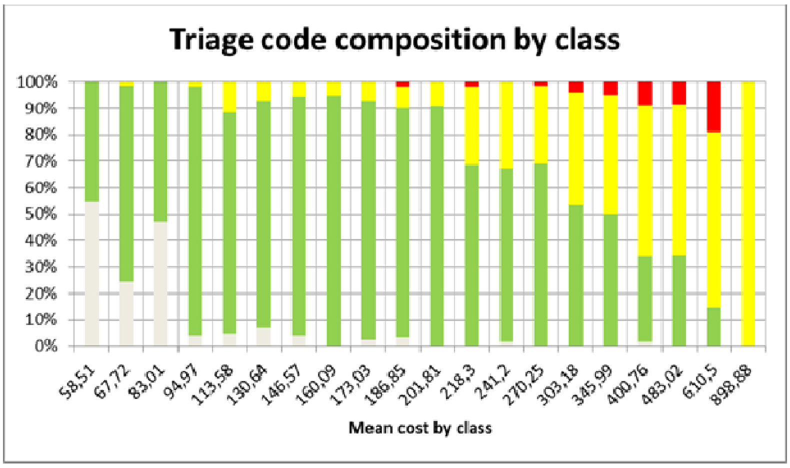


Figure 1: Triage code composition by class

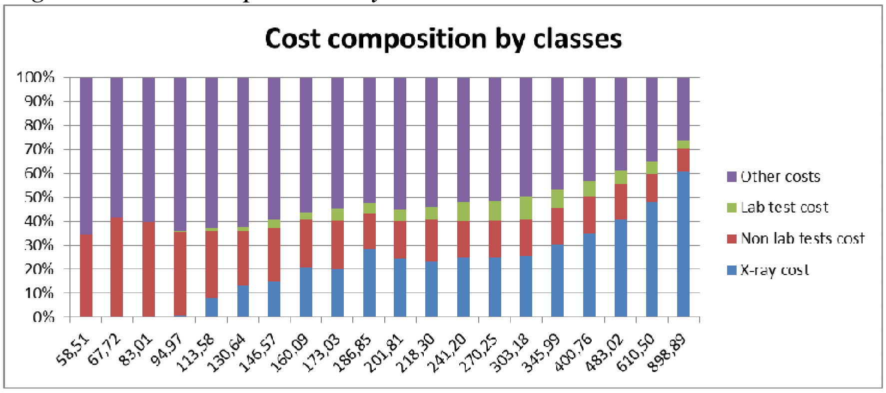
This picture shows that green and yellow codes span among almost of all cost classes, thus making almost impossible to design a prospective payment based on triage codes. The intuition that red codes may not be significantly different from yellow codes confirmed that red codes are enveloped by yellow one and from a cost point of view they do not seem to have any distinguishing characteristic from yellow one. White codes are clustered in the first cost classes while green and yellow overlap for most of the diagram.

We have performed the same analysis by investigating the cost composition inside each cost class in order to understand whether some cost components could be identified as cost drivers. Also in this case, the composition through classes does not seem to be so different. In general, lower cost classes (whose composition shows a prevalence of white and green codes) require a visit and some tests. This result may be intepreted in terms of appropriateness and upcoding.

White codes (inappropriate use of A&ED department) do not need care from this Department. A visit and some reassurance about their health status is sufficient to treat them. It is interesting to note that quite a few of them do not even require any additional test to confirm the diagnosis. Upcoding may exists for the green codes that have received the same form of care (visit followed by discharge). Several may be the reasons for such upcoding, for instance the fact that white codes need to pay a copayment for the use of A&ED.

Also in this case no evidence of it could be find as Figure 4 below shows.

Figure 4: cost composition by class



The large variability observed within classes means that the triage classification using the four codes is not a good indicator of the cost of the treatment; however it may be possible that other classifications still based on triage code may be used. The data presented in Figure 3 seems to show that red and yellow code are not so different from each other; in the other cases it is very difficult to infer conclusions from visual inspection because the tails of the distributions are quite long. To test for statistical differences between the four groups. we have run multinomial logit regression where the dependent variable is the triage code:

where TCì=0 if the triage code is white; TCì=1 if the triage code is green TCì=2 if the triage code is yellow and TCì=3 if the triage code is red. Ci is a set of variables relating to the intensity in the use of resource; Pi are patients characteristics and Ei are characteristics related to the admission.

Intensity of treatment is captured by: the time between the first visit and discharge; the time the medical staff has devoted to the patients, the number of diagnostic tests run for each patient and total cost. Patients characteristics are summarised by their age and the dummy TFP which takes the value 1 if the patient is a Temporarily Present Foreigner and 0 otherwise. Finally the environment in which the admission has taken place is captured by the dummy ROAD which takes the value of 1 if the patient has been victim of a road accident and OWN which takes the value of 1 if the patient has reached A&E with a private car (or driving himself)

Table 5: Results of the multinomial logit

codtri-age		**White**	**Green**	**Yellow**	**Red**
White	1st exam-exit	(base outcome)	-0.233777**	-0.242207***	-0.778413***
	N.NonLabPresc.		-0.3181792	-0.234962	-0.024538
	N.LabTests		-0.0919004	0.0130243	0.053205
	Age		-0.0028568	0.0116622	0.0179279
	TotalCost		0.0350031***	0.0399173***	0.0397894***
	VisitingTime		0.0722656*	0.1051073**	0.1201726***
	TPF		-0.3877211	-0.6291428	0-.9048742
	ROAD		13.49617	12.91392	0-.8191885
	OWN		-1.355939**	-1.444655**	-3.313348***
	Constant		0.0084987	-4.514643***	-7.271592***

Number of obs 1010
Log likelihood -585.35041
LR chi2(27) 604.25
Prob > chi2 0.0000
Pseudo R2 = 0.3404

*Significant at 10% level of significance **Significant at 5% level of significance ***Significant at 1% level of significance

With multinomial logit we have to test for independence of irrelevant alternatives (IIA). Under the IIA assumption no systematic change should occur in the coefficients if we exclude one of the outcome from the model. For this purpose we have performed the Hausman test which shows no evidence that the IIA assumption has been violated, regardless the outcome is excluded from the regression.

The Likelihood-ratio test and the Wald test (see appendix 1 for details) suggests that the variables number of non laboratory prescriptions (N.NonLabPresc) and Temporarily Present Foreigner (TFP)

do not affect the values of the dependent variable. On the other hand the two tests provide a conflicting result with reference to the ROAD variable. The LR test reject, at 10% level of significance, the hypothesis that being victim of a road accident does not affect the dependent variable whereas the Wald accepts it.

Table 6: Wald test for independent variables

Variable: TotalCost			**Wald**	
Group 1 vs Group 2			tests for independent variables	
		df	**chi2**	**P>chi2**
White	**Green**	1	26.775	0.000
White	**Yellow**	1	8.683	0.003
White	**Red**	1	na	na
Green	**Yellow**	1	6.632	0.010
Green	**Red**	1	1.028	**0.311**
Yellow	**Red**	1	0.396	**0.529**

The Wald tests for independent variables comparing, by two, the different “groups” of the dependent focusing on the explanatory variable “TotalCost” is reported in Table 6.

According to it we can accept the hypothesis that the variable "TotalCost" do not affect the values of the dependent variable when comparing Green with Red codes and Yellow with Red codes.

Therefore we note that the coefficient of the variable which represent the total cost per patient is between white and green and between green and yellow is significant at 5% level of significance, whereas it is not between green and red codes.

Finally we have run a multinomial logit where the yellow and red codes have been merged together

Table 7: Multinomial logit merging yellow and red codes

	White	**Green**	**Yellow+Red**
1st exam-exit	0.232 **		-0.0147
N.NonLabPresc.	0.318		0.104
N.LabTests	0.091		0.107 ***
Age	0.002		0.015 **
TotalCost	-0.035 ***	Base outcome	0.004 **
VisitingTime	-0.072		0.034 **
TPF	0.387		-0.247
ROAD	-13.904		-0.658
OWN	1.35 **		-0.179
Constant	-0.094		4.48 **

Number of obs 1010
Log likelihood -529.43
LR chi2(27) 568.82
Prob > chi2 0.00

Significant at 5% level of significance; * Significant at 1% level of significance

In this second case, the results are more homogeneous, but the variability of the green codes is still an issue.

5. Discussion

The analysis presented in this paper represents one of the first attempts to study the relationship between triage codes and the cost of treating patients in A&E. The data usually available through patients files are not sufficient for the analysis, but we could use a unique dataset that has matched patients information with data specifically collected on several aspects relating to the intensity and the cost of care.

The tentative conclusion of our analysis is that crude triage codes cannot be used as a proxy for the cost incurred by the hospital to treat patients. The variance within the same code is too big to make triage codes a suitable candidate.

However, some other interesting results are emerging from our analysis. First of all, yellow and red codes are not statistically different and from a reimbursement point of view they can then be treated in the same way. This would restrict the classes of patients to three instead of one. White codes are different in their cost from yellow+red, while green over-run both categories.

The main message coming from this analysis is that we would need another observable variable to split the green in two categories or to allocate them either to the white code or to the yellow+red code.

6. Conclusions

The Accident and Emergency Departments (A&EDs) are responsible for a large share of overall hospitalization, diagnostic activity, and ultimately health care expenditure.

Most health care systems use retrospective reimbursement systems for A&E, but the system may not be efficient because it may induce hospital to increase the number of tests and it does not allow predicting or controlling the cost of A&E departments. For this reason, finding an alternative way to reimburse this strategic activity is very important from a policy point of view. Ideally, using a PPS system would possible solve some of the problem, but the high level of uncertainty and volatility in the level of resources that are needed to treat each patients is however a serious hurdle to the use of such a payment scheme.

The aim of this study was to provide an accurate estimate of the actual cost the hospital will incur when treating patients in the A&ED and to propose a reimbursement system for this important part of hospital activity We show that crude triage codes cannot be used to reimburse A&E. Red and yellow codes are not different from a cost point of view, hence they can be merged together. This merged group is certainly different from white codes, but the tails of the distribution of the green codes do not allow discriminating between white and green and green and yellow/red.

The next step in our analysis will be to separate patients admitted because of an accident from the others. This should be a more homogeneous group as concerns the use of resources it may help in reducing the variance of the cost of the other patients.

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