A Work Project, presented as part of the requirements for the Award of a Masters Degree in Economics from the NOVA School of Business and Economics.

Do hospitals react to random demand pressure by early discharges?

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A Project carried out in the Applied Policy Analysis area, under the supervision of:
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Lisbon, January 2012

Abstract

This project tries to assess whether hospitals react to random demand pressure by discharging patients earlier than expected. As a matter of fact, combining an unpredictable demand for medical services with limited and, to some extent, fixed medical resources, generates strong incentives to discharge patients earlier than expected when demand is high – increasing the risk of readmission and decreasing the benefit from treatment. This work was conducted as a way to determine whether those incentives actually affect discharging decisions. Analysis of Portuguese hospitals data shows that hospital utilization levels at the time of admission, prior to the admission and post admission do have a negative impact over the length of stay in hospital, although this impact is quantitatively irrelevant. More than that, larger utilization levels have a positive impact over the probability of being discharged at certain days of the week, indicating that an early discharges problem may exist.

Key words

Hospital utilization

Early discharge

Admissions

Length of stay

1. Introduction

The main goal of this project is to assess whether there is a relationship between hospital utilization and discharge decisions, focusing on Portuguese hospitals. As a matter of fact, hospital utilization, as defined by the number of admissions occurring during a certain period at a given hospital,[1] is neither constant nor perfectly predictable, mainly because the demand for medical services has a random element associated.[2] This, in turn, makes it possible to identify a cyclical pattern on hospital utilization – many times related to climate changes or holidays – that triggers a challenge related to medical resources management. Note that, more than proving the existence of these fluctuations, the purpose of this project is to assess their impact over hospital management decisions. In fact, assuming that hospital resources – beds, physicians, among others – are not flexible enough to adjust to these seasonal fluctuations and that, even if they are, this adjustment can be quite costly or even inefficient[3], several problems arise in periods when the number of admissions is larger than the average and restrains the available capacity. Indeed, keeping the level of resources fixed, an increase in the number of admissions creates the need for rationing decisions – including reducing inpatients length of stay. Additionally, it is a well known fact that physicians have the power to influence the time each patient stays hospitalized, thus, in times of congestion, they may feel tempted to discharge patients earlier than expected in order to relieve some resources. Assuming a patient must be hospitalized as long as the marginal benefit from treatment exceeds its marginal cost, this criteria underlying discharges

[1] To be more precise, hospital utilization can be defined as the extent to each individuals use hospital services in a specified period of time − here measured by the total number of admissions.

[2] Indeed, the demand for medical services can be decomposed into two different parts − an elective part and a non-elective part. The former corresponds to scheduled visits and is, by definition, totally predictable − at least in the short-run. Note that the number of elective episodes is perfectly known only after these episodes are scheduled, what makes it unpredictable on a yearly or monthly basis. The latter, on the contrary, respects to emergency episodes and is responsible by introducing some unpredictability in the demand faced by hospitals − individuals do not know neither when they are going to experience a disease episode nor the severity of that episode.

[3] Note than expanding capacity can generate unutilized resources in times were demand is low, what constitutes, also, an inefficient situation.

decisions leads to an inefficient situation that may have some undesirable effects over the health outcome.

This study tries to determine whether the length of stay in hospital is actually affected in times when hospitals face a surge in admissions. One of the main strengths of this project is that it gathers several types of individuals instead of restricting the sample to a specific group of patients like previous studies.[4] Moreover, it accounts for several hospital and patient-specific factors that are prone to influence the length of stay in hospital and that are many times forgotten, biasing the obtained estimates.

This work is structured in the following way: section 2 contains a brief literature review; section 3 shows descriptive statistics concerning the sample at study; section 4 discusses the methodology; sections 5 and 5.1 deal with the Negative Binomial model; sections 6 and 6.1. deal with the Multinomial Logit model; and section 7. provides the main conclusions.

2. Literature Review

It is a well-known fact that hospital utilization suffers from short-term fluctuations associated with unpredictable disease episodes. In the words of Jensen and Kronick (1984), '*much of the short-term fluctuation in nonelective emergent utilization is of random nature − on some days many people are in accidents, have heart attacks, or need an appendix removed; on other days, not as many.*' Those cyclical patterns are frequently subject of study. Many authors argue that hospital utilization is related to climate changes − chronic or pulmonary diseases are more frequent during winter months, for example − or vacation patterns but, still, there is also some evidence of intra-month variation: as far as the Portuguese case is concerned, Costa, Lopes and

[4] Most of these studies are related to a single disease episode or limit the analysis to the comparison between patients admitted during workweek days and weekend days, what may introduce some selection bias.

Boto (2008) find some support in favour of what they call ‘the weekend effect’, meaning that this period is characterized by a lower number of admissions, less discharges and a larger number of deaths than expected.

What is, then, the impact of these short-term demand fluctuations over discharge decisions? Sharma, Stano and Gehring (2006) evaluate whether stochastic fluctuations in hospital demand affect both discharge and admission decisions. The authors develop a theoretical model, within the U.S. framework, which allows them to conclude that patients will be discharged earlier than expected as long as the marginal benefit that hospitals derive form that decision is strong enough. This marginal benefit is associated to the ‘additional’ capacity that can be created through an early discharge and it is, logically, larger the bigger the hospital utilization – assuming some rigidity related to the available resources, early discharges appear as the only way to influence effective capacity levels. In fact, Jensen and Kronick (1984) argue that hospital resources can actually vary through time but still, ‘*the amplitude of these fluctuations (…) would generally be smaller than the amplitude of utilization fluctuations, because institutional constraints such as labor contracts force hospitals to treat some part of labor costs as fixed*’. This, in turn, generates huge incentives to discharge patients earlier than expected in times when utilization is high and, consequently, triggers an inefficient situation as far as the allocation of medical resources is concerned. Actually, using the standard economic criteria for efficiency, and according to Madsen *et al.* (1983), an ideal allocation implies that the patient should stay hospitalized just as long as the benefits from hospitalization no longer justify the expenses. At some point, the risk of post-discharge complications and readmission is so low that it is overwhelmed by the possibility of hospital-related infections and hospitalization is no longer justified.

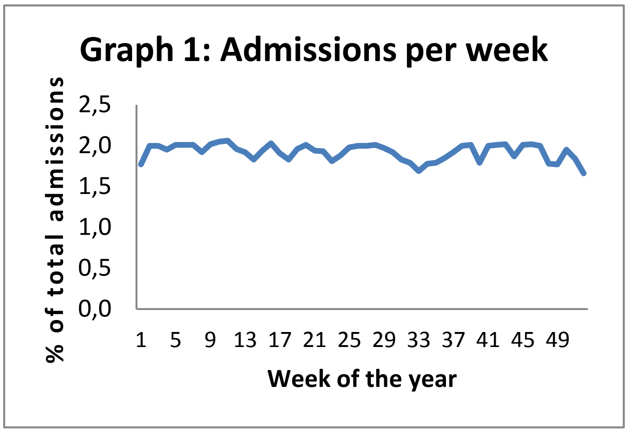
Stearns (1991) states that by acting as a hospital's agent physicians have an incentive to discharge patients earlier and relieve some capacity at times when the hospital is capacity constrained. On the other hand, as a patient's agent, physicians have incentives to choose the length of stay that maximizes the health outcome. The final choice lies somewhere in between, making difficult to identify these effects in the empirical data. Evans and Kim (2005) measure the impact of admissions instability over medical outcomes. The authors restricted their sample to patients admitted during Thursdays in the state of California over the 1996−2000 period because, as the authors argue, hospital staff levels are smaller during weekends when compared to weekdays, what makes them more vulnerable to admission shocks − and, consequently, makes these patients more prone to suffer an early discharge. In their work, Evans and Kim conclude that large shocks in the weekend admissions flow actually tend to reduce the length of stay and increase the probability of readmission, although the coefficients obtained are quite small − even large shocks on weekend admissions have a small impact over the outcomes of patients admitted on Thursdays.

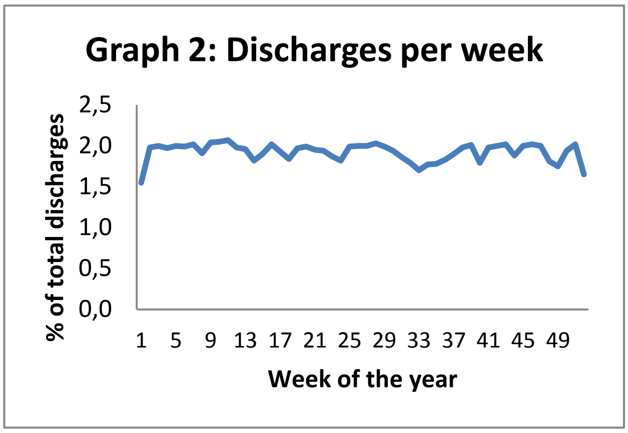
3. Descriptive statistics

This project uses the *Diagnosis Related Groups* (DRG)[5] database, gathering observations from year 2007 to year 2010. The DRG database contains, among others, information regarding both the admission date and the discharge date − information that can be used to confirm whether Portuguese hospital utilization follows the same regular yearly pattern found in previous studies. In order to do that, the following graphs depict the weekly behaviour of both admissions and discharges, showing that the evolution of these two series is quite similar.

[5] For the sake of clarification, DRGs were created as a means to classify patients admitted in hospitals. In that sense, patients are grouped according to their clinical situation and the amount of resources their treatment requires − for example, DRG 270 gathers patients subject to skin and breast procedures without complications.

As far as admissions are concerned, Graph 1 shows that each week gathers approximately 1,9% of total admissions at study, and that this share remains more or less constant over the year.

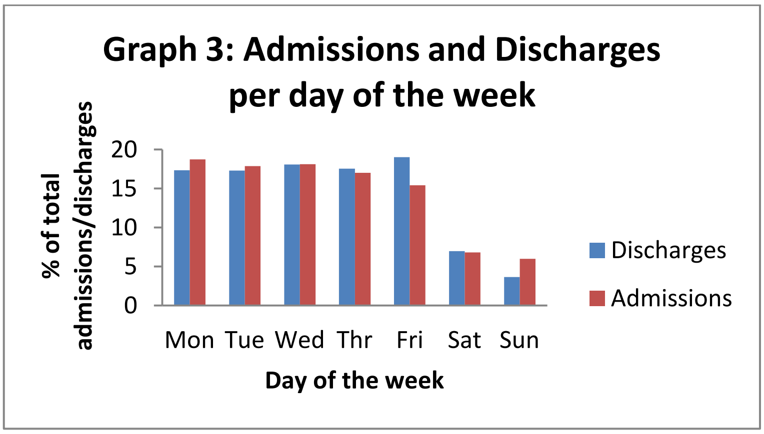




Also, this graph shows that the weekly evolution of admissions is, in fact, correlated with vacation patterns and climate changes. Indeed, under the convention that week 1 stands for the first week of the year and week 52 to the last one, there is a clear trough around week 33, related to summer months. Therefore, winter months – those related to adverse climate changes and flu surges – tend to have a larger number of admissions. Moreover, weeks 52 (1,66%) and 33 (1,69%) – those associated to Christmas and New Year festivities – were those which verified fewer admissions. Finally, weeks 11 and 10 of the year where those when a larger number of admissions was verified – 2,06% and 2,05% of total admissions, respectively.

As far as discharges are concerned, Graph 2 shows that, once again, the average share of weekly discharges is approximately constant around 1,9%. Furthermore, it is also obvious that discharges' fluctuations are, now again as before, associated with holidays: weeks 10 (2,05%) and 11 (2,07%) were also the periods corresponding to a larger number of discharges while weeks 1 (1,5%) and 52 (1,62%) were those with a smaller number of discharges. This may provide some evidence to support the existence of an early discharges problem, as those periods with a larger number of admissions – and, consequently, a bigger utilization– are also the periods with a larger number of discharges.

Having determined the weekly evolution of both admissions and discharges it is also relevant to look at regular daily variations: Graph 3 represents the share of total admissions and discharges per day of the week. The first thing to note is that, now again as before, admissions and discharges display a similar behaviour. Moreover, there is strong evidence in favour of the 'weekend effect' referred in Costa *et al*. (2008): as far as admissions are concerned, Saturday and Sunday are the days with a smaller share, gathering only 6,82% and 5,99% of total admissions and contrasting with an average of approximately 17% for the remaining days of the week; as far as discharges are concerned, Saturday and Sunday gather only 6,97% and 3,66% of total admissions, respectively, while the rest of the days of the week have shares around 18%. More than that, Friday appears to be the day with a larger number of discharges (19,03%) and Monday the day with a larger share of admissions (18,74%).



Using the overall number of observations available allowed to conclude that Portuguese hospital utilization follows a seasonal trend related to climate changes and vacation patterns, as one should expect. However, in order to facilitate the estimation process, the sample available was restricted to the 10 more relevant DRGs – those which corresponded to a larger number of admissions[6] – meaning that the results displayed in the following sections respect to a total number of 1 171 763 observations. Table 1. also includes some statistical information about relevant characteristics of this sample.

Table 1. Relevant statistical information

Panel A. Descriptive statistics – main variables

Variable	Mean	Std. Dev.	Min	Max
age	42,465	30,138	0	100
length	3,188	5	0	825
utilization	784,335	576	1	4173
utilization *ex post*	777,407	572	0	4173
utilization *ex ante*	777,475	572	0	4173
total procedures	3,657	3	0	30
total diagnosis	2,588	2	0	30

Panel B.[7] Sample characteristics

district hospitals	50,67%[8]
central hospitals	44,62%
level1 hospitals	3,06%
teaching hospitals	19,69%
emergency episodes	60,37%
summer admissions	24,37%
Monday discharges	15,79%
male patients	66,30%

4. Methodology

Two different models were used: *(i)* A Negative Binomial (NB) model, using the length of stay as a dependent variable aiming to determine whether hospital utilization has a negative impact over the time each patient stays hospitalized; *(ii)* A Multinomial Logit (ML) model will also be estimated as a means to estimate the average relative probability of being discharged at a given day of the week. It is reasonable to think that if there are significant differences in these probabilities some factors – other than the severity of illness or the time each patient takes to recover – should be having an impact over discharge decisions.

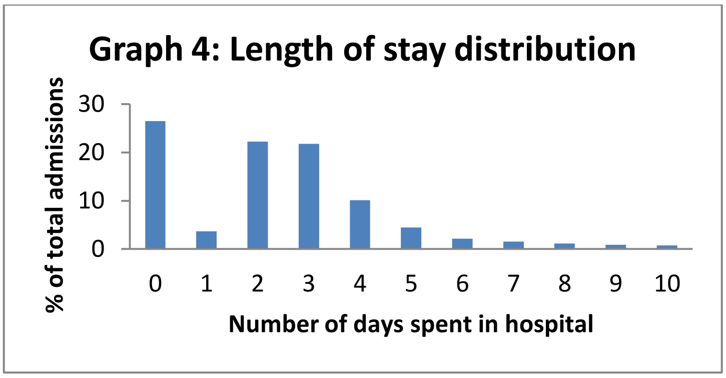
[6] As a matter of fact, the DRGs with a larger number of admissions were those corresponding to radio and chemotherapy. However, since every treatment session corresponds to an admission episode, each patient represented a total of zero days spent in hospital biasing the results of this analysis. The same thing happened with those patients subject to renal dialysis. Consequently, those observations were excluded. The DRGs used as well as the number of admissions within each DRG are shown in appendix 1.

[7] These values are expressed in percentage of total admissions in the sample.

5. The Negative Binomial (NB) Model

One can argue that zero-length-of-stay observations should not be included in a study regarding early discharges – if a patient was not hospitalized how can he be subject to an early discharge? The problem here is that, although these patients did not stay hospitalized, they actually used some medical resources that could be allocated to other individuals. Therefore, this type of admission increases the pressure that is being put over hospital resources, creating incentives to discharge inpatients earlier. Consequently, these observations were also included in the estimation process[9].

This model uses the number of days spent in hospital – a discrete variable – as response variable and, consequently, a count data analysis must be performed.[10] Graph 4 depicts the distribution of the dependent variable *length* and provides evidence for the existence of overdispersion as the distribution looks quite skewed.[11]



[9] On top of that, note that if a patient needed to stay hospitalized but he was immediately discharged due to high utilization levels, one can assume that an early discharge has occurred.

[10] Typically, count data estimation procedures use either the Poisson distribution or the Negative Binomial distribution (NB). While the former assumes the conditional variance to equal the conditional mean, the latter is less stringent and allows for some overdispersion in the data. Following this reasoning, it is necessary to test for the existence of overdispersion in the sample available.

[11] The number of days spent in hospital is truncated at ten because the percentage of total admissions that corresponds to more than ten days spent in hospital is quite small–approximately 4,71% of the sample. These observations are not shown in the graph but, still, they were included in the sample.

In fact, in the table shown below is possible to conclude that the variance is about nine times larger than the mean, indicating that a NB model is preferred to a Poisson one.

Table 2: Statistical information regarding the variable *length*

Obs.	Mean	Variance	Min.	Max.
1 171 763	3,188	28,106	0	825

To be more precise, a likelihood ratio test was conducted, demonstrating that there is statistical significance in favor of overdispersion.[12] Accordingly, the estimation process uses a NB distribution[13]and fits the following model:

$$Y_{ijt}= c+\beta X_{ijt}+\alpha Z_{ijt}+\gamma(\text{Hospital Utilization})_{jt}+\mu(\text{Hospital fixed effects})_j+ YEAR_t+DRG_i+\varepsilon_{ijt}$$

The outcome − in this case the length of stay in hospital − varies according to the patient (i); to the hospital (j); and time (t). The different covariates introduced in the NB model have different purposes and control for distinct factors. For instance, it makes perfect sense to control for patient specific characteristics − one should expect older individuals to stay hospitalized for a longer period than younger ones. In that sense, the vector X includes individual level control variables such as: *(i)* age; *(ii)* gender; *(iii)* the square of age; *(iv)* and an interaction term between age and gender. Another factor that is prone to influence the time each individual stays hospitalized is the severity of illness − it is reasonable to think that the length of stay in hospital varies proportionately with the severity of each case. Therefore, this vector also includes: *(v)* the total number of diagnosis made; *(vi)* and the total number of procedures that the patient was

[12] See appendix II.
[13] Note that it did not make sense to use a Zero Inflated Negative Binomial (ZINB) model instead of a standard NB. Indeed, the distribution of the variable length assumes a particular form − most patients do not stay hospitalized at all or, if they do, they stay hospitalized for no longer than two or three days. The relevant feature here is that there is not a big discrepancy between the number of episodes corresponding to zero length of stay and those with two or three days spent in hospital − 26,26% of total admissions at study correspond to zero days while 22,25% and 21,77% correspond, respectively, to two or three days spent in hospital. Therefore, the use of a ZINB model, which aims to deal with an ‘excess zeros’ problem, would not be justified.

subject to[14]. Note that the total number of diagnosis can also control for the initial condition of each patient. Finally, it is also relevant to capture whether the observation corresponded to an elective admission – which is, by definition, scheduled – or to an emergency episode. Therefore, vector X also includes *(vii)* a dummy variable which is able to inform whether the admission corresponded to a an emergency episode or not.

Furthermore, some variables were included as a means to capture the regularities found in the admissions flow, shown in the descriptive statistics section. As a consequence, vector Z includes variables that are able to distinguish: *(i)* whether the patient was admitted during summer months or not; *(ii)* whether the patient was admitted during the weekend or not; *(iii)* and whether the patient was discharged on a Monday or not. As it was already shown, weekends and summer months are the periods with a smaller number of admissions and, consequently, it is expected that patients admitted during these periods have a larger length of stay. On the other hand, if there is some evidence of the 'weekend effect', one should expect patients discharged Mondays to have a larger length of stay than the others. In addition, three dummy variables indicating the year of admission were also included as a means to capture a possible time trend concerning the length of stay – it is possible that the average length of stay is bigger, for example, in 2009 when compared to 2010.

Nonetheless, the key covariates in this model are those that respect to hospital utilization at the time the patient was admitted. These variables are hospital-specific and are associated with the number of admissions occurring: *(i)* in the day of the week in which the admission occurred[15];

[14] It is relevant to mention that most of the procedures are performed during the first days spent in hospital. Consequently, it is possible to establish a positive relationship between the number of procedures and disease acuity. On the other hand, if that was not the case, one could argue that patients were subject to a larger number of procedures just because they were hospitalized for a longer period of time.

[15] The number of admission occurring in the day of admission will hardly affect the discharging decision. However, this variable was included in the model because of its statistical significance.

(ii) in the day before the admission date; *(iii)* in the week of the admission date; *(vi)* in the week before the admission date; *(vii)* and in the week next to the admission date.[16] Note that there is a rationale underlying the choice of these variables. If a patient is admitted during a period of high hospital utilization − or preceded by high hospital utilization −, one should expect him to have a smaller length of stay, supposing hospital resources are under pressure. Conversely, if the patient is admitted during a period of low utilization, but then there is a surge in admissions in the days that follow the admission date, the length of stay is also likely to be affected.[17] However, the impact of hospital utilization levels can be slightly more complex. In order to deal with this situation, an interaction term between utilization levels in the week prior to admission and in the week after the admission date was introduced. Note that larger utilization levels *ex post* combined with larger utilization levels *ex ante* generate the conditions necessary to encourage an early discharge – the hospital was capacity constrained when the admissions surge occurred. However, higher utilization levels *ex post* combined with low utilization levels *ex ante* will hardly create incentives to discharge patients earlier than expected. Resuming, this means that the effect *ex post* utilization levels have over the length of stay may vary according to utilization levels *ex ante*, and vice-versa.

The model also includes hospital-specific fixed effect variables in order to take into account permanent differences in length of stay across hospitals. Furthermore, some hospital

[16]For example, the number of admissions in the week the patient was hospitalized corresponds to the total number of admissions occurring in week *t*, at hospital *j*, during the year in which the patient was admitted. Conversely, the number of admissions occurring in the week prior to the admission date corresponds to the total number of admission occurring in week *t-1*, in hospital *j*, during the year in which the patient was admitted. As far as the daily utilization variables are concerned, they were constructed in a similar way: if a patient was admitted Thursday, for example, the number of admissions in the previous day corresponds to the total number of admissions that took place in hospital *j*, on Wednesdays, during the year in which the patient was admitted.

[17] The maximum period considered is one week − admissions happening one week before as well as one week after − because most of patients stay hospitalized no more than seven days, and one would be introducing irrelevant information in the model.

characteristics – like whether the observation corresponds to a central hospital, to a district hospital, to a level 1 hospital or to a teaching hospital[18]– were taken into account.

Finally, one should not ignore that the sample at study is composed by a complex set of clinical situations, which vary not only with respect to severity and average length of stay but also with respect to the medical resources allocated to each situation. Take, for instance, DRG 371 and DRG 541: while the former corresponds to normal deliveries, the latter corresponds to patients subject to ecmo or tracheostomy. Logically, these two groups of patients do not compete for the same medical resources,[19] and an increase in the number of admissions concerning deliveries should have little impact over discharging decisions of eco and tracheostomy patients. For that reason, it makes perfect sense to control for the DRG in which the patient is included.

Logically, the term ε_{ijt} stands for the random error.

5.1. <u>The Negative Binomial Model Results</u>

Table 7, in appendix III, contains information regarding the estimates for this NB model – both the coefficients and the Incidence Rate Ratios (IRRs)[20]. As one can see, for simplicity, the hospital-fixed effects were omitted, although they are all statistically significant for the usual significance levels. Also, most of the patient-specific control variables, year dummy variables and hospital type variables are statistically significant, but the analysis of their coefficients is omitted here, for the sake of simplicity.

[18] Both district hospitals and level 1 hospitals have as an intervention area one district, but while the former has all departments the latter has only the most basic ones, like obstetrics and pediatrics. Logically, teaching hospitals also have a teaching section and central hospitals correspond to those with a larger number of different departments. It is reasonable to assume that hospital characteristics will also influence discharge decisions.

[19] Except, of course, for those resources which are common across all groups of patients, like nurses or administrative staff.

[20] IRRs were computed just by taking the exponential of the estimated coefficient. They indicate the proportion by which the counts rate of incidence– in this case the number of days spent in hospital− is expected to decrease when the predictor variable increases by one unit. Therefore, if one of the predictors changes by one unit, one has that (*new length*) =(*old length*)×IRR. To learn more about this see Hilbe, 2010, *Negative Binomial regression* (2nd ed.) p520.

First of all, patients admitted during weekends and summer months exhibit a smaller length of stay than the others,[21] and patients discharged during Mondays evidence a larger length of stay − pointing to the 'weekend effect' referred in Costa *et al.* (2008).[22] Moreover, the number of admissions occurring in the week of admission and in the day prior to the admission date seem to have a statistically significant negative impact over the time each patient stays hospitalized – indicating that larger utilization levels immediately before and at the time of admission tend to decrease the length of stay in hospital. Nonetheless, this impact is quantitatively irrelevant, as the IRR is very close to 1. Indeed, the elasticity of the variable length of stay with respect to utilization levels in the week of admission is just 0,03%. This means that a patient who was supposed to stay hospitalized for three days sees his length of stay reduced by approximately one minute when the number of admissions in that same week increases by 1%.

If one looks at utilization levels both in the week prior to the admission date as well as in the week after it is easy to see that both variables display a negative coefficient. However, since the model includes an interaction term,[23] the interpretation of these estimates should be done carefully. To better understand what are the consequences of having an interaction term, the so-called 'simple slopes' approach was conducted.[24] Basically, this approach consists in computing

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[21] Since those periods correspond to smaller hospital utilization, there are no incentives to discharge patients earlier and relieve medical resources and, consequently, evidence should point towards a larger length of stay. Nonetheless, that is not the case.

[22] Note that it is possible to draw some preliminary conclusions regarding early discharges behavior: if patients discharged Mondays stay hospitalized for a longer period, it means that, preferably, patients are not discharged during weekends. This, in turn, may be related to low hospital utilization levels during weekends, which weaken the need to discharge patients earlier.

[23] It is important to mention that this interaction term actually increases the model's adjusted r squared − from 24,23% to 24,24% − and, consequently, evidence points towards a significant interaction effect between utilization levels *ex ante* and *ex post.* The estimation without the interaction term was performed but it was omitted from this study. More than that, the interaction term is statistically significant for the usual significance levels.

[24] Econometrically, imagine a simple model like $y = \beta_0 + \beta_1 x + \beta_2 z + \beta_3 xz$. This equation can be rearranged in the following way: $y = \beta_0 + \beta_2 z + (\beta_1 + \beta_3 z)x$. This gives directly the marginal effect of x over y. In the 'simple slopes' approach, the slope $(\beta_1 + \beta_3 z)$ is computed for different reference values of the moderating variable z. Both x and z are centered, subtracting the mean, and the interaction term is just the simple product of these centered variables. This implies that, when one wants to compute the marginal

the coefficient associated with the predictor variable keeping the moderator variable constant at different reference values[25] – the mean, one standard deviation below the mean, and one standard deviation above the mean. Intuitively, one can assess the effect of an admissions surge in the week after admission if the utilization levels *ex ante* are at average, below average or above average. The results follow.

Table 3. Simple slopes analysis assuming utilization levels *ex ante* as moderator

		Coefficient associated with *next week admis.*	p>|z|	IRR
Utilization levels *ex ante*	Average	-5,44E-05	0,000	0,999946
	Below average	-9,21E-05	0,000	0,999908
	Above average	-1,67E-05	0,000	0,999983

The first thing to note is that all the coefficients are negative, statistically significant[26], and very close to zero, indicating that, despite being quantitatively irrelevant, the impact of an admissions surge over the length of stay is negative no matter the utilization levels in the week prior to admission. Second, by looking at IRR when utilization levels *ex ante* are above average, it is possible to conclude that patients will see the number of days spent in hospital decreased by a factor of 0,999983 when the number of admissions *ex post* increases by one. The important thing to note here is that, in fact, when utilization levels *ex ante* are at average or below average this reduction is bigger – the contrary one should expect if capacity constraints were motivating early discharges.

effect at the mean, the moderator variable should be set to zero. Conversely, if one wants the moderator to be above the mean, z should assume the value of the moderator's standard deviation, and if one wants to assume values below the mean, z should be minus the moderator's standard deviation. That is why this is also called the 're-centering method' (To learn more about this see Jaccard and Turrisi, *Interaction effects in multiple regression*, p. 29.).

[25] Note that, in this case, utilization levels *ex post* are the predictor variable while utilization levels *ex ante* correspond to the moderator variable.

[26] Testing for the significance of these coefficients implies re-estimating the model, using the same predictor variable as before but changing slightly both the moderator and the interaction term: for example, in order to test for the significance of the coefficient in the 'below average case', the new moderator equals the old one minus the standard deviation – lets call it *zlow* – and the new interaction term equals the product between x and *zlow*. The t-test for this new interaction term gives the significance of these simple slopes.

So far one has been assuming utilization levels *ex ante* as the moderator, and utilization levels *ex post* as the predictor. However, this definition can be reversed.[27] Making an assumption like this allows one to test the impact of an admissions surge –happening prior to admission− if hospitals expect a large number of admissions in the following week, supposing hospitals are rational agents and take that information into account when making decisions regarding resources management. The approach used is exactly the same as before.

Table 4. Simple slopes analysis assuming expected utilization levels as moderator

		Coefficient associated with *previous week admis.*	p>|z|	IRR
Expected utilization levels *ex post*	Average	-7,1E-05	0,000	0,999929
	Below average	-1,08E-04	0,000	0,999892
	Above average	-3,31E-05	0,000	0,999967

Now again as before, note that an admissions surge prior to admission has a quantitatively irrelevant – but statistically significant – negative impact over the time each patient stays hospitalized, independently of future expected utilization levels. Nevertheless, similarly to what happened before, the reduction in the number of days spent in hospital is bigger if expected utilization levels are below average than it is when they are at average or above average.

6. <u>The Multinomial Logit (ML) model</u>

This ML was estimated as a means to compute the probability of being discharged at a given day of the week relative to the probability of being discharged on a Wednesday – the base outcome.[28] As a result, it uses as a dependent variable the day in which the patient was

[27] This may seem a bit strange, but it makes perfect sense after making a strong assumption: lets assume hospitals' expectations regarding future admissions are fully fulfilled, meaning that the expected number of admissions perfectly matches the actual number of admissions occurring one week after the patient was hospitalized.

[28] Remember that, assuming m is the number of possible outcomes − in this case the seven days of the week in which the individuals can be discharged −, a ML model specifies that the probability of individual i being discharged on day j (p_{ij}) is defined as

discharged and controls for the same factors included in the NB model − the patient-specific variables; the hospital type and utilization variables[29]; the year dummy variables; and also the variables that capture the regularities found in the admissions flow.[30] Furthermore, six binary variables were included, indicating the day of the week in which the patient was admitted. In fact, it is reasonable to presume that a patient admitted on a Monday has a different probability of being discharged on a Tuesday when compared to a patient admitted, for instance, on a Friday. Finally the variable length, the number of days each patient stayed hospitalized, was also included as a covariate.

6.1. Multinomial Logit model results

The results will focus on Saturdays and Sundays because those are the days with smaller admissions and discharges flow and, consequently, one should expect a lower probability of being discharged on these days when compared to work days. If bigger utilization levels increase the probability of being discharged during weekend days, one can conclude that hospitals are actually using discharges as a means to deal with demand pressure and this, in turn, indicates that patients may be discharged earlier than expected. Moreover, this analysis will also focus on Fridays. Indeed, remember that, the larger the marginal impact of an early discharge the bigger the incentives to discharge patients earlier. Note that, since staff levels are usually lower during weekends, there is a large marginal benefit from discharging patients during

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$$p_{ij} = \frac{\exp(x_i'\beta_j)}{\sum_{l=1}^{m}\exp(x_i'\beta_l)}, j = 1, \ldots, m \text{ where } 0 < p_{ij} < 1 \text{ and } \sum_{j=1}^{m} p_{ij} = 1$$

Moreover, all the coefficients are interpreted with respect to one base-category, which sees its coefficient being set to zero (To get more information regarding ML models see Cameron and Triverdi, 2009, *Microeconometrics using Stata*, p484).

[29] Note that this ML model was also estimated using the same interaction term introduced in the NB model but, in this case, the predicted probabilities did not change and the marginal effects interpretation became a bit messy. Consequently, for the sake of simplicity, this interaction term was excluded .

[30] The variable *monday* was omitted in this model because it does not make sense to introduce a binary variable for patients discharged Mondays when the objective is to compute, among others, the probability of being discharged Monday.

Fridays. This, in turn, generates strong incentives to discharge patients in this day.[31] Assuming those incentives actually come into play, this analysis should find that there is a larger probability of being discharged Friday.[32]

As a result, the key purpose of this estimation was to determine the average probabilities of being discharged at a given day of the week, to check for significant differences. The average predicted probabilities are shown in appendix IV, table 8: the estimated average probability of being discharged on a Saturday or on a Sunday – 0,1282 and 0,0828, respectively – is pretty small when compared to the probability of being discharged in the remaining days of the week. Recall also that, from the descriptive statistics section, Saturdays and Sundays corresponded to the days of the week with a smaller admissions flow, implicating that there are weaker incentives to discharge patients earlier. On top of that, although discharges are less likely to occur during Sundays, it seems that an increase in utilization levels both *ex post*, *ex ante,* and at the time of admission raises the probability of being discharged Sunday relative to Wednesday – there is a mitigation of the 'weekend effect'.[33] In fact, if the number of admissions increases in the week of admission, in the week prior to the admission, or in the week after the admission, patients have a larger probability of being discharged Sunday. As far as Saturday is concerned, the results are less obvious: the number of admissions in the week of admission is the only utilization variable that has a positive impact over the odds of being discharged Saturday.

Restricting the analysis to Fridays, notice that patients are more prone to be discharged on Friday than in any other day of the week. This result indicates that patients may be subject to

[31] Besides that, lower staff levels during weekends make hospitals more vulnerable to admission surges. Discharging patients Friday may be seen as a way to relieve some capacity and make hospitals less exposed to variations in the admissions flow.
[32] Recall that, as the descriptive statistics results show, Friday was actually the day of the week with a larger number of discharges.
[33] See appendix IV, table 9, referring to the ML model marginal effects for the probability of being discharged Friday, Saturday, and Sunday.

early discharges – controlling for the severity of illness and all the other patient and hospital - specific factors and, also, controlling for the day of admission, patients have a larger probability of being discharged Friday. What is more, looking at the marginal effects, it seems that hospital utilization levels both in the week and in the day before the admission date have a positive impact over the odds of being discharged Friday when compared to Wednesday. Conversely, higher utilization levels at the time of admission and in the week after the admission have a negative impact over the odds of being discharged Friday, but this effect is not statistically significant.

It is reasonable to assume that different hospital departments may discharge patients in determined days of the week with different probabilities. As a result, the previous analysis was performed for each DRG separately. Table 10, still in appendix IV, displays the average estimated probability of being discharged at a given day of the week for each DRG at study.[34] Taking a first glance at the table, it is evident that the probability of being discharged Friday is larger when compared to other days of the week, for most DRGs.[35] If one looks only at DRG14, one of the DRGs with bigger average length of stay in hospital,[36] it is easy to see that the discrepancy between the probability of being discharged Friday or Saturday is huge – there is a 20 p.p. decrease. The same type of result can be found for DRG541, patients who stay hospitalized for 12 days, on average – there is a 16 p.p. decrease when comparing the probability of being discharged Friday and Saturday. On the contrary, if one looks at DRG39, the group of patients within the sample with smallest average length of stay, these two probabilities are basically the same. This indicates that the larger the length of stay in hospital, the bigger the probability of being discharged on a Friday when compared to weekend days

[34] The numbers in blue indentify the day of the week in which patients are more prone to be discharged.
[35] Namely, for DRG 14,162, 629, 541, 373 and 359.
[36] To see the average length of stay per DRG look at appendix V, graph 5.

and, consequently, those patients that stay hospitalized for a longer period are more prone to be early discharged.[37]

The remaining DRGs present a larger probability of discharge either Monday or Wednesday.[38] Recall that, from the descriptive statistics results, these are the days of the week with a larger share of admissions.

7. Conclusions

The main purpose of this work was to figure whether hospitals react to periods of congestion by hastening discharges, generating an inefficient situation. It was found that hospital utilization levels at the time of admission, prior to the admission date and after the admission has occurred do have a negative impact over the time each patient stays hospitalized, although this impact is neither quantitatively significant nor aggravated by utilization levels above average.

This study also shows that Portuguese hospitals utilization shows some regularities in the admission flow – admissions tend to be much lower during weekends as well as during summer months. The estimation process confirmed that the average probability of being discharged during weekend days is much lower when compared to work days, contrasting with a large average probability of being discharged Friday – the day of the week in which discharging patients earlier has larger benefits. Furthermore, the probabilities of being discharged either Sunday or Friday seem to increase with bigger hospital utilization levels. Looking at each DRG separately, it seems that the larger the length of stay the bigger the probability of being discharged Friday and the bigger the discrepancy between the probabilities of being discharged Friday and Saturday.

[37] In fact, according to the ML model marginal effects, the larger the length of stay the bigger is the probability of being discharged Friday.

[38] Except for DRG 371, corresponding to cesarean sessions, whose patients have a larger probability of being discharged Saturday.

Since hospitals will never be able to predict accurately the demand for medical services, some measures can be taken to decrease their vulnerability to admissions surges, so that hospital managers do not feel the need to use discharges as a means to relieve capacity. As it was previously mentioned, demand for medical services is composed by elective episodes, which are predictable in the short-run, and emergency episodes, which introduce a random component in the demand faced by hospitals. Hospitals should use the elective component to offset admission fluctuations related to the non-elective component. For example, as it was shown, the number of admissions during the weekend tends to be much smaller when compared to workdays. Scheduling a larger number of admissions to Saturday and Sunday will attenuate the existing discrepancies and move some patients away from weekdays, the days with larger hospital utilization. This, in turn, will relieve some capacity and decrease the incentives to discharge patients earlier. On the other hand, scheduling admissions to weekend days implies an increase in hospital staff levels during this period. This, in turn, not only decreases the incentives to discharge patients Friday but also makes hospitals less vulnerable to admission surges during the weekend. An analogous reasoning can be made with respect to summer months – scheduling admissions for summer months decreases congestion in the rest of the year.

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Appendices

Appendix I

Table 5: DRGs used during the estimation process.

DRG	Definition	Number of admissions
14	Intracranial hemorrhage or cerebral infarction.	62.796
39	Lens procedures with or without vitrectomy.	230.571
162	Inguinal and femoral hernia procedures, ages 18 to 69, without complicating condition.	60.571
270	Skin subcutaneous tissue and breast procedures without complications.	79.802
359	Uterine procedures.	68.397
371	Cesarean session without complications	88.083
372	Vaginal delivery with complicating diagnosis.	63.185
373	Normal delivery without complications.	156.758
541	Ecmo or tracheostomy with mechanical ventilation.	74.825
629	Newborn>2499g.	286.775

Appendix II

Table 6: NB Coefficient for the overdispersion test[39]

Coefficient	Std. Dev.	95% Conf. Int.	
0,1678385	0,000522	0,1668185	0,1688646

Likelihood-ratio test of alpha=0: chibar2(01) = 4.2e+05 Prob>=chibar2 = 0.000

Appendix III.

Table 7. NB model results

Negative binomial regression	Number of obs.		1171154	
	LR chi2(107)		1,31E+06	
Dispersion = mean	Prob > chi2		0,0000	
Log likelihood = -2041657	Pseudo R2		0,2424	
length	**Coef.**	**Z**	**p>|z|**	**IRR**
age	-0,003184	-11,65	0,000	0,9968
gender	-0,004013	-1,5	0,135	0,9960
agegender	-5,36E-05	-1,1	0,269	0,9999
agesquare	0,000033	14,55	0,000	1,000
emergency	0,2084148	59,85	0,000	1,2317
summer	-0,015848	-9,54	0,000	0,9842

[39] If this α parameter is statistically different from zero, then there is evidence of overdispersion.

weekend	-0,01802	-7,8	0,000	0,9821
monday	0,060849	31,9	0,000	1,0627
total procedures	0,0587942	177,93	0,000	1,0605
total diagnosis	0,0605517	152,03	0,000	1,0624
admissions same week	-3,78E-05	-4,1	0,000	0,9999
admissions same day	1,40E-06	3,62	0,000	1,0000
admissions previous day	-1,45E-06	-5,3	0,000	0,9999
admissions previous week[40]	-7,08E-05	-8,32	0,000	0,9999
admissions next week[41]	-5,44E-05	-6,21	0,000	0,9999
Interaction term	6,59E-08	19,06	0,000	1,0000
drg14	0,5738333	108,65	0,000	1,775
drg39	-2,325253	-431,24	0,000	0,0977
drg162	-0,63652	-125,05	0,000	0,529
drg270	-1,95880	-284,17	0,000	0,1410
drg371	0,0351821	7,24	0,000	1,0358
drg372	-0,255244	-47,42	0,000	0,7747
drg373	-0,347001	-70,28	0,000	0,7068
drg541	0,5323293	97,2	0,000	1,7028
drg629	-0,193867	-22,39	0,000	0,8237
District hospitals	0,1984989	23,44	0,000	1,2196
level1 hospitals	-3,14322	-21,19	0,000	0,0431
Teaching hospitals	0,0001811	0,02	0,982	1,0000
y2007	0,0827113	36,35	0,000	1,0862
y2008	0,0521226	24,78	0,000	1,0535
y2009	0,0175292	8,56	0,000	1,0177
constant	0,5590236	41,84	0,000	-

Appendix IV

Table 8: Average Predicted Probabilities (ML model)

Day of the week	Probability of being discharged[42]	Std. Dev.	Min.	Max.
Monday	0,1579	0,110948	0,017358	0,998931
Tuesday	0,1512	0,121639	0,000905	0,576056
Wednesday	0,1555	0,124056	3,80E-07	0,715866
Thursday	0,1549	0,104269	5,69E-09	0,516145
Friday	**0,1696**	0,10084	0,000164	0,58727
Saturday	0,1282	0,096301	3,10E-18	0,425882
Sunday	0,0828	0,0965	3,68E-12	0,675291

[40] This variable was centered.
[41] This variable was centered.
[42] These figures correspond to the arithmetic average of the ML model predict values.

Table 9: Marginal effects after ML model with respect to length and to hospital utilization variables

Variable	Friday		Saturday		Sunday	
	dy/dx	p>|z|	dy/dx	p>|z|	dy/dx	p>|z|
Admissions same week	-4,81E-06	0,36	3,72E-05	0,000	1,74E-05	0,000
admissions same day	-3,24E-06	0,000	7,82E-09	0,968	-2,57E-06	0,000
admissions previous day	7,38E-07	0,003	-3,12E-06	0,000	-2,33E-06	0,000
admissions next week	-1,11E-06	0,797	-6,21E-06	0,077	1,62E-05	0,000
admissions previous week	1,62E-05	0,000	-1,7E-05	0,000	8,85E-06	0,000
length	0,001573	0,000	-0,00411	0,000	-0,00068	0,000

Table 10: ML model results: probability of being discharged at a given day of the week by DRG

Day of the week	DRG									
	14	39	162	270	629	541	371	372	373	359
Monday	0,161	0,140	0,113	0,214	0,156	0,168	0,162	**0,155**	0,154	0,194
Tuesday	0,180	0,170	0,149	0,200	0,133	0,176	0,130	0,141	0,130	0,141
Wednesday	0,183	**0,191**	0,189	**0,222**	0,128	0,172	0,117	0,137	0,130	0,126
Thursday	0,173	0,165	0,185	0,183	0,142	0,161	0,129	0,147	0,187	0,154
Friday	**0,237**	0,161	**0,190**	0,155	**0,157**	**0,216**	0,160	0,152	**0,192**	**0,197**
Saturday	0,041	0,151	0,131	0,022	0,151	0,060	**0,163**	0,139	0,184	0,130
Sunday	0,025	0,021	0,043	0,004	0,134	0,047	0,140	0,129	0,135	0,058

Appendix V