The Use of Technology in Portuguese Hospitals – the Case of MRI

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Abstract

We study the determinants of MRI use across Portuguese NHS hospitals for patients belonging to specific DRGs.

Using data on individual hospital admissions, we estimate a probit model including individual-, hospital-, time- and region-specific variables in order to explain the probability of a patient being sent for MRI.

Results convey a tightening effect on the hospital's budget constraint in the end of each year. Hospitals seem to account for regional characteristics when defining adoption patterns. Individual-specific variables are good predictors of MRI use. Measures taken by the Government only impact the short run. Finally, the gains from an MRI scan, as far as the probability of death is concerned, occur mainly for less severe patients.

Keywords: technology use; MRI; Portuguese hospitals; patients' survival.

1. Introduction

The expenditure with the Health sector has been steadily increasing in developed economies during the last decades. About half of this growth is due to technological progress, according to the Congressional Budget Office (2008). Some authors go even further and claim that it is not technology itself that is driving up health expenditures, but rather the way it is (inefficiently) adopted and used – Chandra and Skinner (2011).

The aim of this project is to give an insight on the factors that determine the way technology is used. More specifically, we focus on the case of Magnetic Resonance Imaging (hereby MRI) scans carried out at Portuguese National Health System (NHS) hospitals over patients with specific medical conditions, given by a set of Diagnosis Related Groups between 2006 and 2010.

We propose a probit model that accounts for four dimensions that can possibly explain the probability of a patient being sent for an MRI: time, hospital characteristics, individual characteristics and region specificities. If variations in the use of MRI scans cannot be explained by the characteristics of each patient and the associated episode, then they reflect differences either in adoption or in clinical procedures across hospitals.

Overall, we find evidence of a tightening effect on the hospital's budget constraint in the end of the year, meaning that there is a fall in the number of patients being sent for MRI. Results also convey that hospitals adapt their technology adoption patterns to the characteristics of the region they are located in. Measures taken by the Government only impact the short run and the gains from an MRI scan occur mainly for less severe patients.

The remainder of this project goes as follows. The next section presents a brief survey of relevant literature and section 3 gives some background on MRI technology. Methodology is covered in section 4, whereas section 5 presents some descriptive statistics. Section 6 characterizes the datasets and variables used in the empirical analysis, whose results are presented in section 7. Section 8 develops on the effect of an MRI scan on patients' survival. Finally, section 9 concludes.

2. Literature Review

We begin with general considerations regarding the link between technological innovation and health care spending growth and only then we move to literature specifically aimed at studying technology adoption and use.

The Congressional Budget Office (2008) looks in detail into the factors underlying the growth of health care spending in the US. The authors associate about half of the long term growth in health expenditure with technological breakthroughs, their adoption and diffusion.

Both Chandra and Skinner (2011) and Baiker and Chandra (2011) elaborate on the idea that it is not technological progress itself the responsible for the rise in costs, but the mechanisms promoting an inefficient use of technology. In the former piece of literature, the authors defend that countries not adopting treatments with low cost-effectiveness ratios end up with great cost increases and small improvements in health outcomes. In the latter, it is pointed that productive inefficiency can arise from a wrong order of technology adoption (low-value technologies being adopted before high-value ones), which can alter the shape of the production function so that we end up with increasing marginal returns, meaning that one would like to further increase health spending.

As far as technology adoption itself is concerned, there are two theoretical models worth mentioning. In Barros and Giralt (2011), the authors relate the rate of technology adoption with the nature of the payment system in place. Conclusions are that only the homogeneous DRG payment scheme leads to the optimal level of technology adoption by the hospital. Both the heterogeneous DRG system and the cost reimbursement are associated with over-adoption.

Dengler (2006) models the decision of hospitals on the time of technology adoption accounting for two sources of inefficiency: a business stealing effect and a preemption effect. The model is tested against U.S. panel data and the preemption effect is found to be significant but of small magnitude, meaning that there is no big advantage in being the leader rather than the follower as the former cannot prevent the latter from adopting. Hence, it is the business stealing effect that dominates.

The focus on MRI technology is common in the literature. Using U.S. data, Baker (2001) finds evidence that a larger share of managed care activity is associated with a lower adoption probability. Also, being either a large or a specialized hospital has a positive impact on the likelihood of adoption, while variables such as urbanization and the number of hospitals in the neighborhood have a negative effect. Controlling for the presence of MRI substitutes – i.e. computed tomography (CT) – yields similar results. Teplensky et al. (1995) also elaborate on MRI adoption by U.S. hospitals. Using

Cox regression, they find that it is very much driven by the desire of the hospital to be seen as a technological leader and by expectations of future revenues.

Oh et al. (2005) propose a model of determinants of MRI and CT diffusion in which they account for purchasing power, patient's needs, physicians demand, Government regulations and the degree of flexibility of payment methods, both to hospitals and to physicians. The model is tested using cross-sectional data on all OECD countries for 2000. Using multiple regression analysis, they find evidence that both total health expenditure *per capita* (a measure of purchasing power) and flexible payment methods to hospitals positively influence the diffusion of CTs and MRIs.

Kung et al. (2005) use a panel data setting consisting on data regarding Taiwan's population and use multiple regression analysis as a means to explain the determinants of average uses of both CT and MRI per 1000 people per year. Conclusions are that the number of hospital-based physicians, the number of hospital beds, the number of MRI units and the ratio of female population have a positive impact on the average uses of MRI while the average regional income has a negative one. Results for CT are similar.

3. Background on MRI

MRI is an imaging technique that allows for producing high quality images of body tissues, which began to be commercially available in the 80's. Its pace of diffusion was too slow when comparing to similar devices (CT), which may result from the combination of a large initial investment with the operational costs and necessary site preparation. The fact that the clinical role of MRI was still not well-established, implying a high degree of uncertainty regarding the profitability of the devices may also have played a role (Hillman and Schwartz, 1986).

When MRI scanners became available, many people saw this technique as a less costly substitute of exploratory surgery and predicted a fall in health expenditure as a considerable number of surgeries would be replaced by MRIs. However, its nature also makes more people willing to use it, so that the final effect turned out to be an increase in total health expenditure (CBO, 2008).

4. Methodology

First of all, it is worth defining the concept of Diagnosis Related Groups (DRG). It is a method used to classify patients who are admitted at a hospital according to their clinical status and consumption of resources. That is, patients who are made similar diagnosis and hence are expected to consume a similar amount of resources during their stay at the hospital are classified in the same DRG.

To begin with the analysis, we look at the DRG (AP21 version) codes for medical procedures in order to identify those that correspond to MRI scans. These are codes 8891, 8892, 8893, 8894, 8895, 8896, 8897 and 8899. The next step is to identify the ten DRG groups whose patients got more MRI scans. Indeed, because there are so many groups and it would be hard to extract any evidence by considering them all together, we focus on the ten which present a higher absolute frequency of patients getting MRIs. One should note that this approach disables us to account for an eventual second MRI got by the same individual. However, due to the relatively rare occurrence of second MRIs, we do consider the consequences of such simplification to be negligible. For 2010, the corresponding DRGs are 2, 11, 12, 13, 14, 25, 243, 533, 810 and 832. An ordered rank of these ten DRGs using as criteria the number of patients sent for MRI follows.

Table 1: The ten DRGs with higher absolute frequency of patients sent for MRI[1]

DRG	# Patients getting MRI	# MRIs	# Patients getting >1 MRI	Total DRG episodes	% getting MRI
14	2.071	2.130	59	15.159	13,66%
533	634	678	44	5.830	10,87%
2	503	510	7	2.110	23,84%
243	456	496	40	3.505	13,01%
832	455	469	14	2.978	15,28%
11	422	430	8	907	46,53%
25	372	381	9	1.878	19,81%
13	324	429	105	740	43,78%
810	294	300	6	3.316	8,87%
12	293	339	45	1.216	24,10%

As conveyed by column 4, the number of individuals being subject to more than one MRI is low and only in the case of DRG13 one could claim the proposed approach

[1] DRG14, the one whose patients are more often sent to MRI scans corresponds to intracranial hemorrhage or cerebral infarction.

to be flawed. Still, the fact that a relatively high percentage of DRG13 patients get more than one MRI is most likely related to specificities of the associated condition[2].

Also worth considering is the percentage of patients classified in the ten DRGs who were sent for an MRI. In fact, when one looks at the ten above listed DRGs, it is impossible to tell whether the majority of patients classified under that DRG code needs such examination or if it is just the case that there is a large number of patients being classified under that code. Column 6 presents the figures in relative terms for 2010 and one can conclude that the percentage of patients sent for MRI varies a lot depending on the respective DRG, which is probably a consequence of the specificities of the condition associated with each DRG. However, the DRGs that exhibit the highest absolute frequency of patients sent for the examination are not those presenting the highest percentage of patients getting an MRI.

At this point, one might argue that the DRGs whose patients got more MRI scans may vary over time and hence the approach hereby followed would not be correct. Yet, there seems to be some persistence regarding this rank of DRGs. As a matter of fact, for the datasets corresponding to the remaining years the DRGs making it to the ranking are exactly the same, despite some changes in the order. Hence, we shall stick with this list of DRGs for the rest of the analysis, implying no loss of generality.

A feature of the data worth exploring is the evolution of the number of patients being sent for an MRI scan over the year as a tightening effect on the hospital's budget constraint might occur at the end of the year. The next section develops on this matter.

As far as regression analysis is concerned, the dependent variable is the probability of an individual being sent for MRI, which, by construction, only takes values between zero and one. Therefore, we use the probit model as an attempt to find out which factors do actually play a role in explaining the probability of a given individual being sent for an MRI scan.

Another approach to the problem would be a two-part model in which hospitals decide first on whether to adopt MRI technology or not and then decide on how many patients to send for MRI. The probit model is chosen over this alternative because we lack information regarding the place where the MRI was done (inside the hospital vs. outside the hospital in case the hospital does not own the equipment). Thus, we cannot

[2] DRG 13 corresponds to multiple sclerosis and cerebellar ataxia.

know exactly which hospitals adopted MRI technology and when they did so, which makes the two-part model option unfeasible.

We account for individual-, hospital- and region-specific factors when specifying the probit model. As for time variables, these are included as well in order to capture both the tightening on the hospital's budget constraint in the final months of the year and the overtime trend of MRI use. The general model specification is the following[3].

$$\Pr[MRI=1] = \Phi(\beta_0 + \beta_1 IND + \beta_2 TIME + \beta_3 HOSP + \beta_4 REGION) \quad (1)$$

, where MRI is a dummy variable equal to one in case the individual is subject to an MRI during his stay in the hospital and zero otherwise. IND, $TIME$, $HOSP$ and $REGION$ are vectors including the individual-, time-, hospital- and region-specific variables, respectively.

In the end we test whether MRI helps survival by running a probit model whose dependent variable equals one in case the patient has died during his stay at the hospital and zero if not. The dummy variable capturing whether the individual was sent for MRI is included in the regressors, together with other individual- and hospital-specific variables.

5. Descriptive Statistics

In the current section we look at the evolution of the number of patients being sent for MRI scan over the year. One expects it to fall in the last months of the year relatively to the remaining months due to the possible tightening of the hospital's budget constraint. As a matter of fact, such behavior does show up in the data. Using data for 2010, in the case of DRGs 2, 14, 25, 533 and 832 there is a clear downward trend in the number of patients getting MRIs in the last months of the year. As for the remaining DRGs there is only evidence of a decrease for the figure corresponding to December. Still, that figure is the lowest of the year in the vast majority of the considered DRGs. The graphs depicting the evolution of the number of patients belonging to each DRG that were sent for MRI scans in 2010 are shown in the appendix. It is worth noting that the possibility of 'avoiding' an MRI is influenced by

[3] For a more formal presentation of the probit model and deeper understanding of its specificities, see Cameron and Trivedi (2009).

the degree of severity with which the condition corresponding to a certain DRG is associated to[4].

This pattern of behavior is common to all the years considered in the sample. However, descriptive evidence is not enough to state that the tightening of the hospital's budget constraint plays a role in explaining differences in treatment for similar patients. In order to address this point, one needs to perform regression analysis.

6. Data

In this project we use two data sources. First, we use data on individual hospital admissions at NHS hospitals collected by Administração Central do Sistema de Saúde ranging from 2006 to 2010. Individual-, time- and hospital-specific variables are either taken from these datasets or built upon them.

More specifically, individual variables include a dummy for gender, taking value one for females and zero for males; the patient's age expressed in years and its square; an interaction term between gender and age; the number of procedures the patient is subject to and the number of diagnosis he is made, as controls for illness severity; and the mortality rate referring to the individual's DRG for the hospital where he is treated, during the three months previous to his release date.

Time variables consist on the admission year and eleven dummies ranging from January to November in order to account for the admission month.

Hospital variables include a dummy taking value one if the hospital had already been transformed in an EPE[5] at the admission time and zero if not; another taking value one if the hospital belongs to a hospital center at the admission date and zero otherwise; a third one equaling one if a contract was celebrated with the Ministry of Health for the corresponding year and zero otherwise[6]; one taking value one in case of teaching hospitals and zero otherwise; two other dummies taking value one in case of District

[4] Indeed, some graphs depict a higher decline than others. This occurs both in absolute and in relative terms – 15,6% for DRG2 against 69,8% for DRG533.

[5] An EPE hospital is considered to be out of the Government sphere as far as its budget is concerned, as it enjoys an enterprise-like status. Though their expenditures need not be predicted in the General Budget, EPE hospitals are subject to financial control by the Government. Conversely, SPA hospitals belong to the public sphere and their expenses must be predicted in the General Budget.

[6] These contracts are aimed at fixing not only the objectives of the hospital in terms of health care production for a certain time frame, but also the payment that the hospital will receive as a function of its achievements.

and Level 1 hospitals, respectively – Central hospitals are set as benchmark[7]. Hospital size is captured by the total number of patients admitted during a certain year.

We complement the analysis with regional variables taken from Instituto Nacional de Estatística. These are the average income, the percentage of high school and college graduates, the number of physicians per 1000 inhabitants and the percentage of elderly population. We add regional population and population density (simple and squared terms). Variables capturing income and education are available per NUTS II, whereas the remaining ones are available per NUTS III.

We match each individual in the dataset with the region where he receives treatment rather than that where he lives. This allows to test whether hospitals located in different regions differ in clinical practices and adoption patterns.

Regional variables play an additional and important role. They avoid a possible endogeneity problem caused by the introduction of the mortality rate referring to the individual's DRG for the hospital where he is treated during the three months previous to his release date. Indeed, some of the factors simultaneously affecting this regressor and clinical practices are related with the demand side and, thus, included in $REGION$.

The final sample consists in 194.516 individual observations belonging to the ten above mentioned DRGs from which 26.703 were sent for an MRI scan.

7. Empirical Analysis and Results

We run a probit model whose dependent variable is a dummy taking value one in case the individual is sent for MRI and value zero otherwise. The independent variables are those mentioned in the previous section. The results follow in column (1) of table 2. Recall that the coefficients of a probit regression tell us the direction of the marginal effect but not its magnitude. Therefore, whenever marginal effects are mentioned, these are evaluated at the means of the independent variables.

Overall, the pseudo-R^2 of the model is about 16%, which is fairly reasonable as there are many other factors influencing the probability of an individual being sent for MRI that are not being accounted for in the model. Only the coefficient referring to the number of physicians in the region is not statistically distinguishable from zero.

[7] A hospital is classified as either Central, District or Level 1 according to its geographic influence.

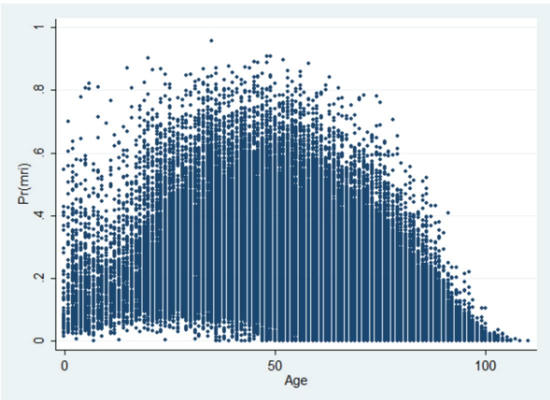
Table 2: Results of probit model estimation

Pr[Mri]	(1)	(2)
Gender	-0.412***	-0.416***
Age	0.033***	0.034***
Age squared	-0.001***	-0.001***
Gender * age	0.006***	0.006***
Total number of procedures	0.099***	0.104***
Total number of diagnoses	-0.052***	-0.050***
Mortality rate	-3.069***	-3.061***
Admission year	-0.032***	0.130***
Admitted in January	0.031*	0.031*
Admitted in February	0.048***	0.042**
Admitted in March	0.068***	0.068***
Admitted in April	0.070***	0.062***
Admitted in May	0.075***	0.066***
Admitted in June	0.045**	0.042**
Admitted in July	0.078***	0.076***
Admitted in August	0.090***	0.093***
Admitted in September	0.084***	0.085***
Admitted in October	0.091***	0.088***
Admitted in November	0.074***	0.076***
Epe hospital	-0.167***	0.122***
Hospital center	-0.085***	-0.041**
Contract with Min. of Health	-0.036**	-0.017
Total patients admitted / 1000	0.007***	0.001**
District hospital	-0.142***	-3.223***
Level1 hospital	-0.614***	-2.683
Teaching hospital	-0.253***	-3.278
Average Regional income	0.005***	-0.000
Region population > 65 (%)	-0.046***	-0.021
# physicians per 1000 inhabitants	0.001	-0.339***
High school graduates (%)	0.047***	-0.023***
College graduates (%)	-0.111***	-0.011

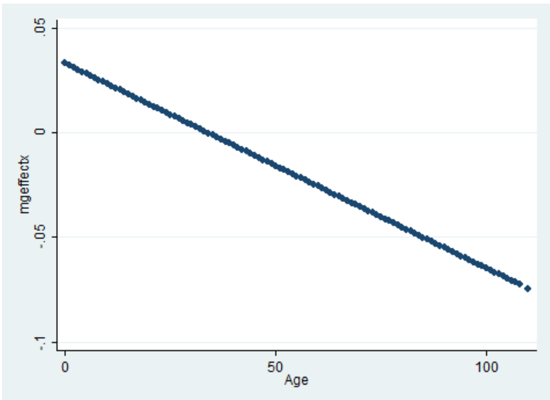
Region population / 100000	-0.155***	-1.259***
Region population / 100000 squared	0.002***	0.057***
Population density / 1000	-0.506***	15.798***
Population density / 1000 squared	0.001***	-0.010***
Constant	60.05***	-256.9***
Hospital fixed-effects	No	Yes
N	194516	194122
R2	0,1599	0,1928

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The patient's age has an interesting pattern of behaviour. Its impact on the probability of being sent for an MRI is positive up to a certain threshold, exhibiting decreasing marginal returns. After that point, we have that the impact of age on the probability of an individual being sent for MRI is negative. By plotting the patient's age and predicted values of MRI one can observe an inverted-U relationship with an inflection point around 33 years old[8]. The exact impact of this variable on the probability of being subject to an MRI depends on the individual's age – it is associated with an expected drop of 0,035 percentage points evaluated at 69,816, the mean of age.



Graphic 1: Scatterplot of individual's age and predicted values of MRI.



Graphic 2: Total marginal effect of age.

The fact that the patient is female is associated with lower probability of being sent for an MRI, pointing to the existence of gender discrimination regarding MRI use.[9]

[8] This coincides with the domain of the ages of patients being sent for MRI, which ranges from 0 to 104.
[9] See Perelman, Mateus and Fernandes (2010) for more on gender differences. They study the case of cardiac heart disease in Portugal and conclude that there is evidence of such discrimination favouring men, especially either prior to acute disease detection or in the case of emergency episodes.

As far as the interaction term is concerned, its coefficient tells us how the impact of age varies according to gender. We have that the interaction term between gender and age bears a positive coefficient. Since the direction of the marginal impact of age varies depending on the value taken by the regressor, it is useful to look at the effect evaluated at the mean. That is, at the mean, the marginal effect associated with age is negative, so we have that its magnitude is lower if the patient is female. In case we are at a point where the marginal effect of age is positive, then being a female is associated with a probability of being sent for an MRI that is higher than that for males.

The mortality rate of the corresponding DRG, for the hospital where the patient was treated, during the three months previous to his release date is also associated with a drop on the probability of being sent for an MRI as its coefficient bears a negative sign. The impact of the severity of the patient's condition, in turn, plays an ambiguous role in explaining the probability of being sent for MRI. In fact, the effects of one extra procedure and diagnosis on the probability of MRI use go in opposite directions: the former is associated with an increase whereas the latter has a negative impact. This result suggests that what matters for the decision on whether to send a patient for MRI is not *how many* diagnoses he is made, but rather *which* diagnoses he is made.

Regarding the time variables, there is evidence of a tightening effect on the budget constraint of the hospital as all the monthly dummies bear a positive coefficient. Therefore, one can conclude that a patient admitted in any month from January to November has a higher probability of being sent for an MRI scan than a similar patient that is admitted in December, other things equal. Hence, we have a difference in procedures that is actually reflecting an inefficiency as it cannot be explained by individual-specific characteristics but rather depends on the time of the year the patient enters the hospital. Additionally, there seems to be an overtime decreasing trend on the probability of an individual being sent for MRI. It is worth highlighting the fact that both these patterns of behaviour vary with the type of hospital that is being considered. The following table summarizes the results per type of hospital.[10]

[10] Corresponding regression tables are presented in the appendix.

Table 3: Time variables per type of hospital

Hospital	Overtime trend	Tightening of budget constraint
All	Negative	Yes
Central	Positive	Yes
District	Not significant	Yes, though not always significant
Level 1	Positive	Not significant

For the hospital specific variables, we have that an individual being treated in hospital which is either an EPE or part of a hospital centre has a lower probability of being sent for MRI than a patient who receives treatment at a hospital which is either an SPA or does not belong to a hospital centre. Likewise, being treated in a hospital which celebrated a contract with the Ministry of Health is associated with a probability of being sent for MRI that is lower than the one of a similar patient treated in a hospital that did not celebrate such contract.

The size of the hospital is positively associated with the probability of MRI use as the coefficient associated with the number of patients admitted during the year bears a positive sign. Conversely, receiving treatment either at a district hospital or a level 1 hospital is associated with a lower probability of MRI use than in the case of central hospitals. This reinforces the idea that the size of the hospital plays an important role as hospitals classified as central hospitals are larger than the others. The fact that the hospital is a teaching hospital exerts a negative impact on the probability of being sent for MRI, compared to those which are not teaching hospitals.

Now focusing on the determinants of health care demand, there is evidence on the fact that the probability of an individual being sent for MRI is higher in regions where average income is higher. The percentage of people above 65, in turn, bears a negative sign suggesting that regions with higher percentage of elderly people tend to use less technology. Education has an interesting effect as a larger percentage of high school graduates is associated with a greater probability of MRI use. However, the higher the percentage of college graduates, the lower the probability of MRI use.

It is worth to develop further on the mechanism trough which these region specific variables affect the probability of an individual being sent for MRI as adoption plays a central role in it. The reasoning goes like this: take a hospital located in a low average income region; most likely, its expectations regarding demand for health care in general and for hi-tech health care devices in particular are much lower than those of a hospital located in a wealthier region because wealthier people demand more health care. Hence, anticipating this lower demand, the hospital is likely to buy less (or even do not buy at all) MRI equipment since it may feel that the large investment is not worth it. As a consequence, other things equal, individuals living in regions with lower average income are less likely to be sent for MRI because there are less scans. An analogous thinking applies to the remaining region-specific variables.

The coefficients of the urbanization variables suggest that the probability of MRI use is lower in more urbanized areas as the overall effect of the urbanization variables at the mean is negative. This result is similar to that obtained in Baker (2001).

Including the hospital fixed effects in the model is a way of considering differences in clinical practice and hospital preferences regarding technology adoption. In order to account for the hospital fixed effects in the model, we introduce 80 dummies in the previously estimated model and set hospital P98 as benchmark. The 80 dummies correspond to 80 of the 81 hospitals in the sample.[11] This model uses fewer observations as those referring to hospitals P12, P32, P46, P55, P63 and P65 are automatically dropped by Stata on the grounds that they predict failure perfectly. P69 is also omitted because of collinearity. Results are presented in column (2) of table 1.

The pseudo-R^2 of this model is 19, 28%, above that obtained by omitting the fixed-effects, meaning that hospital characteristics do matter when it comes to predict the probability of MRI use. This is probably due to differences in the adoption rule across hospitals. The results are somehow different from those of the previous specification. While the impact of individual-specific variables is very similar to the previous one, the time, hospital- and region-specific variables suffered some changes. In the former case, there is still evidence of a tightening effect on the hospital's budget constraint, but the overtime trend of MRI utilization becomes positive. In the case of the hospital-specific variables, we have that being an EPE hospital has now a positive effect on the probability of an individual being sent for MRI. Both the variables corresponding to the hospital where the patient is treated being part of a hospital centre and to hospital size keep exerting similar impacts on the probability of MRI use. The remaining hospital variables lose their significance. As for the region-specific variables, both the number of physicians and the percentage of high school graduates in the region are associated with a lower probability of the patient being sent for an MRI scan. Regarding

[11] One should be aware that the probit model does not accommodate well many dummy variables and including 80 dummies might harm previous results.

the variables capturing the degree of urbanization, the number of inhabitants living in the region still exerts a negative impact when evaluated at its mean, but population density now contributes towards a higher probability of MRI use. The remaining variables contained in this vector become statistically undistinguishable from zero.

We also address the question of whether patients who were transferred from another hospital to the current one have a higher probability of being sent for MRI. Overall, we conclude that the reason why these patients are transferred is more likely to be linked to the fact that the chances of *having access to an MRI scan* in the hospital of origin were low[12], rather than with more severe medical conditions.[13]

At this point we replace the time variables that have been used throughout the analysis by interactions between the admission year and the admission month – i.e. binary variable that equals one if the patient is admitted in January 2010 and zero otherwise. This allows every admission month to have a different impact on the probability that the individual is sent for an MRI depending on the admission year, whereas before the impact was the same regardless of whether the patient was admitted at the hospital in January 2008 and in January 2010.

Therefore, the initial model is estimated again, now including these new time-specific variables rather than the old ones. Eleven equations are estimated: one including all DRGs and ten others including only one DRG - it may be that the effects on the probability of an individual being sent for an MRI scan vary across DRGs and such possibility was disregarded in the previous analysis. A constant is included and January 2006 is set as benchmark. Additional variables are included when necessary in order to account for seasonality effects such as the fall in the number of patients sent for MRI during the summer months. The hospital fixed-effects are disregarded from now on. The results are discussed in the following lines and presented in the appendix.

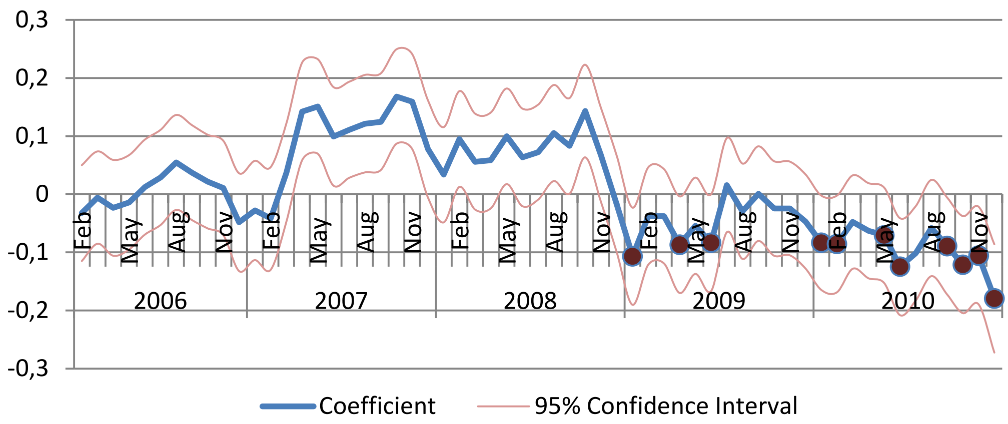
As for the model considering the ten DRGs altogether, the sign of the coefficients bear by individual, hospital and region-specific variables, remains unchanged relatively to the first model specification.

The analysis of the results of the ten probit models regarding each DRG individually is not going to be exhaustive. A brief comparison with those obtained for the whole dataset follows. As far as the significance of the coefficients is concerned, we

[12] Note that here what is important is not whether the hospital has MRI equipment or not. Since the MRI scan can be made out of the hospital, what matters is the access that patients have to the examination.
[13] This matter is further developed in the appendix.

have that several variables are no longer statistically distinguishable from zero. Among those that more often lose their significant are the interaction term between gender and age, the binary variable capturing the celebration of a contract with the Ministry of Health and variables such as population density and population squared. Conversely, the number of physicians in the region gains statistical significance in eight of the ten cases, though its sign varies depending on the DRG that is considered. Regarding both the sign and magnitude of the marginal effects, the vast majority of the effects previously found continues to show up.

Particular emphasis is to be put on the negative coefficients of the new time variables. Indeed, one can associate them with specific events affecting the economic and social spheres, which can be linked with the Health sector and affect the use of MRI technology. The graph below depicts the coefficients associated with the time variables for the regression including all the DRGs.



Graphic 3: Coefficients of the time variables admission year*admission month.

First, we highlight the curious pattern of evolution of the series depicted above: 2007 and 2008 are very similar to each other, presenting a relatively flat trend; in the end of 2008 there is a clear negative jump in the series and from that point on there seems to be a slightly negative trend along the years of 2009 and 2010 (note that, again, these two years are very similar to each other).

The bold dots represent the months whose probit coefficients are both negative and statistically significant: January, April and June, 2009; January, February, May and June, 2010 and the period ranging from September to December, 2010.

The negative coefficient associated with January 2009 may be linked with the Supplementary General Budget and the revision of the Stability and Growth Program which took place during that month. The negative sign corresponding to January and

February 2010 can be linked with the General Budget that was approved in January and included the usual measures aimed at containing public expenditure in the Health sector. The period ranging from May to June 2010, in turn, follows the implementation of a plan developed by the Ministry of Health that was specifically aimed at reducing expenditure in Portuguese hospitals, which started in late May. As for the final months of 2010, they follow the announcement of the 3rd Stability and Growth Program, which occurred on the 29th of September of that year.[14]

As for the remaining bold dots, we could not find any relevant event occurring at the time that could affect technology use by Portuguese hospitals. Nevertheless, one recognizes that the effects of the austerity measures mentioned in the previous paragraphs are in the right direction as a decrease on the probability of a given individual being sent for MRI is reflected in a fall in overall MRI costs. However, it seems that the effect of the austerity measures fades away too rapidly, highlighting the fact that if the Government wants to limit the public expenditure with the Health sector, then it should opt for a structural reform rather than short term measures.

8. MRI effect on patients' survival

Finally, we test whether being sent for an MRI does have a positive impact on the patient's probability of survival. We take DRGs 14, 533 and 810, which are those whose patients more often die and estimate the following probit model.

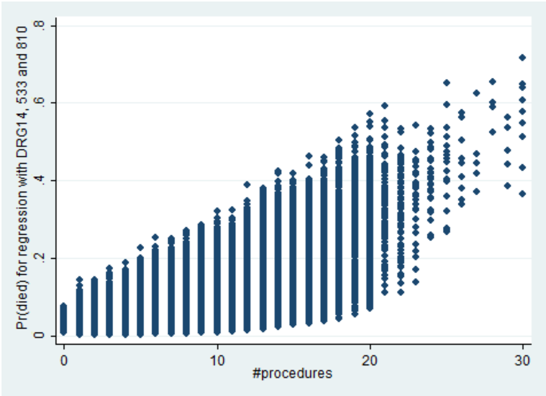
$$\Pr[\,DIED{=}1] = \Phi(\beta_0 + \ \beta_1 MRI + \beta_2 IND{+}\beta_3 HOSP) \qquad (2)$$

, where the dependent variable takes value one if the patient died and zero otherwise. The independent variables are a binary variable equaling one if the patient was sent for an MRI and zero otherwise and two vectors containing the previous individual and hospital variables. Two variables are added to the former vector, which are interactions between the two measures of illness severity and the fact that a patient is sent for MRI.

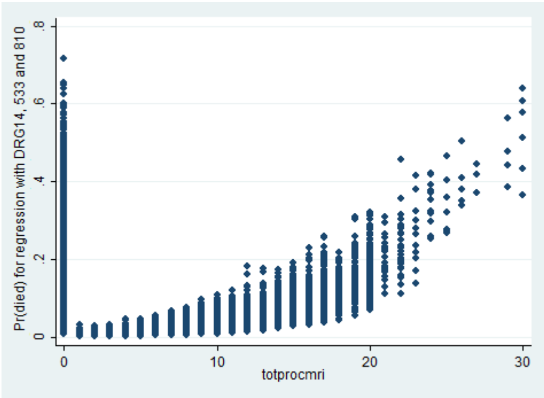
We run four probit models, one for each DRG and another one gathering all the three DRGs. For mean values of both measures of illness severity, being sent for an MRI does help patients' survival as the total impact of being sent for such examination on the probability of death is negative. This occurs in each of the four regressions.

[14] One should highlight that this association does not imply any causality and has no statistical grounds. It may no more than a time coincidence.

The new interaction terms allow us to determine where the main gains in survival come from. Indeed, comparing graphs 3 and 4, one observes that the main gains from an MRI scan occur mainly for the less severe cases. The scatterplots for the other interaction term have a similar shape.



Graphic 4: Scatterplot of number of procedures and predicted values of the probability of death for patients belonging to the 3 DRGs.



Graphic 5: Scatterplot of number of procedures and predicted values of the probability of death for patients belonging to the 3 DRGs, who were sent for MRI.

The above scatterplots also convey the fact that a high percentage of the most severe patients is already being sent for MRI – 4 out of 5 patients who were subject to 29 procedures were sent for the scan. However, those who experience the higher gains from the examination are those suffering from less severe conditions. Thus, in case of a contraction on the budget constraint of a hospital, priority should be given to less severe patients rather than to more severe ones as the former are those who benefit more from the scan. Conversely, in case of patients suffering from very severe conditions (particularly those who are made a large number of diagnoses) being sent for an MRI does not improve patients' survival – this is can be due to an incomplete control of illness severity. Such result seems counterintuitive but comes clear-cut from the total effect of a discrete change of *MRI* from 0 to 1 on the probability of death, which depends on severity of the patient's condition: the coefficient associated with the interaction term of *MRI* with the number of diagnoses the patients is made bears a positive sign and its absolute value exceeds that of the interaction term associated with the number of procedures. In this sense, patients suffering from more severe conditions are probably too ill to benefit from the examination.

Note that one cannot state that an MRI exerts a negative impact on survival as it is no more than a diagnosis tool. Moreover, patients yield benefits from the scanning, other than those related to the probability of death. Such benefits are disregarded in our analysis as these could not be measured properly. If total benefits instead of benefits in terms of probability of death were considered, then conclusions could be altered.

9. Conclusions

This project intends to clarify on the determinants of MRI use for patients with specific medical conditions, who were admitted at Portuguese NHS hospitals during the period ranging from 2006 to 2010.

Overall, individual variables are found to be very good predictors of MRI use, as expected. Indeed, not only their coefficients are very significant, but also their magnitude is independent of model specification. Variables capturing hospital characteristics also play a role, though many lose their significance when hospital fixed-effects are considered in the model specification. As for region-specific variables, one can say that hospitals seem to account for the characteristics of the regions where they are located when deciding on their adoption patterns.

There is evidence of a tightening effect on the hospital budget constraint in the end of the year. This inefficiency suggests that the management of the hospital budget can be improved. An option to be considered would be not sending for MRI less severe cases occurring in the beginning of the year as a means to save resources for more severe cases taking place in the end of the year. Whether correcting this inefficiency will lead to savings is not clear as the number of patients sent for an MRI scan would most likely not fall. Nevertheless, it would certainly increase patient's welfare. Indeed, the total benefits from sending to an MRI a patient who is in a very severe condition are likely to be higher than the costs of not sending someone whose condition is not that severe. Hence, sending for MRI the more severe cases taking place in the end of the year instead of less severe ones occurring in the beginning of the year can be seen as socially desirable according to the Kaldor-Hicks compensation criteria.

MRI scans are found to help patients' survival, mainly for those suffering from less severe conditions. In the case of patients suffering from more severe conditions, the benefits from an MRI scan in terms of probability of survival are dominated by illness severity. Nevertheless, this result is not to be taken too far as there are other benefits from the MRI scan rather than those related to the probability of death. On top of this, the fact that illness severity is also being poorly measured by the total number of procedures and diagnoses is likely to have contributed to the result. Still, if one only cares about patients' probability of death, then a policy implication can be drawn: in case of a fall on the resources available to a given hospital, priority should be given to less severe cases as these are those who benefit the most from an MRI - the examination is likely not to yield any significant benefits as far as the probability of death of patients suffering from more severe conditions is concerned. By adopting this policy we are improving welfare. Indeed, patients in more severe conditions do not significantly benefit from the scan, whereas those suffering from less severe conditions do benefit from it – this is a Pareto move as it allows patients in less severe conditions to be better off without harming those in worse medical conditions (their welfare remains constant). Note that, again, the number of MRIs most likely will not fall. The only change is that the patients being sent for the examination are in a better medical condition.

All in all, given the nature of the inefficiencies found in the use of MRI across Portuguese NHS hospitals for patients suffering from specific conditions, it is not clear whether correcting them would allow for cost reductions. Still, there is definitely room to increase patient's welfare, while keeping constant the amount of resources spent.

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