

# On the tension between standardized and customized policies in healthcare: The case of length-of-stay reduction

(Authors' names blinded for peer review)

Hospitals increasingly adopt standardized policies as a way to improve the efficiency of healthcare delivery. One key policy has been to reduce a patient's length of stay, which is commonly perceived as an effective means of improving patient outcome, as well as reducing the cost per procedure. We put this notion to the empirical test by using a database of 183,712,784 medical records of patients in the English NHS between 1998 and 2012, studying the effects of the NHS's policy of decreasing length of stay for hernia patients. While we found it to be an effective way of reducing the cost per procedure, on aggregate, we also found that it increases the risk of readmission and of death for vulnerable and elderly patients, unduly increasing the long-term failure costs of the operation for these patient groups. Based on our findings we propose a differentiated policy to selectively decrease length of stay, which we estimate could save up to US\$565 per non-emergency hernia procedure (a 19.97% reduction in the cost per procedure). We outline the implications of our findings for medical practice, and discuss the wider theoretical contributions to the wider standardization-customization debate in healthcare operations management.

*Key words:* healthcare operations; patient outcome; standardization; customization; lead-time reduction

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## 1. Introduction

Healthcare costs represent a considerable proportion of the gross domestic product (GDP) across most developed countries; for instance, in 2012, healthcare expenses amounted to \$2.9 trillion in the United States (17.1% of the GDP, or \$9,060 per capita), and \$245.8 billion in the United Kingdom (9.1% of the GDP, or \$3,802 per capita) (World Bank 2015). As a consequence, there has been a growing political emphasis on curbing health-

care expenditures, with a major focus on improving the efficiency of hospital operations (Kaplan and Porter 2011, Farchi and Salge 2017). The adoption of standard policies in hospitals has become a common means by which to increase efficiency (Bohmer 2009): as an example, more and more hospitals have been adopting clinical guidelines to manage the delivery of care (Andritsos and Tang 2014), and hospital managers have been increasingly using process improvement methodologies from the manufacturing context, such as lean production (Farchi and Salge 2017, Radnor et al. 2006, 2012). Despite the increasing levels of adoption of standard policies, ‘one-size fits all’ solutions could have negative consequences in healthcare. Several studies (Fogliatto et al. 2012, Piller et al. 2004, Squire et al. 2004) have suggested that customized solutions can increase the value offered to customers and decrease integration costs.

We propose that, in some contexts, increasing length of stay for some patients can decrease long-term failure costs since tailored solutions can decrease the proportion of readmissions and, in turn, lead to a reduction of the costs that arise as a result of complications. Our study complements earlier studies that have analyzed length of stay as a dependent variable (Aldoescu et al. 2015, KC and Terwiesch 2011). In our study, however, length of stay is an independent variable as we focus on its interaction effects.

We examined the link between length of stay and patient outcome using 183,712,784 medical records of patients in the National Health Service (NHS) since there is a growing interest in the adoption of standard policies in the English healthcare system (Department of Health 2012a). Standardized policies are one of the key features of the Quality, Innovation, Productivity, Prevention (QIPP) program, which has the objective to enhance the management of operations in the NHS (British Medical Association 2010). Given the high correlation between length of stay and hospital expenditures, a specific goal of this program is pushing hospital managers to decrease patients’ length of stay (National Institute

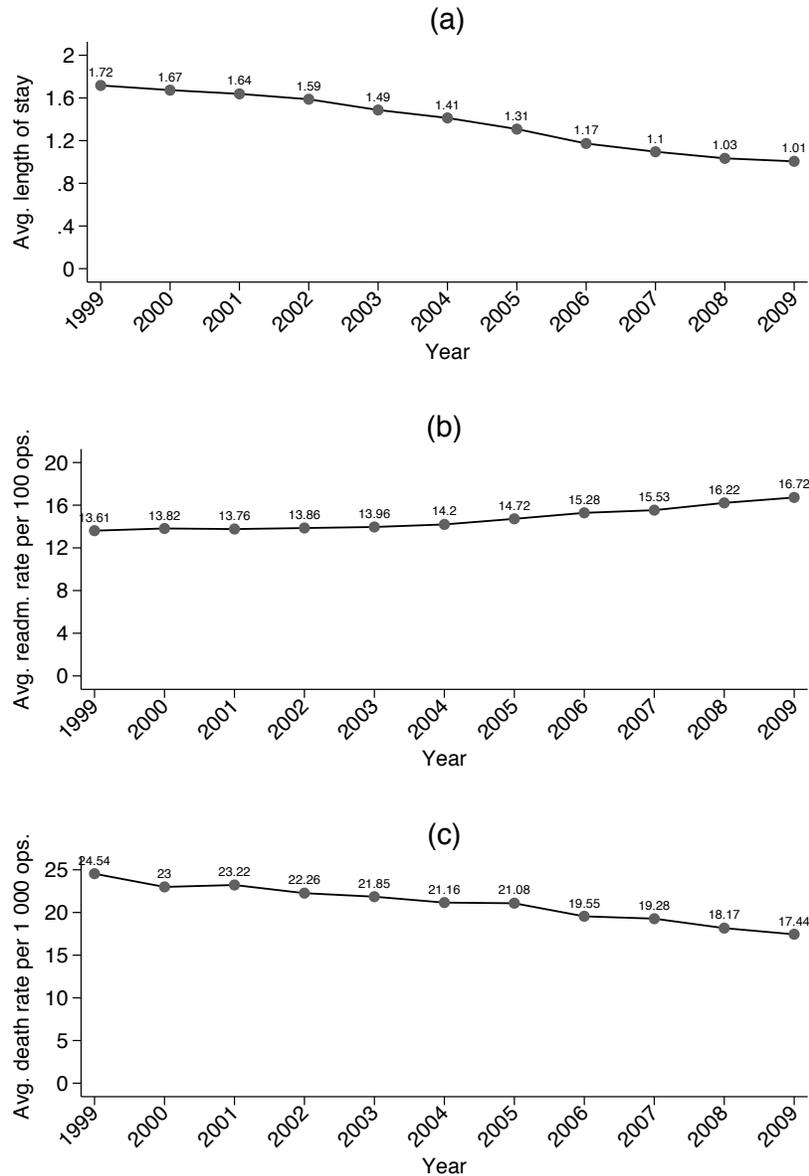
for Clinical Excellence 2012a,b). The motivation behind this decision is that empirical evidence suggests a positive relationship between length of stay and risk of hospital-acquired infections (HAIs) (Hassan et al. 2010, Mitchell and Gardner 2012). However, we argue that an early discharge can also expose some groups of patients to avoidable risk factors such as stress and lack of care.

For the purpose of this study we focused on the most common procedure a general surgeon performs, the hernia repair (Nyhus et al. 1991, Rutkow 2003, Rutkow and Robbins 1993). As shown in Figure 1 that illustrates age/gender adjusted average length of stay and readmission/death rates, inguinal hernia patients have been spending less time in NHS hospitals. However, readmission rates have been increasing sharply, suggesting that some patients are not receiving adequate care and, for this reason, need to be readmitted to hospital. It is important to note that, while readmission rates have been increasing, mortality has been decreasing at a steady pace, indicating that length of stay reduction may not be a significant contributor to a patient's likelihood of death.

One of the reasons for keeping patients in hospital for longer is to monitor them, especially when they have previous conditions or they are very old. In this study, we specifically considered the empirical boundaries of this decision, investigating whether the impact of length of stay reduction is the same for patients of different age and physical condition.

We chose to concentrate on NHS inguinal hernia patients, because this operation is the fifth most common general surgery procedure performed in the English healthcare system, accounting for 0.625% of all procedures performed. The length of stay for hernia patients has declined from approximately six weeks in the 1940s to less than one night in hospital today (Royal College of Surgeons 2013, Scambler 2008). In order to assess the overall impact of readmissions on NHS costs, we calculated the average cost of a hospital readmission

**Figure 1** (a) Average length of stay (number of days from admission to discharge), (b) percentage of hospital readmissions, (c) mortality for inguinal hernia patients between 1999 and 2009, computed using 183,712,784 medical records of patients in the English NHS.



using the methodology illustrated in Department of Health (2012b) (2011 prices). Although decreasing, the average cost of a hospital readmission after inguinal hernia surgery was still more than £1,400 (US\$2,235) in 2009.

We studied the effects of length of stay reduction using Hospital Episode Statistics (HES) and Hospital Estates and Facilities Statistics (HEFS) data. While HES data provides

information on NHS patients such as their demographic profile, the diagnoses from the physicians, and the procedures they undergo, HEFS data provides information on NHS hospitals such as number of beds and teaching status. We controlled for other factors that can affect hospital outcomes, including previous chronic conditions. Finally, we modelled the impact of state of health and age on length of stay using an interaction term.

On a theoretical level, we found that shorter length of stay on aggregate decreases hospital costs. Yet, at its boundaries, it can have negative long-term consequences. In spite of this consideration, the increase of healthcare expenditures is pushing hospital managers toward short-term strategies, such as length of stay reduction, that do not look at the whole cycle of care, but often address only the immediate needs of the patients and result in higher long-term costs (Porter and Teisberg 2006).

The economic implication of this research is that healthcare policies need to consider the case-mix complexity of their patient base when they implement length of stay reduction strategies. Despite the negative long-term effects for sicker patients and the elderly, this research suggests that decreasing length of stay for healthy patients, on aggregate, may be an effective strategy to curb healthcare expenditures. By diversifying the policy, however, one could both reap the benefits from shorter length of stay for the majority of patients, while reducing the risk (and associated cost) of readmission for certain patient groups at higher risk of complications. On balance we estimated that such a diversified policy could save up to £354 (US\$565) per non-emergency procedure, which equates to a 19.97% reduction in total cost for all elective hernia procedures performed on adults.

The next section develops the research hypotheses, Section 3 explains the method used in this research, and Section 4 presents the results of the empirical analyses. Finally, Section 5 discusses the practical relevance of our findings, and outlines our contributions to the debates in healthcare operations management.

## 2. Hypothesis development

Henry Ford famously stated that his customers could buy his cars in any color they wanted “so long as it is black” (York 2010), words that reflect a time period in which custom solutions were not seen as a source of competitive advantage. Standard solutions enable process improvement and the development of best practices to complete a given task (Bohmer 2009). While empirical evidence has reinforced the views expressed in these statements (e.g., Boyer and Pronovost 2010, Fullerton et al. 2014), companies have invested an increasing amount of resources in the attempt to adopt standard solutions and decrease costs. This trend has also driven hospitals (for which, as already discussed, standard policies have historically been seen as unwanted or not applicable) to introduce guidelines and protocols to streamline their processes.

There is a lively debate in academia on whether length of stay is associated with poor patient outcomes. While some researchers support the hypothesis that shorter length of stay leads to poor outcomes (e.g., KC and Terwiesch 2009, Shulan et al. 2013), others suggest that shorter length of stay either has no impact at all or leads to better outcomes (e.g., Bohmer et al. 2002, Hyer et al. 2009, Westert and Lagoe 1995).

In the first group of studies, KC and Terwiesch (2009) investigate cardiovascular surgery in the United States and find a relationship between shorter length of stay and higher risk of death. However, they do not investigate hospital readmissions and their results are based on the analysis of only one hospital. Conversely, Shulan et al. (2013) study readmission rates for a variety of Diagnosis Related Groups, analyzing the Veterans Healthcare Network Upstate New York dataset. However, since they use a cross-sectional approach, they cannot use longitudinal variation to control for omitted variables.

In the second group of studies, Bohmer et al. (2002) investigate discharge destination and readmission rates for coronary artery bypass graft operations in Massachusetts, emphasizing that, while length of stay is a common strategy in healthcare to reduce costs, its impact on outcomes such as readmission and death is not well understood. Since their dataset includes observations only from Massachusetts, they remove patients from other states, concluding that there is no evidence that longer length of stay decreases readmission and mortality rates. However, as in the study by Shulan et al. (2013), Bohmer et al. (2002) use a cross-sectional approach based on logistic regression and, for this reason, cannot use longitudinal variation to control for omitted variables. Moreover, not only do they not include variables to control for hospital characteristics, but they also do not consider patients' deprivation; a variable reflecting social, economic, and housing issues (King et al. 2011); that is likely to have an impact on likelihood of readmission/death, especially in the United States.

In addition, in-depth case studies have been conducted. Hyer et al. (2009) study an integrated trauma center in the United States using a framework based on four dimensions: the human and technical resources dimension, the spatial dimension including physical closeness, the process flow dimension, and the organizational dimension. They find that hospital stay is not necessarily correlated with higher mortality rates and suggest that focus can offset the negative effects of shorter length of stay. Westert and Lagoe (1995) claim that length of stay is "a major variable" to consider for the management of hospitals and use it to investigate hip replacement in two hospitals in the United States and two hospitals in the Netherlands. They analyze its variation for patients aged 65 or above and conclude that shorter length of stay increases the quality of healthcare delivery.

One of the aspects to consider, when interpreting studies that use administrative datasets, is the analysis of what length of stay measures. Given the structure of the most

common datasets (e.g., CMS, Centers for Medicare & Medicaid Services 2015, NHS, The Information Centre for Health and Social Care 2015), control variables include, typically, patient and hospital characteristics but exclude information on whether the operation was successful. Therefore, an increase in length of stay is not only associated with more days of recovery but, also, with complications.

Another question that arises is whether the class of a procedure affects the impact of a variation in its processing time and whether longer length of stay leads to better outcomes only for certain types of operations (Kim et al. 2014). Since recovery times are associated with the complexity and the length of the surgery, the positive effects of longer length of stay such as monitoring and support of patient recovery are plausibly lower for easier procedures such as inguinal hernia surgery.

The healthcare operations management literature, typically, does not contemplate the negative effects associated with number of days spent in the hospital, yet a longer length of stay can also expose healthy patients to the risk of avoidable infections (Hassan et al. 2010, Mitchell and Gardner 2012). In the 1800s wound infections were considered a normal part of the healing process (Sabbatani et al. 2014) and, after more than two hundred years, around 8.2% of patients still acquire an infection when they enter an NHS hospital (National Audit Office 2009). Methicillin-resistant *Staphylococcus aureus* (MRSA) infections, which occur in the surgical site or after the operation and affect open wounds and the bloodstream, and *Escherichia coli* (*E. coli*) infections, which affect the urinary tract, are among the most common (Bazian, edited by NHS Choices 2012, National Audit Office 2009). *Clostridium Difficile* (*C. diff.*) and *Acinetobacter* infections are also very common and affect the gastrointestinal system and the respiratory tract (National Audit Office 2009). Since longer length of stay is associated with higher risk of acquiring a hospital

infection, and since patients who develop an infection during or after the hospital stay need more time to recover and are more likely to experience complications after the hospital discharge, we formulate the following hypothesis:

*HYPOTHESIS 1. Longer patient length of stay is associated with worse patient outcomes such as higher risk of readmission and higher risk of death.*

Assuming that  $h^k(t) = f(\text{lostay}, \mathbf{W})$  where  $k = 1$  denotes the instantaneous risk of readmission and  $k = 2$  the instantaneous risk of death,  $\text{lostay}$  is length of stay, and  $\mathbf{W}$  represents all the other variables, the first hypothesis can be expressed as  $\frac{\delta h^k(t)}{\delta \text{lostay}} > 0$  for  $k = 1, 2$ .

This study responds to the call to investigate the impact of case-mix “severity” on patients’ early discharge (KC and Terwiesch 2009). Patients in poor physical conditions need more time to recover and, for this reason, we expect the benefits of longer length of stay to have a greater impact on them. There is another factor to consider: the need to monitor vital signs is greater for sicker patients since failure to do that can lead to hospital readmission or death.

Patient mobility after the operation, which contributes to the healing process, also requires special attention when considering sick patients (Bazian, edited by NHS Choices 2011). However, while healthy patients are generally able to walk and follow a program of exercises by themselves, sick patients need to stay in the hospital if they require the support of the medical staff to perform these activities.

Since infections are, intuitively, more likely to develop in sicker patients, we must also consider that longer length of stay could expose this class of patients to a higher risk of acquiring an infectious disease. However, there is empirical evidence showing that infections

are not more likely to develop in patients with some common pre-existing conditions (e.g., Appelgren et al. 2001, Chen et al. 2014).

The idea that length of stay should not be the same for both sick and healthy patients is, as discussed, also related to the concept of enforcing a standard process. As suggested in Bohmer (2009), patient selection is one of the possible ways to standardize healthcare processes and hospitals should use different protocols to meet the needs of different types of patients. For example, patients with multiple chronic conditions need a tailored and longer process of care; in the same manner, products in a “job-shop” require a flexible production system and longer lead times (Bohmer 2009).

We can apply standard policies to inguinal hernia surgery because, when we consider healthy patients, we can formalize the treatments they need to receive (Simons et al. 2009). We know that the majority of these patients does not need to spend the night in hospital, which implies that hospital managers can increase day case surgery rates without the fear of causing higher readmission or mortality rates. Conversely, we are required to manage complex hernia patients with a process of care tailored to their needs.

Given these considerations, we formulate the following hypothesis:

*HYPOTHESIS 2. The severity of a patient's illnesses affects the relationship between length of stay and hospital outcomes: the sicker the patient, the greater the benefits of longer length of stay on the risk of readmission and risk of death.*

Assuming that  $h^k(t) = f(\text{lostay}, \text{lostay} * \text{charl\_ind}, \mathbf{W})$  where `charl_ind` measures state of health (via the Charlson index, Charlson et al. 1987, KC and Terwiesch 2011, Kucukyazici et al. 2011), the second hypothesis can be expressed as  $\frac{\delta^2 h^k(t)}{\delta \text{lostay} \delta \text{charl\_ind}} < 0$  for  $k = 1, 2$ .

One of the challenges of discharging patients from a hospital is to find someone who can monitor their condition when they go home (Lee et al. 1998). This problem becomes more complicated with the elderly who live alone. When the pressure to cut costs pushes doctors to send home patients who need a longer period of monitoring, then the risk of readmission and risk of death increase.

It is also well known that the elderly spend more time in the hospital because the likelihood of poor surgical outcomes increases with age (e.g., Anderson et al. 2002, Clement et al. 2008, Marshall et al. 2004). The same considerations about standard policies that we illustrated for sick and healthy patients are also valid when we consider the elderly and young patients.

When we consider the elderly it also becomes less clear whether the benefits of a surgical procedure offset its risks, which often causes general practitioners to delay the decision to refer patients for surgery (Ryynänen et al. 1997). Delayed referrals cause hernias to become more complex and patients to need more time to recover after surgery.

Given these considerations, we formulate the following hypothesis:

**HYPOTHESIS 3.** *The age of a patient affects the relationship between length of stay and hospital outcomes: the older the patient, the greater the benefits of longer length of stay on the risk of readmission and risk of death.*

Assuming that  $h^k(t) = f(\text{lostay}, \text{lostay} * \text{char1\_ind}, \text{lostay} * \text{age}, \mathbf{W})$  where **age** measures age, the third hypothesis can be expressed as  $\frac{\delta^2 h^k(t)}{\delta \text{lostay} \delta \text{age}} < 0$  for  $k = 1, 2$ .

### 3. Method

Our study was conducted in close collaboration and with guidance from the Unit of Health Care Epidemiology at the Medical Sciences Division of the University of Oxford. In order

to study the effects of length of stay reduction, we used a database of 183,712,784 medical records from 1998 to 2012. The database includes medical records from the HES data warehouse, capturing diagnoses, procedures, date of admission and discharge, and demographic information about NHS patients, which have been linked with death certificates provided by the Office of National Statistics using the Oxford record linkage system (Gill and Goldacre 2003). We included information on hospital facilities such as foundation status and number of beds linking HES to HEFS data.

We focused on patients diagnosed with inguinal hernia (ICD-10 code K40) who undergo a surgical procedure (OPCS-4 code T20 and T21) in an NHS public sector hospital between 1999 and 2009. We excluded patients after 2009 because death information is incomplete after January 2011.

We used the variables `age`, `charl_ind`, and `lostay` to test the three hypotheses. The variable `age` measures the individual age of the patient in years at the start of the hospital stay. We used the variable `lostay` to calculate the number of days between admission and discharge, one of the measures most commonly used in the literature (e.g., Carey and Stefos 2011, Hoffer Gittell 2002, Hofmarcher et al. 2002). In order to increase the interpretability of the results, we divided it by its standard deviation. Finally, we included the variable `charl_ind` to calculate the Charlson index, a measure of an individual's state of health (Charlson et al. 1987, KC and Terwiesch 2011, Kucukyazici et al. 2011). We computed it on the basis of more than 280 different diagnoses, using the SAS macro **CharlsonICD10** (Quan et al. 2005, Turner and Burchill 2006).

In order to calculate the statistical association between `lostay` and probability of death and readmission, this research used Cox regression (Guo 2010). We added to the time variables, which are number of days to death and to readmission, an arbitrarily small

constant to account for deaths and readmissions on the last day in hospital. As explained in Section 4.4, we ran two checks to investigate the robustness of our results when considering in-hospital mortality. The censoring date is 12/31/2010 for time to death and 12/31/2011 for time to readmission. This choice is consistent with the data available, since information from death certificates is complete up to January 2011 and information from medical records is complete up to January 2012.

Table 1 lists the control variables that we included in the regression models. At the patient level we included a variable for type of admission and we used the Index of Multiple Deprivation (IMD) to account for socio-economic status (for a more detailed description of this index refer to King et al. 2011). We also included control variables to identify private patients, patients admitted from the waitlist (see Kuntz et al. 2014), and patients admitted during the weekend (see KC and Terwiesch 2009). Previous research has shown that patients that are admitted on Saturday or Sunday are more likely to experience worse outcomes than patients admitted during the rest of the week, (e.g., Aylin et al. 2013, Wise 2012). Risk factors are also gender (Simons et al. 2009), keyhole surgery (Simons et al. 2009), and recurrence (Schumpelick and Fitzgibbons 2010). We included a control variable to account for type of admission. This variable is 1 if the patient is an emergency patient and 0 if he/she is an elective patient. At the hospital level we included variables to control for focus on inguinal hernia surgery and for governance model, since a foundation trust has more managerial and financial flexibility (National Audit Office 2011). We also controlled for workload (see KC and Terwiesch 2009), for number of beds, and for teaching status.

We used the interaction term `lostay*charl_ind` to test the second hypothesis that the impact of length of stay depends on the state of health of the patient, and the interaction term `lostay*age` to test the third hypothesis that the impact of length of stay depends on

**Table 1 List of Control Variables**

Name	Explanation
<code>eme_ind</code>	Emergency patient
<code>focus</code>	Proportion of patients who undergo inguinal hernia surgery in the general surgery department of the hospital
<code>foundation</code>	Foundation status of the hospital
<code>imd_score</code>	IMD score of the patient
<code>laparoscopic</code>	Surgery performed laparoscopically
<code>male</code>	Male patient
<code>n_beds</code>	Number of beds in the hospital
<code>occupied</code>	Proportion of occupied beds in the hospital
<code>private</code>	Private patient
<code>recurrence</code>	Recurrent procedure
<code>teaching</code>	Teaching status of the hospital
<code>waitlist</code>	Patient admitted from the waitlist
<code>week_ind</code>	Patient admitted during the weekend (Saturday or Sunday)

**Table 2 Summary statistics and correlation table**

	Mean(Std. Dev.)	readm	death	age	charl_ind	lostay
<code>readm</code>	0.665 (0.472)	1				
<code>death</code>	0.146 (0.353)	0.215	1			
<code>age</code>	57.902 (18.539)	0.306	0.384	1		
<code>charl_ind</code>	0.160 (0.547)	0.083	0.197	0.171	1	
<code>lostay</code>	1.320 (4.580)	0.077	0.206	0.173	0.204	1

the age of the patient. We demeaned the components of the interaction terms to increase the interpretability of the variables.

The two measures of hospital outcomes we considered are risk of readmission and risk of death. We followed the patients using all the data we have available. Table 2 reports correlation values for the variables of interest in this study. The binary variable `readm`, indicating if a patient is readmitted to hospital and the binary variable `death`, indicating if a patient dies after surgery, are positively related to each other. They are also positively related to `age`, `charl_ind`, and `lostay`.

One of the main drawbacks of using dummy variables to model fixed effects in non-linear models is the incidental parameters problem (Allison 2009). The estimation of fixed effects introduces an error that biases the estimation of the other coefficients. For this reason, in order to include hospital fixed effects, we stratified the regression models. For every observation, we included a baseline hazard that depends on the hospital  $j$  where the

patient undergoes the operation. For example, for  $k = 1, 2$ , given a vector  $\mathbf{x}$  representing the control variables and  $N$  hospitals in the sample, the original formulation of the model with all variables:

$$h_1^k(t) = h_0^k(t) e^{\beta_1 \text{lostay} + \beta_2 \text{charl\_ind} + \beta_3 \text{age} + \beta_{12} \text{lostay} * \text{charl\_ind} + \beta_{13} \text{lostay} * \text{age} + \mathbf{x}\beta_4}$$

becomes the following system of equations:

$$h_{1j}^k(t) = h_{0j}^k(t) e^{\beta_1 \text{lostay} + \beta_2 \text{charl\_ind} + \beta_3 \text{age} + \beta_{12} \text{lostay} * \text{charl\_ind} + \beta_{13} \text{lostay} * \text{age} + \mathbf{x}\beta_4} \quad j = 1, \dots, N$$

In order to calculate the economic impact of a change in length of stay, we computed the marginal effects of this variation. When we consider the model, for a hospital  $j$ , the partial derivative of the hazard function with respect to `lostay` has the following mathematical formulation:

$$h_{2j}^k(t) = \frac{\delta h_{1j}^k(t)}{\delta \text{lostay}} = h_0^k(t) (\beta_1 + \beta_{12} \text{charl\_ind} + \beta_{13} \text{age}) e^{\beta_1 \text{lostay} + \beta_2 \text{charl\_ind} + \beta_3 \text{age} + \beta_{12} \text{lostay} * \text{charl\_ind} + \beta_{13} \text{lostay} * \text{age}}$$

The impact of the variation of `lostay` on risk of readmission or death is the following:

$$h_{3j}^k(t) = \frac{h_{2j}^k(t)}{h_{1j}^k(t)} = (\beta_1 + \beta_{12} \text{charl\_ind} + \beta_{13} \text{age}) \quad (1)$$

We calculated the standard errors of a variation in `lostay` using the formula (Brambor et al. 2006):

$$\begin{aligned} \sigma_{h_{3j}^k(t)}^2 = & \text{var}(\beta_1) + \text{charl\_ind}^2 * \text{var}(\beta_{12}) + \text{age}^2 * \text{var}(\beta_{13}) + \\ & 2 * \text{charl\_ind} * \text{Cov}(\beta_1, \beta_{12}) + 2 * \text{age} * \text{Cov}(\beta_1, \beta_{13}) \end{aligned} \quad (2)$$

In order to validate the findings, we ran a competing risk analysis for the dependent variable probability of readmission, censoring from the study the patients that die. Additionally, we ran the same analysis for the dependent variable risk of death. Patient readmission can, in fact, prevent a patient's death.

## Cost savings

We calculated total costs of care using the cost allocation protocol defined by the UK Department of Health (Department of Health 2012b). Please see Appendix A for more details on this protocol.

We used the costs we calculated to devise a healthcare policy with the objective of minimizing total costs of care. This objective is subject to the constraint of not increasing the risk of readmission or death for any patient. We proposed to use the thresholds for `age` and `charl_ind` identified by solving Equation 1 with the values obtained from the Cox regressions and the competing risk analysis models. We applied this policy to elective patients and patients aged over 18 in our dataset, who are, approximately, 92% of the patient population. We argue that physicians should have total freedom of choice for non-elective patients and minors.

We report total cost savings per procedure in US dollars and the decrease in the cost of the procedure in percentage terms.

## 4. Results

### 4.1. Cox regression models

Table 3 lists the models and the variables we used to test the hypotheses. Table 4 and Table 5 report the results of the Cox regression models and include the total time at risk, that is the sum of the time from discharge to readmission, death or censor date for every patient. The likelihood ratio is consistently less than 0.0001, the number of hospitals is 238, and the total number of observations including emergency and elective patients is 636,616. The tables also report odds-ratios and z-tests for all the independent variables.

As reported in Table 4, the values of the odds-ratios of the variables `age`, `charl_ind`, and `lostay` are significant and greater than 1 in all models. The odds-ratios of the first two variables support the common assumption that the elderly and sicker patients are more

likely to be readmitted. The values of the odds-ratio of the variables `lostay * charl_ind` and `lostay * age` are significant and less than 1 in all models.

**Table 3 Regression models and their variables**

	Model (1)	Model (2)	Model (3)	Model (4)
age	•	•	•	•
charl_ind	•	•	•	•
lostay	•	•	•	•
lostay * charl_ind		•		•
lostay * age			•	•
Control Variables	•	•	•	•

**Table 4 Cox regression models for the dependent variable risk of readmission**

Odds-ratio	Model (1)	Model (2)	Model (3)	Model (4)
age	1.0255*** (84.21)	1.0253*** (83.58)	1.0255*** (84.91)	1.0254*** (84.11)
charl_ind	1.1440*** (31.72)	1.1910*** (40.06)	1.1474*** (32.38)	1.1897*** (39.96)
lostay	1.0126*** (5.47)	1.0276*** (8.40)	1.0193*** (6.58)	1.0299*** (8.53)
lostay * charl_ind		0.9690*** (-16.28)		0.9708*** (-15.22)
lostay * age			0.9993*** (-5.94)	0.9997*** (-3.16)
N. Obs.	636,616	636,616	636,616	636,616
N. of. Hospitals	238	238	238	238
Total time at risk	853,760,626	853,760,626	853,760,626	853,760,626
<i>Likelihood Ratio</i>	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Notes. Standard errors are clustered at the hospital level. Asymptotic z-tests are reported in parentheses. Control variables include `eme_ind` focus, `foundation`, `imd_score`, `laparoscopic`, `male`, `n.beds`, `occupied`, `private`, `recurrence`, `teaching`, `waitlist`, and `week_ind`.

\* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Table 5 reports the results for the outcome variable risk of death and we see that the value of total time at risk is greater than in Table 4. The values of the odds-ratios of the variables `age`, `charl_ind`, and `lostay` are significant and greater than 1 in all models such as those in Table 4. Not surprisingly, the variables `lostay * charl_ind` and `lostay * age` are also significant and less than 1.

The results reported in Table 4 and Table 5 provide evidence to support the first, the second, and the third hypothesis for both the outcome variables.

If we consider Equation 1 and Equation 2, we can calculate when a variation in length of stay is significant and decreases readmission and death rates. Table 6 reports these thresholds and shows that an increase in length of stay decreases, for instance, readmission rates for patients with a Charlson index greater than 2, for patients with a Charlson index of 2 and aged 18 or above, and for patients with a Charlson index of 1 and aged 89 or above.

We can also use Equation 1 to calculate the impact of increasing length stay by one standard deviation. For example, if we have a 66-year-old patient with a Charlson index of 7, increasing length of stay by 4.580 days decreases the risk of readmission by 18.10% and the risk of death by 8.05%, respectively. The effect size is to be expected given that our policy addresses a secondary aspect of the procedure (the post-OP stay) rather than the actual procedure (the surgery), and is in line with other research that analyzed the effects of length of stay in healthcare (Bartel et al. 2016).

**Table 5 Cox regression models for the dependent variable risk of death**

Odds-ratio	Model (1)	Model (2)	Model (3)	Model (4)
age	1.1034*** (118.12)	1.1032*** (117.78)	1.1038*** (118.14)	1.1036*** (117.40)
charl_ind	1.3943*** (41.00)	1.4319*** (44.69)	1.3966*** (41.90)	1.4291*** (44.98)
lostay	1.0354*** (8.11)	1.0457*** (9.48)	1.0582*** (13.68)	1.0617*** (11.45)
lostay * charl_ind		0.9863*** (-5.66)		0.9879*** (-5.36)
lostay * age			0.9988*** (-7.87)	0.9991*** (-4.24)
N. Obs.	636,616	636,616	636,616	636,616
N. of. Hospitals	238	238	238	238
Total time at risk	853,760,626	853,760,626	853,760,626	853,760,626
<i>Likelihood Ratio</i>	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Notes. Standard errors are clustered at the hospital level. Asymptotic z-tests are reported in parentheses. Control variables include `eme_ind` focus, `foundation`, `imd_score`, `laparoscopic`, `male`, `n_beds`, `occupied`, `private`, `recurrence`, `teaching`, `waitlist`, and `week_ind`.

\* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

## 4.2. Competing risk analysis models

The values of the odds-ratios of the variables `age`, `charl_ind`, and `lostay` for the outcome variable risk of readmission are again significant and greater than 1. While the values of the odds-ratios of the variable `lostay * charl_ind` are still significant and less than 1, the value of the odds-ratio of the variable `lostay * age` is significant in Model (3) but not in Model (4).

Also in the case of risk of death, the odds-ratios of the variables `age`, `charl_ind`, and `lostay` are, not surprisingly, significant and greater than 1 and the odds-ratios of the variable `lostay * charl_ind` are significant and less than 1. The odds-ratios of the variable `lostay * age`, however, are not significant.

**Table 6** Age threshold (in years) at which increasing length of stay decreases readmission and death rates significantly ( $p < 0.1$ )

charl_ind	<i>Cox regression</i>		<i>Competing risk analysis</i>	
	readm	death	readm	death
0	-	-	-	-
1	89	-	-	-
2	18	-	-	-
3	0	-	-	-
4	0	90	-	-
5	0	79	-	-
6	0	69	-	-
7	0	60	46	-
8	0	51	11	-
9	0	43	0	-
10	0	34	0	-
11	0	26	0	-
12	0	17	0	-

These results provide evidence to support the first and the second hypothesis for both the outcome variables. While they provide some evidence to support the third hypothesis for the outcome variable risk of readmission, the evidence for the outcome variable risk of death is limited to the coefficients of the odds-ratios being less than 1.

In Table 6, we also report the thresholds at which length of stay decreases significantly readmission and death rates for the competing risk analysis models. Increasing length of stay decreases risk of readmission for patients with a Charlson index greater than 8, for patients with a Charlson index of 8 and aged 11 or above, and for patients with a Charlson index of 7 and aged 46 or above. The impact of length of stay on risk of death is not significant for any values of charl\_ind and age.

#### 4.3. Defining the thresholds for a customized policy

As discussed in Section 3, the customized policy we proposed is based on the thresholds of the Cox and competing risk analysis models that identify the groups of patients that are mostly likely affected by a decrease in length of stay. The shaded area in Figure 2

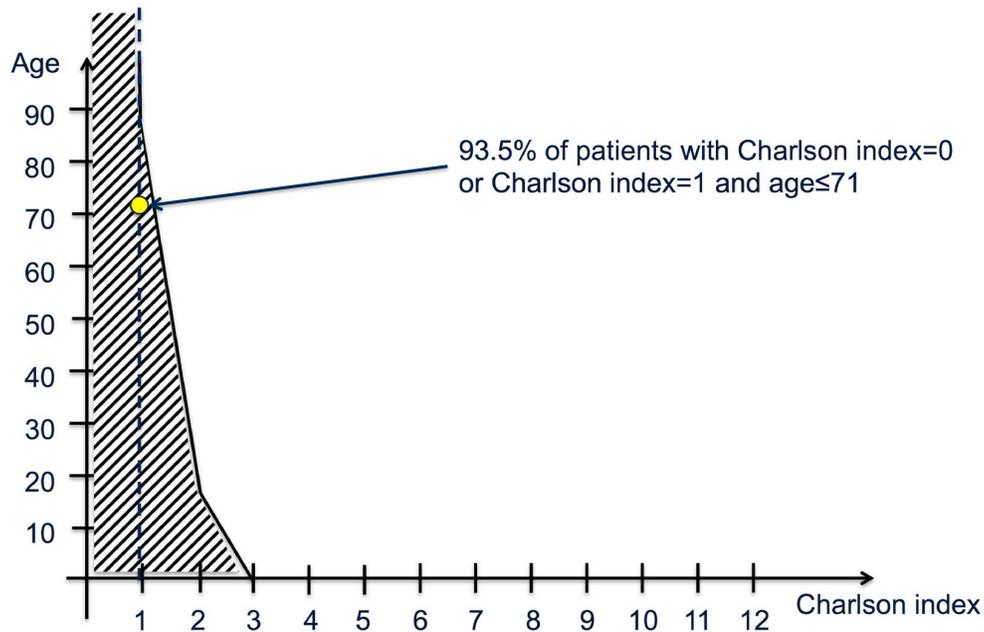
represents graphically the thresholds at which decreasing length of stay does not increase significantly risk of readmission and risk of death for the Cox regression models. In order to offer a conservative estimate of when to reduce length of stay, we calculated the thresholds at which length of stay does not increase the risk of readmission and the risk death without considering statistical significance and we found that (`charl_ind = 1` and `age = 71`) are the thresholds of the Cox regression models and that (`charl_ind = 5` and `age ≤ 33`) are the thresholds for the competing risk analysis models. We selected the thresholds of the Cox regression models because they are more stringent than the thresholds of the competing risk analysis models.

Our findings suggest that patients with (`charl_ind = 0`) and patients with (`charl_ind = 1` and `age ≤ 71`) should be treated as day cases since decreasing length of stay has a positive effect on their risk of readmission/death. Since our objective is to minimize costs, subject to the constraint of not increasing the risk of readmission or death for any patient, we also propose not to modify length of stay for patients with (`charl_ind = 1` and `age > 71`) or with (`charl_ind > 1`). The total cost savings of the proposed algorithm are around £354 (US\$565) per procedure, which equates to a 19.97% reduction in the cost of the surgical procedure.

#### 4.4. Robustness of findings

We performed several robustness tests to assess whether our results are still valid when we changed our sample, the definition of our variables, and the models we used (Clark and Huckman 2012).

First, we ran the regression models changing the definition of sick patient. While a healthy patient is a patient with `charl_ind = 0`, a sick patient is a patient with `charl_ind > 0`. Second, in order to verify that the number of observations to stratify the



**Figure 2** Graphical representation of the thresholds at which increasing length of stay decreases readmission and death rates significantly ( $p < 0.1$ ) for the Cox regression models. The shaded area represents the values of a patient's Charlson index and of a patient's age (in years) at which decreasing length of stay does not increase significantly risk of readmission and risk of death

regressions is sufficient, we increased the minimum number of observations we used to 10. Third, we ran another test excluding patients aged 18 or below because pediatric inguinal hernia surgery is in some ways very different from the surgery on adults (Puri and Höllwarth 2006). Fourth, we reran this test on all the sample, using a dummy variable to identify patients aged 18 or below. Fifth, we changed the definition of elderly patients and define an elderly patient as a patient of  $\text{age} > 65$ . Sixth, we reran this test and define an elderly patient as a patient of  $\text{age} > 80$ . Seventh, we censored patients who die in hospital. Eighth, we changed the models we used and propose a conditional logistic model instead. We did not use logistic regression because in this type of models it is not possible to include hospital fixed effects. Ninth, we investigated reverse causality by employing a

Granger causality test (Granger 1969) on the monthly time series. Tenth, we tested for a possible extrapolation bias using Propensity Score Matching (PSM) (Guo and Fraser 2014, Vansteelandt and Daniel 2014).

In summary, the results of the robustness checks confirm where significant results could be obtained.

## **5. Discussion**

### **5.1. Summary of key findings**

We have investigated the effect of standardized healthcare policies on patient outcomes. Specifically, we have focused on the length-of-stay reduction policy, and have put the notion that reducing the length of stay improves patient outcome to the empirical test. Using the case of inguinal hernia surgery, we find that for the majority of patients decreasing length of stay is associated with lower risk of readmission and risk of death. This result is consistent with the current recommendations of the National Institute for Clinical Excellence and of the Royal College of Surgeons for this procedure (National Institute for Clinical Excellence 2006, Royal College of Surgeons 2013). Considering the fact that we are investigating a secondary effect – as distinct from changes to the surgical procedure itself – the overall effect size is significant. What we show, in essence, is that a standardized policy can have an overall beneficial effect on the patient outcome, yet at the same time be detrimental to certain patients. Our model proposes that these two contrarian views – standardized policy versus customized treatment – can be combined by calculating the thresholds where a shorter length of stay leads to adverse outcomes for the patients. Our findings have both direct practical relevance for the delivery of services, leadership practices, knowledge sharing amongst health care workers, as well as wider theoretical implications for managing healthcare operations. We outline both below, respectively.

## 5.2. Practical relevance

Our results first and foremost confirm the existing doctrine of reducing the length of stay, for hernia surgery, and beyond. The novel aspect of our findings, in practical terms, is the finding that enforcing a uniform policy to reduce length of stay is likely to cause higher readmission and death rates for certain groups of patients or, more specifically, for vulnerable and elderly patients. We also know that a longer stay could expose healthy patients to hazards such as the risk of hospital-acquired infections (HAIs). We find that a customized policy for delivering healthcare to different types of patients may lead, across all patients, to better outcomes. Based on our empirical findings we have calculated the thresholds that would only extend the length of stay for hernia patients with a certain combination of age and vulnerability. Here our findings confirm previous studies, such as (Aldoescu et al. 2015), that also had identified age as a key variable in determining the outcome of the surgery. We have validated our findings by proposing our suggested approach to three general surgeons, also asking them to outline the common reasons in their experience for not discharging hernia patients on the day of surgery. Their rich reflections were largely consistent with the results found in this research, suggesting that only vulnerable and old patients should stay longer in hospital after the surgery to be more closely supervised than otherwise possible. Healthy patients who are not discharged on the day of the operation are, in most cases, patients who choose to stay in the hospital after surgery. Surgeons often do not contest these decisions because of the risk of being sued for medical malpractice. An appreciation of how ‘macro’ policies and ‘micro’ actions related to a specific patient are connected, and how do they influence and co-constitute each other, are challenging questions that healthcare managers and policy makers will need to debate further.

From a policy point of view, this patient group can represent a major opportunity to reduce the average cost per procedure. We estimate that possible savings from reducing

unnecessary stays alone to be US\$565 per procedure, which equates to a 19.97% reduction in the average cost of the surgical procedure. These savings are calculated on the basis of cutting unnecessary long stays for healthy patients. Extrapolated to the total number of 553,413 inguinal hernia procedures performed, this represents a potential cost saving of US\$312,678,345.

We have selected the inguinal hernia procedure as it is the most common surgical procedure in terms of volume, and highly standardized in terms of the procedure itself (Nyhus et al. 1991, Rutkow 2003). While we cannot conclusively comment on other surgical procedures, nor argue that the threshold values can be transferred, our theoretical findings nonetheless strongly suggest that the principle is universal: standardized policies that lead to an improvement on average will be detrimental to some patients. Our findings show that predisposition, such as prior illness, and age are factors that determine whether or not a prolonged convalescence period may be beneficial. As the risk of hospital-acquired infection and the risk of readmission are universal, we propose that this principle also applies generally, and should be factored into the length-of-stay decision for any surgical procedure.

Furthermore, we contribute to the general discourse on the impact of decreasing service time on patient outcome. Prior studies have suggested that decreasing processing time has a negative impact on hospital outcomes because doctors start to “cut corners” when they deliver care to patients (Kuntz et al. 2014) or they “become tired” (KC and Terwiesch 2009). We show that other factors such as hospital-acquired infections may also play a significant role in offsetting the negative impact of a shorter length of stay. Empirical evidence to support this argument has also previously been provided by Bohmer et al. (2002). We extend this work by showing the relevance of hospital effects that so far have not been considered.

### 5.3. Theoretical contributions

Our findings make two main contributions to the wider field of Operations Management in the healthcare context. First, we contribute to the debate on adopting standard policies for healthcare procedures (Bohmer 2009, Boyer and Pronovost 2010). Previous studies have suggested that standard policies such as decreasing length of stay are needed to curb costs and increase the quality of healthcare (Boyer and Pronovost 2010); the adoption of standard policies in hospitals has become a common means by which to increase efficiency. For example, many hospitals have adopted clinical guidelines (standard operating procedures) to manage the delivery of care (Andritsos and Tang 2014).

We both confirm and extend the underlying notion, by qualifying this argument by showing that an excessive emphasis on standard solutions can increase long-term costs. We find that standard policies – while beneficial on aggregate – are not uniformly associated with better results, and that customized solutions can decrease failure costs. This debate is in fact analogous to the standardization versus customization debate in manufacturing. Manufacturing standardized products leads to economies of scale, reducing its unit cost in production; customizing products on the other hand improves the match with customer needs and desires, improving unit profitability (Holweg and Pil 2001, Salvador et al. 2009). Yet more recent research has suggested that manufacturers should merge both approaches, and provide a “multi-modal” approach to order fulfilment that seeks to maximize the outcome, not optimize the efficiency of its delivery (Lawson et al. 2018, Cattani et al. 2010).

We propose that an analogous strategy might prove beneficial in healthcare operations, namely to differentiate its delivery in response to specific customer need. Several studies (Fogliatto et al. 2012, Piller et al. 2004, Squire et al. 2004) have suggested that customized

solutions in manufacturing can increase the value offered to customers and decrease integration costs. Despite the increasing – and justified – adoption of standard policies, “one-size fits all” solutions could have unintended negative consequences in healthcare. We argue that the same theoretical principles that applies in manufacturing also apply to healthcare operations, whereby differentiated (or customized) policies can improve the overall outcome (or value) for the patient as consumer of the service. In essence, we argue that the same tension that manufacturers face when deciding to what degree to customize their product offering equally applies to healthcare providers deciding to what degree their policies can be standardized. More generally, our findings highlight that a more nuanced exploration of context is required when tackling the challenges in healthcare delivery outlined in this article. A new approach to leadership is needed that is capable of addressing complex problems, as distinct from merely accepting and enforcing standard policies. There is a strong theme emerging in studies of change management in healthcare that adaptive leadership styles are needed to support multidisciplinary discussions that consider patient outcome and cost within the context of the wider healthcare system and the changing demographics of its users (Ferlie et al. 2013).

#### **5.4. Limitations and future research**

Our findings should be considered in the light of the limitations of the data available. Although one of the most comprehensive datasets on patient records, HES data does not have a variable to qualify the relative success of a surgical procedure and, therefore, we cannot include this component of the length of patient stay. Another factor to take into account is that while death data comes from death certificates, we only use HES data to calculate readmissions and, consequently, we do not account for patients who leave England or go to a non-NHS hospital. However, we expect these patients to be a minority since the

NHS is a universal system and the probability of undergoing inguinal hernia surgery and, at the same time, leaving England is very low (statistical data on number of UK residents living abroad is provided in Osborne 2012).

A further possible limitation is also the choice of the Charlson Index as a measure of a patient's state of health. The Charlson Index is one of most common measures in the medical literature (Siegel and Olshansky 2011); it captures more than 280 comorbidities (Quan et al. 2005, Turner and Burchill 2006), and it has been called the "best known measure" of a patient's state of health (Newman and Cauley 2012, Smith et al. 2005). We cannot, however, exclude the possibility that other comorbidities omitted herein may also be relevant.

This research is also based on data from NHS public sector hospitals and, therefore, it does not immediately follow that all aspects of it can be extended to other healthcare systems. Nevertheless, healthcare systems similar to the NHS have been adopted in several countries (Costigliola 2012). Moreover, excluding private hospitals eliminates providers that have a lower incentive to decrease readmission rates (Gauld 2009). Finally, we have to consider a possible limitation of the competing risk analysis models that censor patients who die when we study risk of readmission and patients who go back to hospital when we study death. In the case of readmissions, the assumption to censor patients who die seems reasonable since they are leaving the study. In the second case, censoring patients readmitted to hospital is equivalent to removing the most difficult cases, and, for this reason, the Cox regression models may offer better insight on the hypotheses we test.

Our study opens several avenues for further research: first and foremost, confirmatory studies are needed to extend and verify that our findings can be replicated for other surgical procedures, and thereon, for any healthcare procedure. Being able to quantify the

opposing risks and quantify the thresholds at which the outcome flips would allow for the development of data-based decision-support systems that would allow the physician to determine the optimal length of stay for each patient. Such a system could be a prime example of a supervised machine learning application in operations management (Russell and Norvig 2016). Enabled by electronic patient recordkeeping, and the capture of outcome data herein, healthcare provides a fruitful ground for the application of data-driven decision-making tools.

### **5.5. Outlook**

Healthcare systems around the globe are under fiscal pressure to curb expenditures, having to deal with changing demographics and rising costs per treatment. Improving the efficiency of hospital operations has become a cornerstone of the response to these challenges (Kaplan and Porter 2011), and the adoption of standard policies in hospitals has become a common means by which to achieve this goal (Bohmer 2009, Andritsos and Tang 2014, Boyer and Pronovost 2010). Our results show that – as a field – we are only beginning to understand the full implications of the implementation of standard policies. More research is clearly needed to identify all relevant variables that determine patient outcome, the immediate cost of conducting the respective procedure, as well as any cost of failure that may develop in the longer term. Standardization is a powerful tool that is tried and tested in manufacturing, yet offering differentiated policies may be a more effective strategy to decrease long-term failure costs in healthcare. As the field of healthcare operations management matures, we should look to existing operations management theory for inspiration, yet also question its transferability. The most common sentiment healthcare practitioners will express when talking about adopting operations management tools and techniques is that “patients are not widgets, physicians are not robots”, and standardized policies can easily be perceived as

“taylorist” cost-reducing tools (Hartzband and Groopman 2016). Operations management has unquestionably a lot to offer to healthcare, yet we must never lose sight of the context in which it operates.

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## Appendix A Procedure for cost calculations

In order to calculate the costs for a continuous inpatient spell in the dataset used in our study, we first listed all the finished consultant episodes (FCEs) related to the patient's hospital stay. Then, based on this list, we created a CSV file that becomes the input for the HRG Grouper Software v2.34. This file includes, for every medical episode, information such as patient demographics and the diagnoses and procedures he/she underwent. For every record in the input file, the HRG Grouper creates one or more Health Related Groups (HRGs).

The cost allocation described in (Department of Health 2012b) is based on HRGs, on reference costs, on whether the patient is a day case or not, and on a length of stay trimpoint. The Department of Health provides 2011/2012 reference costs and trimpoints for every HRG by type of admission (Department of Health 2012b). We used these reference costs and trimpoints for our calculation.

The total cost of a medical episode for a day case patient thus is calculated as the sum of the primary HRG day case reference cost and of the unit reference costs of the remaining HRGs; the total cost of a medical episode for an ordinary admission is calculated as the sum of the primary HRG ordinary admission reference cost, of the cost of every day of stay exceeding the trimpoint, and of the reference costs of the remaining HRGs.

To summarize, given a patient  $v$ , a hospital  $j$ , and a HRG  $h$ , we used the following information:

- Day case reference cost for primary HRG  $h$ :  $c_h^d$ ;
- Ordinary admission reference cost for primary HRG  $h$ :  $c_h^o$ ;
- Excess ordinary admission reference cost per diem for primary HRG  $h$ :  $e_h^o$ ;
- Trimpoint for primary HRG  $h$ :  $p_h$ ;

- Unit reference cost for every additional HRG  $u$ :  $c_u$ ;

Given a binary variable  $r_{vjht}^d$  that is 1 if there is a day case admission  $v$  to a hospital  $j$  in year  $t$  for a primary HRG  $h$ , and 0 otherwise, and a binary variable  $z_{vjut}$  that is 1 if there is an admission  $v$  to a hospital  $j$  in year  $t$  for an additional HRG  $u$ , and 0 otherwise, the total cost of day case admissions to hospital  $j$  in year  $t$  is the following:

$$\text{cost}_{jt}^d = \sum_v \sum_h c_h^d r_{vjht}^d + \sum_v \sum_u c_u z_{vjut}$$

Given a binary variable  $r_{vjht}^o$  that is 1 if there is an ordinary admission  $v$  to a hospital  $j$  in year  $t$  for a primary HRG  $h$ , and 0 otherwise, and a variable  $l_{vjht}$  that measures the number of days required by an ordinary admission  $v$  to a hospital  $j$  in year  $t$  for a primary HRG  $h$ , the total cost of ordinary admissions to hospital  $j$  in year  $t$  is the following:

$$\text{cost}_{jt}^o = \begin{cases} \sum_v \sum_h c_h^o r_{vjht}^o + \sum_v \sum_u c_u z_{vjut} & \text{if } l_{vj} \leq p_h \\ \sum_v \sum_h c_h^o r_{vjht}^o + \sum_v \sum_h c_h^o r_{vjht}^o (l_{vjht} - p_h) + \sum_v \sum_u c_u z_{vjut} & \text{if } l_{vj} > p_h \end{cases}$$

An example can further illustrate the methodology presented and clarify its details. Let us consider an elective patient that undergoes an inguinal hernia operation. After we run the HRG Grouper Software v2.34 for this procedure, we find that the primary HRG of the operation is FZ18B and that there is an additional HRG XD34Z. In the reference costs tables we find the descriptions of these HRGs and their costs: the first HRG is “Inguinal, Umbilical or Femoral Hernia Procedures, 19 years and over with Intermediate CC” with a cost of £2,050, the second HRG is, instead, “Immunoglobulins, Band 1” with a cost of £1,288. If we further assume that this episode is exceeding its trimpoint by two days, we need to take into account of the excess ordinary admission reference cost per diem which is £340. We can now calculate the total cost of this surgery, which equates to £2,050+£1,288+£340\*2=£4,018.