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Hospital readmission rates: Signal of failure or success?

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ABSTRACT

Hospital readmission rates are increasingly used as signals of hospital performance and a basis for hospital reimbursement. However, their interpretation may be complicated by differential patient survival rates. If patient characteristics are not perfectly observable and hospitals differ in their mortality rates, then hospitals with low mortality rates are likely to have a larger share of un-observably sicker patients at risk of a readmission. Their performance on readmissions will then be underestimated. We examine hospitals' performance relaxing the assumption of independence between mortality and readmissions implicitly adopted in many empirical applications. We use data from the Hospital Episode Statistics on emergency admissions for fractured hip in 290,000 patients aged 65 and over from 2003 to 2008 in England. We find evidence of sample selection bias that affects inference from traditional models. We use a bivariate sample selection model to allow for the selection process and the dichotomous nature of the outcome variables.

Outcome-based measures of quality for hospitals, such as risk adjusted mortality and 28 days readmissions rates from specific type of admissions, are publicly released, for example in the US by the Centres for Medicare and Medicaid Services (CMS), in the UK by the National Centre for Health Outcomes Development (NCHOD), and in Australia by the Australian Institute of Health and Welfare (AIHW). Amongst other things, they are intended to inform patient choice of hospital, to monitor hospital performance and to promote improvement.

Moreover, outcome-based measures are increasingly being used as the basis for financial incentives for providers. For example, the English National Health Service (NHS) has introduced new rules for the reimbursement payments that seek to address rising trends in emergency admissions. From the fiscal year 2011,[1] automatic payments to hospitals will stop for all emergency admissions occurring within 30 days of a previous discharge. Emergency readmissions following elective admissions will receive no payment, while emergency readmissions following non-elective admissions will receive no payment beyond a threshold based on at least a 25% improvement in the historic rate of readmission (Department of Health, 2011). Similarly, the US Congress has passed legislation that allows the CMS to hold hospitals accountable for their readmissions rate (Foster and Harkness, 2010), with the objective of reducing the associated costs and volume of treatment. The Patient Protection and Affordable Care act gives the CMS the authority to penalise hospitals for excess readmissions by reducing reimbursement payments from fiscal year 2013. The initial scope will be limited to 30 days readmissions after heart failure, acute myocardial infarctions (AMI) and pneumonia admissions. Under policies such as these, providing accurate measures of hospital performance on readmission will be crucial if distorted incentives and inefficiencies are to be avoided.

A fundamental requirement of any comparison of hospital readmission rates is the need to ensure that any differences in the clinical risk of patient populations are properly taken into account. Hitherto, this has been achieved through various types of risk adjustment, which adjust a hospital's observed readmission rates for an intervention according to the observed characteristics of the population at risk of readmission. However, where there is unobserved heterogeneity and a significant probability of mortality arising from the intervention, standard risk adjusted models for readmissions are likely to be affected by systematic bias. The mechanism generating the bias can be described as follows. Suppose patients' risk of negative health outcomes (e.g. their underlying health status on admission) is not perfectly observable, and that hospitals differ in their performance on survival rates (e.g. their

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[1] The fiscal year runs from 1 April to 31 March.

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quality of care). Then, other things equal, hospitals that are more successful in saving patients' lives are likely to have a larger share of patients at higher risk surviving the first admission as compared with other hospitals. In these circumstances, hospitals' relative performance on readmissions is determined in part by their difference in the quality of care provided and in part by their difference in the share of patients with un-observably higher risk that survive the first admission. High quality hospitals will then have upward biased readmission rates due to the residual correlation between the data generating process of survival and readmissions that systematically disadvantages such hospitals in any comparison. In the extreme case, one could observe a positive (negative) correlation between hospitals' performance in survival[2] (mortality) and readmission rates, with hospitals with high survival rates experiencing higher readmission rates, and vice versa.

Unless properly taken into account, this identification problem may lead to incorrect inferences about the quality of care provided by individual hospitals and result in incorrect ranking of hospital performance. This in turn may lead to the creation of perverse provider incentives, and faulty design of financial incentive schemes.

In this study we first examine sample selection bias in the identification of hospitals' performance on unplanned readmissions occurring within 28 days of discharge of patients with a primary diagnosis of fractured hip. This intervention is especially relevant for the phenomenon we wish to explore, given the high risk of both mortality and readmission, and great deal of heterogeneity amongst patients. We quantify the bias at the patient level in terms of the unexplained correlation between the residuals of two separate probit models for survival and readmissions, similar to the models used in many applied studies. Second, having identified a bias, we propose a solution to the sample selection problem relaxing the assumption of independence between the data generating process of patient survival and readmission implicitly adopted in most previous empirical applications. We use a bivariate sample selection model that allows for the correlation between survival and readmissions and for the non-linear nature of the data generating process. This model, drawn from the literature on education and labour participation (Greene, 2003), is simple to implement and provides accurate information on both the outcome of interest and the underlying selection process.

We study patients aged 65 and over admitted with a fractured hip to English hospitals over the fiscal years 2003–2008. This group is chosen for several reasons. First, there are well-established medical guidelines on the standard of services and processes of care for this type of admissions and clear links between the guidelines and both mortality and readmission outcomes (National Institute for Clinical Excellence, 2004). Second, rates of unplanned readmissions from this population of patients standardised for age and sex are routinely published by the NCHOD and used by the Care Quality Commission to monitor the performance of English hospitals. Finally, admissions for hip fracture have substantial economic and health implications. It is estimated that fracture and frailty related falls in older people accounted for more than 4 millions hospital bed days in 2006 in England. The combined cost of social and hospital care for this type of injury are reported to be in excess of £1.8 billion per year in the UK (Treml et al., 2011). Injuries from falls are the leading cause of accident-related mortality in older people, and half of the people suffering a hip fracture never return to their original level of independence (Treml et al., 2011).

1. Related literature

A large amount of empirical research has sought to explain the variation in hospital readmission rates observed in many high-income countries (Boutwell et al., 2011; Friedman and Basu, 2004; Vest et al., 2010; Westert et al., 2002; Yam et al., 2010). Identifying the reasons for readmissions can be crucial to securing a reduction in readmissions that are potentially avoidable, thereby reducing healthcare costs and improving health outcomes. Hospital mortality and readmission rates are important indicators of hospital outcomes that are frequently used to assess and publicise hospital and physician performance. They are also often used in health services research to assess issues such as the impact of service organisation (Coyte et al., 2000; Evans and Kim, 2006; Ho and Hamilton, 2000; Lorch et al., 2010), the relationship between hospital inputs and outcomes (Heggestad, 2002; Schreyogg and Stargardt, 2010), the effect of introducing new policies (Evans et al., 2008) and the impact of new technologies (Xian et al., 2011).

The idea behind outcome-based quality indicators such as hospital mortality or readmission rates is that, if appropriate adjustment is made for patient case-mix and external environmental factors, then variations in reported levels of such outcome-based quality indicators are likely to be driven by differences in the (unobservable) quality of hospital services, as reflected in the processes of hospital care and service organisation. For example, the provision of appropriate rehabilitation services for fall and fracture patients is known to have an impact on the risk of readmission (National Institute for Clinical Excellence, 2004); similarly an efficient management of the surgical theatre and staff shifts can reduce the delay before the patients are treated and thus their mortality risk (Bottle and Aylin, 2006). The intrinsic quality attributes are often unobservable by the researcher, because collection of the necessary data is either impossible or highly costly. However, we would expect that hospitals with better quality should have on average better outcomes (as defined above) than their lower quality peers, after controlling for their differences in patient characteristics and environmental factors. Many empirical applications therefore examine unplanned readmissions occurring within 30 days from previous discharge of patients admitted with a similar primary diagnosis, such as hearth failures, AMI, strokes, pneumonia or hip fracture.

The advantage of outcome-based quality indicators is therefore that they can be constructed by using routine administrative data on patient discharges without the need for costly additional information on the process of care. Outcome-based quality indicators can make it feasible for large populations of patients and hospitals to be included in a study and followed for several years. However, these indicators can be inaccurate and have been criticised in the medical literature for their lack of clinical relevance (Lilford and Pronovost, 2010; Shahian et al., 2010). Moreover, some outcome indicators have low correlation with more accurate measures of quality based on the process of care (Bradley et al., 2006; Luthi et al., 2004).

Gowrisankaran and Town (1999) shed some light on the inconsistency between outcome-based and process-based measures of quality. Using patients admitted with pneumonia in South California hospitals from 1989 to 1994, they show that hospital risk adjusted mortality rates are affected by selection bias that invalidates inferences on the quality of care provided. Specifically, if patients' health conditions are not perfectly observable and patients are able to choose the hospital of treatment, then (unmeasurably) sicker patients are more likely to select high quality

[2] Survival rates and mortality rates are complementary terms, i.e. the probability of a patient surviving her/his first admission equals 1 minus the probability of dying in hospital on the first admission. Where possible, we prefer to refer to survival rates rather than mortality rates for consistency with the specification of our empirical model, which is defined over survival rates.

hospitals. Therefore, the differences in mortality rates across hospitals may be determined in part by difference in the quality of care they provide and in part by differences in unobservable patient health conditions. The latter effect systematically disadvantages high quality hospitals, and measures of the processes and outcomes of care might show low correlation. Geweke et al. (2003) provide an elegant econometric solution to correct for this bias by using a structural model that takes into account the patient choice of hospital and the two determinants of the mortality variable.

In general, observational studies based on hospital administrative data have only limited information on the heterogeneity in patient and treatment characteristics, which are therefore only partially observable. In contrast, other study designs in the medical and epidemiology literature, such as retrospective studies or prospective cohort studies, often have access to data describing such heterogeneity and thus are able to provide a better direct control for the latter. Therefore, observational studies need to pay careful attention to the characteristics of the data generating process before any meaningful inference can be made on variations in hospital quality of care, and on the determinants of such variations.

In spite of the large number of empirical applications studying hospital readmissions, only a few have paid attention to the characteristics of the data generating process. Schreyogg and Stargardt (2010) model the hazard of hospital deaths and the hazard of readmissions using two separate Cox regression models and allow for the event of death to be a competing risk for the event of a readmission. Their model for readmissions includes patients dying in hospital as censored observations assuming *independence* between mortality and readmissions. Papanicolas and McGuire (2011) uses a vector of autoregressive (VAR) model to measure the quality of English hospitals over 1996–2008 following the method described in McClellan and Staiger (2000). In a first step they estimate hospital risk adjusted mortality and readmission rates from patient level regressions separately, i.e. assuming independence between these outcomes. In a second step, they estimate a VAR model using the hospital level quality indicators obtained in the first step. Their VAR model provides a synthetic indicator of hospital quality that takes into account information from a hospital's present and past performance on mortality and readmissions estimated in the first step. In contrast, most empirical applications model hospital readmissions using multilevel single index model (e.g. logit or probit) or hazard model (e.g. Cox regression model) without paying much attention to the relationship between the event of a hospital death and a hospital readmission.

2. The model

The sample selection problem can be formulated in terms of an omitted variable problem (Heckman, 1979) in the equation describing the probability of an hospital readmission:

$$\begin{aligned} R_i^* &= \boldsymbol{\beta}_1' \mathbf{x_{1i}} + \varepsilon_{1i} \\ P_{1i} &= P(R_i^* > 0 | \mathbf{x_{1i}}) = \Phi(\boldsymbol{\beta}_1' \mathbf{x_{1i}}) \end{aligned} \tag{1}$$

$$\begin{aligned} S_i^* &= \boldsymbol{\beta}_2' \mathbf{x_{2i}} + \varepsilon_{2i} \\ P_{2i} &= P(S_i^* > 0 | \mathbf{x_{2i}}) = \Phi(\boldsymbol{\beta}_2' \mathbf{x_{2i}}) \end{aligned} \tag{2}$$

$$E(R_i^* | x_{1i}, S_i^* > 0) = \boldsymbol{\beta}_1' \mathbf{x_{1i}} + E(\varepsilon_{1i} | \mathbf{x_{1i}}, S_i^* > 0) \tag{3}$$

Eq. (1) defines the propensity that patient "*i*" is readmitted, R_i^*, as a function of the vector $\mathbf{x_{1i}}$. The latter can include: a Cx1 vector of variables, c_{1i}, describing individual characteristics, such as age, sex, health conditions; a Hx1 vector of dummy variables, h_{1i}, capturing the hospital of first admission; a Zx1 vector of area level variables, z_{1i}, capturing external environmental factors, such as area level characteristics influencing the demand for and supply of health services. The probability of a readmission, P_{1i}, can be expressed as function of the latent process and is often modelled using a standard probit model.

Eq. (2) assumes that the patients admitted to the hospital enter a selection process before being discharged, for example a sample of patients die during the treatment. The selection process can be described by the latent variables S_i^* indicating survival propensity of patient i. The readmission and the survival process are likely to be driven by similar factors in terms of patients, hospitals and environmental characteristics. However, an important difference between the two processes should be highlighted: Eq. (2) is defined over the total sample of patients admitted to the hospital; in contrast, equation 1 is defined over the subsample of patients that survive the first admission only.

Eq. (3) shows that sample selection bias might rise from systematic differences in the populations over which Eqs. (1) and (2) are defined. If the subsample of patients surviving the selection process (Eq. (2)) is systematically different from the sample of patients admitted to the hospital (Eq. (1)), then the last term of Eq. (3) is different from zero, and hence the parameters in the β_1' vectors are not identified. In other words, using the sample of patients surviving the first admission for making inference on the sample of patients admitted to the hospital is invalid.

Now, if we assume that:

(a) $(\varepsilon_{1i}, \varepsilon_{2i})$ are bivariate standard normally distributed with correlation coefficient ρ
(b) $(\varepsilon_{1i}, \varepsilon_{2i})$ are independent from $(\mathbf{x_{1i}}, \mathbf{x_{2i}})$.

Then we can quantify the last term of Eq. (3):

$$E(\varepsilon_{1i} | \mathbf{x_{1i}}, S_i^* > 0) = E(\varepsilon_{1i} | \varepsilon_{2i} > -\boldsymbol{\beta}_2' \mathbf{x_{2i}}) = \rho \lambda_i \tag{4}$$

With $\lambda_i = \varphi(\boldsymbol{\beta}_2' \mathbf{x_{2i}}) / \varphi(-\boldsymbol{\beta}_2' \mathbf{x_{2i}})$ the inverse Mills ratio.

When survival and readmissions are uncorrelated, i.e. $\rho = 0$, inference on the population of patients admitted to the hospital can be made by using Eq. (1). This might be the case if the two processes are truly independent, or equivalently if we are able to make the two processes independent after controlling for the residual heterogeneity conditioning on $\mathbf{x}$, e.g. in a clinical trial study design.

If survival and readmissions are correlated, i.e. $\rho \neq 0$, then using Eq. (1) to make inferences over the population of patients admitted to the hospital results in omitted variable bias described by the term (4).

Why should we expect the survival and readmission process to be correlated? The answer comes from the combination of two factors: first, the characteristics of patients that influence their underlying risk of a negative health outcome are only partially observable, e.g. patient health conditions; and second, unobservable characteristics of patients influencing their mortality risk are also likely to influence their risk of a readmission. Thus, if we are unable to provide appropriate control for these risk factors in the readmission equation, then *ex ante* patients surviving their first admission are expected to have a lower risk of being readmitted than patients dying in the hospital. This condition can be summarised in the following expression:

$$P(R_i = 1 | \mathbf{x_i}, S_i = 1) \leq P(R_i = 1 | \mathbf{x_i}, S_i = 0) \tag{5}$$

When we are able to control for all the relevant risk factors, $\mathbf{x_i}$, the conditional probability of being readmitted for patients surviving the first admission equals the conditional probability for the patients that die in hospital, i.e. the two processes are uncorrelated and $\rho = 0$. Otherwise, we expect that the conditional probability

of being readmitted to be smaller in the subsample of patients that survive the first admission because, for example, they are un-observably healthier than other patients, i.e. $\rho < 0$. Clearly, the potential for sample selection bias is large in population of patients with high mortality risk and large uncontrolled heterogeneity in such risk.

We now assume that hospitals differ in their performance on survival rates after conditioning on observable confounders. In other words, the best performing hospitals are most successful in reducing mortality of patients at higher risk of a negative health outcome. Then we would expect a larger share of un-observably riskier patients to survive their first admission in these hospitals, i.e. there is a larger share of patients with large values of $\rho\lambda_i$ in Eq. (3). Therefore, the relative performance of such hospitals on readmissions is not identified by using Eq. (1) either with respect to the population of patients that survive their first admission or with respect to the total population of patients admitted. The problem of sample selection bias translates to a problem of identification of hospital performance because patients surviving the first admission are no longer randomly assigned to hospitals. We can also predict the sign of the bias. Since the inverse Mills ratio λ_i is non-negative and we expect $\rho < 0$, then the performance of hospital with high survival rates is underestimated due to the effect of the sample selection bias.

We use a bivariate sample selection model to allow for the selection bias and estimate the model over the total population of patients admitted to the hospital, which can be assumed to be randomly allocated after controlling for observable confounders. This model is attractive because it takes into account the non-linear nature of the process that defines mortality and readmissions. The model consists of two equations as follows.

First a selection equation defines the probability of surviving the first admission, S_i, as a function of the latent propensity of surviving S_i^*:

$$S_i^* = \boldsymbol{\beta}_2' \mathbf{x_{2i}} + \varepsilon_{2i}$$
$$S_i = \begin{cases} 1 & \text{if } S_i^* > 0 \\ 0 & \text{if } S_i^* \leq 0 \end{cases} \tag{6}$$

The parameterisation of Eq. (6) is described in Eq. (2).

Second, an outcome equation describes the probability of being readmitted, R_i, as a function of the latent propensity of being readmitted, R_i^* observed only when $S_i^* > 0$

$$R_i^* = \boldsymbol{\beta}_1' \mathbf{x_{1i}} + \varepsilon_{1i}$$
$$R_i = \begin{cases} 1 & \text{if } R_i^* > 0 \\ 0 & \text{if } R_i^* \leq 0 \end{cases} \tag{7}$$

With

(a) $(\varepsilon_{1i}, \varepsilon_{2i})$ are bivariate standard normally distributed with correlation coefficient ρ.
(b) $(\varepsilon_{1i}, \varepsilon_{2i})$ are independent from $(\mathbf{x_{1i}}, \mathbf{x_{2i}})$.

The maximum likelihood function is defined over the probabilities of three possible events:

Surviving and being readmitted:

$$P(R_i = 1, \quad S = 1|\mathbf{x_i}) = \Phi_{\mathbf{B}}(\boldsymbol{\beta}_1' \mathbf{x_{1i}}, \boldsymbol{\beta}_2' \mathbf{x_{2i}}, \rho) \tag{8}$$

Surviving and not being readmitted:

$$P(R_i = 0, \quad S_i = 1|\mathbf{x_i}) = \Phi_{\mathbf{B}}(\boldsymbol{\beta}_1' \mathbf{x_{1i}}, \boldsymbol{\beta}_2' \mathbf{x_{2i}}, \rho) \tag{9}$$

Dying in hospital:

$$P(S_i = 0|\mathbf{x_{2i}}) = \Phi(\boldsymbol{\beta}_2' \mathbf{x_{2i}}) \tag{10}$$

The maximum likelihood is (Van de Ven and van Praag, 1981):

$$ML = \prod_{i=1}^{n_1} \Phi_{\mathrm{B}}(\boldsymbol{\beta}_1' \mathbf{x_{1i}}, \boldsymbol{\beta}_2' \mathbf{x_{2i}}, \rho) \times \prod_{i=n_1+1}^{n_2} \Phi_{\mathrm{B}} - \boldsymbol{\beta}_2' \mathbf{x_{2i}}, \rho \times \prod_{i=n_2+1}^{n} \Phi(-\boldsymbol{\beta}_2' \mathbf{x_{2i}}) \tag{11}$$

where the first n_1 patients survive and are readmitted, the following $n_2 - n_1$ patients survive and are not readmitted, and the last $n - n_2$ die in hospital.

The probability of interest is the probability of a readmission *conditional* on having survived the first admission:

$$\begin{aligned} P(R_i = 1|\mathbf{x_{1i}}, S_i = 1) &= \frac{P(R_i = 1, S = 1|\mathbf{x_i})}{P(S = 1|\mathbf{x_i})} \\ &= P(R_i^* > 0|x_{1i}, S_i^* > 0) \\ &= P(\varepsilon_{1i} \leq -\boldsymbol{\beta}_1' \mathbf{x_{1i}}|\mathbf{x_{1i}}, \varepsilon_{2i} \leq -\boldsymbol{\beta}_2' \mathbf{x_{2i}}) \\ &= \frac{\Phi_{\mathrm{B}}(\boldsymbol{\beta}_1' \mathbf{x_{1i}}, \boldsymbol{\beta}_2' \mathbf{x_{2i}}, \rho)}{\Phi(\boldsymbol{\beta}_2' \mathbf{x_{2i}})} \end{aligned} \tag{12}$$

In the case of no sample selection, this probability is given by Eq. (1). The performance of hospital j in readmissions can be measured in terms of average partial effect (APE) of being treated in hospital A as compare to a baseline hospital. Specifically, the APE is defined as the difference between the conditional probability of a readmission in hospital A and the baseline hospital averaged over all patients in the population:

$$APE_j = \frac{1}{n_2} \sum_{i=1}^{n_2} P(R_i = 1|\mathbf{c_{1i}}, \mathbf{z_{1i}}, \mathrm{h}_{1ji} = 1, S_i = 1) - P(R_i = 1|\mathbf{c_{1i}}, \mathbf{z_{1i}}, \mathrm{h}_{1ji} = 0, S_i = 1) \tag{13}$$

The vectors $\mathbf{c_{1i}}$ and $\mathbf{z_{1i}}$ define the characteristics and the external environmental factors associated with patient i; and h_{1ji} is a dummy variable identifying the hospital *j*.

Alternatively, the performance of the hospital *j* can be defined in terms of average conditional probability, i.e. the first term of Eq. (13):

$$AP_j = \frac{1}{n_2} \sum_{i=1}^{n_2} P(R_i = 1|\mathbf{c_{1i}}, \mathbf{z_{1i}}, \mathrm{h}_{1ji} = 1, S_i = 1) \tag{14}$$

Expression (14) describes the probability of a readmission in hospital *j* averaged over the total population of patients and can be interpreted as the performance on readmission that hospital *j* would have if it had treated the whole population of patients. This measure of hospital performance has three appealing characteristics: (1) it is purged of differences across hospital case mix and external environmental factors, (2) it is measured on a ratio scale, i.e. has no arbitrary zero value, (3) it does not depend on a baseline hospital. In contrast, the APE benefits from only the first of these desirable properties.

The mechanism we are modelling through the bivariate sample selection model is essentially the heterogeneity in the chance of survival of patients with different readmission risk. Both the chance of survival and readmission are affected by patient and hospital

unobserved characteristics, e.g. latent patient health and hospital quality. Although patients can be assumed to be randomly assigned to hospitals at the point of their first admission, this assumption is violated after the survival selection process. We explicitly model such a selection process and allow for the unbiased identification of patient and hospital effects on readmission.

The model is identified under the two assumptions described in (a) and (b). Assumption (a) is a parametric assumption that is needed for the model identification arising from the functional form of the probit models. In order to improve the identification of the model we provide a set of exclusion restrictions, i.e. variables that explain the variation in the probability of surviving (the selection Eq. (6)) and are uncorrelated with the probability of a readmission (the outcome Eq. (7)) after controlling for other factors. We discuss our approach to the exclusion restriction in the following section.

Assumption (b) states that the error terms in Eqs. (6) and (7) are independent of all regressors. We have shown in equation 3 that the hospital effects are potentially correlated with unobservable patient characteristics in the error term. However, such a correlation is an effect of the sample selection bias only, since after controlling for observable confounders patients are assumed to be randomly allocated to hospital on admission.

3. The data

3.1. Population of interest and health outcome variables

Data on patient admissions are extracted from the Hospital Episode Statistics (HES), which comprise records of all publicly funded patients admitted to hospitals in England. We include in our study all hospital emergency admissions during the fiscal year 2003 to 2008[3] of patients aged 65 and over with a primary diagnosis of a fractured hip (ICD-10 codes S70.0, S70.1 and S70.2) at the time of admission. We track the full hospital history of these patients from their first admission to the final discharge home taking into account transfers across different hospitals occurring within the period of inpatient stay. Hospitals with less than 50 relevant admissions per year are excluded from the analysis.

Unplanned readmissions are identified as emergency admissions occurring within 28 days of the patient's last discharge, and wherever they occur they are attributed to the hospital where the patient was first admitted and treated for the fractured hip. We exclude patients admitted or discharged under a mental health specialty and avoid double counting of patients having multiple 28 days readmissions for a fractured hip by including only the first one.[4] Our identification of patient population and readmissions follows the methodology used by the NCHOD in producing hospital standardised readmission rates to monitor hospitals' performance.

We identify in-hospital patient mortality as reported by the hospital at the point of discharge. We do not have data on patients dying at home within 28 days of discharge for the full period covered by our study. However, we have data on mortality occurring within 28 days in any setting (home, hospital or other institution) from 2003 to 2006 and are therefore able to test the robustness of our model to the inclusion of such deaths.

[3] See note 1.

[4] Also, we take into account readmissions occurring in the last month of the fiscal year 2002/3 and the first month of 2009/10.

3.2. Patient characteristics

We include dummy variables for patient age (7 groups) and gender. We measure patient health characteristics on admission (observable risk of a negative heath outcome) by using the Charlson co-morbidity index and a set of dummy variables controlling for specific conditions separately (Bottle and Aylin, 2006): dementia or Alzheimer's (ICD-10 codes F00–F03, G30), diabetes (E10–E14), chronic ischaemic heart disease (I20, I23–I25), chronic lower respiratory disease (J40–J47), heart failure (I50), renal failure (N17–N19), and malignant melanoma (any C code). Also, we include a variable counting the total number of secondary diagnosis in the first episode of care after the patient's admission (Wray et al., 1997). We include dummies for the main type of operations performed, i.e. fixation procedure including primary open or closed reduction and internal or external fixation (OPCS-4 codes W19–25), prostatic replacement of head of femur (W46–48), other procedures including non-orthopaedic ones, and no procedure carried out (the baseline). We follow the classification used in similar studies (Bottle and Aylin, 2006). The controls for the type of operation acts as a proxy for patient health conditions rather than as hospital decision variables, since the scope for varying the choice of procedure is limited for these type of patients. All the variables described above are measured at the individual level and are included in both the patient survival and readmission equations.

3.3. Environmental characteristics at small area level

We provide control for external environmental factors that influence hospital performance but are outside the control of the hospital. We use a battery of indicators capturing the characteristics of the patient small area of residence, known as the lower super output area (LSOA). These are geographical units developed by the Office for National Statistics with an average population of 1500 individuals and a standard deviation of 200. We control for the socioeconomic deprivation in the patient area of residence by using an indicator of income deprivation among older people (IDOPI). This indicator is one of the subdomains of the indices of multiple deprivation 2007 (Noble et al., 2008) and measures the proportion of area residents aged 65 and over living in family relying on means-tested income benefits. We divided the IDOPI into 4 quartiles representing increasing level of deprivation and include these in both the survival and readmission equations.

The distance of the hospital from the patient's place of residence may influence the probability of a readmission, as patients living closer to the hospital have lower costs in accessing hospital services. This could influence the performance of hospitals located in urban areas relative to those located in rural areas where the population is sparse. We include the distance variable both in the mortality and readmission equation.

Hospitals are likely to differ in their propensity to admit similar patients. Part of such variation is due to differences in hospital management and quality of services, and part to factors beyond the control of the hospital. Specifically, characteristics of the local supply and demand for health services might influence hospital propensity to admit and hence readmit (Epstein et al., 2011). For example, a relatively high supply of primary services might reduce hospital care utilisation, while a relatively high supply of hospital providers might increase it. Similarly, the nature of local demand for health services may influence the propensity for hospital readmissions. For example, the total population, the age and gender composition, and the prevalence of disease are likely to put hospital services under different degrees of pressure. Therefore, we need to control for such factors in order to be able to identify the effect on readmissions that is due to hospital management and quality.

To this end, we construct an indicator of the expected volume of all cause emergency admissions in the patient area of residence "a":

$$\hat{e}_a = \hat{\beta}_3' \mathbf{x}_{3\mathbf{a}}$$

where $\hat{e}_a$ is obtained by regressing all cause emergency admissions occurring in area "a" against the area level characteristics of supply and demand captured by the vector $\mathbf{x}_{3a}$. The latter includes number of GPs per 10,000 population, number of hospitals within 30 km, total area population, age and gender composition and prevalence of disease (i.e. atrial fibrillation, cancer, chronic kidney disease, chronic obstructive pulmonary disease, coronary heart disease, diabetes, epilepsy, heart failure, hypertension, hypothyroidism, obesity, stroke and transient ischaemic attack). We estimate $\hat{e}_a$ by running a separate OLS regression using the total population of English LSOAs. This indicator of emergency admissions propensity is then used as a control in the readmission equation only.

Data on the prevalence of disease are submitted yearly by GP practices to the national Quality Management and Analysis System (QMAS) and show the proportion of individuals registered with a GP practice recorded with that condition. We attribute this to small area level using the Attribution Dataset of patient registration addresses within GP practices. The attribution process assumes that prevalence for a particular small area is a weighted sum of the prevalence in each GP practice serving that small area, with weights proportional to the number of the area's residents registered with each GP practice. Both the QMAS data and practice to small area attribution data were obtained from the NHS Information Centre. Number of GPs per 10,000 population is based on GP practice level administrative data on whole time equivalent GPs per registered patient, from the General Medical Services database. This GP practice level variable is then attributed to small level using the same procedure described above, as a weighted average based on the share of GP practice registered patients resident in the small area.

3.4. Exclusion restrictions

In order to improve the identification of our model, we use a set of variables explaining variation in the mortality equation, but assumed to be uncorrelated with patient readmissions. For this purpose we construct indicators for patients being admitted during Christmas or Easter holidays and for the weekday of admission. Hospitals experience difficulties in maintaining appropriate levels of staff during weekends and over long holidays due to higher costs, hence nurse and specialist staff is generally reduced over these periods, and patient mortality risk increases (Dr Foster Intelligence, 2011). However, these indicators can be assumed to be uncorrelated with the risk of a readmission, which depends on post-operative care that can be provided more flexibly over a long period of time once survival has been assured. Also, being admitted over a particular weekday, Christmas or Easter should not be correlated with unobservable characteristics of the patient risk of a negative health outcome. We have tested the association between our exclusion restrictions and the probability of a readmission by including the latter in the probit for readmission (equation 3) and find no statistically significant association. Also, appendix 1 reports differences in mean survivals, readmission, patient age, Charlson index and number of diagnoses disaggregated by Christmas, Easter and week day of admission. There are only small differences in the characteristics of patients by time of admission. Finally, a similar set of variables are used as instruments in a study of the effect of a delay in treatment on mortality in hip fracture admissions (Hamilton, 1999).

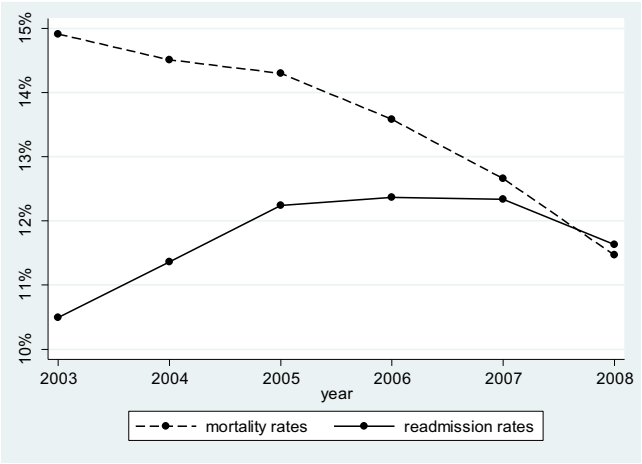

Fig. 1. Unadjusted trends in mortality and readmissions.

4. Results

4.1. Descriptive statistics

Table 1 contains descriptive statistics for all the main variables used in the analysis pooled from the fiscal year 2003 to 2008. The average age in our population of patients is 83.3 years with the largest share falling in the 80–85 (25.6%) and 85–90 (24.6%) age bands; 77.8% are women since bone frailty and osteoporosis are conditions more prevalent in this gender group. Patients admitted have on average 5 diagnoses and their more frequent co-morbidities in the Charlson index are chronic ischaemic heart disease (13.4% of admissions) and chronic lower tract disease (10.9%). The most frequent procedure is a fixation (42.7%), followed by prostatic replacement (37.5%), management of the patient without procedure carried out (15.2%) and other procedures (4.7%). The average patient comes from a small area characterised by 15% of the over 65 population relying on income benefits, with an average distance of 12.8 km from the hospital of first admission and a predicted volume of 129 emergency admissions per year given the characteristics of the local demand and supply of health services.

Fig. 1 shows annual trends in hospital mortality as total deaths over the total patients admitted and annual trends in hospital readmissions as total readmissions over total patient discharged alive after the first admission. Hospital mortality follows a decreasing trend over the full study period, with a steeper trend from the fiscal year 2006. In contrast, readmissions rise noticeably until 2005, stay constant in the following two years and then fall in 2008.

Table 2 shows annual trends in unadjusted outcomes at hospital level. The number of hospitals included in the analysis[5] each year ranges from 151 to 148 and their average volume of relevant admissions rises progressively from 375 to 404. The average hospital survival rate (see note 1) increases progressively from 85.0% to 88.4%, while their average readmission rate increases from 10.9% in 2003 to 13.0% in 2005–2006 and drop back to 11.8% in 2008. The variation in hospital survival rates is stable from 2003 to 2006 with coefficient of variation (i.e. standard deviation over mean) ranging from 4.3% to 4.1%. This variation drops in 2007 and 2008 when the coefficient of variation is 3.6% and 3.4% respectively. The correlation between hospital unadjusted survival rates and readmission rates is positive over the period with larger variation in hospital

[5] Only hospitals with more than 50 admissions per year are included and 3 hospitals merges together over the period considered.

Table 1
Patient level descriptive statistics 2003–2008.

Variable	Obs	Mean	Std. Dev.
Health outcomes			
Readmissions	250,700	0.1192581	0.3240926
Survivals	289,910	0.8647631	0.3419771
Demographics			
Age	289,910	83.26665	7.434723
65–70	289,910	0.047325	0.2123335
70–75	289,910	0.0858473	0.280139
75–80	289,910	0.1590563	0.3657292
80–85	289,910	0.2514608	0.4338536
85–90	289,910	0.2458039	0.4305635
90–95	289,910	0.1553172	0.3622074
95 and over	289,910	0.0551895	0.2283502
Female	289910	0.7774516	0.4159582
Health conditions			
Dementia (ICD-10 codes F00–F03, G30)	289,910	0.0553206	0.2286054
Diabetes (E10–E14)	289,910	0.098465	0.2979429
Chronic ischaemic heart disease (I20, I23–I25)	289,910	0.1341175	0.3407791
Chronic low tract respiratory disease (J40–J47)	289,910	0.1091339	0.3118076
Heart failure (I50)	289,910	0.0574903	0.2327774
Renal failure (N17–N19)	289,910	0.0369046	0.1885278
Malignant melanoma (any C codes)	289,910	0.0345142	0.182546
Charlson index	289,910	0.7533614	1.109684
Total diagnoses	289,910	5.114377	2.505715
Fixation procedure (OPCS-4 codes W19–25)	289,910	0.4266634	0.4945934
Prostatic replacement of head of femur (W46–48)	289,910	0.3745266	0.4840013
other procedure	289,910	0.0470767	0.2118033
No procedure performed	289,910	0.1517354	0.3587648
Environmental factors			
Expected emergency admissions[a]	289,910	128.5546	35.50588
Distance from hospital	289,910	12.84647	25.39315
Income deprivation among older people index (IDAOPI)	289910	0.1524638	0.1128906
Year dummies			
2003	289,910	0.1627735	0.3691595
2004	289,910	0.1622767	0.3687051
2005	289,910	0.1661159	0.3721853
2006	289,910	0.164643	0.3708587
2007	289,910	0.1719868	0.3773696
2008	289,910	0.1722041	0.3775584

[a] Expected values are obtained by regressing observed total emergency admissions in the patient area of residence against the characteristics of demand and supply of health services.

survival (2003–2006) and becomes negative over the period with smaller variation in hospital survival (2007–2008). In other words, the descriptive statistics show that hospitals with better performance on survival rates have worse performance on readmissions when the variation across hospital performance in survival rates is large. The positive correlation between the two health outcomes is superficially puzzling: if hospital quality of care (e.g. organisation and clinical quality) influences survivals and readmissions, then hospital with higher survivals might be expected to have lower readmissions, in which case the correlation should be negative. Indeed, the correlation turns negative when the variation across hospital survival rates is reduced. Using regression analysis we shall show that the observed correlation is the result of a sample selection process in which hospitals with higher survival rates end up having a larger share of patients at high risk of a negative outcome compared to hospitals with lower survival rates.

4.2. Regression analysis

Table 3 contains the estimated average partial effects (APEs) obtained from the probit model on readmission described in equations 1 (column 1), a bivariate sample selection model described in equations 6–7 (column 2 and 3). All models are estimated over pooled observations from 2003 to 2008 and include dummy indicators capturing the hospital fixed effects. The bivariate sample selection model reports a significant and negative residual correlation between the probit on survival and the probit on readmission ($\rho = -0.56$). This suggests that the sample of patients that die in

Table 2
Hospital level descriptive statistics by year.

	2003	2004	2005	2006	2007	2008
Total hospitals	150	151	151	148	148	148
Mean admissions	374.8	373.7	382.2	389.0	404.2	404.0
Mean survival	0.850	0.853	0.857	0.865	0.872	0.884
Mean readmissions	0.109	0.120	0.129	0.130	0.128	0.118
Survival std. dev.	0.037	0.036	0.036	0.035	0.031	0.030
Survival std. dev./mean	0.043	0.043	0.042	0.041	0.036	0.034
Correlation survival readmissions	0.045	0.120	0.168	0.085	−0.040	−0.110

Table 3
Estimated average partial effects (APE) from regression analysis.

Variables	Probit on readmissions		Bivariate sample selection model			
	APE	se	Readmission equation		Selection equation	
			APE	se	APE	se
Demographics (baseline: age 65–70)						
70–75	0.00700**	(0.00329)	0.0116***	(0.00379)	−0.0140***	(0.00261)
75–80	0.0162***	(0.00322)	0.0285***	(0.00430)	−0.0379***	(0.00302)
80–85	0.0287***	(0.00335)	0.0495***	(0.00536)	−0.0632***	(0.00350)
85–90	0.0421***	(0.00362)	0.0746***	(0.00705)	−0.0975***	(0.00420)
90–95	0.0501***	(0.00396)	0.0992***	(0.00963)	−0.151***	(0.00522)
95 and over	0.0489***	(0.00477)	0.116***	(0.0129)	−0.214***	(0.00664)
Female	−0.0258***	(0.00155)	−0.0456***	(0.00306)	0.0562***	(0.00127)
Health conditions						
Dementia	0.0255***	(0.00323)	0.0270***	(0.00362)	0.00117	(0.00247)
Diabetes	0.0133***	(0.00253)	0.00237	(0.00330)	0.0332***	(0.00175)
Chronic ischaemic heart disease	0.00999***	(0.00215)	0.0152***	(0.00255)	−0.0129***	(0.00173)
Chronic low tract respiratory disease	0.00336	(0.00237)	0.00850***	(0.00286)	−0.0175***	(0.00203)
Heart failure	0.0103***	(0.00357)	0.0491***	(0.00708)	−0.0922***	(0.00312)
Renal failure	0.000866	(0.00444)	0.0479***	(0.00900)	−0.117***	(0.00412)
Malignant melanoma	−0.0153***	(0.00436)	−0.0140***	(0.00515)	−0.00660*	(0.00372)
Charlson index	0.00955***	(0.000996)	0.0168***	(0.00147)	−0.0185***	(0.000758)
Total diagnoses	0.00373***	(0.000347)	0.0106***	(0.00109)	−0.0207***	(0.000279)
Procedure (*baseline: no procedure*)						
Fixation procedure	−0.0272***	(0.00197)	−0.0596***	(0.00463)	0.0978***	(0.00149)
Prostatic replacement of head of femur	−0.0294***	(0.00199)	−0.0624***	(0.00469)	0.0992***	(0.00152)
Other procedure	−0.0289***	(0.00353)	−0.0470***	(0.00462)	0.0465***	(0.00342)
Environmental factors (*baseline: least income deprived*[a])						
2nd quartile	0.00160	(0.00196)	0.00379*	(0.00230)	−0.00707***	(0.00173)
3rd quartile	0.00797***	(0.00208)	0.0127***	(0.00250)	−0.0130***	(0.00178)
4th quartile (most income deprived)	0.0136***	(0.00227)	0.0206***	(0.00277)	−0.0187***	(0.00192)
Distance from hospital	−8.37e−05***	(2.94e−05)	−0.000154***	(3.66e−05)	0.000288***	(3.38e−05)
Expected emergency admissions[b]	0.000175***	(2.23e−05)	0.000196***	(2.52e−05)		
Year dummies (baseline: 2003)						
2004	0.00601**	(0.00243)	0.00272	(0.00281)	0.0131***	(0.00184)
2005	0.0109***	(0.00246)	0.00410	(0.00302)	0.0259***	(0.00173)
2006	0.00866***	(0.00245)	−0.00298	(0.00332)	0.0399***	(0.00163)
2007	0.00514**	(0.00240)	−0.0113***	(0.00369)	0.0533***	(0.00152)
2008	−0.00676***	(0.00233)	−0.0299***	(0.00431)	0.0702***	(0.00139)
Patient admitted on (baseline Saturday)						
Sunday					−0.00584**	(0.00231)
Monday					−0.00333	(0.00222)
Tuesday					−0.00222	(0.00220)
Wednesday					−0.00255	(0.00221)
Thursday					0.000233	(0.00219)
Friday					−0.00391*	(0.00222)
Christmas holidays					−0.0158***	(0.00384)
Easter holidays					−0.0102**	(0.00471)
Rho					−0.56064	(−0.05782)
Hospital fixed effects	153		153		153	
Observations	250,700		289,910		289,910	

Notes: Robust standard errors in parentheses.
[a] Income deprivation among older people index (IDAOPI).
[b] Expected values are obtained by regressing observed total emergency admissions in the patient area of residence against the characteristics of demand and supply of health services.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

hospital would be at higher risk of a readmission had they survived their first admission compared to patients who survive (expression (10)). Therefore, the population of patients admitted to the hospital and the sample of patients that survive the first admission differ in their risk of being readmitted after controlling for all observable confounders. This implies that the group of survivors cannot be used as a basis for making inferences on the conditional probability of being readmitted before appropriate correction for the sample selection bias is made.

The differences between the estimated coefficients of the probit and the sample selection model are especially noticeable amongst the variables that describe patient characteristics. The conditional probability of a readmission between each age group over the baseline (patients aged 65–70) almost doubles after controlling for sample selection. In practical terms this means that hospitals experiencing a rise in their share of *admissions* of older patients might underestimate their future increment in readmissions if such projections are based solely on past readmissions of patients with similar age. The difference in the conditional probability between women and men almost doubles (−0.0258 probit; −0.0456 sample selection). The conditional probabilities for many health conditions increase noticeably: chronic ischaemic heart disease (0.010 probit; 0.015 sample selection), chronic lower respiratory disease (0.003 probit; 0.009 sample selection), heart failure (0.010 probit; 0.049 sample selection), renal failure (0.001 probit; 0.048 sample selection). Similar patterns are found in the effect of variations

in the Charlson index (0.010 probit; 0.017 sample selection) and total number of diagnoses (0.004 probit; 0.011 sample selection). The conditional probabilities for each type of operation doubles in the sample selection model reflecting the higher risk of a negative outcome relative to patients managed with no operation (the baseline): fixation (−0.027 probit; −0.060 sample selection), prostatic replacement (−0.029 probit; −0.062 sample selection) other operations (−0.029 probit −0.047 sample selection).

The estimated effects of the external environmental factors on readmissions show more modest differences between the two models: patients in the second income deprived quartile (0.002 probit; 0.004 sample selection), third quartile (0.008 probit; 0.013 sample selection) and most deprived quartile (0.014 probit; 0.021 sample selection) as compared with patients resident in the least deprived quartile of area (the baseline); the effect of living 1 km further away from the hospital (−0.00008 probit; −0.00015 sample selection); the effect of the characteristics of the demand and supply in the patient area of residence (0.00018 probit; 0.00020 sample selection).

The most remarkable difference is found in the annual trend in readmissions estimated by the two models. The probit predictions mirror the trend suggested by the descriptive statistics in Fig. 1. A sharp rise in readmissions over the 2004 (0.006) and 2005 (0.011) as compared with 2003 (baseline), followed by a similar level in 2006 (0.009), a modest fall in 2007 (0.005) and then a sharper fall in 2008 (−0.007). In contrast, the sample selection model identifies no significant change in the year trend from 2003 to 2005 and a reduction in readmissions from 2007 (−0.011) and in 2008 (−0.030). The differences in the two models' predictions should be examined in the light of the predictions from the probit on survivals, which describes the selection process. The latter shows a significant and increasing trend in the probability of surviving the first admission (0.013 in 2004, 0.026 in 2005, 0.040 in 2006, 0.053 in 2007 and 0.070 in 2008 as compared with 2003). The rise in readmissions estimated by the probit model (Table 3, column 1) is generated by the following selection process. An increasing number of patients at risk of negative health outcomes survive their first admission over time, the risk of a negative health outcome is only partially controlled by the probit model, and hence risk adjusted readmissions are predicted to increase over time. The 2003–2006 increment in readmissions disappears after allowing for the sample selection process (Table 3, column 2).

In contrast, the reduction in readmissions observed in 2007–2008 outweighs the selection effect and therefore appears to reflect improvements in standards of care. This effect is captured both by the sample selection model and by the probit model (Table 3, columns 2 and 1 respectively), but is underestimated by the latter. It is also interesting to note that this selection effect also explains the difference in magnitude between the risk adjusted year trend estimated by the probit model (Table 3, column 1) and the unadjusted trend shown in the descriptive statistics in Fig. 1. Probit risk adjusted predictions show a more modest increase in readmissions over time than descriptive statistics, since they capture the *observable* increase in patient risk of a readmission over time. However, the probit model is unable to adjust for the *unobservable* increase in patient risk generated by the selection process, and hence its trend predictions are larger than the trend prediction of the bivariate sample selection model.

Column 3 of Table 3 reports the APEs of the probit model for survival. This model describes the selection process that generates the sample of patients at risk of a readmission. The probability of surviving the first admission decreases with the age of the patient, the total number of diagnoses, the score of the Charlson index, and the income deprivation of the patient area of residence. Almost all the comorbidity dummies are associated with a lower probability of surviving with the sole exception of patients with diabetes. Patient having no operation performed are associated with a lower probability of surviving than patients receiving a fixation or a prostatic replacement. The distance from the hospital is positively associated with the probability of surviving although the effect is virtually zero in magnitude (i.e. 100 km increment in distance is associated with a 0.02 increment in the probability of surviving). This variable is likely to capture the effect of patients who seek care further away from their usual place of residence. Such patients might be relatively more autonomous, informed and healthier than other patients. Moving to our exclusion restriction variables, we find that patients are less likely to survive if admitted on Sunday and over Christmas and Easter holidays. Finally, the year dummies show a progressive increase in the probability of surviving the first admission from 2003 (baseline) to 2008.

Table 4
Correlation between hospital risk adjusted survival and readmission rates.

	2003–2004	2005–2006	2007–2008
Bivariate sample selection	−0.306	−0.213	−0.390
Probit	−0.042	0.089	−0.073

Fig. 2 plots the hospital APE on readmissions from the probit model (left panel) and from the sample selection model (right panel) against the hospital APE on survivals. The hospital APE are estimated using the models in Table 3 and are defined as the difference between the conditional probability of a readmission (survival) in a given hospital and a baseline hospital averaged over of all patients in the population (expression (21)). The hospital APE provides a measure of hospital relative performance in risk adjusted outcomes over the entire period 2003–2008. The slope of the fitted line shows the correlation between the hospital performance on survival and readmissions. The correlation is almost zero when hospital performance is estimated using a probit model for readmission that does not correct for the sample selection, but becomes negative when the performance is estimated using a bivariate sample selection model. Fig. 2 provides evidence that the sample selection at patient level biases the identification of the hospital performance on readmissions, and that sample selection will lead to an underestimation of relative readmission rates amongst hospitals with lower survival rates.[6]

In Table 4 we report the correlation between hospital performance in survival and readmissions obtained from the probit and the bivariate sample selection models, disaggregated by two-year period.[7] The correlation between risk adjusted survivals and readmissions is always underestimated (in absolute value) by the probit with respect to the sample selection model. Also, the probit model predicts a positive correlation in 2005–2006, i.e. hospitals with higher survival rates tend to experience higher levels of readmissions.

The problem of sample selection can be described as an omitted variable problem as we argue in the Model section, i.e. the researcher is not able to control for the unobserved heterogeneity

[6] As a robustness check, we run the analysis excluding two hospital outliers reporting readmission rates 0.25 and 0.18 larger than the baseline hospital. Results at patient level are unchanged as well as the estimated residual correlation coefficient $\rho = -0.52$. Hospital level correlation between risk adjusted survival and readmission rates increase by −0.20 under both the univariate and the bivariate probit models (from −0.01 to −0.20 and from −0.28 to −0.48, respectively). That is, hospital performance on readmissions is still underestimated under the univariate probit for hospital with high survival rates but now has the expected negative sign. However, these two outliers reports higher readmissions every year and hence are likely to be genuine observations.

[7] This ensures a sufficient number of observations to identify the hospital effects. However results do not change even when correlations are computed by each year.

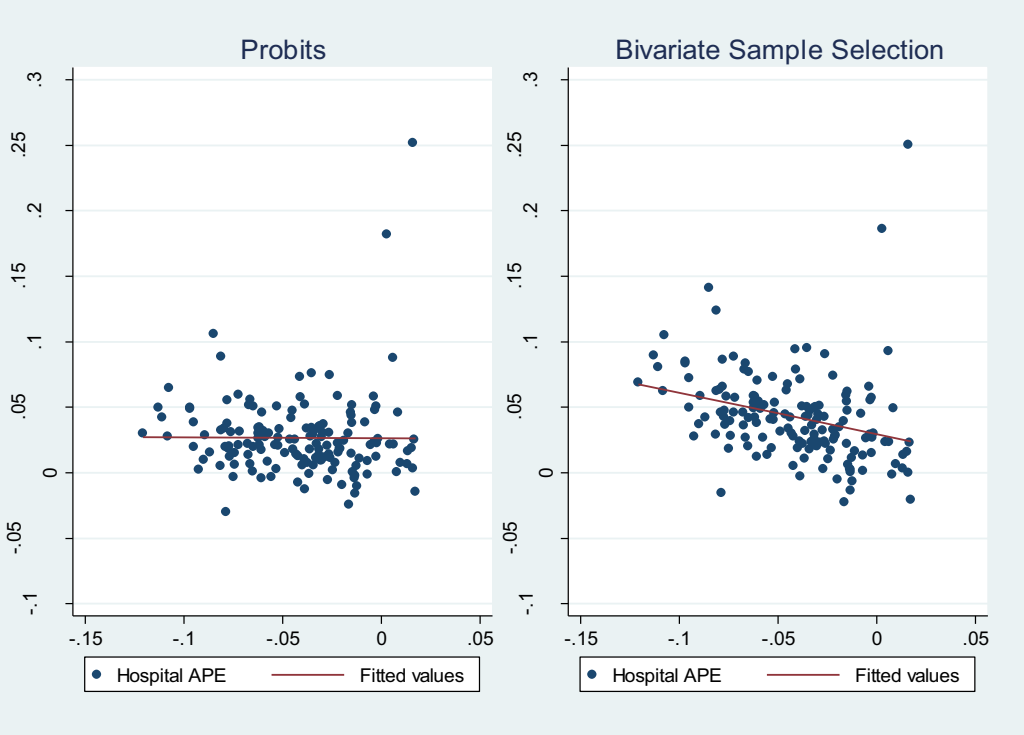

Fig. 2. Hospital performance in risk adjusted survival and readmission rates 2003–2008 – Hospital Average Partial Effects (APE).

Table 5
Estimated residual correlations between the survival and readmission process from models including additional indicators of patient health risk.

	Rho coefficient	Std. error
Model A: Charlson index	−0.7859	0.0505
Model B: A + set of specific health conditions[a]	−0.5324	0.0771
Model C: B + indicator of total diagnoses[b]	−0.5606	0.0578

[a] Dementia or Alzheimer's, diabetes, chronic ischaemic heart disease, chronic lower respiratory disease, heart failure, renal failure, and malignant melanoma.
[b] Model C is the full model presented in Table 3.

in patient health risk that would make the readmission and the survival process independent. Table 5 highlights this idea showing estimated residual correlation coefficients, rho, from three different specification of the model described in Eqs. (6) and (7). Each model specification includes the variables listed in Table 3 with the exception of the patient risk variables that are included progressively: Model A includes only the Charlson comorbidity index, Model B adds a set of indicators for specific health conditions and finally Model C adds a variable counting the total number of patient's diagnoses, i.e. the full model presented in Table 3. Adding more risk variables improves the model identification and also reduces the residual correlation between the survival and readmission process.

Fig. 3 ranks hospitals by increasing average conditional probability (AP) of a readmission as defined in expression (22). This can be interpreted as the conditional probability of a readmission expected for a given hospital had that hospital treated the whole population of patients. The specification of the bivariate sample selection model is the same as in Table 3 column 2. The bottom and

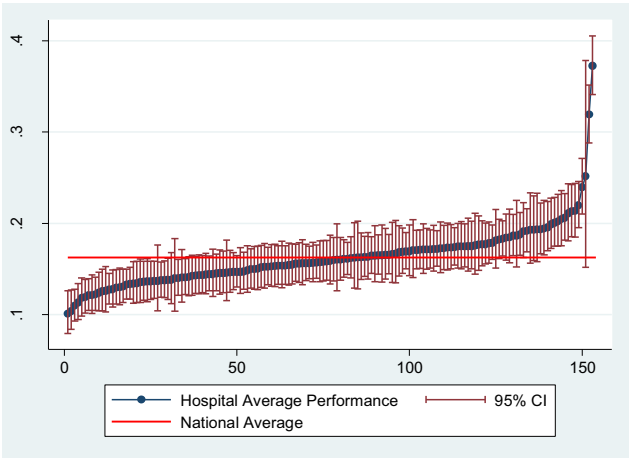

Fig. 3. Hospital risk adjusted readmission rates 2003–2008. Estimated average probabilities using a bivariate sample selection model.

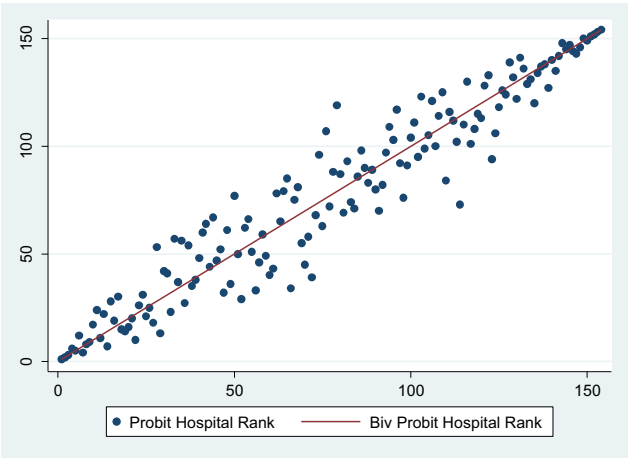

Fig. 4. Hospitals' performance in readmission rates. Hospitals ranked using probit model predictions versus bivariate sample selection predictions.

top quintile of hospitals have a significantly different performance in readmissions over the period 2003–2008. Fig. 4 shows the change in the hospital performance rank between the bivariate sample selection model and the probit model. Hospitals on the 45° line experience no change in their rank using both models, hospitals above (below) the diagonal show a worse (better) performance under the probit model with respect to the sample selection model. The largest changes in ranks affect middle rank hospitals, while hospitals at the extreme top and bottom of the 45° line move less in their ranks.

In sensitivity analysis, we relax the parametric assumption of joint normality that characterises the bivariate sample selection model. We use a semiparametric model described in Gallant and Nychka (1987), which approximates the unknown densities of the latent regression errors by Hermite polynomial expansions and use the approximations to derive a pseudo-ML estimator for the model parameters. Relaxing the distribution assumption does not allow for direct inference on the rho coefficient; also the two models are not nested. However, the estimated residual correlation from the semiparametric model (rho = −0.47) is close to the prediction of the parametric bivariate model (rho = −0.56). Also, the hospital predicted readmissions from the two models are correlated at 87%.

5. Discussion and conclusions

The main contribution of this study is to model hospital performance on readmissions relaxing the assumption of independence between the data generating process of patient survival (or mortality) and readmission that is implicitly adopted in the vast majority of studies on hospital readmissions. We examine all emergency admissions for hip fractures of patients aged 65 and over occurring over 2003–2008 in English public hospitals. We find evidence that ignoring the correlation between mortality and readmission for this procedure results in material sample selection bias in the identification of the hospital effect on readmissions. The bias originates from unobservable patient characteristics that influence his/her risk of a negative health outcome, such as unmeasured patient health conditions, and from differences in hospital mortality rates. Specifically, if patients' health conditions are not perfectly observable, then risk adjustment will be inadequate and hospitals with higher survival rates are more likely to have a larger share of patients at higher risk of a readmission. Therefore, hospitals' performance in readmissions is determined in part by their difference in the quality of care and in part by their difference in the share of unobservably sicker patients. If this hypothesis holds, high quality hospitals with high survival rates will tend to have higher reported readmission rates, and hence their true performance on readmissions will be underestimated.

Evidence of sample selection at patient level comes from the estimated correlation coefficient ($\rho = -0.56$) between the residuals of a risk adjusted probit model on the patient probability of surviving and a risk adjusted probit model on the patient probability of experiencing an emergency admission within 28 days of previous discharge. Also, we find no correlation or positive correlation between the hospital risk adjusted performance in survival and readmission estimated using the two separate probits. The positive correlation suggests that hospitals with better performance in survival rates have worse performance in readmission rates. This association is the opposite of what would be expected if both survival and readmissions are driven by the underlying quality of hospital care, after controlling for patient characteristics and external environmental factors that might influence hospital performance. We argue that this estimated association is the result of ignoring the correlation between the data generating process of survival and readmission.

We implement a solution to the sample selection bias problem by using a bivariate sample selection model that allows for the residual correlation between the probability of survival and readmission. This model is attractive because it also allows for the dichotomous nature of the two outcome variables. Once the sample selection is taken into account, hospitals' risk adjusted performance in survival and readmission rates became negatively correlated with hospitals having high survival rates also having low readmission rates.

The model also allows for sample selection in estimating the differences in the conditional probabilities of a readmission by gender, age and co-morbidity groups. The estimates from the sample selection model are noticeably different from those obtained from the probit model, which assumes independence between survival and readmissions. Specifically, the conditional probabilities by gender and by age groups are from 50% to 100% higher in the sample selection model as compared with the probit model; similar results obtain for the conditional probabilities of patients with chronic ischaemic heart disease, heart failure, renal failure, and chronic low tract respiratory disease. This is not surprising given that these patients are at higher risk of dying during their first admission (relative to patients without the condition), and hence the sample that survives is subject to an intense selection process.

Finally the annual trend estimates derived from the sample selection model differ from the annual trend estimates from the probit model. The former predicts a flat trend in readmissions over 2003–2005 followed by a fall in 2007–2008. In contrast, the latter predicts a rise in readmissions over the 2003–2005 years and a small drop in 2007–2008. The differences between the two models are explained by the increasing trend in survival rates that characterised the 2003–2008 period. As the share of patients surviving their first admission rises over time, so the risk of a negative outcome in the survivors increases over time. The probit model fails to control for the increasing risk inherent in the hospital case-mix, because patient health characteristics are only partially observable. In contrast, the sample selection model provides a better risk adjustment by incorporating information on the selection process over time.

Our study offers strong evidence that ignoring the correlation between the data generating process of survival and readmission may seriously corrupt any inference on readmission for procedures where there is a significant risk of mortality. If the researcher were able to observe all relevant patient characteristics, then survival and readmission probabilities can be estimated independently by conditioning on observables, and hence a simple binary response model on readmission becomes an appropriate instrument of analysis. Unfortunately, most studies, such those using hospital administrative data, have access only to partial information on patient health conditions and treatment characteristics. In this case, our study suggests that a simple test for the residual correlation between patient survival and readmission can provide valuable information on the most appropriate model to use in any empirical analysis of readmissions.

An increasing number of health systems have started to release public reports of hospital performance on readmission rates to inform patient choice of provider and to monitor hospital quality of care. In the US, 30 day emergency readmissions following hospitalisations for pneumonia, acute myocardial infractions (AMI) or heart failure have been reported by the Centre for Medicare and Medicaid Services (CMS) from 2009. In the UK, the NCHOD has from 1998 produced age and gender standardised indicators of hospital 28 days emergency readmission rates following admissions for hip fractures and strokes to inform quality regulators. Australia's

Table 6
Patient mean outcomes and health characteristics by period of admission.

	Survival	Readmissions	Age	Charslon index	Total diagnoses
Christmas					
(Yes)	0.849	0.125	83.419	0.755	5.220
(No)	0.865	0.119	83.263	0.753	5.112
Easter					
(Yes)	0.858	0.121	83.257	0.727	5.029
(No)	0.865	0.119	83.267	0.754	5.116
Week day					
Sunday	0.861	0.121	83.348	0.753	5.125
Monday	0.864	0.119	83.237	0.760	5.117
Tuesday	0.864	0.119	83.243	0.752	5.113
Wednesday	0.864	0.121	83.324	0.762	5.109
Thursday	0.867	0.117	83.243	0.755	5.109
Friday	0.864	0.118	83.272	0.747	5.119
Saturday	0.869	0.119	83.207	0.745	5.109

National Agency for Health and Information uses readmission to hospital within 28 days for selected types of surgery as an indicator of the safety and quality of public hospital care. At the same time, hospitals in these and other countries are under pressure to reduce mortality rates for the same type of admissions for which they are required to reduce their readmission rates.

Conventional hospital readmission indicators currently take no account of the sample selection bias described above, and may therefore offer misleading signals of performance. Using inappropriate indicators of performance might put some hospitals under unwarranted pressure (and conversely may ignore weak performance in other hospitals) and generate perverse incentives for hospital behaviour. The recent efforts to link reimbursement to readmission performance indicators increase the potential for perverse incentives associated with such measures. We find evidence that hospital readmissions are likely to rise as a consequence of falling mortality rates over time, but that reducing both mortality and readmissions is an achievable target. However, if adverse consequences are to be avoided, it will be necessary to develop more analytically satisfactory measures of hospital performance on readmissions along the lines described in this paper.

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Appendix A.

See Table 6.

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