What is the empirical basis for holding hospitals financially responsible for emergency readmission rates?

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17th May 2011

Since 1st April 2011, hospitals in England have no longer been reimbursed for emergency readmissions within 30 days of an elective admission. The intention is to improve the quality of care offered during the elective admission and in the community in the post-discharge period. Depending on how important these factors are in determining readmissions, the risk is that hospitals will engage in adverse patient selection and/or distort length of stay. Using a dataset of 1 million individuals (a 10% random sample) having at least one elective admission between April 2007 and September 2010, we examine how readmission probability relates to patient characteristics, HRG-group and co-morbidities, length of stay, GP quality, area deprivation, provision of community services, and time and hospital fixed effects. We compare models that explain readmission to the same or a different provider, and models that explain readmissions that are excluded or included in the new non-payment policy. We find that readmission rates do vary significantly across hospitals, but there is more between-hospital variation in the types of readmission that are excluded from the non-payment policy that in those that are included. The probability of readmission does not depend on the quality of primary care services or the volume of community health services. The risk of readmission is negatively related to length of stay when the provider will be paid for the additional night's stay. Several patient characteristics are strong predictors of readmission risk, meaning that the new policy may place already vulnerable patients at higher risk of adverse patient selection.

1 Introduction

Hospital readmission rates have for a long time been proposed as indicators of hospital quality (e.g. Acheson and Barr (1965)) and have recently regained policymakers' attention. A new NHS policy aiming to ensure good quality of in-hospital and post-discharge care abandons payment to English hospitals for emergency readmissions occurring within 30 days of discharge from an elective admission (Department of Health, 2011). It has been estimated that this will reduce hospital revenue by GBP 480 million (NHS Confederation, 2011). Similarly, from 2012, US hospitals reimbursed

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under Medicare with higher than expected risk adjusted readmission rates will face overall payment reductions (PPACA, 2010).

Unplanned readmissions have been described as the outcome of two events: an adverse outcome of the initial (or index) admission; and a decision to subsequently readmit the patient (Milne and Clarke, 1990). Naturally, it also depends on the decision to admit for the index admission the patient in the first place. While all of these events are under the control of the hospital, the probability of a patient being readmitted to hospital is the outcome of a variety of factors including patient characteristics and post-discharge care (Heggestad, 2002). New (non)-payment policies that attempt to reduce readmission rates by holding hospitals financially responsible for readmissions may lead to hospitals engaging in adverse patient selection and/or distortions in length of stay in an attempt to avoid the transfer of risk embodied in the new policy. The aim of this paper is to consider the potential for such unintended outcomes and assess the empirical basis of the new policies by estimating the determinants of emergency readmission rates. In particular, we exploit the availability of new data and add to the current literature by estimating the impact of primary care and community care.

1.1 Defining readmission rates

A hospital readmissions occurs when a patient's initial or index admission is followed by another admission within a specified period of time typically measured from discharge from the index admission. Chambers and Clarke (1990) considered readmissions occurring up to 104 days after discharge and found that for all specialties readmission rates peaked in the beginning of the period and flattened out at around 28 days. On this basis they suggested that assessment of readmission rates should not go beyond 28 days of discharge. In his study of "avoidable readmissions", Clarke (1990) found that readmissions within 0-6 days from discharge were more likely to be classified as avoidable than readmissions occurring within 21-27 days. A report from Department of Health (2008) found that the proportion of readmissions occurring within 0-1 and 2-7 days of the original discharge increased, while readmissions occurring within 8-14 and 15-27 days decreased. The new NHS policy covers readmissions occurring within 30 days of discharge.

Ashton and Wray (1996) suggest that readmission rates should only be deemed legitimate indicators of health care quality if a link can be established between in-hospital process of care during the index admission and the probability of readmission. This question was the focus of studies by Clarke (1990), Thomas (1996), and Weissman et al. (1999) who all addressed the question through ex post clinical reviews of readmissions to determine whether the readmission was, using the terminology of Weissman et al., "potentially preventable", according to some predefined standard. These studies failed to establish a firm link between the quality of care of a specific index admission and a subsequent unplanned readmission leading both Clarke and Thomas to question the appropriateness of readmission rates as indicators of hospital quality.

1.2 What influences readmission rates?

Lyratzopoulos et al. (2005) examined factors influencing emergency medical readmission risk in one UK district general hospital. They find that gender, age, number of co-morbidities, LOS, admission method and level of deprivation affected the likelihood of being readmitted. They also found evidence that patients with a primary diagnosis of heart failure and chronic obstructive pulmonary disease/asthma had a higher risk of readmission.

Length of stay (LOS) is one of the factors under the hospital's span of control that has generated most research. LOS is likely to be related to unobserved severity of illness. For example, Williams et al. (2005) found that when controlling for age, gender, number of co-morbidities, deprivation level and proportion of admission to trust which were day cases, longer LOS was associated with higher risk of readmission. They do, however, recognise that the explanation for this is likely to be that more ill patients who for that reason must stay longer in hospital also have a higher risk of being readmitted.

For that reason, instrumental variable (IV) techniques must be applied. This was first done by Malkin et al. (2000) who studied the effect of length of postpartum stays on newborn readmission rates. Using hour of birth and method of delivery as instruments for LOS, this study found that a 12 hour increase in LOS reduced the newborn readmission rate by 0.6 %-points. Amporfu (2008) studied the effect of LOS on readmission rates for maternity patients in British Columbia. Using year of introduction of a policy to reduce LOS and subsequent years as instruments for LOS, and patients distance to hospital as instrument for the speciality classification, she found that lower LOS increased the probability of readmission. In addition she tested whether hospitals' degree of specialisation had an impact on the readmission rate. The risk of readmission was lower the more specialised the hospital was.

A number of studies have focused on the development of algorithms to identify patients with a high risk of readmission on the basis of patient characteristics. If successful, such algorithms may enable PCTs and GPs to seek to prevent readmissions for patient in high risk. In a less positive light, in the light of the new policy of non-payment for readmission, such algorithms may also be used by hospitals to avoid costly patients. By construction these studies do not include controls for quality of treatment or post-discharge measures since they focus on the identification of patients based on administrative data.

Billings et al. (2006) sought to develop an algorithm to identify patients with a high risk of readmission within 1 year based on NHS administrative data, assigning a risk score of readmission of between 0 and 100 for each patient. They found that age, gender, race, number of previous admissions and clinical conditions were predictors of the likelihood of readmission. However, in a validation of the algorithm, at a risk score threshold of 50 % the algorithm identified 54 % of readmitted patients, but incorrectly predicted readmission for 35 % of the patients. Obviously, increasing the risk score threshold to lead to higher sensitivity, but at the same time lower specificity.

Performing a similar exercise on Australian data, Howell et al. (2009) investigated whether readmission could be predicted using routinely recorded inpatient data. They found that age, gender, marital status, indigenous status, socio economic index and remoteness index for patient area, co-morbidities and number of previous admissions could predict readmission, but the method suggested could identify less than half of the subsequent readmissions in a 12 month period and it falsely predicted readmission in 37 % of cases.

An analysis made by the National Centre for Health Outcomes Development (NCHOD) based on data from 1998/9 to 2005/6 attempted to decompose readmission rates into age, gender, method of admission, diagnoses and procedures, geography, demography, deprivation, impact of LOS of initial admission, and impact of multiple emergency readmissions(NCHOD, ????). Univariate analysis found that readmission rates increase with age, is more likely for males than females, and that readmissions rate following an emergency admission were generally 11-12 %, while after elective admissions readmission rates were about 5 pct. Emergency readmission following a medical admission were approximately 12 % while readmissions rates following surgery were about 7 %.

Level of deprivation as measured by the Index of Multiple Deprivation (IMD) groups was also shown to affect. In 2006, the most deprived had a standardised readmission rate of 11.05 pct. while the least deprived had one of 8.71.

The Department of Health (2008) expanded the NCHOD analysis and added data from 2006/07. The analysis showed that readmission rates varied greatly across specialities of the original admission. In 2006, the largest number of readmissions originates from general medicine (12 %), general surgery (9 %), A & E (12 %), Trauma & Orthopaedics (5 %.), and Cardiology (10 %). The study also showed large differences between HRGs with the 15 HRGs of original admissions that leading to most emergency readmissions accounting for 30 pct. of all readmissions. Chronic obstructive pulmonary disease or bronchitis with or without co-morbidities had an emergency readmission rate of 25.5 % and 21.9 % respectively in 2006/07 for the group of 16-74 year olds.

Regarding the HRG of the emergency readmission, the DH study found that the most common HRGs were S19 "Complications of procedures" and E36 "Chest pain <70 without co-morbidities", accounting for 9.2 % of all emergency readmissions in 2006/07. The proportion of emergency readmissions occurring within the same HRG as the index admission was fairly stable at 27 % in 2006/07 compared to 29 % in 2003/04.

Discharge destination may also affect the likelihood of readmission. Camberg et al. (1997) studied whether discharge to own home vs. nursing home affected the likelihood of readmission within 30 days, 6 months, 1 year, and 2 years of discharge for elderly patients with COPD, stroke or dementia. Using survival analysis, controlling for other factors, they found that readmission to nursing home decreased the risk of readmission for COPD and dementia patients bur did not seem to influence the readmission risk for stroke patients.

Apart from anecdotal evidence suggesting that it matters (Robinson, 2010), to the author's knowledge, no large scale studies have addressed the impact of the quality of pre- and post-discharge care. Weinberger et al. (1996). conducted an RCT to evaluate the effect of an intervention of better access to primary care pre- and post discharge consisting of follow-up visits by a nurse and a primary care doctor in up to 6 months after discharge on readmission rates for diabetes, COPD and congestive heart failure patients. They found that their intervention increased the likelihood of readmission and suggests that this may be due to discovery of otherwise undetected medical problems or better communication leading to more readmissions. In a similar UK-based study, Holland et al. (2005) investigated whether two home visits by a pharmacist (patient and carer education, removal of out of date drugs, information of GP of drug reaction and local pharmacist of need of drug compliance help) within two weeks and eight weeks of discharge affected the risk of readmission for elderly patients. This study also found a significantly increased risk of readmission within 6 months for patients receiving the intervention and suggest that this finding might be due the intervention either making patients more aware of their own need for further treatment, or that the additional visits added to the complexity of care for patients or that the likely increased compliance actually created more adverse effects of the medical treatment.

Generally, this lack of evidence of the effect of primary and post-discharge care may be ascribed to lack of data. However, the availability of performance indicators from the Quality and Outcomes Framework (REF(Department of Health, 2003)) allow to consider the importance of primary care quality for readmission rates.

1.3 A new policy for emergency readmissions

As outlined in the NHS white paper, *Equity and excellence: Liberating the NHS* (of Health, 2010a), in financial year 2011/12 the Department of Health has introduced "further incentives to reduce avoidable readmissions and encourage more joined-up working between hospitals and social care for services following discharge" (p. 25). The aim of the policy change is to "drive integration between health and social care by giving PCTs responsibility for securing post-discharge support, with hospitals responsible for any readmissions within 30 days of discharge" (of Health, 2010b, p. 3).

Specifically, hospitals will not be reimbursed for emergency readmissions that have a national tariff within 30 days of discharge following a day case, ordinary elective admission, regular day or night admission (Department of Health, 2011).

The savings the PCTs make from the non-payment policy will be placed in a post-discharge fund along with previously distributed funding for re-ablement and post discharge support. Using these funds, the PCTs are tasked with working with providers, GPs and local authorities to improve post-discharge support to patients within 30 days of discharge (Department of Health, 2011).

With some exemptions the policy includes all readmissions within 30 days of discharge irrespective of whether the initial or readmission takes place within the NHS or the independent sector, whether the initial admission has a tariff or not, and whether it is to the same provider. In the latter case, the readmitting hospital will be reimbursed, and the commissioner will deduct the full tariff for the initial admission from the first hospital regardless of whether the marginal rate emergency tariff was applied to the second provider. An analysis made by the CHKS found that the provider of the index- and re-admission differ in 20 % of the readmissions (NHS Confederation, 2011).

The exclusions from the policy encompass children under 4 years of age, maternity and childbirth, cancer, chemotherapy and radiotherapy patients, multiple trauma patients where the root HRG code of the readmission is VA14 or VA15, emergency admissions after transport accidents, readmissions after self-discharge against clinical advice, emergency transfers between providers where the initial admission was not a readmission, and cross border activity where either the index admission or the readmission is in the devolved administrations. Readmissions following outpatient procedures and A&E visits are also excluded from the policy. Finally, if providers can convince commissioners that a readmission is clearly unrelated, that particular admission may also be excluded from the non-payment policy (Department of Health, 2011).

For non-elective admissions, reimbursement will be subject to locally agreed thresholds which should be set with the aim of reducing the readmission rate by 25% over the previous year, unless following a clinical audit, the commissioner and provider agree that only a lower reduction in readmission rates is possible, or that readmission rates are already as low as possible. In addition, so-called "year of care tariffs" are proposed for specific groups of frequently admitted patients such as diabetes patients.

2 Methods

2.1 Analytical framework

The focus of our model is supply side reactions to different payment schemes with respect to hospital readmission prevention effort. In our framework providers are reimbursed by a third party payer, and health care is free to the consumer at the point of delivery. For this reason, following Ma (1997); to Albert Ma (1994) the demand for health care is an increasing function of quality.

The probability of a patient being admitted to hospital, p, is a function of the demand for hospital care, D, which in turn depends on the hospital's quality q and patient characteristics X. We assume that q is a non-negative concave function of length of stay, λ and an additional non-negative concave readmission prevention effort the hospital may choose to exert, e, both costly to the hospital. Further, we assume that the λ is a visible signal of quality available to patients. Patient characteristics, X , includes demographics such as age and gender, the specificities of the patient's condition, but also the patient's area of residence which partly determines the amount of expected post-discharge care, primary care provider which may affect the probability of needing hospital care. In addition the admission probability depends on the hospitals admission decision, A which, allowing the hospitals the possibility of selection, depends on patient characteristics. Thus, following Milne and Clarke (1990) the threshold for admitting a patient with a certain mix of symptoms may vary across providers, and as we shall return to, may also depend on characteristics that predict readmission risk.

The cost of treating a patient, c depends on HRG, α and is increasing with length of stay, λ. In addition the provision of the specific readmission prevention effort, e is costly to the hospital.

Initially, hospitals are reimbursed by a fixed payment per discharge which depend on the HRG and a per diem tariff β for length of stay above a HRG specific trim point, T. We use the same notation for HRG for the cost and payment variables, although the reimbursement is set independent of the specific cost of treatment.

2.1.1 The hospital's readmission prevention effort

In the following, we consider the hospital's incentive to exert readmission prevention effort under a traditional prospective payment scheme.

Initially, the hospital's profit function for a patient course is

$$p_i(\alpha_i + \beta_i \max\left[(\lambda_i - T_i), 0\right]) + p_r(\alpha_r + \beta_r \max\left[(\lambda_r - T_r), 0\right]) - p_i c(\alpha_i, q_i) - p_r c(\alpha_r, q_r) \quad (1)$$

where subscripts i and r denote the index- and readmission, respectively and

$$p(\cdot) = p\left(D(q, X), A(X)\right) \quad (2)$$

and

$$q(\cdot) = q(\lambda, e) \quad (3)$$

Since the hospital is reimbursed for readmissions, the incentive to engage in a costly readmission prevention effort is limited, as readmission means additional income to the hospital (the moral hazard effect). However, since readmission rates also serve as a signal of quality of care, they affect demand and thus incentivises the hospitals to exert costly effort to prevent readmissions. Adverse selection due to the signalling effect may be present depending on the strength for the quality-demand relationship and the strength of the signal.

2.1.2 Incentivising readmission prevention

From the payer's point of view, "avoidable" hospital readmissions are costly, and may be so to the patient as well. In an attempt to incentivise hospitals to exert more effort in preventing readmissions, the payer may transfer the risk of costly readmissions to the hospital by introducing a new reimbursement scheme under which hospitals are not reimbursed for readmissions that occur within a given timeframe. In that case the hospital profit function for a patient course is

$$p_i(\alpha_i + \beta_i \max\left[(\lambda_i - T_i), 0\right]) - p_i c(\alpha_i, q) - p_r c(\alpha_r, q) \quad (4)$$

The reimbursement for the readmission is now eliminated, and the hospital may attempt to reduce the readmission rate using one of the following strategies. Firstly, the hospital may increase it's quality by increasing e or λ_i or both. This is costly to the hospital, but if this makes $\lambda_i > T_i$ the hospital is reimbursed for this extra effort by the payer. However, since q is also a signal of quality, this strategy is risky, since the hospital may then attract more patients with a high readmission risk. Alternatively, the hospital may react to the new payment policy by manipulating the admission threshold, A. Thus, in the index admission, the hospital may attempt to avoid patients with a high probability of readmission, if this can be inferred on the basis of patient characteristics. This is the safest strategy for a risk averse hospital, and in the remains of the paper we shall explore the possibilities of the hospital following this strategy.

2.1.3 The role of the payer

Until now, we have not considered the role of the payer. Hospital care may be substitutable for other types of post-discharge and pre-admission care (Forder, 2009), the costs of which is also borne by the payer. In the following we focus on the payer's incentive to invest in the prevention of re-hospitalisations, although a similar analysis may be carried out with respect to pre-admission efforts as well.

Under the initial payment system, the payer pays the fixed tariff per discharge, α plus the per diem tariff, β per day the hospital stay exceeds a trim point, T set by the payer. The payer may in addition invest in readmission prevention efforts such as home care. This effort reduces the patient's probability of being readmitted.

Since readmission prevention effort is costly to the payer, but at the same time reduces the likelihood of readmission, the payer must compare the cost of the prevention effort to the costs of readmission and exert effort to the extent that the readmission prevention will lower the expected cost of re-hospitalisation. If a new provider reimbursement scheme is introduced in which the provider is given the financial responsibility for readmissions, the payer's incentive to engage in readmission effort provision is reduced, and we may expect the payer to exert lower readmission prevention effort than before.

2.2 Data

Our dataset is a random 10% sample of 1,029,314 individuals having an elective admission between April 2007 and September 2010 using English Hospital Episode Statistics. The data set consists of 2,506,533 Finished Consultant Episodes, which are periods of care under a consultant or allied healthcare professional within an NHS trust The Health and Social Care Information Centre, 2011. Each hospital stay may consist of more episodes which, ending with a discharge, together form a spell. This may be the case if the patient is transferred between consultants within the hospital. We only consider patients episodes funded by the NHS. Patients discharged as dead are excluded from the analysis.

Our dependent variable is a binary variable taking the value 1 if the patient was readmitted within 30 days from discharge from a elective admission, and 0 otherwise. We do not include discharges to other consultants. The variable was constructed by identifying elective patient spells, defined as spells in which the admission method of the initial episode in a spell was recorded as *elective: from waiting list, booked,* or *planned.* and where a readmission to an NHS hospital occurred within 30 days of discharge from the elective spell and for which the admission method was *acute: via GP, Bed*

Bureau (including Central Bureau), consultant outpatient clinic, or other means, including admission via A&E or another healthcare provider.

We also carry out our analysis using four other subsets of the dependent variables. Two of them relate to the policy exclusions discussed above and are defined as readmissions that are excluded or included in the policy, i.e. where the readmissions does/does not include children under the age of four (measured at the index admission), maternity and childbirth patients (defined as all HRG groups in chapter N in HRG version 3.5), Cancer, chemotherapy and radiotherapy patients, (defined as patients with an index or readmission with a primary diagnosis in ICD-10 codes C00-C97 and D37-D48), patients who are readmitted having self-discharged against clinical advice and patient where the readmission is due to a road traffic accident (defined as readmissions with a primary or secondary diagnosis in ICD-10 codes beginning with a V). In total, 44 % of all readmissions are excluded from the policy using this definition. Note that in our definition we do not consider multiple trauma patients, readmissions without a tariff, and patients having radiotherapy and chemotherapy except those with a cancer diagnosis as defined above. These groups are also excluded from the policy, but our current dataset does not allow us to identify these readmissions. We will address this in later versions of the paper, but do not expect this to change our overall results.

The other set of dependent variables we consider relate to whether the readmission was to the same or a different provider as the index admission. Both types of readmissions are included in the policy, with the readmission provider being reimbursed at the expensive of the index admission provider. We conduct the analysis on both subsets to see whether the contributions of different sets of variables change for the two types of admissions. Approximately 20 % of all readmissions are to a different provider than the index admission.

In addition, the dataset contains information on *admission date, patient age* and *ethnicity, source of admission, diagnosis classified according to the International Classification of Diseases (ICD-10)*, *Healthcare Resource Group (HRG), code of provider, geographical area (Lower Super Output Area) of patient's residence , discharge destination,* and *code of general practice.* In order to assess determinants of the readmission rate, we linked the data to information on Primary Care Trust (PCT) communitt care activity rates (measured as District Nursing Services: Adult: Face to Face First Contacts divided by the population) and GP QOF performance. Since community care data are only available for financial years 2008/09 and 2009/10 we use 2008/09 data for FYI 2007/08 and 2009/10 data for 2010/11. For the same reason we use 2009/10 QOF performance for 2010/11. We also link the data to area deprivation data from the Index of Multiple Deprivation 2007, and the standardised mortality rate for 2004/08. Descriptive statistics are included in table 1.

2.3 Econometric analysis

The aim of our analysis is to determine which factors contribute to the readmission rates after elective admissions, and the impact of hospital controlled variables compared to the impact of factors beyond the hospitals span of control.

Our relationship of interest is

$$y_i* = \mathbf{x_{ik}}\beta_\mathbf{k} + e_i \tag{5}$$

where $y*$ is a latent probability of admission for which we observe 1 if the patient is readmitted and 0 otherwise, and $\mathbf{x_i}$ is a $1 \times K$ vector of explanatory variables observed for individual *i.* At the current stage we estimate a linear probability model using OLS and address the heteroscedasticity problem

Table 1: Descriptive Statistics

	mean	sd	min	max
Male	0	0	0	0
Female	.5197402	.4996103	0	1
< 1 year	0	0	0	0
1-5 year-olds	.0216387	.1455006	0	1
6-10 year-olds	.0164526	.1272082	0	1
11-15 year-olds	.0170123	.1293172	0	1
16-20 year-olds	.0218976	.1463492	0	1
21-25 year-olds	.0282462	.1656754	0	1
26-30 year-olds	.0334945	.1799239	0	1
31-35 year-olds	.0367643	.1881827	0	1
36-40 year-olds	.0488663	.2155885	0	1
41-45 year-olds	.0622832	.2416693	0	1
46-50 year-olds	.0685409	.2526718	0	1
51-55 year-olds	.0712522	.2572457	0	1
56-60 year-olds	.0864345	.2810047	0	1
61-65 year-olds	.1044072	.3057881	0	1
66-70 year-olds	.1023358	.3030894	0	1
71-75 year-olds	.1022931	.3030334	0	1
76-80 year-olds	.0865028	.2811051	0	1
81-85 year-olds	.0559949	.2299119	0	1
86-90 year-olds	.0256374	.1580511	0	1
>91 year-olds	.0056652	.075054	0	1
White	0	0	0	0
Mixed	.0071242	.0841037	0	1
Asian	.0480748	.2139243	0	1
Caribbean	.013472	.1152845	0	1
Black	.0153451	.1229213	0	1
Other	.0106937	.1028557	0	1
Not stated	.022733	.149051	0	1
Not known	.0848762	.2786974	0	1
Usual place of residence	0	0	0	0
Temporary place of residence	.0012268	.0350041	0	1
Penal establishment	.0001636	.0127885	0	1
HSPA (NHS trust)	.0000363	.0060253	0	1
Ward for Gen Pat/YPD/AE department NHS(other)	.0035364	.0593621	0	1
Maternity or neonate ward NHS(other)	.0000531	.0072841	0	1
Ment. ill or learning disabilward NHS(other)	.0002394	.0154699	0	1
Nursing home, residential care home or group home (NHS)	.0001013	.010066	0	1
LA P3 res. acc. where care is provided	.0000818	.0090432	0	1
LA foster care	.0000407	.006379	0	1
Babies born in or on the way to hospital	.0000383	.0061886	0	1
Non-NHS/LA run residential care home	.0001572	.0125365	0	1
Non-NHS run hospital	.00015	.0122469	0	1
non-NHS/LA run hospice	.0000235	.0048516	0	1
Not known	.0009862	.0313887	0	1
2007/08	0	0	0	0
2008/09	.3022426	.4592299	0	1
2009/10	.3006344	.458534	0	1
2010/11	.1247983	.3304901	0	1
January	0	0	0	0
February	.0734481	.2608706	0	1
March	.0792641	.2701505	0	1
April	.092373	.2895518	0	1
May	.092669	.2899681	0	1
June	.0986243	.2981569	0	1
July	.1021463	.3028406	0	1
August	.0926954	.2900051	0	1
September	.0718877	.258302	0	1
October	.0787949	.2694184	0	1
November	.07562	.2643892	0	1
December	.0687643	.253053	0	1
Dist. nursing services F2F activity	.5601402	.2889227	.0010847	5.854946
QOF: Clinical	87.79207	3.400456	27.65502	100
QOF: Organisational	.9670521	.0654103	.0755241	1
QOF: Patient experience	.8146803	.195599	0	1
QOF: Additional	.9759549	.063298	0	1
Standardised Mortality	1.011231	.3466159	.062619	4.409796
Previous Emergency Spells	.7477767	1.739236	0	148
Charlson Index	.7232516	.9081307	0	2
Length of Stay	1.012997	16.0774	0	6247
Observations	2506533			

by using standard errors clustered by individual. We plan to implement non-linear probability models in future versions of the paper.

The explanatory variables are 1) Patient characteristics: Age in 5 years age bands, gender and age and gender interacted, ethnicity and HRG group. In addition we calculate the Charlson index to control for illness severity and include the number of previous emergency spells. 2) Quality of primary care as measured by points-weighted percentage achievement on the QOF clinical indicators, and percentages of available organisational, additional and patient experience points obtained. 3) area deprivation data in the form of the Index of Multiple Deprivation 2007 income score, education, skills and training score, living environment score, and area mortality.

In addition we control for source of admission, discharge destination , method of discharge, whether the index admission was classified as an ordinary admission, day case admission, regular day or night attender and the intended management of the patient. Finally, we include fixed effects for providertrust, primary care trust, financial year, and month of discharge.

2.3.1 Instrumenting length of stay

In line with previous work Malkin et al. (2000); Amporfu (2008, 2010) we expect length of stay to be endogenous to the readmission rate, meaning that patients with longer length of stay are more likely to be readmitted to the hospital than patients with shorter length of stays. The relationship, however, is not due to length of stay it self, but because more severely ill patients also require longer stays and this dimension of severity cannot be sufficiently controlled for with the available data on severity.

In order to address this problem, we instrument LOS using two-stage residual inclusion (2SRI). Following Terza et al. (2008) we assume the readmission probability to be a function of the endogenous length of stay, x_λ, a $1 \times K$ vector of observable exogenous regressors, x_o regressors, and a $1 \times S$ vector of unobservable confounders, x_u that influence the readmission probability and are correlated with LOS:

$$y = M(x_\lambda \beta_\lambda + x_o \beta_o + x_u \beta_u) + e \tag{6}$$

where M is some known possibly non-linear function. The endogeneity problem arises from the correlation between x_λ and x_u. To address this problem we need instrumental variables that are not correlated with x_u , are sufficiently correlated with x_λ and cannot directly be correlated with y or e. Denoting a set of instruments that fulfil these requirements as the $1 \times T$ vector ω where $T \geq S$ we then estimate the auxiliary equation

$$x_{\lambda s} = r_s(\omega \alpha_s) + x_{us} \tag{7}$$

where α_s is a $(K + T) \times 1$ column vector of parameters.

Defining the residuals as

$$\hat{x}_u = x_{\lambda s} - r_s(\omega \hat{\alpha}_s) \tag{8}$$

in the second stage we estimate

$$y = M(x_\lambda \beta_\lambda + x_o \beta_o + \hat{x}_u \beta_u) + e \tag{9}$$

substituting the residuals from the auxillary regression for the unobserved confounders. When M is a linear function, 2SRI is identical to two stage least squares, and yields consistent estimates of β_λ and β_o. See Terza et al. (2008) for a summary of literature that shows the consistency of 2SRI in nonlinear models.

The relevant instruments are required to be correlated with length of stay, but not with the readmission rate other than via their effect on LOS. We hypothesise four variables that would fit this requirement. 1) the mean length of time that patients waiting for treatment in the same speciality at the same hospital have waited at the day of the patient's discharge, 2) The number of emergency admissions to the same speciality at the same hospital on the patient's day of discharge, 3) the individual patient's waiting time and, 4) Whether the patient was admitted to hospital on a Friday.

The first two instruments are intended to measure the amount of pressure for hospital beds on the day the patient was discharged. For the speciality waiting time variable, the logic is that a high waiting time indicates a high demand for hospital beds which the hospital may respond to by shortening LOS. In all cases we may expect the hospital to react by shortening the LOS of the patients currently in their care, but we do not expect the same variables to have a direct impact on the likelihood of readmission, except for the effect through LOS. Regarding individual level waiting, patient may require more treatment the longer they have been waiting, while for the day of the week, our assumption is that patients are more likely to be discharged the closer to a weekend they were admitted, which may shorten LOS if the patient is admitted at the end of the week . At this stage in our analysis, the instruments are evaluated only by their ability to predict x_λ in the first stage and the significance of $\hat{x}_u$ in the second stage.

3 Results

3.1 Descriptive analysis

We begin by examining the unadjusted mean readmission rates over Provider Trusts and Primary Care Trusts (PCTs). The left panel of Figure 1 shows substantial variation in the raw 30 day readmission rate across individual providers who at the point of measurement were not financially responsible for readmissions. This may be compared to the variation in raw readmission rates across PCTs, displayed in the right panel of figure 1. This panel indicates variation across PCTs as well, but of less magnitude than the variation across providers. This suggests that the principal source of organisational variation may be providers rather than payers. This is what we would expect given that the payers currently bears the financial responsibility. As discussed in the analytical framework above, it will be interesting to see whether the transfer of financial risk related to readmissions will narrow the distribution across providers but widen it across PCTs.

Moving to one of the choice variables of the hospital, figure 2 shows that the risk of readmission generally increases with length of stay (LOS). This could indicate that poorer quality, e.g. due to mistakes during hospitalisation leads to longer LOS and higher readmission rates. However, it may also indicate, as suggested in the literature, a need for the application of instruments to capture the endogeneity of LOS. We return to this issue in section 3.6.

Figure 3 shows the readmission hazard rate over the first 30 days after discharge. The figure shows, that the risk of readmission is largest in the early days after discharge, and then declines. This may indicate that if the hospital slightly extends the LOS of the index admission in response to the new policy it may be able to reduce the likelihood of readmission. Since LOS above the trim point is paid for by the PCT, this may be a fruitful strategy for the hospital to adapt, as previously discussed. We

Figure 1: Raw 30 day readmission rates by Provider Trust and Primary Care Trust

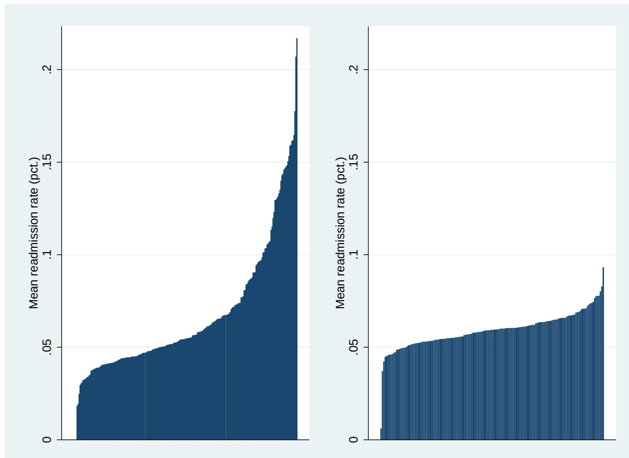


Figure 2: Readmission rates over length of stay (until 99th percentile)

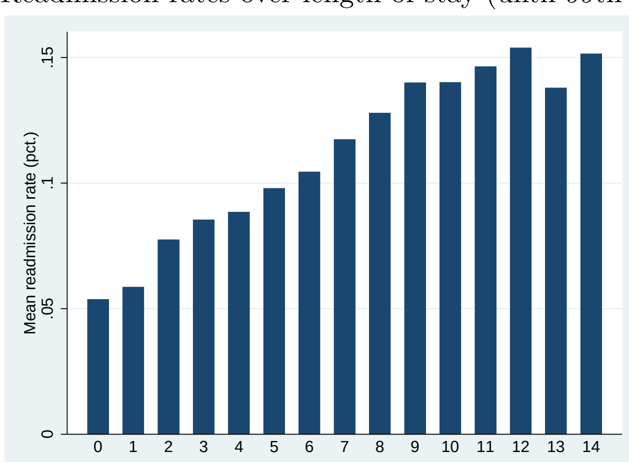
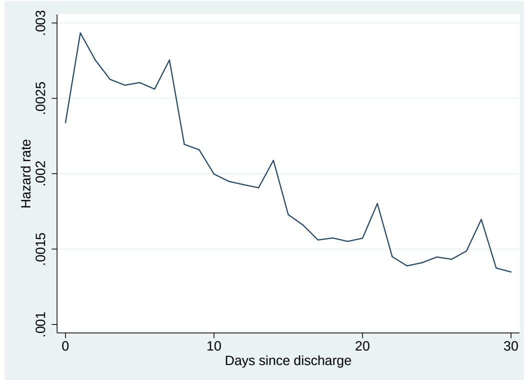


Figure 3: Emergency readmission hazard



did not expect to find the spikes in the hazard rate that appear to occur every 7 days. If hospitals in any way can control when to readmit patients they may attempt to postpone readmission that would otherwise occur during weekends to Mondays. This may explain the observed spikes but that hypothesis needs to be explored further. Another possible explanation may simply be default values in electronic registration systems. In any event, since we focus on readmissions occurring within 30 days from discharge in our analyses this issue should not affect our results, and we leave it to be further explored in future versions of the paper.

3.2 Determinants of readmission rates

In the following sections, the results from our multivariate regression analyses are presented in groups focusing on the joint impact of major variables, time trends in readmission rates, patient characteristics, and primary and community care. In all tables, we present results from analyses performed on five dependent variables: 1) all readmissions; 2) readmissions to the same provider; 3) readmissions to a different provider; 4) readmissions excluded from the new non-payment policy; and 5) readmissions included in the new non-payment policy. As the models are linear, and the dependent variable in 1) is the sum of those in 2) and 3), or 4) and 5), the coefficients in the models for subsets of readmissions can be summed to give the effect on all readmissions.

As hypothesised in the analytical framework, readmission to the same provider may be influenced by the provider's readmission prevention effort (RPE) and the provider's own emergency admission threshold. Readmissions to a different provider are influenced by the RPE at the index admission provider and the emergency admission threshold of other providers. If RPE and admission thresholds are correlated we suspect readmissions to the same hospital to be a less good proxy for hospital quality since the variation caused by variation in admission thresholds is diluted in the rates of readmissions to different providers. High readmission rates to the same provider may be caused by a low admission threshold and not because of a low RPE. Providers may have higher readmission to different providers if there are more local providers or if they can attract more patients for elective admissions from far away. The hospital market in the local geographical area is partially controlled for by our inclusion of PCT dummies. Thus, splitting the results by provider of the readmission lets us separate variation in RPE at the index admission from variation in the emergency admission threshold.

The rationale for excluding some readmissions from the non-payment policy is that these types of readmissions can not be blamed on the hospital, as in the case of self-discharging patients and road traffic accidents, or because readmissions are expected to be part of the treatment package as in the case of cancer. These readmissions should not be influenced by variations in RPE across hospitals and

Table 2: Model summary statistics

	All	Provider		Exclusions	
		Same	Different	Only	None
Constant	0.104^{***}	0.0626^{***}	0.0412^{***}	0.106^{***}	-0.00212
	(6.06)	(4.36)	(3.52)	(9.11)	(-0.14)
Dependent var. mean	0.0597	0.0476	0.0121	0.0262	0.0335
R-squared	0.0604	0.0484	0.0431	0.1034	0.0386
Adj. R-squared	0.0600	0.0480	0.0426	0.1030	0.0382
Number (Obs.)	2506533	2506533	2506533	2506533	2506533
Number (Individuals)	1029314	1029314	1029314	1029314	1029314

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

therefore should show less variation across providers if the provider fixed effects pick up variations in RPE. Thus, splitting the analysis by excluded and included readmissions allows us to to see whether provider effects seem to detect variation in RPE only.

All models contain demographic variables, source of admission, LOS, discharge destination, method of discharge, administrative category, patient classification, intended management, QOF scores, standardised mortality, previous number of emergency spells and the Charlson index as a control for co-morbidities. Summary statistics for all models are presented in table 2 along with dependent variable means and the coefficient of the constant term.

We begin by focusing on the joint significance test of a number of key variables reported in table 2. The new policy holds hospitals financially responsible for readmission rates. For that reason, it is of interest whether, controlling for variables outside the hospital's span of control, there is still significant variation in readmission rates across providers. When controlling for the above mentioned variables, we still find that statistically significant variation across providers, implying that providers can affect readmission rates. The between hospital variation is larger in the readmissions that are excluded from the policy than in the areas included in the policy. This is the opposite of our expectation if the provider fixed effects pick up variation in RPE. We also find higher variation in readmissions to the same provider than to different providers, indicating that these rates are both influenced by RPE and differences in readmission thresholds.

We also find significant variation between PCTs although the variation is smaller than across providers. This confirms the interpretation implied by figure 1. As expected we also find significant variation across HRGs, admission sources, discharge destinations, and discharge methods.

3.3 Time trends in readmission rates

Table 4 suggests that, conditional on the control variables included in our analysis, emergency readmissions occurring within 30 days of an elective spell have decreased compared to the reference year 2007/08. The readmission rate has decreased by about 1.5 %-point from 2007/08 to 2009/10, and this decline is observed for all subsets of readmissions. Note that the differences in the size of the coefficients should be compared to the differences in the mean of the dependent variable. We find higher readmission rates during the spring and summer months. One possible explanation is that hospitals are busier during winter months, and have reduced capacity to readmit patients. In terms of our analytical framework this corresponds to hospitals raising the threshold for readmitting patients. The opposite may of course also be hypothesised, in which case empty beds during summer and spring are filled by hospitals lowering their emergency readmission thresholds.

Table 3: Joint significance tests

	All	Provider		Exclusions	
		Same	Different	Only	None
Joint provider effect					
F statistic	2.851	15.388	12.843	3.516	2.932
df	224.000	224.000	224.000	224.000	224.000
p-value	0.000	0.000	0.000	0.000	0.000
Joint PCT effect					
F statistic	1.678	6.218	9.361	1.487	1.551
df	149.000	149.000	149.000	149.000	149.000
p-value	0.000	0.000	0.000	0.000	0.000
Joint HRG effect					
F statistic	24.539	19.572	8.333	26.959	25.553
df	598.000	598.000	598.000	598.000	598.000
p-value	0.000	0.000	0.000	0.000	0.000
Joint Admission source effect					
F statistic	1.862	1.292	4.900	3.416	1.746
df	14.000	14.000	14.000	14.000	14.000
p-value	0.025	0.203	0.000	0.000	0.040
Joint discharge destination effect					
F statistic	79.767	23.769	57.437	25.181	52.460
df	20.000	20.000	20.000	20.000	20.000
p-value	0.000	0.000	0.000	0.000	0.000
Joint discharge method effect					
F statistic	4.548	2.581	4.226	68.026	852.596
df	2.000	2.000	2.000	2.000	2.000
p-value	0.011	0.076	0.015	0.000	0.000

Table 4: Time variables

	All	Provider		Exclusions	
		Same	Different	Only	None
2007/08	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
2008/09	-0.006^{***}	-0.005^{***}	-0.001^{**}	-0.002^{***}	-0.004^{***}
	(-7.20)	(-6.54)	(-2.73)	(-4.63)	(-5.32)
2009/10	-0.012^{***}	-0.009^{***}	-0.003^{***}	-0.005^{***}	-0.007^{***}
	(-10.74)	(-8.60)	(-5.87)	(-6.59)	(-7.82)
2010/11	-0.015^{***}	-0.012^{***}	-0.003^{***}	-0.006^{***}	-0.009^{***}
	(-11.34)	(-9.63)	(-5.13)	(-7.29)	(-8.00)
January	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
February	-0.000	0.001	-0.001	-0.000	0.000
	(-0.07)	(0.54)	(-1.13)	(-0.48)	(0.29)
March	0.000	0.001	-0.000	-0.000	0.001
	(0.38)	(0.48)	(-0.09)	(-0.37)	(0.74)
April	0.005^{***}	0.005^{***}	0.000	0.001	0.004^{***}
	(4.12)	(4.16)	(0.83)	(1.87)	(3.72)
May	0.004^{**}	0.003^{**}	0.000	0.001	0.003^{**}
	(3.10)	(3.20)	(0.56)	(1.58)	(2.68)
June	0.005^{***}	0.004^{***}	0.000	0.001^{*}	0.003^{**}
	(3.88)	(3.96)	(0.77)	(2.04)	(3.29)
July	0.003^{**}	0.003^{**}	-0.000	0.001	0.002^{*}
	(2.68)	(3.09)	(-0.22)	(1.11)	(2.51)
August	0.004^{***}	0.004^{***}	0.000	0.001	0.003^{**}
	(3.39)	(3.69)	(0.14)	(1.22)	(3.26)
September	0.006^{***}	0.005^{***}	0.001	0.002^{*}	0.004^{***}
	(4.35)	(4.40)	(0.94)	(2.09)	(3.83)
October	0.002	0.002^{*}	-0.000	0.001	0.001
	(1.61)	(2.09)	(-0.50)	(0.88)	(1.35)
November	0.001	0.001	0.000	0.000	0.001
	(1.09)	(0.97)	(0.47)	(0.50)	(0.98)
December	0.003^{*}	0.002	0.001	0.001	0.001
	(2.38)	(1.86)	(1.54)	(1.95)	(1.51)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Patient characteristics

	All	Provider		Exclusions	
		Same	Different	Only	None
Standardised Mortality	0.00359**	0.00171	0.00188***	−0.00055	0.00414***
	(3.17)	(1.61)	(3.50)	(−0.87)	(4.01)
Previous Emergency Spells	0.01644***	0.01227***	0.00417***	0.00599***	0.01045***
	(27.03)	(22.54)	(17.53)	(18.54)	(22.47)
Charlson Index	0.02291***	0.01849***	0.00442***	0.02898***	−0.00607***
	(44.83)	(38.57)	(19.45)	(64.91)	(−16.97)
Length of Stay	0.00004**	0.00003***	0.00001	0.00002***	0.00003*
	(3.27)	(3.73)	(0.97)	(4.38)	(2.09)
Agebands×Gender F	11.346	6.026	5.885	22.433	39.932
Agebands×Gender DF	39.000	39.000	39.000	39.000	39.000
Agebands×Gender p	0.000	0.000	0.000	0.000	0.000
Ethnicity F	28.380	95.002	18.709	3.896	41.354
Ethnicity DF	7.000	7.000	7.000	7.000	7.000
Ethnicity p	0.000	0.000	0.000	0.000	0.000

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Primary and community care variables

	All	Provider		Exclusions	
		Same	Different	Only	None
Dist. nursing services F2F activity	0.002	0.002	0.000	0.002	−0.001
	(0.47)	(0.51)	(0.03)	(0.87)	(−0.25)
QOF: Clinical	−0.000	−0.000	−0.000	0.000	−0.000
	(−0.75)	(−0.06)	(−1.15)	(0.37)	(−1.13)
QOF: Organisational	−0.002	0.000	−0.002	−0.009*	0.007
	(−0.25)	(0.02)	(−0.50)	(−2.02)	(1.40)
QOF: Patient experience	−0.001	0.001	−0.002*	−0.000	−0.001
	(−0.54)	(0.51)	(−1.99)	(−0.13)	(−0.54)
QOF: Additional	−0.011	−0.010	−0.002	−0.003	−0.009
	(−1.61)	(−1.50)	(−0.47)	(−0.55)	(−1.48)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4 Adverse selection

Hospitals may react to increased financial responsibility for readmissions by attempting to avoid patients with a high probability of readmission. As table 5 suggests, hospitals may attempt to avoid patients on the basis of age, Charlson index and number of previous emergency spells. In addition patients from areas with a high standardised mortality rate seem to be slightly more likely to be emergency readmitted to hospital following an elective discharge.

3.5 Primary and community care

Table 6 summarises the impact of primary care and community care on the likelihood of readmission. For primary care we use the reported population achievement for the clinical indicators, and the percentage of obtained points for additional services, patient experience and organisational indicators. We are not able to identify evidence of a significant impact of either community care activity or primary care quality on the likelihood of readmission. The few statistically significant variables are only so at a 5 percent level, which cannot be considered a strong result in a dataset of this size. Since we have access to only two years of data for the nursing time variable at PCT level, we tried running the all readmissions rate without the PCT-dummies. This did not result in a significant effect of community care, either.

Table 7: Instrumenting length of stay

	I			II			III		
	1RF	2RF	2SF	1RF	2RF	2SF	1RF	2RF	2SF
Friday	−0.00876***	0.00092							
	(−13.48)	(1.75)							
Emerg. adm. dis.day (h/s)				0.00004*	0.00000				
				(2.44)	(0.19)				
Waiting time (patient)							0.00001***	−0.00003***	
							(6.07)	(−10.81)	
1st stage residual			0.11199			−0.09414			2.49057***
			(1.86)			(−0.17)			(10.85)
Length of stay			−0.10564			0.10148			−2.48348***
			(−1.75)			(0.19)			(−10.81)
Dependent var. mean	0.2182	0.0554	0.0554	0.2198	0.0546	0.0546	0.2216	0.0540	0.0540
R-squared	0.9116	0.0588	0.0589	0.9103	0.0602	0.0604	0.9056	0.0593	0.0594
Adj. R-squared	0.9116	0.0583	0.0584	0.9103	0.0597	0.0598	0.9056	0.0588	0.0589
Number (Obs.)	2083556	2083556	2083556	1702347	1702347	1702347	1960971	1960971	1960971
Number (Individuals)	887511	887511	887511	765481	765481	765481	865397	865397	865397

	IV			V		
	1RF	2RF	2SF	1RF	2RF	2SF
Friday				−0.01008***	0.00109	
				(−14.58)	(1.92)	
Emerg. adm. dis.day (h/s)				0.00003	0.00002	
				(1.84)	(1.05)	
Waiting time (patient)				0.00001***	−0.00002***	
				(3.80)	(−10.98)	
Waiting time (h/s)	−0.00000	0.00000		−0.00000	0.00000	
	(−0.38)	(0.70)		(−0.88)	(1.23)	
1st stage residual			2.55973			0.26135***
			(0.70)			(4.67)
Length of stay			−2.55186			−0.25359***
			(−0.70)			(−4.54)
Dependent var. mean	0.2266	0.0522	0.0522	0.2273	0.0515	0.0515
R-squared	0.9077	0.0596	0.0597	0.9087	0.0598	0.0598
Adj. R-squared	0.9077	0.0590	0.0591	0.9087	0.0592	0.0592
Number (Obs.)	1599294	1599294	1599294	1548310	1548310	1548310
Number (Individuals)	752394	752394	752394	740622	740622	740622

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6 The impact of length of stay

The results from our instrumental variable regressions are reported in table 7. If hospitals are to distort length of stay, this is most likely to happen when a patient is near to the trimpoint (c.f. the analytical framework). For this reason, this part of the analysis is only carried out on patients with a length of stay within the range of two days below to two days above the trim point[1]. This is reflected in the lower sample size compared to the models in the other parts of the paper. Our four different instruments are applied individually in model I to IV and model V reports results from a model in which all instruments are used together. In each case we report the results from three equations:

- the first-stage reduced form (1RF), in which length of stay is regressed on the same explanatory variables as in the rest of the paper, excluding length of stay, but including the instruments.
- the 2nd stage reduced form using (2RF) the same explanatory variables as in (1RF) but this time with the readmission rate (all readmissions) as the dependent variable. We expect a successful instrument to be significantly correlated with both length of stay and the the readmission rate and to have the opposite sign in the two equations.
- the second-stage structural form (2SF) in which we exclude the instruments but include the residual term, e, from the 1st stage reduced form. If the error term is successful in controlling for unobserved heterogeneity we expect a positive sign on this coefficient and statistical significance at conventional levels.

The coefficient on length of stay from table 6 may now be compared to the instrumented length of stay in table 7 where we expect to observe a change in the coefficient of LOS from positive to negative.

The dummy variable for a Friday admission, the waiting time at patient level, and the mean waiting time for patients at the same hospital specialty all have the expected pattern in the reduced form models. Including the 1st stage residual from these models in the structural form models leads to the expected change in the sign of the coefficient of length of stay. However, the very large coefficients on the residual and length of stay variables may be a sign of under-identification which we will need to examine in further work.

4 Discussion and concluding remarks

Hospital readmission rates have regained attention as indicators of hospital quality. New policies in the NHS and the U.S. Medicare to a larger extent holds hospitals responsible for readmission rates, although it is well known that many factors outside the hospital's span of control also affects the risk of readmission. The aim of this study was to break down the factors influencing the readmission probability. Our results suggest that hospital behaviour has some direct influence on readmission risk, although the available data did not allow us to pin point specific care processes that lead to differences in outcome. We did find, however, that patient characteristics, especially age, gender, severity of illness, previous admission history and the standardised mortality rate in the patient's area of residence significantly influence the risk of readmission. As a response to being held financially responsible for readmission rates, hospitals may use this information in an attempt to avoid patients with a high risk of readmission, or to attempt to attract low risk patients.We were not able to show any significant impact of the quality of primary care or the amount of community care, although the latter may be ascribed to data quality since our data did also no allow us to control for the

[1]defined for each HRG as the upper quartile LOS plus 1.5 times the interquartile range

direct effect of post-discharge care at patient level. We have begun to explore whether changes to a patient's length of stay around the point at which additional days will be paid for by the PCT can reduce the readmission risk.

Another limitation of this study is that no information was available on post-discharge death. Calculating the readmission rate without taking into account patients who die in the community within 30 days of discharge as a result of premature discharge will lead to a downward biased readmission rate (Ashton and Wray, 1996). However, we are not concerned that this problem will significantly influence our results, or at least not alter our conclusions with respect to determinants of readmission rates.

A question we have not yet touched upon is whether holding hospitals financially responsible for readmission may have a moral hazard effect in terms of treatment decisions for the readmission. Hospitals that are not being reimbursed for readmissions may choose less expensive treatment procedures in the readmission in an effort to contain costs. It is not possible to assess this hypothesis yet, since data showing hospital reactions to the increased financial responsibility is not yet available. However, this is hypothesis is a question that may be addressed in later studies.

Similarly we cannot yet consider how hospitals will react to patients that are readmitted to another hospital than the index admission hospital. According to the new NHS policy, the readmitting hospital will in this case be reimbursed with the money being drawn from the index admission hospital. This suggests that hospitals may lower the admission threshold for patients that were initially treated at other hospitals, while increasing the threshold for patients treated at their own hospital. This issue also requires the actual reform to be in operation before it can be explored.

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