A051. Variations in performance of mental health providers in the English NHS: an analysis of the relationship between readmission rates and LOS

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Abstract

Background and Aims

The relative performance and resource use of mental health providers in England is comparatively under-researched. Length-of-stay (LOS) is a key driver of resource use and there are wide variations in LOS. A modified version of Payment by Results (PbR) specific to mental health - the Care Pathways and Packages Approach – has recently been developed. Providers will be paid on the basis of a national tariff based on an average cost which implies that providers may potentially lose or gain if their resource use is above or below the national average in a particular care cluster. The hospital emergency readmission rate can serve as a measure of the quality of mental health care. Evidence on the broader relationship between LOS and readmission is inconclusive. We explore the determinants of LOS for inpatient care, focusing on the impact of readmission rates.

Data and Methods:

We analyse Hospital Episode Statistics (HES) data for 2009/10, using 127,700 inpatient mental health admissions for the 67 mental health providers in England. We compare results from a three-level random effects generalized linear multi-level Poisson model with those from a cross-classified model, which allows a patient to have an admission to more than one provider. We control for various admission-level characteristics such as marital status, carer support, psychiatric history, co-morbidity, legal status and deprivation; patient-level characteristics including age, gender and ethnicity; and provider characteristics such as provider type, capacity, staffing, occupancy, proportion of formal admissions, mortality rates, and readmission rates which have not been calculated nationally before. We obtain Empirical Bayes (EB) estimates of the provider-level random effects, which capture the unexplained residual variation among hospitals.

Results:

The models give broadly similar results with most of the variation in LOS explained by individual characteristics. At an admission-level, the main drivers of LOS are a primary diagnosis of psychosis and formal detention, at a patient-level these are older age and black ethnicity, while at a provider-level, providers that are Mental Health Trusts and the hospital proportion of formal admissions are strong determinants of increased LOS. Preliminary results suggest that LOS is not significantly

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associated with the hospital readmission rate. Ranking providers by residual variation reveals significant differences, suggesting there is scope for some providers to improve their performance.

Conclusions:
Understanding the reasons for variations in LOS and the relationship between LOS and readmission rates can provide valuable insights into differences in performance across hospitals. In acute care, providers are not reimbursed for emergency readmissions within 30 days but our results imply that such a policy may not be as relevant for the mental health care sector.

1. Introduction

The key objectives of the cross-governmental mental health outcomes strategy "No health without mental health" are to improve the quality and efficiency of current services by changing the way that current services are delivered (1). A modified version of Payment by Results (PbR) specific to mental health - the Care Pathways and Packages Approach – has recently been developed to support these aims. The unit of activity (or currency) for this payment system is 21 care clusters based on need rather than diagnosis. The intention is that providers will be paid on the basis of a national tariff based on an average cost which implies that providers that incur costs above the national average in a particular care cluster will potentially lose and providers with below-average costs can potentially gain. This payment system should encourage providers to reduce LOS, as each cluster is given a "review period" which equates to the approximate expectation of how long a service user will stay within a cluster. However, relative performance and resource use of mental health providers in England is comparatively under-researched and current patterns of care need to be understood if the effect of new policies is to be investigated. Using LOS as a proxy for cost and resource use (2) we can therefore explore variation in LOS across providers and the extent to which patient and provider characteristics can explain this variation.

LOS is a key driver of hospital costs, especially when care is staff-intensive as is the case in mental health (3-5). Differences in LOS can reflect differences in patient needs, but can also be indicative of differences in treatment philosophies and practice patterns (6). Hospital emergency readmission rates are increasingly used as performance measures and as a basis for hospital reimbursement (7). A high emergency readmission rate may indicate an inadequate provision of mental health support in the community. It may also represent inadequate in-patient care during the index admission, in particular in relation to inadequate discharge preparedness (8).

The aim of this paper is to examine variation in LOS among mental health providers in England, in particular the relationship between LOS and provider quality as reflected in readmission rates. It considers an array of patient and provider characteristics that can contribute to differences in LOS

across providers including the provider-level readmission rate as a measure of performance. The paper also describes a methodology to quantify the residual unexplained variation as a means of investigating the relative performance of providers. The research makes a unique contribution to research in this field in two ways. First, the analysis uses three levels at which factors influence LOS, by considering admission-, patient- and provider-level variables. Second, the paper uses both hierarchical and non-hierarchical models to explore variation in LOS and also quantifies the residual variation using Empirical Bayes (EB) estimates which are then used in conjunction with comparative standard errors to compare residual variation across providers.

2. Findings from previous literature

Determinants of LOS for psychiatric inpatient care can be classified in terms of admission, patient or provider characteristics. Table 1 gives an overview of the main characteristics considered in previous studies and their relationship with LOS.

Insert Table 1 around here

At an admission-level, diagnostic (primary and secondary diagnoses), treatment (prior service use, involuntary admission) and socio-economic (social support, deprivation) variables are reported as being significantly associated with LOS. In terms of diagnostic variables, the presence of physical co-morbidities as well as a diagnosis of psychosis has been found to be positively associated with longer LOS while a co-morbid diagnosis of substance mis-use disorder is generally reported as reducing LOS (Table 1). There is less consensus in the literature regarding the effect of treatment and socio-economic characteristics. A longer LOS may arise from an involuntary admission if such admissions are indicative of greater severity of illness. Tulloch (2010) report that being married is associated with shorter LOS (9). Rothbard and Schinnar (1996) posit that prior service use may be associated with a shorter LOS as patients who are familiar with the mental health system can be treated and discharged quicker (10). However, prior service use may also be indicative of greater severity of illness thus resulting in a longer LOS (11). Abas et al. (2008) found that greater levels of socioeconomic deprivation in the inpatient's neighbourhood of residence was associated with extended hospitalization after adjustment for demographic factors and primary diagnosis but not after adjustment for comorbid diagnosis, chronicity, function, and severity (12). Dekker et al. (1997) reported negative correlations between LOS and deprivation characteristics which they surmised resulted from deprived areas having a larger number of patients who are frequently readmitted for a short time (13).

At a patient-level, black ethnicity is associated with a longer LOS compared to white or Asian ethnicity (14,15). There is no clear direction regarding the relationship between LOS and gender. McCrone and Lorusso (1999) showed a non-linear relationship between LOS and age (16). A longer

LOS for older people may be somewhat related to the availability of social supports as well as the availability of and access to continuing health and social care (17,18). Moreover, presentations by elderly patients may be medically complex due to a higher risk of medical co-morbidities and adverse reactions to medications (18).

At a provider level, hospital capacity is positively associated with LOS (19) while levels of human resources in terms of healthcare professionals have shown a negative relationship with LOS (20). The positive relationship between LOS and hospital capacity is likely due to a desire or need to keep bed occupancy levels high and may also be related to the provider payment method (e.g. per diem) and hospital efforts to increase revenues (19). Lower numbers of human resources in terms of healthcare professionals may be indicative of cost-cutting efforts on the part of hospitals that consequently reduce quality of care and increase LOS (20).

Evidence on LOS and readmissions

Existing evidence on the relationship between LOS and readmission for mental health care is inconclusive. Shorter initial hospital stays have been shown to be related to higher readmissions (21-25). Conversely, Korkeila et al. (1998) report that a long LOS is associated with an increased risk of multiple readmissions (26). Readmissions that take place within a relatively short period after discharge may be negatively associated with LOS due to the need for a longer inpatient stay to stabilise symptoms and provide adequate treatment while readmissions taking place within a longer period following discharge may be more likely to reflect the influence of factors beyond inpatient hospitalization, such as effective transitional care, the availability of community and family supports, access to primary care, housing and continued access and adherence to prescribed medications (23). This implies an important role for adequate discharge planning in protecting against early readmission (8,27). The association between a long LOS and readmission rates may reflect patient severity in that there may be a small group of more severely ill patients for whom longer hospitalisations or more frequent hospitalisation is possibly more appropriate than outpatient-based care (26). Many previous studies investigated the relationship between LOS and readmissions at the individual patient level. Fewer studies have examined the relationship between patient LOS and provider-level readmission rates and this study makes an important contribution in this regard.

3. Methods

In our data sample, admissions are nested within patients. Some patients have multiple admissions (spells) the majority of which are to the same provider, but for approximately 4% of spells, the admissions are to different providers. We use hierarchical and non-hierarchical models to model these nested data structures.

3.1. Hierarchical Models

Our data sample is comprised of a three-level hierarchy with admissions nested in patients who in turn are nested in hospitals. Figure 1 displays the three-level hierarchical data structure in graphical form. For this model, we assume that patients with multiple admissions attend only one (the first) provider. As a sensitivity analysis we also run the 3-level model for the sample that excludes those patients with multiple providers (4% of spells).

Insert Figure 1 about here

3.2 Non-hierarchical Models

In non-hierarchical models, the data are not structured in a strict hierarchy. For the purposes of this study we consider the cross-classified non-hierarchical data structure. In cross-classified data, lower level units do not belong to one and only one higher level unit. Rather, lower level units belong to pairs or combinations of higher level units formed by crossing two or more higher level classifications with one another, as shown in Figure 2.

Insert Figure 2 about here

3.3. Multi-level generalized linear random effects model

Our choice of estimation model is a random effects multi-level generalised linear model. Multilevel generalised linear models contain multivariate normal random effects in the linear predictor (28). Advantages of the (multi-level) generalised linear model are that predictions are made on the raw scale so no retransformation is required and it allows for heteroskedasticity through the choice of distributional family (29). A three-level generalized linear model can be written as:

$$g^{-1}\{E[\, y_{ijk} \mid x_{ijk,}\, u_{jk}\, v_k]\} = \boldsymbol{\beta}\mathbf{X}_{ijk} + u_{jk} + v_k \equiv \eta_{ijk}$$

where $\mathbf{X}_{ijk}$ is a column vector of admission, patient and hospital characteristics, u_{jk} are random intercepts or level 2 patient specific effects and v_k are level 3 random intercepts or hospital specific effects, $g^{-1}(.)$ *i*s the link function and η_{ijk} is the linear predictor. The conditional expectation of the response, given the covariates and the random effects is:

$$\mu_{ijk} \equiv \{E[\, y_{ijk} \mid x_{ijk,}\, u_{jk,}\, v_k]\} = g(\boldsymbol{\beta}\mathbf{X}_{ijk} + u_{jk} + v_k) = g(\eta_{ijk})$$

We assume that the random effects are multivariate normal and that the covariates are strictly exogenous. The responses are assumed to be conditionally independent, given the covariates and random effects, and have conditional distributions from the exponential family. The conditional variance is given by:

$$\mathrm{Var}\,(y_{ijk}|u_{jk,}\, v_k) = \varphi_{ijk} V(\mu_{ijk})$$

where φ_{ijk} is a dispersion parameter and $V(\mu_{ijk})$ is a variance function specifying the relationship between the conditional variance and conditional expectation. As our response variable (LOS) can be evaluated as count data, a Poisson distribution with a log link is specified. The variance function $V(\mu_{ijk}) = \mu_{ijk}$ and the dispersion parameter $\varphi_{ijk} = 1$. The Poisson distribution assumes that equi-dispersion is present implying that the conditional mean is equal to the variance. For some spells of care the conditional variance may exceed the mean so the assumption of equi-dispersion is too restrictive. Therefore we allow for an extra binomial variation parameter to allow for over- or under-dispersion.

3.4. Empirical Bayes prediction of the Random Effects

Having obtained estimates of the model parameters and treating them as the true parameter values, we can predict values of the level 3 or hospital random effects v_k using Empirical Bayes techniques. This will allow us to quantify the residual variation not explained by the variables in our model and compare this across hospitals in terms of LOS using comparative standard errors. We assume a normal posterior distribution and known model parameters in order to form Bayesian credible intervals using the posterior mean and posterior standard deviation. The posterior standard deviation is commonly used as a standard error of prediction for multilevel generalised linear models (28). The Empirical Bayes estimates of the provider-level random effects are ranked and graphically displayed. The residuals represent hospital departures from the overall mean, so a hospital whose confidence interval does not overlap the line at zero is said to differ significantly from the average at the 5% level.

3.5. Estimation methods

The three-level model is estimated using restrictive iterative generalised least squares (RIGLS) which is equivalent to maximum restricted likelihood (30). The cross-classified model is estimated using the Monte Carlo Markov Chain (MCMC) method. MCMC methods are simulation-based procedures so that rather than simply producing point estimates the methods are run for many iterations and at each iteration an estimate for each unknown parameter is produced. These estimates will not be independent as, at each iteration, the estimates from the last iteration are used to produce new estimates. The aim of the approach is then to generate a sample of values from the posterior distribution of the unknown parameters. For the cross-classified model presented here, the chain is run for 250,000 iterations. Distributional summaries for the parameters are based on these iterations. Parameter estimates are given by the means of these chains, while the standard errors are derived from the standard deviation of these chains. As we have a non-normal response variable we use orthogonal predictors in order to reduce the influence of correlation between chains for the predictor variables (31). The models were estimated in MLwiN 2.28 using the runmlwin command in Stata 12.0 (32).

The coefficients on the predictor variables are expressed using Incidence Rate Ratios (IRRs). The IRR facilitates a semi-elasticity interpretation i.e. a percentage change in number of days of LOS resulting from a one-unit change in the explanatory variable. Therefore, a positive coefficient signals that the variable exerts an upward pressure on LOS and a negative coefficient a downward pressure.

4. Data

4.1. Data sources

Patient-level variables are sourced from Hospital Episode Statistics (HES) data for 2009/10. Provider-level variables are sourced from a number of datasets including HES, Hospital Activity Statistics, the Health and Social Care Information Centre (HSCIC), Care Quality Commission and the Department of Health Staffing Survey. The independent variables comprise a range of patient- and provider-level variables that are likely to influence LOS. Patient-level variables describe demographic, diagnostic, treatment and quality characteristics while provider-level variables supply information on provider type and size, staffing, quality and case-mix.

We restricted our dataset to the 67 mental health providers in England. Prior to conducting analyses, the database was trimmed to be more representative of patients with mental disorders treated by mental health care providers. For this purpose, we dropped the following:

- Observations for admissions to PCTs that do not record an ICD-10 F chapter (Mental and Behavioural Disorders) code or a Health Resource Group (HRG) Version 3.5 T code (Mental Health) (53,641 observations deleted);
- Observations for admissions with age zero that represented babies with a mother receiving mental health care (15 observations deleted);
- Observations for admissions with ages of 1 and 2 years (except if they were treated by a Mental Health Trust or had an F code diagnosis) (11 observations deleted);
- Observations with wrongly coded age (28 observations dropped);
- Observations for patients admitted prior to 1st April 2009 (19,999 observations deleted) so that the dataset consists only of patients with finished episodes that were admitted during 2009/10.

We conduct a sensitivity analysis by re-estimating the models using a dataset that excludes the observations with zero LOS to test if admissions with a positive LOS better reflect greater resource use and are more representative of the population we want to assess.

4.2. Data description

The following section describes the dependent variable – LOS and the admission-, patient- and provider-level explanatory variables used in our analyses.

4.2.1. Dependent variable

The dependent variable LOS- is measured by the time elapsed between admission and discharge dates at spell level. We only take account of admissions that start and finish in 2009/10 thus LOS is truncated at 365 days. LOS per admission ranges from a minimum of 0 days to a maximum of 364 days (Figure 3). There is also substantial variation in LOS between providers (Figure 4).

Insert Figure 3 about here

Insert Figure 4 about here

4.2.2. Admission-level independent variables

Patient transfers to or from another hospital provider can be an indication of patient case-mix with certain providers specializing in the treatment of certain diagnoses. Patient death in hospital is a relatively rare event but it can act as an indicator of the quality of care provided (33). A diagnosis of psychosis indicates severity of patient mental illness. A standardized measure of co-morbidity was constructed by dividing the number of co-morbidities recorded for a patient with an F code recorded as a primary diagnosis by the average number of co-morbidities recorded for psychiatric patients treated by the provider treating the patient. This accounts for provider differences in coding secondary diagnoses and deals with providers systematically "inflating" coding. Severity is also reflected in psychiatric history represented by one or more previous psychiatric admissions. Another severity variable indicates if patients have been formally detained under the Mental Health Act. Marital status and a record of carer support signal the extent of social support available to patients. We include a variable that captures socio-economic deprivation as measured by the Index of Multiple Deprivation (IMD). The IMD is measured at Lower Layer Super Output Area (LSOA) level and subsequently assigned to patients on the basis of residency. LSOAs are a geographic hierarchy with a minimum population of 1000 and a mean of 1500 (34). The IMD has seven domains, of which the IMD Income Domain is included in the dataset. The purpose of this Domain is to capture the proportions of the population experiencing income deprivation in an area (35). A higher score for the Income Domain indicates a greater proportion of the population in the area in which the patient lives experiences income deprivation.

4.2.3. Patient-level independent variables

Age is divided into 5 categories which represent quintiles of the data distribution. Gender is measured as a dummy variable with females as the reference category. Patient ethnicity is categorized into white (the reference category), Asian, black and other ethnicity (e.g. mixed race, or unknown ethnicity).

4.2.3. Provider-level independent variables

Providers of mental health care comprise Mental Health Trusts, Care Trusts and Primary Care Trusts (PCTs)[2]. Two dummy variables are included in the models to indicate if a provider is 1) a Mental Health Trust and 2) has Foundation Trust status. Foundation Trusts differ from other NHS Trusts in that they are independent legal entities and have unique governance arrangements. They are free from central government control, are not subject to the same levels of performance management, have significant financial freedoms and are free to raise capital from both the public and private sectors. Mental Health Trusts provide health and social services for people with mental health problems, in particular specialist services for people with severe mental health problems. The variable "total available beds" provides a measure of hospital size. Total bed occupancy provides an indication of utilisation. The optimal occupancy rate is estimated at around 85% for Mental Health Trusts (36). Human resources variables are measured as the proportion of medical staff from total Full Time Equivalent (FTE) staff and the proportion of nursing staff from total FTE staff. Nurses make up a higher proportion of total FTE staff. The proportion of formal admissions under the Mental Health Act (MHA) provides information on patient severity. We include a variable on formal admissions at provider-level as well as admission-level as we expect providers to have different thresholds for detention.

The study utilises emergency readmission rates for mental health providers which have not been calculated nationally before. These have been specifically calculated for mental health providers using HES data based on inclusion and exclusion criteria adapted from acute providers specified by the Department of Health (37). The HSCIC excludes mental health speciality in its standard calculation of emergency readmission rates for acute providers. In the calculation of readmission rates for mental health providers, the numerator is based on a pair of spells – the discharge spell and the next subsequent readmission spell to reflect emergency admissions within 0-27 days (inclusive) of the last, previous discharge from hospital including those where the patient dies but excluding those with a main speciality of obstetrics or learning disability upon readmission and those where the readmitting spell has a diagnosis of cancer (other than benign or in situ) or chemotherapy for cancer coded anywhere in the spell. The denominator excludes day cases, spells with a discharge coded as death,

[2] From April 1, 2013 PCTs ceased to exist and were replaced by Clinical Commissioning Groups (CCGs) and Local Area Teams (LATs).

spells with obstetric and learning disability specialities and those with a diagnosis of cancer or chemotherapy treatment for any form of cancer in the 365 days prior to admission.

Quality of care is also represented in a number of variables upon which providers are performance managed by the Care Quality Commission. Crisis Resolution and Home Treatment (CRHT) teams provide intensive support for people in mental health crises in their own home and stay involved until the problem is resolved (38). An aim of CRHT teams is to prevent hospital admissions; therefore access to CRHT teams can provide an indication of the level of gate keeping available. This indicator is measured using the number of admissions to the trusts acute wards (excluding admissions to psychiatric intensive care units) that were "gate kept" by the CRHT teams as a percentage of the total number of admissions to the trusts acute wards (excluding admissions to psychiatric intensive care units). The indicator Care Programme Approach (CPA) 7 day follow up measures the extent to which people under adult mental illness specialities on CPA receive follow-up (by phone or face to face contact) within 7 days of discharge from psychiatric inpatient care. Providers are judged to have "achieved" this indicator if at least 95% of patients receive follow up within seven days of discharge. The patient experience score is based on five domains: access and waiting; safe, high quality, coordinated care; better information, more choice; building relationships; and clean, comfortable, friendly place to be (39).

5. Results

5.1 Descriptive statistics

Table 2 presents the descriptive statistics for our data sample.

Insert Table 2 around here

5.2 Models Estimates

Table 3 presents the estimates of the three-level and cross-classified models.

Insert Table 3 around here

The results of both models are relatively consistent with regard to admission-level variables. Variables with a positive association with LOS include transfer-in, co-morbidity, primary diagnosis of psychosis, formal detention, carer support recorded and psychiatric history proxied by one or more previous admissions. Of these, a diagnosis of psychosis and formal detention have the strongest effects on LOS with the magnitude of these effects somewhat diminished in the cross-classified model compared to the three-level model. Moreover, in the cross-classified model the variable

measuring marriage/civil partner has a positive effect on LOS in contrast to the three-level model where marriage/civil partner is negatively associated with LOS.

The only variable with a statistically significant negative association with LOS in both models is transfer-out. The magnitude of this variable is also similar for both models and suggests it has a relatively large impact on shortening LOS. In the three-level model, the variables measuring a secondary diagnosis of substance abuse and income deprivation also have a negative association with LOS but these variables are insignificant in the cross-classified model. Death is not statistically significant in either model, perhaps due to the relatively small number of cases.

All of the patient-level variables have a statistically significant association with LOS in the cross-classified model but age category 3 loses statistical significance in the three-level model. The magnitude of the positive effect of age on LOS is greater for older age groups. Males are associated with a lower LOS compared to females. Black and Asian ethnicities are associated with a longer LOS compared to white ethnicity with black exhibiting a relatively larger effect. Patients of other or unknown ethnic origin are predicted to have a shorter LOS compared to those of white ethnicity.

In terms of provider-level variables, only the variables measuring if a provider is a Mental Health Trust and the proportion of formal admissions under the Mental Health Act are statistically significant in both models. Both variables have a strong positive effect on LOS. In addition, total bed occupancy and proportion of medical staff from total FTE staff are statistically significant in the cross-classified model with the former having a positive influence on LOS and the latter a negative effect. The emergency readmission rate is negatively associated with LOS in the three-level model and positively associated with LOS in the cross-classified model but is not statistically significant in either model.

Of the residual variation not explained by the three-level model, the majority (96%) is at the admission-level, while 3.9% and 0.1% are at the patient- and provider-level respectively. Similarly, in the cross-classified model most of the residual variation is at the admission-level (93.9%) followed by the patient- (5.9%) and provider-level (0.2%).

Results of the sensitivity analysis estimating the 3-level model for the sample that excludes those patients with multiple providers remained stable when compared to the three-level model for the full sample presented here. When admissions with a zero LOS were excluded from the analysis, the results for the admission- and patient-level characteristics were broadly consistent with the results provided here. However, in terms of the provider-level characteristics, foundation trust became statistically significant while mental health trust, bed occupancy and medical staff as a proportion of total FTE staff lost statistical significance in the analysis focused only on positive LOS.

5.3. EB Estimates

While the admission-, patient- and provider-level variables included in the model explain most of the variation in LOS, there remains some residual variation in LOS as captured by the provider random effects. Figures 5 and 6 present the EB estimates of the provider-level residual variation from both the three-level and cross-classified models.

Insert Figure 5 about here

Insert Figure 6 about here

Figures 5 and 6 show that the distributions of the EB estimates are similar for both models with a slightly wider distribution of residual variation from the cross-classified model. Figure 6 also shows that relative to the average performing hospital, the top performing hospital reduces the number of days of LOS by 42% while the worst performing hospital increases the number of days of LOS by 56% due to factors not considered in the model such as variations in efficiency, suggesting that there is potentially scope for some providers to improve their relative performance.

6. Discussion

This paper has sought to investigate the main drivers of variations in LOS for mental health providers in England. We contribute to the current evidence base in a number of ways. The use of hierarchical and non-hierarchical models has allowed us to exploit the multi-level nature of a patient-level dataset with national coverage – the Hospital Episode Statistics (HES) data. HES provides rich information on a wide range of variables related to admission-, patient- and provider-level attributes which enables us to move beyond current literature in this field which considers a more limited range of variables. Moreover, we include provider-level emergency readmission rates calculated using HES data – a valuable addition as the HSCIC does not routinely calculate emergency readmission rates for mental health care providers. This allows us to investigate the relationship between variations in LOS and provider quality of care as measured by the emergency readmission rate.

The three-level hierarchical and cross-classified non-hierarchical models demonstrate a reasonable level of consistency in results. Given the relatively small proportion of patients who move between different providers, we would not expect the results of each model to diverge to a large extent. At an admission-level, we find that diagnostic factors are important determinants of increased LOS. Another strong predictor of increased LOS is an involuntary admission which can also be interpreted as higher severity. The strongest patient-level characteristics are older age – in particular between 68 and 109 years – and black ethnicity. The proportion of formal admissions treated by a provider is a consistently strong predictor of longer LOS at the provider-level with the effect magnified in the cross-classified model. This finding is of particular interest in light of recent suggestions that due to

increasing pressure on inpatient beds, patients are being sectioned under the Mental Health Act in order to secure treatment in hospital (42). Such a practice is likely to increase pressure on available beds given that our model suggests formal admissions are a key driver of longer LOS at both admission- and provider-levels. The only other statistically significant variable at the provider-level in both models is that indicating if a provider is a Mental Health Trust which also exerts a strong upward pressure on LOS. This is unsurprising given that we expect Mental Health Trusts to treat patients with higher severity levels. We find that provider-level readmission rates are not statistically significant in either model meaning we cannot provide a definitive statement on the relationship between quality and resource use with respect to provider performance. Under PbR, providers in the acute sector are not reimbursed for readmissions within 28 days of discharge. However, based on these results, such a policy may not be as pertinent in the mental health care sector.

Our results indicate that admission- and patient-level factors are most predictive of variations in LOS which raises questions about the extent to which providers can influence LOS for mental health care. Moreover, the residual variation at the provider-level is small after conditioning on all patient characteristics, suggesting that while there is some scope for providers to improve their relative performance this is likely to have a relatively small effect on reducing variations in LOS.

There are several limitations to this research. In order to gain a more comprehensive picture of the performance of mental health care providers it is necessary to model the entire care pathway. The majority of mental health care takes place in community-based settings and inpatient care is usually reserved for crisis stabilisation. Thus, by focusing on a relatively narrow segment of the care process we are likely to misrepresent the true performance of mental health care providers. Moreover, consideration of the entire care pathway is likely to provide important insights into the interplay of other factors such as the range of outpatient and community-based services received, accommodation status, and crisis planning among others, not considered in this model that can influence inpatient LOS. Usage of HES linked to the Mental Health Minimum Data Set (MHMDS) – a national –level dataset for specialist mental health care – will allow us to investigate provider performance across the entire care pathway. The interaction between acute and psychiatric inpatient care can also have implications for inpatient psychiatric LOS. In order to account for the truncation of LOS, we could rerun the models using an additional year of data i.e. 2010/11 and thus include admissions that started but did not conclude during 2009/10.

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Table 1. Literature on characteristics associated with LOS

Variable	**Direction of association (Reference)**
Admission-level characteristics	
Physical co-morbidities	Positive (41)

Diagnosis of psychosis	Positive (9, 11, 18, 19, 42,43)
Co-morbid diagnosis of Substance Mis-Use	Negative (11, 44,45)
Legal status	Positive (18,46), Negative (9,45)
Social support	Positive (42), Negative (9)
Prior service use	Positive (11), Negative (10,47)
Deprivation	Positive (12) Negative (13)
Patient-level characteristics	
Age	Positive (11,18 ,42), Negative (19) Non-linear (18,44)
Gender	Positive for males (10,19) , Positive for females (9, 16,42)
Ethnicity	Positive for black ethnicity (14) (15)
Provider-level characteristics	
Hospital capacity	Positive (9, 19,20)
Human resources of healthcare professionals	Negative (19,20)
Readmission rates	Positive (26) Negative (21) (22) (23,24) (25,48)

Figure 1. Three-level hierarchical data structure

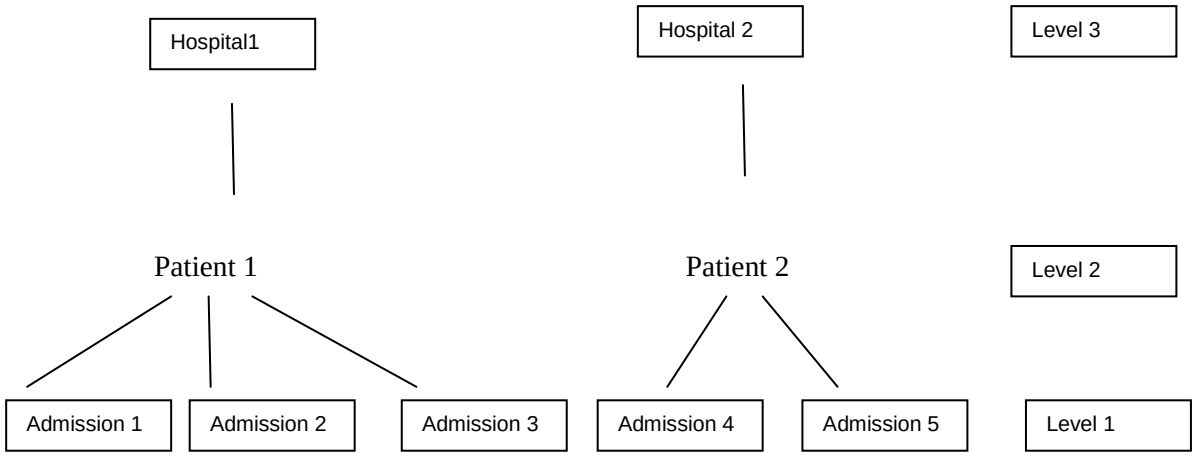

Figure 2. Cross-classified data structure

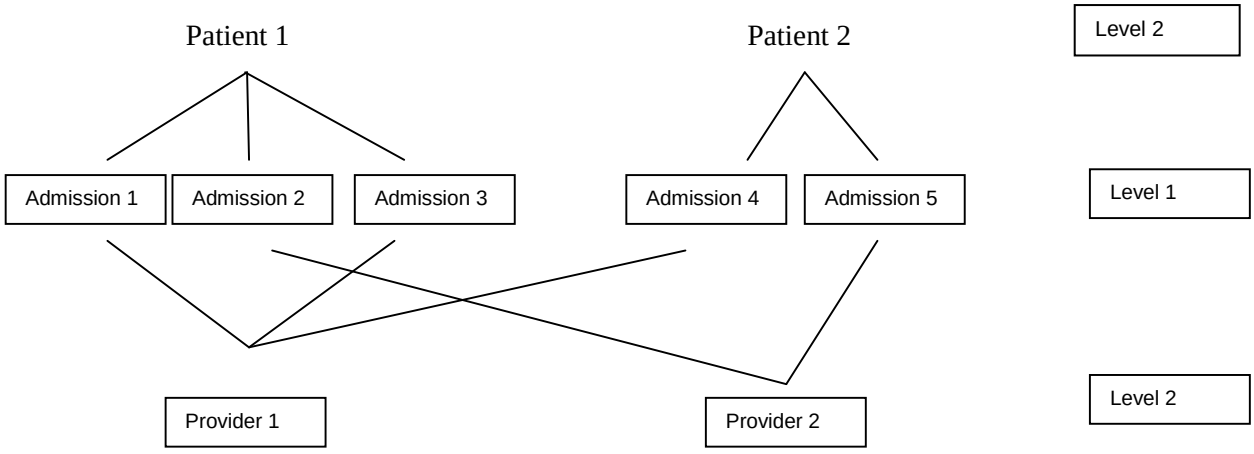

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Length of stay (spell)	131599	31.050	42.461	0	364
Admission-level variables (n=131599)					
Patient transfer-in Dummy Variable	131599	0.209	0.407	0	1
Patient transfer-out Dummy Variable	131599	0.067	0.249	0	1
Patient death in hospital	131599	0.008	0.092	0	1
Standardised measure of comorbidity burden	127594	0.961	3.400	0	301
Primary diagnosis of psychosis	131599	0.118	0.322	0	1
Secondary Diagnosis of Substance Use	131599	0.054	0.225	0	1
Formally detained under Mental Health Act	131599	0.124	0.328	0	1
Carer support recorded	131599	0.068	0.253	0	1
Married/partner	131599	0.181	0.385	0	1
One or more previous psychiatric admission	131599	0.418	0.493	0	1
IMD Income Domain	125043	19.839	13.320	0	83
Patient-level variables (n=91551) [Reference category: Age Category 2 (28-38), Female, Patient ethnicity: White]					
Age Category 1 (3-27)	91305	0.206	0.405	0	1
Age Category 3 (39-47)	91305	0.185	0.388	0	1
Age Category 4 (48-67)	91305	0.210	0.407	0	1
Age Category 5 (68-109)	91305	0.188	0.390	0	1
Patient gender	91515	0.512	0.500	0	1
Patient ethnicity: Asian	91551	0.044	0.204	0	1
Patient ethnicity: Black	91551	0.052	0.222	0	1
Patient ethnicity: other or not known	91551	0.062	0.241	0	1
Provider-level variables (n=67)					
Dummy Variable for Foundation Trust	67	0.628	0.483	0	1
Dummy Variable for Mental Health Trust	67	0.921	0.270	0	1
Total Available Beds	64	511.7	247.3	13.7	1237.2
Total Bed Occupancy (%)	64	84.991	5.694	63.5	97.9
Proportion formal admissions under Mental Health Act	67	0.211	0.097	0.030	0.762
Emergency readmission rate by provider	67	0.116	0.035	0.053	0.226
Care Programme Approach (CPA) 7 day follow up	67	97.098	2.767	82.7	100
Patient experience total score	64	298.615	10.539	273.5	325.8
Access to Crisis Resolution Home Treatment (CRHT) team (gatekeeping)	67	94.527	11.020	9.4	100
Proportion of medical staff from total Full Time Equivalent (FTE) staff	67	0.057	0.021	0.009	0.109
Proportion of nurses from total FTE staff	67	0.322	0.041	0.194	0.4

Table 3. Model estimates

Variable	**Three-level**		**Cross-classified**	
Length of stay (spell)	**IRR**	**Std Error**	**IRR**	**Std Error**
Constant	6.274	7.422	4.440	5.251
Admission-level variables (n=114,483)				
Patient transfer-in Dummy Variable	1.045***	0.009	1.096***	0.004
Patient transfer-out Dummy Variable	0.646***	0.009	0.619***	0.003
Patient death in hospital	0.998	0.035	1.002	0.017
Standardised measure of comorbidity burden	1.011***	0.001	1.016***	0.000
Primary diagnosis of psychosis	1.500***	0.017	1.236***	0.008
Secondary Diagnosis of Substance Use	0.886***	0.015	0.987	0.008
Formally detained under Mental Health Act	1.554***	0.017	1.394***	0.006
Carer support recorded	1.100**	0.030	1.096***	0.027
Married/partner	0.919***	0.010	1.082***	0.010
One or more previous psychiatric admission	1.035***	0.009	1.046***	0.004
IMD Income Domain	0.998***	0.000	1.000	0.000
Patient-level variables (n=80,999) [Reference category: Age Category 2 (28-38), Female, Patient ethnicity: White]				
Age Category 1 (3-27)	1.060***	0.015	1.034**	0.012
Age Category 3 (39-47)	1.017	0.014	1.074***	0.012
Age Category 4 (48-67)	1.364***	0.017	1.393***	0.017
Age Category 5 (68-109)	2.143***	0.028	2.638***	0.033
Patient gender	0.976**	0.008	0.955***	0.008
Patient ethnicity: Asian	1.144***	0.024	1.192***	0.024
Patient ethnicity: Black	1.259***	0.024	1.348***	0.026
Patient ethnicity: other or not known	0.901***	0.016	0.852***	0.013
Provider-level variables (n=61)				
Dummy Variable for Foundation Trust	0.955	0.050	0.940	0.052
Dummy Variable for Mental Health Trust	1.345***	0.113	1.553***	0.125
Total Available Beds	1.000	0.000	1.000	0.000
Total Bed Occupancy (%)	1.005	0.004	1.010*	0.005
Proportion formal admissions under Mental Health Act	2.067**	0.458	2.739***	0.914
Emergency readmission rate by provider	0.485	0.361	1.290	1.100
Care Programme Approach (CPA) 7 day follow up	1.008	0.010	1.004	0.012
Patient experience total score	1.001	0.002	1.001	0.002
Access to Crisis Resolution Home Treatment (CRHT) team (gatekeeping)	0.997	0.005	1.000	0.007
Proportion of medical staff from total Full Time Equivalent (FTE) staff	0.099	0.142	0.065**	0.151
Proportion of nurses from total FTE staff	1.049	0.576	0.959	0.693
Random effects parameters	**Three-level**		**Cross-classified**	
	Estimate	**Std Error**	**Mean**	**Std Dev**
Provider-level	0.025	0.005	0.038	0.008
Patient-level	0.827	0.008	1.283	0.007
Admission-level	20.430	0.152	20.430	0.000

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

Figure 3. LOS by patient spell

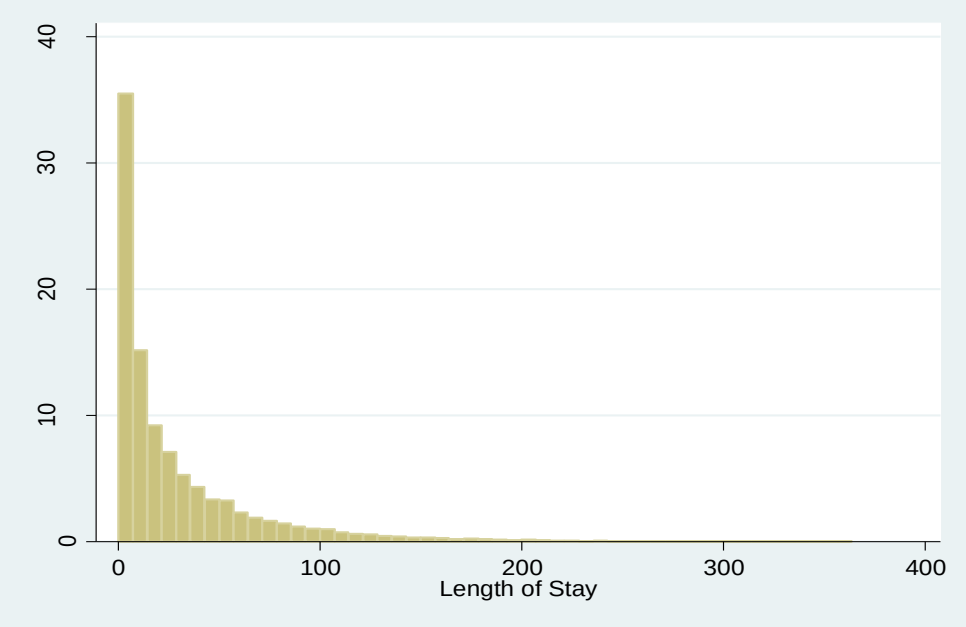

Figure 4. Variation in LOS between providers

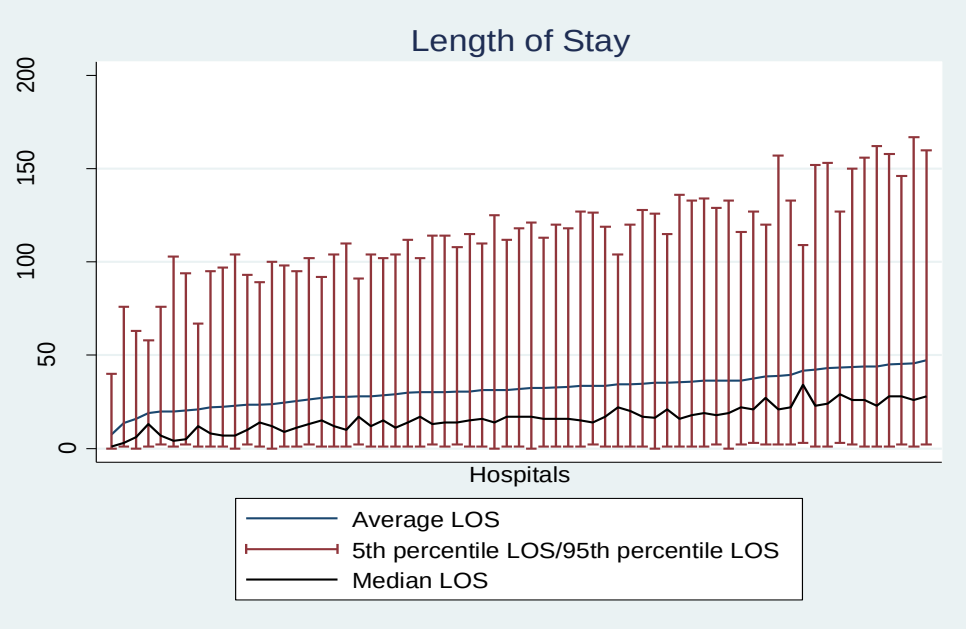

Figure 5. EB estimates 3-level model

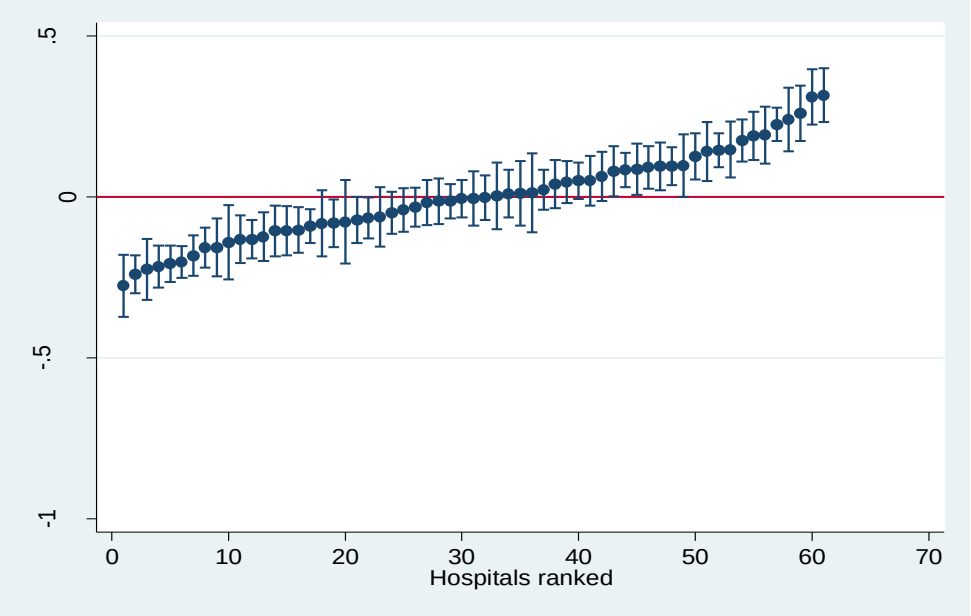

Figure 6. EB estimates cross-classified model