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## Variation in Compulsory Psychiatric In-Patient Admission in England: a Cross-Classified, Multilevel Analysis

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**Abstract** (258 words; 243 words excluding funding statement)

## **Background**

The increasing rate of compulsory admission to psychiatric in-patient beds in England is concerning. Studying variation between places and services could be key to identifying targets for interventions to reverse this. We modelled spatial variation in compulsory admissions in England using national patient-level data, and quantified the extent to which patient, local area and service setting characteristics accounted for this variation.

## **Methods**

Cross-sectional, multilevel analysis of the 2010/11 Mental Health Minimum Data Set (MHMDS). Data were available for 1,238,188 patients, covering 64 NHS Provider Trusts (93%) and 31,865 Census Lower Super Output Areas (LSOAs) (98%). Primary outcome was compulsory admission to a mental illness bed, compared with people admitted voluntarily or receiving only community-based care.

## **Outcomes**

7.5% and 5.6% of the variance in compulsory admission occurred at LSOA- and Provider Trust-levels, respectively, after adjusting for patient characteristics. Black patients were almost three times more likely to be admitted compulsorily than White patients (OR 2.94, 95% CI 2.90-2.98). Compulsory admission was greater in more deprived areas (OR 1.22, 95% CI 1.18-1.27) and in areas with more non-white residents (OR 1.51, 95% CI 1.43-1.59), after adjusting for confounders.

## **Interpretation**

Compulsory psychiatric in-patient admission varies significantly between local areas and services, independent of patient, area and service characteristics. Compulsory admission rates appear to reflect local factors, especially socio-economic and ethnic population

composition. Understanding how these condition access to and use of mental health care is likely to be important for developing interventions to reduce compulsion.

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## Introduction

Many European countries have witnessed increased rates of compulsory admissions to psychiatric in-patient beds in recent decades.<sup>1</sup> In England, the total number of such admissions (excluding short-term assessment orders) exceeded 63,000 in 2015/16, a 9% increase on the previous year and an increase of around 43% since the introduction of the 2007 Mental Health Act (MHA).<sup>2</sup> This is concerning to service users, clinicians, regulators and policy makers,<sup>3-5</sup> particularly since compulsory treatment is stigmatising and may hamper engagement with services.<sup>6</sup> Explanations for greater use of compulsion have been suggested, including increased use of illicit drugs and alcohol, secular changes in support networks,<sup>7,8</sup> fewer psychiatric beds and failure to provide alternatives.<sup>9,10</sup> Attempts to reduce compulsory treatment through advance directives and enhanced crisis care plans have had only modest effects,<sup>11</sup> highlighting the need for further intervention strategies.

Compulsory admission rates vary between places,<sup>9</sup> and this may hold clues to causes of upward national trends. Investment in mental health services, bed capacity and provision of community-based alternatives vary between places,<sup>12</sup> as do patients and the communities in which they live.<sup>13</sup> Elucidating the effects of service setting factors and local area characteristics across large and representative samples, and differentiating these from variation due to differences between patients, may represent the best way to identify intervention targets. Our aims were to describe and model spatial variation in compulsory admissions in England using national patient-level data, and to quantify the extent to which adjusting for patient, local area and service setting characteristics accounted for this variation.

## Methods

### *Data source and study sample*

Compulsory admissions in England are recorded in the Mental Health Minimum Dataset (MHMDS),<sup>14</sup> a mandatory administrative dataset. Individual patient records in the MHMDS include spatial/service setting identifiers (Table 1) allowing linkage to external data sources. We used data for 2010-2011.

<< Table 1 about here >>

Following data quality checks, data from 8 Provider Trusts were excluded, including 3 independent Provider Trusts which lacked spatial identification codes. Of 5 NHS Provider Trusts excluded, one had no in-patient beds and four lacked data on patients' legal status. The final study sample consisted of 1,238,188 patients who received care from 64 NHS Provider Trusts. Due to data-coding errors and missing data, analytic samples for alternative models varied slightly.

### *Outcomes*

The main outcome was compulsory admission, defined as time spent in an in-patient mental illness bed while subject to the Mental Health Act (MHA) (2007). We excluded patients detained under sections of the Act concerned only with conveyance to, and/or assessment in, a Place of Safety, or for short-term ( $\leq 72$  hours) assessment only as these do not in themselves direct admission to an in-patient mental health bed. Likewise, we excluded sections of the Act relating to guardianship or supervised community treatment. Patients detained under short-term assessment sections and subsequently admitted compulsorily to a mental health bed were included in the compulsory admission group; those discharged from short-term

assessment orders or who were admitted voluntarily were not. Patients excluded from the compulsory admission group were included in the unexposed group, which comprised those treated as voluntary inpatients and/or in the community. Around 95% of those admitted compulsorily were detained under MHA Sections 2 and 3. This group also included those subject to Sections 4, 35, 36, 37, 38, 47 and 48.

No single variable in the MHMDS described the study outcome. Rather, it was derived from several variables, including admissions and discharges, bed days, receipt of community treatment, and legal detention status.<sup>15</sup> We were able to identify whether a patient had been admitted compulsorily and the highest level of legal restriction (according to the MHA (2007)) in the reporting period, but not the number or duration of episodes. Therefore, each patient could only be counted once regardless of number of compulsory admissions in the study year.

The unexposed group therefore comprised all patients who received any type of care other than compulsory admission. Cross-tabulating MHMDS data on community treatment (e.g. number of contacts with professionals) with admission data enabled us to identify patients who received only community care.

### *Exposures*

MHMDS contained reasonably complete data (% missing) on a limited number of patient characteristics, namely age (<0.01%), sex (0.03%) and ethnicity (9.6%). Several patient-level variables could not be included in our analysis due to high levels of missing data: marital status (15%); accommodation status (64%), employment status (75%) and diagnosis (81%).

MHMDS spatial identifiers were used to link patient records to external data sources that



included variables characterising local areas and mental health services that were potentially associated with mental health outcomes (Table 4). Data sources and measures used to derive variables at LSOA-level and Provider Trust-level are shown as supplementary material.

### *Statistical analysis*

Multilevel models (MM) were applied using MLWIN<sup>16</sup> to estimate variation in compulsory admission, starting with null (unconditional) models which partitioned total variance in compulsory admission between each level in the model. Five discrete levels were identified in the MHMDS, in addition to patients (Table 1), although computational limitations meant that not all could be included in a single model. Moreover, these levels did not nest neatly within each other, necessitating use of cross-classified multilevel models (CCMMs) and increasing computational complexity.<sup>17</sup> Patients were nested within LSOAs but SOAs were not nested neatly within Provider Trusts, i.e. patients within any one LSOA could be treated in different Trusts. Such cross-classification results in a data structure that, in effect, increases the number of units at the LSOA level. In the examples shown in figure 1, LSOA 2 is represented twice because patients attend Hospital A and Hospital B.

We aimed to specify and estimate the most detailed models possible. Preliminary work suggested that null models with more than four levels, and conditional models with more than three levels, were unstable (ie failed to converge with acceptable MCMC diagnostics); moreover, there was limited variance in compulsory admission at Strategic Health Authority (SHA)-level. We therefore present findings from competing four-level null models, the results of which informed selection of a preferred three-level model. Finally, multivariate models were used to determine how much of the total variance was explained by patient-level

explanatory variables only, and then by explanatory variables at individual, local area- and service setting levels.

Since the outcome was binary, multilevel logistic regression was used. Following convention, we assumed the binary outcome was defined by a continuous latent variable and patient-level variance was standardized to the logistic variance of  $\pi^2/3=3.29$ .<sup>18</sup> In this way, variances at each level could be summed, allowing the proportion of (unexplained) variation, the Variance Partition Coefficient (VPC), to be calculated at each level. As this method only provides an approximate measure of the VPC in models with binary responses, we also calculated Median Odds Ratios (MORs) for our final models.<sup>19</sup> If the MOR is equal to 1, there is no variation between higher-level settings; large (and statistically significant) MORs indicate substantial higher-level variation.

Markov Chain Monte Carlo (MCMC) Bayesian methods were used to estimate all models.<sup>20</sup> All null models were estimated twice, using all available data ( $n=1,149,541$  to  $1,207,916$ ) and then only complete cases ( $n=1,149,541$ ). MCMC diagnostics were used to determine the number of iterations in each model. We examined the estimate trace, the plot of the posterior distribution and the autocorrelation function. The number of chains was evaluated using Raftery-Lewis and Brooks-Draper prospective diagnostics.<sup>20</sup> We used the Bayesian Deviance Information Criterion (DIC) statistic to compare the fit of alternative MMs.<sup>21</sup> Models with lower DIC values suggest a better, more parsimonious model; a difference of 10 or more is considered substantial. DIC values are only comparable across models with the same observed data and hence were estimated using only complete cases.

To estimate variance explained by patient, local area and service setting characteristics, we used the pseudo R-squared approach outlined by Snijders and Bosker<sup>18</sup> (p306). Variance

explained at, for example, patient-level was estimated as the proportion of total variance attributable to the fixed part of a model that included patient-level explanatory variables, divided by the total variance. Total variance is equal to the sum of the variances of the fixed part of the model and (unexplained) variances at each higher level.

The statistical significance of fixed-part estimates were tested by deriving Z ratios and comparing these against a normal distribution. Odds ratios (95% credible intervals, CI) are reported to show their size. We do not report p values, in keeping with standard practice for reporting Bayesian model results.. MORs are directly comparable to these fixed-part odds ratios. Patients were only excluded from analyses where data were missing.

## **Results**

Table 2 shows the characteristics of the study sample. Of these patients, 42,915 (3.5%) had been compulsorily admitted to hospital under the MHA at least once during the study year.

<< Table 2 about here >>

### *Null (unconditional) models*

Table 3 shows alternative null models with four levels. Overall, between 75.1% and 84.5% of the variance in compulsory admission to hospital was at patient-level; between 6.4% and 6.7% was at LSOA-level; between 5.6% and 7.2% was at PCT-level; between 1.9% and 2.7% was at GP-level; and between 6.9% and 12.3% was at Provider Trust-level.

Inclusion of PCTs and Provider Trusts in the same model resulted in reduction in patient-level variance and commensurate increase in variance between Provider Trusts (from about 7% to

about 12%). On further investigation we found that in one-third of Provider Trusts, over 80% of patients originated from a single PCT. It is likely, therefore, that reduced variance at patient level in models 3 and 4 is due to conflation of patient- and higher-level variance caused by clustering of patients within a small number of PCTs per Trust, a problem exacerbated by cross-classification in the data.<sup>16,22</sup> We therefore considered that estimates of higher-level variance in Models 1 and 2 were more reliable than those of Models 3 and 4. Model comparisons using DIC statistic revealed that Models 2 and 3 were superior to Models 1 and 4, with Model 3 fitting slightly better than Model 2. These results indicated that the most appropriate CCMM comprised patients, LSOAs, GP Practices and Provider Trusts.

<< Table 3 about here >>

#### *Multivariate models*

The computationally complex four-level multivariate CCMM produced an unstable solution in terms of MCMC diagnostics. We therefore selected the most important spatial levels for inclusion in more complex models. We did this on the basis of our null models (Table 3, Model 2), and following the *a priori* view that patients and Provider Trusts were essential to any model: the former was the level at which most variation occurred and the latter represented the locus at which compulsory admission decisions are made. We therefore included patient, LSOA and Provider Trust as the three levels in multivariate models.

Table 4 shows the results of patient-LSOA-Provider Trust CCMMs, with and without covariates. The null model was based on an MCMC model with burn-in of 500 and Monitoring Chain Length of 50,000. The model with covariates was run for 100,000 iterations; MCMC diagnostics indicated that burn-in and chain length were sufficiently large.

The null model shows that while the majority of the variance in compulsory admission occurred at patient-level, 8.3% and 7.0% occurred at LSOA- and Provider Trust-levels, respectively. We estimated that patient-level covariates explained 8.0% of the total variance in risk of being compulsorily admitted. Covariates at LSOA- and Provider Trust-levels were estimated as explaining only a further 2.2% of this variance, 1.1% at each of the higher levels. In total, therefore, just over 10% of the total variance in compulsory admission was explained by covariates.

Given the limited explanatory power of covariates, the percentage share of the remaining (unexplained) variance at higher-levels did not change substantially once these were included in the model. Following inclusion of patient-level covariates, variance fell to 7.5% and 5.6% for LSOAs and Provider Trusts, respectively. After further inclusion of LSOA- and Provider Trust-level covariates, this remained unchanged at 7.5% at LSOA-level and fell slightly to 5.2% at Provider Trust-level.

<< Table 4 about here >>

At patient level, after adjusting for all covariates, men had a higher probability of being compulsorily admitted to hospital than women (OR 1.29, 95% CI 1.27- 1.31). Patients who were 18 years old or younger were least likely to be admitted compulsorily; compared with this group, the risk of compulsory admission was greatest among those aged 18–35 years (OR 1.92, 95% CI 1.82-2.02) and fell with age, but remained statistically significant even in the oldest age group (65 years and older) (OR 1.12, 95% CI 1.02-1.22). The largest associations with compulsory admission at patient-level were observed for ethnicity, with Black patients

having the highest rate of compulsory admission compared to the White reference group (OR 2.94, 95% CI 2.90-2.98). Patients of Asian and mixed ethnicity were also significantly more likely to have been admitted compulsorily (Table 4).

At LSOA level, compulsory admission was associated with socio-economic deprivation in a manner which suggested a dose-response effect. Odds ratios for compulsory admission rose steadily by deprivation quintile, to a peak of 1.22 (95% CI 1.18 to 1.27) among those living in LSOAs with deprivation scores in the top quintile (most deprived) compared to those living in the least deprived areas. The association between compulsory admission and ethnic density was also statistically significant and also appeared to show a dose-response effect, with patients living in LSOAs with the most non-white residents having much higher risks of being admitted compulsorily (OR 1.51, 95% CI 1.43-1.59). No statistically significant association was found between compulsory admission and LSOA population density (Table 4).

At Provider Trust level, no statistically significant associations were found between compulsory admission and bed numbers, length of stay, in-patient services performance, Patient Environment and Action Team (PEAT) scores, staff satisfaction or annual number of admissions. Similarly, there was no statistically significant difference in the rate of compulsory admission between London Trusts and those outside the capital. Only one Provider Trust-level covariate was significantly associated with greater compulsory admission: patients receiving care from a Trust whose community mental health services were rated 'same as/better than other Trusts' versus those rated 'worse than other Trusts' (OR 1.93, 95% CI 1.39-2.48).

The limited power of LSOA, Provider-Trust and patient characteristics in explaining spatial variation in compulsory admission is confirmed by the MORs for LSOAs and Provider Trusts (Table 4). After adjusting for all covariates, these were greater than 1 and larger than the ORs for many patient characteristics and all LSOA- and Provider Trust-level characteristics, at 1.86 (95% CI 1.82-1.89) and 1.67 (95% CI 1.51-1.85), respectively.

## **Discussion**

### *Main findings*

We found statistically significant variance at both local area- and service setting-level in compulsory admission in England, independent of patient characteristics. Although most variance in compulsory admission was observed between patients, almost 13% occurred between local areas (LSOAs) and service settings (NHS Provider Trusts), after adjusting for patient characteristics. Slightly more variance was observed between local areas than between Provider Trusts.

Most variance in compulsory admission remained unexplained, even after adjusting for a large number of patient, local-area and service-setting characteristics. We estimated that these covariates explained only around 10% of the total variance in compulsory admission. Most of the explained variance was accounted for by patient-level characteristics; area- and Provider Trust-level characteristics accounted for only just over 2% of total variance in multivariate models. Mean odds ratios (MORs) confirmed the significance of this unexplained higher-level variance in compulsory admission between LSOAs and between Provider Trusts.

The non-significance of most Provider Trust-level variables, including measures relating to bed capacity was notable. However, Trusts with community services rated 'same as/better than'

other Trusts were almost twice as likely to admit patients compulsorily, suggesting that better community mental health services may be associated with increased risk of compulsory admission, perhaps due to greater awareness of treatment needs. This phenomenon has been observed previously, for Assertive Outreach and Crisis Resolution services.<sup>23,24</sup>

We found statistically significant associations at patient and local-area levels. Black patients were almost three times more likely to be admitted compulsorily than White patients, in keeping with evidence from elsewhere,<sup>25</sup> after adjusting for area- and Provider Trust-level characteristics. Compulsory admission was significantly associated with local-area deprivation and the proportion of non-white residents (in LSOAs), after adjusting for other covariates including individual ethnicity.

#### *Strengths and limitations*

This was the largest and most complete study of its kind and the national representativeness of the sample, deriving from routine clinical activity, was a major strength. The complex data structure reflects the real world settings in which patients live and use mental health services. Multilevel models provided a means to examine this complexity. The availability of patient-level data and the ability to link this to area-level variables were strengths.

Routine administrative data sources like MHMDS have limitations. Data were not available to allow us to ascertain the number and duration of compulsory admission episodes.

Consequently, we modelled the likelihood that a patient was compulsorily admitted at some point during the study period. This precluded us from exploring re-admissions and 'revolving door' patients and the contribution they make to compulsory admission rates.



We were limited in the patient, local area- and Trust-level variables that were available and residual confounding was likely. The most significant omission was information about patients' diagnoses, socio-economic status and clinical status.<sup>26</sup> Previous studies have found modest and contrasting associations between individual-level socio-economic status and the incidence of psychotic disorders.<sup>27</sup> We used total number of mental illness beds as we could not distinguish between bed types. The capping of official bed occupancy statistics at 100% may also have biased our findings towards the null and reduced estimates of explained variance.<sup>28</sup> Finally, as this was a cross-sectional study, we could not investigate factors associated with changes in compulsory admission rates.

#### *Interpretation of our findings*

Our findings, based on the first-ever analysis of complete national data, indicate significant (and substantial) variation in compulsory admission at both local area- and Provider Trust-levels. Despite adjusting for a large number of potential confounders, covariates explained only a limited amount of variation. The most likely explanation was the absence of information on key variables, including diagnosis and illness severity, previous history of admission and/or compulsion, engagement with services, isolation, and drug and alcohol use (individual); availability of adequate housing, social care and other support services (area); and bed pressures, crisis intervention response times and local service configuration and quality (Provider Trust).

Nevertheless, our findings suggest that compulsory admission rates are not uniform, and may reflect local factors, such as the challenges of delivering home-based crisis care in areas with high levels of socio-economic deprivation. Further research is needed to elucidate factors that account for spatial variation in compulsory admission, and to understand the ways in

which factors such as area-level deprivation and ethnic density condition access to and delivery of mental health care. And whereas previous interventions to reduce compulsory admission have focused on the individual (patient) level, such as Community Treatment Orders and enhanced care plans,<sup>11</sup> our findings suggest that interventions will need to operate at more than one spatial level to be effective.<sup>29</sup>

### **Contributors**

SW, LT, PK, JS, KB, DC-K and EC had the original idea for this study and were responsible for study hypotheses, design and data specification. SW had overall responsibility for the conduct of the study and is the guarantor of this manuscript. SW, OM and LT were responsible for the analysis strategy. OM undertook the data analysis (with advice from SW, LT and HP) and results were interpreted by all authors. OM and SW had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the analyses. CD was responsible for drafting the present manuscript, through several drafts, and all authors contributed to this. SW, the lead author and the manuscript's guarantor, affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned have been explained.

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responsibility for the decision to submit for publication.

### **Conflicts of interest**

All authors had financial support from the National Institute for Health Research Health Services and Delivery Research Programme (project number 10/1011/70) for the submitted work but no other financial relationships with any organizations that might have an interest in the submitted work in the previous three years or other relationships or activities that could have influenced the submitted work.

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### **Panel: Research in context**

#### **Evidence before this study**

Although several studies have been done in the UK and other European countries to examine individual, local area and service provider factors associated with spatial variation in the use of compulsory admission, few studies have looked at the relative contribution of factors at all three levels simultaneously. We searched PubMed for articles published between January 1, 2000 and December 31<sup>st</sup> 2016 with the search terms: (compulsory[All Fields] AND admission[All Fields]) OR (involuntary[All Fields] AND admission[All Fields]). Over 730 articles

were found, 38 of which were of direct relevance to the present study. Much of the previous work has consisted of ecological studies. By working at a single aggregate level, these studies have been unable to account for the autocorrelation arising from the grouping of patients in higher-level settings, be they local areas or service providers. They have also been unable to provide an estimate of the relative size of the variation at each of the higher-levels, or the contribution of level-specific factors in explaining this variation. This research has also been restricted to sub-national samples, either particular regions, cities or hospitals, limiting both generalisability and the extent of observed variation.

### **Added value of this study**

Our findings are based on the first-ever multilevel analysis of nationally representative service use data in England, comprising data on over 1.2m patients. This study's results confirm the occurrence of spatial variation in rates of compulsory psychiatric admission and show that this occurs to a substantial and significant degree, and independently, between both local areas and mental health service providers. This amounts to strong evidence of significant variation in compulsory admission between both local areas and services, independent of patient characteristics. Although we found highly significant associations between local area socio-economic deprivation and ethnic density, little of the variation between places and service providers was explained by the variables characterising local areas, services or patients themselves.

### **Implications of all the available evidence**

Compulsory admission rates in England vary between people and places to a significant degree. Understanding how local factors, particularly socio-economic deprivation and ethnic

density, condition access to and use of mental health services may be key to developing interventions and strategies to reduce compulsion.

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**Table 1: Spatial/service setting identifiers present in the Mental Health Minimum Dataset 2010-2011**

<b>Spatial/ Service Setting Identifier</b>	<b>Description</b>	<b>Number in England (2010-2011)</b>	<b>Number in study sample (%)</b>
Lower Layer Super Output Area (LSOA)	Local Area of Residence, based on 2001 Census boundaries, typically containing 672 households and 1,614 residents	32,482	31,865 (98%)
GP Practice	Primary Care Provider	10,203	9,492 (93%)
NHS Provider Trust	Provider of Secondary Mental Health Care	69	64 (93%)
Primary Care Trust (PCT)	Commissioner of Secondary Mental Health Care	152	146 (96%)
Strategic Health Authority (SHA)	Responsible for quality of all health care provision	10	10 (100%)



**Table 2: Demographic characteristics of patients receiving secondary care mental health services during 2010/11 in the Mental Health Minimum Dataset**

	Service use status in 2010/11		
	Community care only 1,133,541 (91.5%)	Informal admission only 61,732 (5.0%)	Compulsory admission 42,915 (3.5%)
<b>Sex</b>			
Male	495,945 (43.7%)	31,739 (51.4%)	22,920 (53.4%)
Female	637,177 (56.2%)	29,972 (48.6%)	19,983 (46.6%)
Missing	419 (< 0.01%)	21 (< 0.01%)	12 (< 0.01%)
<b>Age</b>			
<18 years	20,861 (1.8%)	620 (1.0%)	402 (0.9%)
18-35 years	296,268 (26.1%)	16,219 (27.5%)	13,874 (32.3%)
36-64 years	455,252 (40.2%)	26,401 (42.7%)	20,006 (46.6%)
≥65 years	361,078 (31.9%)	17,733 (28.8%)	8,633 (20.2%)
Missing	82 (< 0.01%)	759 (0.01%)	0 (0%)
<b>Ethnicity</b>			
White	911,292 (80.4%)	53,747 (87.1%)	32,130 (74.9%)
Mixed	11,965 (1.1%)	789 (1.3%)	1,027 (2.4%)
Asian or Asian British	41,780 (3.7%)	1,993 (3.2%)	2,771 (6.5%)
Black or Black British	32,116 (2.8%)	2,168 (3.5%)	4,965 (11.6%)
Other ethnicity	19,992 (1.8%)	1,009 (1.6%)	1,052 (2.5%)
Missing	116,396 (10.2%)	2,026 (3.3%)	970 (2.1%)

**Table 3: Results of four-level cross-classified null models**

<b>Model and levels</b>	<b>Variance (se)</b>	<b>% variation (95% CI)</b>	<b>DIC statistic*</b>
<b>Model 1</b>			322,505.7
Patient	3.29	84.5	
LSOA	0.248 (0.008)	6.4 (6.0-6.8)	
GP	0.075 (0.004)	1.9 (1.7-2.1)	
PCT	0.280 (0.036)	7.2 (5.5-8.9)	
<b>Model 2</b>			321,749.2
Patient	3.29	83.7	
LSOA	0.264 (0.010)	6.7 (6.2-7.2)	
GP	0.106 (0.005)	2.7 (2.4-2.9)	
Provider Trust	0.271 (0.053)	6.9 (4.3-9.5)	
<b>Model 3</b>			321,392.94
Patient	3.29	75.1	
LSOA	0.280 (0.008)	6.4 (6.1-6.7)	
PCT	0.271 (0.037)	6.2 (4.5-7.8)	
Provider Trust	0.539 (0.104)	12.3 (7.7-17.0)	
<b>Model 4</b>			324,247.78
Patient	3.29	79.8	
GP	0.108(0.004)	2.6 (2.4-2.8)	
PCT	0.230 (0.032)	5.6 (4.1-7.1)	
Provider Trust	0.496 (0.096)	12.0 (7.5-16.6)	

\*DIC statistic estimated using complete cases only (n=1,149,541)

**Table 4: Results of three-level (patient-LSOA-Provider Trust) cross-classified models**

Level	Covariates		Null model	Patient-level covariates (95% CI)	Patient-, LSOA-, and Trust-level covariates (95% CI)
<b>Patient</b>	<b>Sex</b>	Men		1.29 (1.27-1.31)	1.29 (1.27-1.31)
	<b>Age</b>	Under 18 years		1.00	1.00
		18-35 years		1.96 (1.85-2.07)	1.92 (1.82-2.02)
		36-64 years		1.83 (1.72-1.94)	1.79 (1.68-1.89)
		≥65 years		1.11 (1.00-1.22)	1.12 (1.02-1.22)
	<b>Ethnicity</b>	White		1.00	1.00
		Mixed		1.88 (1.81-1.96)	1.81 (1.74-1.88)
		Asian		1.53 (1.49-1.57)	1.41 (1.37-1.46)
		Black		3.11 (3.07-3.14)	2.94 (2.90-2.98)
		Other		1.06 (0.99-1.13)	1.00 (0.93-1.07)
Missing			0.25 (0.18-0.31)	0.25 (0.18-0.32)	
<b>LSOA</b>	Deprivation (least to most deprived) <sup>1</sup>	First quintile			1.00
		Second quintile			1.14 (1.09-1.18)
		Third quintile			1.20 (1.16-1.24)
		Fourth quintile			1.21 (1.17-1.26)
		Fifth quintile			1.22 (1.18-1.27)
	Population density (least to most densely populated) <sup>2</sup>	First quintile			1.00
		Second quintile			1.02 (0.97-1.07)
		Third quintile			1.04 (0.99-1.09)
		Fourth quintile			1.01 (0.96-1.06)
		Fifth quintile			1.01 (0.95-1.07)
	Ethnic density (% white British inhabitants) <sup>3</sup>	95–100%			1.00
		81-94%			1.14 (1.10-1.18)
		68-80%			1.28 (1.23-1.34)
		22-67%			1.40 (1.34-1.46)
		1-21%			1.51 (1.43-1.59)
<b>Provider Trust</b>	Bed capacity <sup>4</sup>	%occupied beds			1.01 (0.99-1.03)
	Length of stay <sup>5</sup>	Median stay (days)			0.99 (0.98-1.01)
	Community mental health services performance <sup>6</sup>	Worse than other Trusts			1.00
		Same/Better than other Trusts			1.93 (1.39-2.48)
		Missing			1.12 (0.21-2.03)
	Inpatient mental health services performance <sup>7</sup>	Worse than other Trusts			1.00
		Same/Better than other Trusts			1.01 (0.56-1.45)
		Missing			1.45 (0.66-2.24)
	PEAT <sup>8</sup>	Privacy and dignity score			1.18 (0.67-1.69)
	Staff Survey <sup>9</sup>	%Staff satisfied with care			0.99 (0.97-1.02)
	Hospital admissions <sup>10</sup>	No. mental health admissions			1.00 (1.00-1.00)
	Trust location	London			1.00

		Outside London			0.74 (0.32-1.17)
<b>Unexplained variance (SE)</b>					
Patient			3.29	3.29	3.29
LSOA			0.323 (0.009)**	0.284 (0.007)**	0.283 (0.008)
Provider Trust			0.271 (0.051)**	0.213 (0.039)**	0.195 (0.045)
<b>%Unexplained variance (VPC)† (95% CI)</b>					
Patient			84.7	86.9	87.6
LSOA			8.3 (7.9-8.8)	7.5 (7.1-7.9)	7.5 (7.1-7.9)
Provider Trust			7.0 (4.4-9.6)	5.6 (3.6-7.6)	5.2 (2.8-7.5)
<b>MOR‡ (95% CI)</b>					
LSOA			1.94 (1.90-1.97)	1.86 (1.83-1.88)	1.86 (1.82-1.89)
Provider Trust			1.83 (1.66-2.06)	1.71 (1.57-1.90)	1.67 (1.51-1.85)

† Variance partition coefficient

‡ Mean odds ratio

1. English indices of deprivation 2010: Department for Communities and Local Government.
2. Mid-2010 population estimates: Office for National Statistics.
3. 2011 Census aggregate data: Office for National Statistics.
4. Beds Open Overnight: Department of Health.
5. Hospital Episodes Statistics: Department of Health.
6. NHS Community Mental Health Service User Survey, 2011: Care Quality Commission.
7. Mental Health Acute Inpatient Service Users Survey, 2009: Healthcare Commission.
8. Patient Environment and Action Team (PEAT) scores, 2010: Health and Social Care Information Centre.
9. NHS Staff Survey, 2010: Care Quality Commission.
10. Hospital Episodes Statistics: Department of Health.

## Supplementary Material

### External data sources linked to patient-level MHMDS records

Data Source	Measure	Level	Time Frame	URL Reference
<b>Department for Communities and Local Governments' English Indices of Deprivation</b>	Deprivation	LSOA	2010	<a href="https://www.gov.uk/government/statistics/english-indices-of-deprivation-2010">https://www.gov.uk/government/statistics/english-indices-of-deprivation-2010</a>
<b>Office for National Statistics' Mid-2010 Population Estimates</b>	Population density	LSOA	2010	<a href="http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/sape/soa-mid-year-pop-est-engl-wales-exp/mid-2002-to-mid-2010-revised/stb---super-output-area-population-estimates--mid-2002-to-mid-2010--revised-.html">http://webarchive.nationalarchives.gov.uk/20160105160709/http://www.ons.gov.uk/ons/rel/sape/soa-mid-year-pop-est-engl-wales-exp/mid-2002-to-mid-2010-revised/stb---super-output-area-population-estimates--mid-2002-to-mid-2010--revised-.html</a>
<b>Office for National Statistics' 2011 Census Estimates</b>	Ethnic density	LSOA	2011	<a href="http://infuse.ukdataservice.ac.uk/">http://infuse.ukdataservice.ac.uk/</a>
<b>Department of Health's Beds Open Overnight (BOO) Data</b>	Available and occupied mental health beds	Provider Trust	2010/11	<a href="https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/bed-data-overnight/">https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/bed-data-overnight/</a>
<b>Department of Health's Hospital Episode Statistics (HES)</b>	Median length of stay; Number of mental health hospital admission episodes	Provider Trust	2010/11	<a href="http://digital.nhs.uk/catalogue/PU/B02570">http://digital.nhs.uk/catalogue/PU/B02570</a>
<b>NHS Community Mental Health Service User Survey</b>	Performance on a variety of domains including health and social care workers, medication, helpfulness of talking therapies, care plan management, crisis care and day-to-day living	Provider Trust	2011	<a href="http://www.nhssurveys.org/survey/515">http://www.nhssurveys.org/survey/515</a>

<b>Healthcare Commission's Mental Health Acute Inpatient Service Users Survey</b>	Performance on a variety of domains including ward accommodation, staff communication, medications and treatment and patient rights	Provider Trust	2009	<a href="http://dx.doi.org/10.5255/UKDA-SN-6421-1">http://dx.doi.org/10.5255/UKDA-SN-6421-1</a> .
<b>Health and Social Care Information Centre's Patient Environment and Action Team (PEAT) Scores</b>	Performance in patient safety in the following areas: environment, food, and dignity and respect	Provider Trust	2011	<a href="http://www.nrls.npsa.nhs.uk/patient-safety-data/peat/">http://www.nrls.npsa.nhs.uk/patient-safety-data/peat/</a>
<b>NHS Staff Survey</b>	Performance on workplace environment including workloads, training, staff communication, health and well-being	Provider Trust	2010	<a href="http://www.nhsstaffsurveys.com/Page/1023/Past-Results/Staff-Survey-2010-Detailed-Spreadsheets/">http://www.nhsstaffsurveys.com/Page/1023/Past-Results/Staff-Survey-2010-Detailed-Spreadsheets/</a>

## Supplementary material

### Multilevel models

A multilevel model (MLM), also known as a hierarchical model, is a statistical model designed to work with data that is clustered or grouped. For example patients may be grouped in residential neighbourhoods and also within treatment centres or hospitals which, in turn, may be grouped within geographical regions or management areas. MLMs capture the complexity of factors that influence (health) outcomes across these different levels or contexts. For example, individual characteristics or personal traits (e.g. age, gender, behaviours) may influence an individual's risk of poor health but health may also be influenced by the characteristics of residential neighbourhood such as the area's socio-economic deprivation profile, population density, pollution levels or social and cultural norms. Similarly, hospital characteristics and regional governance structures may influence the quality and level of care that any one patient receives. Multilevel modelling approaches ensure that the influence that each of these levels has on the outcome is modelled correctly and their relative effects are not conflated. Furthermore, the models can also acknowledge that the association between an outcome and an explanatory variable might vary according to different types of context or settings. For example, the strength and direction of the relationship between (say) ethnicity and mental health at the individual level may vary according to neighbourhood deprivation.

The variance or heterogeneity in any particular outcome can also be apportioned across the different levels and comparisons can be made between a null (or empty) model and subsequent models which contain explanatory variables. This is similar in concept to observing the changes in the  $R^2$  statistic in an ordinary regression model whereby the value (usually expressed as a percentage) estimates how much of the original variation in the outcome variable has been explained by one or more of the explanatory variables. In models where the outcome is categorical, the calculation of  $R^2$  is more problematic and a number of alternative approaches can be used to approximate this. For a full description of their application in MLMs, see (1).

Importantly, MLMs acknowledge that individuals nested or clustered within any one group are more likely to behave similarly and observations are therefore not independent. Standard errors around modelled estimates are adjusted in MLMs to take this clustering into account. A good introduction to MLM is provided by (2) and (3). Excellent tutorial material and information on software to run multilevel models can be found on the website for the Centre for Multilevel Modelling at the University of Bristol ([www.bristol.ac.uk/cmm](http://www.bristol.ac.uk/cmm)).

### Markov Chain Monte Carlo (MCMC) Bayesian estimation

Parameter estimates (ie constants, gradients and variances) in multilevel models can be generated using traditional frequentist maximum likelihood methods or via Bayesian MCMC approaches. The latter have many advantages when outcomes are categorical, model structures are complex and when there are only a few higher level units.

In frequentist approaches the sample of data is just one from all the infinite number of samples that could have been selected. Model parameters are estimated with the goal of having as close fit to the data as possible (maximum likelihood) and the standard error of estimates may be used to infer characteristics of the population. Usually a significance value (p value) is used to indicate the likelihood that the finding was not due to random (chance) variation (ie what the data can reveal about the sample and the population from which it was

derived), and a confidence interval may also be calculated. This interval specifies the range of values within which a population parameter will be found within a given level of probability. Importantly a frequentist approach does not take into account any prior beliefs about the parameter values. By contrast, a Bayesian approach is not concerned with the idea of samples drawn from hypothetical populations but instead builds sequences of models which incorporate 'prior' knowledge into the process of estimating likely values of the resultant 'posterior' estimates (ie the posterior distribution). These posterior estimates are then used as the prior knowledge in each of the subsequent iterations of the model. With a Bayesian approach the results are scrutinised in terms of the degree of support for a particular parameter given the data and these prior beliefs. Bayesian models can be run with a high degree or low belief in a prior value. For example, results from previous well established research could be used to provide priors with strong support. Alternatively if there was reason to have less faith in a particular prior then this could also be taken into account (known as diffuse or flat priors) and the number of model runs (iterations) would be increased.

Bayesian methods are computationally intensive and Markov Chain Monte Carlo estimation is the sampling engine used to generate a distribution of estimates for each parameter (ie the posterior distribution).<sup>1</sup> Rather than generating a point estimate with its associated standard error and p value (as in the frequentist approach), this posterior distribution is used to derive model results. The modal value will represent the most common draw across the iterations (ie across the simulations) and the 95% *credible interval* (the Bayesian alternative to a confidence interval) around this modal value can be found at the 2.5% cut-offs when the values are ranked. Unlike a frequentist confidence interval, a Bayesian credible interval applies to the parameter and not the data. It indicates the range within which the parameter falls, at the 95% level of probability. The use of p values is not appropriate because the Bayesian approach estimates the likely values of the resultant posterior estimates (i.e. the posterior distribution) rather than testing null hypotheses.

When models and data structures are very complex, the number of MCMC iterations (the 'chain length') required to find acceptable parameter estimates may be very large and models may run for several hours or even days. MLwiN (4) provides a number of prospective and retrospective diagnostic measures which can be used to inform the chain length and evaluate the results of the MCMC process. These are fully documented elsewhere (5) but a summary of some key diagnostics are given below.

First a 'burn-in' period of runs is used to establish starting values for the parameter estimates after which a chain length of several thousand iterations are used to create the posterior distribution of the estimates. Results from the burn-in may be unstable and so they are not included in the posterior distribution.

A trace graphic (ie the value of the estimate at each iteration plotted in sequence) should exhibit random noise and not show any trending or 'stickiness' (ie blocks of very similar values) which would suggest that the chain length is insufficient and more runs are needed to generate stable estimates.

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<sup>1</sup> There are many different MCMC algorithms. MLwiN, for example uses a combination of Gibbs sampling and Metropolis-Hastings sampling. A more detailed description of how they work and their application is given by (5).



The 'stickiness' of the values can also be assessed via the autocorrelation function which provides the correlation between the trace values and the trace values lagged by 1,2 etc. Whilst a degree of autocorrelation is to be expected in the initial runs of the model, this should eventually head towards zero.

The Raftery-Lewis diagnostic indicates the chain length ( $N_{hat}$ ) required to estimate a specific quantile of the posterior distribution to a stated level of tolerance and precision (6). This is therefore a useful prospective diagnostic to help set the chain length (ie the number of simulations required by the model). Similarly the Brooks-Draper diagnostic indicates the required simulations to provide the posterior mean to a stated level of precision and confidence (5).

## References

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