Contextual risk factors for the common mental disorders in Britain: a multilevel investigation of the effects of place

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Study objective: To test hypotheses about associations between area level exposures and the prevalence of the most common mental disorders (CMD) in Britain. A statistically significant urban-rural gradient was predicted, but not a socioeconomic gradient, in the prevalence of CMD after adjusting for characteristics of individual respondents. The study tested the hypothesis that the effects of area level exposures would be greatest among those not in paid employment.

Design: Cross sectional survey, analysed using multilevel logistic and linear regression. CMD were assessed using the General Health Questionnaire (GHQ). Electoral wards were characterised using the Carstairs index, the Office of National Statistics (ONS) Classification of Wards, and population density.


Participants: Nearly 9000 adults aged 16–74 living in 4904 private households, nested in 642 electoral wards.

Main results: Little evidence was found of statistically significant variance in the prevalence of CMD between wards, which ranged from 18.8% to 29.5% (variance 0.035, SE 0.026) (p=0.11). Associations between CMD and characteristics of wards, such as the Carstairs index, only reached statistical significance among those who were economically inactive (adjusted odds ratio for top v bottom Carstairs score quintile 1.58, 95% CI 1.08 to 2.31) [p<0.05].

Conclusions: There may be multiple pathways linking socioeconomic inequalities and ill health. The effects of place of residence on mental health are greatest among those who are economically inactive and hence more likely to spend the time at home.

Despite evidence of causal associations between individual level socioeconomic deprivation and higher rates of psychiatric morbidity, comparatively little is known about how the places where people live affect their mental health. Studies of geographical inequalities in rates of the most common mental disorders (CMD), anxiety and depression, have provided inconsistent but intriguing findings. In the UK, two early studies found no evidence of statistically significant variation in the prevalence of CMD between regions (which have populations comprising several million people), after adjusting for the characteristics of individual respondents. A more recent study reported similar findings at electoral ward level (average population 5500), in which areas were classified using a standard census based compositional measure of socioeconomic deprivation. Similar findings have also been reported in Amsterdam, at three levels: borough (average population 33 000), neighbourhood (average population 8000), and postcode sector (average population 9500). By contrast, a household survey in Illinois found a small but statistically significant association between depressive symptoms and deprivation at the level of US census tracts (average population 4000), after controlling for individual level risk factors.

In contrast with these mainly negative findings, a number of British studies have found a higher prevalence of CMD among people living in urban areas, compared with rural or suburban areas. At least one study found that suicide rates were also higher in urban than in rural areas in Britain, although rates may vary with gender and both area level and individual socioeconomic factors, particularly unemployment. However, studies in New Zealand and the USA found little evidence of an urban/rural gradient in the prevalence of CMD. These inconsistencies may be partly attributable to differences in methodology, including differences in the definition of “urban” areas. While most studies have quantified urbanicity according to population density, others have used more subjective, impressionistic definitions on the grounds that ward level population density may not reflect smaller scale contextual variation.

Advances in multilevel modelling enable potential risk factors for a given outcome to be studied at more than one level simultaneously, along with cross level interactions. However, most previous studies have failed to take into account variability between households, resulting in over-estimates of variance at higher levels. Associations between health outcomes and area level exposures tend to diminish with the number of individual level confounders included in models, suggesting that some of the observed area level effect may reflect variation at the individual level. Even if there is little residual area level variation in rates of CMD once individual characteristics have been taken into account, it does not mean that complex heterogeneity is absent. Different relations for different types of people across place may exist, but these interactions can only be fully explored if models are specified correctly, and designed to test theoretically informed hypotheses. For instance, one study found that the effects of household level exposures on self rated health varied with economic activity.

We sought to address these limitations by analysing data on persons in UK electoral wards using measures of place that reflect both socioeconomic composition and urbanicity, and by extending the notion of “place” to include the household. The main aim of this study was to quantify independent

Abbreviations: CMD, common mental disorders; BHPS, British Household Panel Survey; GHQ, General Health Questionnaire
associations between the prevalence of depression and (a) area level indices of socioeconomic deprivation, and (b) urbanisation, at population density, after adjusting for individual socioeconomic status. We set out to test the hypotheses that (1) the prevalence of CMD in Britain is higher to a statistically significant degree among people living in urban areas, compared with rural and suburban areas, after adjusting for the socioeconomic status of individual respondents; and (2) the prevalence of CMD will be higher to a statistically significant degree among people living in areas with the highest levels of socioeconomic deprivation, before but not after adjusting for the socioeconomic status of individual respondents. A further aim was to test for interactions between exposures at different levels, and to explore variations in the prevalence of CMD within urban and rural areas. On the grounds that those who are economically inactive are likely to spend more time at home, we also tested the hypothesis that (3) the effects of area level exposures would be greatest among those not in paid employment.

METHODS

Data were derived from the first wave of the British Household Panel Survey (BHPS) that was carried out in autumn 1991. The BHPS is an annual survey of a representative sample of households in England, Wales, and Scotland. Households were selected for the BHPS using a two stage, implicitly stratified clustered probability design, with postcode sectors as primary sampling units. The population of postcode sectors was first ordered into 18 regions (16 standard of three linked, ward level indices, only one of which could be information that might permit identification of respondents. To preserve respondents’ anonymity, we were restricted to a total of three linked, ward level indices, only one of which could be analysed at a time.

We therefore chose, a priori, to use (a) the Carstairs index of socioeconomic deprivation, (b) the Office of National Statistics (ONS) classification of wards into 14 groups, and (c) a measure of population density given as the number of 25–64 year olds per square kilometre. The first two of these were based on data collected in the 1991 census and the density measure was derived from re-worked 1991 census data that attempted to adjust for the census undercount. The Carstairs index is based on Z scores of four person level (compositional) variables for each ward: male unemployment, households with no car, overcrowding (over one person per room), and head of household in registrar general’s social class IV or V. Both Carstairs scores and population densities were rounded to integer values. The BHPS investigators truncated the tails of the distribution of Carstairs scores, to protect the identities of survey respondents.

The ONS classification of wards comprises 14 principal groups and 43 clusters of electoral wards, based on their demographic and socioeconomic composition. More than 30 census variables were used to generate this classification, including age, ethnicity, household composition, education, housing tenure, employment status, and the proportion of residents working in different occupations. Although no direct measures of the physical environment were used, proportions of respondents living in terraced and purpose built housing were included. Groups and clusters were derived by ONS using Ward’s method, a two stage cluster analysis technique, followed by a k-means procedure with iteration at cluster level to ensure wards were assigned to the cluster with the smallest dissimilarity between it and the cluster centroid. The final classification was designed to ensure that clusters were homogenous and sufficiently populous to permit the study of geographical patterns. Particular attention was paid to the face validity of clusters, so that they might be recognisable and meaningful to users. Groups and clusters were given names by the originators of classification, for ease of reference, based on the general characteristics of cluster members – sometimes combined with [their] geographic attributes. These names were therefore intended as shorthand, rather than precise descriptions. A full list of groups and clusters, and portraits of each, are available elsewhere.

Associations with the prevalence of CMD were estimated in two ways: (a) for each of the 14 groups, and (b) for “rural areas” versus the rest. Three groups, namely “rural fringe”, “rural area”, and “prosperous area” groups were aggregated to produce a single dummy variable representing “ONS rural grouping”. This ‘rural’ aggregation was done a priori, on the basis of the geographical distribution of the groups in question, the identities of the clusters included within each group, and population densities. As table 1 shows, the three rural groups were those with the lowest population densities. The mean population density in the “ONS rural grouping” was lower than that in the remaining 10 ONS groups, to a statistically significant degree (difference between means 1242.5, 95% CI 1179.1 to 1305.9) (p<0.001).

Individual and household exposures

Individual and household level confounders were chosen both to mirror the indices used to construct the Carstairs index, the area level measure of socioeconomic status used in this study, and using existing evidence concerning known risk factors for CMD. At the individual level, age, sex, marital status, ethnicity, employment status, and number of current physical health problems were included. Employment status was classified using three categories: employed (in paid employment), unemployed (available for and seeking paid employment), and economically inactive (not currently available for employment). The last group includes the retired, full time students, those unable to work on health grounds, and full time carers.

Potential household level confounders were: social class of the head of household, structural housing problems (any major
problem, or two or more minor problems from a list comprising damp, condensation, leaking roof and rot in wood, low income (household income below half the median income for the sample), household access to a car, and overcrowding (more than two household members per bedroom).

Statistical analysis

Multilevel approaches offer substantive improvements over traditional regression methods, particularly for hierarchical datasets such as the BHPS. All analyses were undertaken using MLwiN, which takes account of the clustering of persons in households and households in wards when estimating standard errors. Individuals (level 1) were nested within households (level 2), within electoral wards (level 3). Multilevel analyses were undertaken using a logit link function and assumed non-constant, between individual variance based on a Bernoulli distribution. In the logistic models, parameters were estimated using second order Taylor expansion with predictive quasi-likelihood (PQL). This estimation procedure is considered superior to first or second order marginal quasi-likelihood (MQL) when clusters, such as households, are small (see Goldstein, chapter 7). While the quality of parameter estimates may be more accurate still for small clusters using Markov chain Monte Carlo (MCMC) methods, this method is computationally intensive and was therefore used to check our main findings. Differences between methods were expected to be more pronounced for estimates of variance at the household than at the ward level. Differences using second order PQL and MCMC methods were noted where appropriate.

Base models were used to estimate associations with each contextual (level 3) variable prior to adjusting for individual and household level characteristics. Each model was then adjusted for individual and household level variables. Given the variable number of respondents per ward (range 1 to 60), sensitivity analyses were undertaken excluding (a) wards with only one respondent, and (b) wards with five or fewer respondents. Statistical significance of individual fixed estimates was tested using a single Wald test against a \( \chi^2 \) distribution. While approximate Wald tests can be used to assess the higher level variances, problems are encountered because of the distribution of the parameter estimates when variances are close to zero (negative variances cannot exist). Therefore, the 95% interval estimates (the "credible interval") derived from MCMC procedures are also reported for the random parameters of the models. Multivariate Wald tests were also used to assess blocks of interactions between individual and area level exposures.

RESULTS

After excluding “deadwood” addresses, 73.6% of households (n=551) participated in the first wave of the BHPS. This resulted in a sample of 9522 people aged 16–74, of whom 94.3% (n=8978) completed the GHQ. Study respondents were nested within 4904 households. The total number of electoral wards represented was 642, with a mean of 14 and a median of 11 respondents per ward (range 1 to 60). The prevalence of CMD was 24.7% among individuals, across all households and wards.

Table 1 shows the population density and unadjusted prevalence of CMD in each of the 14 ONS groups. Using the ONS classification of wards, the lowest prevalence of CMD (18.8%) was found among respondents in rural areas (table 1). This rate was lower to a statistically significant degree than that observed in 7 of the remaining 13 groups, namely Metropolitan Professionals, Deprived City Areas, Deprived Industrial Areas, Lower Status Owner Occupiers, Industrial Areas, Mature Population, and Middle Britain.

Table 2 summarises the results of the multilevel models investigating contextual effects. We found evidence of interactions between characteristics of wards and employment status, in keeping with our hypothesis that associations between characteristics of places and CMD would be greatest for those most likely to spend more time at home (table 2). However, in analyses based on the full dataset, the interaction with employment status was only statistically significant for Carstairs score in the unadjusted model (\( \chi^2=16.063, df=8, p=0.04 \)). Associations between Carstairs score, rurality (“ONS rural grouping” versus the rest), population density, and CMD only reached statistical significance among the economically inactive.

Random variances were estimated at the household and area levels before and after including specific explanatory variables in the fixed part of our models. In the null model, before specifying any characteristics of individuals, households or wards but taking account of the nested structure of the dataset, we found statistically significant variance in the prevalence of CMD between households (variance 0.565, SE 0.077) (Wald 53.84, p<0.001) but not between wards (variance 0.035, SE 0.026) (Wald 2.53, p=0.11). Slightly different findings were obtained using MCMC methods, particularly at the household level where variance was estimated to be 0.794 (credible interval 0.54 to 1.057 with 100,000 chains). The ward level variance using MCMC methods was 0.032 (credible interval 0.001 to 0.098). The household level variance was little affected by specifying characteristics of wards, and remained statistically significant (although attenuated) after adjusting for individual and household level risk factors, irrespective of statistical method. The (non-statistically significant) ward level variance was reduced substantially by specifying ward level characteristics (particularly ONS groups), and approached zero in all cases on adjusting for individual and household level risk factors.

DISCUSSION

In keeping with a number of previous studies, our findings indicate that there is comparatively little independent area level variance in the prevalence of the CMD. Like most previous studies, we found no evidence of a statistically significant overall association between the prevalence of CMD and socioeconomic deprivation, as measured by the Carstairs index. Our findings were particularly notable for demonstrating interactions between area level exposures and individual employment status, in keeping with at least one previous study. Associations between CMD and population...
density. Carstairs score (socioeconomic deprivation) and urbanicity were only statistically significant among the economically inactive.

**Measuring the CMD**

The study was limited by use of the GHQ rather than a standardised clinical interview. Associations between individual level risk factors, such as low income, and rates of CMD are generally larger in studies using a standardised interview. As the GHQ is sensitive to recent change in psychological functioning, “false positives” might have included persons with mild or transient psychological disturbance, which should have biased associations towards the null. Although physical ill health also leads to “false positives”, study findings were adjusted for the number of current physical health problems. As the GHQ is a measure of recent changes in mental functioning, “false positives” might have included persons who were adjusted for the number of current physical health problems.

Other limitations of the study

This was a cross sectional study, precluding causal inference. While our findings do not contradict the view that deprived persons are clustered in deprived areas, the variance within wards in the prevalence of CMD was far greater than that between wards. While reverse causality and/or selection bias are often invoked as explanations for geographical clustering, it is difficult to see how these processes might have contributed to our (mainly) negative findings with regard to area level variance. It is difficult to see how selective health related mobility, local authority housing allocations or systematic area based labour market disadvantage might lead to less variation in CMD between wards. These processes may however have contributed to the modest urban-rural gradient in the prevalence of CMD among the economically inactive.

Perhaps the most salient feature of any study of this nature is the size of area studied. “Neighbourhoods” remain difficult to define or delineate, but are unlikely to be coterminous with electoral wards. Wards may be too large and heterogeneous to permit the detection of contextual effects. It is notable that the one study to report positive findings quantified contextual deprivation at the smallest spatial scale. This is consistent with evidence of statistically significant associations between rates of CMD and specific features of the built environment assessed across small areas, after adjusting for characteristics of individual residents. The variance observed at household level in this study may have been partly attributable to exposures operating at an intermediate level between ward and household. This view is supported by the failure of household and individual level exposures to substantially reduce the household level (level 2) variance.

Like many studies, we were forced to rely on standard measures of “social deprivation” based on the aggregated socioeconomic characteristics of local residents. The high correlation between area level deprivation and individual socioeconomic status may explain the absence of a statistically significant association with the former, after controlling for the latter. Future research should be based on theoretically based compositional measures, or true “contextual” measures of place that cannot be reduced to the aggregated characteristics of local residents. Despite the large size of the study sample, the number of unemployed informants was comparatively small (n=604). It is possible that the failure to find statistically significant associations between area level exposures and CMD in this group, or interactions between area level exposures and employment status, represents type II error.

**Conclusions**

Variance in the prevalence of the CMD between electoral wards in the UK is modest, particularly when compared with...
that between individuals, and between households. Associations between ward level socioeconomic deprivation, urbanicity, and population density, and the prevalence of CMD varied with individual employment status, and were strongest among the economically inactive, who are likely to spend the most time at home.

Further research is needed to understand why the effects of place vary to seem with individual employment status. Research is also needed to address prior questions, namely how and why the most deprived individuals come to be living in (or fail to “escape” from) socioeconomically deprived areas, which also tend to be the most densely populated and the in (or fail to “escape” from) socioeconomically deprived areas, Research is also needed to address prior questions, namely how and why the most deprived individuals come to be living in (or fail to “escape” from) socioeconomically deprived areas, which also tend to be the most densely populated and the most urban. Investigating the effects and determinants of adverse physical and psychosocial environments are therefore a priority. Until we understand these processes, it will be difficult to design effective area level interventions to reduce inequalities in mental health.

ACKNOWLEDGEMENTS

We are indebted to Professor Nick Buck of the Institute for Social and Economic Research for his help in obtaining and managing the BHPS dataset with ward level indices. The data (and tabulations) used in this (publication) were made available through the UK Data Archive. The data were originally collected by the ESRC Research Centre on Micro-social Change at the University of Essex, now incorporated within the Institute for Social and Economic Research. Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

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Funding: this study was funded by the Wellcome Trust.

Conflicts of interest: none declared.

REFERENCES

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