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Does the level of wealth inequality within an area influence the prevalence of depression amongst older people?

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Abstract

This paper considers whether the extent of inequality in house prices within neighbourhoods of England is associated with depressive symptoms in the older population using the English Longitudinal Study of Ageing. We consider two competing hypotheses: first, the wealth inequality hypothesis which proposes that neighbourhood inequality is harmful to health and, second, the mixed neighbourhood hypothesis which suggests that socially mixed neighbourhoods are beneficial for health outcomes. Our results are supportive of the mixed neighbourhood hypothesis, we find a significant association between neighbourhood inequality and depression with lower levels of depression amongst older people in neighbourhoods with greater house price inequality after controlling for individual socio-economic and area correlates of depression. The association between area inequality and depression is strongest for the poorest individuals, but also holds among the most affluent. Our results are in line with research that suggests there are social and health benefits associated with economically mixed communities.

Keywords

depression; area effects; neighbourhood; inequality; mix; wealth; deprivation

Introduction

This paper examines whether neighbourhood wealth inequality is associated with risks of depressive symptoms (from hereon referred to as depression) amongst the elderly in England using house price sales as a proxy for area wealth. We test two competing hypotheses, the ‘wealth inequality hypothesis’ and the ‘mixed neighbourhood hypothesis’, that predict associations between depression and area inequality that act in opposing directions. The wealth inequality hypothesis is based on the premise that greater inequality drives poorer health outcomes as a result of stresses associated with harmful social comparison, less cohesive neighbourhoods and as a consequence of lower support for public investment of time and money in communal facilities, services and infrastructure (Lorgelly & Lindley

2008). So, under this hypothesis we would expect higher risks of depression in the most unequal areas. Alternatively, the mixed neighbourhood hypothesis proposes that a degree of inequality within a neighbourhood can have positive influence on various social outcomes including health. The focus here tends to be on homogenous poorer areas where it is argued that residents have reduced social opportunities as a result of cultures of worklessness, crime or substance abuse (Musterd & Andersson 2005) or, alternatively, because of overstretched public services with little incentives for the private sector to invest within the area (Ostendorf et al. 2010). The thinking goes that these problems are mitigated by socio-economic mixing. Thus, under the mixed neighbourhoods hypothesis we would expect lower risks of depression in the most unequal areas, particularly for the poorest individuals.

Depression is a growing health issue in both developing and developed countries; major depressive disorders are ranked 11th in the global causes of years lost due to disability and are the 4th most important cause of years lost due to disability in Western Europe (Murray et al. 2012). There is particular interest in depression in later life because the consequences are particularly severe. Depression is a strong predictor of suicide in older people and has important implications for the onset and progression of other health problems (e.g. disability, morbidity and mortality) (Beekman et al. 1995; Blazer 2003). Avoidance of depression in later life is an important aspect of 'healthy ageing' (Simons et al. 2000) that is recognised as essential to mitigate the challenges associated with global projected trends towards more elderly populations.

Depression is associated with a number of individual socio-economic and demographic characteristics. For example, the condition is more prevalent amongst women, those who are single, living in care institutions, suffering from other health problems and who have fewer social contacts (Rodda et al. 2011; Chapman & Perry 2008; Beekman et al. 1995). Depression exhibits a strong social gradient with higher risks for the lower social classes explained by psychosocial, behavioral (e.g. smoking, excessive alcohol consumption and lack of physical exercise), and physical health factors (Koster et al. 2006). Additionally, research suggests that characteristics of place of residence, such as deprivation and poor neighbourhood perception are associated with depression independently of individual risk factors (Yen & Kaplan 1999; Stafford et al. 2011; Hooge and Vanhoutte 2011). Older people are thought to be particularly susceptible to area influences as a result of greater attachments to their neighbourhood that stem from living in an area longer, spending more time day to day within their neighbourhood (especially if retired or less mobile) and making more use of local services compared to younger people (Bowling & Stafford 2007; Stafford et al. 2011; Beard et al. 2009).

The hypothesis that the greater income or wealth inequality within a society the less well that society performs according to a range of social indicators, including health outcomes, has attracted a great deal of debate within academic, policy and media circles. Although the wealth inequality hypothesis was originally developed to explain differences in health *between* countries, researchers have attempted to assess the extent to which the inequality hypothesis holds for areas *within* countries (for a review see (Wilkinson & Pickett 2006). Findings on associations between area inequality and health are thought to be influenced by the health measure under investigation, the geographical scale of analysis, methodological

factors such as the control variables that are included or whether a single or multilevel model is used (Riva et al. 2007). More generally, area effects are usually small, meaning that determining such an effect, after accounting for the relevant individual characteristics, is often difficult. However, a small area effect can have a significant impact on population health as it applies to each member living within an area (Craig 2005). A review of international studies suggests that the wealth inequality hypothesis is most salient for large geographical areas and in countries with high levels of sub-national inequality such as the USA (Subramanian & Kawachi 2004; Wilkinson & Pickett 2006).

Within the UK there is little consensus on the impact of area inequality on health. For example, in terms of self-reported health, some studies show no association with area inequality (Lorgelly & Lindley 2008; Gravelle & Sutton 2009), whilst others find increasing area inequality to be associated with both better (Craig 2005) and worse (Weich et al. 2002) health outcomes. Although most research in the UK focuses on self-reported health, two studies on mental health (measured using the General Health Questionnaire and the Mental Health Inventory (MHI-5)) reveal an association in the opposite direction to that postulated in the inequality hypothesis; for persons with the lowest incomes or in the poorest areas, increasing levels of inequality within UK regions appear to have a protective effect in terms of mental health (Fone et al. 2013; Weich et al. 2001). This finding is in line with the mixed neighbourhood hypothesis, although neither paper explicitly refers to this body of literature. Weich et al. (2001) also report an association of better mental health in more equal areas for the most affluent and so it appears that the effects of area inequality are sensitive to social position, a finding noted elsewhere (Dahl et al. 2006). National contextual factors are also important; a Brazilian study (Filho Chiavegatto et al. 2013) reports an association between depression and area inequality in the opposite direction (higher risks of depression in the more unequal areas) to that observed by Fone et al. (2013) and by Weich et al. (2001) for people with the lowest incomes. It is argued that the greater extent of inequality in Brazil (compared to countries such as the UK) drives the health harmful social comparison that underlies the association observed between area inequality and depression (Filho Chiavegatto et al. 2013).

The mixed neighbourhood hypothesis has a long history with important impacts on planning policy that can be traced back to the 19th Century in England and the Garden City movement. In the UK, the emphasis on positive aspects of mixed communities formed a key element of Government policy under New Labour (ODPM 2005) and in legislation around planning permission that requires new developments to have a proportion of affordable housing. Mixed neighbourhoods have been championed by influential organisations such as the Joseph Rowntree Foundation, a charity concerned with social justice, tackling poverty and building sustainable communities. Similar legislative aims have been enacted in the Netherlands, France, Germany, Sweden and Finland (Musterd & Andersson 2005) and in the USA (Cheshire 2009).

However, the evidence in favour of the mixed neighbourhood hypothesis is inconclusive. Studies that examine the effects of programmes to reduce concentrations of poverty e.g. the Moving to Opportunity scheme and Hope IV scheme in the USA) reveal mixed results and limited evidence to suggest individuals moved to more mixed area were better off than those

who did not (Cheshire 2009; Manley et al. 2012). Other research, usually using survey data sources, reveals no, or limited, evidence in favour of the benefits of mixed neighbourhoods for health and other social outcomes (Graham et al. 2009; Ostendorf et al. 2010; Atkinson & Kintrea 2001; Galster et al. 2008; Musterd & Andersson 2005).

This paper makes three contributions to these literatures. First, we extend existing research on the association between area inequality and depression to the older population, a group thought to be particularly susceptible to area health effects. We might expect clearer area effects on depression as a result, especially as research has suggested the area effects associated with social mix do indeed vary across population groups (Galster et al. 2008). Second, we use house price sales as our main measure of area inequality rather than the more commonly used indicator of income. This is a valuable contribution because for many people, and particularly older people, property is a major financial asset. Additionally, house prices are a particularly stark and visible form of wealth inequality in the UK across regions and neighbourhoods where factors such as demand for housing close to desirable schools have exacerbated divisions. Third, we test the effect of area inequality on a health outcome (depression) at a finer geographical scale within England than in much of the previous research, assessing whether the level of neighbourhood inequality influences risk of depression across Middle Super Output Areas (average population 7,200) (MSOAs).

In summary, the central aim of the paper is to test two hypothesis relating to the theorised impact of neighbourhood inequality (measured here using house prices) on depression. Under the mixed neighbourhood hypothesis we would expect to see a negative association between area inequality and depression with increases in area inequality associated with lower probabilities of depression. Alternatively, under the wealth inequality hypothesis we would expect to observe a positive association between depression and area inequality so that increases in area inequality are associated with increases in probabilities of depression.

Data and Methods

The main data source for this research is the English Longitudinal Study of Ageing (ELSA) (Banks et al. 2012), a representative sample of the population aged 50 and over, living in private households in England. In this paper we use the first wave (2002/3) of data, which contains a sample selected from the Health Survey for England. Our analysis is based on the core sample, excluding partners. In line with other research on area health effects (e.g. Craig (2005)), we also exclude those who report their economic activity as permanently sick to reduce the possibility of reverse causation; i.e. that low income is the result rather than a determinant of poor health. This gives a final sample size of 10,644. Full details of the ELSA survey methodology are provided by Taylor et al. (2003).

ELSA, like most other social surveys, suffers from a degree of non-response that has the potential to bias estimates. The ELSA wave 1 sample is drawn from a list of households that had previously participated in another survey, the Health Survey for England (HSE) (1998, 1999, 2001), giving the potential for non-response at two stages; during the collections of the HSE data and when drawing the ELSA sample from the HSE. Fortunately, individual response rates to both the HSE and ELSA (wave 1) are relatively good varying between 67%

and 70% for the three HSE datasets (1998, 1999 and 2001) and attaining 67% in ELSA. The HSE samples are considered sufficiently representative of the target population (private household population in England) that non-response weights were not created. Whilst non-response weight are calculated and provided for ELSA these have very little impact on estimates and are intended to provide a foundation for future approaches to deal with the greater levels of attrition anticipated in future waves of the survey (Taylor et al. 2003).

Within wave 1 of ELSA, item non-response is very low, as illustrated by table 1. However, the data on income, wealth and savings involves some imputation and the use of unfolding brackets where if respondents refuse or are unable to give an answer a banded estimate of income or wealth is derived from further questions. Where income data is banded or missing, conditional hot-deck imputation is used to create a continuous estimate. Continuous financial estimates were given directly by over 90% of respondents for many aspects of wealth and income (e.g. take home pay, net profit, State pension, property). The areas with lowest levels of continuous answers (savings and current accounts and savings income) still attained 79% and 64% respectively. Further information on the prevalence of continuous, banded and missing data on income and wealth is provided in Annex 9.1 of Taylor et al. (2003). In summary, analysis of the impact of response in wave 1 of ELSA suggests it does not have a major impact on estimates and so we can be reasonably confident that the survey provides a representative sample of the health and circumstances of the English population aged over 50 living in private households (Taylor et al. 2003).

We use the Centre for Epidemiologic Studies-Depression Scale (CES-D) (Radloff 1977) to give a measure of depression based on the prevalence of depressive symptoms. We use a shortened version of the CES-D which includes 8 items and has been shown to give robust results comparable to the widely used 20 item scale and other measures of depression such as the Short Form Composite International Diagnostic Interview (Steffick 2000). We use a dichotomous depression variable for this analysis and following advice in the literature (Steffick 2000) employ a cut-point of four symptoms or more to indicate depression.

ELSA provides a number of individual characteristics that are correlates of depression and which we use as explanatory variables in models. Age (in years), sex and ethnicity (collapsed to categories of White and Non-White) provide the demographic controls in our analysis. We use two measures of socio-economic position. First individuals are grouped into quintiles of non-pension wealth, a measure which includes the net financial and physical wealth and net housing wealth for each benefit unit or household (a benefit unit is defined as a single individual or a married/cohabiting couple). We use a measure of household rather than individual wealth because in the vast majority of cases older couples deal with finances jointly. We exclude pension wealth from our wealth measure because individuals holding state pensions and private defined benefit pensions accrue rights to future income that are not easily collected in a survey. Additionally, pension wealth is known to be particularly age dependant, declining throughout an individual's retirement which is not the case, on average, for other forms of family wealth (Crawford and Tetlow, 2012). More information on wealth in ELSA is provided by Banks and Tetlow (2009). Second, we use a variable indicating level of educational qualifications comprising categories of degree or higher, below degree and no qualifications. Finally, we use two variable on the circumstances of older people; economic

activity which is divided into categories of retired, employed, looking after home/family and unemployed and living arrangements which is divided into categories of single, living as a couple, separated and widowed. Table 2 gives summary statistics on the sample characteristics. All the ELSA variables in the analysis reported are collected in the face-to-face part of the ELSA interview.

We use Middle Super Output Area (MSOA) as our neighbourhood geography. MSOAs are used in the dissemination of census data and were designed to improve the reporting of small area statistics. There are 7,193 MSOAs in England and Wales, with an average population of 7,200. There are three neighbourhood characteristics in our models: wealth inequality, wealth level and deprivation. Our measure of area wealth inequality draws on Land Registry data on the distribution of house price sales within an area, obtained from the Office for National Statistics (<http://www.neighbourhood.statistics.gov.uk/dissemination/>). We use the 2nd, 25th, 50th, 75th and 98th percentiles of house price sales to calculate an area Gini Index that provides a measure of the level of inequality (or mix (Simpson 2006)) within an area (MSOA). A Gini Index summarises the wealth distribution over a population, and can theoretically range from 0, when everyone in the population has exactly the same wealth, to 1, when one person possesses all wealth. Data on house prices across the whole range of percentiles are not included in the Land Registry data provided by the Office for National Statistics, so we fit a polynomial of order three to the observed data and calculate our Gini Index based on this fitted data. We calculate our Gini coefficients using data for 2003/4 as information for house price sales prior to 2003 is not available.

It is important to note two differences between the house price measure of inequality used in this paper and those commonly used in the literature on the mixed neighbourhood and wealth inequality hypotheses. First, neighbourhood mix is often based on tenure types (e.g. (Graham et al. 2009)), perhaps reflecting policies that aim to encourage this form of variability in order to promote social/economic mixing within a neighbourhood. Second, measures of area inequality are more commonly based on income rather than housing wealth. Despite these differences we argue that use of inequality in house prices is appropriate because it is plausible that the mechanisms underlying each hypothesis might act through house price inequality. As noted earlier, inequalities in housing wealth are particularly visible and so could easily form the basis of health harming comparison within a neighbourhood. Similarly, a mix of house prices within an area is likely to contain a socially varied population with benefits around neighbourhood culture and services that are anticipated for the poorest in particular. Indeed, policy research on mixed areas argues that mixing tenure within an area is explicitly designed to bring about economic and social mix of the resident population (Tunstall & Fenton 2006). Thus, we argue that the use of mix in neighbourhood house prices is a reasonable and innovative indicator given the research aims of this paper.

We use the median house price to reflect the average level of wealth in an area and use the 2004 Indices of Multiple Deprivation (DCLG 2004) as a measure of area deprivation for each neighbourhood. The Indices of Multiple Deprivation are based on a weighted average of various domains of deprivation including income, employment, health and disability, education, skills and training, housing and services, living environment and crime. We

estimate deprivation scores for MSOAs using the mean score for the lower super output areas within each MSOA (on average there are 5 LSOAs in each MSOA). Median neighbourhood house price and deprivation are treated as continuous variables in our models due to the observed depression gradient across these variables (figure 3). To aid interpretability in our models we standardise all our neighbourhood measures of median house price and deprivation so that coefficients show the impact on risk of depression of an increase in deprivation/house price by 1 standard deviation of the neighbourhood characteristic. We use quintiles of area inequality in our models, rather than a continuous variable, because of the lack of a clear gradient in prevalence of depression across the distribution of area inequality (figure 3). The distribution of neighbourhood characteristics is shown in figure 1.

One methodological issue associated with the use of house prices as a measure of area inequality/wealth is whether there is differential turnover in the sale of housing that is related to house price which might then bias estimates of area wealth/inequality. For example, if turnover of more expensive houses is generally slower than that of cheaper houses then areas of predominantly expensive housing will tend to underestimate the 'true' extent of housing wealth/inequality. A review of the literature does not suggest a strong relationship between housing turnover and house price, with other factors such as the relationship between initial listing price and selling price (Merlo and Ortalo-Magne 2000), the sellers motivation to sell (Glomer et al. 1998) and aspects of estate agents advertising strategy (Benefield et al. 2009) being more important predictors of the time a house is on the market.

We fit multilevel models to predict depression, with individuals nested within neighbourhoods (Middle Super Output Areas). A multilevel approach provides one means of accounting for the non-independence of the mental health of individuals living in the same area. In our models we allow the intercept to vary randomly across neighbourhoods, enabling estimation of the proportion of the total variability in depression that is attributable to each level of the model (individual and neighbourhood). We fit a number of models to assess how area level effects change as individual and area correlates of depression are included. Model 1 is a variance components model which allows the variability in depression to be apportioned to levels of individual and neighbourhood. In model 2 we include neighbourhood inequality along with age, age squared and sex, giving maximum opportunity for the association between area inequality and health to be uncovered. In model 3 we add each of the individual correlates of depression to the explanatory variables of model 2 in order to assess whether any associations between neighbourhood inequality and depression are robust to the socio-economic characteristics of the resident population. In model 4 we add neighbourhood wealth (median house price) and then in model 5 we add neighbourhood deprivation to determine whether such aspects of place of residence influence the relationship between area inequality and depression in previous models. Model 5 is specified below, whilst each of the other models (models 1-4) are reduced versions of this full model:

Let:

π_{ij} = the probability of being depressed for individual i ($i=1, \dots, 10,2931$) in MSOA j ($j=1, \dots, 2,822$)

x_{bij} = a set of b ($b=1, \dots, 16$) explanatory variables relating to individual characteristics (age, age squared, sex, quintiles of individual wealth, ethnicity, living arrangements, education, economic activity)

z_{aj} = a set of a ($a=1, \dots, 6$) explanatory variables relating to MSOA characteristics. Each individual within an MSOA has the same value for these characteristics. There are 6 variables in total including; 4 dummy variables relating to area inequality quintiles (reference category is the most equal quintile of areas), a (continuous) area wealth variable (median area house price) and a (continuous) deprivation variable (Indices of Multiple Deprivation (2004)).

$$\log \frac{\pi_{ij}}{1 - \pi_{ij}} = \beta_{0j} + \sum_{b=1}^{16} \beta_{bij} x_{bij} + \sum_{a=1}^6 \alpha_{aj} z_{aj}$$

Where:

$$\beta_{0j} = \beta_0 + \alpha_{0j}$$

α_{0j} is the random effect at the MSOA level, an allowed to vary departure from the grand mean. $\alpha_{0j} \sim N(0, \sigma_{0j}^2)$

Finally, in model 5a we extend model 5 (above) to investigate whether associations between depression and area inequality differ according to individual wealth by introducing an interaction between area inequality and individual wealth. In model 5a, tertiles of individual wealth, rather than quintiles as in model 5, are used in order to preserve sample sizes across the interaction between wealth and area inequality.

An important area of debate within research on area inequality regards the individual level variables that should be included in the model. Clearly, failure to include individual characteristics that influence health will limit inferences that can be made about the impact of area characteristics on health (Diez-Roux 2010). However, where individual variables reflect part of the causal pathway between an area effect and depression, then inclusion of such variables might negate the impact of area inequality on probability of depression. There is no consensus as to the variables that should be included in models that test for area health effects; for example, Wilkinson and Pickett (2006) suggest that even individual income should not be included in models, whilst Subramanian and Kawachi (2004) argue that individual income and area inequality have independent effects if a multilevel approach is used. In our full model (5), we choose not to include individual outcomes of limiting long term illness, smoking and alcohol consumption because they might reflect aspects of the

¹This sample total differs to that reported earlier (10,644) due to item non-response across explanatory variables in the full model

very area effects we are attempting to capture. However, in practice, inclusion of these variables in our model did not affect any of the conclusions drawn.

All models use *'runmlwin'*, a module developed by the Centre for Multilevel Modelling that allows multilevel models to be fitted in MLwiN from within Stata (Leckie & Charlton 2012). The logistic regression models are estimated using quasi-likelihood methods in MLwiN. We generated an initial set of model estimates using marginal quasi-likelihood (MQL) (order 1) and then used these initial estimates as starting values in an estimation procedure involving predictive (or penalized) quasi-likelihood (PQL) (order 2). We also fitted models using Monte Carlo Markov Chain methods, which gave very similar estimates of fixed and random parameters and did not influence any of our conclusions on area effects. In the models we fit, on average there are 4 people per MSOA. The literature on sufficient sample sizes for multilevel modelling finds that even if group sizes are very small (down to 5 units per group) estimates of regression coefficients and variance components are unbiased as long as there are a large number of groups (more than 50) (Mass and Hox, 2005). In our models we have over 2000 MSOAs and so whilst we flag the issue of small MSOA sample sizes we feel the large number of MSOAs will ensure our results are fairly robust.

Results

A key challenge of analysis on area health effects is untangling the influence of different area characteristics on a particular outcome. An understanding of the correlation between area characteristics within the model (in this case neighbourhood inequality, median house price and deprivation) is useful in this regard. As might be expected, median house price and level of deprivation display a strong negative correlation ($R=-0.5$) with more expensive housing areas associated with less deprived areas (see figure 2). The relationship between area inequality and median house price is less clear with a modest positive correlation ($R=0.1$) such that increases in neighbourhood inequality are associated with increases in median house price. The relationship is particularly unclear for the areas with the cheapest housing which contain many examples of neighbourhoods of both low and high inequality. If the correlation is restricted to areas with a median house price of more than £150,000, the relationship between area inequality and median house price is stronger ($R=0.4$). The neighbourhoods with the most expensive housing are largely also amongst the most unequal. Area deprivation and area inequality display a very weak negative correlation ($r=-0.01$).

Figure 3 gives the proportion of people with depression according to quintiles of neighbourhood inequality, median house price and deprivation, as well as individual wealth. Levels of depression are lower outside the quintile of neighbourhoods with the most equal house prices. Although there is little evidence of any gradient in risks of depression across the other quintiles of inequality, this exploratory analysis is supportive of the mixed neighbourhood hypothesis; levels of depression are lower in more mixed compared to the most economically homogenous areas. A strong gradient of increasing risk of depression with increasing house prices and decreasing deprivation is apparent. However, the descriptive area results described reflect to some extent the characteristics of people living within them. For example, poorer people are known to live in the most deprived areas and, as illustrated in figure 3, the poorest people are most likely to suffer from depression.

Table 3 gives the odds ratios from the multilevel multivariate stepwise model. In model 2, which includes age, age squared, sex and area inequality as explanatory variables, older people who reside in neighbourhoods ranked within the two most unequal quintiles of neighbourhood house prices have lower risks of depression than those in neighbourhoods where the distribution of house prices is more equal. The magnitude of the association between neighbourhood inequality and depression is slightly attenuated in model 3, after individual socio-economic correlates are added to the model, but remains statistically significant. The odds ratios for the impact of area inequality on depression change little when median neighbourhood house price and deprivation are added to the model and the lower odds of depression in the two most unequal neighbourhood quintiles relative to the most equal quintile of neighbourhoods remains significant in the final model (model 5). In model 5 the odds of depression are lower by around 20% in the most unequal area relative to the most equal area, a differential similar to that illustrated in figure 3 (and model 2). So, after controlling for individual and area correlates of depression, the association between area inequality and depression is in line with the mixed neighbourhood hypothesis; lower odds of depression are found outside the areas that are most homogenous in terms of house prices.

There is evidence to suggest that increases in the median house price of a neighbourhood is associated with lower risks of depression (see model 4), however, this result is not robust to inclusion of neighbourhood deprivation in the model (see model 5). Older people living in the most deprived neighbourhood suffer from greater risks of depression independently of the individual correlates of depression in the model. It appears that the area deprivation and median house price act in similar ways, but neighbourhood deprivation emerges as a more important determinant of the odds of depression. An increase in deprivation of 1 standard deviation of the deprivation distribution results in an increase in the odds of depression of almost 10%. This differential is much reduced compared to that displayed in figure 3 which does not account for social composition of deprived areas.

The most striking, but not unexpected result, is the health gradient across quintiles of individual wealth whereby risk of depression steadily deteriorates with increasing wealth (Models 3, 4 and 5). The risk of depression amongst the most affluent quintile of older people is half that of the poorest quintile and this differential does not change when we include variables for smoking and alcohol consumption in our model. Similarly, other individual characteristics are related to depression in expected ways: odds of depression are greatest for those who are separated/widowed, unemployed, non-white, current smokers and who have no qualifications or a limiting long term illness.

The majority of the variability in depression stems from the individual level rather than the neighbourhood. If we assume that the level one (individual) variance can be approximated by $\pi^2/3$ (Goldstein et al. 2002) then a variance components model reveals 89% of the variability in depression to be attributable to the individual and 10% to the neighbourhood, with a slight fall in the proportion of variation attributable to neighbourhood in the final model which includes all individual and area characteristics (9%). This is a relatively large area effect of neighbourhood on depression relative to other UK-based research perhaps reflecting the finer scale of geography in this paper. For example, in Scotland just under half

of 1% of the variability in self-reported illness is attributable to substantially larger district geography (average UK district population=120,000) (Craig 2005).

As noted in the introduction, the hypothesis that mixed neighbourhoods are beneficial to social outcomes including health is usually applied to the poorest individuals. In order to assess whether our findings on area inequality vary according to individual wealth we add an interaction between wealth and area inequality to model 5 (see table 4). In table 4, the odds ratios associated with area inequality indicate the effect of area inequality for the poorest tertile of individuals. In line with expectation, we see that a clear association between area inequality and depression for the poor where residency outside the most equal areas is associated with lower risks of depression. For older people with medium or higher levels of individual wealth, the interaction odds ratios serve to reduce the protective impact of area inequality (on depression) compared to that observed for the poorest. These interaction terms are largest for the middle tertile of individual wealth. Figure 4 gives the predicted probabilities from these models providing evidence to suggest that living outside the most equal areas is most protective on odds of depression for the poorest older people but also, to a lesser extent, the most affluent. We also fitted models for each wealth tertile separately which gives results in line with the figure 4 and table 4 (results not shown here) and described above.² We also investigated whether the association between depression and area inequality varied according to sex and broad age groups (distinguishing those above and below retirement age), but we did not find any differences in this association across these groups.

Discussion and conclusions

Our results support the mixed neighbourhood hypothesis. Risk of depression amongst older people living in England is lower in neighbourhoods with a greater mix of house prices and this association is independent of individual correlates of depression and other neighbourhood characteristics (area deprivation and median neighbourhood house price). The association between neighbourhood mix in house prices and depression appears most salient for the poorest people but we also find some evidence that it holds to a lesser extent for the most affluent. We do not find evidence to support the wealth inequality hypothesis at neighbourhood level in terms of depression amongst older people: more unequal neighbourhoods are not associated with higher risks of depression.

A number of pathways are suggested in the literature on the benefits of mixed neighbourhoods. For example, poorer people may have lower levels of depression in more socially mixed areas through avoidance of health harming cultures that might arise in particularly deprived neighbourhoods (Musterd & Andersson 2005). Similarly, the presence of people with middle and higher incomes within an area may help sustain social and health facilities and services that are beneficial to aspects of health including depression (Ostendorf et al. 2010). Thus, the benefits of social mixing for poorer people are seen in the either the access to social resources, or role socialisation that comes through wider social networks

²Allinson (1999) points out a flaw in comparing logit coefficients across groups if this involves interaction terms or separate models. However, sensitivity testing involving models with depression operationalised using a continuous variable (ces-d score) did not affect our findings.

(Berkman & Glass 2000) Richer people, who most likely live in more equal affluent, rather than poor areas, may face different stresses. These might include pressures to keep up with their neighbours (relative wealth hypothesis) (Gravelle & Sutton 2009)) or to maintain a sufficient income to cover the high costs of housing in desirable neighbourhoods. It is plausible that a sense of achievement may be felt by richer individuals living in mixed areas by social comparison with their neighbours. The mixed neighbourhood hypothesis (and associated policy) tends to focus on poorer individuals and deprived areas; homogenous high income neighbourhoods are not considered problematic for individuals living within them despite clear evidence of strong segregation for the most wealthy (Musterd & Andersson 2005). Our finding that rich older people also appear to have lower levels of depression in neighbourhoods that contain a greater mix of house prices is therefore worthy of further attention.

Whilst the results presented here do not support the wealth inequality hypothesis for neighbourhoods we do not claim to undermine its validity as a theory for differences in outcomes between societies. Rather, we point out that a degree of inequality (or mixing) at a neighbourhood level, particularly for poorer people can have positive outcomes linked to neighbourhood cultures or services. However, we stress the point that our results also confirm that poorer people are most at risk of depression whatever the characteristics of their neighbourhood and their position relative to other in society is a key factor in explaining such inequality. The conclusions here are in line with the emerging consensus that health harming comparisons across social classes are most salient at a societal or country level (Wilkinson & Pickett 2006) not within neighbourhoods:

‘the health of people in a deprived neighbourhood is worse not because of inequalities within that neighbourhood, but because they are deprived in relation to the wider society’ (Wilkinson & Pickett 2007). Whilst this research suggests that more economically mixed areas are associated with lower levels of depression, it is also the case that other aspects of a mixed area might be beneficial to mental health. For example, if a mix in house prices also leads to a mix of ages in an area, one cause of lower depression for older people might be inclusion and neighbourly contact with younger people and families. We point to such analyses as important avenues of further research.

There are alternatives to the Gini Index as a measure of neighbourhood inequality in house prices. We test the robustness of our findings to alternative measures by also fitting our models with area inequality quantified using the ratio of the 75th percentile of house price sales to the 25th percentile of house price sales. We obtain equivalent findings should we use this alternative measure of neighbourhood inequality (results not shown).

In the research we present here, neighbourhood deprivation, quantified using the multidimensional Indices of Multiple Deprivation measure, is associated with depression amongst older people. Deprivation acts in a similar way to the median house price but has a stronger influence on depression with median house price no longer significantly associated with depression once deprivation is added to the model. We conclude from this that a number of aspects of a neighbourhood’s character, rather than a single element, such as neighbourhood wealth (housing or income) are likely to influence older people’s mental

health. A number of research papers have found an association between the physical and social aspects of a neighbourhood in which an individual lives and the physical and mental health of that individual (Cummins et al. 2005; Diez Roux & Mair 2010; Pickett & Pearl 2001; Duncan et al. 1995). Research on the impact of area deprivation on older people's health suggests that a range of aspects of the neighbourhood, including socio-economic status, quality of the local environment, residential instability, neighbourhood perceptions and crime are associated with the physical and mental health of older people, their life satisfaction and health related behaviours such as participation in physical activity and social interactions (Beard et al. 2009; Bowling & Stafford 2007).

A key strength of this study is that our findings are based on representative samples of the community dwelling population aged over 50 in the US and England. Further to this the paper make a number of contributions to the literature; we utilise house prices as a proxy for wealth enabling assessment of the wealth inequality and mixed neighbourhood hypotheses for a new population group (older people) and at lower geographical scales than in other analysis in England. In doing so, we adds to an emerging body of research that suggests neighbourhood mix is beneficial for mental health (Weich et al. 2001; Fone et al. 2013) and provide a baseline set of findings for development in future research. One direction that such research might take is to exploit the longitudinal aspect of ELSA data to consider how characteristics of neighbourhood, such as inequality, influence trajectories of depression. The longitudinal and rich detail of ELSA data, including life histories, is ideally suited to investigation of causal mechanisms underlying the association we identify between depression and neighbourhood house price inequality (social interactive, environmental, geographical and institutional – see Galster (2012)) including testing of hypotheses around 'dosage effects' linked to the duration of exposure to particular neighbourhood conditions (Galster 2012). However, issues of sample size within ELSA are likely to be an issue here, particularly for the substantively interesting group who move to a new area during the course of the study, and we suggest a boosted sample of elderly migrants as a valuable avenue for future data collection.

Whilst our findings are in line with existing research in the UK (Weich et al. 2001; Fone et al. 2013), we would not claim they apply equally in other countries where contextual factors may result in different relationships between area inequality and depression (e.g. see Filho Chiavegatto et al. (2013)). International analysis offers another valuable extension to this research with the potential to obtain greater understanding of the contextual casual mechanisms underlying area health effects observed.

There are also some limitations of the analysis conducted that should be considered when interpreting the results. First, there is a risk that in controlling for individual correlates of depression, many of which are also related to neighbourhood selection, it becomes difficult to identify persons in a particular neighbourhood with a given set of characteristics. This prohibits the exchangeability necessary for meaningful causal contrasts across neighbourhood exposures. For example, we may be concerned as to whether there are sufficient poor individuals in the least deprived areas, or alternatively rich individuals in the most deprived areas, to derive robust results on the association between area deprivation and depression. However, cross-tabulations do reveal reasonable counts across area types, such

as, 194 (7%) of the richest individuals in the most deprived quintile of areas and 336 (18%) of the poorest individuals living in the least deprived areas. Similar concerns apply to the area variables in our model (5) and in particular we focus on the strong correlation between area deprivation and the median area house price. As might be expected, we observe very few people living in areas of low deprivation and low median house price (see figure 2). However, removing median house price from model 5, makes almost no difference to the other coefficient estimates and so it seems reasonable to conclude our findings on area effects and depression are robust to this issue.

A second limitation of our study relates to the modifiable areal unit problem where by different scales or different boundaries at the same scale might lead to different conclusions around area effects (Openshaw 1977). Issues of small sample sizes at finer geographies than MSOAs, such as lower super output areas, prevent us from exploring this issue directly. However, a study in Wales found lower levels of common mental disorders (among adults) in lower super output areas (average population 1,558) with greater income inequality; a result in line with our findings but a finer geographical scale (Fone et al. 2013). The existing research tends to suggest that the wealth inequality hypothesis becomes increasingly salient at the expense of the mixed neighbourhood hypothesis as the area of study tends towards national geographies (Wilkinson and Pickett 2006). Most importantly the procedure used to develop the MSAO boundaries, involving criteria of proximity (compact shape) and social homogeneity as well as independent validation by local policymakers, suggests that they provide a meaningful measure of a neighbourhood as experienced by residents.

A third limitation is that our main measure of an individual's socio-economic position, quintiles of household wealth, does not take into account differences in individual circumstances. For example, it is likely that distributions and levels of wealth vary with age with lower levels of wealth after retirement compared to before. Similarly, older people providing financial support to dependants may have low disposable incomes despite being relatively wealthy. Encouragingly, examination of age-specific wealth quintiles reveals little change by age. Additionally, inclusion of information on educational qualification in our models provides a further aspect of socio-economic position to complement our wealth measure.

In conclusion, it is already well established that an individual's economic position is a key predictor of health and our study strongly confirms this for older people in England with respect to depression. Those in the richest quintiles of individual wealth are half as likely to suffer from depression compared to the poorest individuals. We do not find evidence to support the wealth inequality hypothesis in terms of neighbourhood inequality and depression in older people in England; greater neighbourhood inequality is not associated with higher risk of depression. Conversely, our findings suggest that for poor people living outside the most equal areas has a protective effect in regard to depression, supporting the mixed neighbourhood hypothesis. Additionally, we find increased risks of depression in the most deprived areas. Both area effects on depression are significant after controlling for individual correlates of depression, perhaps reflecting the greater susceptibility of older people to neighbourhood health effects (Bowling & Stafford 2007; Stafford et al. 2011; Beard et al. 2009). Policymakers concerned with addressing inequalities in depression at the

older ages might consider targeting levels of neighbourhood deprivation and social mix as well as the circumstances of individuals.

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Figure 1.

Distribution of neighbourhood inequality (Gini of house prices), median house price and Indices of Multiple deprivation score (MSOAs in England). Source: Indices of Multiple Deprivation (2004) and Land Registry house price sales (2003/4)

a: The greater the neighbourhood IMD score the greater the level of deprivation within that area

Figure 2.

Relationship between area house price inequality and area median house price and between area median house price and deprivation Source: Indices of Multiple Deprivation (2004) and Land Registry house price sales (2003/4)

Figure 3.

Prevalence of depression by quintiles of area inequality (house price Gini), area median house price, area deprivation (IMD) and individual wealth. Source: ELSA (wave 1), Indices of Multiple Deprivation (2004) and Land Registry house price sales (2003/4)

Figure 4.

Model probabilities of depression from model including interactions between, i. quintiles of neighbourhood inequality and tertiles of individual wealth. Source: ELSA Wave 1, Indices of Multiple Deprivation (2004) and Land Registry house price sales (2003/4)

Notes: Calculation of the model probabilities assume that all other variables assume the reference category or, for continuous variables, the mean value. Only significant interaction terms were included in the predictions

There are some issues associated with interpretation of logit coefficients across groups in this way (Allinson 1999). However, our conclusions are identical in an OLS model framework using ces-d score as a continuous dependent variable suggesting the findings reported are valid.

Table 1**ELSA 8 item Centre for Epidemiologic Studies-Depression scale**

Centre for Epidemiologic Studies-Depression scale (8 items)	
Now think about the past week and the feelings you have experienced. Please tell me if each of the following was true for you much of the time during the past week:	
1. (Much of the time during the past week), you felt depressed?	
2. (Much of the time during the past week), you felt that everything you did was an effort?	
3. (Much of the time during the past week), your sleep was restless?	
4. (Much of the time during the past week), you were happy?	
5. (Much of the time during the past week), you felt lonely?	
6. (Much of the time during the past week), you enjoyed life?	
7. (Much of the time during the past week), you felt sad?	
8. (Much of the time during the past week), you could not get going?	

Table 2

Descriptive statistics of the ELSA sample. Source: ELSA (wave 1)

Individual-level variables		
	Number	%
Depression		
Depressed	1,865	17.5
Not depressed	8,779	82.5
Missing	0	0
Gender		
Males	4,822	45.3
Females	5,822	54.7
Missing	0	0
Economic activity		
Retired	5,772	54.2
Employed	3,607	33.9
Looking after home/family	1,092	10.3
Unemployed	118	1.1
Missing	55	0.5
Living arrangements		
Single	518	4.9
Couple	7,378	69.3
Separated	810	7.6
Widowed	1,854	17.4
Missing	84	0.8
Ethnicity		
White	10,344	97.2
Non-White	288	2.7
Missing	12	0.1
Limiting long term illness		
No limiting long term illness	7,293	68.5
Has a limiting long term illness	3,342	31.4
Missing	9	0.1
Educational qualifications		
Degree or higher	1,227	11.5
Below degree	4,947	46.5
No qualifications	4,442	41.7
Missing	28	0.3
Wealth quintiles		
Least well off	2,091	19.6
2nd least well off	2,091	19.6
Middle wealth quintile	2,092	19.7
2nd most well off	2,090	19.6

Individual-level variables		
	Number	%
Most well off	2,089	19.6
Missing	191	1.8
Age^a		
50-54	1,813	17.0
55-59	1,927	18.1
60-64	1,522	14.3
65-69	1,669	15.7
70-74	1,435	13.5
75-79	1,068	10.0
80-84	780	7.3
85+	430	4.0
Missing	0	0

Table 3

Multilevel odds ratio of depression by individual correlates of depression, neighbourhood inequality (house price Gini), neighbourhood median house price and neighbourhood deprivation (IMD2004). Source: ELSA Wave 1, Indices of Multiple Deprivation (2004) and Land Registry house price sales (2003/4)

		Model 1 Odds ratio (95% ci)	Model 2 Odds ratio: 95% ci	Model 3 Odds ratio (95% ci)	Model 4 Odds ratio (95% ci)	Model 5 Odds ratio (95% ci)
Individual wealth	1. Poorest			1	1	1
	2			0.86 (0.73-1.01)	0.85 (0.72-0.99)	0.87 (0.74-1.02)
	3			0.63 (0.53-0.75)	0.63 (0.54-0.76)	0.67 (0.56-0.80)
	4			0.51 (0.42-0.61)	0.51 (0.43-0.64)	0.55 (0.45-0.68)
	5. Richest			0.44 (0.36-0.55)	0.48 (0.38-0.60)	0.50 (0.40-0.62)
Education	Degree or higher			1	1	1
	Below degree			1.01 (0.81-1.27)	1.00 (0.80-1.26)	1.00 (0.80-1.26)
	No qualifications			1.49 (1.18-1.88)	1.46 (1.15-1.85)	1.44 (1.14-1.83)
Living arrangements	Single			1	1	1
	Couple			0.88 (0.68-1.14)	0.87 (0.67-1.12)	0.88 (0.68-1.15)
	Separated			1.40 (1.03-1.89)	1.39 (1.03-1.88)	1.40 (1.04-1.90)
	Widowed			1.45 (1.10-1.91)	1.43 (1.09-1.88)	1.46 (1.11-1.92)
Economic activity	Retired			1	1	1
	Employed			0.88 (0.72-1.06)	0.89 (0.73-1.04)	0.89 (0.73-1.08)
	Looking after home/family			1.15 (0.95-1.39)	1.16 (0.95-1.40)	1.16 (0.96-1.40)
	Unemployed			2.41 (1.52-3.82)	2.43 (1.53-3.85)	2.41 (1.52-3.82)
Ethnicity	White			1	1	1
	Non-White			2.79 (2.09-3.73)	2.86 (2.14-3.82)	2.65 (1.97-3.57)
Neighbourhood inequality	1. Most equal areas		1	1	1	1
	2		0.83 (0.68-1.01)	0.84 (0.68-1.03)	0.83 (0.68-1.02)	0.84 (0.69-1.03)
	3		0.90 (0.74-1.08)	0.93 (0.77-1.13)	0.92 (0.76-1.12)	0.94 (0.77-1.13)
	4		0.77 (0.64-0.93)	0.81 (0.67-0.98)	0.81 (0.67-0.98)	0.81 (0.67-0.98)
	5. Least equal areas		0.78 (0.64-0.94)	0.81 (0.67-0.99)	0.82 (0.67-0.99)	0.81 (0.67-0.99)
	Median neighbourhood house price				0.93 (0.86-0.99)	0.92 (0.86-0.99)
	Neighbourhood deprivation (IMD)					1.09 (1.01-1.18)
Random parameter estimate						
	Neighbourhood	0.38 (0.27-0.50)	0.36 (0.25-0.47)	0.33 (0.21-0.45)	0.33 (0.21-0.45)	0.32 (0.20-0.44)
	Proportion of variance at neighbourhood level	0.10	0.10	0.09	0.09	0.09

Age, age squared and sex are included in each of the model reported in this table but coefficients are not reported here.

Table 4

Multilevel odds ratio of depression by individual correlates of depression, neighbourhood inequality (house price Gini), neighbourhood median house price and neighbourhood deprivation (IMD2004) including interaction between area inequality and individual wealth. Source: ELSA Wave 1, Indices of Multiple Deprivation (2004) and Land Registry house price sales (2003/4)

Explanatory variables (wealth* area inequality interaction)		Model with no interactions*	Model with interaction between individual wealth and area inequality
1. Most equal tertile of areas		1	1
2. 2 nd most equal quintile of areas		0.85 (0.69-1.04)	0.67 (0.50-0.91)
3. Middle quintile of area equality		0.94 (0.78-1.14)	0.74 (0.56-0.98)
4. 2 nd most unequal quintile of areas		0.82 (0.68-0.99)	0.65 (0.49-0.85)
5. Most unequal quintile of areas		0.82 (0.67-1.00)	0.71 (0.54-0.94)
Middle wealth tertile	1. Most equal tertile of areas		1
Middle wealth tertile	2. 2 nd most equal quintile of areas		1.57 (1.02-2.41)
Middle wealth tertile	3. Middle quintile of area equality		1.45 (0.96-2.19)
Middle wealth tertile	4. 2 nd most unequal quintile of areas		1.69 (1.13-2.52)
Middle wealth tertile	5. Most unequal quintile of areas		1.54 (1.00-2.36)
Most wealthy tertile	1. Most equal tertile of areas		1
Most wealthy tertile	2. 2 nd most equal quintile of areas		1.34 (0.79-2.28)
Most wealthy tertile	3. Middle quintile of area equality		1.57 (0.97-2.56)
Most wealthy tertile	4. 2 nd most unequal quintile of areas		1.25 (0.77-2.01)
Most wealthy tertile	5. Most unequal quintile of areas		0.99 (0.60-1.62)

* There are slight differences between the coefficients from the model with no interactions and those in table 3 from model 5. This is because the models fitted in table 4 use tertiles of individual wealth rather than quintiles as in model 5 (table 3)