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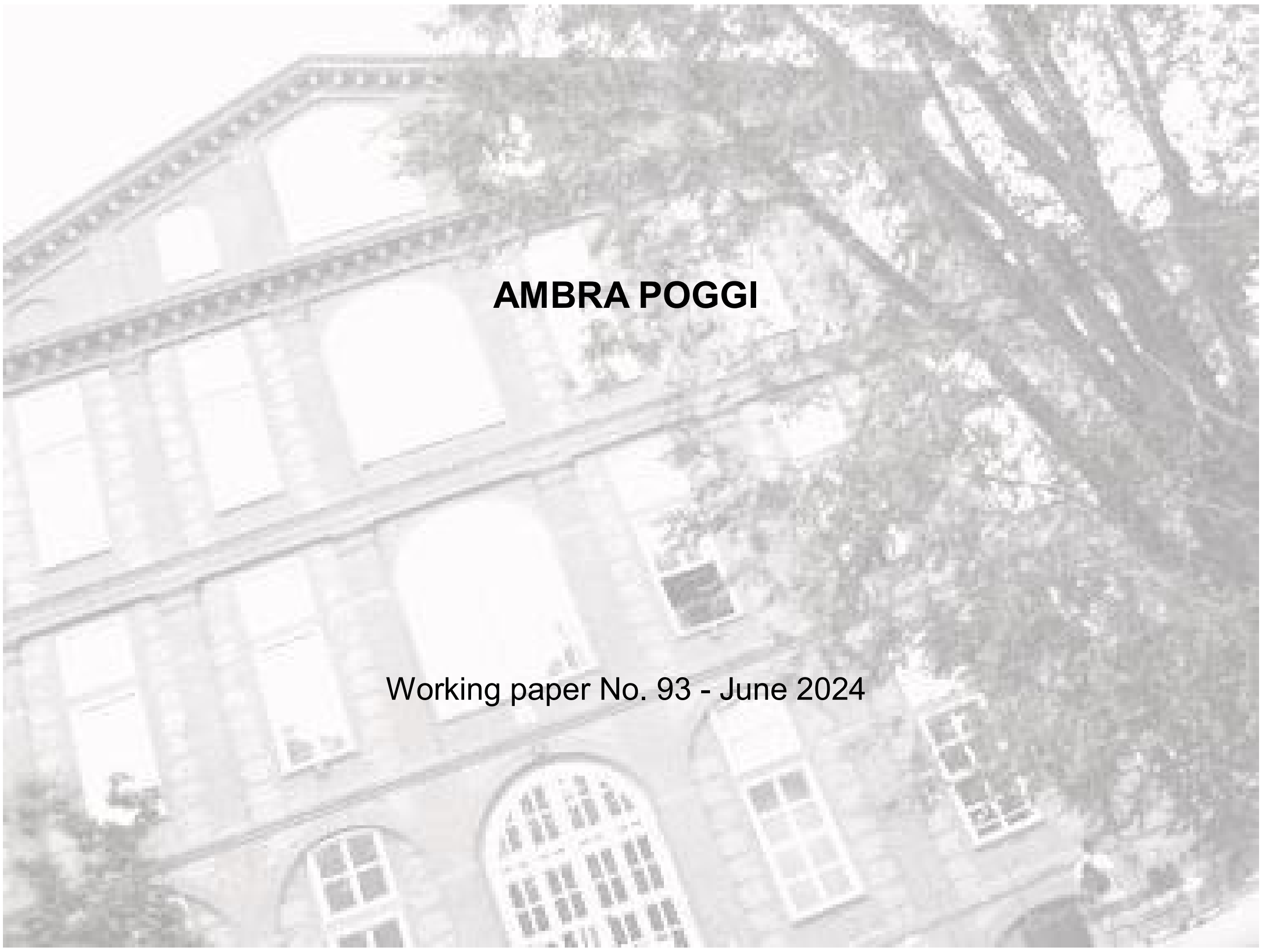
CAN COHESION REDUCE PERSISTENCE OF MENTAL HEALTH PROBLEMS IN MINORITY ETHNIC AREAS?



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Can cohesion reduce persistence of mental health problems in minority ethnic areas?

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Abstract

Background - Mental health problems refer to non-specific psychological distress that cover symptoms of anxiety, depression, stress, and somatic complaints. For some individuals, mental health problems are only temporary, while for others, mental health problems can last for several months.
Methods – Our aim is to investigate the persistence of mental health problems. First, we model mental health problems as a dynamic process where individual current mental health problems depend on mental problems in previous months. Second, we explore the association of ethnic density on the evolution of individual's mental health over time and its interplay with ethnic diversity, ethnic minority status and neighbourhood cohesion.
Results – We find evidence of positive mental health problems persistence. In high-ethnic-density and high-ethnic-diversity areas, persistence is significantly higher. In these areas, co-ethnicity seems to have a limited protective role, while neighbourhood cohesion seems to play a more important role in protecting from isolation and, at the end, decreasing persistence of mental health problems.
Conclusions— According to our findings, policy makers should promote cohesion especially in high-ethnic-density and high-ethnic diversity areas.

JEL Codes: I10, A14, C13, C23, J15
Keywords: mental health, ethnicity, persistence, neighborhood cohesion, panel data

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1. Introduction

Mental health problems in the general population are often assessed with measures of non-specific psychological distress that cover symptoms of anxiety, depression, stress, and somatic complaints (Goldberg and Goodyer, 2005). Such symptoms are common in the UK population, with nearly 21% of people reporting psychological distress in 2019 (Daly and Robinson, 2021). Mental health problems may have negative consequences for individuals' quality of life, and for the mental health of persons in their social environment. Mental health conditions account for 7% of all ill health in the UK and cost UK economy at least £117.9 billion per year (approximately 5% of UK GDP). This includes direct costs of services, lost productivity at work and informal care costs (McDaid and Park, 2022). Given the impact of mental health problems on individuals and society, better insight in mental health dynamics is required.

For some individuals, mental health problems are only temporary and wanes within weeks. For others, mental health problems can become chronic and last for several months. Persistent mental health problems can be expected to have higher costs for the society than short-term acute problems. Our *first* contribution is to model mental health problems as a dynamic process where individual current mental health problems depend on mental health problems in previous months. We also control for observed and unobserved individual heterogeneity. Following Blundell and Bond (1998), we estimate our model using the System General Method of Moments (GMM). The estimated effects of the lagged dependent variables give the possibility to determine the cumulative influence of the measured past. Thus, estimating with lagged dependent variables provides a measure of mental health problems persistence. Our findings indicate evidence of positive persistence.

Different mechanisms that may give rise to persistence. The latter may arise due to structural reasons such as differing abilities to deal with new health shocks depending on previous health status, or willingness to investments in health that changes as health status evolves. For example, people may be less prone to invest in their health after a health shock that lowers their returns to that investment (Carro and Traferri, 2014). Processes of discouragement due to previous health status may reduce treatment efforts and persistence may arise. Stigma effects may imply that individuals suffering metal health problems face systematically isolation that worsens mental health in future periods. In facts, isolation may increase anxiety and stress. Isolation may also lead to a decay of social capital, less social support, and inabilities to deal with health shocks as results of previous health status. For ethnic minority groups, stigma can increase feelings of loneliness, social isolation, and decrease social support necessary to deal with new health shocks. This may lead to persistent mental health problems. However, residency in areas of higher co-ethnic density might confer mental health benefits through enhanced social support and buffering against social isolation and exclusion for marginalised groups (Bécares et al, 2018). Also living in high cohesive neighbourhoods might confer mental health benefits reducing the risk of isolation and lack of support and, at the end, mental health problems persistence. Therefore, in our view, area characteristics can have important roles in determining the dynamics of health.

Our *second* contribution is, therefore, to assess whether the mental problems persistence may vary across areas depending on areas characteristics. In particular, we focus on differences across the Local Authorities (LAs) of England exploring the role of ethnic density and its interplay with ethnic diversity, ethnic minority status and neighborhood cohesion. Our findings indicate that mental health problems persistence is significantly higher in high-ethnic-density and high-ethnic-diversity areas. In these areas, co-ethnicity seems to have a limited protective role, while neighbourhood cohesion seems to play a more important role in protecting from isolation and, at the end, decreasing persistence of mental health problems. Therefore, the policy implication is clear: policy makers should promote integration to strengthen cohesion in high-ethnic-density and high-ethnic diversity LAs for improving individual mental health and reducing the costs for the society.

As far as we know, no studies to date have analysed in detail as we do mental health problems persistence. To address this gap in the literature, we use data from the 2020-2021 UK Understanding Society COVID-19 survey and we focus on England. The main advantage in using these data is having monthly observations during a period characterized by an "exogenous shock" (the Covid-19 pandemic and the initial full national lockdown) that increased stress, anxiety, and risk of social isolation everywhere in England. Thus, this context is able to emphasise the individuals' structural differences in dealing with new health shocks depending on previous health status, as well as differences in the abilities to manage health problems that changes as health status evolves.

The paper is structures as follows. Literature review is presented in Section 2. Section 3 introduces our econometric approach. In section 4, we introduce the dataset and our key variables. Section 5 presents our results. Robustness analysis is performed in Section 6. Section 7 concludes and discuss the policy implications of the results.

2. Literature review

The COVID-19 pandemic has created a global health crisis that prompted governments to execute extraordinary social distancing measures and restrictions to combat the disease within their own countries. In England, the first full national lockdown started on 23 March 2020 and by mid-April the peak of the first wave was reached and restrictions were gradually eased. Most lockdown restrictions were lifted on 4 July 2020. On 14 September, restrictions for gathering in England were tightened and people were once again legally prohibited from meeting more than six people socially A second and a third national lockdown began respectively in November 2020 and January 2021 in response to rising cases. From March 2021 restrictions were irreversibly eased following the roadmap out of lockdown.

Restrictions produced a severe economic downturn and mental-health related repercussions (Bell and Blanchflower, 2020; Moreno et al., 2020; Miao et al., 2021; Breedvelt et al., 2022; Ferber et al., 2022). The pandemic has caused a tremendous amount of stress and anxiety for many (Holmes et al., 2020). For example, some individuals experienced anxiety about personal health and worries about the health of family members with existing medical conditions (Shevlin et al., 2020). The social distancing restrictions increased social isolation (Armitage and Nellums2020) and the economic downturn caused concerns about financial insecurity (Fernandes2020). Both social isolation and financial insecurity contributed to psychological distress (Brooks et al., 2020; Paul and Moser2009). In this context, longitudinal studies are important since they allow for a direct comparison of person-by-person mental health both before and throughout the duration of the pandemic. Using the UK Household Longitudinal Study, Pierce et al. (2020 and 2021) showed that compared with pre-lockdown, the prevalence of mental health problems was significantly higher in late April 2020 (approximately 1 month into lockdown) and this was particularly pronounced among females and younger age groups. Using the same dataset, Daly et al. (2020) found that mental health problems (GHQ-12 score $\geqslant$3) increased by 13.5 percentage points from 24.3% in 2017–2019 to 37.8% in April 2020 and remained elevated in May (34.7%) and June (31.9%). All sociodemographic groups examined showed statistically significant increases in mental health problems. The increase was largest among those aged 18–34 years, followed by females and high-income and education groups. Levels of mental health problems subsequently declined between April and June 2020 but remained significantly above pre-COVID-19 levels. Quintana-Domeque et al (2022) investigate whether the deterioration in mental health has been persistent. They use longitudinal data from a representative sample of the UK and compare self-reported mental health at three time points (2017–2019, April

2020 and March 2021), for the whole sample and by sex and ethnicity. They do not find evidence that the level of mental health goes back to pre-pandemic levels.

Longitudinal studies allow also to model mental health as a dynamic process and, therefore, provide more detailed evidence about persistence. As far as we know, there is relatively little empirical evidence exploring the dynamics of health and no studies focusing on the pandemic period. Contoyannis, Jones and Rice (2004), using a categorical indicator of mental health and a dynamic ordered probit model, take a random effects approach to estimate persistence controlling for unobserved heterogeneity in the level equation. The model shows strong positive persistence and heterogeneity accounting for around 30% of the unexplained variation in health. Halliday (2008) use a different random effects approach to model the evolution of self-assessed health over the life cycle as a first order Markov process which allows for persistence and unobserved heterogeneity. He finds large degree of heterogeneity, a modest degrees of persistence for half the population, and a degree of persistence near unity for the remaining population. Carro and Traferri (2014) estimate a dynamic ordered probit of a self-assessed health status with two fixed effects: one in the linear index equation and one in the cut points. Their estimates show that persistence is large and significant even after controlling for unobserved heterogeneity and some forms of objective health measures. We contribute to this literate as follows. First, we use a continuous indicator of self-assessed mental health, allowing for more detailed information on individual health problems compared to previous studies. Second, we model the evolution of health as a second order Markov process (specification that, according to our results, should be preferred to the first order Markov process one). Third, we explore whether mental health persistence differs across geographical areas.

The degree of persistence of mental health problems can differ across population sub-groups since both exposure and reaction to stressors may differ across groups. Also, environmental factors can play a role in mental health (Becares et al., 2017; Olives et al., 2013; Schofield et al., 2016).

Differences in exposure to stressful events are partly attributable to group differences in socioeconomic status (Neff, 1984; Warheit et al., 1975). Moreover, empirical evidence shows that minorities react with greater psychological distress than whites to unpleasant events (Mirowsky and Ross, 1990; Myers et al., 2002; Ulbrich et al., 1989; Warheit et al., 1973). Blacks, especially those at the low end of the economic spectrum, report not only a great number of stressful life events but also stronger responses to them, or greater distress, than whites in a variety of domains (Myers and Hwang, 2004).

About environmental factors, the ethnic composition of the neighbourhood may impact on mental health of residents. The “ethnic density hypothesis” suggests that members of ethnic minority groups have better mental health when they live in areas with higher proportions of people from the same ethnicity (Shaw et al., 2012) or in areas of higher ethnic diversity (Awaworyi Churchill et al., 2017). The reason behind this proposed protective effect is that greater ethnic density can relieve the stress of racial discrimination, low social status and socioeconomic disadvantage while providing a safety net of social support and sense of community that enhanced social capital (Becares et al., 2017; Hurd et al., 2013). The empirical findings for an “ethnic density effect” on mental health, although mixed, generally support a protective effect in adults (Shaw et al., 2012). The association between mental health and ethnic diversity is less clear. Astell-Burt et al (2012) find no ethnic diversity association with mental health for any of the ethnic groups they measure. Georgiades et al (2013) draw the same conclusion from the same index but using nationally representative data on adolescents in the United States from the Longitudinal Study of Adolescent Health.

Studies based in the United States find that for African American (Hurd et al., 2013) and Chinese American (Lee et al., 2014) adolescents the association between co-ethnic density and mental health is mediated by perceived social support. Research also suggests that neighbourhoods with high levels of ethnic diversity have correspondingly lower levels of social cohesion (Putnam, 2007). Research in the UK found that whilst ethnic diversity is negatively related to generalized trust, there is no evidence that it impacted on attitudes towards neighbours (Fieldhouse and Cutts,2010; Van der Meer T., 2015). Laurence (2014) observes that social contact moderates the negative effect of community diversity: for those that have formed ties, diversity has no detrimental effect. Social cohesion includes the provision of social support, practical help, interpersonal contacts and reciprocity, and the sharing of information across social networks. Social cohesion encourages closer adherence to public health guidelines through care for the collective (Jewett et al., 2021), promotes trust and creates a sense of belonging (OECD, 2012). As results, levels of social cohesion are associated with health outcomes, engagement with health behaviours, and resilience and emotional wellbeing (Long et al., 2022; Ware, 2023; Zangger, 2023). Thus, cohesion enhancing social support and contacts can mediate the impact of stressful events on mental health (probably also reducing mental health problems persistence). This could be extremely important in areas characterised by high ethnic density. To explore this issue is one of the aims of this paper.

3. Econometric model

We estimate the following linear dynamic panel data model:

(2) $$y_{it} = \sum_{j=1}^{q^y} \gamma_j y_{it-j} + \sum_{j}^{q^x} x'_{it-j}\beta_j + a_i + u_{it}$$

with many individuals $i = 1,2, ..., N$ and few time periods $t = 1,2, ..., T$. The dependent variable y_{it} is a continuous variable measuring mental health problems of individual i at time t, and y_{it-j} is the mental health problems of period t-j. The vector of explanatory variables is x_{it}, where the regressors

x_{it} can be strictly exogenous, weakly exogenous/predetermined, or endogenous. a_i is the unobserved individual-specific effect, and u_{it} is an error that varies over both individuals and time. The unobserved individual-specific heterogeneity can be correlated with the regressors x_{it-1}, and it is correlated by construction with the lagged dependent variables. γ_j describes the dynamics of health: values larger than zero determine whether the mental health sequence $\{y_{it}\}$ features persistence.

Equations (1) can be consistently estimated using the generalized method of moments (GMM) approach. The two models popularly implemented are the "difference" GMM estimator (Arellano and Bond, 1991) and the "system" GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). However, when T is small as in our case, the difference GMM estimator could be substantially biased. Moreover, the system GMM estimator has some advantages for the following reasons (Roodman, 2009a): (i) system GMM improves efficiency compared to difference GMM; (ii) any gaps in a panel—and our dataset is unbalanced—are magnified by difference GMM when compared to system GMM; (iii) in system GMM, one can include time-invariant regressors, which would disappear in difference GMM. About the latter point, including time-invariant variables does not affect the coefficient estimates for other regressors (Roodman, 2009a), however the estimated coefficients of time-invariant variables can be of interest. Kripfganz and Schwarz (2019) show that the two-stage approach is more robust against misspecification than the system GMM estimators that obtain all parameter estimates simultaneously. Therefore, we use the two-stage system GMM approach, and we include time-invariant explanatory variables as appropriate. Small sample correction is also applied as appropriate.

The system GMM allows for more instruments. However, too many instruments relative to the cross-sectional sample size can cause biased coefficient and standard error estimates and weakened specification tests (Roodman, 2009a). Instrument proliferation can lead to substantial under rejection of overidentification tests, thus incorrectly signaling that the model is correctly specified when it is not. To reduce the number of instruments, we collapse the set of instruments (Roodman, 2009a, 2009b; Kiviet, 2019).

Finally, the following post estimation diagnostic tests are performed to provide proof for validity of estimates. First, we test if u_{it} is serially uncorrelated. u_{it} has first-order serial correlation, but we want to exclude higher-order serial correlation. Absence of higher-order serial correlation of u_{it} is crucial for the validity of y_{it-2} , y_{it-3}, etc. as instruments, and similarly for the instruments of predetermined and endogenous x_{it}. Arellano and Bond (1991) suggest an asymptotically N(0, 1) distributed test statistic for the null hypothesis: H_0 : Corr(u_{it}, u_{it-j}) = 0, j > 0. The model passes this specification test if H_0 is rejected for j = 1 and not rejected for j > 1. In our case, the model passes the test when the evolution of mental health is modelled as a second order Markov process. Second, we test the validity of overidentifying restrictions using the Hansen (1982) test. Under the null hypothesis, the overidentifying restrictions are valid.

4. Data and main variables

This paper is based on the Understanding Society COVID-19 study (Institute for Social and Economic Research, 2020) and focus on England. The Understanding Society COVID-19 study is built upon the UK Household Longitudinal Study (UKHLS), also known as Understanding Society. From April 2020 to September 2021,[2] participants of the UKHLS, who were aged sixteen or over, were asked to complete a short web-survey. This survey covered the changing impact of the pandemic on the welfare of UK individuals, families, and wider communities. The questionnaire asked questions

[2] The first wave was fielded in April 2020, with monthly waves until September 2020. From September 2020 onwards the survey was fielded every two months.

about health, health behaviours, demographics (e.g. ethnic minority status), and economic conditions.

Our key variable is the measure of mental health problems. We use the Generalized Health Questions (GHQ-12), a 12-item validated survey measure for assessing individuals' mental health status (Goldberg and Williams, 1988). The GHQ-12 measures common mental health problems of depression, anxiety, somatic symptoms, and social withdrawal. Items assess the respondent's state and whether that differs from 'normal', focusing particularly on the ability to carry out regular functions, or the appearance of new and distressing symptoms. Each item is rated using a Likert scale ranging from 0 ("Not at all") to 3 ("Much more than usual"). Then, a summative score across all 12 items is computed. The resulting rating reflects mental health status in relation to usual status, with higher scores indicating poorer mental health. Note that the GHQ-12 approximates to a normal distribution and can be used as a continuous measure in multivariate analysis (Propper et al., 2005). The usual socio-demographic controls are included in our analysis and information about environmental characteristics at Local Authority level is taken into account.

After dropping cases with missing information, we are left with a resulting analysis sample of 9137 individuals. Descriptive Statistics are reported in Table 1.

Local Authorities characteristics

England consists of 317 Local authorities (LA).[3] The Understanding Society COVID-19 study provides information about the Local Authority (LA) where the individual resides. We merge relevant 2011 Census data into our dataset using the LA identifier. We focus on the following characteristics.

[3]Local Authority (LA), also referred to as a council or borough, is a local government in England. Details: https://www.gov.uk/guidance/local-government-structure-and-elections .

- *Ethnic density* is defined as the percentage of the total population accounted by each of the minority ethnic groups resident in the LA at the time of the 2011 Census and derived for (i) Asian or Asian British, (ii) Black, African, Caribbean and Black British, (iii) mixed or multiple ethnic groups, (iv) White and (v) other ethnic groups. Individual ethnicity is dichotomized into white British and ethnic minority, and an overall ethnic density variable is derived (that is the proportion of the total population in each LA who were ethnic minority residents).
- *Co-ethnic density* is defined as the proportion of people from the same ethnicity background living in the respondent's LA.
- *Ethnic diversity* is defined using the Shannon Diversity Index (sometimes called the Shannon-Wiener Index), that is a way to measure the diversity of groups in a community. Denoted as H_j, this index is calculated as:

$$H_j = -\sum_{i=1}^{s} p_{ij} \ln (p_{ij})$$

where s is the number of ethnic groups, and p_{ij} is the proportion of individuals of group i living in LA j. The higher the value of H, the higher the diversity of groups in a particular LA. The lower the value of H, the lower the diversity. A value of H=0 indicates a LA that only has one ethnic group. The value of H ranges from 0 to H_{max}. However, we normalize the index to range from 0 to 1, divining H by H_{max} (that is ln(s)).[4]
- The individual perceptions of *neighbourhood cohesion* are measured using the Buckner's instrument of neighbourhood cohesion that includes three constructs: the degree of neighbouring within the neighbourhood, the psychological sense of community, and the level of attraction to the neighbourhood (Buckner, 1988). It ranges from 1 (lowest cohesion)

[4] This index is also known as Evenness Index. A low value indicates that one or few groups dominate the community. A high value indicates more diversity.

to 5 (highest cohesion) on a continuous scale. We use the adapted version of the Buckner's instrument elaborated by the UKHLS[5] and included in wave 9. Thus, neighbourhood cohesion is merged using the individual identifier into our dataset. In the UKHLS, interview waves span three overlapping years, so that wave 9 runs from 2017 to 2019. Neighbourhood cohesion is dichotomized into low-cohesion (1th quartile) and medium-high cohesion (other quartiles). The neighbourhood cohesion variable reports pre-pandemic individual perceptions that can be used as exogenous variable in the analysis.

Figure 1 represents differences in ethnic density across LAs (left panel). Figure 1 also shows the high-ethnic-density LAs (that are LAs with at least 25% of the total population who are ethnic minority residents) highlighting differences in terms of ethnic diversity. We identify 41 high-ethnic-density LAs. Note that 27 of them are London boroughs. The others are Birmingham, Blackburn with Darwen, Coventry, Leicester, Luton, Manchester, Nottingham, Oadby and Wigston, Reading, Sandwell, Slough, Watford and Wolverhampton. The London borough of Newham registers the highest ethnic density: ethnic minority residents are the 71% of the population.

5. Empirical results

Our empirical analysis is split into two sections. The first involves testing whether there is evidence of mental health problems persistence. The second involves exploring whether we observe differences in persistence across Local Authorities.

[5] The Buckner's instrument includes 18 items and has been validated and widely used in the literature (e.g. Teo and Chum, 2020). The adapter version includes 1 item measuring attraction to the neighbourhood, 3 items measuring neighbouring and 4 measuring psychological sense of community.

Mental health persistence

Table 2 reports results of estimation of Equation (1) across various estimators. Model 1 shows the results of the pooled OLS estimator and Model 2 shows the results of the fixed effects (within) OLS estimator. Both regressions use robust standard errors clustered by individual. These estimates are informative because they provide the upper and lower bound for the autoregressive coefficients for mental health problems (for details see Bond, 2002). As can be seen, the upper bounds are equal to 0.5 and 0.3 respectively for the first order and second order autoregressive terms. The lower bounds are close to zero. Models 3 to 5 employ GMM estimators and robust standard errors. Models 3 employs the difference GMM estimator, whereas in Model 4 and 5 we report the results from the two-step system GMM estimators. Model 5 includes time constant variables (age, gender, ethnic minority status, education, neighborhood cohesion perception) as additional controls. In all GMM specification, unemployment is treated as endogenous. In all GMM estimates the autoregressive coefficients are positive and highly statistically significant, and they lie within the bound given by Model 1 and 2. The estimated coefficients of the first order and second order autoregressive terms are approximately 0.22 and 0.06 respectively, indicating positive persistence of mental health problems.

Persistence across Local Authorities

Since Model 4 presents an adequate specification for estimating persistence (and we are mainly interested in the estimates of the autoregressive coefficients), we use this specification for estimating mental problem persistence across Local Authorities (LAs).

In Table 3, we split our sample in two groups: people living in high-ethnic-density LAs (that are LAs with at least 25% of the total population who are ethnic minority residents) and people living in the remaining LAs (Samples 1 and 2). In high-ethnic-density LAs, mental health problems persistence is slightly higher: the autoregressive coefficients are slightly higher, and the differences are statistically significant (the first autoregressive coefficient is 0.231 vs 0.229, and the second autoregressive coefficient is 0.08 vs 0.061).

We find evidence that, in high-ethnic-density LAs, minority people benefit from co-ethnic social support and protection against social isolation and exclusion of marginalized groups. In facts, we find that, in these LAs, minority people exhibit lower mental health problems persistence than white British people. In other words, in high-ethnic-density LAs, minority people exhibit lower autoregressive coefficients that white British people (the first autoregressive coefficient is 0.26.2 vs 0.183, and the second autoregressive coefficient is 0.092 vs 0.062). See Table 3, Samples 3 and 4.

However, co-ethnic support/protection could be lower if high-ethnic-density LAs present high levels of ethnic diversity. In Table 4, we split the high-ethnic-density LAs in 3 groups of equal size depending on ethnic diversity (representing respectively high, medium and low-ethnic diversity LAs). Then, we compare high-ethnic-diversity LAs versus the remaining LAs (Samples 1a and 1b). We find that mental health problems persistence is significantly higher in high-ethnic-diversity LAs. In the latter areas, the first and the second autoregressive coefficients rise to respectively 0.328 and 0.186. This means that an individual experiencing mental health problems over two subsequent periods experience high persistence. In high-ethnic-density and high-ethnic-diversity LAs, there is still some evidence of co-ethnic protection associated with lower mental health problems persistence (Table 4, Samples 1c and 1d). However, neighbourhood cohesion seems to have strongest supportive and protective effects that co-ethnicity. In high-ethnic-density and high-ethnic-diversity LAs, both the first and the second autoregressive coefficients rise to respectively 0.426 and 0.263 if the individuals perceive low levels of neighbourhood cohesion (Table 4, Sample 1e). Instead, the first and the second autoregressive coefficients decrease to respectively 0.257 and 0.140 if the individuals perceive medium-high levels of neighbourhood cohesion (Table 4, Sample 1f).

6. Robustness analysis on the measure of mental health

As explained in Section 4, we use the GHQ-12 for assessing individual mental health. Even if the GHQ-12 is often regarded as measuring only a single dimension of psychological health, several authors suggested that the GHQ-12 contained two or three clinically meaningful factors (Werneke et al, 2000). Several two-factor solutions have been proposed and validated using component factor analysis techniques (e.g. Andrich and Schoubroeck, 1989; Politi et al. 1994). These two factors most commonly involve a “Depression/Anxiety” construct and a “Social Dysfunction” construct (given by GHQ-12 items 2, 5, 6, 9, 10 and 11, and 1, 3, 4, 7, 8 and 12, see Table 5). “Depression/Anxiety” relates to the emotional component of psychological distress, whereas “Social Dysfunction” relates to the social functioning of the distressed individual. This structure has been identified as the best fit to data from the UK (Smith et al. 2010). Graetz (1991), Martin (1999) and Worsely and Gribbin (1977) proposed three-factor solutions, which most commonly identify “Social Dysfunction”, “Depression/Anxiety” and “Loss of Confidence”. This 3-factor structure has been widely used and supported by several work also in the UK (e.g. Cheung, 2002; Martin& Newell, 2005; Shevlin & Adamson, 2005). However, the two-factor solution seems to fit the best our data (see below).

As previous studies, we perform a principal component factors analysis as a dimension reducing strategy to produce a small number of indicators from the GHQ-12 items. Factor analysis is a statistical data reduction technique used widely in psychology to explain variability among observed random variables in terms of fewer unobserved random variables called factors. In general, factor analysis models the observed variables as linear combinations of the factors, plus normally distributed error terms. The algorithm produces a factor structure matrix representing the correlations between the variables and the factors and is called the factor loading matrix. The interpretation of each factor is marked by high loadings on a certain sub-sample of attributes that give information on a specific kind of unobservable. We perform an oblique rotation allowing factors to be correlated, which makes it easier to interpret the resulting factors.

The results of our data reduction exercise are reported in Table 5. We identify two factors that together explain the 63% of the total variance. These factors are: (i) anxiety, depression, and loss of confidence (ADL); (ii) social dysfunction. The Kaiser–Meyer–Olkin measure of sampling adequacy reports a value of about 0.94, confirming that the variables have enough in common for the factor analysis to be valid. Each factor has a zero mean and unit variance by construction. We use these factors as dependent variables, and we partially repeat the analysis performed in Section 5. Results are reported in Table 6.

We find evidence of mental health problems persistence in terms of both ADL and social dysfunction. (Table 6, columns 2 and 3). We compare mental health problems persistence in high-ethnic-density LAs and in the remaining LAs. Our findings indicate high levels of mental health problems persistence in high-ethnic-density LAs, especially in terms of social dysfunction (Table 6, Sample 1a vs Sample 1b). Finally, estimates of mental health problems persistence (in terms of both ADL and social dysfunction) are especially high in high-ethnic-density and high-ethnic-diversity LAs exhibiting low cohesion (Table 6, Sample 1f).

7. Conclusions

Mental health problems in the general population have negative consequences for individuals' quality of life and imply large costs for the society. Using the 2020-2021 UK Understanding Society COVID-19 survey and GMM approach, we seek a better understanding of mental health dynamics. We model mental health problems as a dynamic process where individual current mental health problems depend on mental health problems in previous months. And we explore the association of ethnic density on the evolution of individual's mental health over time and its interplay with ethnic diversity, ethnic minority status and neighbourhood cohesion.

We find the following results. *First*, we find evidence of positive persistence of mental health problems. Persistence may be due to differences in abilities to deal with new health shocks depending on previous health status, or in willingness to improve health that decreases as health worsens. *Second*, we find that mental health problems persistence is significantly higher in high-ethnic-density and high-ethnic-diversity areas. Minority people may face less economic resources for dealing with health shocks and they can experience stigma and isolation. If this case, living in areas lacking economic and social resources can enhancing difficulties in managing health depending on previous health status. *Third*, in these areas, co-ethnicity seems to have a limited protective role, while neighbourhood cohesion seems to play a more important role in protecting from isolation and, at the end, decreasing persistence of mental health problems. Thus, our results partially confirm the idea that residency in areas of higher co-ethnic density might confer mental health benefits through enhanced social support and buffering against social isolation. However, residency in high cohesive neighbourhoods seems to confer more mental health benefits than co-ethnicity.

According to our results, the policy implication is clear: policy makers should promote cohesion in high-ethnic-density and high-ethnic diversity areas. However, ethnic diversity and cohesion are potentially antithetical, given 'tendencies' among humans to prefer their own ethnic group. Often the increase in ethnic diversity is associated with the decline in social cohesion. This negative relationship between diversity and social cohesion occurs because in ethnically heterogeneous communities there is increased threat and fear that can lead to a withdrawal from social relationships and community life (Putnam, 2007). Therefore, institutional responses are required to tackle the social divisions that work against cohesion. It is important to invest in social capital-building initiatives. For example, local grassroots projects, that bring people together to work towards common goals, could help to foster positive engagement and relationships. It is also important to promote a more inclusive and diverse sense of national identity, one that recognises and celebrates the contributions of people from various cultural and ethnic backgrounds. The aim should be eroding disparities and inequalities on the one hand, and nurturing the social infrastructure of neighbourhoods, social relations, interactions and ties on the other.

References

Andrich, D., Schoubroeck, L. Van, (1989) "The General Health Questionnaire: a psychometric analysis using latent trait theory", Psychol. Med. 19, 469–485.

Arellano, M. and O. Bover (1995) "Another Look at the Instrumental Variable Estimation of Error - Components Models," Journal of Econometrics, 68, 29–51

Arellano, M. and S. Bond, (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," Review of Economic Studies, 58, 277–97

Armitage, R. and Nellums, L.B. (2020) "COVID-19 and the Consequences of Isolating the Elderly", *The Lancet Public Health*, 5, e256

Aron, A., Aron, E. N., & Smollan, D. (1992) "Inclusion of Other in the Self Scale and the structure of interpersonal closeness" *Journal of Personality and Social Psychology*, 63, 596-612

Astell-Burt T, Maynard MJ, Lenguerrand E, Harding S. (2012) "Racism, ethnic density and psychological well-being through adolescence: evidence from the Determinants of Adolescent Social Well-Being and Health longitudinal study", *Ethn Health.*,17(1-2):71-87

Bécares L, Dewey ME, Das-Munshi J. (2018) "Ethnic density effects for adult mental health: systematic review and meta-analysis of international studies", *Psychol Med.*, 48(12):2054-2072.

Bell, D., and Blanchflower, D. (2020) "US and UK LABOUR MARKETS before and during the COVID-19 CRASH", *National Institute Economic Review*, 252:R52-R69

Blundell, R. and S. R. Bond (1998) "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," Journal of Econometrics, 87, 115–43

Breedvelt, J. J., Tiemeier, H., Sharples, E., Galea, S., Niedzwiedz, C., Elliott, I., & Bockting, C. L. (2022) "The effects of neighbourhood social cohesion on preventing depression and anxiety among adolescents and young adults: rapid review", *BJPsych open*, 8(4), e97.

Brooks SK, Webster RK, Smith LE, Woodland L, Wessely S, Greenberg N, Rubin GJ. (2020) "The psychological impact of quarantine and how to reduce it: rapid review of the evidence", *Lancet*, 395(10227):912-920

Buckner, J. C. (1988) "The development of an instrument to measure neighborhood cohesion", *American Journal of Community Psychology*, 16(6), 771–791

Carro, J. and A. Traferri (2014) "State Dependence and Heterogeneity in Health Using a Bias Corrected Fixed Effects Estimator", *Journal of Applied Econometrics*, vol. 29, issue 2, 181-207

Cheung, Y.B. (2002) “A confirmatory factor analysis of the 12-item General Health Questionnaire among older people” 739–744.

Contoyannis, P., Jones, A., and N. Rice (2004) “The dynamics of health in the British Household Panel Survey”, Volume19, Issue4, Pages 473-503

Daly M, Sutin AR, Robinson E. (2022) “Longitudinal changes in mental health and the COVID-19 pandemic: evidence from the UK Household Longitudinal Study”, *Psychological Medicine*, 52(13):2549-2558

Fernandes, N. (2020) “Economic Effects of Coronavirus Outbreak (COVID-19) on the World Economy”, *SSRN Electronic Journal*

Fieldhouse E., & Cutts D. (2010) “Does diversity damage social capital? A comparative study of neighbourhood diversity and social capital in the US and Britain”, Canadian Journal of Political Science, 43(2):289–318.

Goldberg, D. and Goodyer, I. (2005) “*The origins and course of common mental disorders*”. Routledge

Graetz B (1991) “Multidimensional properties of the General Health Questionnaire”, *Soc Psychiatry Psychiatr Epidemiol*, 26:132-138.

Halliday, T. J. (2008) “Heterogeneity, state dependence and health”, *The Econometrics Journal*, 11(3), 499–516.

Hansen, L. P. (1982) “Large sample properties of generalized method of moments estimators”, *Econometrica*, 50 (4): 1029–1054

Holmes EA, O'Connor RC, Perry VH, Tracey I, Wessely S, Arseneault L, Ballard C, Christensen H, Cohen Silver R, Everall I, Ford T, John A, Kabir T, King K, Madan I, Michie S, Przybylski AK, Shafran R, Sweeney A, Worthman CM, Yardley L, Cowan K, Cope C, Hotopf M, Bullmore E. (2020= “Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental health science”, *Lancet Psychiatry*, 7(6):547-560

Jackson, M.O., Rogers, B.W. and Y. Zenou (2017) “The economic consequences of social network structure”, *Journal of Economic Literature* 55(1): 1-4

Jewett, R. L., Mah, S. M., Howell, N., & Larsen, M. M. (2021) “Social cohesion and community resilience during COVID-19 and pandemics: A rapid scoping review to inform the United Nations research roadmap for COVID-19 recovery” International Journal of Health Services, 51(3), 325-336

Kiviet, J. F. (2019) “Microeconometric dynamic panel data methods: Model specification and selection issues”, MPRA Paper 95159, Munich

Kripfganz, S. and C. Schwarz (2019) “Estimation of linear dynamic panel data models with time-invariant regressors”, *Journal of Applied Econometrics*, Volume34, Issue4, Pages 526-546

Laurence, J. (2014) “Reconciling the contact and threat hypotheses: does ethnic diversity strengthen or weaken community inter-ethnic relations?”, *Ethnic and Racial Studies* 37: 1328-1349

Long, E., Patterson, S., Maxwell, K., Blake, C., P´erez, R. B., Lewis, R., McCann, M., Riddell, J., Skivington, K., Wilson-Lowe, R., et al. (2022) “Covid-19 pandemic and its impact on social relationships and health” *J Epidemiol Community Health*, 76(2), 128– 132

M. Pierce, H. Hope, T. Ford, S. Hatch, M. Hotopf, A. John, E. Kontopantelis, R. Webb, S. Wessely, S. McManus, K.M. Abel (2020) “Mental health before and during the COVID-19 pandemic: a longitudinal probability sample survey of the UK population”, *Lancet Psychiatry*, 7 pp. 883-892

M. Pierce, S. McManus, H. Hope, M. Hotopf, T. Ford, S.L. Hatch, A. John, E. Kontopantelis, R.T. Webb, S. Wessely, K.M. Abel (2021) “Mental health responses to the COVID-19 pandemic: a latent class trajectory analysis using longitudinal UK data”, *Lancet Psychiatry*, 8, pp. 610-619

Martin AJ (1999) “Assessing the multidimensionality of the 12-itemGeneral Health Questionnaire”, *Psychol Rep*, 84(3 Pt1):927-935.

Martin, C.R., Newell, R.J. (2005) “The factor structure of the 12-item General Health Questionnaire in individuals with facial disfigurement”, *J. Psychosom. Res*. 59, 193–9.

McDaid, D. and Park, A-L. (2022) “*The economic case for investing in the prevention of mental health conditions in the UK*”, London: Mental Health Foundation.

Miao, J., Zeng, D., and Shi, Z. (2021) “Can neighborhoods protect residents from mental distress during the COVID-19 pandemic? Evidence from Wuhan”, *Chinese Sociological Review*, 53(1), 1–26.

Moreno, C., Wykes, T., Galderisi, S., Nordentoft, M., Crossley, N., Jones, N., & Arango, C. (2020) “How mental health care should change as a consequence of the COVID-19 pandemic”, *The Lancet Psychiatry*, 7(9), 813-824.

OECD. (2012). *Perspectives on Global Development 2012: Social Cohesion in a Shifting World*.

Paul, K.I. and K. Moser (2009) “Unemployment impairs mental health: Meta-analyses”, *Journal of Vocational Behavior*, 74(3):264–282

Politi PL, Piccinelli M, Wilkinson G (1994) “Reliability, validity and factor structure of the 12-item General Health Questionnaire among young males in Italy”, *Acta Psychiatr Scand*, 90:432-437.

Propper, C., Jones, K., Bolster, A., Burgess, S., Johnston, R., and Sarker, R. (2005). Local neighbourhood and mental health: evidence from the UK. *Social Science & Medicine*, 61(10), 2065–2083.

Putnam, R. D. (2007) “Diversity and community in the twenty-first century the 2006 Johan Skytte prize lecture”, *Scandinavian Political Studies*, 30(2): 137–174

Quintana-Domeque, Climent and Proto, Eugenio. "On the Persistence of Mental Health Deterioration during the COVID-19 Pandemic by Sex and Ethnicity in the UK: Evidence from Understanding Society", *The B.E. Journal of Economic Analysis & Policy*, vol. 22, no. 2, 2022, pp. 361-372.

Roodman, D. (2009a) “A note on the theme of too many instruments”, *Oxford Bulletin of Economics and Statistics*, 71 (1): 135–158.

Roodman, D. (2009b) “How to do xtabond2? An introduction to difference and system GMM in Stata”, *Stata Journal* 9 (1): 86–136.

Shevlin, M., Adamson, G. (2005) “Alternative factor models and factorial invariance of the GHQ-12: a large sample analysis using confirmatory factor analysis”, *Psychol. Assess*. 17, 231–236.

Smith, A.B., Oluboyede, Y., West, R., Hewison, J., House, A.O. (2013) “The factor structure of the GHQ-12: the interaction between item phrasing, variance and levels of distress”, *Qual. Life Res.* 22, 145–52

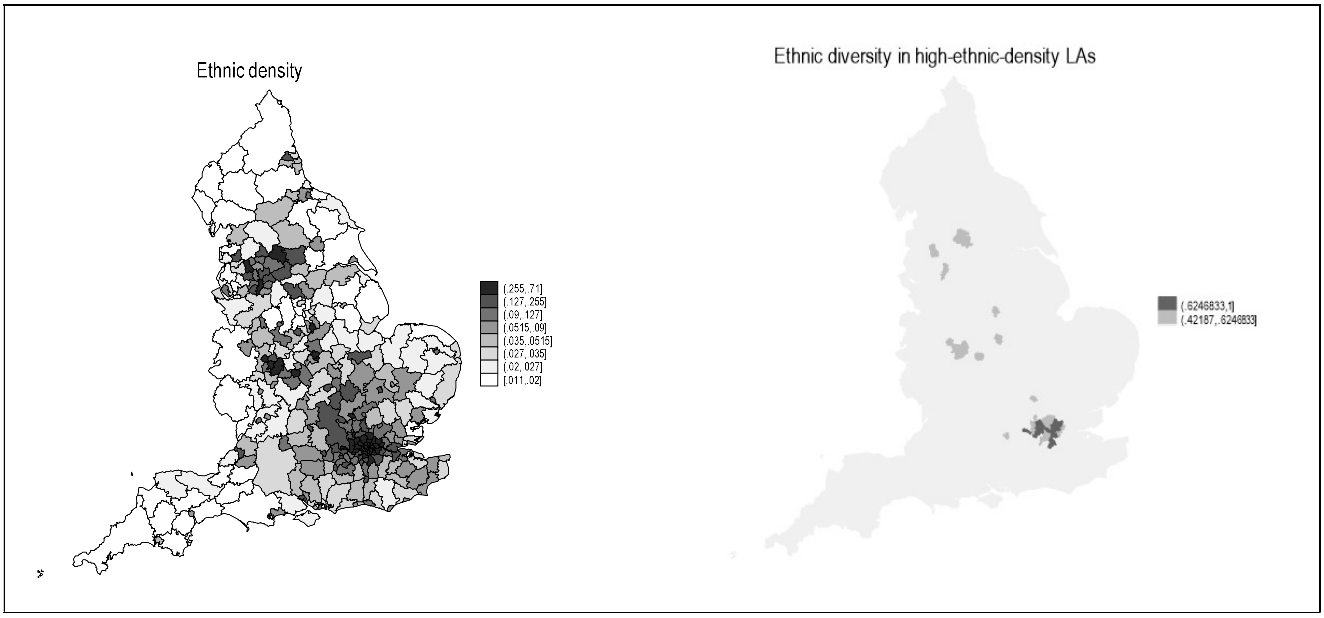
Van der Meer T. (2015) “Neither bridging nor bonding: A test of socialization effects by ethnically diverse voluntary associations on participants’ inter-ethnic tolerance, inter-ethnic trust and intra-ethnic belonging”, *Social Science Research*, 55; 63–74.

Ware, P. (2023). “Social Cohesion and Covid-19: an integrative review”, mimeo medRxiv

Werneke U, Goldberg DP, Yalcin I, Ustun BT (2000) “The stability of the factor structure of the General Health Questionnaire”, *PsyMed*, 30:823-82

Zangger, C. (2023). Localized social capital in action: How neighborhood relations buffered the negative impact of COVID-19 on subjective well-being and trust. *SSM- Population Health*, 21, 101307

Figure 1. Local Authorities by ethnic density



Note: high-ethnic-density LAs are Birmingham, Blackburn with Darwen, Coventry, Leicester, Luton, Manchester, Nottingham, Oadby and Wigston, Reading, Sandwell, Slough, Watford and Wolverhampton, 12 inner London boroughs (Wandsworth, Kensington and Chelsea, Islington, Hammersmith and Fulham, Camden, Greenwich, Westminster, Lambeth, Hackney, Southwark, Lewisham, Tower Hamlets) and 15 outer London boroughs (Kingston upon Thames, Merton, Barnet, Enfield, Hillingdon, Haringey, Barking and Dagenham, Croydon, Waltham Forest, Hounslow, Ealing, Redbridge, Harrow, Brent, Newham)

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Gender	0.583	0.493	0	1
Age	54.904	15.675	17	94
Living as a couple	0.722	0.448	0	1
household size	2.605	1.251	1	12
High education	0.174	0.379	0	1
Ethnic minority status	0.109	0.311	0	1
Low neighbourhood cohesion perception	0.203	0.403	0	1
Unemployment status	0.016	0.126	0	1
GHQ-12	12.092	5.814	0	36

Table 2. Estimates

Dependent varaible: GHQ-12	Model 1 OLS			Model 2 FE			Model 3 Diff-GMM			Model 4 System GMM			Model 5 System GMM		
	Coef		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**
Lag1(GHQ-12)	0.468	***	0.007	-0.024	**	0.010	0.220	***	0.017	0.220	***	0.017	0.226	***	0.017
Lag2(GHQ-12)	0.305	***	0.007	-0.097	***	0.008	0.063	***	0.014	0.064	***	0.014	0.066	***	0.014
unemployment	0.604	***	0.197	1.467	***	0.325	1.057	*	0.615	1.032	*	0.591	1.076	*	0.584
Living in couple	-0.251	***	0.046	-0.151	***	0.161	-1.182	***	0.103	-1.181	***	0.102	-0.827	***	0.098
Household size	0.007		0.019	0.019		0.063	0.232	***	0.035	0.232	***	0.035	0.028		0.037
Gender	0.226	***	0.034										0.886	***	0.082
Age	0.023	***	0.008										0.049	***	0.015
Age squared	0.000	***	0.000										-0.001	***	0.000
High education	-0.040		0.042										-0.102		0.094
Ethnic minority	-0.025		0.060										0.015		0.135
Low cohesion	0.347	***	0.049										1.066	***	0.118
Time dummies	yes		yes	yes		yes	yes		yes	yes		yes	yes		yes
Constant	1.675	***	0.232	13.044	**	0.223	8.193	**	0.365	8.178	***	0.362	7.290	***	0.539
Hansen J-test							[0.328]			[0.328]			[0.350]		
AR(1)							[0.000]			[0.000]			[0.000]		
AR(2)							[0.620]			[0.620]			[0.613]		
Number of instruments							17			17			23		

***p < 0.01, **p < 0.05, *p < 1; In all GMM specifications, unemployment is considered as endogenous. The row for the Hansen J-test reports the p-values for the null hypothesis of instrument validity. The values reported for the Diff-in-Hansen test are the p-values for the validity of the additional moment restriction necessary for system GMM. The values reported for AR(1) and AR(2) are the p-values for first and second order autocorrelated disturbances in the first differences equations. No. Obs.: 43469. No. Individuals: 9137.

Table 3. Ethnic density neighbourhoods

Dependent variable: GHQ-12	Sample 1 High ethnic density			Sample 2 Other neighbourhoods			Sample 3 High ethnic density White British Medium-high cohesion			Model 4 High ethnic density Minority individual Low cohesion		
	Coef		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**
Lag1(ghq)	0.231	***	0.035	0.219	***	0.019	0.263	***	0.041	0.183	***	0.067
Lag2(ghq)	0.080	***	0.030	0.061	***	0.016	0.092	***	0.034	0.062		0.055
Covariates and time dummies	yes		yes	yes		yes	yes		yes	yes		yes
Constant	8.118	***	0.806	8.145	***	0.400	7.089	***	0.904	9.583	***	1.487
No.obs	6,801			36,668			4369			2,432		
No. Individuals	1521			7,616			946			575		
Hansen J-test	0.976			0.123			0.770			0.957		
AR(1)	0.000			0.000								
AR(2)	0.830			0.696			1.000			0.878		
Number of instruments	17			17			17			17		

***p < 0.01, **p < 0.05, *p < 1; Model 4 (System GMM estimator), see Table 2

Table 4. Neighbourhoods with high ethnic density by ethnic diversity and minority status

Dependent varaible:	Sample 1a High ethnic density High ethnic diversity			Sample 1b High ethnic density Medium-low diversity			Sample 1c High ethnic density High diversity white British			Sample 1d High ethnic density High diversity Minority individual			Sample 1e High ethnic density High diversity Medium-high cohesion			Sample 1f High ethnic density High diversity Low-high cohesion		
GHQ-12	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**	**Coef**		**Robust SE**
Lag1(ghq)	0.328	***	0.054	0.188	***	0.044	0.356	***	0.071	0.318	***	0.083	0.257	***	0.075	0.426	***	0.063
Lag2(ghq)	0.186	***	0.049	0.032		0.035	0.263	***	0.071	0.132	**	0.063	0.140	**	0.062	0.263	***	0.079
Covariates and time dummies	yes		yes	yes		yes	yes		yes	yes		yes	yes		yes	yes		yes
Constant	5.906	***	1.239	9.111	***	0.986	4.841	***	1.730	6.146	***	1.726	6.900	***	1.548	4.307	**	1.842
No.obs	2,073			4,728			1,026			1,047			1,522			551		
No. Individuals	473			1,048			243			230			350			123		
Hansen J-test	0.330			0.849			0.480			0.798			0.129			0.679		
AR(1)	0.000			0.000			0.000			0.000			0.000			0.000		
AR(2)	0.637			0.868			0.637			0.725			0.163			0.377		
Number of instruments	17			17			17			17			17			17		

***p < 0.01, **p < 0.05, *p < 1; Model 4 (System GMM estimator), see Table 2

Table 6. Method: principal-component factors (oblique rotation)

Factor loadings and unique variances	Anxiety, depression, loss of confidence	Social Dysfunction	Uniqueness
1 concentration		0.6118	0.4335
2 loss of sleep	0.7624		0.4037
3 playing a useful role		0.7536	0.4207
4 capable of making decisions		0.7543	0.3565
5 constantly under strain	0.8161		0.3131
6 problem overcoming difficulties	0.7966		0.2721
7 enjoy day-to-day activities		0.6627	0.5279
8 ability to face problems		0.6551	0.3812
9 unhappy or depressed	0.7473		0.2649
10 losing confidence	0.7531		0.2719
11 believe worthless	0.6544		0.405
12 general happiness		0.5978	0.3897
Overall Kaiser–Meyer–Olkin measure			0.9362

Table 7

	All sample		Sample 1b High ethnic density Medium-low diversity		Sample 1a High ethnic density High diversity		Sample 1f High ethnic density High diversity Low-high cohesion	
	Coef	**Robust SE**	**Coef**	**Robust SE**	**Coef**	**Robust SE**	**Coef**	**Robust SE**
Dependent variable (y) is Anxiety, Depression, Loss of Confidence								
Lag1(y)	0.205 ***	0.018	0.168 ***	0.055	0.208 ***	0.056	0.332 ***	0.099
Lag2(y)	0.076 ***	0.015	0.014	0.049	0.183 ***	0.053	0.150 **	0.067
Covariates								
Constant	0.121 **	0.047	-0.126	0.178	0.305 *	0.166	0.730 ***	0.249
Dependent varaible (y) is Social Dysfunction								
Lag1(y)	0.226 ***	0.022	0.137 **	0.058	0.301 ***	0.066	0.458 ***	0.074
Lag2(y)	0.080 ***	0.017	0.055	0.046	0.107 *	0.059	0.228 *	0.130
Covariates								
Constant	-0.071	0.081	-0.279	0.307	0.018	0.154	0.243	0.268
No.obs	43469		4,728		4,728		551	
No. Individuals	9137		1048		1048		123	
Number of instruments	17		17		17		17	

***p < 0.01, **p < 0.05, *p < 1; Specifications as in Model 4 (System GMM estimator), Table 2