Neighbourhood-level Deprivation and Depression: Evidence from the South African National Income Dynamics Study

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Abstract

Background: Depression contributes substantially to the burden of disease in South Africa, with recent reports illuminating both the economic and public health implications for the country. In comparison with the available knowledge of individual-level risk factors for depression, relatively little is known about how neighbourhoods affect the mental health of the people living in them, especially in low- and middle-income countries where virtually no research has been done.

Methods: Using nationally representative data (N=11,955) from the South African National Income Dynamics Study (NIDS) and the South African Indices of Multiple Deprivation (SAIMD) modelled at small-area level, this study tested associations between neighbourhood-level deprivation and depression, after controlling for individual-level covariates. Depression in NIDS was assessed using the Centre for Epidemiological Studies Short Depression Scale (CES-D10), and data on covariates was also obtained from NIDS. This is the first study to merge the SAIMD and NIDS datasets, achieved by mapping NIDS household GPS co-ordinates with the SAIMD shapefile.

Results: Results showed a significant positive association between neighbourhood-level deprivation and depression using the composite SAIMD ($p=0.04$) as well as the individual domains. Living environment deprivation ($p=0.001$) and employment deprivation ($p=0.004$), respectively, were the two most salient domains in predicting this relationship, while education deprivation at the neighbourhood level was not a significant predictor of depression.

Conclusions: Findings supported the hypothesis that there is a positive association between living in a more deprived neighbourhood and mental ill-health of the residents, even after controlling for individual-level covariates. Longitudinal research into the causal mechanisms of this relationship would take this area of inquiry usefully forward. This study suggests that alleviating structural poverty might reduce the burden of depression in South Africa.

Keywords: depression, neighbourhood-level deprivation, NIDS, SAIMD, South Africa

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Background

It is estimated that mental disorders contribute 7.4% to the global burden of disease (Whiteford et al., 2013). To date, the evidence in this research area relates primarily to high-income countries. Epidemiological data on mental health in low- and middle-income countries (LMIC) has only emerged in the literature over the past decade (Gureje, Lasebikan, Kola & Makanjuola, 2006) but a growing body of evidence suggests that patterns in Africa are similar to those in high-income countries (HIC) (Lopez, Mathers, Ezzati, Jamison, & Murray, 2006). Depression constitutes the highest proportion of all mental and substance abuse disorders globally (Whiteford et al., 2013) and projections are that it will be the second leading cause of disability in the world by 2020 (World Health Organization [WHO], 2006). Nationally representative studies in South Africa have shown comparatively high levels of depression, with estimates ranging from 4.9% to 7.9% for 12-month prevalence (Ardington & Case, 2010; Williams et al., 2008). The global role of impairment reported by the majority of depression sufferers is that their ability to work is undermined, thus signalling the impact of depression on gross domestic product (Lund, Myer, Stein, Williams & Flisher, 2013).

There is a long tradition of inquiry into the relationship that exists between socioeconomic adversity and poor mental health outcomes at the individual level. A robust body of literature from HIC attests to the existence of this relationship, with variables such as low income (Melzer, Fryers & Jenkins, 2004), unemployment, low education and social class (Lorant et al., 2003), and financial strain (Weich, Sloggett & Lewis, 1998) showing associations with poor mental health outcomes. Conversely, financial and physical assets have been shown to safeguard against common mental disorders (Muntaner et al., 1998). More recently, evidence has begun to emerge on the nature of the 'poverty–mental health' relationship in LMIC (Patel & Kleinman, 2003). A systematic review of 115 studies by Lund and colleagues (2010) reported that 79% of multivariate analyses showed positive associations between poverty measures and common mental disorders, while negative associations were only reported for 6% of the studies.

Neighbourhoods and Mental Health

While the relationship between poverty and mental health has been primarily examined at the individual level, more recent studies have begun to use the neighbourhood in which the individuals are 'nested' as a unit of analysis. At neighbourhood level, alternative risk factors for depression can begin to be identified, which may not be apparent at the individual level.

Several studies now report a significant association between mental health and various neighbourhood characteristics, after controlling for individual factors. A review by Truong and Ma (2006) showed significant associations for 27 of the 29 studies examined across a variety of neighbourhood features and mental disorders. For example, low neighbourhood socioeconomic status (SES) and poor social cohesion were significantly and independently associated with poor mental health status after adjusting for individual SES (Fone et al., 2007). The effects of more tangible aspects of neighbourhoods on mental health, such as community-based grassroots organisations and shared public spaces for recreation, have been associated with improved mental health outcomes in China (Shen, 2014), illustrating how creating a sense of community and promoting shared values through physical structures can be valuable.

From a theoretical perspective, the neighbourhood context can be seen as particularly germane to depression and depressive symptoms for several reasons. In simple terms, neighbourhood characteristics can function as either stressors or buffers (Aneshensel & Sucoff, 1996; Ross, 2000). Features like lack of neighbourhood resources, violence or poor social cohesion could function as stressors, while physical and social characteristics of neighbourhoods like access to social support may function as buffers (Kubzansky et al., 2005).

Though research in this area is still in its infancy, a promising body of empirical literature has begun to show significant associations between neighbourhood characteristics and depression (Mair, Diez Roux & Gaela, 2008; Truong & Ma, 2006). A comprehensive review in this area reported significant associations after controlling for individual-level characteristics in 37 of the 45 studies examined (Mair et al, 2008). In a systematic review of neighbourhood characteristics and depression in adults it was found that neighbourhood social disorder was consistently associated with depressive symptoms and that higher neighbourhood SES functioned as a protective factor against depression (Kim, 2008).

Very different patterns of associations have been found between area-level contextual variables and mental health status in urban and rural areas (Peterson, Tsai, Petterson & Litaker, 2009). The effect of neighbourhood disadvantage on depression has been found to be significantly greater in urban areas compared to non-urban areas (Rudolph, Stuart, Glass & Merikangas, 2014). Stressors in urban deprived settings are possibly very different from the stressors experienced in rural deprived settings. Factors such as prevalence of violence

(Slopen et al., 2012), availability of green spaces (Lee & Maheswaran, 2011) and residential instability (Gaela, 2011) have all been associated with emotional disorders.

The Neighbourhood as a Unit of Analysis

It is increasingly being recognised that the neighbourhood contributes to health effects. First, explanations based exclusively on individual symptoms or characteristics are seen as being incapable of capturing certain critical determinants of ill-health and are thus inadequate (Schwartz, Susser & Susser, 1999). Consideration of the characteristics of the groups and contexts in which individuals are located has been emphasised as a necessary element in understanding health outcomes (Diez Roux, 2004). The social and physical characteristics of places of residence might play important roles in explaining health problems and could enable place-based interventions as informed additions to individual-based interventions (Sampson, Morenoff & Gannon-Rowely, 2002; Diez Roux, 2004). Secondly, interest has been directed towards understanding the relationship between social inequality and health (Diez Roux, 2007). Neighbourhood characteristics may be significant contributors to health inequalities because place of residence is often determined by socioeconomic position with poor neighbourhoods characterised by various kinds of deprivation.

Limitations in the Literature

Scrutiny of the literature in this field shows the virtual absence of such research in LMICs. All 45 studies reviewed by Mair and colleagues (2008) were from HICs with all but two conducted in the USA and the UK. Of the 28 studies reviewed by Kim (2008), all but one Taiwanese study by Yen, Rebok, Yang and Lung (2008) were from HICs. It is thus clear that research is needed in LMICs. Tomita and Burns (2013) attempted to address this gap with a cross-sectional study exploring correlations between neighbourhood social capital and depression in South Africa, and found that perception of social trust and the extent to which participants ‘preferred’ living in their neighbourhoods were significantly associated with mental well-being. However, a limitation of this study was the risk of same-source bias that accompanies a study in which self-report data is used for both the outcome variable and the neighbourhood variable of interest. This can occur because of correlated measurement error or because the dependent variable affects the reporting of the neighbourhood variable (Diez Roux, 2007). This appears to be the first such study to be carried out in South Africa and represents a promising start but further exploration of neighbourhood variables and mental health issues is needed. In particular, the use of research designs exploring the relationship between independently sourced composite neighbourhood-level indices and mental health outcomes would take this area of enquiry forward.

South Africa presents a unique environment in which to further explore how neighbourhoods impact on mental health outcomes. Apartheid social planning not only conflated race and class but located inequality, poverty and exclusion geographically by neighbourhood. This legacy still pervades South Africa's demographic organisation with inequality and race remaining highly conflated (McIntyre, Muirhead & Gibson, 2002). Research into area-level deprivation in South Africa shows clear patterns with regard to the geographic location of deprivation. A recent report illustrated that former homeland areas still remain the most deprived regions in the country (Noble, Zembe, Wright & Avenell, 2013). There is clearly a paucity of this kind of research in LMICs, and in South Africa in particular. It is clear that research into how neighbourhood context influences mental health outcomes in South Africa could usefully inform the nature and direction of public policy in attempting to reduce the mental health burden.

The research undertaken in this project will explore associations between neighbourhood-level deprivation and depression in a nationally representative South African sample. It will avoid the same-source bias problem by combining comprehensive individual-level depression and socioeconomic data with independently sourced area-level deprivation data. The geographical units to be used were designed to represent more realistic approximations of neighbourhoods, thereby addressing various neighbourhood conceptualisation issues.

Methods

Design and Setting

This study is apparently the first of its kind to be conducted in South Africa and one of very few in LMICs. The study used data collected as part of the National Income Dynamics Study (NIDS), commissioned by the South African Presidency in 2006 (Leibrandt, Woolard & de Villiers, 2009) and combined this data with the South African Indices of Multiple Deprivation (Noble, Barnes, Wright & Roberts, 2010). The NIDS data is the first nationally representative dataset to capture the dynamic nature of both individual and household-level changes in expenditure, incomes, assets, access to services, education, employment, health and other dimensions of well-being (Leibrandt et al., 2009). The Centre for Epidemiologic Studies Short Depression Scale (CES-D 10) was included in the NIDS adult questionnaire; these scores will constitute the measure of the dependent variable – depression – in the study.

At neighbourhood level, there has been little consensus in the literature regarding selection of appropriate variables or proxies to represent concepts like poverty or deprivation. Composite indices are a promising category of area-level variable as they are seen as being more inclusive and sophisticated measures of poverty and deprivation (Lund et al., 2013b; Pickett & Pearl, 2001). The Centre for Analysis of South African Social Policy (CASASP) at Oxford University has been developing Indices of Multiple Deprivation for different area levels since 2001 (Noble et al., 2010). The concept of what constitutes a 'neighbourhood' is in itself not simple. We naturally think of neighbourhoods as geographical units, but within the literature there has been limited consensus regarding how these units should be constructed and operationalised. Problems occur when there is a disjuncture between how residents and researchers perceive these units as this reduces the probability of finding strong effects (Ward, 2007).

The study will make use of one of the latest versions of the South African Indices of Multiple Deprivation (SAIMD), which have been modelled at datazone-level. The conception of the datazone unit of analysis has been an important contribution as it allows analysis of geographical units containing approximately 2000 inhabitants and "describes pockets of deprivation by maximising social homogeneity and population density homogeneity" (Avenell, Noble & Wright, 2009; p.6). The datazone represents a more specific and meaningful unit with which to analyse deprivation than larger areas such as wards, districts or municipalities (Noble et al., 2010). This is because these areas are often far too large for a fine-grained analysis of small area-level effects and the variation present in such large areas limits the potential to comment on factors like neighbourhood-level deprivation (Diez Roux, 2007). This study used the datazones, as operationalised by CASASP, to represent neighbourhoods, helping to counter a perceived key shortcoming in many area-level studies that proxies of neighbourhoods seldom reflect the actual neighbourhoods and underlying constructs appropriately (Diez Roux, 2004). This SAIMD data will be merged with the NIDS data to enable an analysis of individuals 'nested' within neighbourhoods.

The study is a cross-sectional design that will investigate the association between neighbourhood-level deprivation in 2007 as the predictor variable and individual depression scores in 2008 as the outcome variable, with controls for other individual covariates included.

Participants

NIDS is the first national panel study to be conducted in South Africa. In 2008, the first wave of the study was completed by South African Labour and Development Research Unit (SALDRU) located at the University of Cape Town and has been made available for public use.

The NIDS team employed a stratified two-stage cluster sample design to determine the households that would be included in the base wave of the study. Private households from every province constituted the sample (Leibbrandt et al., 2009). The spread of sampling units for the base wave per province and per geography type closely mirrored a 'master sample' used by Stats SA between 2004–2007 for various household surveys and was thus seen as satisfactorily representative in this regard (Leibbrandt et al., 2009).

Each household member aged 15 or older was requested to complete an adult questionnaire. Further, the oldest woman in each household or the next resident most knowledgeable about living arrangements completed a household questionnaire. Data for this study will come from both the individual and household questionnaires as well as the individual and household-derived variable files created by NIDS. Wave 1 sampled approximately 16, 800 adults spread across 400 primary sampling units. The response rate for households in wave 1 was 69%, but once a household had been sampled, the individual response rate within that household was 93.3% (Leibbrandt et al., 2009). In order to extrapolate the results from the sample to the population and declare national representativeness, the sampling weights constructed by NIDS have been used in the analysis of the data. The post-stratification sample weights provided by NIDS were applied to the dataset.

Measures

Centre for Epidemiologic Studies Short Depression Scale (CES-D 10)

The NIDS adult questionnaire includes the ten-item CES-D, a shorter form of the original 20-item version of the scale developed by Radloff (1977). The scale was designed to measure depressive symptoms in the general population and is one of the five most commonly used self-report measures of depressive experiences (Wood, Taylor & Joseph, 2010). The CES-D has good psychometric properties, displaying high convergent validity with clinical scales such as the Beck Depression Inventory (r=0.81) (Wood et al., 2010) and the Zung Self-Rating Depression Scale (r=0.90) (Wood et al., 2010). It correlates well with its original 20-item predecessor, losing little in the line of psychometric properties (Shrout & Yager, 1989). Originally designed to measure depression symptoms in the general population, the CES-D 10 best conceptualises depression on a continuum rather than a dichotomy (Radloff, 1977). Various studies have used a cut-off score of ten and above to determine 'caseness' for depression. However, this has not been validated in a South African setting (Eaton et al., 2004; Radloff, 1977) and it must be noted that this does not represent a clinical diagnosis. The CES-D has been used in various South African studies involving depression (Hamad et al., 2008; Myer et al., 2008). The questions explore frequency of occurrence of certain feelings and behaviours in the previous week. Responses are recorded on a 4-level Likert-type scale of frequency ranging from 'rarely or none of the time' to 'all of the time'. Recent evidence suggests that the best way to conceptualise the scale is as a single continuum ranging from emotional well-being to depression (Wood et al., 2010). The alpha value for the sample in this study was 0.74, which was in line with similar studies (Cole et al., 2004).

Area-level Deprivation

Participants for the NIDS study were selected from 400 primary sampling units; these were census enumerator areas provided by Statistics South Africa, across all nine provinces. For each household sampled, a specific geo-location was recorded. In 2010, the Department for Social Development commissioned the CASASP research unit to develop indices of multiple deprivation at datazone level.

The South African Indices of Multiple Deprivation (SAIMD) used in this study were constructed from Statistics SA 2007 Community Survey data, which sampled 274, 348 dwelling units across all nine provinces in South Africa (Noble et al., 2010). It is a nationally representative household survey designed to provide information on the population between censuses. The indices were constructed along four domains using eleven indicators. These deprivation domains are: income and material, employment, education, and living environment. Table 1 provides a summary of the domains and indicators used by CASASP (Wright & Noble, 2009).

To summarise, an overall deprivation score was constructed for each datazone ranging from 0–400, with higher scores indicating greater deprivation. This represents the sum of the exponentially transformed domain ranks of the domain scores (Wright & Noble, 2009). The four domains were equally weighted in the construction of the overall deprivation score. Each individual dimension was given a score from 0–100. Both the composite SAIMD index and the individual domain raw scores were converted into z-scores in order to more meaningfully interpret their coefficients. Comparing these individual dimensions should enable the study to identify some of the more specific causal pathways between neighbourhood deprivation and depression. This will contribute towards identifying specific neighbourhood features that are influencing mental health outcomes; a problem regularly mentioned in the literature (Diez Rouz, 2007; Pickett & Pearl, 2001).

Table 1

Description of Individual Domain Construction

Deprivation Domain	Income and Material	Employment	Education	Living Environment
Purpose	To capture the proportion of the population experiencing income and/or material deprivation in a datazone	To measure the proportion of working-age people involuntarily excluded from employment in a datazone	To measure the proportion of adults aged 18-65 with no secondary schooling in a datazone	To identify the proportion of people living in poor-quality environments in a datazone
Indicators	• Number of people living in households with monthly incomes < 40% of the mean equivalent household income (R1003 per month in Feb 2007) • Number of people living in a house without a refrigerator • Number of people living in a house with neither tv nor radio	• Number of people who are unemployed using official definition • Number of people not working because of illness or disability	• Number of adults aged 18-65 with no secondary schooling	• Number of people living in houses with no piped water • Number of people living in houses without a pit latrine or flush toilet • Number of people living in households without electricity for lighting • Number of people living in a shack • Number of people living in overcrowded households
Calculation	A simple proportion of people living in households experiencing one or more of the deprivations was calculated	A simple proportion was calculated of adults who were unemployed divided by the total economically active population aged 15-65 plus those unable to work due to sickness/disability	This domain was calculated as a simple rate for 18-65 year olds	A simple proportion of people living in households experiencing one or more deprivations was calculated

Note. Overcrowding was present if number of people in the household divided by number of rooms was greater than or equal to two.

Individual-level Covariates

A comprehensive set of questions relating to socioeconomic, demographic and general health information was included in the NIDS questionnaires. Without proper consideration of relevant individual-level information in the analysis, neighbourhood-level variables are likely to act ‘partially or entirely as proxies for individual attributes and, as such, a partition of the contribution of each to the chosen health outcome of depression becomes impossible’ (Pickett & Pearl, 2001, p.116). Two of the most consistent findings across the depression literature in developing and developed contexts are that as age increases so does risk of depression (Ardington & Case, 2010) and that females are at greater risk of depression than males (Das et al., 2007; Lund et al., 2013). Being married or living with a partner is also widely regarded as a significant protective factor against common mental health disorders (Das et al., 2007). Education is seen as a strong protective factor for depression. Evidence from developing countries has shown education to be negatively and significantly associated with depression (Araya, Lewis, Rojas & Fritsch, 2003; Ardington & Case, 2010). Employment status is widely viewed as an important covariate for common mental health disorders, with secure employment acting as a protective factor (Lund et al., 2010a). While findings on the association between income and depression have been inconsistent, they have still shown significant association in many studies, with low income representing a risk factor (Lund et al., 2010a). Ardington and Case (2010) found that depression scores in NIDS were highly skewed across racial groups, with the African subsample displaying significantly higher rates of depressive symptoms. Negative life events such as the death or serious illness of a family member, theft or destruction of household property, or job loss have been reported as germane predictors of common mental disorders (Myer et al., 2008). An interaction between negative events and deprivation will be explored to see how deprivation salience varies in the presence and absence of negative events.

In order to mirror the SAIMD neighbourhood-level domains with the individual covariates, certain other individual-level variables were constructed using the NIDS data. A binary durable goods variable was constructed by ascertaining whether an individual lived in a house which was without a refrigerator, television or radio. Secondly, a binary individual-level living environment deprivation variable was calculated which measured whether people were living in houses without on-site running water, electricity for lighting, a toilet or pit latrine, or were living in shacks. These composite binary variables have been included to bring about consistent matching of the individual-level variables to the neighbourhood-level deprivation variables.

Based on the above literature, the following covariates will be included:

- **Age** – included as a continuous variable.
- **Gender** – included as a dummy variable with male as the reference group.
- **Education** – included as a dummy variable of less than grade 9-level education and more than grade 9-level education, with below grade 9 as the reference group.
- **Marital status** – included as a variable with the following categories: married, living with partner, divorced/separated, never married and refused (wave 3 only), with married as the reference category.
- **Employment status** – included with the following categories: employed, not economically active and unemployed discouraged, with employed as the reference group.
- **Household Income** – included as a continuous variable converted into a z-score for ease of interpretation.
- **Ethnicity** – included under the following categories: black, coloured, Asian/Indian, white, with black as the reference category.
- **Urbanicity** – included as a dummy variable of urban and rural with rural as the reference category.
- **Negative events** – included as a dummy variable with presence of at least one negative event versus no negative events, with presence of at least one event as the reference category.
- **Durable goods deprivation** – included as a dummy variable with durable goods deprived and not deprived as the categories, and not deprived as the reference category.
- **Living environment deprivation –** included as a dummy variable with living environment deprived and not deprived as the categories, and deprived as the reference category.

Specific Aims and Hypotheses

The principal aim of this research is to determine whether neighbourhood-level deprivation is associated with high levels of depression in a representative South African adult sample. The following hypotheses will be tested:

For composite deprivation score:

1. High levels of area-level deprivation will be positively associated with depression, when controlling for individual confounding variables.

For individual dimensions of deprivation:

2. These analyses will then be repeated, but instead of using a composite deprivation score, the specific relationships between depression and separate aspects of deprivation as conceptualised by CASASP (income and material deprivation, employment deprivation, education deprivation, and living environment deprivation) will be explored. This will permit investigation of the more salient dimensions in predicting depression.

Ethical Considerations

The study made use of secondary datasets that had previously been processed through ethics committees. NIDS was granted ethical clearance by the UCT Commerce Faculty Ethics Committee (Leibbrandt et al., 2009) and this study was approved by the Humanities Research Ethics Committee at UCT. However, the study required access to the NIDS secure data, as it was necessary to link the geo-locations of the households in NIDS to their respective SAIMD scores for the neighbourhood in which they were located. This clearance was applied for and granted by the Datafirst secure data services who did not consider the anonymity of the NIDS participants to be threatened because this study was only reporting on the associations by deprivation in areas and excluded names of individuals or places.

Statistical Analysis

All statistical analyses were carried out using the STATA 12 software package. The NIDS adult questionnaire dataset was initially merged one-to-one with the individual-derived dataset. The derived datasets comprise variables that NIDS has created using the raw data. These variables are often prefixed by ‘best_’ and indicate that they have already been verified and cleaned. Thereafter the household questionnaire and household-derived datasets were merged into the master data set. Variables that needed to be created from the NIDS raw data such as the durable goods, negative events and living environment dummy variables were generated and calculated accordingly. The CES-D10 scores were summed in order to calculate a total score for depressive symptoms. An ado-file defines a STATA command. In order to merge the SAIMD datazone boundaries and scores with the NIDS data, a specially tailored ado-file, ‘gpsbound’, developed by researchers at SALDRU (Brophy, Daniels & Musundwa, 2014) was used. This enabled the GPS co-ordinates (geo-location) of each NIDS household to be fitted to its respective datazone via the polygon shape file provided by CASASP that specifies all of the datazone boandaries. This resulted in each individual having a neighbourhood-level SAIMD composite score as well as a score for each of the individual domains. As such, individuals with missing GPS co-ordinates and CES-D10 scores were excluded from the sample (N=206), however this subsample did not differ in any significant way from the rest of the sample.

Survey data such as NIDS is characterised by sampling, clustering and stratification. These three features are contingent on the study design and process of data collection. Statistical software packages like STATA will by default analyse data under the assumption that cases have been selected by the process of simple random sampling; however in the case of survey data, a much more sophisticated and intricate process of sampling has occurred. Consequently it is necessary to incorporate the sample weighting, clustering and stratification into the statistical analyses to ensure that point estimates and standard errors are accurate and not flawed or underestimated. The sampling weights regulate for the fact that not each observation has the same probability of being selected. Thus the weights are calculated as the inverse of the probability of being sampled (Wittenberg, 2009). Subsequent to this, these design weights were post-stratified which is an adjustment process to make the sample look like the population (Wittenberg, 2009). The Stats SA midyear population estimates were used as the reference for this adjustment.

The 'cluster' corrections were applied in the weighting process, and this had a bearing on the types of models that could be used in the statistical analysis. When a sample design is two-stage, a Primary Sampling Unit or 'cluster' is initially sampled and then units of households and individuals are sub-sampled from within the cluster. The assumption of simple random sampling ignores the fact that two people within the same cluster or PSU are likely to be more similar than two people chosen at random from the population due to what can be referred to as a 'cluster effect' (Wittenberg, 2013). If standard errors are not corrected for cluster effects, the cluster effects are more likely to produce significant associations, but these would be premised by the assumption that they do not exist in the data. This is very seldom true (Wittenberg, 2013). There are various reasons why these effects may exist. It could be that people in neighbourhoods have the same infrastructure and access to resources or that neighbourhoods may share common features relating to language, culture, and attitudes (Wittenberg, 2013). Certainly, in a context like South Africa with its long history of geographically structured oppression, it is important to consider cluster effects in the data.

The svy-set command in STATA was used to apply the NIDS post-stratification weights and cluster corrections to the sample. This effectively introduced an equivalent measure of control into the models that area-level specific and individual-level specific random effects on the intercepts would have achieved. Therefore Ordinary Least Squares survey regressions were conducted instead of multilevel mixed-effects models; it is not possible to run random effects models in STATA when the svy-set command is being utilised.

A two-stage process was used to test each of the hypotheses. Initially deprivation was the only predictor variable for depression – the results of which are presented in the bivariate correlations (Table 4). The second stage introduced controlling for all the specified individual-level covariates. This enabled the partialling out of the neighbourhood effect. Models were run for the composite SAIMD, as well as for each of the four domain scores.

Results

For the adult sample of the first wave of NIDS, 12,448 individuals were successfully mapped to datazones using the GPS co-ordinates and had completed the CES-D10 portion of the individual adult questionnaire. Of these individuals, 11,955 had all the necessary data for incorporation into the full models. These are the individuals on whom the descriptive statistics are reported.

Table 2 details the socio-demographic descriptive statistics for all the categorical variables used in the analysis. The sample is slanted in favour of females, who represent over 60% of participants. This is more pronounced than the national estimate of 52% female to male ratio in the population (StatsSA, 2007). Age ranged from 15 to101 years (M=37.58, SD = 17.05) in 2008. In terms of population categories, the African subsample constitutes approximately 80% of the total. Approximately half of the sample was never married, while roughly 30% are married. Regarding education, 55% of the sample had been educated to at least grade 9-level, the first recognised year when children are legally allowed to leave school in South Africa. For employment status categories, ‘not economically active’, which refers to individuals neither employed nor seeking employment – such as retirees or scholars and students– represents approximately 41% of the sample and constitutes the most populous category. The ‘employed’ category represents approximately 40% of the sample. The remaining 20% is made up of ‘unemployed strict’ which denotes individuals who have actively sought out employment opportunities in the past four weeks, and ‘unemployed discouraged’ which represents individuals who would like to have worked in the past month but have not actively searched for a job in that period (Ranchhod, 2009).

In terms of living deprivation, the majority of the sample (53.8%) was deprived in 2008 according to the living environment variables included in this binary. However, only 44% were deprived of durable goods in 2008. At least one ‘negative life event’ had been experienced in the preceding year by 21.6% of the sample in 2008. The split between urban and rural dwellings was largely even, with 51% of the sample living in rural areas.

Table 2
Descriptives: Categorical socio-demographic variables (N=11,995)

Variable	
Gender	
Female	7,473 (62.5%)
Male	4,482 (37.5%)
Race	
African	9,494 (79.41%)
Coloured	1,568 (13.12%)
Asian/Indian	163 (1.36%)
White	730 (6.11%)
Marital Status	
Married	3,516 (29.41%)
Living with partner	1,050 (8.78%)
Widow/widower	1,011 (8.46%)
Divorced or separated	351 (2.94%)
Never married	6,027 (50.41%)
Education	
Below Gr 9	5,437 (45.48%)
Above Gr 9	6,518 (54.52%)
Employment Status	
Not economically active	4,888 (40.89%)
Unemployed discouraged	781 (6.53%)
Unemployed strict	1,482 (12.40%)
Employed	4,804 (40.18%)
Living Deprivation Status	
Not deprived	5,526 (46.22%)
Deprived	6,429 (53.78%)
Durable Goods	
No	5,265 (44.04%)
Yes	6,690 (55.96%)
Urban	
Rural/traditional	6,096 (50.99%)
Urban	5,859 (49.01%)
Negative Events	
None	9,470 (79.37%)
One or more	2,466 (20.63%)

The continuous variables are presented in Table 3. The CES-D10 scores had a mean of 8 in 2008. There is some variability in the data, with the standard deviation over 4. The SAIMD composite index, which represents a combination of the four domains that follow it, has a mean value of 145.59 and standard deviation of 85.61 for the sample. The large standard deviation indicates the high level of variability in the deprivation of the datazones. The actual range of the data also highlights the very large variation in deprivation levels, which almost matches the theoretical range of 0-400. For the individual domains, the Income and Material deprivation domain and the Living Environment domain have the highest means of 77.30 and 68.05 respectively. The Education domain is the lowest of the four domains with a mean of 33.68, less than half that of the Living Environment domain. It is also noteworthy that the maximum values of the Income and Material domain and Living Environment domain are greater than 99 out of a possible 100, where the maximum value for Education is 77.87 out of a possible 100. The household monthly income has some noticeable features. The standard deviation is very large for the estimates. There is also a considerable difference between the means and the medians; for example, mean household monthly income for the sample was R4791 and the median was R2327. Putting these figures into perspective against the national poverty line of R524 per person a month (Bhorat, Oosthuizen & Van der Westhuizen, 2011) shows that many households represented in this study would fall below the poverty line.

Table 3
*Descriptive statistics: Continuous Variables in sample (*N=11,955)

Variable	Actual Range	Possible Range	Mean (Std Dev.)	Median	IQR
CES-D10	0-30	0-30	8.01 (4.76)	7	5-11
Composite Deprivation Index	4.08-368.23	0-400	145.59 (85.61)	138.21	79.73-207.96
Income and Material Deprivation	2.5-99.41	0-100	77.30 (24.49)	87.99	67.67-94.18
Employment Deprivation	5.23-87.08	0-100	43.348(21.41)	44.68	25.05-61.05
Education Deprivation	4.00-77.87	0-100	33.68 (16.06)	34.02	22.31-44.74
Living Environment Deprivation	1.35-99.91	0-100	68.05 (32.81)	81.72	40.55-97.78
Age	15-101	-	37.58 (17.05)	35	23-50
Household Income	0-136968.7	-	4791.78 (8146.99)	2327.71	1271.94-4837.72

Table 4 contains weighted bivariate associations between CES-D10 scores and all area-level and individual-level independent variables. Beta coefficients, standard errors and p-values are presented for each of the variables. The table reveals strong associations ($p<0.001$) between the composite SAIMD and depression scores. This relationship holds for all four individual domains as well. The positive coefficients indicate that individuals living in more deprived datazones reported significantly more symptoms of depression. All area-level deprivation variables have been converted to z-scores to allow for more meaningful interpretation. The coefficients represent the change in the CES-D10 score per standard deviation increase in the deprivation variable.

All individual-level covariates, except for the negative events binary variable, show strong significant associations with the CES-D10 scores. The values on the household income variable have also been converted into z-scores; thus a one standard deviation increase in household income elicits a 0.82 decrease in depression score. In the sample, being male is significantly associated with fewer depressive symptoms and a similar relationship holds for being younger. Race category appeared to be quite a salient predictive factor with coloured, Asian/Indian and white participants presenting significantly fewer depressive symptoms when compared with African participants. Being married appears to be a strong protective factor, with all other categories showing significantly more depressive symptoms. Having been educated up to at least grade 9 and not being deprived of durable goods or in the living environment also function as protective factors against depressive symptoms. People living in urban environments display significantly more depressive symptoms than those who live in rural areas. Employed participants seemed to fare far better than those in all the other employment categories. Those who had actively sought work without success showed significantly more depressive symptoms than the non-economically active participants.

Table 4

Weighted bivariate associations between 2008 CES-D10 scores and all area-level and individual-level independent variables

CES-D10	*B*	*SE*	*P>t*
SAIMD Composite Index	0.92	0.12	<0.0001
SAIMD Income and Material	0.88	0.10	<0.0001
SAIMD Employment	0.95	0.12	<0.0001
SAIMD Education	0.83	0.14	<0.0001
SAIMD Living Environment	0.91	0.12	<0.0001
Age	0.02	0.00	<0.0001
HH Income	-0.82	0.10	<0.0001
Male	-0.91	0.13	<0.0001
Race [African]			
Coloured	-1.57	0.38	<0.0001
Asian/Indian	-2.01	0.85	0.018
White	-3.20	-0.30	<0.0001
Marital status [Married]			
Living with partner	1.50	0.26	<0.0001
Widow/widower	2.36	0.28	<0.0001
Divorced/separated	1.56	0.59	0.008
Never married	0.72	0.18	<0.0001
Gr 9 or more education	-1.81	-0.18	<0.0001
Durable goods	-1.50	0.19	<0.0001
Living deprived	1.28	0.25	<0.0001
Urban	0.80	0.26	0.002
Employment status [Employed]			
Not economically active	0.77	0.16	<0.0001
Unemployed discouraged	0.90	0.31	0.004
Unemployed strict	1.61	0.24	<0.0001
Negative events dummy	0.09	0.21	0.677

Note. Beta coefficients (standard errors) from linear regression; a higher CES-D10 score represents more depressive symptoms, therefore a positive coefficient implies more depressive symptoms and a negative coefficient fewer depressive symptoms.

Square brackets indicate reference group for categorical variables

Is Neighbourhood-level Deprivation Associated with Depression?

The hypothesis that high levels of neighbourhood-level deprivation (2007) would be positively associated with depression (2008) after controlling for individual-level covariates (2008) was supported by the results from the models. Table 5 contains five models: the Composite SAIMD, followed by each of the domains – Income and Material, Employment, Education and Living Environment. Beta coefficients (standard errors) are presented along with significance levels. Results of full multivariate linear regression models are presented in Table 5.

The full model for the composite deprivation index was significant: $F(20,345) = 20.70$, $p < 0.0001$ and had an $R^2 = 0.113$. The composite multiple deprivation coefficient's significance remained after the inclusion of all the individual-level covariates B=0.31 (0.15), $p = 0.042$, thus confirming the initial hypothesis.

Salience of Separate Domains of Deprivation

Four identical linear models were run with individual domains of deprivation as the first regressors in the model instead of the composite index of multiple deprivation. Overall, the coefficients for the remaining explanatory variables remained quite similar across all the domains and resembled the original model closely. Of the four domains, Living Environment Deprivation was the most salient: B=0.53 (0.16), p=0.001. The Employment Deprivation domain was also a strong predictor: B=0.38(0.13), p=0.004, while the Income and Material Deprivation domain was below the 5% level of significance: B= 0.35(0.16), p=0.02. The Education Deprivation domain was the least significant of all the area-level explanatory variables (p=0.07).

The diagnostics for the models displayed no problems with multicollinearity, heteroscedasticity or undue influence of outliers and the assumption of normality of residuals was met (see Appendix A).

Table 5

Full linear models for 2008 CES-D10 depression scores and deprivation domains (N=11,955)

CESD10	Composite Index	Income and Material	Employment	Education	Living Environment
Deprivation	0.31 (0.15)*	0.36 (0.16)*	0.38 (0.13)**	0.28 (0.15)	0.53 (0.16)**
Age	0.03 (0.01)***	0.03 (0.01)***	0.03 (0.01)***	0.03 (0.01)***	0.03 (0.01)***
Male	-0.69 (0.13)***	-0.68 (0.13)***	-0.68 (0.13)***	-0.7 (0.13)***	-0.66 (0.13)***
Marital status [married]					
Living with partner	0.85 (0.26)**	0.8 (0.26)**	0.84 (0.26)**	0.82 (0.26)**	0.8 (0.26)**
Widow/widower	0.88 (0.28)**	0.87 (0.28)**	0.86 (0.28)**	0.89 (0.28)**	0.88 (0.28)**
Divorced/separated	1.8 (0.52)***	1.78 (0.53)***	1.76 (0.52)***	1.82 (0.52)***	1.79 (0.52)***
Never married	0.48 (0.2)*	0.45 (0.2)*	0.44 (0.19)*	0.47 (0.2)*	0.44 (0.2)*
Race [African]					
Coloured	-1.23 (0.34)***	-1.13 (0.32)***	-1.15 (0.34)***	-1.32 (0.34)***	-1.11 (0.32)***
Asian/Indian	-0.4 (0.93)	-0.36 (0.9)	-0.33 (0.94)	-0.48 (0.91)	-0.27 (0.91)
White	-2.16 (0.39)***	-1.95 (0.4)***	-2.03 (0.4)***	-2.18 (0.39)***	-1.93 (0.38)***
Gr. 9 or more education	-0.95 (0.16)***	-0.94 (0.16)***	-0.97 (0.16)***	-0.91 (0.16)***	-0.95 (0.16)***
Employment status [employed]					
Not economically active	0.19 (0.17)	0.19 (0.17)	0.16 (0.17)	0.23 (0.17)	0.2 (0.18)
Unemployed discouraged	0.34 (0.32)	0.33 (0.32)	0.31 (0.32)	0.37 (0.32)	0.34 (0.32)
Unemployed strict	1.11 (0.21)***	1.09 (0.21)***	1.07 (0.21)***	1.15 (0.21)***	1.08 (0.21)***
HH Income	-0.25 (0.12)*	-0.22 (0.12)	-0.24 (0.12)*	-0.24 (0.12)*	-0.23 (0.12)
Durable goods	-0.61 (0.19)**	-0.62 (0.18)***	-0.68 (0.19)***	-0.61 (0.18)**	-0.61 (0.18)**
Living environment deprived	0.16 (0.3)	0.16 (0.3)	0.17 (0.29)	0.2 (0.29)	-0.01 (0.3)
Urban	0.55 (0.27)*	0.52 (0.26)*	0.44 (0.25)	0.57 (0.26)*	0.73 (0.28)**
Negative events	0.14 (0.17)	0.14 (0.17)	0.16 (0.16)	0.17 (0.18)	0.2 (0.17)
Negative events x deprivation	-0.35 (0.2)	-0.41 (0.2)*	-0.43 (0.21)*	-0.21 (0.2)	-0.3 (0.19)
Constant	7.29 (0.43)***	7.29 (0.43)***	7.44 (0.42)***	7.24 (0.44)***	7.22 (0.44)***

Note.*p<.05. **p<.01.***p<.001

Beta coefficients (standard errors) from linear regression; a higher CES-D10 score represents more depressive symptoms, therefore a positive coefficient implies more depressive symptoms and a negative coefficient fewer depressive symptoms

Square brackets indicate reference group for categorical variables

Urbanicity

The results partially confirmed that living in a deprived neighbourhood would only be associated with high depression outcomes for individuals in urban settings. The urban dummy variable in the linear model for 2008 predicted that living in an urban setting would add significantly to symptoms of depression with a *B*=0.55 (0.27), *p*= 0.04. One notable trend is seen in the impact of urbanicity across the four domains of deprivation– it appears to be most salient in the Living Environment Deprivation domain: *B*=0.73 (0.28), *p*=0.009.

Interaction Effect: Negative events * Deprivation

To clarify the effect of the interaction between negative life events and deprivation on depression, a further model was run. The coefficients and standard errors were calculated by reversing the dummy variable for negative events. The results of this interaction are reflected in Table 7 below, where beta coefficients for each of the deprivation indices when negative events were present are displayed. The non-significance of the p-values in the table indicates that in the presence of negative events such as a death in the family, neighbourhood-level deprivation is no longer a significant predictor of depression. Essentially, this shows that when no negative events are experienced, the relationship between deprivation and depression is strong and higher deprivation leads to increases in depression scores. However, when negative events are experienced, this relationship no longer prevails; the negative events become a central predictor and in effect ‘crowd out’ the effect of neighbourhood deprivation.

Table 6

Relationship between Depression, Negative Life Events (NLE), and Deprivation

	B	*SE*	t-value	P>t
Composite Index x NLE	-0.041	0.21	-0.19	0.85
Income and material x NLE	-0.048	0.20	-0.24	0.81
Employment x NLE	-0.050	0.21	-0.23	0.82
Education x NLE	0.065	0.21	0.31	0.75
Living environment x NLE	0.230	0.20	1.15	0.25

Note. Beta coefficients (standard errors) from linear regression; a higher CES-D10 score represents more depressive symptoms, therefore a positive coefficient implies more depressive symptoms and a negative coefficient fewer depressive symptoms

Discussion

Neighbourhood Deprivation Predicts Depressive Symptoms after Controlling for Individual Covariates

Using combined data from the SA-NIDS and the SAIMD, this study aimed to ascertain whether deprivation at neighbourhood level is positively associated with depression. The results suggest that individuals living in more deprived neighbourhoods display more depressive symptoms than those living in less deprived neighbourhoods and this effect persists after controlling for a number of individual-level covariates of depression. The area-level effect matters. This section will consider how the major findings fit within the relevant domain of literature, the limitations of this study and, finally, what these findings indicate for research, practice and policy.

Certain protective and risk factors have consistently been associated with depression within individuals; these include being female, old, uneducated or unemployed (Ardington & Case, 2010; Das et al., 2007; Lund et al., 2013). A long and comprehensive tradition of inquiry into individual-level predictors of depression already exists but, as has been highlighted in this report, epidemiological interest has also begun extending beyond the individual to include an area-level perspective where group and systemic factors may operate. It is argued that explanations based solely on individual-based evidence are not able to capture certain essential contributing factors to illness and disease (Diez Roux, 2007).

This argument suggests that, over and above individual-level factors like gender, age and education, certain mechanisms operating at the neighbourhood-level affect resident individuals' depression levels. What the composite SAIMD and the individual domains appear to be doing is functioning as proxies for certain features, attributes or effects – both physical and social – that these neighbourhoods exert on the individual inhabitants. These could take the form of place-bound effects, effects of shared social backgrounds or peer effects, to name a few (Diez Roux, 2007; Lund et al., 2013b; Wittenberg, 2013).

The discussion hereunder will consider what these deprivation variables represent both directly and indirectly in neighbourhood contexts, as well as some of the possible implications for highly deprived neighbourhoods.

Income and Material Deprivation

A high-scoring neighbourhood on the Income and Material Deprivation domain is one where most residents are living on an income less than 40% of the mean household income (which was R1003 per month in February 2007 when the statistics were gathered) as well as one in which the residents lack durable goods such as refrigerators, televisions or radios. The highest scoring datazone in this domain presented with 99.41 out of a possible 100. This does not of course mean that 99,5% of residents in the datazone were income and materially deprived, as the score represents an exponentially transformed domain rank of the domain scores (Noble, Dibben & Wright, 2010), but it does mean that the datazone is very close to the most deprived such domain in the country. Results from the linear model from this domain suggest that as the number of households with very low monthly incomes and few durable goods increase in neighbourhoods, individuals living in these neighbourhoods display more depressive symptoms.

The aggregated effect of a community's financial impoverishment has implications beyond that of individual circumstance. It is important to begin to explore some of the possible mechanisms whereby neighbourhood effects filter down to an individual level in the form of influential stressors or buffers that can affect mental well-being. Literature in this area points to possibilities such as "fear of crime, witnessing violence, poor neighbourhood quality and lack of access to social resources" (Lund, Stansfeld & De Silva, 2013; p. 134) as factors that contribute to common mental disorders. Such factors are more likely to be salient in neighbourhoods with high levels of poverty (Sampson et al., 2002) and, hence, residents experience unfulfilled needs and dissatisfaction that may be risk factors for depression. In situations of high material deprivation, cognitions relating to hopelessness, loss of control and helplessness have been linked to depression outcomes (Kopp, Skrabski & Szedmak, 2000).

Employment Deprivation

Neighbourhoods where a large proportion of the working-age population (aged 15–65) is involuntarily excluded from employment present with high scores on this domain of deprivation. The employment domain was the second most salient in the effect it exerted on depression. The association between high levels of involuntary unemployment in communities and depression outcomes can be understood by exploring certain relevant underlying constructs. A starting point, and perhaps the most obvious outcome of highly concentrated levels of unemployment, is that this facilitates delinquency, deviant peer affiliation (particularly among adolescents) and crime of various forms (Sampson et al., 2002). In South Africa, areas characterised by high rates of economic exclusion and poverty, where prospects of upward mobility are small, are highly susceptible to gang-related activity (Lemanski, 2004). Experiments in social psychology have shown that prolonged deprivation along with basic needs not being satisfied can lead to reporting of internal, stable and global attributions. This leads to feelings of incompetence and inefficiency as well as powerlessness and helplessness (Mal, Jain & Yadav, 1990). This in turn creates a perception of loss of control over ones circumstances and often a sense of hopelessness (Mal et al., 1990). The concomitant effects of anxiety and relative helplessness on mental health outcomes in such milieus are well documented (Ross, 2000).

Education Deprivation

At an individual level, education has been consistently found to be a strong protective factor against depression (Araya et al., 2003; Ardington & Case, 2010). However the results indicated that it was not as significant at the neighbourhood level. There are various possibilities for this discrepancy. A high average level of education, or lack thereof, may have implications for other neighbourhood characteristics like level of employment or income and material deprivation. However, in this study education functions as a powerful proximal factor at the individual level; when it is aggregated and operates at a distal level, it is not as strong a predictor. Ross (2000) reported a similar finding, where education level in the neighbourhood was not a significant predictor of depression, while at an individual level it was highly significant. This may be because it is a more distant and indirect protective factor, so in comparison to factors that affect people's lived experience more immediately, it does not appear to exert as strong an influence. It must also be noted that the SAIMD definition of education deprivation is a relatively crude measure, thus less likely to display a particularly clear association with depression. However this should not serve to undermine its importance and interrelatedness with other more directly related factors.

Living Environment Deprivation

This domain was the most salient in the 2008 cross-sectional analysis. It documents the proportion of people in neighbourhoods living in poor quality environments characterised by lack of access to running water, toilets and electricity. Overcrowding and shack dwelling are included here. Various mechanisms could account for why this kind of deprivation at neighbourhood level affects individual depression outcomes. It is likely that where a large percentage of houses lack these basic amenities, this may serve as a proxy for deprivation of other resources and facilities within these communities. The more direct effect of this could relate to feelings of heightened insecurity, danger and humiliation among community residents. In areas with high population density and lack of resources such as toilets in houses and adequate lighting, the living environment lends itself to crime and violence (Schonteich & Louw, 2001). Robins (2014) highlights the "inextricably intertwined sanitation, safety and dignity issues" (p.494) that confront residents in Khayelitsha township daily. Such characteristics are prevalent in many South African townships where levels of violent crime are very high (Lemanski, 2004). Other possible ameliorative factors like street lighting or proximity to public services such as police stations or health care facilities are also likely to be lacking in these neighbourhoods. Evidence from studies in the Northern Cape Province indicated that women viewed having electricity and lighting in their neighbourhood as the most important factor in improving their living conditions as it reduced their susceptibility to crime, physical violence and sexual assault (Louw & Shaw, 1997; Schonteich & Louw, 2001). The appearance of a neighbourhood that constantly reminds its residents of pervasive poverty and a threatening environment is likely to cause stress in the individuals living there and contribute to mental ill-health (Ross, 2000; Sampson, 2002).

Composite Index of Multiple Deprivation in Neighbourhoods

Some useful direction can be found in the substantial body of sociological literature and theorising which can assist in elucidating some of the social processes and mechanisms that affect health outcomes like depression. Sampson and colleagues (2002) propose that two fundamental social processes operating at the neighbourhood level can be classified as 'social capital' and 'norms and collective efficacy'. Social capital can be seen as consisting of cognitive, structural, bonding, bridging and linking mechanisms amongst social groups (Lund, Stansfeld & De Silva, 2013). Norms and collective efficacy can be seen in the degree of mutual trust in communities and the extent to which expectations about neighbourhoods are shared among residents (Sampson et al., 2002). These factors will in turn contribute to the willingness of community members to intervene in situations of crime or where other community members are in need of assistance. In essence, social cohesion in neighbourhoods regulates levels of informal social control and solidarity. High levels of neighbourhood social capital and its cognitive component, social cohesion, have consistently shown protective qualities for a variety of health outcomes, including common mental disorders and depression (Almedom, 2005; Macinko & Starfield, 2001; Ross, 2000). In South Africa, work that utilised NIDS depression and survey data identified a negative association between neighbourhood social capital and individual-level depression (Tomita & Burns, 2013).

However, the results of the present study may indicate that concentrated levels of deprivation, disadvantage and economic exclusion make it very difficult to foster the social capital, cohesion and collective efficacy that can protect residents from the stressors associated with physical and mental ill-health (Sampson et al., 2002).

Limitations

This section will outline some of the limitations of this study and some more general limitations associated with this area of inquiry. The first potential limitation is that the SAIMD modelled at datazone level are still classified by CASASP as ‘experimental statistics’ because they are based on modelled estimates (Noble, Dibben & Wright, 2010). This is because the statistics were based on the 2007 Community Survey. This survey is only considered robust down to municipality level as the 2001 census data was very outdated. As such, the research team used a combination of direct and synthetic estimation techniques in order to construct best linear unbiased estimators (Noble, Dibben & Wright, 2010). This notwithstanding, the statistics have been validated in an urban setting, and the City of Johannesburg has used them to inform local policy (Wright, 2014).

Secondly, it must be acknowledged that this work refers to symptoms of depression rather than a formal diagnosis with a cut-off score. Increasing scores indicated increases in depressive symptoms. Most of the literature suggests that the CES-D10 measure conceptualises depression on a continuum of well-being (Radloff, 1977; Wood et al., 2010). Certain studies have used a cut-off score of 10 and above to indicate depressed cases, but this has not been validated in South Africa or any other LMIC.

A third limitation is the lack of inclusion of a ‘neighbourhood tenure’ variable. Regrettably NIDS did not include a direct question about how long residents had been living in their particular neighbourhood. Efforts were made to derive a ‘tenure’ variable using other variables in the dataset but unfortunately this resulted in a large reduction in the sample size because of missing data and data inconsistencies. Thus inclusion of a ‘tenure’ variable in the models was not feasible. Without a tenure variable it is not possible to investigate cumulative exposures and lagged effects (Diez Roux, 2007). Questions relating to the length of time necessary for neighbourhood conditions to influence health outcomes could not be explored comprehensively without this variable.

Fourthly, though results indicated that an urban environment was positively associated with depression, it was not possible to investigate whether or not the relationship between deprivation at the neighbourhood level primarily affects depression in urban environments, as has been illustrated in other studies (Petersen et al., 2009; Rudolph et al., 2014). The reason was that certain datazones had too few sampled residents for the statistical software to conduct an appropriate moderator analysis.

Fifthly, a cross-sectional analysis limits any discussion of causality. This area of research would benefit greatly from longitudinal studies which can address same-source bias and reverse causation issues (Mair et al., 2008) (see Appendix B for reasons why this was not pursued in the present study). Another benefit of the longitudinal design is its ability to explore time lags and cumulative effects of neighbourhoods on depression (Diez Roux, 2007).

Finally, it must be acknowledged that even though multiple deprivation indices represent a far more sound proxy for relevant neighbourhood-level constructs than simple aggregated income proxies, they remain rather limited substitutes for the actual features of neighbourhoods, both physical and social, that are assumed to influence health outcomes (Diez Roux, 2007).

Future Directions for Research

This field of inquiry still lacks a comprehensive theoretical framework to guide the trajectory of research, as most work has been of a purely applied nature. As has emerged from the discussion, there is a need to move beyond using proxies and to begin carefully operationalising and investigating the specific neighbourhood constructs that are believed to affect well-being. In colloquial terms – we need to get down to the 'nitty gritty' of how neighbourhoods actually impact on the health of their residents. Almost all research in this domain has been quantitative and statistically rigorous, yet it seems that the area could benefit greatly from some mixed methods and qualitative inquiry in order to better understand and operationalise these neighbourhood mechanisms. There is also a need to embrace the multidisciplinary nature inherent in this work and collaborate with disciplines like Sociology, Anthropology, Economics and City and Regional Planning. Examples might be employing the sociological technique of systematic social observation in neighbourhoods (Sampson et al., 2002), or the relatively new GIS technique of gravimetric modelling that measures accessibility to resources within small areas (Giles-Corti & Donovon, 2002).

A natural progression that has emerged from this particular study is to explore whether social capital and, more specifically, social cohesion modifies the association between neighbourhood deprivation and mental health. Theory and evidence suggest that socially cohesive neighbourhoods facilitate informal social control which improves well-being of residents (Sampson et al., 2002). There is also evidence that mental ill-health is associated with area-level deprivation, but that this relationship is modified in cases of high social cohesion in neighbourhoods (Fone et al., 2007). Recently, research using NIDS data found significant negative associations between neighbourhood social capital and depression (Tomita & Burns, 2013). Following on from the significant association found between neighbourhood-level deprivation and depression in this study, it seems logical to explore how neighbourhood social capital and deprivation interact in relation to depression.

This study, carried out on a nationally representative sample, provides empirical support for the relationship between neighbourhood deprivation and depression. Hopefully this will generate impetus for further inquiry into the relationship between neighbourhood variables and a range of other important health outcomes in South Africa.

Implications for Practise

At the opening address to the1989 Organisation for Appropriate Social Services in South Africa (OASSSA) conference, Joel Kovel (1990) – an American psychiatrist and author– argued cogently that:

> This is the goal of any organisation such as OASSSA – to overcome the tendency to see things in terms of two separate realms, a world of mental illness on the one hand, and of social deprivation on the other (p.16).

Though South Africa is a very different place 25 years later, this statement remains as pertinent now as it was then. Various forms of deprivation clearly have effects on mental health outcomes. Policy makers need to incorporate this understanding into their intervention strategies. Policy should be integrated across disciplines in order for interventions to be most effective. Strategies that have not traditionally been considered health-based, like housing and urban planning are likely to contain important cross-fertilisations for health outcomes. Neighbourhoods are the units in which these strategies become actualised, in terms of the roll-out of integrated policies (Diez Roux, 2007). Providing neighbourhoods with adequate services and resources such as street lighting, water, electricity and access to public transport could all have potentially beneficial implications for mental health outcomes in a ‘preventive’ way. A possible complementary approach could be to bolster neighbourhood access to mental health services in deprived communities, as well as developing and supporting their social support systems. Existing NGOs, religious support networks and sport and recreational facilities are possible areas that could benefit from support. Assisting these grassroots networks with training and practical communal resources and facilities could have a meaningful impact on deprived communities suffering high rates of mental ill-health. This may operate in an interactive or reciprocal fashion in relation to neighbourhood factors, in that community-based mental health interventions can lead to economic improvements at individual and household levels (Lund et al., 2011) and ultimately at neighbourhood levels.

Conclusion

Do the neighbourhoods we live in affect our mental and physical health? Does living in a deprived neighbourhood have negative health consequences? This study addressed these questions by exploring the association between neighbourhood deprivation and depression in a nationally representative sample of South African adults. This is the first empirical investigation into this relationship in an African country and is one of very few in LMICs. It is also the first application of the SAIMD in the prediction of mental health outcomes. The results support the hypothesis that there is a strong association between living in a more deprived neighbourhood and the mental ill-health of the residents, even after individual-level covariates have been controlled for. This has demonstrated the existence of a key relationship for public health research and should be seen as a precursor to further investigation into the specific neighbourhood mechanisms that drive this process, such as social cohesion, physical resources and structures, or collective efficacy. Within the purview of research into poverty and mental health, this study illustrates another benefit of structural poverty alleviation and effective service delivery to policymakers.

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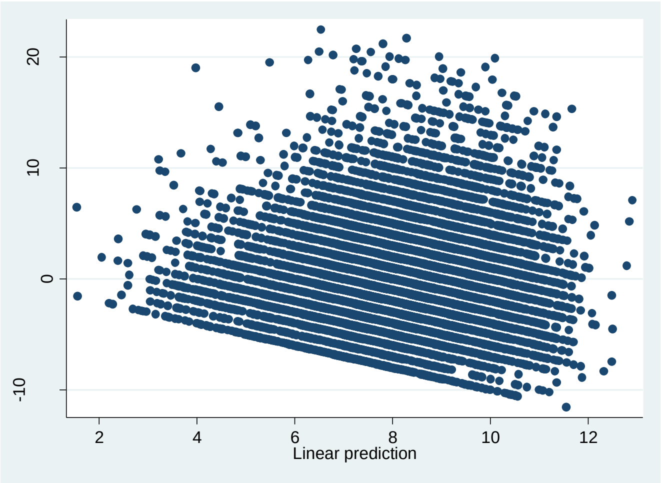
Appendix A

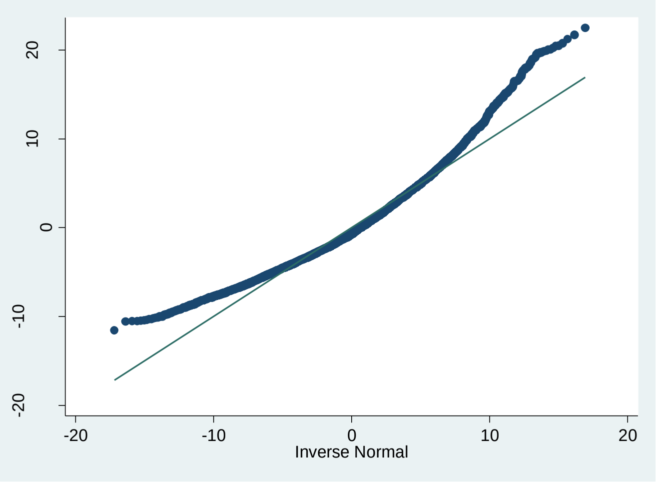
Assumptions for Linear Model:

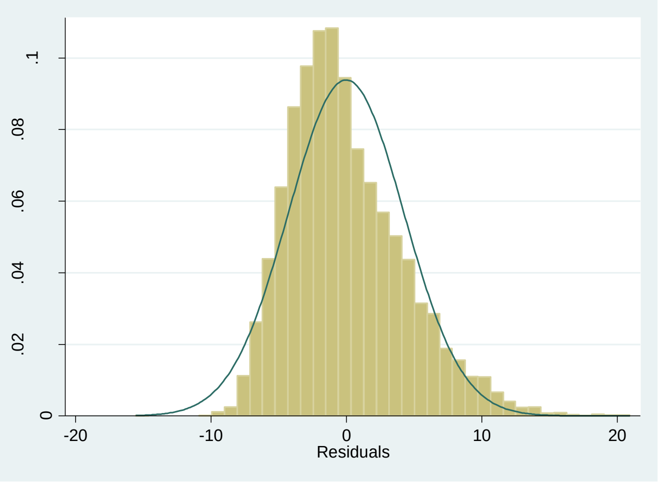
Composite Deprivation Index (Model 1)

Non-heteroscedasticity: There appears to be some sort of lower bound on this scatter plot. This could indicate a consistent lower or upper limit that is being overestimated in the model. However this is still sufficient to fulfil the assumption of normality.



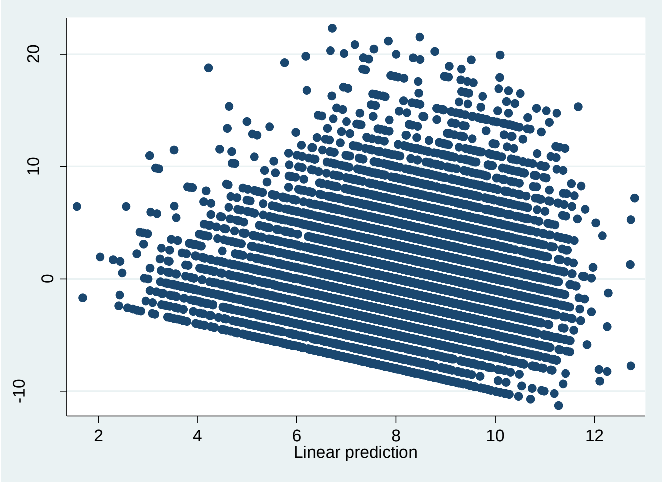
Normality: There is a slight departure from normality evident in the qq plot and histogram below. The upper and lower portions are moving away from the line in the qq plot and this is manifests in the slight right skewness in the histogram. Overall, however, the patterns of residuals are sufficient to fulfil the requirements of normality for the models.



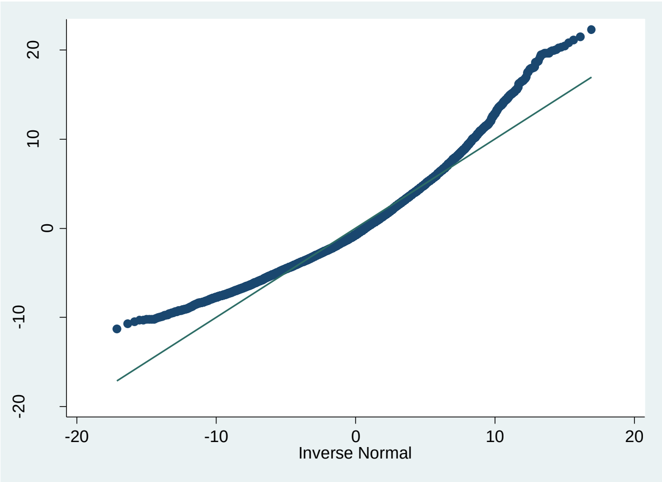


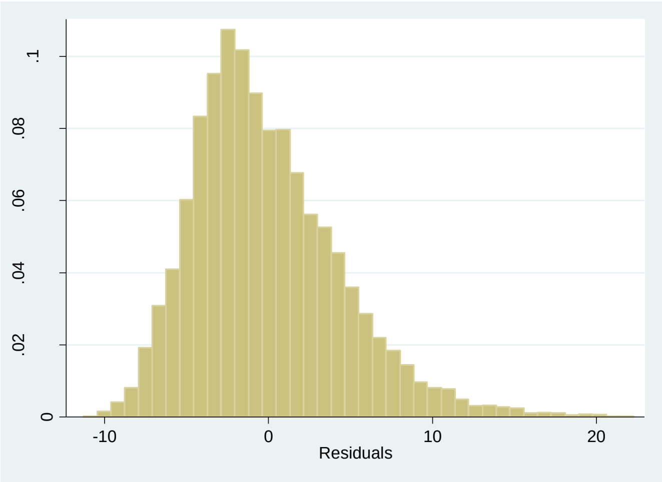
Income and Material Deprivation Index (Model 2)

Non-heteroscedasticity:



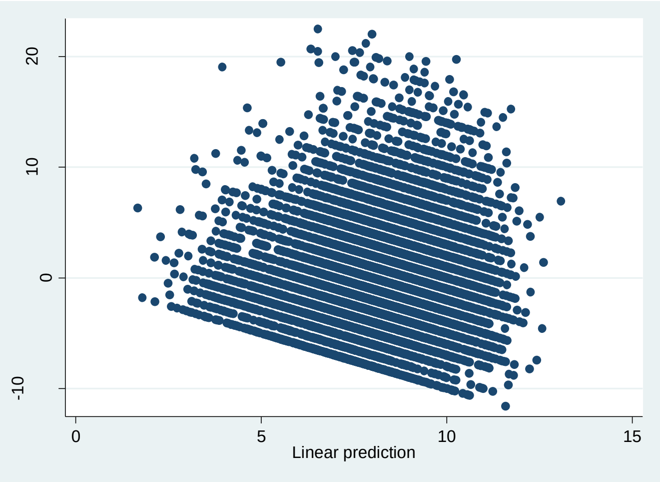
Normality:



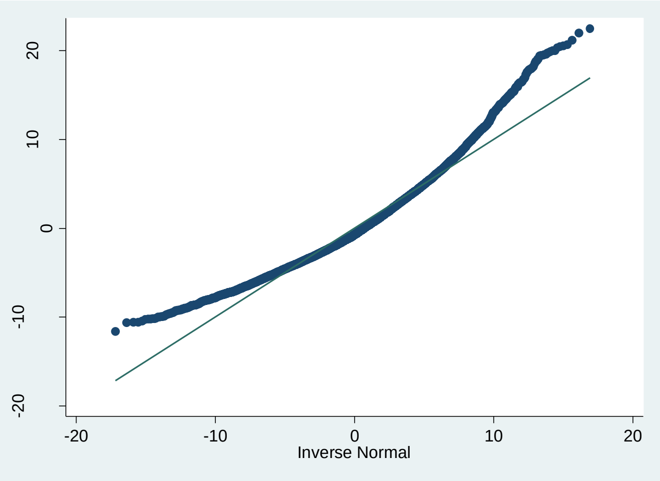


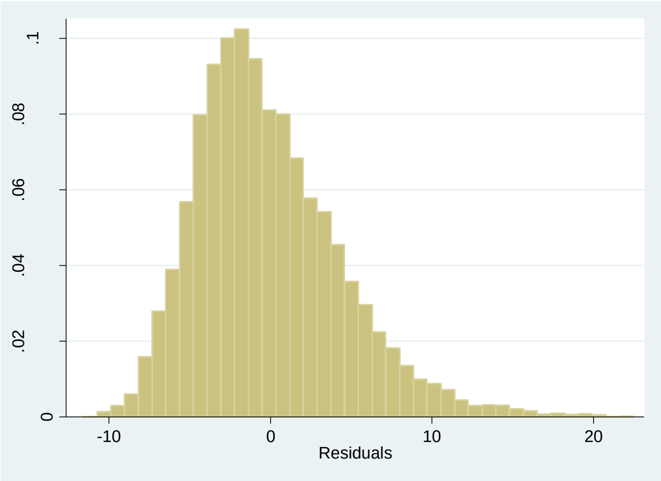
Employment Deprivation Index (Model 3)

Non-heteroscedasticity:



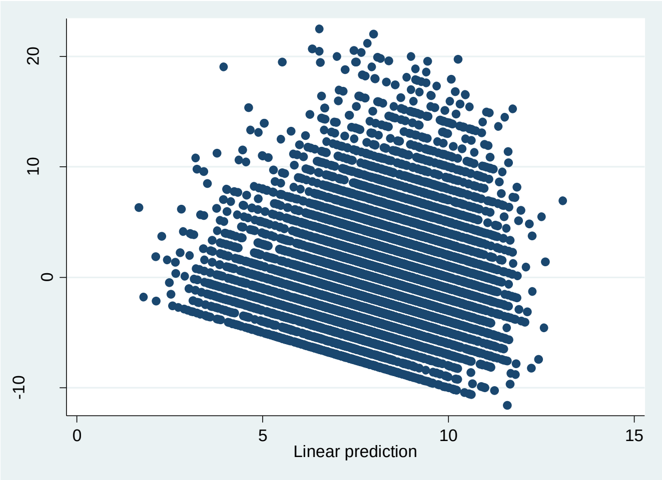
Normality:



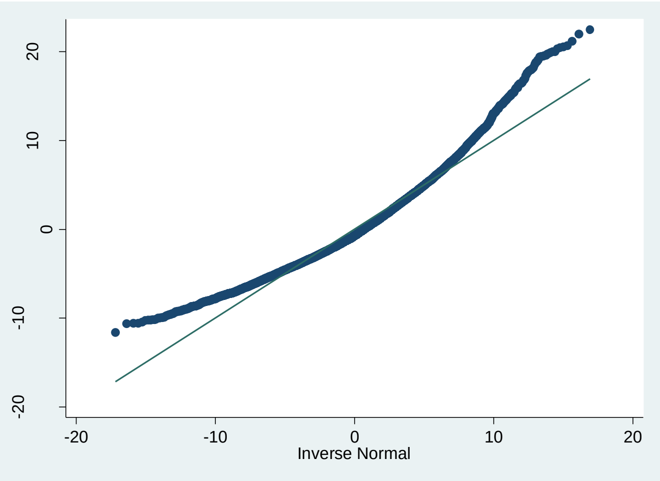


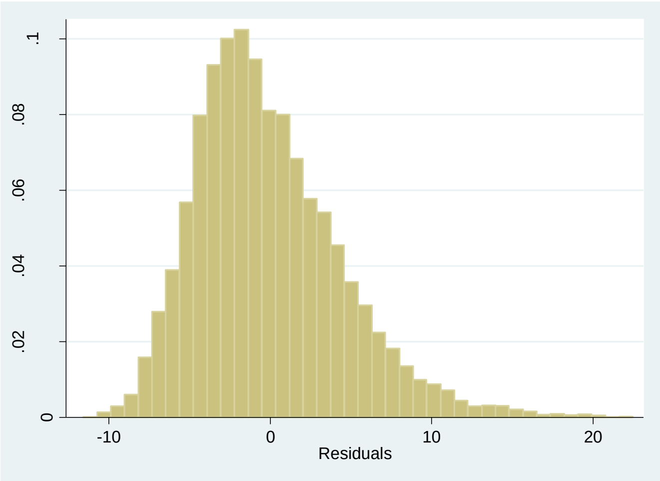
Education Deprivation Index (Model 4)

Non-heteroscedasticity:



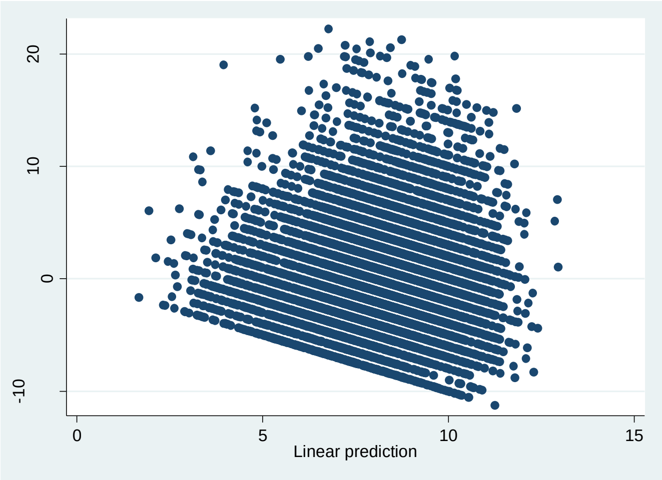
Normality:



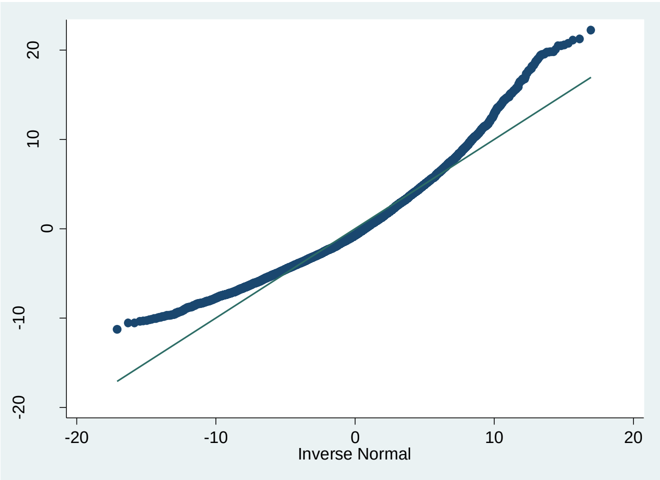


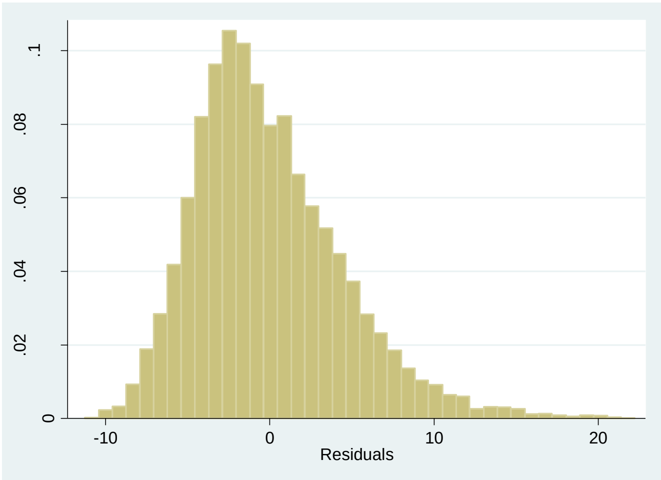
Living Environment Deprivation Index (Model 5)

Non-heteroscedasticity:



Normality:





Appendix B

Data was available from NIDS for 2012, and as such the possibility for a longitudinal analysis of the data presented itself. However, there seemed to be some quite striking changes in relationships between depression scores and certain covariates between the two time points, and these raised concerns. Thus it was decided that a cross-sectional study on the 2008 data would be preferred to a longitudinal design due to concerns with the 2012 data. Certain covariates that are very well established in depression literature, such as gender, were very strong in 2008 but completely disappeared in the 2012. This appendix will discuss some steps that were undertaken in systematically attempting to identify the source of error or reason behind the changes.

A possible account for this error could have been the difference in the sample from 2008 to 2012. Only 9,931 of the 11,955 individuals included in the 2008 models were sampled again in 2012. To test whether this was the source of the error, bivariate regressions for both time points were run only on the group of individuals for whom there was data from both time points. However, for the identical group of individuals, some stark incongruities remained for certain covariates.

Errors or major changes in the demographic characteristics of the sample between the two time points needed to be eliminated as a potential possibility. Initial comparisons of the descriptive statistics of the large 2012 sample and the smaller 2012 sample did not reveal any particularly arresting changes between any of the socio-demographic variables. T-tests were run on certain variables to see if any differences were significant, but only the ‘unemployed discouraged’ category of the employment status variable had changed significantly between the waves. The demographic characteristics had in the sample had not changed in any way that could account for the unexpected relationships.

The unexpected relationships between CES-D10 scores and a range of demographic and individual socioeconomic variables that we know have a strong relationship with depression such as gender, age, education, employment status were explored at the bivariate level. The literature suggests that being female, older, less educated and unemployed are some of the most consistent risk factors for depression. In 2008 all of these relationships reflect very strongly in the models. However in 2012, they all lose power and significance. The bivariate associations between demographic variables and depression at each of the two time periods are displayed in Table 7. The most drastic change is observed in the gender effect, which was

B= -0.84(0.14), p<0.0001 in 2008, and changed to *B*= -0.25 (0.15), p=0.10 from in 2012. Age also loses a large amount of significance, but only just remains significant at the 5% level, *B*= 0.026(0.004), p<0.0001 in 2008, which changed to *B*= 0.013 (0.006), p=0.034 in 2012. Another stark change is seen with the employment status category. Being strictly unemployed in 2008 was a very strong predictor of higher depression (p<0.0001), however, at the bivariate level this changed to p=0.044 in 2012, while being 'not economically active' became a much stronger predictor of high depression between the two time points, B=0.67(0.16) in 2008 to B=1.30 (0.20) in 2012. Education became less significant, but still retained a large degree of its predictive capacity.

Table 7

Weighted bivariate associations between 2008 and 2012 CES-D10 scores and certain individual-level independent variables(N=9931)

CES-D10	*B*	*SE*	t-value	*P>t*
Gender (Male)				
2008	-0.84	0.14	-6.49	<0.0001
2012	-0.24	0.15	-1.64	0.102
Age				
2008	0.026	0.004	5.51	<0.0001
2012	0.013	0.006	2.22	0.034
Employment Status (employed)				
2008				
Not economically active	0.67	0.16	3.52	<0.0001
Unemployed discouraged	0.37	0.31	1.22	0.22
Unemployed strict	1.36	0.24	5.23	<0.0001
2012				
Not economically active	1.30	0.20	6.55	<0.0001
Unemployed discouraged	0.12	0.56	0.22	0.82
Unemployed strict	0.48	0.24	2.02	0.044
Education (Gr 9 or more)				
2008	-1.67	0.17	-10.09	<0.0001
2012	-1.34	0.16	-8.28	<0.0001

Note. Beta coefficients (standard errors) from linear regression; a higher CES-D10 score represents more depressive symptoms, therefore a positive coefficient implies more depressive symptoms and a negative coefficient fewer depressive symptoms

The next step was to assess the CES-D10 depression measure to see if this could explain the data inconsistencies. The alpha level dropped from 0.74 (0.18) in 2008 to 0.64 (0.13) in 2012. This is quite a substantial drop in the internal consistency of the instrument. Thus the items were explored in order to try and improve this low alpha. When the two positively worded items were removed from the measure, the alpha improved to 0.74(0.19). The bivariate regressions were then run on this new 8-item scale to see whether this changed the pattern of the data to accord with the 2008 results, and general depression literature. However, even with the improved alpha level, the inconsistencies persisted in the data between the two time points, as displayed in Table 8.

Table 8
Weighted bivariate associations between 2012 CES-D8 scores and certain individual-level independent variables(N=9937)

CES-D8	*B*	*SE*	t-value	*P>t*
Gender (Male)	-0.25	0.13	-1.9	0.06
Age	0.008	0.005	1.5	0.13
Employment Status (employed)				
Not economically active	0.74	0.17	4.36	<0.0001
Unemployed discouraged	-0.40	0.44	-0.91	0.36
Unemployed strict	0.26	0.22	1.20	0.23
Education (Gr 9 or more)	-0.87	0.16	-5.53	<0.0001

Note. Beta coefficients (standard errors) from linear regression; a higher CES-D8 score represents more depressive symptoms, therefore a positive coefficient implies more depressive symptoms and a negative coefficient fewer depressive symptoms

It is puzzling that the gender effect, age effect and effect of employment status change so distinctly in the four years that elapse between data collection. It is hard to believe that in this short period one of the most consistent findings in depression literature - that women are significantly more prone to depression than men - has been overturned. As such, it may be worth considering some alternative possibilities for these results. The length of the adult questionnaire which contains the CES-D10 measure should be considered for possible fatigue effects, particularly given that the 'depression' scale is administered very late in the interview schedule. Particular attention should also be paid to the difference between the overall NIDS questionnaire in 2008 and 2012, as a number of new sections were added. Another option could be to explore how depression scores vary by fieldworker to see if any unusual patterns emerge that might suggest expedient falsification of data. It is very important for the NIDS team to investigate this issue and take the necessary action to resolve it and improve the CES-D10 instrument's efficacy in further waves.