Case Study

Immigrant maternal depression and social networks. A multilevel Bayesian spatial logistic regression in South Western Sydney, Australia

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\textbf{A B S T R A C T}

The purpose is to explore the multilevel spatial distribution of depressive symptoms among migrant mothers in South Western Sydney and to identify any group level associations that could inform subsequent theory building and local public health interventions. Migrant mothers (n = 7256) delivering in 2002 and 2003 were assessed at 2–3 weeks after delivery for risk factors for depressive symptoms. The binary outcome variables were Edinburgh Postnatal Depression Scale scores (EPDS) of >9 and >12. Individual level variables included were: financial income, self-reported maternal health, social support network, emotional support, practical support, baby trouble sleeping, baby demanding and baby not content. The group level variable reported here is aggregated social support networks. We used Bayesian hierarchical multilevel spatial modelling with conditional autoregression. Migrant mothers were at higher risk of having depressive symptoms if they lived in a community with predominantly Australian-born mothers and strong social capital as measured by aggregated social support networks. These findings suggest that migrant mothers are socially isolated and current home visiting services should be strengthened for migrant mothers living in communities where they may have poor social networks.

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1. Introduction

We have previously reported on individual level psychosocial predictors of postnatal depression in South Western Sydney (Eastwood et al., 2011) and proposed that the findings were consistent with group-level socioeconomic deprivation, neighbourhood environment, social capital and ethnic diversity having causal effects on postnatal depressive symptomatology and other perinatal outcomes. In that study migrant mothers had a higher risk of depressive symptoms.

The finding is consistent with previous individual-level studies of maternal depression among recent migrants to Australia (Brown and Lumley, 2000; Brown et al., 1994;
Lansakara et al., 2009; Williams and Carmichael, 1985). Of direct relevance to this study are the findings of Stuchbery colleagues (1998) who undertook a study of Vietnamese, Arabic and Anglo-Celtic mothers in South West Sydney specifically to examine which deficits in their social support network were associated with postnatal depression among mothers of a non-English speaking background. Among Vietnamese mothers low mood was associated with a poor quality relationship with their partner and a perceived need for more practical support from him. For Arabic women low mood was associated with a perceived need for more emotional support from their partners. The authors noted the importance of postnatal rituals which involve support from extended family. In their study 64 percent of Vietnamese and 61 percent of Arabic women did not have their mothers with them.

In an analysis of 70 studies on culture and postnatal depression social support was identified as important. Specifically the review highlighted the importance of the woman’s perception of support (Bina, 2008). It is apparent that for migrant women expectations and availability of support plays an important role in relation to depressive symptoms at least at the individual level.

There is strong empirical evidence to support the proposition that individual-level social networks protect mothers from depression (Beck, 2001; Bennett et al., 2004; Cox et al., 1987; Gottlib et al., 1991; O’Hara and Swain, 1996; O’Hara, 1995; O’Hara et al., 1984; Seguin et al., 1999; Zajicek, 1981). Little is known, however, of the role played by group-level social networks, or social capital. At the aggregated level social networks, or social capital, is a group attribute that makes available certain types of resources (i.e. information, instrumental resources and social reinforcement) to members of the group, or community. Members of the group may, however, also be denied access to those resources. Of interest to us, therefore, was the role that may be played by group-level social networks in predicting depressive symptoms among migrant mothers (Kawachi et al., 2008b, p. 3).

The study reported here uses multilevel Bayesian hierarchical spatial modelling techniques to explore spatial relationships between aggregated postnatal depressive symptoms and aggregated social support networks among migrant mothers, while controlling for individual level covariates. The study is part of a critical realist mixed method program of research that aims to build a theoretical model of the mechanisms by which multilevel factors might influence the developmental origins of health and disease.

2. Methods

2.1. Study design

The analysis reported here is part of an exploratory ecological study of aggregated rates of self-reported postnatal depressive symptoms in South Western Sydney Area Health Service from 2002–2003. The main 2002–2003 study ($n = 15,389$) utilises a sub-sample of a larger dataset collected from 1998–2006. The study included: individual level logistic regression (Eastwood et al., 2012b), cluster analysis (Eastwood et al., 2013a), ecological factor analysis, visualisation of maps of co-variants, ecological likelihood and Bayesian linear regression (Eastwood et al., 2013b), and Bayesian spatial and multi-level analysis. The results of a multilevel Bayesian spatial analysis of migrant mothers ($n = 7256$) are reported here. There were no significant findings in the multi-level analysis of Australian-born mothers.

2.2. Study setting

The setting is all suburbs in four local government areas (LGAs) in South West Sydney, New South Wales, Australia. The individual-level data available for study was coded by suburb of residence. The suburb of residence was chosen as the closest group-level administrative unit to naturally occurring local neighbourhood environments. There were 101 suburbs available to study using the 2001 Census maps.

The area has a diverse multicultural population with 28.4% of the population born overseas compared with 17.8% for the rest of NSW. Twenty percent of infants are born to women from South East, North East or Southern Asia. The area also has substantial social disadvantage with lower education attainment and lower income levels than other parts of NSW. Based on composite socio-economic indices, approximately two-thirds of the area is significantly disadvantaged.

2.3. Outcome variable

From 2000 a routine survey of mothers with newborn infants, the Ingleburn Baby Information System (IBIS), was commenced. The survey included the Edinburgh Postnatal Depression Scale (EPDS) (Cox et al., 1987), which has been widely used to study individual-level maternal perinatal depressive symptoms. The EPDS was administered at the time of first well baby visits. Both EPDS >9 and EPDS >12 are supported by previous studies as screening cut-off points in English-speaking populations (Buist et al., 2002; Cox et al., 1987) to indicate need for further assessment and, with EPDS >12, to signal the probability of meeting formal diagnostic criteria for depressive illness. The EPDS has been validated for a number of other languages and ethnic groups (Cox and Holden, 2003). South Western Sydney studies have found that Vietnamese and Arabic translations of EPDS were acceptable to the women and appear to be suitable screening instruments for distress and depression (Barnett et al., 1999). In this study the EPDS was administered to non-English speaking mothers through interpreters.

2.4. Individual level independent variables

The IBIS survey contains 45 items which are both clinical (e.g. weight) and parental self-report in nature. Forty variables were selected for exploratory data analysis based on prior knowledge, the findings of published research and the findings of the qualitative arm of the main study. The individual level covariates included in the multilevel models were those identified in the final parsimonious models.
of individual level likelihood-based logistic regressions (Eastwood et al., 2012a). For analysis of an outcome of EPDS >9 they are: financial income, self-reported maternal health, social support network, emotional support, practical support, baby trouble sleeping, baby demanding and baby not content. For analysis of an outcome of EPDS >12 they are: financial income, self-reported maternal health, social support network, emotional support, baby trouble sleeping problem, and baby demanding.

2.5. Group level independent variable

The selection of group level variables for analysis was principally influenced by concepts emerging from interviews with experienced maternal and child health practitioners, group interviews with mothers of infants and latent variables identified in individual level non-linear principal component analysis (Eastwood et al., 2012b). The domains assessed as measurable at the suburb level were: social networks, capital and cohesion; "depressed community", health behaviours, access to services and ethnic segregation or integration.

2001 Census data were used for the majority of the group level candidate variables. NSW crime statistics and aggregated individual level study data were also used. At the suburb level there was an extensive range of possible variables in the 2001 Census dataset. We used the derived Index of Relative Social Deprivation (IRSD) (ABS, 2002) and the Index of Concentrated Extremes (ICE) (Massey, 2001) as two indices of disadvantage. For concepts such as social cohesion and social capital, there were no candidate variables in the census data. We therefore used aggregated variables (social networks and "no regret leaving suburb"), while acknowledging the possibility of same-source bias identified by Radenbush and others (Duncan and Radenbush, 1999; Radenbush and Sampson, 1999) cited by O’Campo (2003). Three measures of ethnic diversity were analysed as recommended by Galster (2004) namely the Diversity Index (Maly, 2000), Entropy Index (Modarres, 2004) and the Simpson’s Index (Simpson, 1949). We will report in this study on the Maly Index.

Forty seven candidate group-level variables were analysed using exploratory factor analysis, likelihood OLS linear regression and univariate and multivariate Bayesian spatial regression (Eastwood et al., 2013b). Thirty one of those empirical variables and six latent variables from the factor analysis were analysed using Bayesian spatial multilevel regression (see Supplemental Table).

2.6. Visualisation

We visually examined maps of standardised morbidity ratios (SMRs) of aggregated EPDS and Bayesian spatial autocorrelation smoothed relative risks. Open domain software SaTScan (Kulldorff et al., 1998) was used to test for the presence of clusters of EPDS >9 and EPDS >12 (Eastwood et al., 2013a). Visualisation also included the mapping of the spatial distribution of the candidate group level variables (Eastwood, 2011). We will report here the visual spatial distribution of migrant mothers, aggregated social support networks and EPDS.

2.7. Statistical analysis

A three stage multilevel modelling strategy was used as described by Macnab et al. (2004). The strategy begins with a simple null model and proceeds to include individual factors, group-level factors, and unexplained variability. Congdon (2006) notes that structured conditional autoregressive (CAR) variation is appropriate when subjects are clustered by neighbourhood and β is spatially correlated. We therefore used Bayesian hierarchical spatial modelling with CAR for the multilevel studies as used by Wong and colleagues (Wong et al., 2009). The conditional autoregressive (CAR) component used data from an adjacency matrix for the study area which was generated using the Adjacency Tool in GeoBUGS 1.1. (Spiegelhalter et al., 2003)

The modelling strategy first identified a parsimonious logistic regression model at the individual level using a frequentist approach. The covariates thus identified where then fitted using a Bayesian logistic regression model in WinBUGS (Spiegelhalter et al., 2003) with non-informative priors for the intercept and parameters (Model 1). We assumed the outcome distribution to be Bernoulli where:

Model 1  Logit(p) = a0 + a1 * X1 + a2 * X2 + a3 * X3

Model 1 was fitted introducing each covariate sequentially. Having fitted the logistic regression at the individual level we then added a random intercept effect at the suburb level (Model 2) where the prior distribution for the random intercept was given a normal distribution.

Model 2  Logit(p) = a0 + a1 * X1 + a2 * X2 + a3 * X3 + a[area]

To take into account the spatial correlation of the suburbs we then added a CAR prior to the suburb level random intercept. Having assessed the models with suburb level random intercepts we proceeded to introduce suburb level covariates. Each covariate was fitted separately.

We used the Deviance Information Criterion (DIC) to assess and compare models. Smaller values of DIC indicate better fitting models. To compare DIC values we carried out several runs using different initial values and random-number seeds (Spiegelhalter et al., 2002). Based on the results we chose to distinguish between models where the DIC varies by more than one. In the results tables we also report the pD which is the number of effective parameters in the model. A comparison of DIC suggested that the spatial models (Model 2 with spatially structured random effects) were better supported by the data. As expected the numbers of effective parameters for all the CAR models were less than expected (Law and Haining, 2004). Significance was assessed as nonzero regression coefficients at 95% credible interval. The covariate, that when added, resulted in the largest decrease in DIC was then analysed together with each of the remaining covariates. The process was repeated by adding further covariates until the DIC could be reduced no further. The final Model(s) are reported for: IRSD, ICE, Maly Index and aggregated no social support network.
The specification of priors for the parameters is important in Bayesian inference. There have been no previously reported Bayesian studies of postnatal depressive symptoms; and therefore for the intercept we used a “vague” prior with a normal distribution, a mean of zero and large variance $N(0, 10,000)$. For the variance or precision of the random effects we used the commonly used hyper-prior of Gamma $(0.5, 0.0005)$ as recommended by Kelsall and Wakefield (2002). Sensitivity analysis was undertaken.

All models assessed were run using two chains simultaneously. The initial burn in was 5000 iterations. As previously, convergence was monitored by visual examination of the trace plots of the samples for each chain, autocorrelation graphs, and the Gelman–Rubin convergence statistic. Convergence had occurred by 5000 iterations in all cases. These samples were discarded as “burn-in”. Each chain was then run for a further 5,000 iterations, giving 20,000 samples (10,000 from each chain) with acceptable Monte Carlo (MC) errors (less than 5% of the sample posterior standard deviation). These samples were used to generate the posterior distributions from which the estimates of the parameters are obtained.

We used the map decomposition strategy developed by Law and Haining (2004) to visualise the results of the best fitting models. The map decomposition method allows separate mapping of the contribution made by the explanatory covariate variables, spatial clustering, and heterogeneity. Unlike spatial linear regression, the spatial logistic regression model will not allow for the specification of an unstructured heterogeneity term. The map decomposition method thus allows separate mapping of the explanatory variable and residual spatial clustering.

The individual level likelihood-based logistic regression was undertaken using SPSS 17. All Bayesian analysis was undertaken in WinBUGS 1.4 (Spiegelhalter et al., 2003). The relative risks were mapped using ArcGIS 3.2 (Environmental Systems Research Institute, 2008).

2.8. Ethics approval

The study obtained ethics approval from the Human Research Ethics Committee, South Western Sydney Area Health Service and from the University of NSW Human Research Ethics Committee.

3. Results

Fig. 1 shows the distribution of mothers born in Australia and those not born in Australian. The IBIS data is for the years 2002–2003. The highest concentration of Australian born mothers is in the southern and south eastern areas (Fig. 1a). The highest concentration of mothers not born in Australia is in the northern areas (Fig. 1b).

Fig. 1. Distribution of (a) Australian born mothers, (b) Not Australian born mothers, IBIS Data 2002–2003.
Fig. 2 maps show the Relative Risks of the two ecological Bayesian CAR models. The relative risk of EPDS >12 for Australian-born mothers is greatest in the northern and southern areas (Fig. 2a). The relative risk of EPDS >12 for mothers not born in Australia is greatest in the south (Fig. 2b).

Fig. 3 shows the spatial distribution of mothers reporting no social support network. The highest rates are in the northern suburbs.

3.1. Spatial multilevel logistic regression

The multilevel Bayesian Model described was fitted to the population sample of mothers not born in Australia (n = 7256). Table 1 show the DIC and pD values for individual level logistic models with covariates and for a model with suburb level CAR. The multilevel CAR models with covariates – aggregated No Support, IRSD, ICE and Maly Index are also shown.

The notable finding from the not born in Australia multilevel model is a large decrease in the DIC when the random effects CAR term was added indicating that there is between suburb variability. The covariates No Support and Maly Index both further reduced the DICs for both the EPDS >9 and EPDS >12 analyses. The covariate No Support had, however, a negative coefficient. We will examine this finding further. The two measures of social deprivation – IRSD and ICE both reduced the DIC significantly for the EPDS >9, but not EPDS >12 analyses.

3.2. Final reported EPDS >12 spatial multilevel not born in Australia with No Support as the fixed effect

We have elected to report here in detail the EPDS >12 Multilevel model with No Support as the suburb-level fixed effect. We have also provided map decomposition to enable visualisation which will contribute to interpretation.

Table 2 shows the posterior means for the intercept and covariate parameters in the multi-level model. The Monte Carlo (MC) errors are acceptable. The 95% coefficient credible interval for No Support does not include zero and is therefore a significant finding.

Table 3 shows the posterior means for the odds ratio of each covariate in the EPDS >12 Multilevel model. The odds of EPDS >12 were decreased in suburbs with increased loading of No Support. The 95% odds ratio credible interval for No Support does not include 1 and is therefore a significant finding.

The covariate No Support is a measure of weak social networks or weak social capital at the suburb level. The finding of a negative coefficient can be interpreted to mean that migrant women are less likely to be depressed in suburbs with weak social capital (i.e. northern suburbs) and
conversely they are more likely to be depressed in suburbs with strong social capital (i.e. southern suburbs).

### 3.3. Map decomposition

We have used “map decomposition” to visualise the results of the final model (Fig. 4). This allows for high and low areas of relative risk to be identified as well as an assessment of the contribution made by the covariates, and spatially structured random effects (no unstructured effects were possible).

To assist interpretation we have included the multilevel model with no suburb level fixed effect (Fig. 4a). Clustering of EPDS >12 can be seen in the southern suburbs in a similar pattern to that observed previously for non-Australian born mothers (Bayesian CAR model RR – Fig. 2b). Fig. 4b shows the final model and Fig. 4c the RR contribution from No Support. The unexplained spatial residual (Fig. 4d) is strongest in the southern suburbs. The implication is that covariates that would eliminate the spatial residual have not been included in the model and possibly have not been identified among the candidate variables.

### 4. Discussion

In our previous studies we have identified that migrant mothers were at higher risk of postnatal depressive symptoms and our cluster analysis, reported in this journal (Eastwood et al., 2013a), identified high rates of depressive symptoms in communities with a greater percentage of migrant mothers. Paradoxically visual examination of Figs. 1 and 2 identified that mothers not born in Australia had higher rates of depressive symptoms in communities with higher concentration of mothers born in Australia. The reverse was also true.

The spatial multilevel study reported here has found a significant contextual, or group-level, effect as evidenced by the falls in DIC when the suburb level CAR is added to the model. For less serious depressive symptoms (EPDS >9) there is an independent effect of suburb level social deprivation, which did not hold for the EPDS >12 analysis. The Maly Index of Neighbourhood Diversity also had an independent contextual effect on depressive symptoms indicating that suburbs with less ethnic diversity may be protective. We have focused in this study on the paradoxical finding that weak social networks may be protective at a group-level while it is well established that strong social support networks are protective at the individual-level.

As noted earlier, the strong association of depressive symptoms with the mother being born in a country other than Australia is consistent with previous Australian studies. Williams and Carmichael (1985) found in a Melbourne study that 35% of multi-ethnic, low socio-economic status mothers with infants had significant depression. This was greatest among recent immigrants. The finding has important implication for the delivery of maternal and child health services in South Western Sydney where a high proportion of migrants and refugees settle. The ethnic diversity in South West Sydney is not uniform with some migrant groups settling predominantly in certain suburbs and local government areas. We postulate that the degree of ethnic diversity in a community may moderate the association of country of birth with depressive symptoms. For example, communities with more homogenous ethnic mix might have lower rates of depressive symptoms if common culture and language affords a protective benefit.

In the study reported here we mapped the distribution in our IBIS dataset of mothers who were born in Australian and not born in Australia (Fig. 1). We have also mapped the smoothed Bayesian CAR relative risks for EPDS >12 for mothers born and not born in Australia (Fig. 2). Visual analysis of those maps clearly shows higher rates of depressive symptoms among migrant mothers living in communities with low rates of migrant mothers. Similarly Australian-born mothers are more likely to have depressive symptoms if they are living in the northern suburbs where there is a higher percentage of migrant mothers. For the main study (not reported here) we visually examined a range of candidate ecological variables that might contribute to our understanding of this phenomenon including: sole parenthood, volunteer rates, housing, income, schooling and ethnic diversity. Visualisation of the spatial distribution of the aggregated variable no social support networks suggested that the absence of strong social support networks at the group level might be protective for migrant mothers.

The main effect multilevel logistic regression model had a significant reduction in the DIC when the suburb level...
random intercept was added. In the stratified analysis this improvement in the model fit was not found for mothers born in Australia but was found for migrant mothers (Table 1). Similarly the addition of group level co-variants to the model for Australian mothers resulted in no reduction in DIC. These findings suggest that for Australian mothers the spatial distribution is mainly explained by variation in the distribution of individual level covariates and that the spatial distribution is predominantly a compositional effect.

By contrast for migrant mothers there appears to also be a contextual or ecological effect as demonstrated by the significant reduction in DIC when the suburb level random intercept was added. The addition of the aggregated variable, No Support, resulted in a further significant reduction in the DIC. Examination of the coefficients and odds ratios, in Tables 2 and 3 respectively, demonstrates that the group level covariate No Support has a protective effect. There is thus a clear inference that some of the contextual effect is due to either the protective effect of weak

### Table 1

<table>
<thead>
<tr>
<th>EPDS &gt;9 Models</th>
<th>pD</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual level models</td>
<td></td>
<td></td>
</tr>
<tr>
<td>a + FINSIT+b</td>
<td>1.923</td>
<td>5496</td>
</tr>
<tr>
<td>a + FINSIT + SPNET</td>
<td>3.007</td>
<td>5406</td>
</tr>
<tr>
<td>FINSIT + SPNET + SPEMO+</td>
<td>4.071</td>
<td>5375</td>
</tr>
<tr>
<td>FINSIT + SPNET + SPEMO + SPRAC</td>
<td>4.977</td>
<td>5361</td>
</tr>
<tr>
<td>FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP</td>
<td>6.251</td>
<td>5300</td>
</tr>
<tr>
<td>FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP + BDEMAND</td>
<td>6.806</td>
<td>5293</td>
</tr>
<tr>
<td>FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP + BDEMAND + BCONTENT</td>
<td>7.909</td>
<td>5278</td>
</tr>
<tr>
<td>FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP + BDEMAND + BCONTENT + HEALTH</td>
<td>8.950</td>
<td>5221</td>
</tr>
</tbody>
</table>

| Multi-level CAR models |      |     |
| +Suburb CAR | 26.386 | 5200 |
| +IRSD | 24.295 | 5198 |
| +ICE | 23.249 | 5198 |
| +Maly Index | 21.032 | 5197 |
| +Aggregated No Support (−ve coefficient) | 12.394 | 5198 |

| EPDS >12 Models |      |     |
| Individual level models |      |     |
| a + FINSIT+b | 1.887 | 3249 |
| a + FINSIT + SPNET | 3.047 | 3173 |
| FINSIT + SPNET + SPEMO+ | 4.040 | 3142 |
| FINSIT + SPNET + SPEMO + SPRAC | 5.043 | 3131 |
| FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP | 6.154 | 3093 |
| FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP + BDEMAND | 6.75 | 3091 |
| FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP + BDEMAND + BCONTENT | 8.048 | 3091 |
| FINSIT + SPNET + SPEMO + SPRAC + BTSLEEP + BDEMAND + BCONTENT + HEALTH | 9.172 | 3062 |

| Multi-level CAR models |      |     |
| +Suburb CAR | 18.498 | 3053 |
| +IRSD | 15.300 | 3054 |
| +ICE | 17.186 | 3053 |
| +Maly Index | 14.829 | 3051 |
| +Aggregated No Support (−ve coefficient) | 12.233 | 3049 |

**Legend:** EPDS (Edinburgh Postnatal Depression Scale), FINSIT (financial situation), SPNET (no social support network), SPEMO (no emotional support), SPRAC (no practical support), BTSLEEP (baby difficult sleeping), BDEMAND (baby demanding), BCONTENT (baby not content), HEALTH (poor self reported health), IRSD (Index of Relative Social Deprivation), ICE (Index of Concentrated Extremes), CAR (Conditional Autoregression), pD (Effective number of parameters in the model), DIC (Deviance Information Criteria).

### Table 2

| Coefficients for the covariates in the EPDS >12 “No Support” Model. |
|-----------------------------|-----------------|-----------------|----------------|----------------|----------------|
| Mean | SD | MC error | 2.50% | Median | 97.50% |
| Intercept | −2.697 | 0.072 | 0.00172 | −2.841 | −2.695 | −2.558 |
| Financial situation | 0.376 | 0.056 | 0.00001 | 0.267 | 0.375 | 0.485 |
| Social support | 0.236 | 0.043 | 0.00001 | 0.154 | 0.238 | 0.321 |
| Emotional support | 0.459 | 0.126 | 0.00212 | 0.216 | 0.461 | 0.706 |
| Practical support | 0.369 | 0.119 | 0.00217 | 0.140 | 0.370 | 0.600 |
| Baby trouble sleeping | 0.185 | 0.059 | 0.00128 | 0.067 | 0.185 | 0.297 |
| Baby demanding | 0.082 | 0.056 | 0.00116 | −0.029 | 0.083 | 0.190 |
| Baby not content | 0.078 | 0.052 | 0.00001 | −0.024 | 0.078 | 0.180 |
| Self-reported health | 0.330 | 0.054 | 0.00001 | 0.224 | 0.329 | 0.437 |
| No support network | −0.137 | 0.044 | 0.00121 | −0.225 | −0.138 | −0.050 |

**Legend:** SD (standard deviation), MC (Monte Carlo).
suburb-level social networks, or conversely a detrimental effect of strong suburb-level social networks. Of relevance to this analysis are the concepts of bonding and bridging forms of social capital. Kawachi and colleagues (Kawachi et al., 2008a) observe that “regardless of whether one subscribes to the social cohesion school of social capital or the network school, consensus now exists about the importance of distinguishing between bonding and bridging social capital”. Bonding social capital refers to resources that can be accessed within social groups whose members are alike in terms of their social identity. The term “bridging capital” is used to describe the process whereby resources are accessed by individuals and groups through their connections that cross class, race, cultural and other boundaries of social identity.

Bonding capital may have detrimental effects and a key to improving health may be increasing access to resources outside of immediate social milieu (Kawachi et al., 2008a). We consider here that the covariate No Support might represent a lack of bonding social capital at the group level. The reverse is strong bonding social capital which in our study would be found in the southern suburbs where migrant mothers are more likely to have depressive symptoms.

The impact of social capital on mental health has been recently reviewed by Almedom (2005), Almedom and Glandon (2008). Those reviews found that social capital could be both an “asset and a liability with respect to the mental health of those in receipt of and those providing services and other interventions”. The review included both individual level and ecological level studies but none of the studies reviewed were in relation to perinatal mental health.

Stafford and colleagues (2008) found no evidence of a main effect of social capital on mental health. For people living in deprived circumstances, however, an association between social capital (contact amongst local friends) and lower reporting of common mental disorders was found. Of relevance to the findings of this study was the finding that elements of bonding social capital were associated with higher reporting of common mental disorders. Similarly Caughy and others (Caughy et al., 2003; Ziersch and Baum, 2004), found that strong bonding ties within disadvantaged communities may be a detriment to the health of residents.

Little is known regarding the impact of bonding social capital upon migrants. As noted previously, Australian individual-level studies have found higher rates of maternal depression to be associated with lack of partner and family support (Chu, 2005; Nahas and Amasheh, 1999; Stuchbery et al., 1998). Studies of the mental health of migrants suggest a complex relationship between ethnic density, country of origin, social networks, and social capital and health outcomes (Pickett et al., 2009; Seeman, 2011).

### Table 3
Odds ratio for the covariates in the EPDS >12 “No Support” Model.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Mean</th>
<th>SD</th>
<th>MC error</th>
<th>2.50%</th>
<th>Median</th>
<th>97.50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial situation</td>
<td>1.459</td>
<td>0.08158</td>
<td>0.00129</td>
<td>1.306</td>
<td>1.456</td>
<td>1.624</td>
</tr>
<tr>
<td>Social support</td>
<td>1.270</td>
<td>0.05471</td>
<td>0.00001</td>
<td>1.167</td>
<td>1.269</td>
<td>1.379</td>
</tr>
<tr>
<td>Emotional support</td>
<td>1.596</td>
<td>0.20220</td>
<td>0.00338</td>
<td>1.242</td>
<td>1.585</td>
<td>2.026</td>
</tr>
<tr>
<td>Practical support</td>
<td>1.456</td>
<td>0.17370</td>
<td>0.00322</td>
<td>1.149</td>
<td>1.447</td>
<td>1.823</td>
</tr>
<tr>
<td>Baby trouble sleeping</td>
<td>1.205</td>
<td>0.07107</td>
<td>0.00154</td>
<td>1.070</td>
<td>1.204</td>
<td>1.346</td>
</tr>
<tr>
<td>Baby demanding</td>
<td>1.087</td>
<td>0.06079</td>
<td>0.00126</td>
<td>0.972</td>
<td>1.086</td>
<td>1.210</td>
</tr>
<tr>
<td>Baby not content</td>
<td>1.083</td>
<td>0.05657</td>
<td>0.00101</td>
<td>0.976</td>
<td>1.081</td>
<td>1.197</td>
</tr>
<tr>
<td>Self-reported health</td>
<td>1.393</td>
<td>0.07634</td>
<td>0.00119</td>
<td>1.251</td>
<td>1.390</td>
<td>1.548</td>
</tr>
<tr>
<td>No support network</td>
<td>0.872</td>
<td>0.03882</td>
<td>0.00113</td>
<td>0.799</td>
<td>0.871</td>
<td>0.951</td>
</tr>
</tbody>
</table>

Legend: SD (standard deviation), MC (Monte Carlo).

Fig. 4. Decomposition of EPDS >12 Multilevel Regression with “No Support” as suburb level fixed effect.

4.1. Methodological matters

The individual level study used a secondary data source, with the variables available for study limited to those...
included in the IBIS questionnaire. Consequently we are unable to analyse variables that might have been included if the survey had been specifically designed for the study of postnatal depression. Selection bias may have occurred from refusal and non-response in the study population and depressed women may be less inclined to consent to participate. The EPDS response rate of 87 per cent at the first visit is high and sufficient for the purposes of this study. Recall, interviewer or responder biases may have been present in the survey data. A particular problem of self-reporting surveys is that they are influenced by the mental status of the subject. Depressed women are more likely to have a negative view of their circumstances.

The limitations of ecological studies in making inferences regarding individual-level associations based on group-level data are well established (Greenland, 1992). The findings of our ecological spatial regression (Eastwood et al., 2013b) suggested that mothers were more likely to have depressive symptoms if they lived in communities with weak social support networks. Those findings may have reflected a compositional effect. Multilevel studies such as that reported here enable the simultaneous examination of the effects of group level and individual level variables on individual level outcomes (Duncan et al., 1995). Causal inference is assisted by this approach.

For the assessment of social cohesion and social capital there were no candidate variables available from census data or the annual health survey. We used aggregated no social support network which may have been subject to same-source bias as identified by Radenbush and others (Duncan and Raudenbush, 1999; Raudenbush and Sampson, 1999).

The size (n = 15,389) of the main study of EPDS is significant. A recent Australian national study reported on 12,361 postnatal women who completed a postnatal EPDS (Buist et al., 2008). Fergusson and colleagues (1996) interviewed 9316 and other large studies have included samples less than 3000 women (NHMRC, 2000). With the exception of an area-level study of poverty and postpartum psychosis (Nager et al., 2006) we have found no previous published ecological or multilevel studies of perinatal depression.

Another strength of the current multilevel study is the use of Bayesian hierarchical approaches to spatial autocorrelation thus addressing the limitations of linear methods which treat each suburb as being independent of surrounding suburbs. The map decomposition strategy developed by Law and Haining (2004) also proved useful and in particular raised questions regarding the spatial distribution of unexplained components.

5. Conclusion

In our study migrant mothers were at higher risk of having depressive symptoms if they were living in a predominantly Australian-born, disadvantaged community, with strong bonding/social network social capital. These findings suggest that migrant mothers are socially isolated in these communities. The South Western Sydney region has a number of multicultural home visiting services. The implication of these findings is that multicultural home visiting support is also required for migrant mothers living in more communities where they may have poor social networks.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.sste.2013.04.003. These data include Google maps of the most important areas described in this article.

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