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RESEARCH PAPER

Spatial Heterogeneity and Subjective Wellbeing: Exploring the Role of Social Capital in Metropolitan Areas Using Multilevel Modelling

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Abstract

The role of social capital, the social networks that influence human wellbeing has been explored by empirical research in the US and Europe, however no study so far has undertaken a systematic investigation of the impact of the various dimensions of social capital in metropolitan areas. Addressing this gap in knowledge can have practical and policy-oriented implications by contributing to more informed decision-making processes in metro areas, better targeted interventions and ultimately an improved quality of life for residents. This study adopts a multi-level modelling approach to investigate life satisfaction and social capital heterogeneity within metropolitan areas in Australia. Our dataset was collected by the Household Income and Labour Dynamics in Australia survey and includes almost 4,000 individual respondents. Our results show that social trust, social engagement and connection, and a psychological sense of community measured at an individual level have a strong positive influence on individual life satisfaction. Conversely negative individual perceptions about neighbourhood criminality and shabbiness are associated with a lower level of life satisfaction. The application of a model using random slope coefficients for social capital variables suggests that most of the spatial heterogeneity between census districts is explained by between-individual (compositional) variations, rather than contextual differences. Only social connection and engagement appeared to have a distinctive contextual influence. These findings confirm the importance of social inclusion in enhancing wellbeing for everyone and may inform social policy on how to promote social networks in urban areas by all levels of government.

Keywords Subjective wellbeing · Life satisfaction · Social capital · Multi-level modelling · Australia

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1 Introduction

Subjective wellbeing[1] (SWB) has attracted growing interest in empirical economics' research in recent years. Regressing life satisfaction (LS) scores against a set of individual predictors including economic and non-economic (socio-demographic) factors is a means to investigating SWB. Several studies have also included contextual factors like socio-economic disadvantage or income inequality (Alesina et al., 2004; Kubiszewski et al., 2019b; Oishi et al., 2011), environmental factors (Bertram & Rehdanz, 2015; Kubiszewski et al., 2019a) or climate variables (Brereton et al., 2008; Lignier et al., 2023). However, much of this empirical research ignored the different levels of interaction between contributors and wellbeing and thus risk potential endogeneity, i.e., some factors influence LS at an individual (age, education) or household level (income, house ownership), while other are macro-level factors impacting at a neighbourhood or regional level. Research that used a multilevel analysis approach to examine those different levels of interaction has been undertaken in various countries including Europe (Aslam & Corrado, 2012; Neira et al., 2018; Pittau et al., 2010), the United Kingdom (UK) (Ballas & Tranmer, 2012), the United States (US) (Fernandez & Kulik, 1981) and New Zealand (Aminzadeh et al., 2013); however to our knowledge, this approach has never been applied to urban neighbourhoods in Australia.

The term social capital[2] is used by social scientists to refer to the social networks and associated effects such as trust and norms of reciprocity that influence human wellbeing (Coleman, 1988; Helliwell & Putnam, 2004). At an empirical level, it has been described as "the shared knowledge, norms, rules and networks that facilitate collective experience within a neighbourhood" (Vemuri et al., 2011, p. 6). Social capital (alongside natural capital, human capital and built capital) is also one of the domains contributing to human wellbeing identified by Costanza et al. (2013) and its importance has been documented in LS studies at various scales: country (Helliwell & Putnam, 2004; Lawless & Lucas, 2010; Layard, 2005); regional (Ballas & Thanis, 2022; Rentfrow et al., 2009) and local (Aminzadeh et al., 2013; Vemuri et al., 2011). While human and social capital variables have often been considered in Australian LS research (Kubiszewski et al., 2019a; Shields et al., 2009), we are missing a systematic analysis of the impact of different dimensions of social capital (Helliwell & Putnam, 2004) on LS. This investigation seeks to address this gap, placing a particular focus on social capital influence at individual and neighbourhood levels.

Geographic clustering of LS scores has been reported in Europe (Jokela et al., 2015; Okulicz-Kozaryn, 2011; Rentfrow et al., 2015), the US (Rentfrow & Jokela, 2016) and Canada (Helliwell et al., 2019; Ziogas et al., 2023). In this research, we focus on geographic variations between neighbourhoods within an urban/ suburban context. For this purpose, we selected two metropolitan areas of Australia. One is on the East coast, in southeast Queensland centred around Brisbane, the other on the West coast around Perth (Fig. 3, Appendix C). Brisbane and Perth are both classified as "Beta" cities according to

[1] Subjective wellbeing (SWB) is a broad concept that refers to the way individual evaluate their lives (Diener et al., 2018). The different dimensions of SWB: *hedonic* and *eudaimonic* have been discussed in the literature (Deci & Ryan, 2008; Helliwell, 2003; OECD, 2013). Life satisfaction is generally accepted as the cognitive component of SWB and is the concept used in the majority of wellbeing studies (Cummins, 2018).

[2] Some authors use the term "human capital" when meaning "social capital". However following the framework in Costanza et al. (2013), we identify "human" capital as a set of personal level characteristics such as skills, knowledge, education and training, while social capital refers to group/ community level characteristics.

the Globalisation and World Cities Research Network (GaWC, 2020). These two regions are comparable in population and geographical spread and have growing demographic and economic significance. Larger metropolitan areas could have been chosen for this study, however, results from previous SWB research in Australia point to a different pattern of relationship between LS and LS predictors in Greater Perth compared to elsewhere across the country (Lignier et al., 2023) and we sought to put this particular assumption to the test.

Our large sample (nearly 4,000 respondents) mean that our findings have relevance beyond the two regions investigated here. They may be of interest when developing public policies that aim to enhance social cohesion and trust within local communities, specifically, public policies on urban social infrastructure.

The rest of this article is structured as follows: Section 2 briefly reviews the relevant literature; the methodology used for our project is described in Section 3, while results are presented in Section 4. We discussed our findings in Section 5, while in Section 6, we summarise our findings and discuss their practical implications.

2 Literature Review

2.1 Geography of Wellbeing

Geography of wellbeing refers to the study of spatial variations in the level of wellbeing and the factors that impact wellbeing (Weckroth et al., 2022). Findings from this body of research show that even after adjusting for differences in individual backgrounds and characteristics, significant differences exist between countries (Layard, 2005; Veenhoven, 2008), regions (Aslam & Corrado, 2012; Helliwell et al., 2019; Okulicz-Kozaryn, 2011; Pittau et al., 2010) or neighbourhoods (Ballas & Tranmer, 2012). There is some indication that geographical contexts affect LS more than momentary happiness (Schwanen & Wang, 2014).

Studies in the US and Canada report that people living in rural areas are happier than urban residents (Fernandez & Kulik, 1981; Helliwell et al., 2019), however evidence from Europe shows little difference in the level of quality of life between rural and urban areas in the richest countries of the European Union, while in the poorer countries of Eastern and Southern Europe, people residing in rural areas appear to have a lower perceived quality of life (Shucksmith et al., 2009). Others have emphasised that the degree of remoteness may be a better predictor of wellbeing than rurality: Gilbert et al. (2016) found that while residents living in remote rural areas in Scotland had a higher level of LS, there was no significant difference between accessible rural areas and urban areas.

Studies that investigated the variations in LS within urban areas found that variables such as accessibility, commuting time, safety, level of pollution and climate variables were contributing factors (Brereton et al., 2008; Ferrer-i-Carbonell & Gowdy, 2007; Stutzer & Frey, 2008; Weckroth et al., 2022). The influence of population density on LS is contested: some argue that overall district density has no significant impact (Ala-Mantila et al., 2018; Ferreira et al., 2013), others report that high density at census block level has a negative effect (Cramer et al., 2004; Helliwell et al., 2019; Li & Kanazawa, 2016). According to Ettema and Schekkerman (2016) and Ala-Mantila et al. (2018), subjective variables such as perceived quality of neighbourhood, perceived safety and subjective distance to amenities appear to be more significant predictors of wellbeing than objective characteristics.

The spatial attributes described above are often intertwined with socio-economic factors such as income inequality and unemployment level in the neighbourhood (Ala-Mantila et al., 2018). The relationship between income inequality and wellbeing is not clear. Higher inequality has been associated with lower reported levels of wellbeing in Europe (Alesina et al., 2004) and in the US (Alesina et al., 2004; Oishi et al., 2011). However when using state level data, Glaeser et al. (2016) found that inequality had a small positive influence on happiness while Florida et al. (2013) noticed that it had no influence in metropolitan areas. It seems however that areas where there is a high inequality in LS have lower levels of average LS (Kubiszewski et al., 2019a; Ziogas et al., 2023). The influence of area level unemployment on individual wellbeing has also been examined: the consensus is that contextual unemployment has a positive influence on individual wellbeing as it acts as a social norm and softens the negative impact of individual unemployment (Clark, 2003; Clark & Oswald, 1994; Powdthavee, 2007).

2.2 The Importance of Social Capital

The significance of local or regional social capital as a predictor of individual wellbeing has been confirmed by studies in Europe (Aslam & Corrado, 2012; Mouratidis, 2019; Neira et al., 2018; Weckroth et al., 2022), the US (Vemuri & Costanza, 2006; Vemuri et al., 2011) and New Zealand (Aminzadeh et al., 2013). Social capital is sometimes included in the analysis as a single proxy factor (Florida et al., 2013; Subramanian et al., 2000), however others integrate different dimensions of social capital as distinct variables: frequency of social contacts (Yuan, 2016), social trust (Subramanian et al., 2000) and community involvement (Gilbert et al., 2016). Trust in institutions is sometimes distinguished from trust in people and social networks from formal networks.

Social trust is the belief that those around you (neighbours, family etc.,) can be trusted and is considered a strong indicator of social capital at aggregate level (Helliwell & Putnam, 2004; Yuan, 2016). The positive relationship between institutional trust, freedom and happiness has been documented in many studies (Bruni, 2006; Frey & Stutzer, 2000; Veenhoven, 2000), while the national average level of interpersonal trust has been shown to have a positive effect on SWB (Helliwell, 2003). When aggregated at the regional level, social trust and institutional trust were positively correlated with LS, but the influence of the aggregate regional mean variables was found to be stronger than the individual effect (Aslam & Corrado, 2012). Social networking is strongly associated with both higher levels of LS and higher levels of happiness (Aslam & Corrado, 2012; Neira et al., 2018), but not with eudaimonic wellbeing (Gilbert et al., 2016).

Individual perceptions about the neighbourhood social and physical attributes have also been used as measures of social capital (Aminzadeh et al., 2013). A psychological sense of community, that is the perception that neighbours are helpful and could be relied upon if necessary, the feeling that one belongs to the community has been found to be associated with higher levels of LS (Ma et al., 2018; Shields et al., 2009; Vemuri et al., 2011). Conversely, negative perceptions about the level of crime (Ambrey et al., 2014) and physical deterioration such as derelict buildings, litter and noise (Ettema & Schekkerman, 2016;

Mouratidis, 2019) or pollution (MacKerron & Mourato, 2009) were reported as negative drivers of LS.

2.3 Multi-Level Analysis and Heterogeneity

Multi-level analysis is a way to control for endogeneity caused by grouping (nested) behaviour of individuals. Multi-level analysis investigating geographic heterogeneity has been applied to a variety of topics including: self-rated health in US states (Subramanian et al., 2000); SWB across census districts in the UK (Ballas & Tranmer, 2012); adolescent well-being in New Zealand neighbourhoods (Aminzadeh et al., 2013); SWB across regions of Europe (Aslam & Corrado, 2012; Neira et al., 2018; Pittau et al., 2010) and in neighbourhoods of Finland (Weckroth et al., 2022).

Multi-level Modelling (MLM) is the technique of statistical analysis that examines the influence of contextual factors on LS using the hierarchical structure of the data. MLM is particularly suitable for studying the role of contextual factors such as geography based cultural and socio-economic differences, in shaping up lifestyle behaviour (Ballas & Tranmer, 2012; de Leeuw & Meijer, 2008). MLM allows the group coefficients (intercepts and slopes) to be modelled and provides separate estimates of individual and contextual effects at different levels. (Pittau et al., 2010). MLM estimates variations both within and between the groups by allowing intercepts and slopes to vary simultaneously (Gelman & Hill, 2007).

The effects of contextual factors on the dependent variable have been described in various literatures as heterogeneity, however it is important to distinguish between two types of heterogeneity: *between-context* from *between-individual* heterogeneity (Duncan et al., 1998). Between-context heterogeneity is a higher-level form of heterogeneity that reflects differences *between* groupings or regions. On the other hand, between-individual refers to differences at a micro-level and reflects the different characteristics of the people *within* the grouping/region (Duncan et al., 1998; Neira et al., 2018).

3 Methodology

3.1 Data

This study uses data from Wave 18 (2018) of the Household Income and Labour Dynamics in Australia (HILDA) survey. HILDA is a nationally representative study designed to examine various aspects of Australian households that periodically collects information relating to social capital. Special permission is required to access the restricted version of the HILDA survey.

The descriptive summary of the database used for this study is as follows: 3,869 individual respondents nested[3] into 2,176 households nested into 390 level 2 statistical areas. A level 2 statistical area (SA2) is determined by population size (average 10,000). This means that the geographic size of a district may vary from a small neighbourhood in densely populated inner suburbs, to a relatively large area (several hundred km^2) in outer metropolitan districts (Australian Bureau of Statistics, 2016).

[3] The relevance of the nested structure of the data to the Multi-Level Modelling approach is discussed in the next Sect. (3.2).

The comparative statistics between the reference populations and our sample (Table 1) indicate that both metropolitan regions share similar key demographic and socio-economic characteristics except for the proportion of people born overseas and people speaking a Language Other than English (LOTE) that is higher in Greater Perth than in SE Queensland. Respondents in our sample are older on average and households have a much higher median income compared to the reference populations. People born overseas in particular people who speak a LOTE, are significantly under-represented. This selection bias could have implications for the generalisation of our findings, especially the under-representation of immigrants, as empirical evidence suggests that ethnicity has a significant influence on SWB (Bruna, 2021; Helliwell et al., 2019).

3.2 Statistical Analysis

We adopt a three-level MLM for our analysis, with Level 1 representing the individual component, Level 2 the household component and Level 3 the SA2 component. Apart from modelling group coefficients, the use of MLM decomposes the total random variation into individual and group components. While group level predictors are themselves of interest, their inclusion may also reduce the unexplained group level variation which can be interpreted as a measure of the importance of the predictor (Pittau et al., 2010). The number of clusters should be large enough (>30) and the groups heterogeneous (Hox, 1998). MLM can be applied even where some groups have a size of 1 as long as there is a sufficient number of larger groups (Snijders & Berkhof, 2008). In this research, households with one observation were all retained, however all SA2 districts with less than 2 observations were discarded from the sample as groups with a single observation were problematic when estimating a model with random slope coefficients. The different metropolitan regions could arguably

Table 1 Statistical profile of the study sample compared to reference populations

	Reference Population		Sample
	Greater Perth	**S E Queensland**	Total
N (population) n (sample)	2,305,394	3,565,856	3,869
n (Greater Perth Sample)			1,340
n (SE Queensland sample)			2,529
Area (sqkm)	31,218	20,786	
Density (pop/ sqkm)	74	172	
Median age	37.5	37.4	45.2
Median weekly household income ($)	1,833.3	1,790	2,571
People with University degree (%)	25.6	25.5	25.1
People born overseas (%)	39.6	31.6	23.1
People who speak LOTE at home (%)	22.5	18.4	7.1
Households who own home (%)	70.6	63.1	66.6
Low-income household (< $650/ week) (%)	16.0	14.9	10.9
High-income household (> $3000 / week) (%)	26.0	24.0	29.3

a Source 2021 census: https://www.abs.gov.au/census/find-census-data/quickstats/2021/5GPER have been treated as an additional level of analysis. However, considering that we only have two clusters, we opted to treat regions as a fixed effect in our estimation.

3.3 Variables

The selection of variables (Table 2, Appendix A) reflects the three-level nested design: individual level variables, household level variables, statistical area level variables. Social capital variables are discussed separately.

3.3.1 Individual and Household Level Variables

The selection of relevant individual socio-demographic variables was guided by the literature: age, gender, health, employment, marital status, and education level. We also include variables specific to the Australian context such as indigenous status, and 'speak a LOTE at home' as a proxy for non-English speaking background (Ambrey & Fleming, 2014; Shields et al., 2009).

Household type was included as a potential predictor of LS (Ballas &Tranmer, 2012), with 'lone person household' being the baseline and three identified types: 'couple without children' 'couple with children' and 'single parent'. Household income is represented by 'relative income' based on the evidence that relative income matters more than absolute income as predictor of LS (Clark et al., 2008). House ownership is also retained as a potential predictor (Ballas & Tranmer, 2012; Kubiszewski et al., 2018).

3.3.2 Statistical Area (SA2) Level Variable

Contextual variables representing SA2 socio-economic conditions were selected based on their potential relevance according to the literature. Income inequality is best represented by the Gini coefficient. In the absence of Gini coefficient data at SA2 level, two statistics were retained as a proxy for the measure of inequality: percentage of low-income households (with a weekly income < A\$650) and percentage of high-income households (with a weekly income ≥ \$A3,000). These variables can be assumed to represent respectively the bottom and the top of the Lorenz curve that determine the Gini coefficient (Florida & Mellander, 2016). We also include a contextual variable representing the area average unemployment level for 2018[4]. Rather than incorporating raw neighbourhood population density as an independent variable, we distinguish between urban and suburban neighbourhoods by using a dummy identifying neighbourhoods that are more sparsely populated (less than 100 people per km^2) (Neira et al., 2018). Some previous studies have identified a small influence of neighbourhood ethnicity on individual LS (Fernandez & Kulik, 1981). We identify percentage of people speaking a LOTE at home (Kubiszewski et al., 2019b) as a proxy for ethnic diversity in the neighbourhood.

The contextual influence of the environment and the climate is also considered. To this purpose, we include the following variables: natural vegetation index (NDVI) representing "greenness" (Kubiszewski et al., 2019b), average rainfall, and maximum temperature in summer (Florida et al., 2013).

[4] As this data was not variable at SA2 level, we use the data for SA4 level instead.

3.3.3 Social Capital Variables

Following the methodology adopted in Aslam and Corrado (2012), Aminzadeh et al. (2013) and Neira et al. (2018), social capital was captured by the survey instrument at respondent level. District averages for each variable were then calculated using sample design weights.

Informed by the relevant literature discussed in Section 2, six dimensions of social capital are initially identified for this project: social trust, social connection, social engagement, psychological sense of community, neighbourhood perceived crime and safety, neighbourhood perceived shabbiness. Psychological sense of community reflects the individual's perception about the neighbourhood social cohesion and social harmony. The construct was first introduced by Vemuri et al. (2011) who labelled it social capital index. A similar variable was used by Aminzadeh et al. (2013) who combined it with neighbourhood perceived safety into an overall 'social cohesion' construct. The details for each social capital construct are shown in Table 2 and underlying survey questions can be found in Table 7, Appendix A. Cronbach Alpha calculations reveal a high level of internal consistency for each construct. Institutional trust was not believed to be relevant here as the neighbourhoods investigated are subject to very similar political and governance structures.

Pairwise correlations between the different constructs were estimated. A high level of correlation was found between social connection and social engagement at both individual (0.51) and district level (0.75). To avoid multicollinearity issues, the two constructs were merged into an 'engagement and connection' composite variable. Similarly, neighbourhood perceived safety and neighbourhood perceived shabbiness with correlations at 0.60 and 0.70, were merged into 'neighbourhood safety issues & shabbiness'.[5]

3.4 Unexplained Group Level Heterogeneity

Some of the group level random effects identified by the analysis could be correlated with the regressors, for instance heterogeneity in social capital variables between SA2 could be correlated with the corresponding individual regressors. While using a MLM model, this heterogeneity can be resolved by including the group means for these variables in the regression (Mundlak, 1978). To avoid problematic multicollinearity between the individual level variables and the group mean variables, we use a mean centred level 1 covariate as an

[5] Merging by straight averaging was possible as underlying ordinal variables were measured on the same scale: 1 to 6 for both social connection and social engagement; 1 to 5 for perceived crime and safety and perceived shabbiness.

Table 2 Initial social capital constructs

Construct	Number of underpinning items	Cronbach alpha
Social trust	1	N/A
Social connection	6	0.623
Social engagement	7	0.744
Psychological sense of community	5	0.878
Neighbourhood perceived crime & safety	4	0.869
Neighbourhood perceived shabbiness	4	0.688

instrumental variable (Snijders & Berkhof, 2008), this makes it possible to assess the relative position of the individual as well as the effect of the absolute group factors.

When calculating the district mean for social capital variables, design weights reflecting the difference in probability of selection of different individuals are used to correct for sampling bias (Aslam & Corrado, 2012). As the HILDA weight represents the probability of an individual being selected by reference to the entire population (Watson, 2012), a corrected weight is calculated by reference to the statistical district to reflect the probability of being selected within the district. The aggregate mean social capital variable $(\bar{C}_k)$ is determined as follows:

$$\bar{C}_k = \frac{1}{k_D} \times \sum_{i=1}^{k_D} w_{di} \times C_{ijk}$$

where w_{di} is respondent *i* weight in the district, k_D is the number of respondents in the district and C_{ijk} is the social capital variable measure of respondent *i*.

3.5 Estimated Regression Models

Six successive models are estimated. Model 0 is an empty model of individuals nested within households nested within SA2 areas with no independent variables:

$$y_{ijk} = \beta_{000} + v_{00k} + u_{0jk} + e_{ijk} \tag{0}$$

where β_{000} is the overall LS mean, v_{00k} is the intercept adjustment for each SA 2 area, u_{ojk} is the intercept adjustment for each household and e_{ijk} is an individual error term. $i = 1 \ldots I$ represents individual respondents, $j = 1 \ldots . J$ represents households, and $k = 1 \ldots . K$ represents SA2 areas.

Model 1 extends Eq. (0) by including individual level socio-demographic variables:

$$y_{ijk} = \beta_{000} + \gamma_{100} X_{ijk} + v_{0k} + u_{0jk} + e_{ijk} \tag{1}$$

where X_{ijk} is a vector of individual socio-demographic variables.

Model 2 extends Eq. (1) by including household level variables:

$$y_{ijk} = \beta_{000} + \gamma_{100} X_{ijk} + \gamma_{010} Z_{jk} + v_{0k} + u_{0jk} + e_{ijk} \tag{2}$$

where Z_{kj} is a vector of household level variables.

Model 3 extends Eq. (2) by including mean-centred individual social capital variables as well as the aggregate value of the social capital variables at SA2 levels, and contextual socio-economic and environmental variables.

$$y_{ijk} = \beta_{000} + \gamma_{100} X_{ijk} + \gamma_{010} Z_{jk} + \delta_{100}(C_{ijk} - \bar{C}_k) + \delta_{001} \bar{C}_k + \theta_{001} D_k + v_{0k} + u_{0jk} + e_{ijk} \tag{3}$$

where C_{ijk} is a vector of social capital variables at individual level, $\bar{C}_k$ is the aggregate mean of a social variable for area *k* and D_k is a vector of contextual variables for area *k*.

Model 4 extends Eq. (3) and accounts for between-group heterogeneity by making the coefficients of the individual social variables dependent on the SA2 area. Snijders and Bosker (2011, p. Chapter 5) recommend using the primary variable rather than the centred variable as the control individual level variable.

$$y_{ijk} = \beta_{000} + \gamma_{100}X_{ijk} + \gamma_{010}Z_{jk} + \delta_{100}C_{ijk} + \delta_{001}\bar{C}_k + \theta_{001}D_k + v_{0k} + v_{1k}C_{ijk} + u_{0jk} + e_{ijk} \tag{4}$$

where v_{1k} is the slope adjustment term for the social capital variable 1 in area *k*.

Model 5 modifies Eq. (4) and instead of using random slope coefficients for C_{ijk}, introduces cross-interaction terms between the individual social capital variables and their mean at SA2 level.[6] This interaction term for social capital variables is $\delta_{101}C_{ijk}\bar{C}_k$. This means that the slope of the individual social capital variables effectively vary depending on the SA2 as it does for Model 4; however instead of producing one coefficient estimate per area as in Model 4, it produces two unique estimates: δ_{100} and δ_{001} (Neira et al., 2018).

$$y_{ijk} = \beta_{000} + \gamma_{100}X_{ijk} + \gamma_{010}Z_{jk} + \delta_{100}C_{ijk} + \delta_{001}\bar{C}_k + \delta_{101}C_{ijk}\bar{C}_k + \theta_{001}D_k + \theta_{101}X_{ijk}D_k + v_{0k} + u_{0jk} + e_{ijk} \tag{5}$$

To minimise the possibility of heteroskedasticity, models were estimated using robustness checks such as robust variances and independent residuals (Pek et al., 2018). We checked for normality of residuals using visual tests including kernel density and standardised P-P plot (Figs. 1 and 2, Appendix B); given the large sample limitation of the Shapiro-Wilk test (Royston, 1982).

4 Results

4.1 Descriptive Statistics

Descriptive statistics are summarised in Table 3. The average LS in our sample is 7.94 on a 0–10 scale which is very close to the 7.91 Australian within-person average for the period 2000-17 reported by Kubiszewski et al. (2020). Figure 4 (Appendix C) provides some visual evidence of the geographical clustering in both metropolitan regions. Comparison of social capital average scores with results from prior research is often meaningless because of differences in scales and methodologies. Variations of aggregate scores between neighbourhoods remain high with a standard deviation well over 50% of the variation at individual level. Figures 5, 6, 7 and 8 (Appendix C) visually illustrate the diversity in social capital variables across neighbourhoods in both metropolitan areas.

4.2 Model 0 (Empty Model)

Results for Model 0 (null hypothesis) are shown in Table 4. Random intercept effects are significant at all levels. The intraclass correlation coefficient (ICC) measures the correlation between observations within a particular class. It is calculated as the ratio of the between-cluster variance and the sum of between and within cluster variances (Raudenbush & Samp-

[6] Interaction terms are also included for ethnicity and unemployment.

Table 3 Summary descriptive statistics for selected variables

Variable	*n*	Mean	Std. dev.	Min	Max
Life satisfaction (0–10) (Dependent variable)	3,868	7.942	1.428	0	10
Individual variables					
age	3,869	45.23	18.94	15	99
female (0/1)	3,869	0.53	0.50	0	1
indigenous (0/1)	3,869	0.03	0.17	0	1
speak LOTE (/1)	3,869	0.07	0.26	0	1
higher education (0/1)	3,869	0.25	0.43	0	1
self -assessed health (1–5)	3,567	3.33	0.95	1	5
unemployed (0/1	3,869	0.04	0.20	0	1
Household variables					
couple no children (0/1)	3,868	0.31	0.46	0	1
couple with children (0/1)	3,869	0.28	0.45	0	1
single parent (0/1)	3,869	0.10	0.31	0	1
household inc. (A$ '000 per year)	3,869	134	137	0	2,608
household relative inc.	3,869	1.41	1.40	0	36.23
own home (0/1)	3,869	0.67	0.47	0	1
Social capital variables (individual)					
social trust	3,586	4.63	1.69	1	7
engagement & conn.	3,575	3.07	0.81	0.83	6.5
psych sense of community	3,605	3.96	1.08	0.75	7
neighb. safety issues & shabbiness	3,595	2.52	0.70	1	5
District social capital variables (aggregate mean)					
sa2_ social trust	3,869	4.56	0.82	0.89	6.70
sa2_ connection & engagement	3,869	3.07	0.48	0.78	5.66
sa2_ psych. sense of community	3,869	3.96	0.65	0.88	6.38
sa2_safety issues & shabbiness	3,869	2.50	0.43	0.48	4.22
Sa2 contextual variables					
sa2_ sparsely populated (0/1)	3,869	0.10	0.30	0	1
sa2_prop speak LOTE (%)	3,869	17.5	10.8	4	66.1
sa2_prop, low income (%)	3,869	15.6	5.4	4	35.3
sa2_proportion high income (%)	3,869	24.7	10.5	5	56.9
sa2_proportion higher ed (%)	3,869	23.7	12.0	5.1	55.4
sa2_prop. unemployed (%)	3,869	5.9	1.3	4	9.3
sa2_natural vegetation index	3,869	0.304	0.102	0.043	0.562
sa2_annual rainfall (mm)	3,869	953.7	285.8	591.3	1613.9
sa2_maximum temp in Summer (°C)	3,869	30.3	1.1	26.2	33.5

Table 4 Intercept and random effect parameters for the null hypothesis model

Observations (n)	3,869		
Intercept β_{000}	7.819		
Random effect:	Estimate	Std dev.	ICC
Level:			
SA2 v_{00k}	0.109***	0.027	0.053
Household u_{0jk}	0.546***	0.055	0.318
Respondents e_{ijk}	1.406***	0.049	

Significant at *** $p<0.01$ level **$p<0.05$ level * $p<0.1$ level

Table 5 Summary statistics for Model 1 and Model 2

	Model 1		Model 2	
Observations (n)	3,566		3,566	
	Coeff	Std err	Coeff	Std err
Intercept	6.421	0.164	6.294	0.170
Individual variables:				
age	-0.040***	0.006	-0.048***	0.006
age square	0.001***	0.000	0.001***	0.000
female	0.129***	0.040	0.148***	0.040
indigenous	0.086	0.166	0.138	0.165
speak LOTE	-0.101	0.089	-0.102	0.088
higher education	-0.059	0.044	-0.112***	0.044
self-assessed health	0.601***	0.027	0.584***	0.027
unemployed	-0.325***	0.125	-0.276**	0.123
Household variables:				
couple no children			0.227***	0.059
couple with children			0.297***	0.058
single parent			-0.054	0.085
relative household income			0.059***	0.021
own house			0.193***	0.057
greater Perth (dummy)	-0.169***	0.059	-0.184***	0.057
Random effect -intercept:				
SA2 level	0.065***	0.018	0.051***	0.017
household level	0.313***	0.056	0.299***	0.055
individual level	1.228***	0.068	1.217***	0.066
Aikake Information Criteria	11712.61		11649.71	

Significant at *** $p<0.01$ level **$p<0.05$ level * $p<0.1$ level

son, 1999). The ICC at SA2 level is small compared to the ICC at household level revealing an important variance between household clusters.

4.3 Model 1 and Model 2

Model 1 incorporates level 1 socio-demographic variables while household variables are added in Model 2. Results for both models are shown in Table 5. The significant drop in the SA2 random intercept variance (from 0.109 for Model 0 to 0.051 for Model 2) shows that a large portion of the initial between-group heterogeneity in LS between SA2 is explained by socio-demographic variables.

Being healthy is by far the most important positive contributor of LS. Age (in quadratic form) is another significant contributor; being female is a positive factor; being unemployed is associated with lower LS, as is having a higher education. Among household type variables, living as a couple either with or without children has a positive effect on LS compared to living in a single person household. Relative income measured as the ratio between household income and median income in the statistical area is a positive contributor as is house ownership. Finally, the fixed effect dummy variable for the Greater Perth region is highly significant indicating a different pattern of relationship for that region.

4.4 Models 3, 4 and 5

These models introduce social capital variables at individual and SA2 levels as well as contextual variables at SA2 level. Summary statistics for each model are shown in Table 6. Model 3 allows for random intercepts, i.e., it captures between-context heterogeneity. Model 4 allows for random slope coefficients for the social variables. This captures between-individual heterogeneity through group dependence (Snijders & Bosker, 2011). Model 5 includes interactions terms for the social capital variables without random slopes. This may provide explanations for the geographical variability of the individual social capital coefficients (Schynz, 2002). We also include interactions terms for ethnicity and unemployment.

The introduction of social capital variables causes a further drop in the random intercept variance at SA2 level from 0.051 (Model 2) to 0.036 (Model 3). Random effects of intercept at SA2 level remain significant for Models 3 and 5. Coefficients for most individual and household level factors remain stable across Models 3, 4 and 5 with little variation from Model 2. However, the coefficients for 'speaking LOTE' and 'being unemployed' lose their significance in Model 5 when an interaction term with the area level variable is introduced.

Results for Model 3 show that individual social trust, 'engagement and connection' and 'psychological sense of community' are significant positive contributors of LS. Conversely, 'perception about safety issues and shabbiness' has a significantly negative relationship with LS. Area level aggregate for social trust and 'social engagement and connection' are also positively associated with individual LS, but aggregate 'psychological sense of community' has no significant influence. The aggregate mean 'neighbourhood safety issues and shabbiness' has a significant negative coefficient. Coefficients for aggregate social capital means tend to be somewhat larger that coefficients for corresponding variables at individual level.

In Model 4 slope coefficients for individual social capital variables vary across SA2. The only coefficient for which the variation is significant is 'neighbourhood safety issues and shabbiness'. The average coefficients for individual social capital variables are remarkably similar to those obtained for Model 3. Coefficients for SA2 aggregate are much smaller than in Model 3 and become non-significant. This outcome, similar to the results in Neira et al. (2018) suggests that the heterogeneity in the effect of social capital variables between SA2 is likely to be attributable to between-individual heterogeneity rather than between-group heterogeneity (Duncan et al., 1998).

Model 5 introduces cross-level social capital interaction terms and explores the possible causes for between-individual heterogeneity (Duncan et al., 1998). The results suggest that 'engagement and connection' is the only social capital variable, for which the contextual term and the individual term have a combined effect on LS. In other words, the impact of *individual* social engagement and connection on individual LS is influenced by the *overall*

Table 6 Summary statistics for Models 3, 4 and 5

	Model 3		Model 4		Model 5	
Observations (n)	3,478		3,470		3,470	
	Coeff	Std. err.	Coeff	Std. err.	Coeff	Std. err.
Intercept	5.849	0.970	5.813	0.959	4.720	1.296
Individual variables:						
age	-0.045***	0.006	-0.045***	0.006	-0.045***	0.006
age square	0.001***	0.000	0.001***	0.000	0.001***	0.000
female	0.088**	0.039	0.088**	0.039	0.086***	0.039
indigenous	0.197	0.169	0.189	0.167	0.185	0.168
speak LOTE	-0.138	0.087	-0.143*	0.086	0.154	0.180
higher education	-0.182***	0.047	-0.178***	0.047	-0.179***	0.047
self-assessed health	0.514***	0.026	0.513***	0.026	0.513***	0.026
unemployed	-0.307**	0.120	-0.313***	0.120	-0.585	0.613
Household variables:						
couple no children	0.206***	0.054	0.204***	0.054	0.212***	0.054
couple with children	0.247***	0.058	0.252***	0.058	0.256***	0.058
single parent	-0.050	0.083	-0.040	0.085	-0.037	0.084
relative household income	0.041*	0.024	0.042*	0.024	0.042*	0.023
own house	0.114**	0.056	0.114**	0.056	0.114**	0.056
Social capital: individual[a]:						
social trust	0.055***	0.014	0.055***	0.014	0.063	0.079
engagement & connection	0.192***	0.034	0.192***	0.033	0.605***	0.157
psych. sense of community	0.069***	0.023	0.069***	0.023	-0.036	0.129
safety issues & shabbiness	-0.161***	0.038	-0.163***	0.038	-0.113	0.198
SA2 social capital aggregate:						
social trust	0.074**	0.035	0.023	0.035	0.023	0.093
engagement & connection	0.264***	0.065	0.065	0.069	0.490***	0.187
psych. sense of community	0.088	0.054	0.020	0.054	-0.078	0.146
safety issues & shabbiness	-0.192**	0.076	-0.033	0.076	0.021	0.221
SA2 contextual variables:						
sparsely populated	0.119	0.103	0.092	0.102	0.123	0.102
prop low income	-0.001	0.008	-0.001	0.008	-0.001	0.008
prop high income	-0.003	0.004	-0.003	0.004	-0.003	0.004
prop speak LOTE	-0.001	0.003	-0.002	0.003	0.001	0.003
prop unemployed	-0.007	0.026	-0.005	0.026	-0.006	0.026
natural vegetation index (sa2)	-0.035	0.405	0.040	0.406	-0.017	0.411
Annual rainfall (sa2)	0.000	0.000	0.000	0.000	0.000	0.000
Max temp in summer (sa2)	-0.002	0.030	-0.001	0.030	0.000	0.030
Greater Perth (D)	-0.128*	0.077	-0.113	0.077	-0.128*	0.077
Interaction terms indiv x SA2						
social trust					-0.002	0.017
engagement & connection					-0.132***	0.049
psych. sense of community					0.026	0.032
safety issues & shabbiness					-0.020	0.078
speak LOTE					-0.013*	0.007
unemployed					0.046	0.102
Random effect_ intercept:						
SA2 level	0.036**	0.016	0.000	0.000	0.038**	0.016
household level	0.253***	0.052	0.245	0.051***	0.250***	0.052

Table 6 (continued)

	Model 3		Model 4		Model 5	
Individual level	1.169***	0.065	1.164	0.064***	1.167***	0.065
Random effect_ slope:						
social trust			0.000	0.000		
engagement & connection			0.000	0.000		
psych. sense of community			0.000	0.000		
safety issues & shabbiness			0.008	0.003***		
Aikake Information Criteria	11172.03		11150.17		11149.82	

[a] mean centred variable in Model 3, full variable in Model 4 and Model 5' Significant at *** $p<0.01$ level **$p<0.05$ level * $p<0.1$ level

level of social engagement and connection in the area. Both the individual and mean variables have higher coefficients than in the previous models, however the interaction term coefficient is significantly negative.

None of the other contextual socio-economic variables appear to have a significant influence on LS. The introduction of an interaction term between the individual variable and the contextual variable for 'speak LOTE' and unemployment in Model 5 does not fundamentally alter this pattern. The interaction term for 'speak LOTE' has a weakly significant negative effect. Likewise, the environmental contextual variables representing green vegetation and climate are not found to significantly impact LS. The fixed effect identifier for Greater Perth is weakly significant in Model 3 and 5 and below significance level in Model 4.

5 Discussion

The small unexplained random effect at SA2 level in Model 3 suggests that socio-demographic variables and social capital variables explain much of the variations in LS between SA2. It is much larger than the random effect at group level in the Aslam and Corrado (2012) and Neira et al. (2018) studies where the clusters were large regions in the EU, but it is comparable to the variance at neighbourhood level in Aminzadeh et al. (2013) regression models.[7] The unexplained random effect at household level remains relatively large as in Ballas and Tranmer (2012) indicating the presence of idiosyncratic differences between households.

The importance of factors representing social capital at individual level is confirmed by this research. Specifically, social trust (Helliwell & Putnam, 2004; Neira et al., 2018; Subramanian et al., 2000) and 'engagement and connection' (Aminzadeh et al., 2013; Gilbert et al., 2016; Yuan, 2016) are significantly positive contributors of LS. The variable 'psychological sense of community' that reflects individual perception about the level of social connection and harmony within the neighbourhood also has a positive impact on LS. The same outcome was reached by Aminzadeh et al. (2013) (social cohesion) in their study of adolescent wellbeing in New Zealand. Conversely, Vemuri et al. (2011)' social capital index based on the same dimensions was not found to be a significant driver of LS in metropolitan Baltimore.

[7] Aminzadeh et al. (2013) measured wellbeing on a 0 to 5 scale, so the absolute value of the variance of the intercept is predictably lower than for this study.

Individual perception of safety issues and shabbiness in the neighbourhood has a significant negative impact on LS reflecting existing evidence (Ettema & Schekkerman, 2016; Mouratidis, 2019). This outcome might be surprising as the actual rate of violent crime[8] in both metropolitan areas is around 1,200 per 100,000 which is close to the Australian average (Australian Bureau of Statistics, 2023), but much lower than for Philadelphia, a comparable Beta ranked city in the US.[9] This result is consistent with previous evidence that incidence of crime has little relationship with people's perception of crime (Veenhoven, 2002) and that perceived crime levels are more significant negative contributors to LS than actual crime levels (Ambrey et al., 2014; Larson, 2010).

Our study finds little evidence of contextual influence for social capital factors on LS: the results from the random slope coefficients model suggest that differences between SA2 are generally attributable to compositional effects rather than contextual effects. The exception is 'social engagement and connection" where the aggregate variable has a strong positive coefficient when an interaction term with the individual level variable is included. This suggests that the neighbourhood level of social connection and engagement interacts with the corresponding variable at individual level. The negative interaction factor can be interpreted as meaning that where aggregate social engagement and connection is high, the influence of individual level engagement and connection will be reduced. Only very few studies have considered the influence of area level social connection and engagement on individual LS. Aminzadeh et al. (2013) found a positive influence for membership in community organisations, Neira et al. (2018) reported a positive association for informal and formal networks, but no significant influence for civic engagement, a result also reached by Aslam and Corrado (2012). When interpreting these results, it is important to bear in mind that the two latter studies examined large regions (NUTS1-3) in different countries in Europe rather than urban neighbourhoods.

The influence of urbanity/ rurality was measured through the 'sparsely populated' dummy. It appears that this variable was not a significant contributor confirming earlier outcomes that a 'rural' residence has no significant influence on wellbeing when the area is accessible (Gilbert et al., 2016; Weckroth et al., 2022). Neither of the two proxy variables for income equality are significant. This outcome aligns with some earlier results (Florida et al., 2013; Weckroth et al., 2022), but challenges others, for instance Ala-Mantila et al. (2018) found that people had a higher Quality of life where the proportion of high income earners was higher.

Individual ethnicity has often been identified as a possible determinant of LS, but very few studies have considered the influence of neighbourhood ethnicity. The consensus is that being of a non-English background (Kubiszewski et al., 2018) or belonging to an ethnic minority (Aminzadeh et al., 2013; Oswald & Wu, 2011) is associated with lower LS levels. A recent Canadian study also found that neighbourhoods with a high proportion of foreign born had lower average LS (Ziogas et al., 2023). The analysis of our data shows no significant influence for ethnicity on LS at either individual or neighbourhood level. However, the negative coefficient for the interaction term suggests that being a person of non-English

[8] Rate of violent crime included the following prosecuted offenses: homicide, assault including sexual assault, robbery, theft, abduction and unlawful entry with intent.

[9] Rate of violent crime for Philadelphia in 2018 was 8,043 per 100,000: US Federal Board of Investigation, 2018 Crime in the United States : https://ucr.fbi.gov/crime-in-the-u.s/2018/crime-in-the-u.s.-2018/tables/table-8/table-8-state-cuts/pennsylvania.xls.

speaking background living in a neighbourhood with a high level of non-English speakers may have a negative impact on LS. We need to interpret this result with caution considering that non-English speakers were under-represented in our sample.

Our study confirms earlier findings that being unemployed tends to be associated with lower levels of LS. There is also strong empirical support in the literature for the argument that contextual unemployment might mitigate the effect of individual unemployment by acting as a social norm (Ballas & Tranmer, 2012; Clark, 2003; Powdthavee, 2007). This finding for contextual unemployment is not replicated in our study even when we include an interaction term. This might be explained by the relatively low level of contextual unemployment in our area of study (5.9%) at the time of survey. By comparison the unemployment rate in South Africa for the Powdthavee study was around 13% (Powdthavee, 2007) and it was 8.6% in the UK in 1991 (World Bank, 2023) when the data used by Ballas & Tranmer was collected.

Vegetation index was found to be a statistically significant LS factor in previous research (Kubiszewski et al., 2019b); similarly, temperature and to a lesser extent rainfall, have been found to influence average LS (Brereton et al., 2008; Florida et al., 2013; Lignier et al., 2023). Neither of these environmental variables significantly impact LS in our sample. While previous research that examined the influence of climate and the environment on LS covered regions with different climates, our study covered areas where climate variations are small. A similar conclusion to ours was reached from data collected in the urban area of Baltimore (US) (Vemuri et al., 2011).

Individual socio-economic variables mostly behave as expected from similar research in Australia. Age is a consistent predictor with a U shape non-linear relationship (Frijters & Beatton, 2012); being female is associated with higher levels of LS. Evidence about the influence of sex on LS is mixed, with some studies predicting a positive association for female (Kubiszewski et al. 2019; Neira et al., 2018) others a negative association (Aminzadeh et al., 2013; Ballas & Tranmer, 2012). The negative association between having a university degree and LS that was noted in some studies is confirmed here (Ambrey & Fleming, 2014).

According to our results, household structure matters: couples with or without children seem to have higher LS levels compared to single person households. This differs somewhat from earlier MLM studies in the UK where couples without children had higher levels of LS but couples with children had lower levels (Ballas & Tranmer, 2012).[10] House ownership is consistently a significant positive predictor of LS. This aligns with earlier results from the UK (Ballas & Tranmer, 2012) and Australia (Kubiszewski et al., 2018), but a US study found that home ownership was a negative predictor of metropolitan wellbeing (Florida et al., 2013). Relative household income is a significant positive contributor of LS in all models reflecting predictive models by Clark et al. (2008). Household income was also found to be a positive contributor in many LS/ social capital studies (Aslam & Corrado, 2012; Neira et al., 2018; Rentfrow et al., 2009).

A secondary objective of this study was to test whether the seemingly different pattern of relationship between LS and LS determinants in the Greater Perth region was confirmed. The two regions were identified through the inclusion of a fixed effect dummy variable. The significantly negative coefficient for the Greater Perth dummy in Models 1 and 2 seem to

[10] Some Australian studies also reported that the number of children in the household was negatively associated with LS (Ambrey & Fleming, 2014; Kubiszewski et al., 2018).

support previous findings that *ceteris paribus* a certain configuration of LS determinants would result in lower predicted LS in that region (Lignier et al., 2023). The coefficient remains negative when social capital and contextual variables are introduced but with a much weaker level of significance. This might suggest that the positive effect of social capital variables on LS in Greater Perth somewhat mitigates the differences with other regions.

6 Conclusion

The primary objective of this study was to analyse the influence of individual and contextual social capital variables on LS within a metropolitan context in Australia using MLM. This study is the first one, to the best of our knowledge, that uses MLM with three levels of aggregation to investigate LS and social capital in metropolitan regions within a single country.

We find that only a moderate proportion of the unexplained variation in LS prediction was attributable to differences between spatial clusters, while the difference between households is much more significant. These results reflect similar findings from MLM studies at neighbourhood scale conducted in the UK and in New Zealand. We also find that most of the spatial heterogeneity is probably attributable to compositional effects (i.e., different characteristics of respondents living in different area) rather than contextual effects (variations linked to the specific social capital characteristic of the area).

Our results corroborate previous findings that factors such as social trust, social engagement connection, and psychological sense of community representing individual contribution to social capital are strong positive contributors of individual LS. Negative individual perceptions about the neighbourhood such as safety issues and physical deterioration seem to have a deeper (negative) impact on LS, than positive perceptions about the neighbourhood social attributes. The influence of contextual social capital on individual LS appears to be limited to the interaction between individual and aggregate levels of social connection and engagement. Overall, our findings are consistent with the hypothesis that social capital will shape individual wellbeing (Coleman, 1988; OECD, 2001); however they do not support previous findings of a significant influence for contextual socio-economic variables such as income inequality, contextual un-employment and neighbourhood ethnicity.

Our research has several limitations. Firstly, as noted in our methodology section, our sample is somewhat biased towards older people with higher income, and households from non-English speaking background are under-represented. This may explain the non-significance of some contextual variables such as income inequality, unemployment and ethnicity. Secondly, the number of respondents in some of the SA2 is very small, consequently idiosyncratic individual data may have a disproportionate effect on the area means (Helliwell et al., 2019). Thirdly, we do not account for possible spillover effects where average level of LS and social capital for an area could be influenced by neighbouring areas (Ziogas et al., 2023). Finally, as noted by Neira et al. (2018), the lack of consistency in the definition of social capital dimensions and the absence of independently measured aggregate social capital indicators make inter-research comparisons hazardous.

Notwithstanding the above caveats, we believe our research contributes to knowledge about the impact of social capital on individual wellbeing. Our methodology can be replicated to other metropolitan areas anywhere in the world and applied to other wellbeing indicators such as happiness or mental health. Our findings will inform government social policy in urban areas, for instance the building of urban infrastructure that promote social access and encourage social activities such walking paths, community playgrounds, and the remedying of physical urban deterioration and crime to reinforce the perception of personal safety. As argued by Wilkinson and Pickett (2009), the positive impact of community engagement and connection and individual psychological sense of community on SWB suggest that access to urban and social infrastructure needs to be accompanied with better inclusion of all groups within the community to achieve better social outcomes.

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Declarations

Ethical Approval This project did not involve the collection of primary data and ethical approval was required.

Informed Consent The use of the HILDA restricted data base required special approval from the Australian Department of Social Services (Application #454732 approved on 6/01/2021).

Conflict of Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ala-Mantila, S., Heinonen, J., Junnila, S., & Saarsalmi, P. (2018). Spatial nature of urban well-being. *Regional Studies*, *52*(7), 959–973. https://doi.org/10.1080/00343404.2017.1360485.

Alesina, A., Di Tella, R., & MacCulloch, R. (2004). Inequality and happiness: Are europeans and americans different? *Journal of Public Economics*, *88*(9), 2009–2042. https://doi.org/10.1016/j.jpubeco.2003.07.006.

Ambrey, C., & Fleming, C. (2014). Life satisfaction in Australia: Evidence from ten years of the HILDA Survey. *Social Indicators Research*, *115*, 691–714. https://doi.org/10.1007/s11205-012-0228-0.

Ambrey, C., Fleming, C., & Manning, M. (2014). Perception or reality: What matters more when it comes to crime in your neighbourhood. *Social Indicators Research*, *119*(2), 877–896.

Aminzadeh, K., Denny, S., Utter, J., Milfont, T., Ameratunga, S., Teevale, T., & Clark, T. (2013). Neighbourhood social capital and adolescent self-reported wellbeing in New Zealand: A multilevel analysis. *Social Science and Medicine*, *84*, 13–21. https://doi.org/10.1016/j.socscimed.2013.02.012.

Aslam, A., & Corrado, L. (2012). The geography of well-being. *Journal of Economic Geography*, *12*, 627–649. https://doi.org/10.1093/jeg/lbr041.

Australian Bureau of Statistics (2016). *Australian Statistical Geography Standard: Volume 1-Main Structure and Greater capital city Statistical Areas, July 2016*. Retrieved from Canberra: https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016?OpenDocument.

Australian Bureau of Statistics (2023). 9/2/2023). Recorded Crime Offenders: Statistics about offenders proceeded against by police.

Ballas, D., & Thanis, I. (2022). Exploring the geography of subjective happiness in Europe during the years of the Economic Crisis: A Multilevel Modelling Approach. *Social Indicators Research*, *164*, 105–137. https://doi.org/10.1007/s11205-021-02874-6.

Ballas, D., & Tranmer, M. (2012). Happy people or happy places? A multilevel modeling Approach to the analysis of happiness and well-being. *International Regional Science Review*, *75*(1), 70–102. https://doi.org/10.1177/0160017611403737.

Bertram, C., & Rehdanz, K. (2015). The role of urban green space for human well-being. *Ecological Economics*, *120*, 139–152. https://doi.org/10.1016/j.ecolecon.2015.10.013.

Brereton, F., Clinch, J. P., & Ferreira, S. (2008). Happiness, geography and the environment. *Ecological Economics*, *65*, 386–396. https://doi.org/10.1016/j.ecolecon.2007.07.008.

Bruna, F. (2021). Happy cultures? A Multilevel Model of Well-being with individual and contextual human values. *Social Indicators Research*, *164*, 55–77. https://doi.org/10.1007/s11205-021-02858-6.

Bruni, L. (2006). Civil happiness. *Economics and Human Flourishing in Historical Perspective*. https://doi.org/10.4324/9780203488119.

Clark, A. (2003). Unemployment as a Social Norm: Psychological evidence from Panel Data. *Journal of Labor Economics*, *21*(2), 323–351.

Clark, A., & Oswald, A. (1994). Unhappiness and unemployment. *The Economic Journal*, *104*(424), 648–659.

Clark, A., Frijters, P., & Shields, M. (2008). Relative income, happiness and utility: An explanation of the Easterlin Paradox and other puzzles. *Journal of Economic Theory*, *46*(1), 95–144.

Coleman, J. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology, 94*, S95- S120. Retrieved from https://www.jstor.org/stable/2780243.

Costanza, R., Alperowitz, G., Daly, H., Farley, J., Franco, C., Jackson, T., & Victor, P. (2013). Building a sustainable and desirable Economy-In-. *Society-In -Nature*. ANU.

Cramer, V., Torgesen, S., & Kringlen, E. (2004). Quality of life in a city: The effect of population density. *Social Indicators Research*, *69*(1), 103–116. https://doi.org/10.1023/B:SOCI.0000032663.59079.0b.

Cummins, R. (2018). Subjective wellbeing as Social Indicator. *Social Indicators Research*, *135*, 879–891. https://doi.org/10.1007/s11205-016-1496-x.

de Leeuw, J., & Meijer, E. (Eds.). (2008). *Introduction to Multilevel Analysis*. Springer.

Deci, E., & Ryan, R. (2008). Hedonia, eudaimonia, and wellbeing: An introduction. *Journal of Happiness Studies*, *9*, 1–11. https://doi.org/10.1007/s10902-006-9018-1.

Diener, C., Oishi, S., & Tay, L. (2018). Advances in subjective well-being research. *Nature Human Behaviour*, *2*, 253–260. https://doi.org/10.1038/s41562-018-0307-6.

Duncan, C., Jone, K., & Moon, G. (1998). Context, composition and heterogeneity: Using multilevel models in health research. *Social Science and Medicine*, *46*(1), 97–117.

Ettema, D., & Schekkerman, M. (2016). How do spatial characteristics influence well-being and mental health? Comparing the effect of objective and subjective characteristics at different spatial scales. *Travel Behaviour and Society*, *5*, 56–67. https://doi.org/10.1016/j.tbs.2015.11.001.

Fernandez, R., & Kulik, J. (1981). A Multilevel Model of Life Satisfaction: Effects of Individual Characteristics and Neighborhood Composition. *American Sociological Review, 46*(6), 840–850. Retrieved from https://www.jstor.org/stable/2095082.

Ferreira, S., Akay, A., Brereton, F., Cunado, J., Martinsson, P., Moro, M., & Ningal, T. (2013). Life satisfaction and air quality in Europe. *Ecological Economics*, *88*, 1–10. https://doi.org/10.1016/j.ecolecon.2012.12.027.

Ferrer-i-Carbonell, A., & Gowdy, J. (2007). Environmental degradation and happiness. *Ecological Economics*, *60*, 509–516.

Florida, R., & Mellander, C. (2016). The Geography of Inequality: Difference and determinants of wage and income inequality across US Metros. *Regional Studies*, *50*(1), 79–92. https://doi.org/10.1080/00343404.2014.884275.

Florida, R., Mellander, C., & Rentfrow, P. (2013). The happiness of cities. *Regional Studies*, *47*, 613–627. https://doi.org/10.1080/00343404.2011.589830.

Frey, B., & Stutzer, A. (2000). Happiness, Economy and Institutions. *The Economic Journal*, *110*, 918–938.

Frijters, P., & Beatton, T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior and Organization*, *82*, 525–542. https://doi.org/10.1016/j.jebo.2012.03.008.

GaWC (2020). The World according to GaWC 2020. Retrieved from https://www.lboro.ac.uk/microsites/geography/gawc/world2020t.html.

Gelman, A., & Hill, J. (2007). *Data Analysis using Regression an Nultilevel/ Hierarchical Models*.

Gilbert, A., Colley, K., & Roberts, D. (2016). Are rural residents happier? A quantitative analysis of subjective wellbeing in Scotland. *Journal of Rural Studies*, *44*, 37–45. https://doi.org/10.1016/j.jrurstud.2016.01.002.

Glaeser, E., Gottlieb, J. D., & Ziv, O. (2016). Unhappy cities. *Journal of Labor Economics*, *34*(S2). https://doi.org/10.1086/684044.

Helliwell, J. (2003). How's life? Combining individual and national variables to explain subjective wellbeing. *Economic Modelling*, *20*, 331–360.

Helliwell, J., & Putnam, R. (2004). *The social context of wellbeing* Philosophical Transactions, (359, 1449). London.

Helliwell, J., Shiplett, H., & Barrington-Leigh, C. (2019). How happy are your neighbours? Variation in life satisfaction among 1200 Canadian neighbourhoods and communities. *Plos One*, *14*(e210091). https://doi.org/10.1371/journal.pone.0210091.

Hox, J. (Ed.). (1998). *Multilevel modelling: When and why*. Springer.

Jokela, M., Bleidorn, W., Lamb, M., Gosling, S., & Rentfrow, P. (2015). Geographically varying associations between personality and life satisfaction in the London metropolitan area. *PNAS, 112*(3), 725–730. Retrieved from www.https://doi.org/10.1073/pnas.1415800112.

Kubiszewski, I., Zakariyya, N., & Costanza, R. (2018). Objective and subjective indicators of life satisfaction in Australia: How well do people perceive what supports a good life? *Ecological Economics*, *154*, 361–372. https://doi.org/10.1016/j.ecolecon.2018.08.017.

Kubiszewski, I., Jarvis, D., & Zakariyya, N. (2019). Spatial variations in contributors to life satisfaction: An Australian case study. *Ecological Economics*, *164*, 1–10. https://doi.org/10.1016/j.ecolecon.2019.05.025.

Kubiszewski, I., Zakariyya, N., & Jarvis, D. (2019b). Subjective wellbeing at different spatial scales for individual satisfied and dissatisfied with life. *Peer J*, *7*, 1–25. https://peerj.com/articles/6502/.

Kubiszewski, I., Zakariyya, N., Costanza, R., & Jarvis, D. (2020). Resilience of self-reported life satisfaction: A case study of who conforms to set-point theory in Australia. *Plos One*, 1–18. https://doi.org/10.1371/journal.pone.023716.

Larson, S. (2010). Regional wellbeing in tropical Queensland, Australia: Developping a dissatisfaction index to inform government policy. *Environment and Planning*, *42*, 2972–2989.

Lawless, N., & Lucas, B. (2010). Predictors of regional well-being: A county level analysis. *Social Indicators Research*, *101*(3), 341–357. https://doi.org/10.1007/sl.1205-010-9667-7.

Layard, R. (2005). *Happiness: Lessons from a new science*. Allen Lane.

Li, N. P., & Kanazawa, S. (2016). Country roads, take me home. To my friends: How intelligence, population density, and friendship affect modern happiness. *British Journal of Psychology*, *107*, 675–697. https://doi.org/10.1111/bjop.12181.

Lignier, P., Jarvis, D., Grainger, D., & Chaiechi, T. (2023). Does the climate impact satisfaction with life? An Australian spatial study. *Weather Climate and Society*, *15*(1), 159–175. https://doi.org/10.1175/WCAS-D-22-0063.1.

Ma, J., Dong, G., Chen, Y., & Zhang, W. (2018). Does satisfactory neighbourhood environment lead to a satisfying life? An investigation of the association between neighbourhood environment and life satisfaction in Beijing. *Cities*, *74*, 229–239. https://doi.org/10.1016/j.cities.2017.12.008.

MacKerron, G., & Mourato, S. (2009). Life satisfaction and air quality in London. *Ecological Economics*, *68*, 1441–1453. https://doi.org/10.1016/j.ecolecon.2008.10.004.

Mouratidis, K. (2019). Compact city, urban sprawl, and subjective well-being. *Cities*, *92*, 261–272. https://doi.org/10.1016/j.cities.2019.04.013.

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica, 46*(1), 69–85. Retrieved from https://www.jstor.org/stable/1913646.

Neira, I., Bruna, F., Portella, M., & Garcia_Aracil, A. (2018). Individual Well-Being, Geographical Heterogeneity and Social Capital. *Journal of Happiness Studies*, *19*, 1067–1090. https://doi.org/10.1007/s10902-016-9840-z.

OECD (2013). *OECD Guidelines on Measuring Subjective Wellbeing*. Retrieved from https://doi.org/10.1787/9789264191655-en.

OECD (2001). *The Well-being of Nations: The Role of Human and Social Capital*. Retrieved from Paris.

Oishi, S., Kesebir, S., & Diener, C. (2011). Income inequality and happiness. *Psychological Science*, *22*(9), 1095–1100. https://doi.org/10.1177/0956797611417262.

Okulicz-Kozaryn, A. (2011). Geography of European life satisfaction. *Social Indicators Research*, *101*, 435–445. https://doi.org/10.1007/sl1205-010-9671-y.

Oswald, A., & Wu, S. (2011). Well-being across America. *The Review of Economics and Statistics*, *93*(4), 1118–1134.

Pek, J., Wong, O., & Wong, A. (2018). How to address non-normality: A taxonomy of approaches, reviewed, and Illustrated. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.02104.

Pittau, G., Zelli, R., & Gelman, A. (2010). Economic disparities and life satisfaction in European regions. *Social Indicators Research*, *96*, 339–361. https://doi.org/10.1007/s11205-009-9481-2.

Powdthavee, N. (2007). Are there geographical variations in the psychological cost of unemployment in South Africa? *Social Indicators Research*, *80*, 629–652. https://doi.org/10.1007/sl1205-006-0013-z.

Raudenbush, S., & Sampson, R. (1999). Ecometrics: Toward a science of assessing ecological settings, with application to the systematic Social Observation of neighborhoods. *Sociological Methodology*, *29*(1), 1–41. https://doi.org/10.1111/0081-1750.00.

Rentfrow, P., & Jokela, M. (2016). Geographical psychology: The spatial Organization of Psychological Phenomena. *Current Directions in Psychological Science*, *25*(6), 393–398. https://doi.org/10.1177/0963721416658446.

Rentfrow, P., Mellander, C., & Florida, R. (2009). Happy States of America: A state-level analysis of psychological, economic, and social well-being. *Journal of Research in Personality*, *43*(6), 1073–1082. https://doi.org/10.1016/j.jrp.2009.08.005.

Rentfrow, P., Jokela, M., & Lamb, M. (2015). Regional Personality differences in Great Britain. *Plos One*, *10*(3), e0122245. https://doi.org/10.1371/journal.pone.0122245.

Royston, J. P. (1982). An Extension of Shapiro and Wilk's W Test for Normality to Large Samples. *Applied Statistics, 31*(2), 115–124. Retrieved from https://www.jstor.org/stable/2347973.

Schwanen, T., & Wang, D. (2014). Well-being, context, and everyday activities in space and time. *Annals of the Association of American Geographers*, *104*(4), 833–851. https://doi.org/10.1080/00045608.2014.912549.

Schynz, P. (2002). Wealth of nations, individual income and life satisfaction in 42 countries: A multi-level approach. *Social Indicators Research*, *60*, 5–40.

Shields, M., Price, S., & Wooden, M. (2009). Life satisfaction and the economic and social characteristics of neighbourhoods. *Journal of Population Economics*, *22*, 421–443. https://doi.org/10.1007/s00148-007-0146-7.

Shucksmith, M., Cameron, S., Merridew, T., & Pichler, F. (2009). Urban–rural differences in quality of life across the European Union. *Regional Studies*, *43*, 1275–1289. https://doi.org/10.1080/00343400802378750.

Snijders, T., & Berkhof, J. (Eds.). (2008). *Diagnostic checks for Multilevel models*. Springer.

Snijders, T., & Bosker, R. (2011). *Multilevel Analysis: an Introduction to Basic and Advanced Multilevel Modelling (2nd edition)*: Sage Publications.

Stutzer, A., & Frey, B. (2008). Stress that doesn't pay: The commuting paradox. *Scandinavian Journal of Economics*, *110*(2), 339–366. https://doi.org/10.1111/j.1467-9442.2008.00542.x.

Subramanian, S. V., Kawachi, I., & Kennedy, B. P. (2000). Does the state you live in make a difference? Multilevel analysis of self-rated health in the US. *Social Science and Medicine*, *53*(1), 9–19.

Veenhoven, R. (2000). Freedom and Happiness: A comparative study of 46 nations in the early 1990s. In E. Diener, & E. Suh (Eds.), *Culture and subjective wellbeing*. MIT Press.

Veenhoven, R. (2002). Why social policy needs subjective indicators. *Social Indicators Research*, *58*, 33–45.

Veenhoven, R. (2008). *Comparability of Happiness across nations* Paper presented at the International Meeting of the Psychometric Society, Tokyo, Japan.

Vemuri, A., & Costanza, R. (2006). The role of social, human, built and natural capital in explaining life satisfaction at the country level: Toward a Nation Wellbeing Index (NWI). *Ecological Economics*, *58*, 119–133.

Vemuri, A., Grove, J. M., Wilson, M., & Burch, W. (2011). A tale of two scales: Evaluating the relationship among life satisfaction, Social Capital, Income, and the Natural Environment at Individual and Neighborhood levels in Metropolitan Baltimore. *Environment and Behavior*, *43*(1), 3–25. https://doi.org/10.1177/0013916509338551.

Watson, N. (2012). *Longitudinal and Cross-sectional Weighting Methodology for the HILDA Survey* HILDA Project Technical Paper Series, (2/12). Melbourne.

Weckroth, M., Ala-Mantila, S., Ballas, D., Ziogas, T., & Ikonen, J. (2022). Urbanity, neighbourhood characteristics and Perceived Quality of Life (QoL): Analysis of individual and contextual determinants for Perceived QoL in 3300 Postal Code areas in Finland. *Social Indicators Research*, *164*, 139–164. https://doi.org/10.1007/s11205-021-02835-z.

Wilkinson, R., & Pickett, K. E. (2009). *The spirit level. Why more equal societies almost always do better*. Bloomsbury Publishing.

World Bank (2023). Unemployment (% of total workforce)(modeled ILO estimate)-United Kingdom. Retrieved from https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?locations=GB.

Yuan, H. (2016). Structural Social Capital, Household income and life satisfaction: The evidence from Beijing, Shanghai and Guangdong-Province, China. *Journal of Happiness Studies*, *17*(2), 569–586. https://doi.org/10.1007/s10902-015-9622-z.

Ziogas, T., Ballas, D., Koster, S., & Edzes, A. (2023). Happiness, space and place: Community area clustering and spillovers of life satisfaction in Canada. *Applied Research in Quality of Life*. https://doi.org/10.1007/s11482-023-10203-x.