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Child social exclusion and health outcomes

A study of small areas across Australia

Summary

The Australian Institute of Health and Welfare (AIHW) and the University of Canberra's National Centre for Social and Economic Modelling (NATSEM) have collaborated to explore links between the risk of social exclusion and health outcomes in Australian children at the small-area level.

Social exclusion is a broad concept that is used to describe social disadvantage and lack of opportunity. NATSEM developed the child social exclusion (CSE) index for 0–15 year olds using data predominantly from the 2006 Census. The index aims to capture the risk of social exclusion experienced by Australian children at the small-area level (mostly Statistical Local Areas—SLAs). It is made up of five domains related to social exclusion: socioeconomic circumstances, education, connectedness, housing and health service access.

This project linked the CSE index with data on children's health outcomes in the form of potentially preventable hospitalisations (PPHs) and avoidable deaths among 0–14 year olds.

Findings

The findings show that Australian children living in small areas with a high risk of child social exclusion have, on average, worse health outcomes than children living in other areas. This is the case in remote as well as in non-remote areas.

PPH rates were associated with the risk of child social exclusion:

- Areas with a relatively high risk of child social exclusion also had relatively high average rates of PPH.
- PPH rates were much higher in the areas that had the highest risk of child social exclusion than in all other areas.
- A high risk of child social exclusion was associated with high PPH rates for children both in remote and non-remote areas.

- Children living in *Remote* and *Very remote* areas had higher rates of PPH than would be expected based on the CSE index alone.

Areas with a relatively high risk of child social exclusion also had relatively high rates of avoidable deaths. The estimated annual rate of avoidable deaths among the 20% of children who lived in the areas with the highest risk of child social exclusion was 32 per 100,000 children. This is more than twice as high as the 15 avoidable deaths per 100,000 children that occurred among the 20% of children who lived in the areas with the lowest risk of child social exclusion.

The findings suggest that geographical modelling of disadvantage at the small-area level may be a valuable tool to help focus policy programs aimed at improving the health and wellbeing of Australia's children. Characteristics of areas with unexpectedly good or poor health outcomes given their score on the CSE index can be used to identify other factors that, like remoteness, have an association with children's health outcomes that is independent of social exclusion.

Contents

1 Introduction

Social exclusion is a broad concept used to describe social disadvantage and lack of resources, opportunity, participation and skills (Levitas et al. 2007). A growing number of studies worldwide have found links between social exclusion (or its components) and health outcomes. Most of these studies have investigated variation in social disadvantage and health outcomes either at the individual level or at a large geographical level (region or country). While these approaches are useful for exploring the relationship between social exclusion and health outcomes, they are limited in their capacity to inform local policy initiatives or targeted distribution of resources at the local level.

In Australia, the National Centre for Social and Economic Modelling (NATSEM) developed the child social exclusion (CSE) index to estimate the risk of social exclusion experienced by children aged 0–15 (Abello et al. 2012; Harding et al. 2009). The CSE index is based on data on socioeconomic circumstances, education, connectedness, housing and health service access from the Australian Bureau of Statistics (ABS) 2006 Census of Population and Housing, the 2009 National Assessment Program—Literacy and Numeracy (NAPLAN) and the 2009 Australian Early Development Index (AEDI). A summary of the domains and variables included in the CSE index is provided in Table A1 (Appendix A). The CSE index estimates the risk of child social exclusion in small areas (based on the Statistical Local Areas, or SLAs, of the ABS Australian Standard Geographical Classification) all over Australia. This makes it possible to study outcomes associated with child social exclusion in a manner that is well suited to inform program delivery at the local level.

Because the CSE index is area based (rather than individual based), it estimates the risk of child social exclusion experienced by the total population of all children living in an area. There is, of course, variation in the actual level of social exclusion experienced by individual children within each area.

A recent study by Butler et al. (2013) found a relationship between the CSE index and rates of hospital admissions for ambulatory care sensitive conditions (ACSCs) (using a similar definition of ACSC as the one used for potentially preventable hospitalisations (PPHs) in this study) among 0–4-year-old children in small areas across Victoria (Local Government Areas, as ACSC data were not available at the SLA level). Their study was the first to confirm the association between social exclusion and poor health outcomes in Australian children.

This bulletin presents the results of a collaborative effort between the Australian Institute of Health and Welfare (AIHW) and NATSEM to explore the relationship between the risk of social exclusion (using the CSE index) and health outcomes in Australian children. The combination of NATSEM's data on child social exclusion and the AIHW's data on children's health outcomes, both at the small-area (SLA) level, represents a unique opportunity to produce the first national study of the relationship between social exclusion and health outcomes in children. PPHs and avoidable deaths were used as measures of health outcomes. In addition to being the only suitable health outcomes with data available at the SLA level, PPHs and avoidable deaths are widely used as indicators of

broader health outcomes that are sensitive to the effectiveness of the primary health-care system and policies aimed at modifying risk factors (for example, Page et al. 2006; Page et al. 2007). In Australia, they are also performance indicators for the National Healthcare Agreement and in the National Health Performance Framework as measures of high-quality and affordable primary and community health services.

Aims

The main aim of the project was to investigate whether there is an association between the risk of child social exclusion and children's health outcomes in Australia at the small-area level. If such an association existed, the project also aimed to identify areas that had unexpectedly good or poor health outcomes given their risk of social exclusion and investigate whether these were influenced by the remoteness of the areas.

Methods

The project used NATSEM's CSE index as a measure of risk of child social exclusion, and data on potentially preventable hospitalisations (PPHs) and avoidable deaths among children aged 0–14 from the AIHW's National Hospital Morbidity Database and National Mortality Database. Although the CSE index is for children aged 0–15, data on PPHs and avoidable deaths were extracted for 0–14 year olds due to the availability of corresponding population data required to calculate rates. The statistical analysis undertaken for avoidable deaths required the calculation of estimated rates for 0–15 year olds based on observed rates for 0–14 year olds.

The results of the project are presented in chapters 2, 3 and 4. Chapter 2 gives a brief overview of how child social exclusion, PPHs and avoidable deaths vary geographically. Chapters 3 and 4 then present the results regarding the associations between child social exclusion and PPHs and between child social exclusion and avoidable deaths, respectively.

For some of the analyses, the areas were ranked based on their CSE index score and divided into quintiles such that each CSE index quintile contained 20% of the total population of the 0–15 year olds that was used when the index was created. The resulting groups of areas are referred to as CSE index quintiles. For more details on the methods, refer to Appendix A.

2 The geography of child social exclusion and health outcomes

Child social exclusion

Earlier work has shown that the risk of child social exclusion varies geographically in Australia. Abello et al. (2012) found that children in capital cities were less likely to be at risk of social exclusion than children in other areas. There was also much variation between states and territories. New South Wales, Queensland and the Northern

Territory all had relatively high proportions of children at risk of social exclusion compared with other jurisdictions (Abello et al. 2012).

This study analysed variation in CSE index scores across the Australian Standard Geographical Classification (ASGC) Remoteness Areas. A higher CSE index score indicates a higher risk of social exclusion. The average risk of child social exclusion increased with remoteness (Table 2.1).

Table 2.1: Child social exclusion (CSE) index score by remoteness area

Remoteness area	Mean CSE index score	Standard deviation	Minimum	Maximum
Major cities	15.2	10.8	0.5	51.5
Inner regional	17.5	8.1	2.3	62.4
Outer regional	20.8	9.2	5.9	63.0
Remote	28.2	19.3	5.1	86.0
Very remote	47.2	22.7	2.2	81.2

Source: AIHW analysis of CSE index and remoteness area (2006 ASGC).

Potentially preventable hospitalisations

Using the same selection of conditions that was used to define PPHs in this study, Page et al. (2007) found substantial geographical variation in rates of PPH (referred to as 'ambulatory care-sensitive conditions' in their study). For the population as a whole, socioeconomically disadvantaged areas generally had higher rates than other areas (Page et al. 2007). There was also variation between states and territories. While most jurisdictions had rates of PPH that were close to the national average (within 11%), the rates of the Australian Capital Territory were much lower and the rates of the Northern Territory much higher (Page et al. 2007).

Looking specifically at rates of PPH in children, the current study found that the rates increased with remoteness, from 22 per 1,000 children in *Major cities* to 48 per 1,000 children in *Very remote* areas (Table 2.2).

Table 2.2: Annual PPH rates[(a)] of children aged 0–14, by remoteness area, 2006–07 to 2008–09

Remoteness area	Mean PPH rate[(a)]	Standard deviation	Minimum	Maximum
Major cities	21.8	6.4	5.8	69.8
Inner regional	23.8	11.1	5.4	138.1
Outer regional	24.5	10.9	3.5	64.2
Remote	38.2	27.3	7.1	168.5
Very remote	47.8	29.0	4.4	193.6

(a) Age-standardised hospital separations per 1,000 children aged 0–14 (area-based average).

Source: AIHW National Hospital Morbidity Database.

Avoidable deaths

Page et al. (2006) found geographical variation in avoidable deaths in Australia and New Zealand. There were strong socioeconomic gradients in rates of avoidable deaths in both countries; the most disadvantaged areas had the highest rates (Page et al. 2006). In Australia, there was also some variation between states and territories. However, with the exception of the Northern Territory, which had a much higher rate of avoidable deaths, all jurisdictions had rates that were within 15% of the national average (Page et al. 2006).

In this study, rates of avoidable deaths in children were much higher in *Very remote* areas than in all other areas (Table 2.3). However, the rate for *Very remote* areas is sensitive to random year-to-year variation in numbers of avoidable deaths. The relatively small total population size and limited number of areas mean that there are few avoidable deaths and much variation in rates between areas.

Table 2.3: Rates[(a)] of avoidable deaths of children aged 0–14, by remoteness area, 2007

Remoteness area	Rate of avoidable deaths[(a)]
Major cities	22.1
Inner regional	22.0
Outer regional	29.6
Remote	29.6
Very remote	112.5

(a) Number of avoidable deaths per 100,000 children aged 0–14. Rates are the total rates by Remoteness Area, as numbers of avoidable deaths are too small for area-based analysis to be presented.

Source: AIHW National Mortality Database.

3 Potentially preventable hospitalisations and social exclusion

Children living in areas with a relatively high risk of child social exclusion also experienced relatively high rates of PPH. The rate of PPH was 75% higher among the 20% of children who lived in the areas with the highest risk of child social exclusion than among the 20% who lived in the areas with the lowest risk. Statistical analysis confirmed that there were significant differences in the likelihood that children living in areas in the different quintiles of the CSE index would experience PPH (analysis of variance (ANOVA): $F_{4,1107} = 38.01$, $p < 0.0001$) (see Appendix A for details of statistical analyses). This means that the difference in PPH rates seen between the CSE index quintiles was of a large magnitude in absolute terms and also highly statistically significant.

The average PPH rate increased with increasing risk of child social exclusion across all CSE index quintiles (Table 3.1 and Figure 3.1). However, the largest increase was between the quintile with the second-highest risk of child social exclusion and the quintile with the highest risk (45% higher). The 20% of children who lived in the areas with the highest risk of social exclusion experienced particularly high rates of PPH compared with children who lived in areas in all other quintiles. This was statistically significant (post-hoc Tukey test: all $p < 0.05$); however, the differences between the other quintiles were not significant (post-hoc Tukey test: all $p > 0.05$).

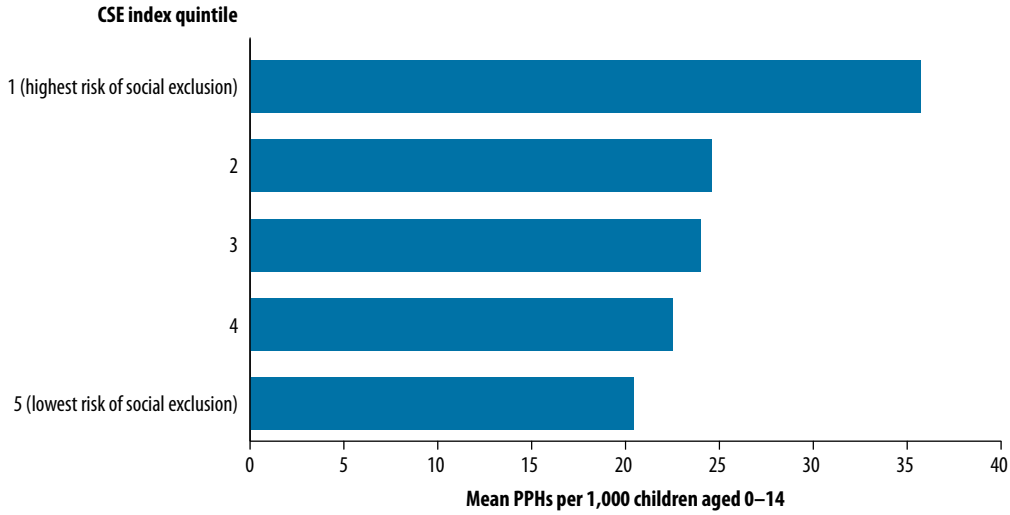
Table 3.1: Annual PPH rates[(a)] of children aged 0–14, by CSE index quintile, 2006–07 to 2008–09

CSE index quintile	Mean PPH rate[(a)]	Standard deviation	Minimum	Maximum
1 (highest risk of social exclusion)	35.7	24.6	4.4	193.6
2	24.6	10.8	7.1	83.2
3	24.0	10.7	5.4	108.5
4	22.5	9.5	3.5	75.3
5 (lowest risk of social exclusion)	20.4	6.4	8.9	45.6

(a) Age-standardised hospital separations per 1,000 children aged 0–14 (area-based average).

Source: AIHW National Hospital Morbidity Database.

Table 3.1 also shows that there is much variation in PPH rates among the areas within each quintile, as indicated by the standard deviation and minimum and maximum PPH rates, especially among the areas that are home to the children subject to the highest risk of child social exclusion (rate range of 4–194 per 1,000 children). All quintiles include areas with very low PPH rates as well as areas with high PPH rates. This suggests that factors not captured by the CSE index also affect PPH rates at the small-area level.



Source: AIHW National Hospital Morbidity Database.

Figure 3.1: Annual PPHs per 1,000 children aged 0–14, by CSE index quintile, 2006–07 to 2008–09

Remoteness and child social exclusion

Child social exclusion and health outcomes in non-remote areas

Living in *Remote* or *Very remote* areas is associated both with a high risk of child social exclusion and poor health outcomes. To ensure that the association between risk of child social exclusion and children's PPH rates was not entirely due to remote areas having high PPH rates, the analysis was repeated excluding *Remote* and *Very remote* areas.

PPH rates still increased with increasing risk of child social exclusion across the index quintiles. Again, the largest increase was seen between the 2 quintiles with the highest risk of child social exclusion (Table 3.2), although this increase was not as dramatic as when *Remote* and *Very remote* areas were included in the analysis (Table 3.1). There were still statistically significant differences between index quintiles with *Remote* and *Very remote* areas excluded (ANOVA: $F_{4, 934} = 11.9$, $p < 0.0001$). This means that there is an association between PPH rates and risk of child social exclusion in non-remote areas.

It should be noted that *Remote* and *Very remote* areas have a higher proportion of Aboriginal and Torres Strait Islander people than other areas. Indigenous status is not accounted for in the CSE index, and this study did not investigate whether child social exclusion affects health outcomes differently for Indigenous and non-Indigenous people. This would be an important area for further investigation.

Table 3.2: Annual PPH rates[(a)] of children aged 0–14 in non-remote areas, by CSE index quintile, 2006–07 to 2008–09

CSE index quintile	Mean PPH rate[(a)]	Standard deviation	Minimum	Maximum
1 (highest risk of social exclusion)	26.9	12.0	10.4	138.1
2	23.6	8.4	9.2	64.2
3	23.0	9.8	5.4	108.5
4	21.9	8.4	3.5	69.8
5 (lowest risk of social exclusion)	20.0	5.9	8.9	40.7

(a) Age-standardised hospital separations per 1,000 children aged 0–14 (area-based average).

Source: AIHW National Hospital Morbidity Database.

Remoteness and residual PPH rate

Linear regression was used to define the relationship between the CSE index and PPH rate. This was done in order to determine how the PPH rates of individual areas deviate from what would be expected based on their risk of child social exclusion alone. The deviation, or residual PPH rate, of each area can be used to identify areas with unexpectedly high or low PPH rates and therefore aid in the search for factors that influence PPH rates independently of the factors that are included in the CSE index. In this study, residual PPH rate was used to test whether the high PPH rates generally experienced by children living in remote areas are higher than what would be predicted based on their risk of child social exclusion.

The index scores, the square of the index scores and the cube of the index scores were all included in linear regression models in order to find the model that was best able to predict an area's PPH rate based on its CSE index score (see Appendix A). Given that PPH rates increased the most between the two quintiles with the highest risk of child social exclusion, the best model was likely to include the square or the cube of the index scores. Based on the analysis, the best model was found to be:

'PPH rate' = 0.00705 × ('CSE index')2 + 21.74056.

This model was used to calculate the residual PPH rate for each area; that is, how much the PPH rate of each area deviated from the rate predicted by the model based on the risk of child social exclusion (Table 3.3, Figure 3.2).

On average, *Major cities* as well as *Inner regional* and *Outer regional* areas had PPH rates that were slightly lower than the model predicted based on their risk of child social exclusion (negative residual PPH rates). Conversely, *Remote* and *Very remote* areas had PPH rates that were well above what the model predicted (positive residual PPH rates).

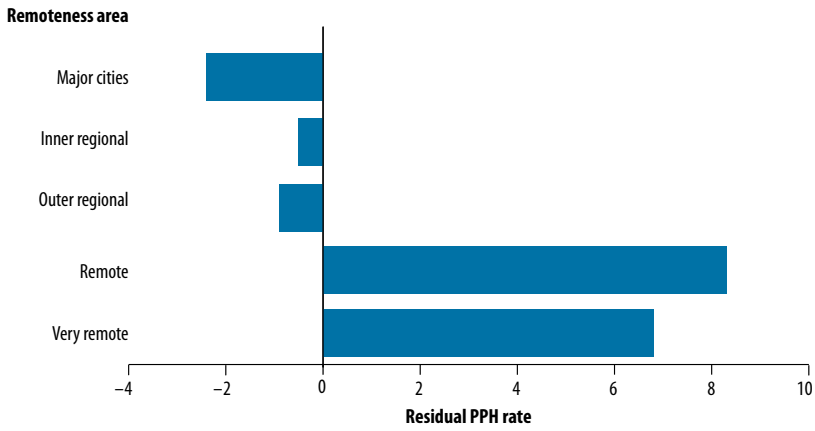
There were significant differences between the residual PPH rates of areas in the different remoteness categories (ANOVA: $F_{4, 1107} = 16.36$, $p < 0.0001$). *Remote* and *Very remote* areas had significantly higher residual PPH rates than *Major cities*, *Inner regional* and *Outer regional* areas (non-remote areas) (post-hoc Tukey test: all $p < 0.05$). There were no significant differences between any non-remote categories or between *Remote* and *Very remote* areas (post-hoc Tukey test: all $p > 0.05$). This means that children in *Remote* and *Very remote* areas have higher PPH rates than what would be expected based on their risk of child social exclusion alone. Children's PPH rates appear to be influenced by factors that are not captured by the CSE index in these areas.

Table 3.3: Annual residual PPH rates[(a)] of children aged 0–14, by remoteness classification, 2006–07 to 2008–09

Remoteness classification	Mean residual PPH rate[(a)]	Standard deviation	Minimum	Maximum	Number
Major cities	–2.4	6.0	–16.4	47.6	383
Inner regional	–0.5	10.3	–20.4	89.0	263
Outer regional	–0.9	10.9	–20.5	39.7	293
Remote	8.3	25.6	–47.2	137.0	82
Very remote	6.8	29.8	–40.7	167.4	91

(a) The difference between the number of age-standardised hospital separations per 1,000 children aged 0–14 predicted based on the CSE index score and the number actually observed. The residual PPH rate is 0 when the observed rate is identical to the rate predicted based on the CSE index.

Source: AIHW National Hospital Morbidity Database.



Note: The residual PPH rate is 0 when the observed rate is identical to the rate predicted based on the CSE index.

Source: AIHW National Hospital Morbidity Database.

Figure 3.2: Residual PPH rates of children aged 0–14, by remoteness classification, 2006–07 to 2008–09

As mentioned earlier in this section, this study did not investigate how Indigenous status may influence the effects of child social exclusion. It is possible that the relatively high proportion of Indigenous people in *Remote* and *Very remote* areas, and the poorer health outcomes known to be experienced by this group, are part of the explanation for the high residual PPH rates in these areas.

4 Avoidable deaths

Rates of avoidable deaths among children aged 0–15 were estimated based on observed rates for children aged 0–14 (see Appendix A for further details on methods).

Estimated rates of avoidable deaths among children aged 0–15 increased with increasing risk of child social exclusion. There were more than twice as many avoidable deaths among the 20% of children who lived in the areas with the highest risk of child social exclusion than among the 20% who lived in the areas with the lowest risk (Table 4.1, Figure 4.1)—that is, 32 avoidable deaths per 100,000 children compared with 15 per 100,000 children, respectively. The difference in the number of avoidable deaths between the index quintiles is highly statistically significant (chi-square test: $X^2 = 49.9$, degrees of freedom = 4, $p < 0.00001$).

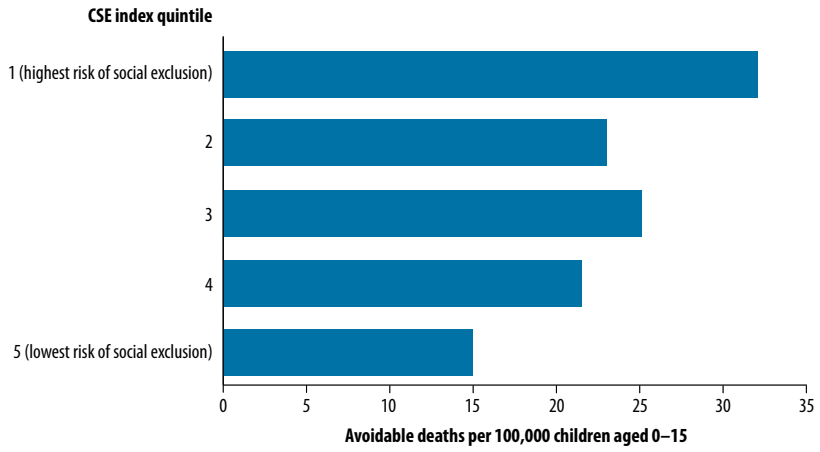
Rates of avoidable deaths were too low to allow the analyses based on individual areas that were conducted for PPH rates, including the calculation of the residual rates of avoidable deaths (see Appendix A).

Table 4.1: Estimated[(a)] avoidable deaths of children aged 0–15, by CSE index quintile, 2007

CSE index quintile	Avoidable deaths (number)	Total population (number)
1 (highest risk of social exclusion)	240	747,511
2	175	759,398
3	189	752,010
4	163	756,553
5 (lowest risk of social exclusion)	114	757,980
Total	**881**	**3,773,452**

(a) See Appendix A for details of methods.

Source: AIHW National Mortality Database.



(a) See Appendix A for details of methods.

Source: AIHW National Mortality Database.

Figure 4.1: Estimated[(a)] rate of avoidable deaths of children aged 0–15, by CSE index quintile, 2007

5 Discussion

The results presented in this bulletin show that Australian children living in small areas with a high risk of child social exclusion have, on average, worse health outcomes than children living in other areas. As the risk of child social exclusion increases, so do the rates of both PPHs and avoidable deaths. Butler et al. (2013) found a similar association between risk of social exclusion and rates of PPH in 0–4 year olds living in small areas in Victoria. This study confirms that this association also exists for 0–14 year olds across Australia, and shows that there is a similar association between risk of social exclusion and avoidable deaths in this age group.

The most dramatic increase in PPH rates with increasing risk of child social exclusion was found between areas in the index quintiles with the second-highest and highest risks of child social exclusion. However, this pattern was less pronounced when *Remote* and *Very remote* areas were excluded from the analysis. The results for non-remote areas were

similar to the results of Butler et al. (2013) who, in Victoria—a state with no *Very remote* areas and few *Remote* areas, found a more even increase in PPH rates across the five index quintiles for 0–4 year olds.

Remote and *Very remote* areas had higher PPH rates than would be expected solely based on their CSE index scores. This suggests that the PPH rates of children living in these areas are also affected by factors that are not associated with social exclusion or at least not captured by the CSE index.

Of course, not all factors that influence health outcomes in children are captured by the CSE index. One way to identify other important factors would be to follow the approach taken with respect to remoteness in this study. Characteristics of areas with unexpectedly good or poor health outcomes given their score on the CSE index can be used to identify factors that, like remoteness, have an association with children's health outcomes that is independent of social exclusion.

In conclusion, this study shows that aspects of disadvantage that are captured by the CSE index are associated with variation in children's health outcomes at the small-area level in both remote and non-remote areas of Australia. This suggests that geographical modelling of disadvantage at the small-area level may be a valuable tool to help focus policy programs aimed at improving the health and wellbeing of Australia's children.

Appendix A: Methods

Child social exclusion (CSE) index

The CSE index estimates the risk of social exclusion experienced by children aged 0–15 in small areas (based on Statistical Local Areas—SLAs) all over Australia. The CSE index is made up five domains: socioeconomic circumstances, education, connectedness, housing and health service access, and is based on data from the Australian Bureau of Statistics (ABS) 2006 Census of Population and Housing, the 2009 National Assessment Program—Literacy and Numeracy (NAPLAN) and the 2009 Australian Early Development Index (AEDI). Refer to Table A1 for a list of the variables included in the CSE index.

For detailed descriptions of the creation of the CSE index, see Harding et al. (2009), Tanton et al. (2010) and Abello et al. (2012).

Table A1: Summary of the domains and variables used in the CSE index

Domain	Measure
Socioeconomic	Sole parent family
	Bottom income quintile
	No parent in paid work
Education	No family member completing Year 12
	NAPLAN reading and numeracy score
	Low AEDI score
Connectedness	No internet at home
	No parent doing voluntary work
	No motor vehicle
Housing	High rent and low income
	Overcrowding
Health service access	Ratio of general practitioners
	Ratio of dentists

Source: Abello et al. 2012.

CSE index quintiles

For some of the analyses, the areas were ranked based on their CSE index score and divided into quintiles such that each CSE index quintile contained as close to 20% as possible of the total population of 0–15 year olds that was used when the index was created (area-based population quintiles). It is not possible for the resulting CSE index quintiles to contain exactly 20% of the total population because they are made up of areas with varying population sizes, and some of these areas will have the same CSE index score.

Potentially preventable hospitalisations

Hospitalisations are allocated a principal diagnosis code based on the World Health Organization's International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM). The fifth edition of the ICD-10-AM was used for hospitalisation data for 2006–07 and 2007–08, and the sixth edition was used for 2008–09 (NHHC 2006, 2008).

The selection of ICD-10-AM codes that was used for reporting in the Australian Institute of Health and Welfare (AIHW) report, *Australian hospital statistics 2010–11* (AIHW 2012), was used to define potentially preventable hospitalisations (PPHs) in this study. This selection of ICD-10-AM codes is also consistent with the codes used by the Victorian Ambulatory Care Sensitive Conditions Study (Victorian Government Department of Human Services 2004) and the *Atlas of avoidable hospitalisations in Australia: ambulatory care-sensitive conditions* (Page et al. 2007).

Hospitalisations of newborns (unqualified days only), hospital boarders and admissions for the purpose of posthumous organ procurement were excluded from all analysis.

Records of PPHs for children aged 0–14 by SLA were extracted from the AIHW's National Hospital Morbidity Database. Not all states and territories provided information on the area of usual residence of the patient in the form of an SLA code for all presentations. In addition, not all states and territories provided the version of SLA specified in the national minimum data set. Where necessary, the AIHW mapped the supplied area of residence data for each presentation to the same SLA version and to remoteness area categories based on the ABS Australian Standard Geographical Classification (ASGC) Remoteness Structure for 2006. This mapping was done on a probabilistic basis. Because of this, the SLA and remoteness area data for individual records may not be accurate; however, the overall distribution of records by geographical area is considered useful.

Three years of PPH data (2006–07, 2007–08 and 2008–09) were combined to reduce the influence of stochastic annual variation within individual SLAs. The data were then summarised by SLA according to the 2006 ASGC using correspondence files provided by the ABS.

Population

The ABS estimated resident populations (ERPs) at June 2006, 2007, 2008 and 2009 by SLA on 2006 ASGC boundaries were used to estimate the December populations for 2006–07, 2007–08 and 2008–09 by SLA on 2006 ASGC boundaries. This was done by calculating the average of the preceding and subsequent June ERPs, to estimate the December population. The AIHW held ERP data by 5-year age groups for 2006, 2008 and 2009 on 2006 ASGC boundaries. ERP data for 2007 (on 2007 ASGC boundaries) were concorded to 2007 ERP on 2006 ASGC boundaries using an ABS correspondence file.

Rates of potentially preventable hospitalisations

PPH and ERP data for each year were merged and annual rates of PPH were calculated for 0–4 year olds, 5–9 year olds, 10–14 year olds and 0–14 year olds for all SLAs. Average annual rates of PPH were then calculated for each SLA based on the 3 years.

Remoteness

This bulletin uses the ASGC, which groups geographical areas into five classes (*Major cities, Inner regional, Outer regional, Remote* and *Very remote*). These classes are based on Census Collection Districts and are defined using the Accessibility/Remoteness Index of Australia (ARIA). The ARIA is a measure of the remoteness of a location from services provided by large towns or cities.

Some SLAs cover multiple remoteness areas. To be able to use a remoteness variable with five discrete levels in the analysis, each SLA was assigned a value corresponding to the remoteness category with the greatest proportion of its population.

Geography

The analysis in this bulletin is predominantly based on SLAs in the ASGC.

Due to small populations, SLAs have been aggregated to Statistical Subdivisions in the Australian Capital Territory and to Council Wards in Brisbane in the geography used for the CSE index. It was therefore necessary to aggregate data on PPH rates and remoteness in the same way for the Australian Capital Territory and Brisbane.

This was straightforward for remoteness as the vast majority of people in all aggregated areas lived in *Major cities*.

PPH rates were aggregated such that the contribution from each SLA to the overall PPH rates of the aggregated areas was proportional to its share of the population of the aggregated area or areas it was included in. PPH rates were then merged with remoteness data and the CSE index.

Age standardisation

PPH rates vary with age in children. PPH rates were therefore age-standardised to enable comparisons of PPH rates between areas with different age profiles. The contributions of the 3 age groups (0–4, 5–9 and 10–14 year olds) to the overall rate for 0–14 year olds were standardised to conform to the 2001 Australian standard population. The total population of 0–14 year olds in this population is made up of 32% 0–4 year olds, 34% 5–9 year olds and 34% 10–14 year olds. For each small area, the overall age-standardised PPH rate for 0–14 year olds was calculated by taking the sum of the crude rate of each age group multiplied by the proportion of the same age group in the standard population of 0–14 year olds.

All analyses were carried out using both crude and age-standardised PPH rates. The Pearson's correlation between crude and age-standardised rates was 0.994 (near perfect

positive correlation) and the results were very similar regardless of whether crude or age-standardised PPH rates were used. All analyses presented in this bulletin are based on age-standardised rates.

Residual PPH rates and remoteness

Linear regression models were explored with PPH rate as the response variable and with the raw index scores for each area, the square of the index scores and the cube of the index scores as explanatory variables. The ability of models with all possible combinations of these explanatory variables to predict the observed PPH rates was evaluated. A model only including the square of the index scores was the only model that could not be improved significantly by adding one or both of the other explanatory variables. This model was used to calculate the residual PPH rates that were then used in the analysis with remoteness.

Statistical tests

PPHs and CSE index

All recorded PPHs for all areas included in the CSE index were used in this study. This means that statistical tests are not necessary to make statements about differences in the actual rates that occurred in areas over the 3 years. However, a child experiencing a PPH can be seen as a stochastic event occurring with a certain risk that may vary between areas. The observed rate in an area is therefore only one of a large number of potential rates of PPH that each could have occurred with a probability that depends on this risk. Statistical tests using the observed rates as estimates of the risk of PPH and treating them as a random sample drawn from the potential rates are necessary to evaluate the association between the risk of PPH and child social exclusion.

A one-way analysis of variance (ANOVA) was used to show that the risk of children experiencing PPH varied between areas in different quintiles of the CSE index ($F_{4,\ 1107} = 38.01$, $p < 0.0001$). The underlying assumptions of the ANOVA require that the distribution of PPH rates is normal within all quintiles of the CSE index. A Kolmogorov-Smirnov test found no statistically significant deviations from the normal distribution in any of the quintiles (all $p > 0.05$). Another underlying assumption is that the variance in PPH rate between areas is equal within all CSE index quintiles. However, the performance of the ANOVA is robust to deviations from this assumption, and the likely effects of any deviation would, in this case, depend on the number of areas in each quintile (see, for example, Zar 1996). As indicated by the standard deviations in Table 3.1, the quintile with the highest risk of child social exclusion had a variance in PPH rates that was substantially higher than the variance in all other areas. As this quintile included the highest number of areas of any quintile (quintiles are based on total population, not number of areas), this should make the ANOVA more conservative (that is, less likely to find a significant result). Furthermore, a Kruskal-Wallis test, a non-parametric equivalent of the one-way ANOVA that is even less sensitive to deviations from the assumption of equal variances, also found highly significant differences in PPH rates between quintiles ($p < 0.0001$).

The Tukey post-hoc test that was used to test for significant differences between the PPH rates of pairs of quintiles also relies on the assumption that the variance in PPH rate is equal in all quintiles. Because of the issue with unequal variances discussed above, Welch's *t*-tests (a type of *t*-test that does not require the variances of the two groups it is comparing to be equal) was also used to compare the PPH rates of all pairs of quintiles. The Welch's *t*-tests confirmed that there were highly significant differences in PPH rate between the quintile with the highest risk of child social exclusion (quintile 1) and all other quintiles (all $p < 0.0001$). They also found significant differences between quintiles 2 and 4 ($p = 0.03$), 2 and 5 ($p < 0.0001$), 3 and 5 ($p < 0.0001$) and 4 and 5 ($p = 0.01$).

A one-way ANOVA was also used to show that the risk of children living in non-remote areas experiencing PPH varied between areas in the different CSE index quintiles ($F_{4, 934} = 11.9$, $p < 0.0001$). Here, there was much less variation in the variances in PPH rate between the quintiles than when *Remote* and *Very remote* areas were included in the analysis.

Residual PPH and remoteness

Linear regression was used to find the model that best described the relationship between the CSE index scores and the PPH rates of the small areas. Studentised residuals were calculated and inspected to make sure that no outliers among the data points had a strong influence on any of the models that were evaluated. After models with all possible combinations of the CSE index, the square of the CSE index and the cube of the CSE index as explanatory variables had been tested, a model including only the square of the CSE index was found to be the only model that could not be significantly improved by adding any of the other explanatory variables (see Chapter 3). This model was then used to generate residual PPH rates for all areas.

A one-way ANOVA was used to show that residual PPH rate changed with remoteness area ($F_{4, 1107} = 16.36$, $p < 0.0001$). Here, the variance in PPH rate among *Remote* and *Very remote* areas was much greater than among non-remote areas (as indicated by the standard deviations presented in Table 3.2). In this case, the two categories with the greater variance included the smallest number of areas. This should make the ANOVA less conservative—that is, more likely to find a significant result (Zar 1996). However, a non-parametric Kruskal-Wallis test (see above) showed the same highly significant result as the ANOVA ($p < 0.0001$).

A Tukey post-hoc test was used to test for significant differences between the PPH rates of pairs of remoteness areas. Welch's t-tests were used to confirm the significant differences found by the Tukey test between *Remote* and *Very remote* areas and all other areas (all $p \leq 0.0002$). Again, there were no significant differences between other areas (all $p > 0.05$). Welch's t-test, unlike the Tukey test, does not rely on the assumption of equal variances between categories.

Avoidable deaths

The International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10) codes that were used for the 2012 cycle of reporting of the National Healthcare Agreement's progress indicator for avoidable deaths (PI 20—including both treatable and preventable causes of death) were used to define avoidable deaths in this study. Records of avoidable deaths were extracted from AIHW's National Mortality Database.

The number of avoidable deaths among 0–14 year olds was extracted for all SLAs for the years 2006–2010. This age range was used due to the availability of ERP data by SLA. These data were then merged with ERP data (refer to 'Population' earlier in this appendix) to enable calculation of rates of avoidable deaths for all SLAs. Areas with no recorded avoidable deaths were assumed to have had no avoidable deaths. Annual rates of avoidable deaths were low. For each year, there were many areas with no deaths recorded and most of the remaining areas had one to a few deaths. This means that comparing rates and residual rates for individual areas is not very meaningful, even when data from several years are aggregated. It is simply not possible to get accurate estimates of the extent to which individual areas deviate from a mean or a predicted rate. It also means that the distribution of death rates across areas is not ideal for analyses like ANOVA and linear regression or for identifying individual areas with unexpectedly high or low rates of avoidable deaths.

However, it is still possible to analyse how rates of avoidable deaths vary across the groups of areas defined by the 5 index quintiles. There are enough deaths in 1 year for this type of analysis. By analysing data from only 1 year, it is possible to focus on mortality rates as they were close to the time when the data on which the CSE index is based were collected. Mortality data for 2007 were selected for use in the analysis because data were available on the necessary 2006 ASGC boundaries for this year, and it was the year immediately following the 2006 Census from which most of the data used to calculate the CSE index were derived.

Rates of avoidable deaths were calculated for the geography used for the CSE index and merged with the index in the same way as discussed for rates of PPHs above. The rates were based on numbers of deaths among 0–14 year olds as a group and were therefore not age-standardised.

Chi-square test

As with PPHs (see above), avoidable deaths are stochastic events that occur with a certain risk. Statistical tests are necessary to assess whether this risk varies between areas in the different CSE index quintiles.

The number of estimated avoidable deaths and survivors (children who did not die because of avoidable causes, including children who died from non-avoidable causes) were calculated for all areas in each quintile of the CSE index. A chi-square test based on these estimated counts was used to test whether there were significant differences in the risk of avoidable deaths between the CSE index quintiles. This test requires the counts

of children who died from avoidable causes to be compared with all children who did not die from avoidable causes. That is why counts of children who did not die are placed in the same category as children who died from non-avoidable causes. To link with the CSE index quintiles, the number of avoidable deaths was estimated for the population of each quintile in the following way:

1. The actual overall rate of avoidable deaths was calculated based on all areas in each quintile. The rate was based on deaths registered in 2007 and the 2007 estimated resident population of 0–14 year olds—both based on the 2006 ASGC (the geography used for the index).
2. An estimated number of deaths for each CSE index quintile was then calculated by multiplying the overall rate of avoidable deaths in the areas in the quintile by the total population of 0–15 year olds living in the areas in the quintile in 2006 according to the population data that were used to create the index quintiles.

Expected counts above 5 or 10 in all cells are usually considered necessary for the chi-square test to be accurate. In this study, based on the overall proportion of children who died from avoidable causes, all CSE index quintiles had expected counts of 175 or more children who died from avoidable causes and of 747,336 or more children who did not die from avoidable causes. The chi-square test found that the differences in the number of children who died from avoidable causes between the CSE index quintiles were significantly greater than what would be expected to occur by chance if the underlying risks were the same in all quintiles ($X^2 = 49.9$, degrees of freedom = 4, $p < 0.00001$).

Appendix B: Data sources

AIHW National Hospital Morbidity Database (NHMD)

The NHMD is compiled by the Australian Institute of Health and Welfare (AIHW) from data supplied by the state and territory health authorities. The purpose of the NHMD is to collect information about care provided to admitted patients in Australian hospitals (excludes non-admitted patient care provided in outpatient clinics or emergency departments). The scope of the NHMD is episodes of care for admitted patients in all public and private acute and psychiatric hospitals, free-standing day hospital facilities and alcohol and drug treatment centres in Australia. Hospitals operated by the Australian Defence Force, corrections authorities and in Australia's offshore territories are not in scope but some are included.

Hospital records are for 'separations' and not individuals. Separation (referred to in this bulletin as 'hospitalisation') is the term used to refer to the episode of admitted patient care, which can be a total hospital stay (from admission to discharge, transfer or death) or a portion of a hospital stay beginning or ending in a change of type of care (for example, from acute care to rehabilitation). As there can be multiple admissions for the same individuals, hospital separations should not be interpreted as counts of persons or as measures of incidence or prevalence of the disease or condition in question.

The collection contains administrative, demographic and clinical data.

Data availability: annual from 1993–94 onwards.

Data quality statement: available for data from 2010–11 onwards. The data quality statement for 2010–11 is available at <http://meteor.aihw.gov.au/content/index.phtml/itemId/511338>.

Further information is provided on the AIHW website at <http://www.aihw.gov.au/hospitals/australian-hospital-statistics/>.

AIHW National Mortality Database

The AIHW National Mortality Database includes information on the factors that caused death, and other information about the deceased person, such as age at death, place of death, country of birth and, where applicable, the circumstances of their death. The cause of death data are sourced from the Registrars of Births, Deaths and Marriages in each state and territory and the National Coronial Information System and compiled and coded by the Australian Bureau of Statistics (ABS).

Data availability: annual from 1964 onwards.

Data quality statement: this is available on the ABS website at <http://www.abs.gov.au/Ausstats/abs@.nsf/0/3F9DD0533D6C4C4CCA2576F6001396CC>.

Further information is provided on the AIHW website at <http://www.aihw.gov.au/deaths/aihw-deaths-data/>.

Child social exclusion (CSE) index

The child social exclusion (CSE) index is a geographical index of social exclusion risk for children in Australia. It combines economic and social factors that are specifically related to child outcomes. The index is calculated at the Statistical Local Area (SLA) level, which generally equates to Local Government Areas (LGAs).

Further information is provided on the National Centre for Social and Economic Modelling website at <http://web.natsem.canberra.edu.au/maps/AUST_CSE/atlas.html>.

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Abbreviations

ABS	Australian Bureau of Statistics
ACSC	ambulatory care sensitive condition
AEDI	Australian Early Development Index
AIHW	Australian Institute of Health and Welfare
ANOVA	analysis of variance
ASGC	Australian Standard Geographical Classification
CSE	child social exclusion (index)
ERP	estimated resident population
NAPLAN	National Assessment Program—Literacy and Numeracy
NATSEM	National Centre for Social and Economic Modelling
NCCH	National Centre for Classification in Health
PPH	potentially preventable hospitalisation
SLA	Statistical Local Area

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