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Methodology for Synthesising Estimates of Indigenous Child Health

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Katie Palin and Daniel Elazar

Analytical Services Branch

Sven Silbern and John de Maio

Telethon Institute for Child Health Research

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For further information, please contact Mr Jonathon Khoo, Analytical Services Branch on Canberra (02) 6252 5506 or email <analytical.services@abs.gov.au>.

CONTENTS

METHODOLOGY FOR SYNTHESISING ESTIMATES OF INDIGENOUS CHILD HEALTH

Katie Palin and Daniel Elazar
Analytical Services Branch

and

Sven Silbern and John De Maio
Telethon Institute for Child Health Research

ABSTRACT

This paper presents the methods used to explore the feasibility of synthesising estimates of Indigenous child health and wellbeing for regions in Queensland and the Northern Territory. This project was commissioned by the Telethon Institute of Child Health Research (TICHR) with funding provided by the Rio Tinto Aboriginal Child Health partnership, a collaboration between Western Australia, Queensland, Northern Territory and Australian governments and TICHR.

The aim of the project was to explore the feasibility of deriving estimates of Indigenous child health for Queensland and the Northern Territory using data from the Western Australian Aboriginal Child Health Survey (WAACHS) and other national datasets, such as the Census of Population and Housing. The WAACHS was conducted by TICHR during 2000–01 and provides information on health, mental health, education and other socioeconomic outcomes for Indigenous children.

Specifically, this paper outlines the technique for creating synthetic estimates for Queensland and the Northern Territory and outlines the underlying assumptions which must hold before the methodology can be used. A key assumption is that the state or territory where a person lives has no significant impact on the relationship between their health and wellbeing and their social and economic circumstances. The evidence to support this assumption was inconclusive. Given this we have not created synthetic estimates for the Queensland and the Northern Territory. However, the methodology documented in this report should be useful to researchers undertaking a similar exercise.

1. INTRODUCTION AND NATURE OF THE PROBLEM

1.1 Background

In 2006 the Australian Bureau of Statistics (ABS) released a research paper, "Synthesising Estimates of Indigenous Child Health Based on the W.A. Aboriginal Child Health Survey (Rawnsley *et al.*, 2006). This paper presented development work investigating the feasibility of using synthetic methods for estimating Indigenous child health and wellbeing for regions in Queensland and the Northern Territory based on the Western Australian Aboriginal Child Health Survey (WAACHS). This work was reviewed by the ABS Methodology Advisory Committee (MAC), where members raised concerns about the assumptions underlying the estimation and made suggestions about the methodology.

This paper describes additional work investigating these key assumptions. Although the method did not prove to be feasible in this case, we think that the process used to test these assumptions could be useful to others undertaking a similar exercise.

1.2 Introduction

The Indigenous population in Australia has health outcomes far below those of the rest of the population (Australian Bureau of Statistics, 2002a). Studies have shown that the health conditions suffered by Indigenous people can be linked to factors which appear at a very early age or even before birth (Zubrick *et al.*, 2004).

The Western Australian Aboriginal Child Health Survey was conducted by the Telethon Institute for Child Health Research (TICHR) from May 2000 to June 2002 and was the first large-scale epidemiological survey of Indigenous children and young people in Australia. The primary objective of the WAACHS was to identify the developmental and environmental factors affecting the health of Indigenous children and young people. These factors are important to identify in other jurisdictions with large numbers of Indigenous children. However, to date, similar surveys have not been conducted outside of Western Australia.

ABS and TICHR undertook a joint project to explore the feasibility of synthesising estimates of Indigenous child health and wellbeing for regions in Queensland and the Northern Territory based on the WAACHS. This paper investigates the key assumptions underlying the synthetic estimation method used in the project. The key indicator variables modelled were self harm and tropical/glue ear. [1] These variables

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1 The self harm question asks "Have you ever deliberately harmed yourself, talked about death or suicide, or attempted suicide?". The tropical/glue ear question asks: "Have you ever had runny ears (tropical ear or glue ear)?" Low birth weight (less than 2,500 grams at birth) was also considered but not modelled as the factors that impact on low birth weight, such as gestation period and mother's age, are not available nationally.

were chosen as they represent the key variables which should help reflect the issues which arise when modelling a larger set of variables.

1.3 The nature of the problem

Extrapolating estimates to Queensland and the Northern Territory represents an extreme case of an out of sample estimation problem. This technical problem is a particular form of small area estimation, where survey data is modelled to produce results at a fine level of disaggregation. However, there is no measured response variable (*Y* variable) for Queensland and the Northern Territory.

The problem (in its most simple linear form) is illustrated by the equations below. In Western Australia we were able (via the WAACHS) to measure both the response and explanatory variables and specify a model. As only the explanatory variables were available in Queensland and the Northern Territory, the parameters from Western Australia were applied to the explanatory variables in Queensland and the Northern Territory in order to make predictions for those jurisdictions.

$$\begin{aligned} y_j^{WA} &= \beta_0^{WA} + \beta_1^{WA} x_{1j}^{WA} + \beta_2^{WA} x_{2j}^{WA} + e_j^{WA} \\ \hat{y}_j^{Qld} &= \hat{\beta}_0^{WA} + \hat{\beta}_1^{WA} x_{1j}^{Qld} + \hat{\beta}_2^{WA} x_{2j}^{Qld} \\ \hat{y}_j^{NT} &= \hat{\beta}_0^{WA} + \hat{\beta}_1^{WA} x_{1j}^{NT} + \hat{\beta}_2^{WA} x_{2j}^{NT} \end{aligned}$$

where j is each child, β_i are the model coefficients and x_i are the explanatory variables. The estimates for Queensland and the Northern Territory were therefore based on the relationship between the response and explanatory variables observed in Western Australia.

Key assumptions are imposed when applying the Western Australian models to Queensland and the Northern Territory. The fundamental assumption is that the relationships identified for Western Australia are similar to those in Queensland and the Northern Territory. That is, jurisdiction (state or territory) has no impact on health outcomes after taking into account an individual's social and economic circumstances.

These assumptions can be thought of as a set of criteria that must be met for synthetic estimation to be a viable option for generating estimates for Queensland and the Northern Territory.

The remaining sections of the paper are structured as follows: Section 2 provides a further discussion of these assumptions; Section 3 outlines the methodology used to test these assumptions; Section 4 presents selected results; and Section 5 concludes and discusses the lessons learnt from this project which could be applied to future work.

2. ASSUMPTIONS

2.1 Relationships hold across jurisdictions and population groups

In order to create synthetic estimates of health indicators for Queensland and the Northern Territory, the models estimated in Western Australia must be applied to data from Queensland and the Northern Territory. As such, a major assumption underlying this project is that there is no significant jurisdictional effect beyond that which is explained by the variables used in the model. In essence, we are interested in determining whether the strength and direction of the relationships between specific health outcomes and a set of explanatory variables observed in Western Australia are the same in Queensland and the Northern Territory.

It is important that relationships hold not only across jurisdictions but also across populations. Separate estimates are not possible for Aboriginal children and Torres Strait Islander children due to the small number of Torres Strait Islander children surveyed in the WAACHS. Given that models based on data from Aboriginal children will be used to create synthetic estimates for both Aboriginal and Torres Strait Islander children it is important to investigate whether health outcomes are expected to differ significantly between Aboriginal children and Torres Strait Islander children. Although this tropical/glue ear and low birth weight are not available nationally, it is possible to investigate the relationship of other health outcomes across jurisdictions and population groups. Various health outcomes and general characteristics of each population were investigated using the *2001 National Health Survey : Indigenous component* (Australian Bureau of Statistics, 2002b) and the *2004–05 National Aboriginal and Torres Strait Islander Health Survey* (Australian Bureau of Statistics, 2006). The results of analysis indicated there are no obvious differences between the Aboriginal population and Torres Strait Islander population for the variables tested. A summary of this analysis can be found in the Appendix A.

2.2 Validity of models constructed for Western Australia

It is assumed that models with reasonable explanatory power can be developed from the WAACHS. To assess this we need to consider the statistical accuracy of the models and their plausibility.

There are a range of diagnostics that can be examined to demonstrate the strength of the model fit. These include:

- the goodness of fit statistics (such as the Hosmer and Lemeshaw test);
- the statistical significance of the estimated coefficients for each explanatory variable in the model;
- the predictive power of the model in terms of the R-square and mean square error; and

- the accuracy of synthetic estimates for regions in Western Australia when compared to direct estimates for the same region based solely on the WAACHS.

If the models do not satisfy the above accuracy requirements, then synthetic estimation is not a viable option for producing estimates for Queensland and the Northern Territory. However, if the models do meet accuracy requirements then the plausibility of the models must be considered. The plausibility of the model can be considered in two ways:

- the plausibility of the explanatory variables in terms of direction and magnitude of their coefficients; and
- the plausibility of the predicted indicators (response variables) in terms of how well their spread across regions is consistent with local knowledge.

The validity of the estimated models is examined in the results section (Section 4) of this paper.

2.3 Comparability of variables

As previously mentioned, the WAACHS is used to develop models for Western Australia and, conditional on their being no jurisdiction effect, the coefficients from the model can then be used in Queensland and the Northern Territory. Therefore, it is necessary for the explanatory variables used in Queensland and the Northern Territory models to be similar to the explanatory variables used from the WAACHS.

For the variables used in the Queensland and the Northern Territory models to be similar to the explanatory variables used from the WAACHS, it is necessary to find a data source that has comparable data items. The models created for self harm and tropical ear include variables such as age, sex, employment status and other socio-economic variables which are also available in the Census of Population and Housing.

It is ABS practice to collect survey data using standard definitions (and questions) and the WAACHS development drew on ABS standards. Therefore, those variables common to the WAACHS and the Census are comparable indicating that the Census is an appropriate data source to use to create synthetic estimates for Queensland and the Northern Territory. Also, the Census has data available for small areas whereas other national health and indigenous surveys did not have complete coverage of all areas in Queensland and the Northern Territory.

The models developed for Western Australia include contextual variables which are based on the characteristics of the area a child lives in rather than the characteristics of the child. The nature of these contextual variables imply that they can be created using Census data for the Western Australian models and hence are not created using the WAACHS data. In such cases, comparability requirements are not an issue.

3. METHODOLOGY USED

3.1 Testing the jurisdictional effect assumption

In testing for a jurisdictional effect, we are interested in whether the model explaining a specific health outcome for children in Queensland and the Northern Territory is the same as the model explaining that health outcome for children in Western Australia. As stated in Section 2, we are interested in determining whether the strength and direction of the relationships between specific health outcomes and a set of explanatory variables observed in Western Australia are the same in Queensland and the Northern Territory.

The strength and direction of the relationships observed between specific health outcomes and a set of explanatory variables is measured by the estimated coefficients in a model. Therefore, the approach used to test for a jurisdictional effect is to create a nested model for Western Australia, Queensland and the Northern Territory and test whether the estimated coefficients differ significantly between the two jurisdictions.

The data used to test for a jurisdictional effect needs to be available in all three states. In this analysis, the *2001 National Health Survey* (Australian Bureau of Statistics, 2002a), the *2001 National Health Survey: Indigenous component* (Australian Bureau of Statistics, 2002b) and the *2004–05 National Aboriginal and Torres Strait Islander Health Survey* (Australian Bureau of Statistics, 2006) were used to create separate models for the general population and for the Indigenous population. The model to test for a jurisdictional effect was designed to be as close as possible to the model used in synthetic estimation:

- Models were created at a person level using logistic regression (as discussed in Section 3.2).
- The predictor variables in these testing models were two health related variables: high risk of alcohol abuse, and high or very high risk of stress (based on Kessler psychological test).[2]
- The set of explanatory variables used to test for a jurisdictional effect were similar to the variables used in the predictive models for self harm and tropical ear. The variables used were:
    - age of the individual;
    - sex of the individual;

2 Ideally the predictor variables would be tropical/glue ear and self harm. However, these variables were not collected on the 2004–05 NATSIHS..

    - percentage of Indigenous people in the Statistical Sub Division (SSD) of residence who are CDEP participants;
    - employment status of person;
    - currently studying;
    - receiving welfare or pension payments;
    - living in an overcrowded house (i.e. more than two people per bedroom);
    - number of Indigenous communities in the SSD of residence;
    - currently smokes or not; and
    - average ARIA++ score of the ATSIC region of residence. [3]
- An indicator variable for jurisdiction is also included in each model which is interacted with each explanatory variable.

Evidence for a jurisdictional effect is based on a hypothesis test that the coefficients of these interaction terms with the indicator variable are equal to zero. The joint significance of these coefficients is determined by a Wald test where the null hypothesis is that the coefficients of interest are jointly equal to zero. Under the null hypothesis, the test statistic has an asymptotic chi-square distribution. If the test statistic is significant we reject the null hypothesis and conclude there is evidence to suggest a jurisdictional effect. However, if the test statistic is not significant then there is not enough evidence to suggest a jurisdictional effect and hence the assumption holds.

The survey weights were taken into account when developing the models, however the full survey weights are not appropriate as the explanatory variables used in the models are likely to contain some of the design information from the weights. Therefore, an adjustment to the weights is required to account for design information in the explanatory variables. If an adjustment to the weights is not made then the design information will essentially be over accounted for in the model estimation : both in the contributing weights and in the explanatory variables. This will mean that model parameter estimates and their standard errors will be incorrect, leading to incorrect inferences. The Q-weight method [4] was used to adjust the weights to account for the design information contained in the explanatory variables.

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3 With the abolition of ATSIC Regional Councils and the establishment by the Office of Indigenous Policy Coordination of regional Indigenous Coordination Centres (ICCs), changes have been made to the geographic regions used for producing statistics in relation to Indigenous peoples. While it is recognised that ATSIC regions no longer exist, we have kept these regions to provide continuity with other WAACHS products.

4 The technical details underlying the Q-weight method are discussed in Pfefferman and Sverchkov (2003).

The Q-weight method consists of the following steps:

1. Run a separate model where the population weight is the dependent variable and the explanatory variables are the same explanatory variables used in the main model.
2. Derive Q-weights by taking the original survey weights and dividing them by the predictions of the model estimated in step 1.
3. Replace the survey weights with the derived Q-weights to weight the model.

The models used to test for a jurisdictional effect use the Q-weights rather than the full survey weights. The results of the tests are outlined in Section 4.

3.2 Creating synthetic estimates: Model based approach

Synthetic estimates of health indicators for Queensland and the Northern Territory are generated by creating a model for Western Australia using the WAACHS data. This model describes the relationship between certain health outcomes and socio-demographic and other variables such as age, sex, socioeconomic status and area type for Western Australia. The estimated coefficients from the model are then applied to an auxiliary data set to obtain predictions for each region in Queensland and the Northern Territory.

The statistic of interest in this analysis is the proportion of Indigenous children with a particular health outcome in each ATSIC region [5] in Queensland and Northern Territory. There are two possible approaches to create area level estimates of health outcomes:

- fit area level models; and
- fit person level models and aggregate predictions up to area level.

Both approaches were investigated. However, the area level model did not produce reasonable results due to the small number of areas. [6] Therefore, the approach adopted was a person level model and this methodology is discussed below.

5 See footnote 3 on page 7.

6 The performance of area level models was measured by the significance of individual variables in the models and goodness of fit tests.

3.2.1 *Logistic regression*

Due to the binary nature of the response variables, the person level models used are in logistic form which models the probability of a child having a specific health characteristic as opposed to not having the health characteristic. The general form of the model is:

$$y_i \sim Bernoulli(1, p_i)$$
$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) = X_i\beta$$

where p_i = whether child i has a specific health characteristic, and

X_i = the matrix of explanatory variables.

The first stage of the modelling process is to create a well specified model for Western Australia that investigates the relationships between specific health outcomes and a set of explanatory variables. A model fits the data well if it has appropriate levels for goodness of fit statistics, statistically significant estimated coefficients for each explanatory variable in the model and plausible explanatory variables in terms of the direction and magnitude of their coefficients. Goodness of fit measures do not always detect whether the model is mis-specified: that is, these measures do not detect omitted variables and incorrect functional form.

The predictive power of the model is also of importance for synthetic estimation and may be investigated in terms of the mean square error, tests against direct estimates for bias, additivity to higher level aggregates and adjusted R squared .

Once a model is chosen, the estimated coefficients may be used to create predictions for specific areas. Before applying the estimated coefficients to Queensland and the Northern Territory it is useful to create predictions for Western Australia. The advantage of doing this is that the predictions using the auxiliary data set may be compared to the direct estimates from the WAACHS to give an indication of the robustness of the model in creating synthetic estimates.

3.2.2 *Including random effects*

A decomposition of the amount of variation in specific health outcomes at an area, family and child level showed that for the variables of interest (self harm in particular), a significant amount of variation occurred at an area level. A random effect can capture some of the variation between different areas not accounted for by the other variables in the model.

In general, random effects can be included in a model as follows:

$$\text{logit}\left(p_i\right) = \log\left(\frac{p_i}{1-p_i}\right) = X_i\beta + V_L$$

The random effect parameters V_L enter the model in a linear form. In this case, the L represents area.

When including random effects in a model for small area estimation, it is important to specify the random effect such that it is common to all jurisdictions. For example, specifying the random effect by geographic level is not appropriate regions in one jurisdiction do not directly correspond to the regions in another jurisdiction. A potential specification for a random effect in this analysis is the level of remoteness of the area the child lives in. This measure of remoteness is common across all jurisdictions.

Random effects take account of area level effects that are not explained by the model coefficients. Including random effects in a model improves the accuracy of the standard errors associated with the estimated coefficients. Both the random effects model and the synthetic model gave estimated coefficients that were of similar magnitude.

Random effects models can be further extended to a multilevel model. A multilevel model takes into account the hierarchical structure of the data by including random effects at various levels. So for this example, there is a child within a family within an area. A multilevel model was also considered and, similar to random effects, the standard errors associated with the coefficients varied though the size of the coefficients did not vary considerably. Therefore, for simplicity, the remainder of the analysis undertaken in this paper uses logistic regression without random effects.

In the random effects model described at the beginning of this section we have only randomised the intercept term. But it is also possible to randomise model slopes at either the family or area levels.

3.3 Testing models and estimates

Testing the validity of the models created for Western Australia is an important aspect of the modelling process. The validity of the models can be assessed via a number of tests and plots.

3.3.1 Model diagnostics

The first step in evaluating a model is to consider the significance of the estimated parameters via the individual p-values. Parameters that are not statistically significant are often removed from the model, but we may choose to keep some variables in the model even though they are not significant. This may occur for two reasons; firstly, if there is a strong theoretical reason to include the variable; and secondly, if it is needed to maintain a base case for a set of related variables. For example, a continuous variable may be split into a set of quintile indicator variables with the bottom quintile being the base case. If the indicator variable representing the second quintile is not statistically significant and removed from the model then the base case becomes the bottom two quintiles. Therefore, the insignificant variables should remain in the model to preserve the bottom quintile as the base case.

The Hosmer and Lemeshow test is a goodness of fit test based on a chi-square test where the null hypothesis is that there is no difference between the observed and model-predicted values of the dependent variable. The null hypothesis is that the model fit is adequate.

The R-square is another measure of adequacy of the model. However, for a logistic model it can not be interpreted in the same way as the R-square in a linear model as the percentage of variance explained by the model. Rather, it is a measure of the predictive power of the model with higher values of the statistic indicating higher predictive power of the model. The max-rescaled R-square is preferred for logistic models as it rescales the R-square value so that the maximum value is 1.

3.3.2 Quality diagnostics

The last stage of the modelling process is to produce predictions for the dependent variable based on the estimated coefficients. A test for the adequacy of the predictions is to plot the direct estimates from the survey against the modelled estimates. If the model produces reliable predictions then the graph should produce a line that is not significantly different from a 45 degree line and whose intercept is not statistically different from zero. It is possible to check this via a statistical test by regressing the modelled predictions on the direct estimates. If there is no bias, the intercept of the line should not be significantly different from zero, and the slope should not be significantly different from one. While this test gives a guide to the reliability of the predictions it is hard to fail this test in practice.

The final test of the adequacy of the model is to consider the Relative Root Mean Square Error (RRMSE). The RRMSE is a measure of the error on each prediction from the model, assuming that there is no model mis-specification. As such the RRMSE reflects errors involved in estimating the model parameters and the variation of residuals and random effects variance components (if present).

4. RESULTS

4.1 Tests for jurisdictional effect

Given that we do not have estimates of our variables of interest for each jurisdiction (i.e. self harm and tropical/glue ear), other variables must be used to investigate the existence of a jurisdictional effect. In this analysis, high risk alcohol, and high or very high stress were used as modelling variables.

It is important to note that the models estimated must be of sufficient quality to provide a reliable test for a jurisdictional effect. The quality of the models may be assessed via the diagnostics available for logistic regression including adjusted R-square, Hosmer and Lemeshow test and the significance of individual parameters.

Unfortunately, for each data set used, the models estimated were not of sufficient quality to accurately determine the existence of a jurisdictional effect. Specifically, after accounting for the impact of the design in the explanatory variables via Q-weights, very few explanatory variables included in the model were statistically significant. [7]

As a result of the poor quality model, the results from the Wald test on the jurisdictional effect were inconclusive. Given that the model did not allow us to adequately test this assumption, it appears that for these variables we can not assume there is no state or territory impact on health status outcomes.

4.2 Reliability of synthetic models for Western Australia

Based on the literature relating to self harm and tropical ear, the relationships between health outcomes and the set of explanatory variables are expected to be similar across jurisdictions. For example, it is expected that the probability of a child taking any actions associated with self harm increases with age regardless of the jurisdiction the child lives in. However, the degree to which the probability increases is unknown for Queensland and the Northern Territory due to the lack of conclusive evidence as to the existence of a jurisdictional effect. As such, predictions for Queensland and Northern Territory were not created.

Models can be created for Western Australia and the reliability of these models and their ability to create accurate predictions for Western Australia is still of interest. Self harm and tropical/glue ear were chosen to investigate the feasibility of creating synthetic estimates for Queensland and the Northern Territory using a Western Australian model based on the WAACHS.

These models have been adjusted to take into account the survey design.

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7 The estimated models have not been included in this report due to insufficient quality.

It was found that the probability of a child taking any actions associated with self harm as opposed to not engaging in self harm:

- increased with age (between 4 years and 17 years);
- increased as the percentage of Indigenous people in the Statistical Subdivision that consume alcohol increased;
- marginally increased as the number of Indigenous communities in the Statistical Subdivision increased;
- marginally decreased as the percentage of Indigenous people in the Statistical Subdivision that are in a CDEP program increased;
- decreased as the level of remoteness increased;
- decreased if the child attended school as opposed to not attending school;
- decreased if the child lived in an overcrowded house rather than a house that was not overcrowded (a house was defined to be overcrowded if it housed more than two people per bedroom).

Considering the diagnostics of the model:

- the goodness of fit statistics were within the range of what would generally be considered acceptable for a model of this type but are probably not adequate for prediction.
- there is no evidence of bias in the estimates (this was done at the Statistical Subdivision (SSD) level, which is finer than ATSIC region [8] level, to ensure a sufficient number of data points).

Based on the sign and direction of the estimated coefficients, and the results of the diagnostic tests, the model appears to be reliable for Western Australia. The complete set of results are presented in Appendix B.

It was found that the probability that a child has had tropical/glue ear in the last 12 months as opposed to not having tropical/glue ear:

- was greater for males than females;
- increased as the level of remoteness increased;
- increased as the percentage of Indigenous people in the Statistical Subdivision with highest level of education between year 11 and 12 increased;
- decreased with age (between 4 years and 17 years);
- decreased as the median income for the Statistical Subdivision increased;

8 See footnote 3 on page 7.

- decreased as the number of Indigenous communities in the Statistical Subdivision increased.

It should be noted that these models did not take into account external factors such as where the Indigenous Medical Services are situated.

Considering the diagnostics of the model:

- the goodness of fit statistics were within the range of what would generally be considered acceptable for a model of this type but probably not adequate for prediction.
- there is no evidence of bias in the estimates (this was done at the Statistical Subdivision (SSD) level to ensure a sufficient number of data points).

Based on the sign and direction of the estimated coefficients, and the results of the diagnostic tests, the model appears to be reliable for Western Australia. The complete set of results are presented in Appendix C.

5. CONCLUSION AND LESSONS FOR FUTURE WORK

This paper has examined the feasibility of using the WAACHS and other national datasets to model key indicator variables for Queensland and the Northern Territory. In order to create synthetic estimates for Queensland and the Northern Territory, a number of assumptions are necessary. For the information and data available, we cannot say that all assumptions hold. Specifically, we could not state that the fundamental assumption holds, that is the relationships identified in the WAACHS data for Western Australia are similar to those in Queensland and the Northern Territory. However, it is still possible to test the method for Western Australia and our results showed that the models seemed reasonable for this jurisdiction.

For the reader interested in applying the methodology outlined in this paper to a similar analytical problem, there are two points to consider in order to improve the chances of a successful outcome.

First, it is useful to investigate potential sources of auxiliary data that would provide additional explanatory variables to help improve the fit of the models. For example, hospital and morbidity data held by the Australian Institute of Health and Welfare, Medicare data or data from Indigenous medical services could have been useful in this study. Crime statistics data held in certain jurisdictions may also be of value. Data holdings such as these, are of course not without their problems. These include methods of identifying Aboriginal and Torres Straight Islander people, scope, definitions and data collections methods. Following identification of such data sources, a careful assessment needs to be made as to whether errors in the data are at a level that may outweigh potential improvements to model specification and fit.

Secondly, before predictions can be made for out of sample areas like the Northern Territory and Queensland, it is necessary to demonstrate that there is no jurisdictional effect or a method is used that makes adjustments for any such effects. The approach we used, of testing for jointly significant interactions between state indicators and each of the covariates, resulted in model failure due to a large number of covariates in the model. Including just significant covariates in the model may overcome this problem. Another approach worth considering is to apply the Heckman model (Heckman, 1979). Under this approach, the propensity to be an Indigenous person from Western Australia (as opposed to be an indigenous person from a state other than Western Australia) is modelled based on a range of covariates. In a nutshell, an extra variable derived from the residuals from this model is then incorporated into the desired models fitted to the observed WAACHS data to account for the bias between Western Australia and the other jurisdictions.

In summary, the method used to create synthetic estimates involved estimating a person level model (a logistic model) and aggregating to the area level. Based on the significance of individual variables and goodness of fit tests, the method appeared to produced good results for Western Australia. This indicates that, theoretically, the method of creating synthetic estimates for specific health outcomes for Queensland and the Northern Territory based on models for Western Australia could be feasible for other variables as long as all the assumptions hold. However, we were not confident to produce synthetic estimates as the presence of a jurisdictional effect could not be disproved.

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APPENDIXES

A. COMPARING ABORIGINAL PEOPLE WITH TORRES STRAIT ISLANDER PEOPLE

The tables presented in this appendix compare the self assessed health status and alcohol and tobacco consumption of Aboriginal people and Torres Strait Islander people at the national level. They indicate similar responses for these variables.

A.1 Distribution of self assessed health status across Aboriginal and Torres Strait Islander national populations

Self assessed health status	*Aboriginal*	*Torres Strait Islander*
Excellent / Very good	44.1%	44.9%
Good	32.4%	32.3%
Fair / Poor	23.4%	22.8%

Source: *National Aboriginal and Torres Strait Islander Health Survey, 2004–05.*

A.2 Distribution of alcohol and tobacco consumption across Aboriginal and Torres Strait Islander national populations

Alcohol and tobacco consumption	*Aboriginal*	*Torres Strait Islander*
Current daily smoker	44.1%	44.9%
Risky alcohol consumption in the last 12 months	32.4%	32.3%

Source: *National Aboriginal and Torres Strait Islander Health Survey, 2004–05.*

B. SELF HARM MODELS

The coefficients in the model measure the log odds of the event (i.e. the individual self harmed / talked about self harm) for a unit increase in the particular variable. For example a coefficient of –0.3782 for the attends school variable implies that for a child that attends school their log odds of self harming / talking about self harm are 0.3782 lower than that of a child who does not attend school, other things being equal.

B.1 Model parameter estimates for self harm[1]

Explanatory variable	*Coefficient*	*p-value*	*Odds ratio[2]*
Intercept	–2.2502	<0.0001	
Age of child in years	0.0652	0.0001	1.067
Average ARIA[3] score of CD that child lives in	–0.0782	<.0001	0.934
Child attends school (compared to not attending school)	–0.3782	0.0387	0.685
Child lives in an overcrowded house (overcrowded means average of more than two people per bedroom)	–0.5822	0.0003	0.559
Child lives in ATSIC region[4] that has less than 20% Indigenous population (compared to ATSIC region with greater than 20% of the population Indigenous)	–1.0456	0.0156	0.351
Number of Indigenous communities in the SSD	0.0108	0.0007	1.011
% of Indigenous population in SSD that are in CDEP	–0.0206	0.0550	0.980
% of SSD that consume alcohol	0.0363	0.001	1.037

1 Modelling the probability that an individual self harmed/ talked about self harm as opposed to not (self harm=1, not self harm=0)

2 Note the odds ratios are calculated by exponentiating the coefficients.

3 ARIA is the Accessibility/Remoteness Index of Australia.

4 See footnote 3 on page 7.

We can also discuss the model results in terms of odds ratios. The odds ratio is a measure of association between the explanatory variable and the response variable. Odds ratios of less than 1 indicate that children with those characteristics are less likely to self harm compared to the reference category (controlling for other variables). Odds ratios of more than 1 indicate that children with those characteristics are more likely to self harm compared to the reference category.

For continuous variables such as age, the odds ratio relates to a change in the odds of self harm for every year increase in age. For example, odds of 1.067 for age of child means that every year increase in a child's age increases the odds of self harm by 1.067 times or alternatively every year increase in the child's age increases the odds (risk) of self harm by 6.7%.

B.2 Variables tested but not found to be significant for self harm model

Other variables considered that were not statistically significant
% of Indigenous people in SSD that are employed
School retention rate for children aged 15+
% of Indigenous people aged 15+ in SSD that have highest level of education between Years 7 and 10
Median income for the SSD
% of Indigenous population in ATSIC region[1] that currently smoke
% of ATSIC region with high risk or medium risk alcohol consumption
Sex of Child
% of people in SSD with level of schooling at least Year 11, Year 12 or tertiary
Child lives in area that has a SEIFA score in the bottom 20% (compared to middle quintiles)
Child lives in area that has a SEIFA score in the top 20% (compared to middle quintiles)
Main language spoken by carer is an aboriginal language

1 See footnote 3 on page 7.

B.3 Model diagnostics for self harm model

Diagnostics	*Value*	*p-value*
R-Square	21.7%	–
Max-rescaled R-Square	22.2%	–
Hosmer and Lemeshow Goodness of Fit test	8.0555	0.4281 *

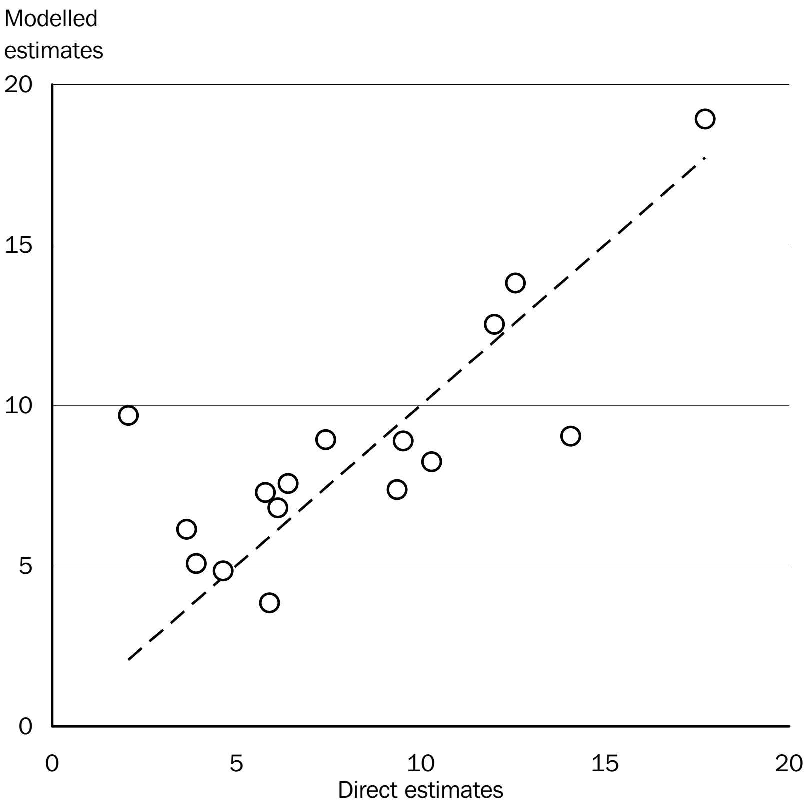
* Want a p-value of >0.05

B.4 Bias test statistics for self harm model (using Statistical Subdivision estimates)

*Bias test**	*Estimate*	*Standard error*
Intercept	0.5177	1.7826
Slope	0.8865	0.1892

* The 95% confidence interval for the intercept should contain 0 and the slope should contain 1.

B.5 Scatter plot of modelled estimates versus direct estimates



B.6 Self harm model estimates for Western Australia including direct estimates from WAACHS[1]

ATSIC region[3] (WA)	*Direct estimate*	*Modelled estimate*	*RRMSE[2]*
Broome	26%	27%	6.2%
Derby	15%	10%	9.6%
Geraldton	9%	8%	8.5%
Kalgoorlie	6%	5%	16.6%
Kununurra	6%	9%	9.8%
Narrogin	10%	8%	11.2%
Perth	13%	13%	5.6%
South Headland	8%	8%	10.7%
Warburton	3%	4%	23.0%

1 Population of Indigenous children aged 4–17 years within the ATSIC region.

2 The Relative Root Mean Square Error (RRMSE) is a measure of the error on each prediction from the model, assuming that there is no model mis-specification.

3 See footnote 3 on page 7.

C. TROPICAL / GLUE EAR MODEL

The coefficients in the model measure the log odds of the event (i.e. the individual has had tropical/glue ear) for a unit increase in the particular variable. For example a coefficient of 0.1808 for the sex of child implies that for males their log odds of having tropical/ glue ear is 0.1808 higher than females, other things being equal.

C.1 Model parameter estimates for tropical / glue ear[1]

Explanatory variable	*Coefficient*	*p-value*	*Odds ratio*[2]
Intercept	0.5149	0.4612	
Age of child in years	–0.0258	0.0015	0.9750
Sex of child (Male=1, Female=0)	0.1808	0.0296	1.1980
Average ARIA[3] score of CD that child lives in	0.0527	<0.0001	1.0540
Median income for the SSD	–0.0102	0.0010	0.9900
% of Indigenous people aged 15+ in SSD that have highest level of education between Years 11 and 12.	0.0333	0.0376	1.0340
Number of communities in the SSD	0.0073	0.0050	1.0070

1 Modelling the probability that an individual self harmed/ talked about self harm as opposed to not (self harm=1, not self harm=0)

2 Note the odds ratios are calculated by exponentiating the coefficients.

3 ARIA is the Accessibility/Remoteness Index of Australia.

We can also discuss the model results in terms of odds ratios. The odds ratio is a measure of association between the explanatory variable and the response variable. Odds ratios of less than 1 indicate that children with those characteristics are less likely to have had tropical/glue ear compared to the reference category (controlling for other variables). Odds ratios of more than 1 indicate that children with those characteristics are more likely to have had tropical/glue ear compared to the reference category.

For continuous variables such as age, the odds ratio relates to a change in one unit. For example, the odds that a child has had tropical/glue ear is 0.975 times that of a child one year younger. Alternatively, an odds of 0.975 for age of child means that every year increase in a child's age decreases the odds of tropical/glue ear by 2.5%.[9]

It should be noted that the majority of the explanatory variables in this model are continuous and while the odds ratios are close to 1 there is sufficient discriminatory power for different values of the explanatory variable. For example, for median income, for each dollar increase the odds of a child having tropical /glue ear decreases

9 Calculated as (0.975 – 100) times by 100, which is –2.5.

by 1% [10] and thus when there are significant differences in median income (e.g. $100) the odds for a child having tropical /glue ear have decreased markedly.

C.2 Variables tested but not found to be significant for tropical/glue ear model

Other variables considered that were not statistically significant
Child attends school (compared to not attending school)
School retention rate for children aged 15+
% of Indigenous people aged 15+ in SSD that have highest level of education between Years 7 and 10
Child lives in an overcrowded house (overcrowded means average of more than two people per bedroom)
% of Indigenous population in ATSIC region[1] that currently smoke
Child lives in ATSIC region that has less than 20% Indigenous population (compared to ATSIC region with greater than 20% of the population Indigenous)
% of Indigenous people in SSD that are employed
% of Indigenous people in SSD that attend school and are part time
% of Indigenous people aged 15+ in SSD that have a tertiary education
Main language spoken by carer is Indigenous language (compared to not Indigenous language)
% of Indigenous population in SSD that are in CDEP
% of ATSIC region with high risk alcohol consumption
Child lives in area that has a SEIFA score in the bottom 20% (compared to the middle quantiles)
Child lives in area that has a SEIFA score in the top 20% (compared to the middle quantiles)

1 See footnote 3 on page 7.

C.3 Model diagnostics for tropical / glue ear model

Diagnostics	*Value*	*p-value*
R-Square	11.05%	–
Max-rescaled R-Square	11.07%	–
Hosmer and Lemeshow Goodness of Fit test	10.9373	0.2053 *

* Want a p-value of >0.05

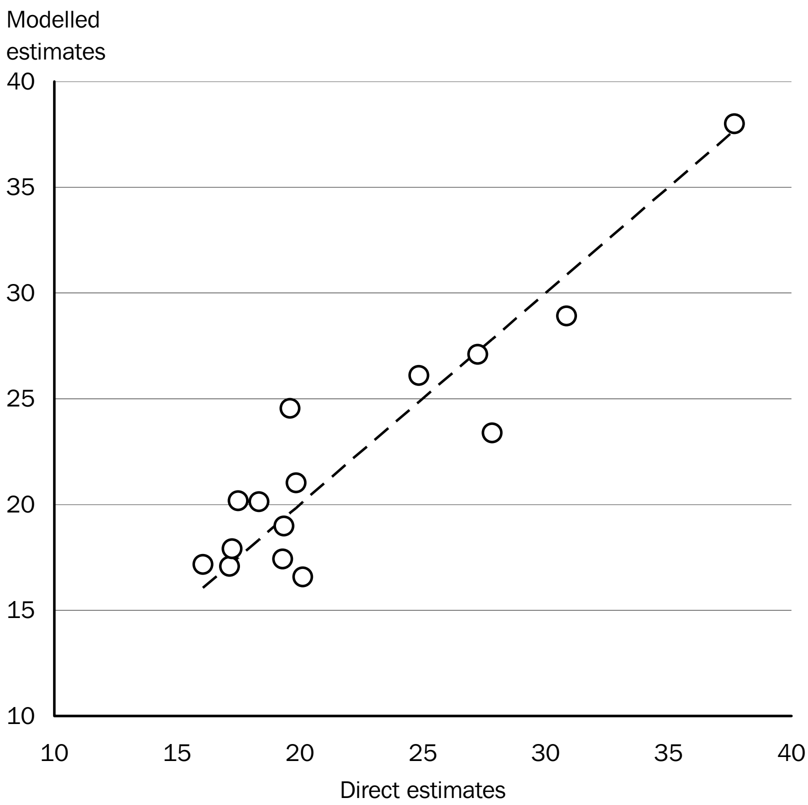
C.4 Bias test statistics for tropical / glue ear model (using Statistical Subdivision estimates)

*Bias test**	*Estimate*	*Standard error*
Intercept	–1.6371	2.6875
Slope	1.0882	0.1195

* The 95% confidence interval for the intercept should contain 0 and the slope should contain 1.

10 (0.990 – 1) times by 100.

C.5 Scatter plot of model estimates versus direct estimates



C.6 Tropical /glue ear model estimates for Western Australia including direct estimates from WAACHS[1]

ATSIC region[3] (WA)	*Percentage of population*	*Modelled estimate*	*RRMSE[2]*
Broome	24%	30%	5.0%
Derby	28%	28%	5.4%
Geraldton	24%	24%	3.9%
Kalgoorlie	22%	25%	4.9%
Kununurra	25%	25%	4.8%
Narrogin	18%	19%	4.1%
Perth	18%	18%	2.9%
South Headland	26%	21%	5.0%
Warburton	30%	34%	5.0%

1 Population of Indigenous children aged 4–17 years within the ATSIC region.

2 The Relative Root Mean Square Error (RRMSE) is a measure of the error on each prediction from the model, assuming that there is no model mis-specification.

3 See footnote 3 on page 7.

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