



Small area indicators of well-being for older Australians

**Technical Report - Full results from the
modelling**

PREPARED BY

Robert Tanton, Yogi Vidyattama and Riyana Miranti
For the Benevolent Society

FEBRUARY 2016

ABOUT NATSEM

The National Centre for Social and Economic Modelling was established on 1 January 1993, and supports its activities through research grants, commissioned research and longer term contracts for model maintenance and development.

NATSEM aims to be a key contributor to social and economic policy debate and analysis by developing models of the highest quality, undertaking independent and impartial research, and supplying valued consultancy services.

Policy changes often have to be made without sufficient information about either the current environment or the consequences of change. NATSEM specialises in analysing data and producing models so that decision makers have the best possible quantitative information on which to base their decisions.

NATSEM has an international reputation as a centre of excellence for analysing microdata and constructing microsimulation models. Such data and models commence with the records of real (but unidentifiable) Australians. Analysis typically begins by looking at either the characteristics or the impact of a policy change on an individual household, building up to the bigger picture by looking at many individual cases through the use of large datasets.

It must be emphasised that NATSEM does not have views on policy. All opinions are the authors' own and are not necessarily shared by NATSEM.

© NATSEM, University of Canberra 2016

All rights reserved. Apart from fair dealing for the purposes of research or private study, or criticism or review, as permitted under *the Copyright Act 1968*, no part of this publication may be reproduced, stored or transmitted in any form or by any means without the prior permission in writing of the publisher.

National Centre for Social and Economic Modelling

University of Canberra ACT 2601 Australia

Phone + 61 2 6201 2780

Fax + 61 2 6201 2751

Email natsem@natsem.canberra.edu.au

Website www.natsem.canberra.edu.au

Author Email Robert.tanton@canberra.edu.au

Introduction

The Index of Wellbeing for Older Australians is an index developed by NATSEM for the Benevolent Society. The index is intended to be a tool for a range of stakeholders including policy-makers and planners in government, service providers and researchers. It will enable them to identify the wellbeing of the older population within local geographic areas, and provide information to assist in the development and targeting of services.

The main report shows the method for the modelling, a map of the index, a comparison with the ABS Socio-Economic Index for Areas (SEIFA) (Australian Bureau of Statistics, 2004), a discussion of the results, some policy implications, the limitations, and further work.

This technical report shows the full results from the principal components analysis (PCA) for each domain, and a technical description of how the domains were combined to form the final index. A full description of the PCA method can be found in (Dunteman, 1989).

In this report, the results for each domain are shown in separate sections. The first table shown for each domain is the correlation table, which shows how each of the indicators are correlated with each other. Indicators that are highly correlated (greater than 0.95) can cause problems with the PCA analysis, and so one of the indicators is removed. We would hope to have reasonable correlations between indicators, and any with a low correlation will be removed in the next step.

For each domain, we then show the loadings (or weights) for the indicators against each of the first 3 components. Where loadings are less than 0.3, then the indicator with the lowest loading is removed, as it does not add much to the final index. This is the same cut-off used by the ABS for the SEIFA index (ABS, 2004), and NATSEM for the Child Social Exclusion index (Harding, McNamara, Daly, & Tanton, 2009).

Once an indicator is removed, the PCA is run again and the indicator with the next lowest loading is removed. This iterative process continues until all indicators have loadings above 0.3.

Once all indicators have a loading above 0.3, there may be indicators that we try to reintroduce to test if the loading is now above 0.3. The reason for this is that some of the indicators interact, so removing an indicator may now mean that another indicator previously removed now has a loading above 0.3.

We then looked at the eigenvalues, which show whether the first component is the best component, or whether the other components can be used. The eigenvalues are plotted using a scree plot, and we are looking for a sudden levelling of the eigenvalue. If the second component still explains a lot of the correlation, then this is a potential secondary index; whereas if the first index explains most of the correlation, and the scree plot levels out at the second component, then the second and further components can be eliminated as they are not explaining much of the correlation between the indicators.

This technique is most useful where all indicators are used for the PCA, and the different components identified through the PCA can then be split into domains like education, participation, etc. For this index, we have started from a theoretical construct which identified the domains, rather than letting the data and PCA identify the domains. This method then uses separate indicators for

each domain, and runs a separate PCA for each domain, and then aggregates the first components of each domain as the index for that domain. So the second and further components in each PCA are not as important, and can become difficult to interpret.

Further, the first component will always explain most of the correlation between the indicators, and traditionally this has been the component used for the index. The ABS follows this method in their Socio-Economic Index for Areas (SEIFA) and NATSEM has used it in their Child Social Exclusion indexes. Therefore, for this index, while the scree plots are shown for information, we have always used the first component in the PCA for the index.

The rest of this paper goes through each of the domains, and presents the results – the correlation matrix, the loadings as each indicator is removed, the final loadings and indicators used in the sub-index, and the scree plot for the eigenvalues. Note that the tables of loadings use the indicator mnemonics, and the full description of the indicator can be found in the correlation matrix, the first table for each domain.

This technical paper also outlines the method for bringing all the sub-indexes together.

Participation domain

The correlation between the indicators for Participation domain are shown in Table 1. It can be seen that there is a very high correlation between the labour force participation rate and the employment rate (0.9984). Because of this high correlation, we dropped the labour force participation rate, and kept the employment and unemployment rates.

Table 1: Correlation matrix for Participation domain

		Labour force participation rates for older people	Employment rates for older people	Unemployment rates for older people	Caring other children	% of older people who provide care to their children and/or grandchildren (daily)	% of older people who provide care to their children and/or grandchildren (daily and several days)	% of older people who had no access to a car to drive	annual cost of older people using public transport (bus, ferry, rail or taxi)	% of older people who have no access to the Internet	% of older carer	% of older people who cannot speak English well or not at all	% Volunteer
		lbr_ptcp_rns	emp_rate_cns	unemp_rate_cns	carech_h_cns	carech_ly_hil	carech_ay_hil	no_car_cns	ann_cost_p1	no_int_hil	old_carer_cns	not_well_eng	volunt_cns
Labour force participation rates for older people	lbr_ptcp_rns	1											
Employment rates for older people	emp_rate_cns	0.9984	1										
Unemployment rates for older people	unemp_rate_cns	-0.0813	-0.1324	1									
Caring other children	carech_h_cns	0.1363	0.1314	0.0282	1								
% of older people who provide care to their children and/or grandchildren (daily)	carech_ly_hil	0.141	0.1375	0.0327	0.2202	1							
% of older people who provide care to their children and/or grandchildren (daily and several days)	carech_ay_hil	0.1591	0.1534	0.0792	0.2039	0.821	1						
% of older people who had no access to a car to drive	no_car_cns	-0.2537	-0.2602	0.1423	-0.1221	-0.0849	-0.0306	1					
annual cost of older people using public transport (bus, ferry, rail or taxi)	ann_cost_p1	-0.0479	-0.0517	0.0943	0.0829	-0.2266	0.0533	0.2575	1				
% of older people who have no access to the Internet	no_int_hil	-0.3901	-0.3844	-0.006	-0.4335	-0.5123	-0.3046	0.0775	0.2645	1			
% of older carer	old_carer_cns	-0.383	-0.3752	-0.0561	-0.2692	-0.1453	-0.2098	-0.3212	-0.1523	0.2558	1		
% of older people who cannot speak English well or not at all	not_well_eng	-0.2322	-0.237	0.1418	0.138	-0.0281	0.0058	0.4919	0.24	-0.0022	-0.01	1	
% Volunteer	volunt_cns	0.4293	0.4332	-0.131	-0.0085	0.0523	-0.0327	-0.3457	-0.1182	-0.1197	-0.1365	-0.5829	1

The principal components analysis was run next, and the results are shown in Table 2. It can be seen that there is a very low weight for the unemployment rate. This was because many areas had 0 unemployment rate for those older than 65, so this indicator was removed from the index.

Table 2: Results from PCA on participation domain

Variable	Comp1	Comp2	Comp3
emp_rate_cns	0.3827	-0.1271	0.3953
unemp_rate~s	-0.0622	0.2257	-0.0353
carech~h_cns	0.2577	0.2454	0.1282
carec~ly_hil	0.4298	0.2631	-0.3748
carec~ay_hil	0.3621	0.3206	-0.2547
no_car_cns	-0.2373	0.4132	0.2389
ann_cost_p~l	-0.1816	0.2190	0.4130
no_int_hil	-0.4330	-0.1814	0.0309
old_carer_~s	-0.2271	-0.2487	-0.5638
not_well_e~s	-0.2322	0.4806	-0.0192
volunt_cns	0.2918	-0.3953	0.2720

The results from this run are shown in Table 3. It can be seen that the variable for older carers had a very low weight so this was the next variable removed.

Table 3: Results from PCA on participation domain without unemployment

Variable	Comp1	Comp2	Comp3
emp_rate_cns	-0.4343	0.0905	0.3402
carech~h_cns	-0.2029	0.4109	-0.0758
carec~ly_hil	-0.2969	0.2866	-0.3920
no_car_cns	0.3490	0.3694	0.1979
ann_cost_p~l	0.2498	0.1632	0.5078
no_int_hil	0.3926	-0.3890	0.2525
old_carer_~s	0.1749	-0.4231	-0.4797
not_well_e~s	0.3684	0.4268	-0.1461
volunt_cns	-0.4212	-0.2555	0.3355

The results after removing this indicator are shown in Table 4. It can be seen that the indicator % providing care to children from the Census (carech~h_cns) has a low weight, so this was the next indicator removed.

Table 4: Results from PCA on Participation domain after removing % older carers

Variable	Comp1	Comp2	Comp3
emp_rate_cns	-0.4115	0.0406	0.3324
carech~h_cns	-0.1267	0.4636	0.4523
carec~ly_hil	-0.2917	0.4381	-0.2791
no_car_cns	0.3783	0.2297	-0.0418
ann_cost_p~l	0.2983	-0.0273	0.7330
no_int_hil	0.3638	-0.5133	0.0173
not_well_e~s	0.4221	0.4285	0.0357
volunt_cns	-0.4324	-0.3015	0.2578

The results after removing this indicator are shown in Table 5. The next variable with a loading of less than 0.3 was the care provided to children or grandchildren from the HILDA (carec~ly_hil), so this indicator was removed and the results shown in Table 6.

Table 5: Results from PCA on Participation domain after removing providing care to children from the Census

Variable	Comp1	Comp2	Comp3
emp_rate_cns	-0.4096	0.0789	0.5805
carec~ly_hil	-0.2654	0.5549	-0.0897
no_car_cns	0.3887	0.2673	0.2766
ann_cost_p~l	0.3075	-0.1961	0.6778
no_int_hil	0.3248	-0.5674	-0.1500
not_well_e~s	0.4544	0.3999	0.1522
volunt_cns	-0.4518	-0.3066	0.2709

Table 6: Results from PCA on Participation domain after removing care provided to children or grandchildren from the HILDA

Variable	Comp1	Comp2	Comp3
emp_rate_cns	-0.4102	-0.3361	0.5076
no_car_cns	0.4260	-0.2560	0.2366
ann_cost_p~l	0.2831	0.2919	0.7658
no_int_hil	0.2431	0.7444	-0.0234
not_well_e~s	0.5112	-0.3779	0.0920
volunt_cns	-0.4998	0.1985	0.3015

It can be seen that the no internet (sourced from modelling of the HILDA dataset) is the next indicator with a low loading, so we used the slightly different definition of internet availability from the Census with the results shown in Table 7. The loading for this indicator was larger than 0.3.

Table 7: Results from PCA on Participation domain after replacing no internet from census

Variable	Comp1	Comp2	Comp3
emp_rate_cns	-0.3917	-0.3539	0.3473
no_car_cns	0.4585	0.0797	0.2887
ann_cost_p~l	0.2442	-0.3206	0.7292
no_int_cns	0.2603	0.7682	0.2666
not_well_e~s	0.5203	-0.3368	-0.0603
volunt_cns	-0.4881	0.2491	0.4354

The next variable to remove was the annual cost of public transport (ann_cost_p~l) and the results are shown in Table 8.

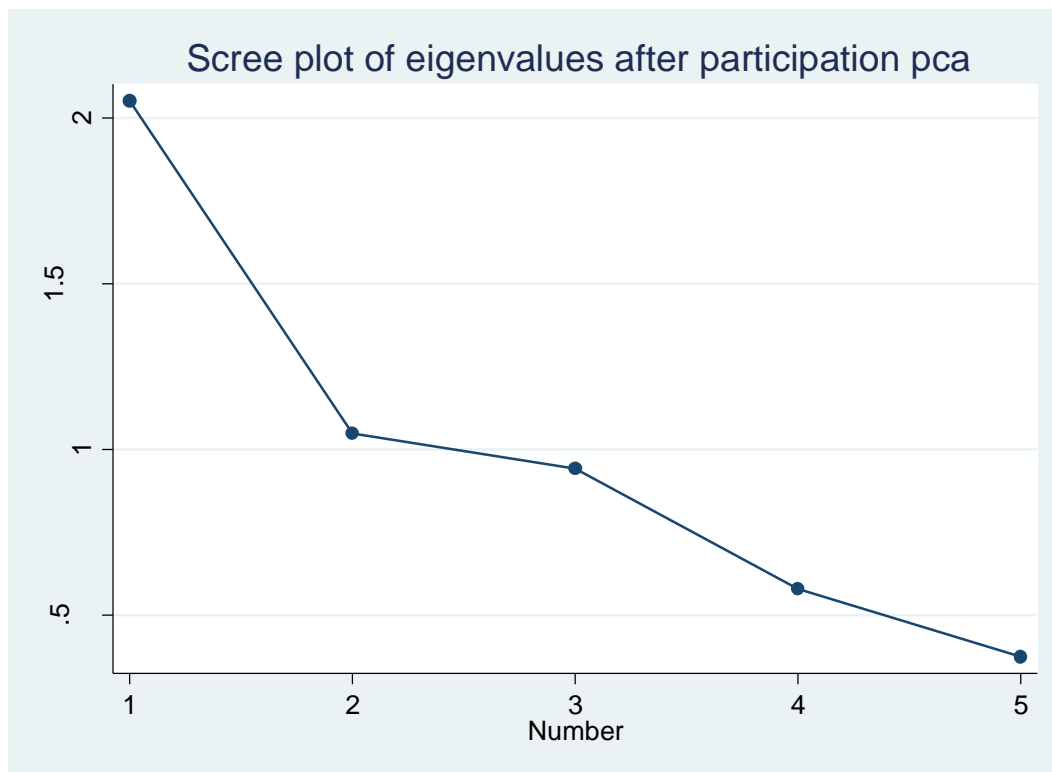
Table 8: Results from PCA on Participation domain after removing the annual cost of public transport

Variable	Comp1	Comp2	Comp3
emp_rate_cns	-0.4032	-0.0366	0.7392
no_car_cns	0.3731	0.4497	0.5753
no_int_cns	0.3603	0.6858	-0.1843
not_well_e~s	0.5219	-0.3687	0.2977
volunt_cns	-0.5441	0.4361	0.0103

All loadings were now reasonable (above 0.3), and so we now looked at adding one of the indicators that we had some strong theoretical background for including to see if it was significant after other indicators had been removed. This was the caring for children from either the Census or HILDA. These two indicators still had low loadings after they were added back in, so were left out of this domain.

The scree plot for this domain is shown in Figure 1. It can be seen that there is a levelling out at component 2.

Figure 1: Scree plot for Participation domain



The final index for the participation domain was one where a higher value signified lower participation, or lower well-being. This means the index was inverted so higher values signified greater wellbeing, which is what we wanted for our final index.

Education Domain

The education domain had three indicators, and a correlation matrix is shown in Table 9. It can be seen that there are reasonable correlations, with no correlation above 0.95 but all above 0.8.

Table 9: Correlation Matrix, Education domain

		% older pe cy12_cns	% older pe cy10_cns	% older pe qual_cns
% older people Completed Year 12	cy12_cns	1		
% older people Completed Year 10	cy10_cns	0.861	1	
% older people with post school qualifications	qual_cns	0.8841	0.8961	1

The results from a principal components analysis on this domain is shown in Table 10. It can be seen that all the loadings are very high, so this domain was left as it is.

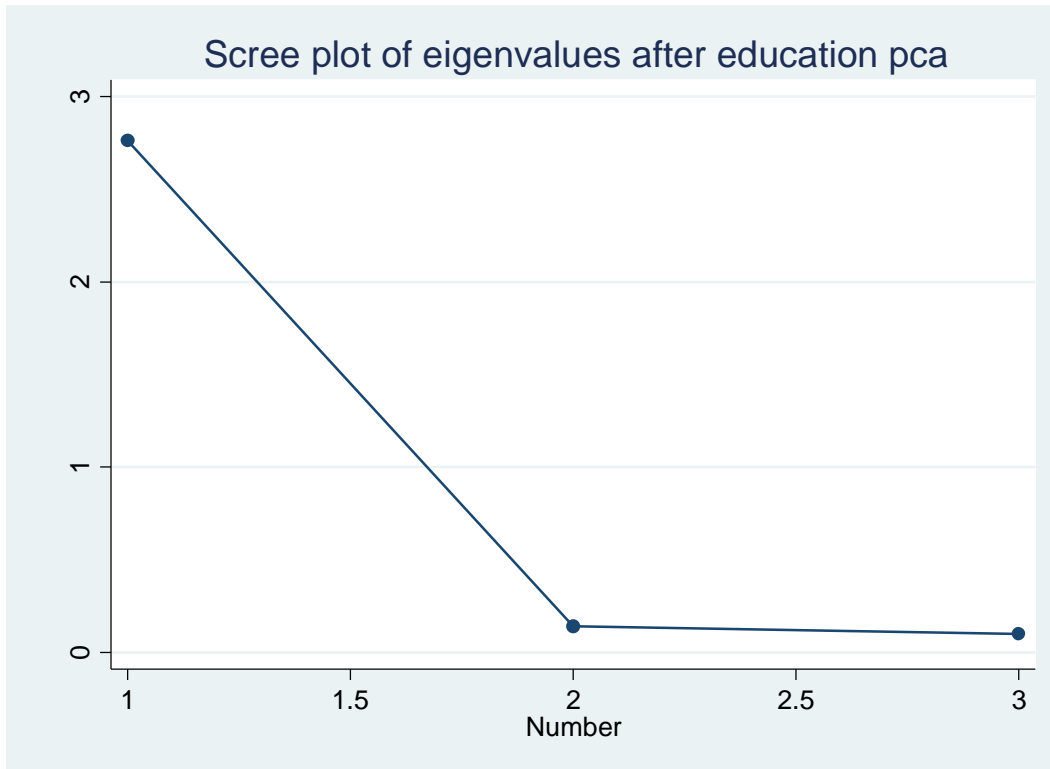
The scree plot is shown in Figure 2. It can be seen that there is a sudden levelling of the eigenvalues at component 2, so none of the other components added to explaining the correlation.

The results indicate that a higher value for the index is associated with higher education, or greater well-being.

Table 10: Results from a PCA on the Education domain

Variable	Comp1	Comp2	Comp3
cy12_cns	0.5739	0.7676	0.2853
cy10_cns	0.5766	-0.6262	0.5249
qual_cns	0.5816	-0.1367	-0.8019

Figure 2: Scree plot, Education domain



Resources Domain

The next domain was the Resources domain, and the correlation matrix is shown in Table 11. It can be seen that there are some low correlations with % of older people who could not raise certain amount of \$ in emergency within a week, and we would expect this indicator to drop out in the PCA.

Table 11: Correlation Matrix, Resources domain

		Poverty Rate for older people	% of old people with age pension	% of older people with the Age Pension as the major source of income	% of older people who have no superannuation payments	% of older people who could not raise certain amount of \$ in emergency within a week.	% older people who pay public/private rent and are in the bottom income quintile of the equivalised household
		pov_rate_sih	age_pensio~n	age_pensio~h	no_super_sih	not_raise~s	rent_botto~h
Poverty Rate for older people	pov_rate_sih	1					
% of old people with age pension	age_pensio~n	0.5596	1				
% of older people with the Age Pension as the major source of income	age_pensio~h	0.7705	0.7947	1			
% of older people who have no superannuation payments	no_super_sih	0.5011	0.527	0.5781	1		
% of older people who could not raise certain amount of \$ in emergency within a week.	not_raise~s	0.1272	0.1619	0.1273	0.1699	1	
% older people who pay public/private rent and are in the bottom income quintile of the equivalised household	rent_botto~h	0.5254	0.1664	0.3618	0.4865	0.0818	1

The results from the PCA with all indicators is shown in Table 12. As expected, the % of older people who could not raise a certain amount of money in an emergency within a week had a very low loading and dropped out of the index.

Table 12: Results from a PCA on the Resources domain

Variable	Comp1	Comp2	Comp3
pov_rate_sih	0.5347	-0.1108	-0.2645
age_pensio~h	0.5210	-0.0780	-0.5294
no_super_sih	0.4836	0.0218	0.1458
not_raise_~s	0.1513	0.9810	0.0355
rent_botto~h	0.4311	-0.1371	0.7920

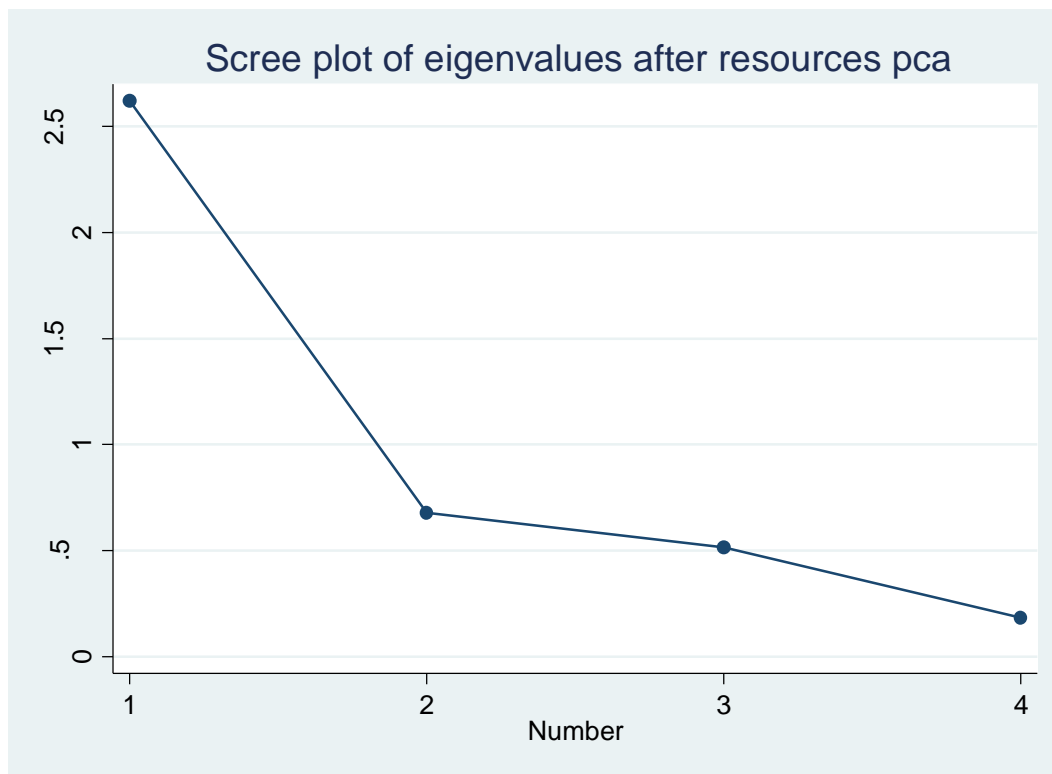
The results for the index without this indicator are shown in Table 13. It can be seen that all indicators now have a loading above 0.3, so this was the final index used for the resources domain. The results indicate that a higher value is associated with lower well-being, so this index was transformed so a higher value was associated with higher well-being.

Table 13: Results from a PCA on the Resources domain after removing % of older people who could not raise certain amount of \$ in emergency within a week

Variable	Comp1	Comp2	Comp3
pov_rate_sih	0.5421	-0.2652	-0.4432
age_pensio~h	0.5273	-0.5276	-0.0340
no_super_sih	0.4858	0.1541	0.8317
rent_botto~h	0.4382	0.7922	-0.3328

The scree plot for this domain is shown in Figure 3. It can be seen that there is a levelling of eigenvalues at component 2.

Figure 3: Scree plot, Resources domain



Housing Domain

The next domain was housing, and the correlation matrix is shown in Table 14. It can be seen that there were some very low correlations in this domain, particularly around homelessness. We would expect many of these indicators to drop out in the PCA.

Table 14: Correlation Matrix, Housing domain

		% of older p	% of older p	% of older p	% of older p	homeless	exphomeless	% of older p
		pay_mort_c	rent_cns	pub_hous_	hous_stres	hmless_cns	hmless_exp	rent_asst_s
% of older people who are still paying mortgages	pay_mort_cns	1						
% of older people who are still renters	rent_cns	-0.102	1					
% of older people living in public housing	pub_hous_cns	-0.0989	0.8166	1				
% of older Australians in housing stress	hous_stres~h	0.3199	0.6183	0.5078	1			
homeless	hmless_cns	-0.1146	0.1039	-0.0219	0.0046	1		
exphomeless	hmless_exp~s	0.1395	0.1409	0.1336	0.1955	0.0777	1	
% of older people receiving rent assistance	rent_asst_~h	0.2459	0.33	0.0458	0.7116	0.151	0.176	1

The PCA with all indicators is shown in Table 15. It can be seen that the homelessness indicator had a very low loading, so this indicator was removed.

Table 15: Results from a PCA on the Housing domain

Variable	Comp1	Comp2	Comp3
pay_mort_cns	0.1252	0.6276	-0.0141
rent_cns	0.5223	-0.3554	-0.0334
pub_hous_cns	0.4509	-0.4686	0.0878
hous_stres~h	0.5561	0.1946	-0.1873
hmless_exp~s	0.2007	0.1991	0.9413
rent_asst_~h	0.3982	0.4274	-0.2641

The results from the index without homelessness is shown in Table 16. It can be seen that paying a mortgage has a very low loading. This may be because there were not many older people in this situation, so there were a lot of 0's across the country. This indicator was removed.

Table 16: Results from a PCA on the Housing domain after removing % homelessness

Variable	Comp1	Comp2	Comp3
pay_mort_cns	0.1132	0.6377	0.7241
rent_cns	0.5401	-0.3309	0.0332
pub_hous_cns	0.4674	-0.4570	0.3557
hous_stres~h	0.5647	0.2378	-0.0579
rent_asst_~h	0.3976	0.4674	-0.5871

The results after removing paying mortgage are shown in Table 17. It can be seen that all indicators now have high loadings. Some final testing on the pay mortgage and renters variables showed that these two were measuring the same concept – so replacing pay renters with pay mortgage meant pay mortgage had a loading above 0.3 (see Table 18). In the end, renting was left in as it had a higher loading.

The results show that a higher value was associated with lower well-being, so the final index was transformed so that higher values represented higher well-being, consistent with what we wanted for the final index.

Table 17: Results from a PCA on the Housing domain after removing % paying mortgage

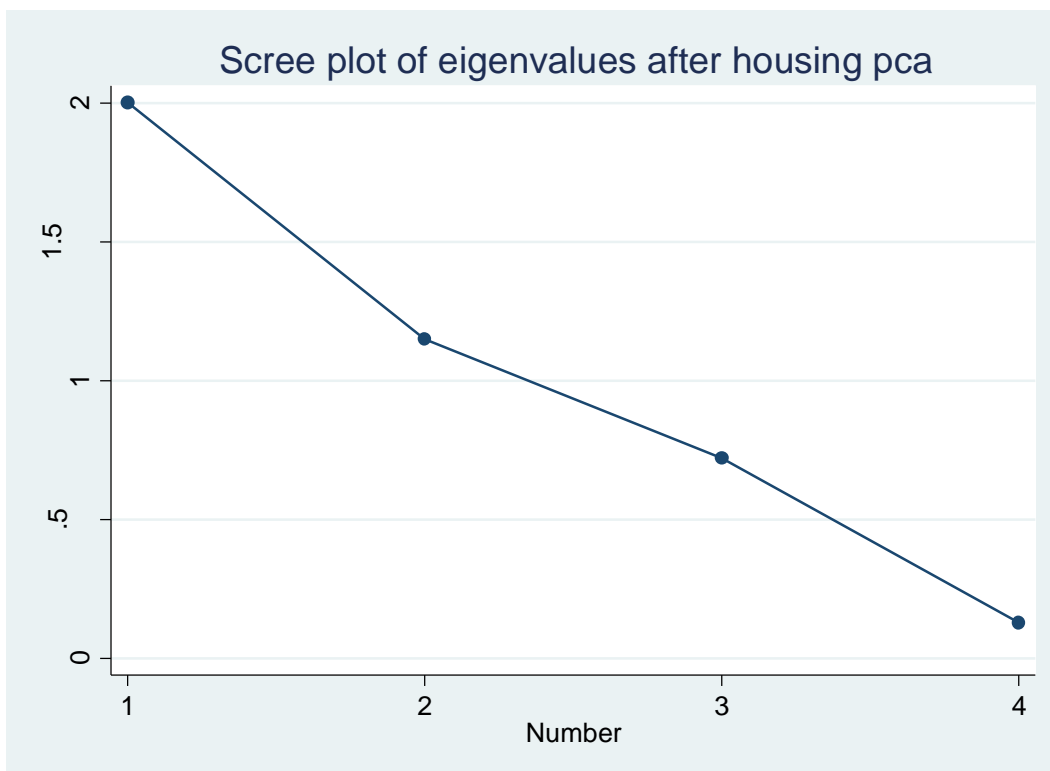
Variable	Comp1	Comp2	Comp3
rent_cns	0.5566	-0.3059	0.6022
pub_hous_cns	0.4853	-0.5549	-0.2160
hous_stres~h	0.5544	0.2986	-0.6728
rent_asst_~h	0.3839	0.7137	0.3716

Table 18: Results from a PCA on the Housing domain after removing % renting and adding back % paying mortgage

Variable	Comp1	Comp2	Comp3
pay_mort_cns	0.3230	-0.6148	0.7002
pub_hous_cns	0.3346	0.7450	0.4017
hous_stres~h	0.6761	0.1192	-0.0351
rent_asst_~h	0.5715	-0.2297	-0.5892

The scree plot for this domain is shown in Figure 4. It can be seen that for this domain, there is no levelling out of the eigenvalues after component 1, as we have seen with other domains. Due to the small number of indicators in this domain, and the problems interpreting the components after the first component, we have used the first component as the index for this domain.

Figure 4: Scree plot, Housing domain



Functional Ability Domain

The correlation matrix for the Functional ability domain is shown in Table 19. It can be seen that there are no very high correlations, but many low correlations which we would expect to drop out in the PCA. The first PCA for the functional ability domain is shown in Table 20. It can be seen that there are a number of indicators with low loadings, and the first step was to remove the two indicators on the provision of HACC services (L_COMMCARE~D and H_COMMCARE~D) which had a very low weight. The results are shown in Table 21.

Table 19: Correlation matrix, Functional ability domain

		need_ass_cns	aged_care_~s	need_1_4_dss	need_5_mor~s	needun~4_dss	needun~e_dss	hacc_clien~d	hours_assi~d	l_commcare~d	h_commcare~d
% need for assistance with core activities	need_ass_cns	1									
% of older people who use aged care services	aged_care_~s	0.6481	1								
% need assist for 1 to 4 activities	need_1_4_dss	0.3821	0.133	1							
% need assist for 5 or more activities	need_5_mor~s	0.5519	0.1146	0.6022	1						
% need and unmet assist for 1 to 4 activities	needun~4_dss	0.1086	0.0392	0.417	0.2029	1					
% need and unmet assist for 5 or more activities	needun~e_dss	0.2818	0.0664	0.505	0.5535	0.3053	1				
% Home and Community Care clients	hacc_clien~d	-0.0572	-0.1868	0.1867	0.0749	0.1336	0.1505	1			
Hours of assistance of Home and Community Care per old people	hours_assi~d	0.0366	-0.1465	0.0882	0.0721	0.0838	0.0723	-0.6471	1		
% Low Level community packaged care	l_commcare~d	0.0924	0.0113	0.0379	0.021	0.0406	0.0303	-0.0076	0.0235	1	
% High Level community packaged care	h_commcare~d	0.01	0.0036	0.0177	0.0094	0.0022	0.0147	-0.0592	-0.0116	0.6653	1

Table 20: Results from a PCA on the Functional Ability domain

Variable	Comp1	Comp2	Comp3
need_ass_cns	0.4219	-0.3040	-0.0850
aged_care_~s	0.2205	-0.4360	-0.1376
need_1_4_dss	0.4824	0.0728	-0.0152
need_5_mor~s	0.4859	-0.0238	-0.0539
needun~4_dss	0.2895	0.1400	0.0272
needun~e_dss	0.4298	0.0852	-0.0114
hacc_clien~d	0.1324	0.5896	0.0969
hours_assi~d	0.1139	0.5366	0.1290
l_commcare~d	0.0668	-0.1472	0.6875
h_commcare~d	0.0339	-0.1661	0.6864

Table 21: Results for the Functional ability domain after removing two of the HACC variables

Variable	Comp1	Comp2	Comp3
need_ass_cns	0.4398	-0.2126	0.4545
aged_care_~s	0.2745	-0.3608	0.5865
need_1_4_dss	0.4779	0.0578	-0.2334
need_5_mor~s	0.4556	0.0127	-0.1640
needun~4_dss	0.3061	0.0786	-0.3514
needun~e_dss	0.4294	0.0406	-0.2767
hacc_clien~d	0.1000	0.6479	0.2333
hours_assi~d	0.0843	0.6274	0.3371

The next set of indicators with low loadings were the number of HACC clients (HACC_CLIEN~D) and the hours of assistance provided (HOURS_ASSI~D). These two indicators were removed and the results are shown in Table 22.

Table 22: Results for the Functional ability domain after removing the number of HACC clients and hours

Variable	Comp1	Comp2	Comp3
need_ass_cns	0.4501	0.4784	-0.0915
aged_care_~s	0.2941	0.6975	0.2777
need_1_4_dss	0.4757	-0.2511	-0.0013
need_5_mor~s	0.4566	-0.1766	-0.5022
needun~4_dss	0.3034	-0.3404	0.8038
needun~e_dss	0.4289	-0.2729	-0.1269

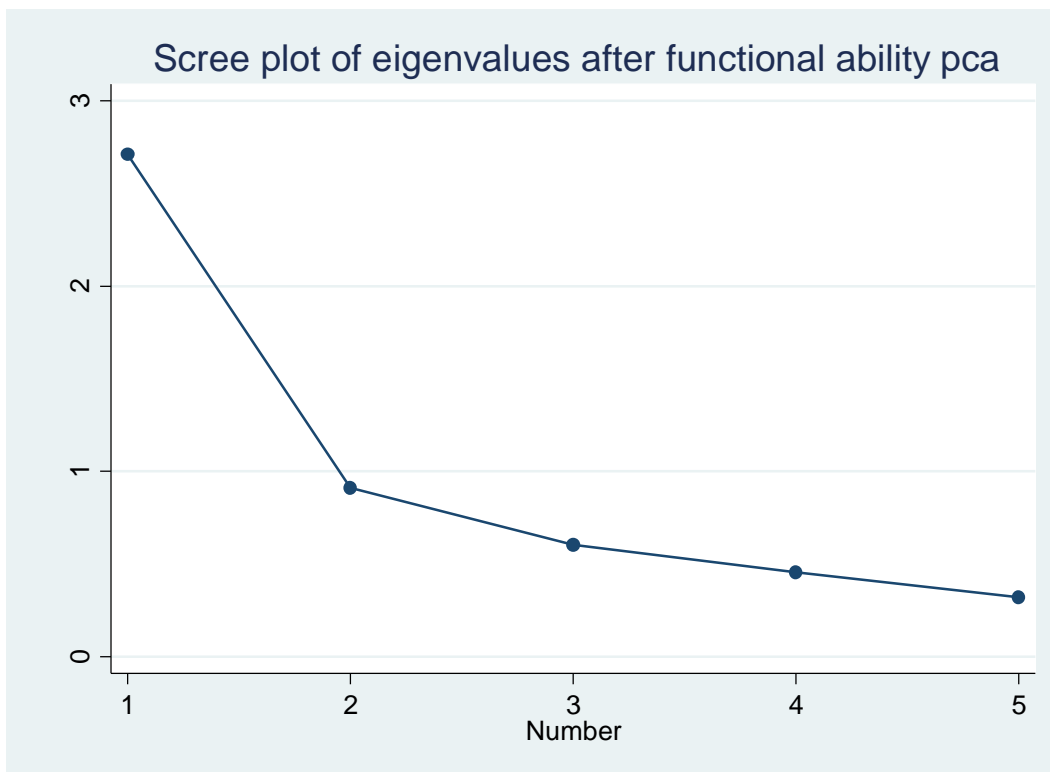
The final indicator with a loading below 0.3 is the proportion of older people who use aged care services. The results from the PCA after removing this indicator is shown in Table 23. It can be seen that all the loadings are now above 0.3, so this was the final index used for the Functional ability domain. It can be seen that higher values were associated with lower well-being, so the index was transformed so that higher values represented higher well-being, consistent with what we wanted in the final index.

Table 23: Results from a PCA on the Functional ability domain after removing the % of older people who use aged care services.

Variable	Comp1	Comp2	Comp3
need_ass_cns	0.4092	-0.4894	0.6411
need_1_4_dss	0.5111	0.1160	0.0004
need_5_mor~s	0.4967	-0.3264	-0.1907
needun~4_dss	0.3308	0.7957	0.3848
needun~e_dss	0.4639	0.0860	-0.6360

The scree plot for this domain is shown in Figure 5. It can be seen that this domain follows the levelling out of components after the first component.

Figure 5: Scree plot, Functional ability domain



Method for bringing the sub-indexes together

The index for each domain was calculated using the loadings identified above, and then the domains were transformed using a log transformation which means they can then be averaged to create the final index. This log transformation is taken from (Noble et al., 2004). The log transformation is:

$$\text{index_log_d1} = -23 \cdot \log(1 - \text{index_prop} \cdot (1 - \exp(-100/23)))$$

where index_prop is the rank of the area scaled to the range [0,1]. The area with the lowest rank will have an index_prop of $1/n$, and the area with the highest rank will have the value n/n (or 1), where n is the total number of areas being ranked.

Any missing values (ie, where data were not available for at least one of the domains) were removed as this transformation could not be calculated for these areas. The final index was then calculated by averaging the five domain index_log :

$$\text{Index} = (\text{index_log_d1} + \text{index_log_d2} + \text{index_log_d3} + \text{index_log_d4} + \text{index_log_d5})/5.$$

Due to the way that the sub-indexes had been formulated, for the final index, higher scores represented higher wellbeing.

References

- Australian Bureau of Statistics. (2004). *Census of Population and Housing : Socio-Economic Indexes for Areas (SEIFA) 2001 Technical Paper*. ABS Cat # 2039.0.55.001, ABS: Canberra.
- Dunteman, G. (1989). *Principal Components Analysis*. Newbury Park, CA: Sage University Paper series on Quantitative Applications in the Social Sciences No. 07-069.
- Harding, A., McNamara, J., Daly, A., & Tanton, R. (2009). Child Social Exclusion: An Updated Index From the 2006 Census. *Australian Journal of Labour Economics*, 12(1), 41 – 64. Retrieved from <http://www.business.curtin.edu.au/files/266hardingFINAL.pdf>
- Noble, M., Wright, G., Dibben, C., Smith, G., McLennan, D., Anttila, C., ... Lloyd, M. (2004). *The English Indices of Deprivation 2004*. Office of the Deputy Prime Minister: London.