



Australian Government
Productivity Commission

Developing an Index of Regional Adaptive Capacity

Transitioning Regional Economies
Technical Supplement to the Initial Report

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Developing an index of regional adaptive capacity

Described in this technical supplement to the initial report on Transitioning Regional Economies are the data and techniques used to construct the single metric of regional adaptive capacity. The approach is based on a statistical technique called principal component analysis (PCA), which has been widely used to create regional indexes of socioeconomic disadvantage, vulnerability, resilience and adaptive capacity (chapter 2). Section 1 explains the method and the decisions made in using PCA to construct the index of regional adaptive capacity. The indicators included in the index were grouped according to the five capitals framework outlined in chapter 2 of the initial report, and the data sourced are largely from the ABS 2011 Census of Population and Housing. Data sources and data transformations are described in section 2.

Section 3 contains the results from the PCA. The sensitivity of each region's index value was tested using bootstrapping and by examining the effect of excluding variables in the index (section 4). An overview of the results is provided in section 5, with a detailed discussion in chapter 4. Attachment A contains a spreadsheet of index scores for each region, including a breakdown of the factors that contribute to each region's index score, and the 90 per cent confidence intervals of the region's score.

Although the index of adaptive capacity has been used to rank regions according to their risk of failing to adjust to transitional pressures, it should not be used as a predictor of actual outcomes. These outcomes are the result of many decisions made by individual workers and businesses, as well as the type and magnitude of disruptions that occur, which have not been captured in the index (chapter 2).

1 Index methodology

PCA is a method of summarising data by reducing the number of variables in a dataset into a new dataset with fewer variables (O'Rourke and Hatcher 2013). The smaller set of variables can be used to construct indexes. This section begins by first providing a brief introduction to PCA, including a simple hypothetical example, and then explains how the technique was applied in creating the index of regional adaptive capacity.

Principal component analysis

PCA summarises data by creating a new set of variables called ‘principal components’. These are linear combinations of the original variables that are uncorrelated with each other and capture the total variation in the original dataset. The total number of principal components created is the same as the original number of variables. However, the first principal component accounts for the largest amount of variation in the original dataset, the second principal component accounts for the next largest amount, and so on.

Although the principal components created through the technique are uncorrelated with each other, they are correlated with the original variables. An interpretation of a principal component can be formed based on the original variables it is most strongly correlated with. Insight into which variables are most relevant in explaining the variation in the data can be gained by examining the proportion of variance explained by a principal component, along with its interpretation.

Provided that the first few principal components capture a sufficient amount of variation in the original data and can be interpreted in a meaningful way, an analyst can choose to retain just these principal components for further analysis (rather than the full set of variables in the original data) (O’Rourke and Hatcher 2013, p. 3). The decision of how many principal components to retain is discussed further below.

PCA produces a score for each observation in the dataset on each principal component created. For a PCA with K observed variables, the formula for calculating observation i ’s score on the p^{th} principal component is:

$$PC_{pi} = w_{1p}X_{1i} + w_{2p}X_{2i} + \dots + w_{Kp}X_{Ki}$$

where:

- PC_{pi} is observation i ’s score on the p^{th} principal component
- X_{ki} is observation i ’s standardised value of the k^{th} observed variable
- w_{kp} is the weight attached to the k^{th} observed variable for the p^{th} principal component, obtained from the PCA.

A simple illustration

An example of how PCA transforms data is illustrated using a hypothetical dataset on employment and year 12 attainment rates for six regions (table 1). The first step illustrates the standardisation of the original variables (by subtracting the mean of the variable and dividing by its standard deviation). Standardised variables have means of zero and standard deviations of one.¹ PCA is then applied to generate the weights on each variable for each

¹ Standardisation ensures that variables with different units of measurement are treated on a comparable basis in the PCA.

principal component, as well as the principal components themselves. In this example, most of the variation in the data can be represented by the first principal component, which accounts for 97 per cent of the total variation in the data. Therefore, this component summarises most of the variation in year 12 attainment and employment rates. It is highly correlated with both variables, and could be interpreted as a simple human capital index. An analyst could choose to retain just this principal component and capture most of the variation in the original data.

The transformation of data points from the original variables to the principal components is illustrated diagrammatically in figure 1.

Table 1 Principal component analysis — illustrative transformation
Hypothetical dataset on year 12 attainment and employment rates

Step 1: Standardisation

Region (i)	Original variables (%)		Standardised variables (X_{ki})	
	Year 12	Employment	Year 12	Employment
1	34	22	-1.43	-1.53
2	47	50	-0.74	-0.16
3	55	45	-0.32	-0.41
4	69	51	0.42	-0.11
5	80	77	1.01	1.16
6	81	75	1.06	1.06
Mean	61.00	53.33	0.00	0.00
Std dev.	18.90	20.48	1.00	1.00

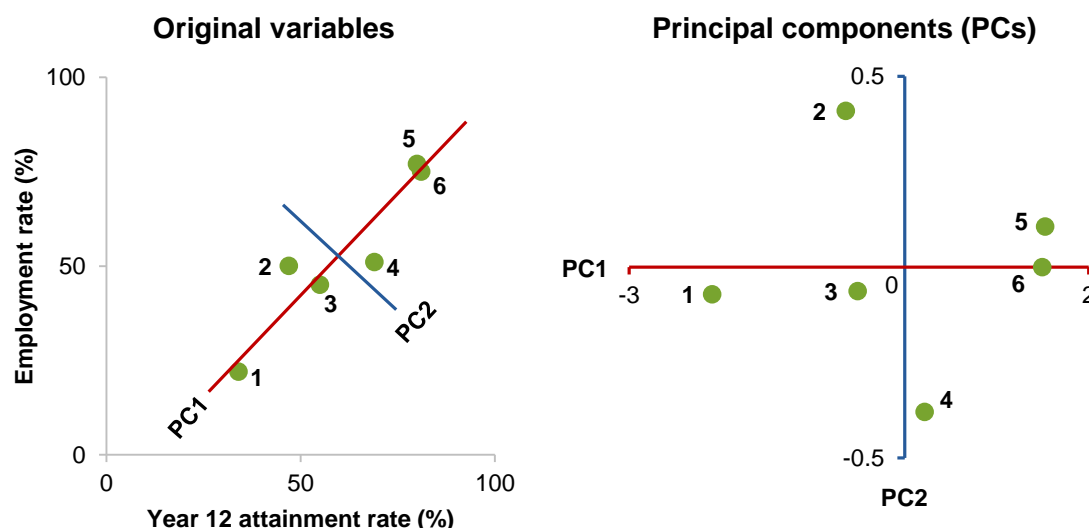
Step 2a: PCA weights

Principal components (PCs)	Weights (w_{kp})		Correlations		Cumulative proportion of variance explained
	Year 12	Employment	Year 12	Employment	
PC ₁	0.71	0.71	0.98	0.98	0.97
PC ₂	-0.71	0.71	-0.18	0.18	1.00

Step 2b: PCA scores ($PC_{pi} = w_{1p}X_{1i} + w_{2p}X_{2i}$)

Region	Principal components (PC_{pi})	
	PC ₁	PC ₂
1	-2.09	-0.07
2	-0.64	0.41
3	-0.51	-0.06
4	0.22	-0.38
5	1.53	0.11
6	1.50	0.00

Figure 1 **Principal component analysis — illustrative visualisation**
Hypothetical dataset on year 12 attainment and employment rates



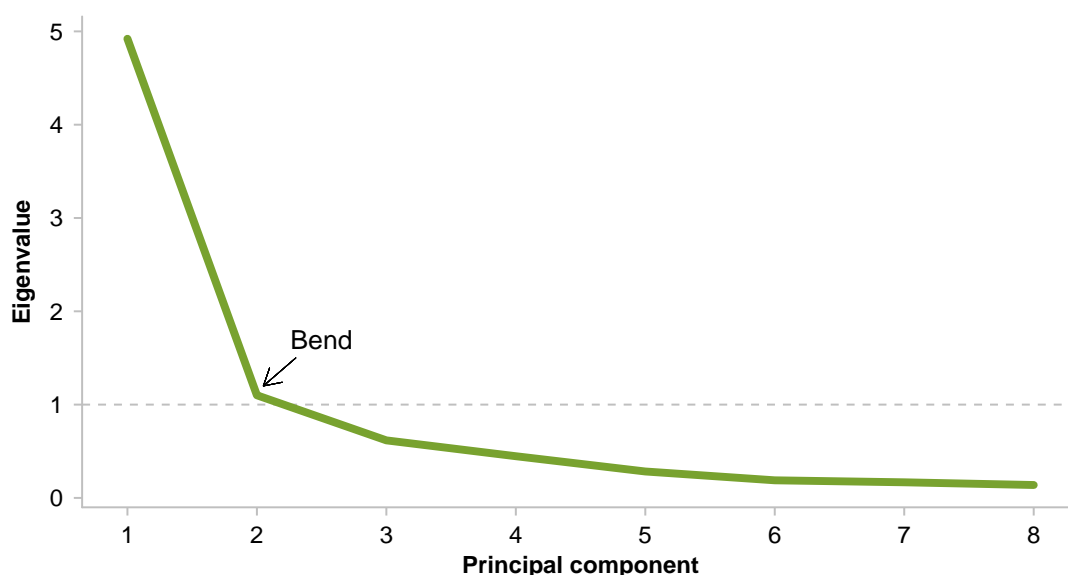
Determining the number of principal components to retain

Choosing the number of principal components to retain from a PCA requires a degree of judgment. Although there are some guidelines, there are no strict rules on how to make this decision. Drawing on O'Rourke and Hatcher (2013), four criteria are commonly used.

Scree test

The first criterion is the scree test, which involves plotting the eigenvalues (amounts of variance explained by the principal components respectively) in order. This plot is known as a scree plot, and a hypothetical example is provided in figure 2. If there is an elbow-like bend in the plot, with the first set of components before the bend having large eigenvalues (explaining a large amount of the variation) and the other set from the bend onwards having relatively small eigenvalues (explaining little variation), then the components in the first set are retained. In figure 2, the first principal component (the only component before the bend) would be retained. Unlike in figure 2, in many cases, there is no clear bend in the plot and other criteria must be considered.

Figure 2 **Scree plot example**



Eigenvalue-one

The second criterion is to retain components with eigenvalues greater than one. Each standardised observed variable contributes a unit of variance to the total variance in the dataset, so any principal component that has an eigenvalue greater than one contributes more than an observed variable. Applying this criterion to the example used for figure 2, the first two principal components would be retained because they have eigenvalues greater than one (as shown by the dashed line).

Cumulative proportion of variance explained

The third criterion involves retaining components until the cumulative proportion of variance explained is greater than a given threshold, usually 70 or 80 per cent (O'Rourke and Hatcher 2013, p. 19). Applying this to the example in table 1, the first principal component would be retained because it alone captures 97 per cent of the total variation.

Interpretability

Finally, the interpretability of components needs to be considered. Principal components are retained if the main factors contributing to those components (the variables with the largest weights or correlations) can be interpreted in a meaningful way. As in the example in table 1, the first principal component is highly correlated with both year 12 attainment and employment, and could be interpreted as a simple measure of human capital.

Nested PCA and index construction

A nested approach was used to create the index of regional adaptive capacity. PCA was applied repeatedly to separate groups of variables, and a weighted sum of the retained components was used to form the index, resulting in a score for each region.

In particular, PCAs were conducted on groups of variables considered important to adaptive capacity, where variables were categorised based on the five capitals framework described in chapter 2. Separate PCAs were performed on variables in each capital domain that consisted of more than one variable — human, financial, natural and physical. A number of principal components from these were retained (based on the criteria described above).² In addition to the retained principal components, two other indicators were separately included in the index — an indicator of social capital (measured by the rate of volunteering) and a measure of industry diversity. Both of these indicators were also standardised. The signs on these indicators and each retained principal component were flipped where necessary so that a higher value indicated greater adaptive capacity. The index of adaptive capacity was a weighted sum of these indicators and principal components.

Two judgments were made in constructing the index.

The first concerned the weighting of each retained component within each capital domain. These were weighted according to the relative shares of variance explained by the components in the relevant PCA. For example, if the first two human capital components were retained for the index, and these accounted for 60 and 20 per cent of the total variance in human capital factors respectively, then the first component was given a weight of $0.6/(0.6 + 0.2) = 0.75$, and the second component was given a weight of 0.25 for the human capital domain. (The actual weights are presented in section 3.) This weighting approach ensures that the factors that were more important to a particular domain (represented by the first principal component) made a greater contribution to the index than other factors within that domain (represented in other retained components).

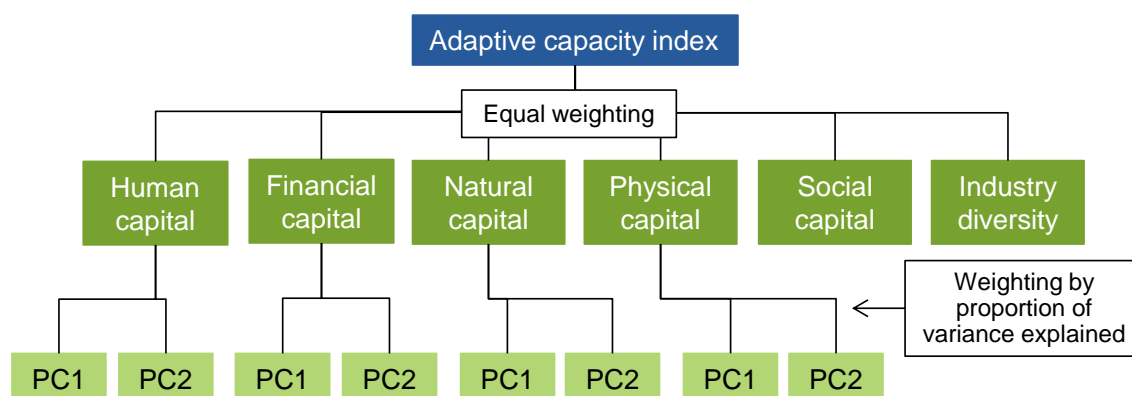
The second decision involved weighting each of the five capitals and industry diversity in the index. Noble et al. (2003) describe various possible approaches to weighting scores across different domains to form an aggregate index. These include approaches driven by theory, empirics, policy relevance and consensus of opinion. The relative importance of a type of capital to a region's adaptive capacity is likely to differ depending on the type of shock that it is adjusting to. Balance between the five capitals is also an important consideration because minimum levels of one capital type might be needed to effectively use another type (Nelson et al. 2009, p. 20). For these reasons, each domain was equally weighted. In effect, this means that each domain was summed. Equal weighting approaches have been used in many other studies that construct indexes of similar concepts (for example,

² A variant of PCA involves 'varimax rotation', which changes the weights on each variable in each component and can aid in their interpretation. Varimax rotations were investigated for the current analysis but did not meaningfully change interpretations of retained components. Therefore, unrotated principal components were used for the index.

in creating an index of potential community economic resilience (Dinh et al. 2016) and an index of community vulnerability (ABARE–BRS 2010)).

The separate domains and weighting approaches used in the adaptive capacity index are summarised in figure 3.

Figure 3 **Weighting factors in the adaptive capacity index**



2 Regional data and adaptive capacity indicators

In constructing the index, data were used that:

- included indicators that were a measure or proxy measure of factors considered relevant to adaptive capacity
- covered all regions of Australia
- were sufficiently granular to enable the analysis of smaller regions (including those with small populations that might not be adequately captured in survey data)
- included indicators that were consistently defined across the regions.

There are challenges in obtaining suitable data on regional-level indicators that meet these criteria. Although various organisations and government departments collect data at a regional level, these data are not necessarily consistent, both in terms of the geographical boundaries of regions and in the definitions of particular indicators. This limits the data that can be included within a single metric for all regions in Australia.

A key source of data that do meet these criteria is the ABS Census of Population and Housing. The most recently available Census data are from 2011. A number of other data sources were also used to obtain measures of factors considered relevant to adaptive capacity. These data sources and the indicators included in the index are discussed below, following a description of the regions included in the analysis.

Regions included in the index

The analysis was conducted at the Statistical Area Level 2 (SA2), which is part of the Australian Statistical Geography Standard. Key sources of nationally consistent data, such as the Census of Population and Housing, are available at this level. SA2s aim to represent a community that interacts together socially and economically, and have an average population of about 10 000 (ABS 2011a). In urban areas, an SA2 could cover a single suburb (such as Surry Hills or Darlinghurst in Sydney), whereas in sparsely populated and remote areas, an SA2 could cover a much larger geographic area (for example, East Pilbara in Western Australia has a land area of nearly 40 million hectares). There were 2214 SA2s in 2011, however, some SA2s were excluded from the analysis for the following reasons.

- 18 special purpose SA2s represented non-geographic categories. Specifically, for each of the nine state and territory groups (including ‘other territories’), there were two non-geographic categories — one that represented people who were in transit, offshore or on board vessels on Census night, and one for people who had no usual address.
- 3 SA2s represented Australian territories other than the Northern Territory and the ACT. These were Cocos (Keeling) Islands, Christmas Island and Jervis Bay.
- 104 additional SA2s had fewer than 10 dwellings and/or less than 100 working-age residents. These regions include large national parks, airports and industrial areas.
- 4 additional SA2s had missing data on property prices (an indicator used in the index, described below). These regions were Lord Howe Island in New South Wales, and Nhulunbuy, East Arnhem and Anindilyakwa in the Northern Territory.

A list of all excluded geographical regions can be found in appendix B. The analysis was conducted on the remaining 2085 SA2 regions.

Data sources

Access to the 2011 Census of Population and Housing was crucial to obtaining consistent data on many of the indicators included in the index of adaptive capacity. The Commission had an in-posted staff member at the ABS to access Census data on particular indicators of adaptive capacity at the SA2 level for the analysis in the initial report. The 2016 Census of Population and Housing data were not available for the initial report, but the Commission plans to incorporate that Census into an updated version of the index for the final report.

Other sources of data used to obtain indicators include:

- ABS National Regional Profile
- ABS Remoteness Structure and the Accessibility/Remoteness Index of Australia
- ABS Building Approvals
- ABS Selected Government Pensions and Allowances
- CoreLogic property price data.

To ensure consistency with the 2011 Census data, 2011 data from other sources were also used wherever possible. Due to limited data availability, 2012 data were used for one variable (land used as national parks or nature reserves, an indicator under natural capital).

Adaptive capacity indicators

Adaptive capacity summarises the endowments that a community can draw upon to respond to a change in economic conditions. In the index of adaptive capacity, these endowments are grouped under human, financial, natural, physical and social capital categories, as well as a separate indicator of industry diversity (chapter 2).

Indicators sourced from the Census were based on proportions of people living in a region who met the criteria of the particular indicator. For example, the proportion of working-age people who had completed year 12 in each region was used as the indicator of year 12 attainment. Basing the analyses on proportions of people (rather than numbers of people) ensured that regions with different population sizes were analysed on a comparable basis. People who did not answer the relevant question in the Census were excluded from both the numerator and denominator in the calculation of proportions.

The initial set of available indicators was refined following an examination of correlations and initial PCAs. Variables were excluded if they were reasonably highly correlated with, and captured similar concepts to, other variables in the same capital domain. This was based on judgment, rather than a specific correlation threshold. For example, year 12 attainment rates and tertiary qualification attainment rates both captured education under the human capital domain and had a correlation of over 0.9, so only year 12 attainment was included in the analysis. As another example, year 12 attainment rates had reasonably high correlations (of about 0.7) with the proportion of people working in high-skilled occupations and the proportion of people working in relatively low-skilled occupations. Although they are related, the year 12 attainment variable is intended to capture education while the latter two variables also capture skills and experience. Of the skill-related variables, only the proportion of people in high-skilled occupations was included in the analysis, while the proportion in low-skilled occupations was dropped. Both year 12 attainment and high-skilled occupation variables were kept in order to capture both these aspects of human capital.

Variables were also excluded if they explained relatively little variation in the capital grouping according to initial investigations using PCA. For example, a measure of the proportion of the population that was Indigenous was initially included under human capital. However, in examinations of early PCA results, this variable was only reasonably highly correlated with the fourth principal component, which would not have been retained according to the rule of retaining principal components until the cumulative proportion of variance explained is at least 70 per cent. Therefore, it was dropped from the index.

The refinement of indicators included in the metric mainly focused on those under the human capital domain. For some types of capital (such as physical capital), very few indicators were available so there was less scope to inspect and refine those in the metric.

The indicators included in the index are described below.

Human capital

Human capital captures the knowledge, experiences and capabilities of people in regional communities that can be used to take advantage of positive economic events, or to help counter negative events. It incorporates labour and factors that influence the scope for individuals to adapt to changes in their circumstances, such as education, skills and health. The proportion of employed people who manage their own business was included as a proxy for entrepreneurship (table 2).

Table 2 Human capital indicators included in index

<i>Indicator^a</i>	<i>Description</i>	<i>Mean</i>	<i>Standard deviation</i>
year12	Proportion of the population aged 15–64 who have completed at least year 12	0.69	0.12
skill1	Proportion of the employed population in highly skilled occupations ^b	0.30	0.11
employed	Proportion of the labour force who are employed	0.94	0.03
own_business	Proportion of the employed population who were owner managers of a business (incorporated or unincorporated)	0.16	0.06
youth_engage	Proportion of 15–19 year olds engaged in work or study	0.77	0.09
disability	Proportion of the population aged 15–64 who need assistance with core activities	0.03	0.01

^a Data sourced from the 2011 Census of Population and Housing unless otherwise indicated. ^b In the Australian and New Zealand Standard Classification of Occupations (ANZSCO), skill level 1 occupations (the most highly skilled) have a level of skill corresponding to a bachelor degree or higher qualification, or at least five years of relevant experience (ABS 2005).

Source: Productivity Commission estimates.

Financial capital

Financial capital captures the capacity of regional communities to draw on savings and credit in response to changing economic circumstances. Although measures of savings and credit are not available at the SA2 level, they have been proxied by other indicators that reflect a regional community's scope to save and access credit, particularly income and wealth-related variables (table 3).³

³ Although home ownership has been included as a positive indicator of adaptive capacity due to the wealth attached to it, it might also have a negative impact on adaptive capacity by limiting mobility.

Table 3 Financial capital indicators included in index

<i>Indicator^a</i>	<i>Description</i>	<i>Mean</i>	<i>Standard deviation</i>
high_income	Proportion of the population with equivalised total household income greater than \$1250 per week ^b	0.24	0.14
govt_payment ^c	Proportion of the population who received a government pension or allowance (excludes Family Tax Benefit)	0.25	0.08
property_prices ^e	Weighted average of median house and unit sale prices (\$'000)	419.24	196.30
own_home	Proportion of the population who live in an owner-occupied dwelling (with or without mortgage)	0.70	0.14

^a Data sourced from the 2011 Census of Population and Housing unless otherwise indicated. ^b Equivalised household incomes can be seen as an indicator of the economic resources available to a standardised household (ABS 2011b). Changing the threshold for high income from to \$1000 or \$1500 did not substantially change results. ^c Data sourced from ABS Selected Government Pensions and Allowances, 2011 (ABS 2013) through ABS.Stat. SA3-level data were attributed to the SA2 level assuming that all SA2s in the same SA3 had the same proportions of people receiving government payments. ^e Monthly data sourced from CoreLogic. Average house and unit prices for 2011 were calculated as the average of monthly medians. These were weighted by sales volumes for each property type to construct the overall property price variable.

Source: Productivity Commission estimates.

Natural capital

Natural capital captures a region's natural resources, such as land that can be used for production (agriculture and mining) and national parks and nature reserves (potential sources of tourism). These natural endowments can provide regional communities with a source of comparative advantage and opportunities for undertaking economic activities. Land use indicators were represented as shares so that regions with differing total land sizes were analysed on a comparable basis (table 4).

Table 4 Natural capital indicators included in index

<i>Indicator^a</i>	<i>Description</i>	<i>Mean</i>	<i>Standard deviation</i>
agri_land ^{b,c}	Proportion of land used for agriculture	0.26	0.35
nature_land ^b	Proportion of land used as national parks or nature reserves (2012)	0.04	0.10
mining_emp	Proportion of the employed population working in the mining industry	0.02	0.05

^a Data sourced from the 2011 Census of Population and Housing unless otherwise indicated. ^b Data sourced from the ABS National Regional Profile, 2010–2014, Cat. no. 1379.0.55.001. ^c In some cases, calculated proportions exceeded 1 due to data anomalies. Proportions were capped at a maximum of 1.

Source: Productivity Commission estimates.

Indicators that are able to capture both the quantity and quality of land that could be used for agriculture and mining would be ideal. However, data on the value and quality of minerals were not available and nor was an indicator of land used for mining at the SA2 level. Mining resources were proxied by the share of mining employment in a region.

An indicator of the proportion of employed people working as farmers or farm managers (instead of the share of land used for agriculture) was also examined, so that agriculture and mining could be analysed using similar measures. This led to a change in PCA results and some changes in adaptive capacity rankings as a consequence (although the group of least adaptive regions remained fairly stable). It is unclear which agriculture measure is the most appropriate proxy. There are also some issues with the current data on agricultural land at the SA2 level. The underlying source of these data is the ABS Agricultural Census, which is completed by agricultural businesses who may have land in multiple SA2 regions. However, all the agricultural land for a business is attributed to the business' office location, leading to some anomalies in the data (such as agricultural land exceeding total land in some SA2 regions).

Further consideration of which is the most appropriate indicator will be undertaken for the final report.

Physical capital

Physical capital captures a region's capacity to access infrastructure, equipment and technology to adapt to economic change. There are limited data on physical infrastructure such as road, rail, ports and air transport. An indicator of regional remoteness, based on the ABS Remoteness Structure and the Accessibility/Remoteness Index of Australia, was used as a measure of access to services and infrastructure (table 5).

Table 5 Physical capital indicators included in index

<i>Indicator^a</i>	<i>Description</i>	<i>Mean</i>	<i>Standard deviation</i>
broadband	Proportion of the population with a broadband internet connection	0.78	0.10
remoteness ^b	Based on accessibility/remoteness index (0 to 15)
buildings ^c	Value of non-residential building approvals (\$'000 per capita)	1.96	15.78

^a Data sourced from the 2011 Census of Population and Housing unless otherwise indicated. ^b Data sourced from the ABS Remoteness Structure. This is a categorical structure based on unpublished values of the Accessibility/Remoteness Index of Australia (ARIA) (Hugo Centre 2015). Index value thresholds for each remoteness category are published by the ABS. An indicator of remoteness was created by attributing the midpoint of the range of each remoteness category's index values to each region within that category. Summary statistics are not included in the table due to the underlying categorical nature of the variable. ^c Data sourced from ABS Building Approvals, Australia, 2011, Cat. no. 8731.0 through ABS.Stat.

Source: Productivity Commission estimates.

Social capital

Social capital captures regional community connections and social cohesion. Communities with strong social capital are better able to share ideas and work towards common goals, and thus form a community response to economic adjustment pressures. Data on social capital are scarce, particularly at the SA2 level. One indicator of social capital was included in the index of adaptive capacity for the initial report — the rate of volunteering in a region (table 6). The rate of volunteering provides some information about how connected people are to their local communities (DIRD 2016, p. 66). Further investigation will be undertaken to assess whether other indicators of social capital can be used in the index for the final report.

Industry diversity

A diversified economic base is generally considered to have a positive effect on economic performance and adaptive capacity (but, as discussed in chapter 2 and further below, promoting diversification for its own sake is not always better and its inclusion in the index is contested). Industry diversity is considered to positively contribute to a region's adaptive capacity because the more diverse a region's economy, the more flexible its allocation of resources is likely to be, allowing it to more effectively adjust in the face of disruptive events (Dinh et al. 2016). Further, the greater the diversification, the less susceptible a region is to any shock affecting a specific sector (ABARE–BRS 2010, p. 11).

Industry diversity was captured in the index of adaptive capacity through the Herfindahl index (table 6). This has been used as a measure of industry concentration in other studies that examine regional resilience and vulnerability (for example, Alasia et al. 2008, p. 16; Hill et al. 2011, p. 12). The Herfindahl index was calculated for each region as the sum of the squared shares of employment in each of the 19 industry divisions in the Australia and New Zealand Standard Industrial Classification. This was then scaled from 0 to 100 using a min-max transformation $\left(\frac{x - \min(x)}{\max(x) - \min(x)} * 100\right)$. Regions that have a higher score on the index have a less diverse mix of industries.

Table 6 Other indicators included in index

<i>Indicator^a</i>	<i>Description</i>	<i>Mean</i>	<i>Standard deviation</i>
volunteering	Proportion of the population who volunteered	0.21	0.06
herfindahl ^b	Herfindahl index of industry concentration (0 to 100)	7.94	8.70

^a Data sourced from the 2011 Census of Population and Housing unless otherwise indicated. ^b Calculated based on Census data on industry of employment, according to Australia and New Zealand Standard Industrial Classification (ANZSIC) divisions.

Source: Productivity Commission estimates.

Industry diversity might have a positive effect on adaptive capacity in general, but there is a question about whether the relationship is strictly increasing — some specialisation is likely to be beneficial but too much may leave a region vulnerable. In addition, different regions might have different optimal levels of diversity based on size and geography. Further consideration of the measure of industry diversity will be undertaken for the final report.

3 Correlations and principal component analysis results

Correlations between indicators

An examination of correlations was used as a first check to decide which variables were included in the PCA for a particular capital type. Highly correlated variables that captured similar concepts as each other were consolidated (section 2). Correlations also provide an indication of which variables might have high correlations with the same principal component in the PCA. Tables 7 to 10 show the correlations between the selection of indicators included in the index within human, financial, natural and physical capital types respectively.

Table 7 Correlations between human capital indicators^a

	<i>year12</i>	<i>skill1</i>	<i>employed</i>	<i>own_business</i>	<i>youth_engage</i>	<i>disability</i>
<i>year12</i>	1.00	0.70	0.38	-0.04	0.57	-0.71
<i>skill1</i>	0.70	1.00	0.36	0.33	0.46	-0.53
<i>employed</i>	0.38	0.36	1.00	0.25	0.48	-0.49
<i>own_business</i>	-0.04	0.33	0.25	1.00	0.25	-0.03
<i>youth_engage</i>	0.57	0.46	0.48	0.25	1.00	-0.40
<i>disability</i>	-0.71	-0.53	-0.49	-0.03	-0.40	1.00

^a Refer to table 2 for a description of indicators and their sources.

Source: Productivity Commission estimates.

Table 8 Correlations between financial capital indicators^a

	<i>high_income</i>	<i>govt_payment</i>	<i>property_prices</i>	<i>own_home</i>
<i>high_income</i>	1.00	-0.74	0.73	-0.06
<i>govt_payment</i>	-0.74	1.00	-0.55	0.10
<i>property_prices</i>	0.73	-0.55	1.00	0.04
<i>own_home</i>	-0.06	0.10	0.04	1.00

^a Refer to table 3 for a description of indicators and their sources.

Source: Productivity Commission estimates.

Table 9 Correlations between natural capital indicators^a

	<i>agri_land</i>	<i>nature_land</i>	<i>mining_emp</i>
<i>agri_land</i>	1.00	-0.04	0.16
<i>nature_land</i>	-0.04	1.00	0.04
<i>mining_emp</i>	0.16	0.04	1.00

^a Refer to table 4 for a description of indicators and their sources.

Source: Productivity Commission estimates.

Table 10 Correlations between physical capital indicators^a

	<i>broadband</i>	<i>remoteness</i>	<i>buildings</i>
<i>Broadband</i>	1.00	-0.66	0.00
<i>Remoteness</i>	-0.66	1.00	-0.01
<i>Buildings</i>	0.00	-0.01	1.00

^a Refer to table 5 for a description of indicators and their sources.

Source: Productivity Commission estimates.

Correlations between indicators and principal components

Tables 11 to 14 display PCA results for human, financial, natural and physical capital. The correlations between indicators and principal components are presented in each table, as well as the cumulative proportions of total variance captured by the principal components, and eigenvalues. These results were used to determine the number of principal components to retain, according to the eigenvalue-one, cumulative proportion of variance explained (with a threshold of 70 per cent) and interpretability criteria (section 1). Retained components are presented in bold font within the tables.

Applying the above criteria resulted in two principal components being retained for each PCA.

- For human capital, the first principal component can be thought of as representing skills and employment, and the second as representing entrepreneurship.
- For financial capital, the first principal component can be thought of as representing financial capacity, and the second as representing home ownership.
- For natural capital, the first principal component can be thought of as representing resources used for agriculture and mining production, and the second as representing nature (in the form of national parks and nature reserves).
- For physical capital, the first principal component can be thought of as representing regional connectivity, and the second as representing new infrastructure.

Table 11 Human capital PCA results^a

	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	<i>PC4</i>	<i>PC5</i>	<i>PC6</i>
Correlations						
<i>year12</i>	0.85	-0.37	0.19	-0.07	-0.03	-0.29
<i>skill1</i>	0.81	0.07	0.46	0.09	-0.30	0.17
<i>employed</i>	0.68	0.21	-0.63	0.19	-0.25	-0.03
<i>own_business</i>	0.29	0.91	0.19	0.14	0.17	-0.10
<i>youth_engage</i>	0.74	0.14	-0.15	-0.62	0.13	0.09
<i>disability</i>	-0.79	0.31	0.07	-0.35	-0.36	-0.11
Cumulative proportion	0.52	0.71	0.82	0.92	0.97	1.00
Eigenvalue	3.11	1.13	0.71	0.57	0.33	0.15

^a Bolding indicates the principal components (PCs) that were retained and the indicators with the highest correlations with these components.

Source: Productivity Commission estimates.

Table 12 Financial capital PCA results^a

	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	<i>PC4</i>
Correlations				
<i>high_income</i>	0.94	-0.01	-0.01	0.35
<i>govt_payment</i>	-0.86	-0.09	0.46	0.20
<i>property_prices</i>	0.85	-0.17	0.46	-0.19
<i>own_home</i>	-0.08	-0.99	-0.12	0.01
Cumulative proportion	0.59	0.84	0.95	1.00
Eigenvalue	2.36	1.02	0.43	0.20

^a Bolding indicates the principal components (PCs) that were retained and the indicators with the highest correlations for these components.

Source: Productivity Commission estimates.

Table 13 Natural capital PCA results^a

	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>
Correlations			
<i>agri_land</i>	0.76	-0.19	0.62
<i>nature_land</i>	-0.01	0.97	0.25
<i>mining_emp</i>	0.76	0.20	-0.62
Cumulative proportion	0.39	0.73	1.00
Eigenvalue	1.16	1.01	0.80

^a Bolding indicates the principal components (PCs) that were retained and the indicators with the highest correlations for these components.

Source: Productivity Commission estimates.

Table 14 Physical capital PCA results^a

	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>
Correlations			
<i>broadband</i>	0.91	-0.01	0.41
<i>remoteness</i>	-0.91	0.00	0.41
<i>buildings</i>	0.01	1.00	0.00
Cumulative proportion	0.55	0.89	1.00
Eigenvalue	1.66	1.00	0.34

^a Bolding indicates the principal components (PCs) that were retained and the indicators with the highest correlations for these components.

Source: Productivity Commission estimates.

Creation of a single metric

As described in section 1, each retained principal component and the standardised measures of social capital and industry diversity were combined using a weighted sum to form the index of adaptive capacity. The actual weights are presented in table 15. The weight of each retained principal component within each capital domain was determined using the proportion of variance explained by the principal component in the PCA. For example, the two retained human capital components accounted for 71 per cent of the total variation, with the first component accounting for 52 per cent (table 11). Therefore, the weight given to this first principal component was $0.52/0.71 = 0.73$ (fourth column of table 15). Each of the six categories of variables (five capital domains and industry diversity) had equal weights in the metric. This means that the overall weight given to the first human capital component was $0.73/6 = 0.12$ (final column of table 15). The same method was applied to produce weights for all other elements of the metric.

The signs on the second principal component for financial capital (which was negative with respect to home ownership) and the Herfindahl index measure (which was negative with respect to industry diversity) were reversed before they were included in the metric so that higher values indicated greater adaptive capacity.

For the presentation of results, regions were grouped into four categories according to their index value. Regions in the most adaptive category (256 regions) and the least adaptive category (244 regions) had index values greater than one standard deviation away from the mean. The remaining regions were classed into above average (837 regions) and below average (748 regions) categories depending on their index value.

Table 15 Weights of principal components and indicators in the index

<i>Category</i>	<i>Weight of category in index (%)</i>	<i>Retained principal component (PC) or indicator</i>	<i>Weight of PC or indicator in category (%)</i>	<i>Weight of PC or indicator in index (%)</i>
Human capital	16.67	PC1 (skills and employment)	73.32	12.22
		PC2 (entrepreneurship)	26.67	4.45
Financial capital	16.67	PC1 (financial capacity)	69.88	11.65
		PC2 (home ownership)	30.12	5.02
Natural capital	16.67	PC1 (agriculture and mining)	53.43	8.90
		PC2 (nature)	46.57	7.76
Physical capital	16.67	PC1 (regional connectivity)	62.44	10.41
		PC2 (new infrastructure)	37.55	6.26
Social capital	16.67	Volunteering	100.00	16.67
Industry diversity	16.67	Herfindahl	100.00	16.67
Total	100.00		-	100.00

Source: Productivity Commission estimates.

4 Sensitivity testing

Sensitivity testing was conducted to see how much each region's index values varied in response to:

- performing PCA on all indicators at once rather than separately by capital type
- changes in the sample of regions included in the analysis
- changes in the indicators used to assess adaptive capacity.

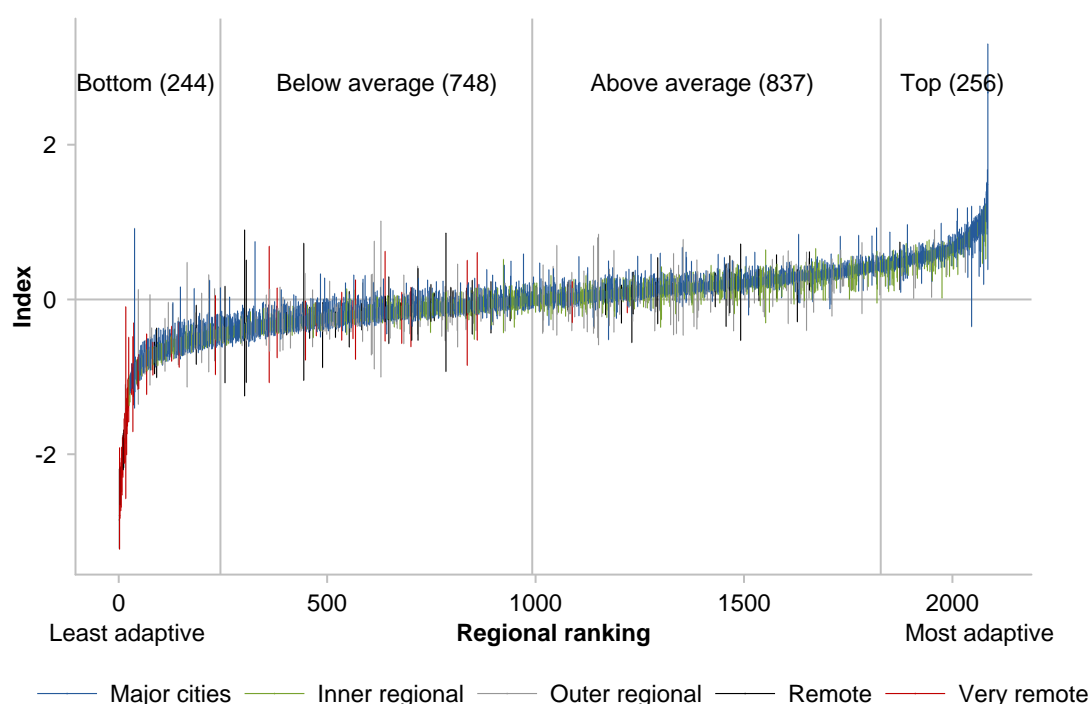
Results from the first sensitivity test (in which a metric was constructed from a PCA on all indicators at once) were similar to the results from the index reported in the initial report. The correlation between the two indexes was 0.88, and about three quarters of the regions in the least adaptive category of both indexes were the same.

The last two aspects of the sensitivity testing were done concurrently through a bootstrapping technique. Because the true adaptive capacity of a region is unknown, the true error in the region's adaptive capacity index value is also unknown. Bootstrapping uses the empirical distribution function of the original sample as an approximation for the true probability distribution of the population to help give a sense of the variability in the index of adaptive capacity. It involves running the same analysis many times on multiple new samples of data that are constructed by random sampling with replacement from the initial dataset. These new samples have the same number of observations as the initial dataset. (This means that the new samples will likely have multiple observations of a particular region, while other regions may not appear in a particular sample at all.)

In the current analysis, 1000 bootstrap samples were formed, and the sensitivity of the index results to these changes in the sample of regions could be examined. For each of the 1000 bootstrap samples, one indicator of adaptive capacity was removed from the analysis each time in order to assess the effect of small changes in the set of indicators on the index results. Every indicator was tested by removing each one in turn. As there were a total of 18 indicators, that means there was a total of 18 000 calculations of the index for each region using this bootstrapping technique.

The distribution of each region's index values from the bootstrapping analysis was examined to see how sensitive the results were, and the 5th and 95th percentiles of each region's distribution of index values were plotted (figure 4). It was found that many regions had particularly large intervals, indicating greater uncertainty in their index values and relative rankings.

Figure 4 High uncertainty in the rankings of adaptive capacity
Index values for each region and their 90 per cent confident intervals, regions sorted from lowest to highest^a



^a Regions are defined by the ABS Statistical Area Level 2 classification. The top and bottom group of regions are defined as those above and below one standard deviation of the mean index value of adaptive capacity across all regions. Regions are ordered based on their index value, where the whiskers represent the upper and lower 5 percentiles (90 per cent confidence intervals) of the region's index value across bootstrapping analysis. Remoteness of regions is represented in the colouring of the lines. Of the bottom 244 regions, 126 are in major cities, 45 are inner regional, 35 outer regional, 8 remote and 30 very remote.

Source: Productivity Commission estimates.

The rankings of more remote regions tend to be more sensitive to changes in indicators, mainly due to physical and natural capital factors, as well as industry diversity. For example, the very remote SA2 of Newman, a mining region in Western Australia, is categorised as being below average in adaptive capacity. The main contributors to its index score are its high natural capital and low industry diversity. Newman's score on the index changes vastly when these indicators are removed from the index. Based on its lower confidence limit from the bootstrapping analysis, it would be placed in the least adaptive capacity category, whereas according to its upper confidence limit, it would be placed in the most adaptive capacity category.

Sensitivity testing results are discussed further in chapter 4. Attachment A contains a spreadsheet of index scores for each region, as well as their 90 per cent confidence intervals based on the bootstrapping analysis.

5 Results discussion

A map of the relative adaptive capacity of regions across Australia is presented in figure 5. The least adaptive regions are spread across all areas of Australia, including remote, regional and urban areas. Appendix B contains further maps for each state and territory, as well as lists of regions by their category of adaptive capacity, in alphabetical order.

The relative numbers of regions and of people within the least adaptive category are illustrated in figures 6 and 7 respectively. When compared with the national shares of regions by remoteness, a relatively larger share of the least adaptive regions are those in major cities and very remote areas (figure 6). In terms of numbers of people, an even larger share are in major cities, particularly in Sydney, Melbourne and Adelaide (figure 7). The share of people in the least adaptive very remote regions (while still large compared with the national share of people in very remote regions) is smaller when compared with the share of least adaptive *regions* that are very remote, due to the sparse populations in these areas.

The least adaptive regions can also be examined by their main sources of employment (chapter 4). Manufacturing is the main source of employment for about 40 per cent of these regions, including over 70 per cent of the least adaptive regions in major cities. This compares to only 11 per cent of regions not in the least adaptive category. In contrast, the share of services in regions that are the least adaptive is much lower than for all other regions — about 50 per cent compared to 75 per cent.

There are very few regions with mining as their main source of employment in the least adaptive category. The regions that do fit this description are in very remote areas and tend to have low rates of broadband access, suggesting that other physical infrastructure and services in these areas may also be limited, thus affecting their adaptive capacity.

A more detailed discussion of the index of adaptive capacity results can be found in chapter 4.

Figure 5 **The adaptive capacity of Australia's regions**

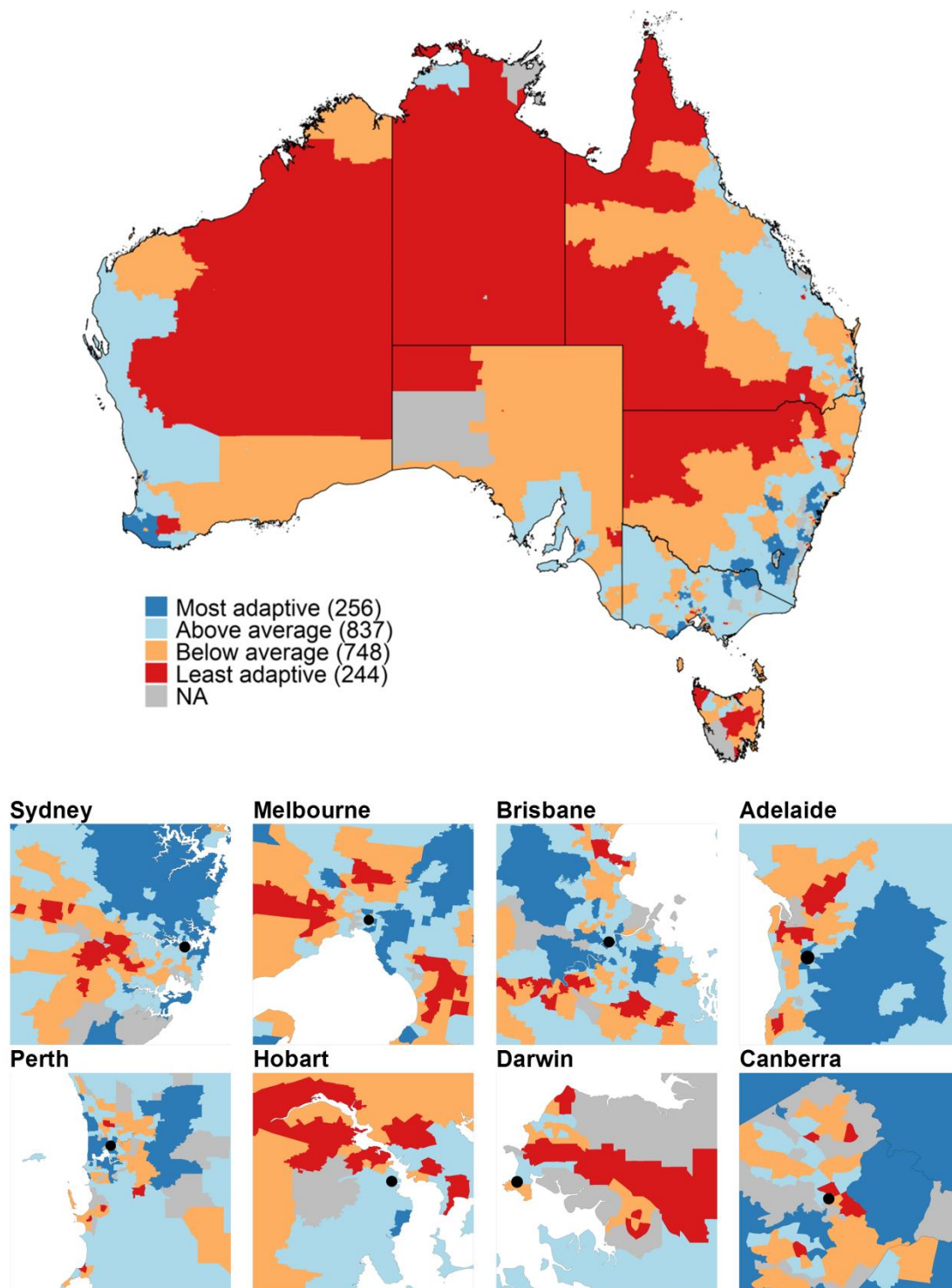
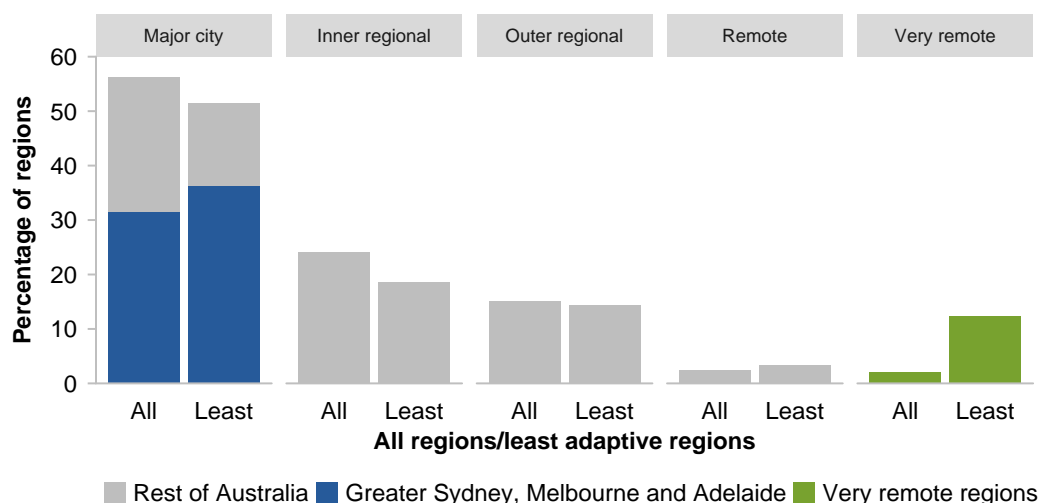
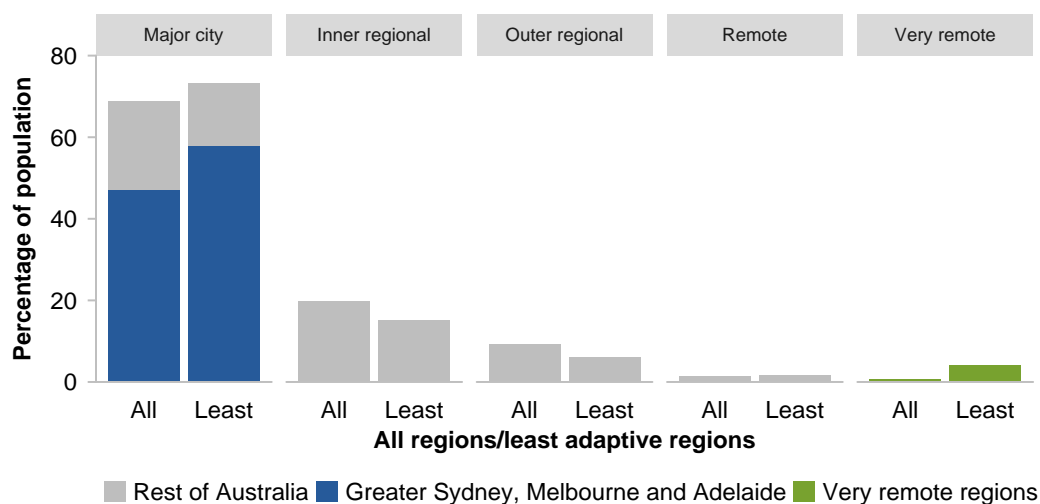


Figure 6 A relatively large share of regions in the least adaptive category are in major cities and very remote areas



Source: Productivity Commission estimates.

Figure 7 A higher share of the population in the least adaptive regions reside in major cities and very remote areas



Source: Productivity Commission estimates.

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