Regional Employment resilience during Australia's early COVID-19 public health response: An analysis of the Payroll Jobs Index data series

Scott Baum (s.baum@griffith.edu.au)
Griffith University
William Mitchell
University of Newcastle

Research Article

Keywords: COVID-19, Australia, employment, recession, payroll jobs data

Posted Date: April 14th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1552220/v1

Abstract

The COVID-19 pandemic has had significant impacts on regional economies and in particular has been reflected in the ability of some regions to perform better in the face of an economic downturn than others. Set in the context of regional economic resilience, this paper presents an exploratory analysis of the impact of a national COVID related shut-down in Australia on employment resilience across regions. Using data on the changes in payroll jobs, the paper identifies clusters of regions that can be differentiated according to their resilience during this period. The paper explores a range of possible determinants of regional resilience differences and suggests an agenda for a larger research endeavour.

Introduction

The COVID-19 pandemic has caused significant economic disruption in countries across the globe. Within Australia, once initial case numbers began to climb, the Federal Government introduced a range of measures in an attempt to stop the spread of the virus. While these were aimed at dealing with the public health emergency, the unintended economic consequences were wide-ranging, especially impacting on labour markets as the national economy was largely locked-down.

From a regional science perspective, the COVID-19 imposed lockdown provides an interesting case study on the impacts of such an endogenous shock on regional economic performance and in particular on the performance of labour markets. It is clear, for example, that in the period following 30th March 2020, when national public health stay at home orders came into effect, employment across the country took a significant hit. The Australian Bureau of Statistics Payroll jobs index (Australian Bureau of Statistics, 2020b) recorded a change in total wages between 14 March and 4 April of -6.7 per cent and an estimated unemployment rate of 6.2 per cent and an underemployment rate of 13.7 per cent (Australian Bureau of Statistics, 2021).

Placing this declining labour market performance into a regional science context, we might ask how have different regions responded in employment terms. Have some regions done better than others? Have they been less affected by the broader economic slowdown, or put another way, have some regions shown a higher level of resilience to the downturn than others? Over the past decade, especially since the Global Financial Crisis, understanding the ways different regions react to economic shocks has been an area of increasing regional science focus, often being framed within the context of regional resilience. Borrowing from a long-established tradition in biology and environmental science, regional resilience is defined as

> The capacity of a regional or local economy to withstand or recover from market, competitive and environmental shocks to its developmental growth path, if necessary by undergoing adaptive changes to its economic structures and its social and institutional arrangements, so as to maintain or restore its previous developmental path, or transit to a new sustainable path characterised by a fuller and more productive use of its physical, human and environmental resources (Martin & Sunley, 2015).

As a concept, regional resilience has been presented as a useful lens with which to view the heterogeneous nature of economic shocks across regions (Giannakis & Bruggeman, 2017). Empirically, the study of regional resilience has taken many forms ranging from the use of case studies, and the development of resilience

indices, to more complex time-series and structural economic models (Martin & Sunley, 2015), and have utilised a number of approaches to measure and operationalise resilience.

While some resilience measures are straightforward, comparing regions according to the percentage rise or fall in a particular indicator (i.e. employment), others, conceptualising regional resilience as regional changes relative to national changes, have used different approaches. For example, Han and Goetz (2013) compare actual regional output with trend output, with the difference being considered an illustration of the level of resilience in any one region. The less a region's actual output deviates from the trend output, then the higher the relative level of resilience. Martin, Sunley, Gardiner, and Tyler (2016), using a slightly different approach, measured regional resilience in terms of how regional change deviated from national-level change. In doing so they argued

> since of interest is how different regions (or localities or cities) are affected by a common (nationwide) recession, a particular type of expected or 'counterfactual' reaction suggests itself, namely, the resistance and recovery of the national economy as a whole (Martin et al., 2016, p. 565).

Indicators such as these allow for comparison between regions and the tracking of resilience over time, and in the case of an economic shock allow the researcher to being to understand how different regions might be expected to perform.

Over-and-above the issue of measurement, an important question about regional resilience is why it might vary between regions (Grabner, 2021). In a sense this is the most important question from a policy perspective as understanding the drivers of resilience provide insights into the kinds of policy prescriptions might be most appropriate. In the wake of the Global Financial Crisis, a significant body of work emerged that attempted to provide a greater understanding of regional resilience by considering the regional determinants of variations in resilience.

For instance Martin et al. (2016) considering the impact of recessionary shocks on regions in the United Kingdom identified a number of key findings including, that different shocks resulted in varying outcomes across regions at different time points and that factors including industry structure and region-specific or competitiveness effects could be viewed as important factors in explaining differences in regional resilience. In a similar long-run analysis of economic shocks across Italian regions between 1970 and 2011 Lagravinese (2015) found that among other things, the presence of large concentrations of manufacturing industry and the presence of temporary workers were associated with weaker regional resilience, while in contrast larger concentrations of public sector employees and service industries were associated with greater levels of resistance (resilience) in the face of economic downturns.

Considering the question of resilience in the United States following the Global Financial Crisis, Ringwood, Watson, and Lewin (2019) used monthly employment data for U.S. counties and found that counties dependent on agriculture significantly outperformed nonfarming-dependent counties when controlling for urban-rural hierarchy. In addition, manufacturing-dependent metro counties outperformed other places, but in total all manufacturing counties were outperformed by not manufacturing-dependent metro-based counties. In a similar paper, focusing on US metropolitan regions (MSAs) Doran and Fingleton (2018) compared actual and predicted employment paths to develop a measure of the impact of the Global Financial Crisis. In explaining

the differences in resilience and recovery between metropolitan regions, the authors find that MSAs that exhibited higher levels of specialisation were more adversely impacted by the economic crisis, but that the same high levels of specialisation helped during the period of recovery. In addition, they note that for regions recording significant structural change during the crisis period negative impacts were reduced and that the contextual effects of the broader region a MSA is located in is also important for explaining resilience and recovery.

In Australia, Courvisanos, Jain, and K. Mardaneh (2016) investigated regional resilience across Local Government Areas following the Global Financial Crisis and major drought and identified groups of regions that were differentiated by both weak and strong regional resilience and industry. Strong resilience was found in high-income regions across rural, regional and metro-core and periphery and was associated with industries including mining, construction transport and utilities, especially in rural localities. Weaker resilience was especially dominant in the metro-core which reported far more functional regions than other areas.

Similar questions about regional resilience have begun emerging in a small but growing collection of literature focusing on the economic shocks associated with the COVID-19 pandemic. Importantly, these emerging studies find that regional economic resilience is influenced not only by factors that may be, a-priori, thought to help or hinder resilience but also by a number of factors peculiar to the pandemic such as the extent of public health measures and the introduction of specific government support packages. For instance, Turgel, Chernova, and Usoltceva (2021) analysing data for urbanised regions in Russia find that there are both significant differences between the impact of the COVID-19 pandemic on the economic performance of regions and that these differences can be explained by a number of factors including the severity of health-related restrictions on enterprises and the level of regional support. They found that regions with significant population shares and large numbers of small and medium-sized businesses were the most vulnerable to the COVID induced economic slowdown, while regions where agro-industrial and industrial organisations were strongest and whose enterprises were able to continue operating, showed greater stability. Focusing on regional economic resilience in Northeast China, Hu, Li, and Dong (2022) find that regional resilience was shaped by a region's industry structure, the level of regional innovation, industry specialisation, openness and the level of government support. Importantly, they note that government public-health measures to contain the spread of the pandemic were especially important in shaping resilience and the level of recovery any one region experienced. Brada, Gajewski, and Kutan (2021) focusing on employment changes in Central and Eastern Europe find that the level of regional economic resilience is driven by the ability of regions to be able to alter their economic structure during downturns and part because of the presence of strong spatial spillover effects where highly resilient regions feed off other highly resilient regions.

The issues outlined above set the context for the remainder of the paper. Using data from the Australian Bureau of Statistics Payroll Jobs Index series (Australian Bureau of Statistics, 2020b) the paper develops an analysis of employment trajectories for Australian regions focusing on the initial period of national lockdown (DATES). The paper has several aims:

1. To identify the/ patterns of employment change across Australian regions and in turn scope out variations in levels of regional resilience.

2. Consider the variable that may help understand the patterns identified.

3. Illustrate the usefulness of the Payroll Jobs Index series to measure employment trajectories across regions.

Methodology, Data And Approach

The empirical objective of this paper is to undertake a regional level analysis of the changes occurring in employment during the first phase of the Australian government's COVID-19 public health response. In doing so the paper considers two points. Firstly, what are the patterns of employment change across regions, and secondly, how can these differences be understood in terms of a range of possible differentiating variables?

Determining patterns of change

The existing literature dealing with the question of regional employment change has offered a range of possible approaches, depending on the types of data used and the overall aim of the investigation. In this paper, we use a longitudinal database of fortnightly changes in the Australian Taxation Office's single-touch payroll data that is downloadable as a benchmarked index from the Australian Bureau of Statistics (see above). Given the number of data points contained within the dataset, we utilise a data clustering approach to develop sub-groups and identify the broad patterns evident within the data.

Several methods are available to cluster or partition data into meaningful sub-groups. Clustering methods range from approaches that are largely heuristic to more formal modelling procedures that adopt statistical models to group data. The challenge of analysing the data used in this paper is to identify a suitable clustering approach that produces robust outcomes when using longitudinal data. In this paper, we use the longitudinal k-means (KML) (Genolini & Falissard, 2010) algorithm in R to undertake the analysis. Longitudinal k-means is a widely used approach within the health and social sciences literature and has been shown to produce robust results in a number of comparison studies (Den Teuling, Pauws, & van den Heuvel, 2020; Genolini & Falissard, 2010).

Data

As noted above, in undertaking the clustering process we make use of the Australian Taxation Office payroll data, expressed in terms of an index of payroll jobs across Australia. The index is benchmarked to a value of 100 in the week where Australia recorded its 100th confirmed case of COVID-19 (week ending 14 March 2020). For the analysis conducted here, we use data for the period from 14th March 2020 to 25th April 2020 (Australian Bureau of Statistics, 2020a). This represents the period of time from which the country's strict public health lockdowns came into effect to the time when nationwide restrictions began easing (Stobart & Duckett, 2022). Rather than using the raw index as provided by the Australian Bureau of Statistics, we transform the data to measure the deviation in the payroll jobs index of each region at each point in time when compared to the corresponding national level index numbers (similar to approaches suggested by (Martin & Sunley, 2015) and others). A positive number implies that the region is performing better than the national average (i.e. the index number for a given period is higher than that for Australia), while a negative number reflects the opposite scenario. In this way, we are measuring how, as a result of the public health measures, individual regions are performing relative to the overall national level trend.

Identifying differentiating variables

Apart from clustering the regions to identify the different patterns of employment change, the aim of the paper is also to consider how the clusters differ from one another. There are a number of possible approaches including the use of some form of multivariate discriminant analysis (Baum, O'Connor, & Stimson, 2005; Hill, Brennan, & Wolman, 1998) or the visual examination of confidence intervals around the mean for each cluster (Masson & Loftus, 2003). For the analysis presented in this paper, we utilise a simple analysis of variance (ANOVA) approach with appropriate multiple comparison tests. This allows us to identify significant differences in group means across a range of variables (see below) and understand how the individual clusters differ from each other.

Data

The data used to compare the cluster outcomes are presented in Table 1. They represent a group of variables that may be assumed, a-priori, to aid in understanding the differential outcomes of employment across regions. They include measures of industry specialisation (Herfindahl-Hirschman Index), data on industry sector employment, levels of employment remuneration, human capital and labour force structure. All of the data relate to the characteristics of people as measured in the Australian Bureau of Statistics' usual residence census geography. This provides the most appropriate alignment with the payroll jobs index which relates to the residential address of the employee.

Table 1
2016 Census of Population and Housing data

Specialisation Index for 2016 (Herfindahl-Hirschman Index)
% of persons employed in Agriculture, Forestry and Fishing
% of persons employed in Mining
% of persons employed in Manufacturing
% of persons employed in Electricity, Gas, Water and Waste Services
% of persons employed in Construction
% of persons employed in Wholesale Trade
% of persons employed in Retail Trade
% of persons employed in Accommodation and Food Services
% of persons employed in Transport, Postal and Warehousing
% of persons employed in Information Media and Telecommunications
% of persons employed in Financial and Insurance Services
% of persons employed in Rental, Hiring and Real Estate Services
% of persons employed in Professional, Scientific and Technical Services
% of persons employed in Administrative and Support Services
% of persons employed in Public Administration and Safety
% of persons employed in Education and Training
% of persons employed in Health Care and Social Assistance
% of persons employed in Arts and Recreation Services
% of low income jobs
% of part-time jobs
Unemployment rate of sub-region
% of employed persons with low education

Spatial units

For this paper, the main consideration when choosing a spatial unit for analysis is to ensure comparability between the units used to measure payroll jobs and the units available within the Australian Bureau of Statistics census geography framework. Payroll jobs data is available at either the Statistical Area 3 or Statistical Area 4 level of aggregation. Whilst either could have been used, SA3s were chosen in this instance. The ABS design SA3s to

provide a regional breakdown of Australia. They generally have a population of between 30,000 and 130,000 people. In regional areas, SA3s represent the area serviced by regional cities that have a population over 20,000 people. In the major cities, SA3s represent the area serviced by a major transport and commercial hub (Australian Bureau of Statistics, 2017, para 4).

As such, the SA3s provide a useful level of aggregation to consider regional employment outcomes.

Results

Determining patterns of regional employment change

As indicated above, the first stage of the analysis presented in this paper focuses on determining the broad patterns of regional employment change during the initial COVID-19 lockdowns in Australia. To do so, we utilised the longitudinal k-means (kml) package run in the R environment. As with most clustering approaches an important decision needs to be made regarding the number of clusters to choose. One solution discussed in the literature and utilised within the KML framework is to run the k-means algorithm a number of times varying the initial number of seeds each time and then selecting the “best” number of clusters according to some quality criterion (Genolini & Falissard, 2010). The default measure in KML is the Calinski and Harabatz criterion, and for interpretation, the measures are presented in a graphical form (Fig. 1). Over-and-above formal ‘quantitative’ methods of cluster choice, it is also often the case that a cluster solution will be chosen on the basis of face validity. In this case, as Gittleman and Howell (1995, p. 424) have argued that a ‘far more compelling for our purposes than any mechanical rule, however, is whether, …, the cluster analysis produces… groups that are meaningful’.

Given the outcome presented in Fig. 1, it might be reasonable to argue for either the 3, 4 or 5 cluster solution, as these provide relatively similar Calinski and Harabatz scores, especially in the early stages of the rerunning process. Following an initial scan of the clusters, including the membership of each group, it was decided that the output containing 4 clusters would be used for further analysis.

Figure 2 presents the average trajectories obtained from the KML analysis using the 4-cluster solution. The information presented in Fig. 3 relates to the relative share of each of the clusters comparing urban areas with regional and rural areas. Figure 4 presents information for the relative shares of the four clusters between Australian States and Territories. These 2 figures represent a regional concentration ratio. The regional concentration ratio is a version of a location quotient. It determines the extent to which any region (e.g. state) has an overconcentration of localities in a particular cluster. The RCR is calculated by considering the percentage distribution of particular clusters in each region divided by the percentage distribution of that cluster across all regions. An RCR greater than 1 indicates that the number of a particular cluster in a particular region is overrepresented. An RCR less than 1 indicates the opposite outcome. Details on individual SA3s included in each cluster can be obtained from the authors.

Given that the payroll jobs index variable was transformed to represent regional employment resilience, the four trajectories represent four different scenarios in relation to resilience across regions. Trajectories A and B represent regions that in general performed better (more resilient) than the average across time, while trajectories C and D represent regions that performed worse (less resilient).

Cluster A contains 117 SA3s or 35.2 per cent of the total. It is one of two clusters identified as having high regional resilience. Over the lockdown period, the deviation from the average payroll jobs index was 0.61. In relative terms, Cluster A regions were more likely to be regional or rural/remote and were relatively overrepresented in Victoria, Western Australia and the Australian Capital Territory. The geographic distribution implied by the regional concentration ratios is also evident in the individual state maps presented in Figs. 5 to 12. Cluster B represents the second group of regions that may be considered to represent regions that exhibited high levels of employment resilience. The cluster contained 34.0 per cent of the entire sample of SA3s and over the period of analysis had an average payroll jobs index deviation of + 1.35. In relative terms, SA3s in this cluster were more likely to be located in major urban regions and were more likely to be in New South Wales, Queensland, Northern Territory and the Australian Capital Territory. Again, as with cluster A, the individual state geographies can be seen in Figs. 5 to 12 and reflect the findings & the relative distributions.

Cluster C represents the first of 2 groups of regions exhibiting lower resilience. Around one-quarter (25.3 per cent) of the SA3s in the analysis are in this cluster. The overall trend in payroll jobs index deviation can be seen in Fig. 2 whereby the cluster displayed minor deviations early in the period seeing increases from early April 2020. The negative deviations were only small as suggested in the average deviation of -0.60. The regions in this in this cluster are relatively more concentrated in non-major urban areas and in the states of Victoria, South Australia, and Tasmania. As with the previous clusters, these patterns are also evident in the maps presented in Figs. 5 to 12. The final cluster (cluster D) represents the second of the groups with low employment resilience. It is clear from Fig. 2 that this group of regions suffered significant job losses during the period, with an average deviation of -2.76. In relative terms the regions in this cluster were more likely to be located in rural/regional areas and although present in each state, were over-represented in Queensland and Tasmania. These patterns are also indicated in the maps presented in Figs. 5 to 12.

Table 2
Average deviation from the national average

	Percent of SA3s	Average deviation
Cluster A	35.20%	0.61
Cluster B	34.00%	1.35
Cluster C	25.30%	-0.60
Cluster D	5.40%	-2.76
Source: Authors' calculations		

Identifying differentiating variables

The second component of the analysis presented in this paper is to consider the factors that may aid in differentiating the patterns represented by the four clusters outlined above. A range of indicators was thought to possibly provide points of difference between the four clusters (see methodology). To consider these

differences, Table 3 presents the results of individual ANOVA tests for each variable across the cluster outcomes. Table 4 presents the results of the multi- comparison tests illustrating the significant differences between clusters.

Of the 23 variables considered, 12 exhibited significant ANOVA recording significant F- statistics at the 0.05 level:

- Per cent employed in Construction
- Per cent employed in Wholesale Trade
- Per cent employed in Accommodation and Food Services
- Per cent employed in Financial and Insurance Services
- Per cent employed in Rental, Hiring and Real Estate Services
- Per cent employed in Professional, Scientific and Technical Services
- Per cent employed in Administrative and Support Services
- Per cent employed in Education and Training
- Per cent employed in Health Care and Social Assistance
- Per cent employed in Arts and Recreation Services
- Per cent of part-time jobs
- Per cent with low education

Table 3
Analysis of variance results

	Cluster A	Cluster B	Cluster C	Cluster D	Total
Herfindahl-Hirschman Index	959.4	961.9	932.8	919.6	951.4
% of persons employed in Agriculture, Forestry and Fishing	4.53	4.86	6.17	3.27	4.99
% of persons employed in Mining	2.38	2.99	1.30	0.49	2.21
% of persons employed in Manufacturing	6.90	6.82	6.60	4.24	6.65
% of persons employed in Electricity, Gas, Water and Waste Services	1.02	1.19	1.06	0.89	1.08
% of persons employed in Construction **	**7.43**	**8.95**	**7.15**	**6.59**	7.83
% of persons employed in Wholesale Trade **	**2.57**	**2.87**	2.42	**1.60**	2.58
% of persons employed in Retail Trade	10.99	10.78	10.77	10.25	10.82
% of persons employed in Accommodation and Food Services **	**7.36**	**6.60**	**8.29**	**13.37**	7.66
% of persons employed in Transport, Postal and Warehousing	4.15	4.67	4.33	3.56	4.34
% of persons employed in Information Media and Telecommunications	0.97	0.99	1.05	1.59	1.03
% of persons employed in Financial and Insurance Services **	**1.85**	**1.72**	**1.92**	**4.05**	1.94
% of persons employed in Rental, Hiring and Real Estate Services **	**1.63**	**1.50**	**1.67**	**2.48**	1.64
% of persons employed in Professional, Scientific and Technical Services **	**5.24**	**4.87**	**5.21**	**7.61**	5.23
% of persons employed in Administrative and Support Services **	**2.83**	**2.78**	**3.02**	**4.03**	2.93
% of persons employed in Public Administration and Safety	6.01	6.68	6.23	6.10	6.30
% of persons employed in Education and Training **	**10.21**	**9.82**	9.21	**7.72**	9.69
% of persons employed in Health Care and Social Assistance **	**13.97**	**11.82**	**13.79**	11.89	13.08
% of persons employed in Arts and Recreation Services **	**1.65**	**1.35**	**1.74**	**2.68**	1.63
% of low income jobs	20.2	19.6	20.6	19.5	20.1
% of part-time jobs **	**35.7**	**33.1**	**36.4**	36.7	35.1

**= Significant @ 0.05

	Cluster A	Cluster B	Cluster C	Cluster D	Total
Unemployment rate of sub-region	6.7	6.8	6.6	7.3	6.8
% of employed persons with low education **	35.9	**37.2**	36.0	**33.7**	36.2
**= Significant @ 0.05					

The F- statistics provide an indication of the overall significance of the variable. To begin to understand the differences between the clusters on the globally significant variables we can look at the results of the multi-comparison tests run as part of the ANOVA process. These tests identify which cluster/s differ significantly from others, and are presented in table 4.

One of the first points of distinction to note from the multi-comparison outcomes is the outcomes for the 2 clusters exhibiting the smallest levels of payroll jobs index deviation (resilience measure). When clusters A and C are compared, significant between cluster outcomes are recorded for variables- accommodation and admin. The SA3s showing higher levels of employment resilience (cluster A) had lower average levels of employment in Accommodation and Food Services and Administrative and Support Services.

In contrast to Clusters A and C, the two groups that recorded the more extreme levels of high and low employment resilience (Cluster B and D) recorded widely varying employment characteristics. Of the 23 variables included in the analysis, 10 were significant when the multi-comparison tests are considered. The direct comparison of cluster B to cluster D shows that higher employment resilience is associated with higher proportions of employment in Construction, Wholesale Trade, and Education and Training and higher proportions of employees with low education attainment. In contrast, lower the lower employment resilience of Cluster D is associated with higher proportions of employment in Accommodation and Food Services, Financial and Insurance Services, Rental, Hiring and Real Estate Services, Professional, Scientific and Technical Services, Administrative and Support Services, and Arts and Recreation Services.

Table 4: Results for multi-comparison tests

	Cluster A compared to	Cluster B compared to	Cluster C compared to	Cluster D compared to
Cluster A		-Construction - Accommodation - Health Care - part-time	- Accommodation (+) - Administrative (+)	-Wholesale Trade - Accommodation - Financial - Real Estate -Professional - Administrative - Education - Arts
Cluster B	-Construction - Accommodation - Health Care - part-time		-Construction - Accommodation - Administrative - Health Care - Arts - part-time	-Construction (-) -Wholesale Trade (-) - Accommodation (+) - Financial (+) - Real Estate (+) -Professional (+) - Administrative (+) - Education (-) - Arts (+) -low education (-)
Cluster C	- Accommodation (-) - Administrative (-)	-Construction - Accommodation - Administrative - Health Care - Arts - part-time		- Accommodation - Financial - Real Estate -Professional - Arts

	Cluster A compared to	Cluster B compared to	Cluster C compared to	Cluster D compared to
Cluster D	-Wholesale Trade - Accommodation - Financial - Real Estate - Professional - Administrative - Education - Arts	-Construction (+) -Wholesale Trade (+) - Accommodation (-) - Financial (-) - Real Estate (-) -Professional (-) - Administrative (-) - Education (+) - Arts (-) - low education (+)	- Accommodation - Financial - Real Estate -Professional - Arts	

Conclusion And Discussion

This paper has presented an analysis of regional employment resilience across Australia during the national could-19 lockdown. The strict lockdown, which lasted several weeks had almost immediate impacts on employment resulting in widely varying levels of employment resilience. The paper had 3 basic aims. Two empirical aims related to contributing to an understanding of regional employment resilience. A further methodological aim was related to the use of the Australian Bureau of Statistics Payroll Jobs Index series as an indicator of regional employment resilience.

What did the analysis presented above suggest about regional employment resilience in the early period of the COVID-19 economic shutdown in Australia? The paper has shown a distinct pattern & regional employment resilience existed during the COVID-19 lockdown with some regions being characterised as resilient and others as lagging. While the patterns are complex in a comparative sense, it is clear that regional employment resilience is driven to some extent by the presence of employment in industries deemed ‘essential’, while negative or low resilience is driven by an employment structure with heavier reliance on either non-essential industries or in industry's that are reliant heavily on face-to-face interactions, or the ability of people to travel. Given that there is well understood economic geography of industry and employment characteristics, it is little wonder that the types of patterns identified here have emerged. Inner cities where agglomeration economies have resulted in the concentration of certain businesses - finance, real estate, administrative support services – have, as a result of the government-imposed national shutdown, seen employment suffer. Similarly, regional tourist zones reliant on international and intra-national travel have also had their employment resilience tested.

Interestingly, the heterogeneity shown in regional employment resilience seems to have been immune to the effects of the Australian Government’s "Job keeper" program, which, when introduced on the 30th March 2020, was meant to offset the negative employment impacts of shutdowns. At least for the period considered here, the impacts of this intervention appear to largely place neutral having no discernible impact a regional employment resilience.

The mythological aim follows directly from these empirical aims. The results of the analysis suggest that the Payroll Jobs Index series is potentially a useful indicator with which to consider both short and long run transitions and changes in regional employment. The space-time nature of the dataset means that research questions involving regional resilience and recovery can be considered in some detail. Being able to undertake these kinds of analysis has been hampered in the past due to the availability of appropriate data sets. Often researchers are reduced to using census data collected at two distinct and often lengthy time periods which may not capture short-run changes and transitions or allow a comprehensive understanding of periods of decline and recovery. The use of such data, when properly applied, should provide a robust evidence base with which to design and appraise policy measures aimed at building and/or repairing regional economies.

The analysis presented in this paper does carry with it several caveats. Clearly, the clustering process used is open to debate and possible criticism depending on the type of clustering method used. Here we used longitudinal K means clustering. Others have suggested that a more robust result may be obtained by using a clustering algorithm such as Latent Class Growth Models or GMM (Den Teuling et al., 2020). Whether the use of such approaches results in an improvement or modification of the results identified here is an interesting question, and one which will be tested in future papers. Another important caveat relates to the choice of cluster numbers. Clearly, the choice made here was driven by both the statistical testing regime and also more qualitative approaches. There is no denying that cluster number choice impacts the outcomes just as the choice of clustering approach does. As there is generally no universally agreed or best approach to cluster number selection, it is prudent to keep in mind the choice method when reviewing the analysis and discussion presented here.

Finally, there are questions about the choice of spatial units. In this paper, we have chosen to use Statistical Area 3 regions. However, the payroll jobs index series is also available at the next highest level of aggregation (SA4s) The areas chosen will obviously impact on the outcome and interpretation- the Modifiable Area Problem- resulting in an often-vexed choice between detail and interpretability. This is not to say that one level of aggregation is right and the other is wrong, but rather that the potential for issues needs to be kept in mind when considering the analysis and discussion presented here.

It is clear, at the time of writing, that the full impacts of COVID-19 are still being played out. This paper has set out an exploratory analysis of regional economic resilience during the first phase of national public-health lockdowns. Future research of this ilk informed by the significant regional science literature on regional economic performance will be required to fully understand the impacts of COVID-19 on regional economies, not only in Australia, but elsewhere.

Declarations

Funding: Not applicable

Conflicts of interest/Competing interests: The authors declare no competing interests.

Availability of data and material: Data is available from the author upon request

Code availability: Not applicable

References

1. Australian Bureau of Statistics. (2017). 1270.0.55.001 - Australian Statistical Geography Standard (ASGS): Volume 1 - Main Structure and Greater Capital City Statistical Areas, July 2016 Retrieved from https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/1270.0.55.001Main+Features10018July%202016?OpenDocument
2. Australian Bureau of Statistics. (2020a). Weekly Payroll Jobs and Wages in Australia. Retrieved from https://www.abs.gov.au/statistics/labour/earnings-and-work-hours/weekly-payroll-jobs-and-wages-australia/latest-release#state-and-territory
3. Australian Bureau of Statistics. (2020b, September 9). Weekly Payroll Jobs and Wages in Australia, Week ending 22 august 2020. Retrieved from https://www.abs.gov.au/statistics/labour/earnings-and-work-hours/weekly-payroll-jobs-and-wages-australia/week-ending-22-august-2020
4. Australian Bureau of Statistics. (2021). Labour Force, Australia, Detailed. Retrieved from https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release
5. Baum, S., O'Connor, K., & Stimson, R. (2005). *Fault lines exposed: Advantage and disadvantage across Australia's settlement system*: Monash University ePress.
6. Brada, J. C., Gajewski, P., & Kutan, A. M. (2021). Economic resiliency and recovery, lessons from the financial crisis for the COVID-19 pandemic: A regional perspective from Central and Eastern Europe. International Review of Financial Analysis, *74*, 101658.
7. Courvisanos, J., Jain, A., & K. Mardaneh, K. (2016). Economic resilience of regions under crises: A study of the Australian economy. Regional Studies, *50*(4), 629–643.
8. Den Teuling, N., Pauws, S., & van den Heuvel, E. (2020). A comparison of methods for clustering longitudinal data with slowly changing trends. Communications in Statistics-Simulation and Computation, 1–28.
9. Doran, J., & Fingleton, B. (2018). US metropolitan area resilience: insights from dynamic spatial panel estimation. Environment and Planning A: Economy and Space, *50*(1), 111–132.
10. Genolini, C., & Falissard, B. (2010). KmL: k-means for longitudinal data. Computational Statistics, *25*(2), 317–328.
11. Giannakis, E., & Bruggeman, A. (2017). Determinants of regional resilience to economic crisis: a European perspective. European Planning Studies, *25*(8), 1394–1415.
12. Gittleman, M. B., & Howell, D. R. (1995). Changes in the structure and quality of jobs in the United States: Effects by race and gender, 1973–1990. ILR Review, *48*(3), 420–440.
13. Grabner, S. M. (2021). Regional economic resilience: Review and outlook. Economic Resilience in Regions and Organisations, 21–55.
14. Han, Y., & Goetz, S. (2013). *Predicting the economic resilience of US counties from industry input-output accounts.* Paper presented at the Southern Regional Science Association Annual Meeting, Washington, DC, USA.
15. Hill, E. W., Brennan, J. F., & Wolman, H. L. (1998). What is a central city in the United States? Applying a statistical technique for developing taxonomies. Urban Studies, *35*(11), 1935–1969.

16. Hu, X., Li, L., & Dong, K. (2022). What matters for regional economic resilience amid COVID-19? Evidence from cities in Northeast China. Cities, *120*, 103440.
17. Lagravinese, R. (2015). Economic crisis and rising gaps North–South: evidence from the Italian regions. Cambridge journal of regions, economy and society, *8*(2), 331–342.
18. Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: conceptualization and explanation. Journal of economic geography, *15*(1), 1–42.
19. Martin, R., Sunley, P., Gardiner, B., & Tyler, P. (2016). How regions react to recessions: Resilience and the role of economic structure. Regional Studies, *50*(4), 561–585.
20. Masson, M. E., & Loftus, G. R. (2003). Using confidence intervals for graphically based data interpretation. Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale, *57*(3), 203.
21. Ringwood, L., Watson, P., & Lewin, P. (2019). A quantitative method for measuring regional economic resilience to the great recession. Growth and Change, *50*(1), 381–402.
22. Stobart, A., & Duckett, S. (2022). Australia's Response to COVID-19. Health Economics, Policy and Law, *17*(1), 95–106.
23. Turgel, I. D., Chernova, O. A., & Usoltceva, A. A. (2021). Resilience, robustness and adaptivity: Large urban Russian Federation regions during the COVID-19 crisis. Area Development and Policy, 1–23.

Figures

Figure 1

Calinski and Harabatz scores

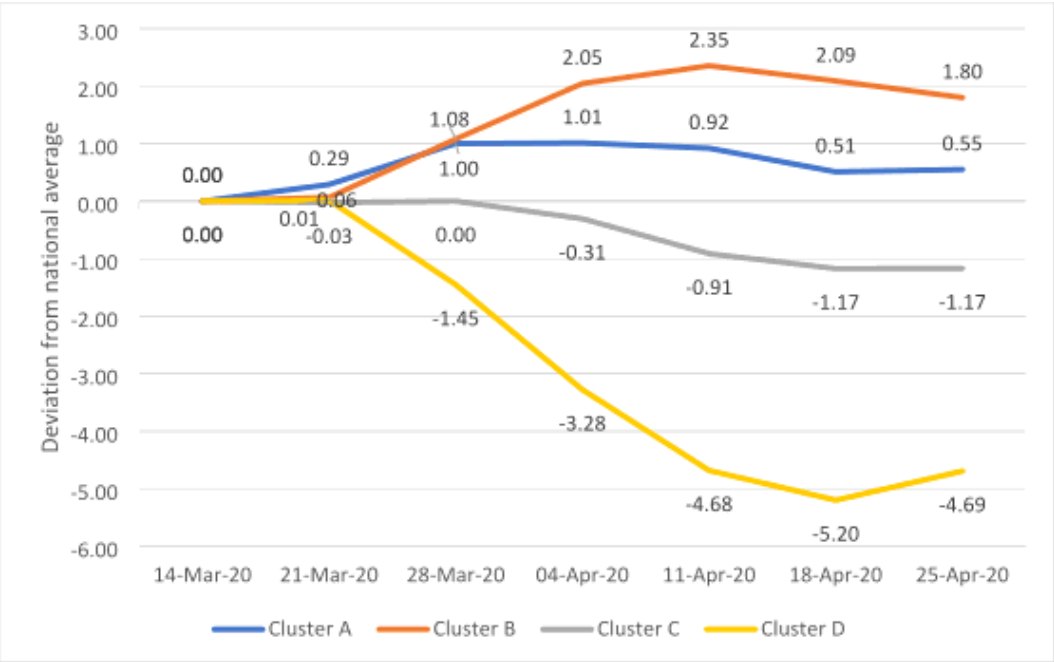

Figure 2

Average trajectories, four cluster solution

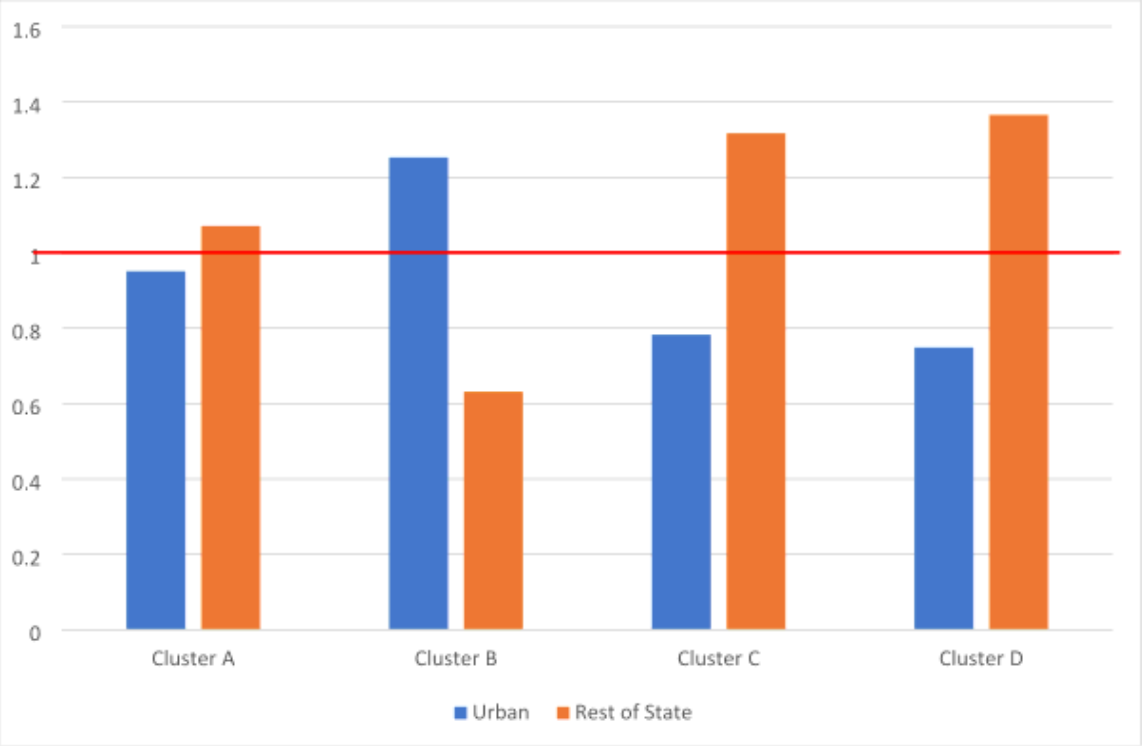

Figure 3

Regional Concentration Ratio, 4 clusters Urban and regional/remote araes

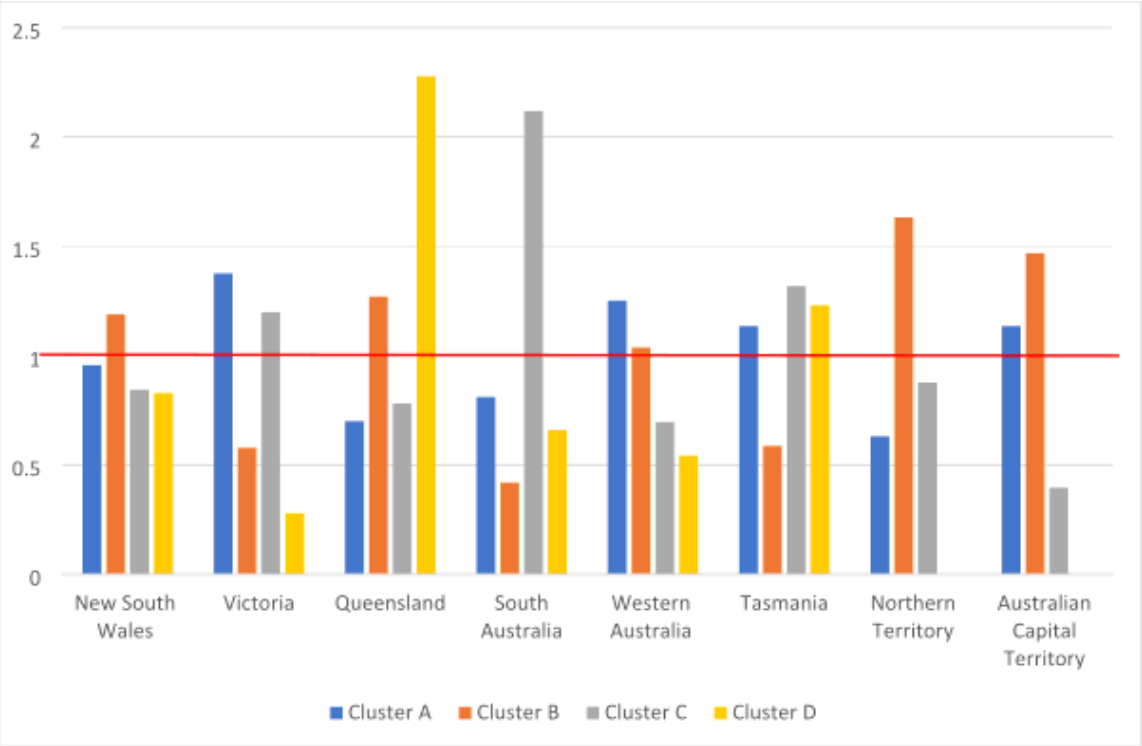

Figure 4

Regional Concentration Ratio, 4 clusters States and Territories

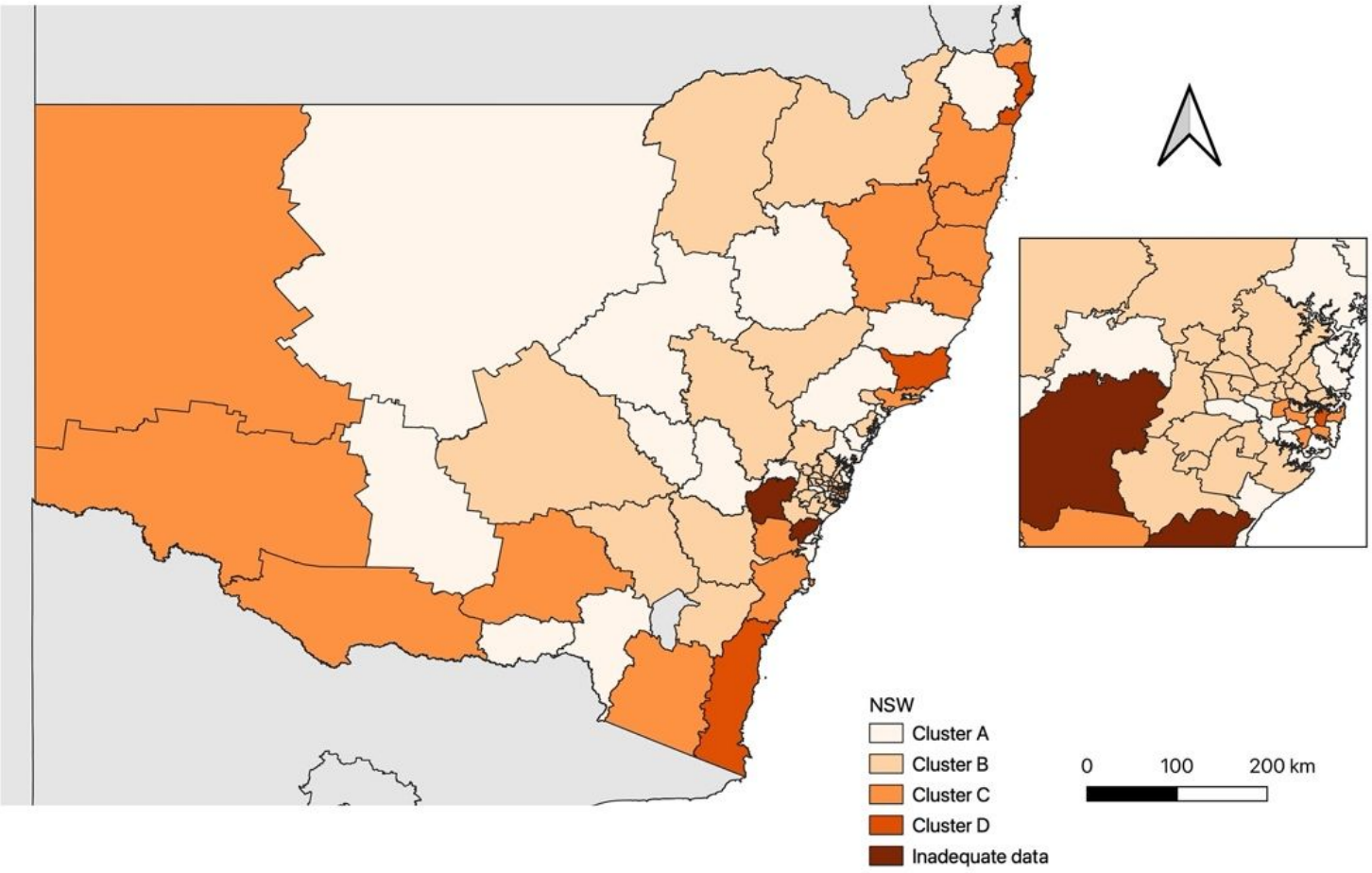

Figure 5

Employment trajectory clusters, New South Wales (Sydney inset)

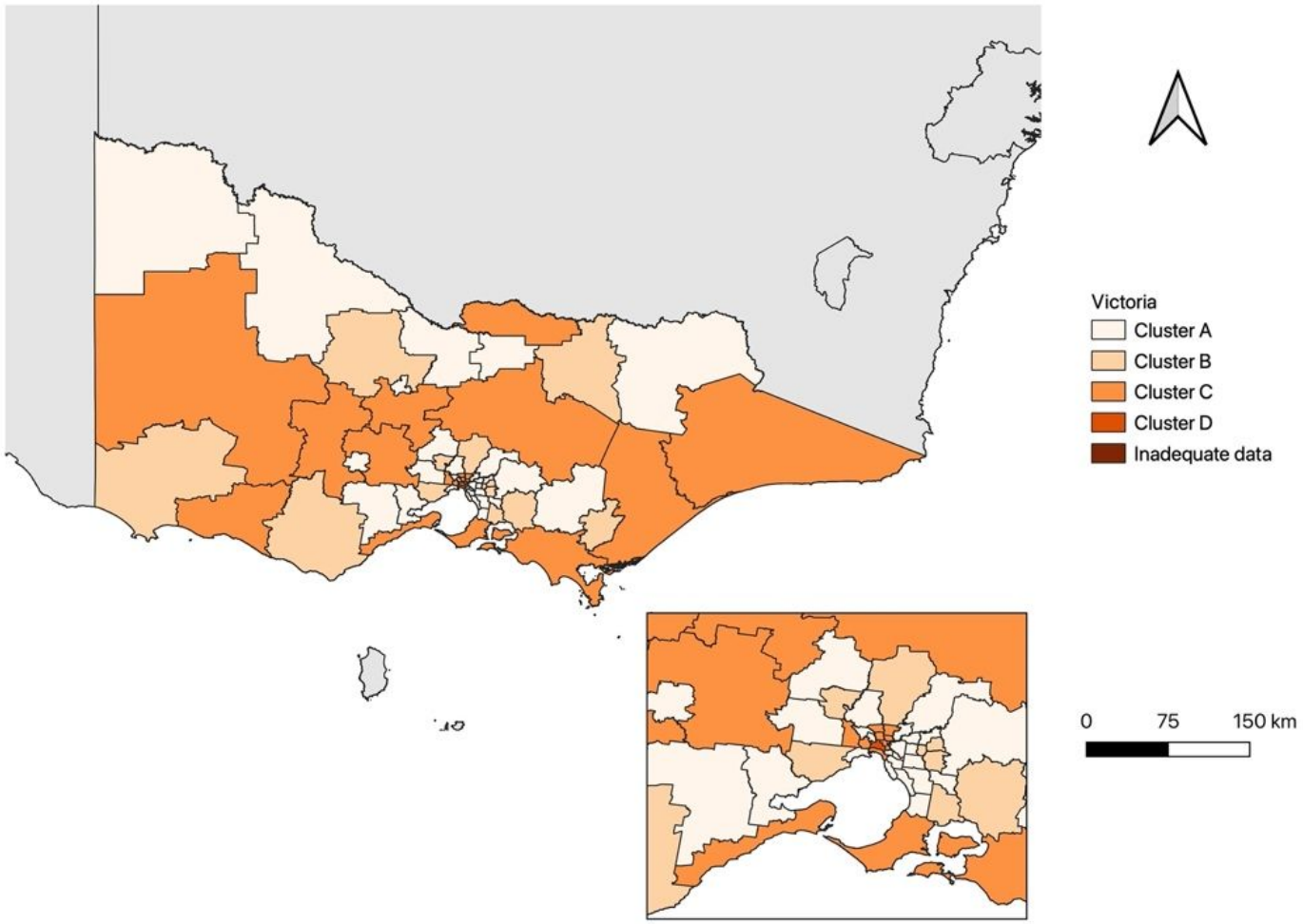

Figure 6

Employment trajectory clusters, Victoria (Melbourne inset)

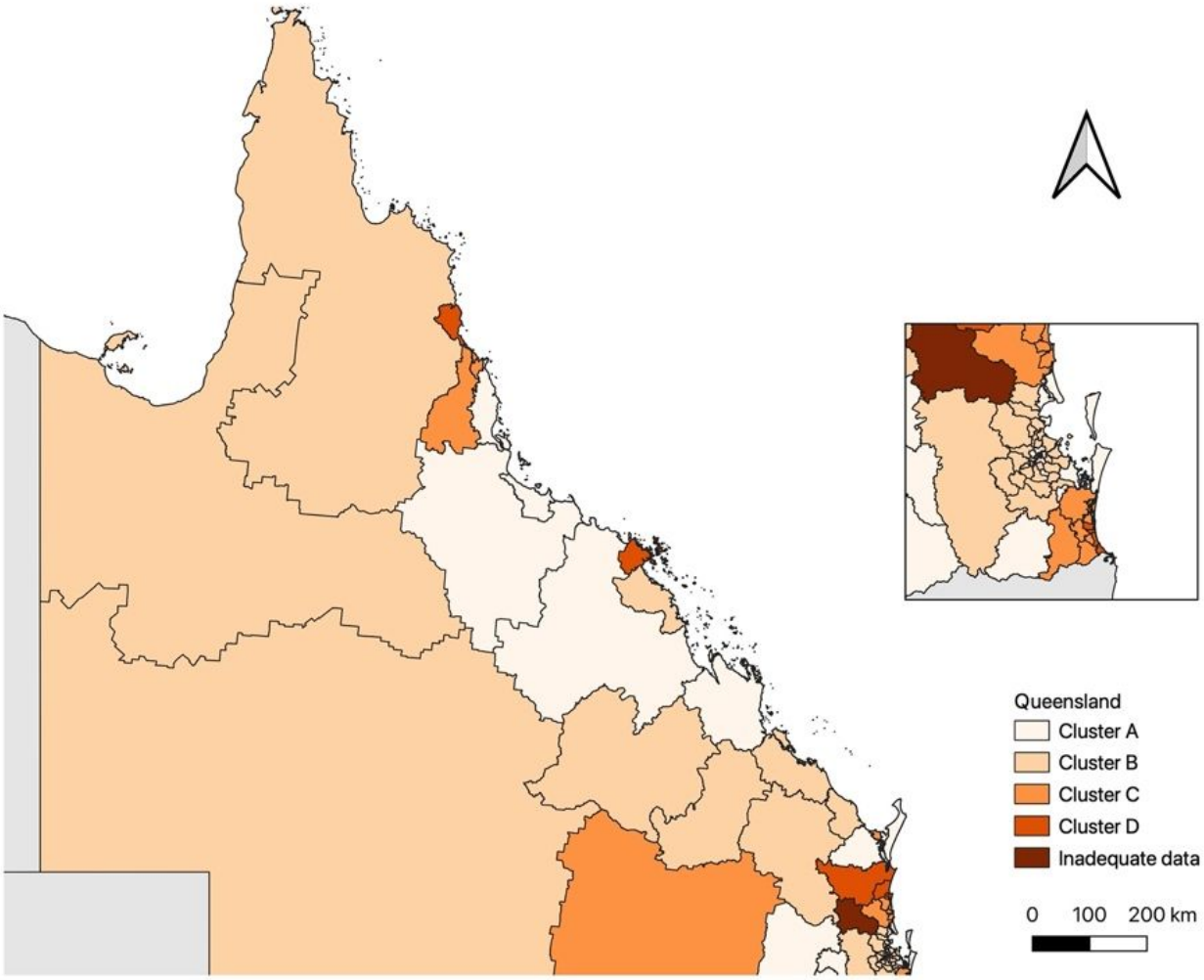

Figure 7

Employment trajectory clusters, Queensland (Brisbane inset)

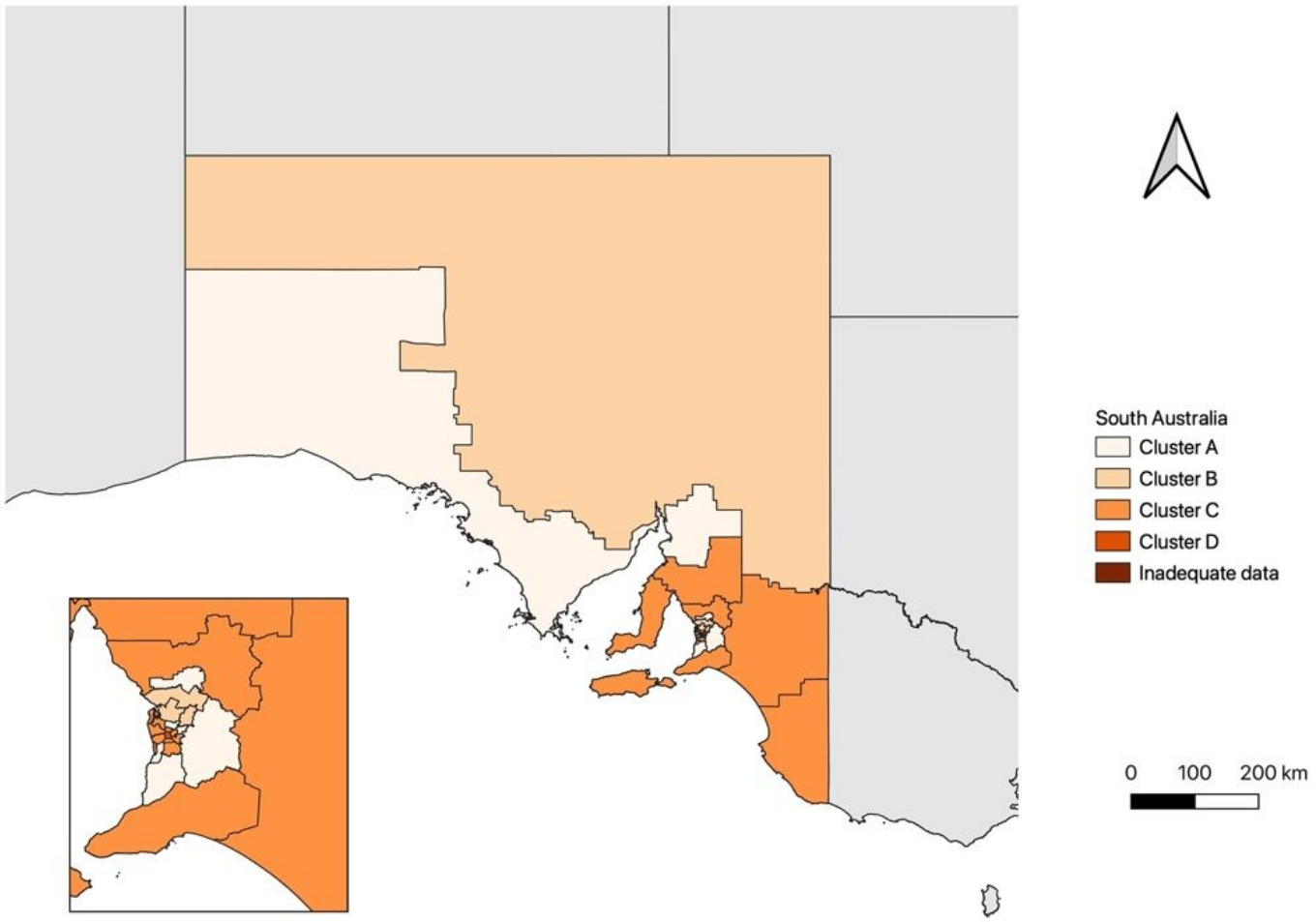

Figure 8

Employment trajectory clusters, South Australia (Adelaide inset)

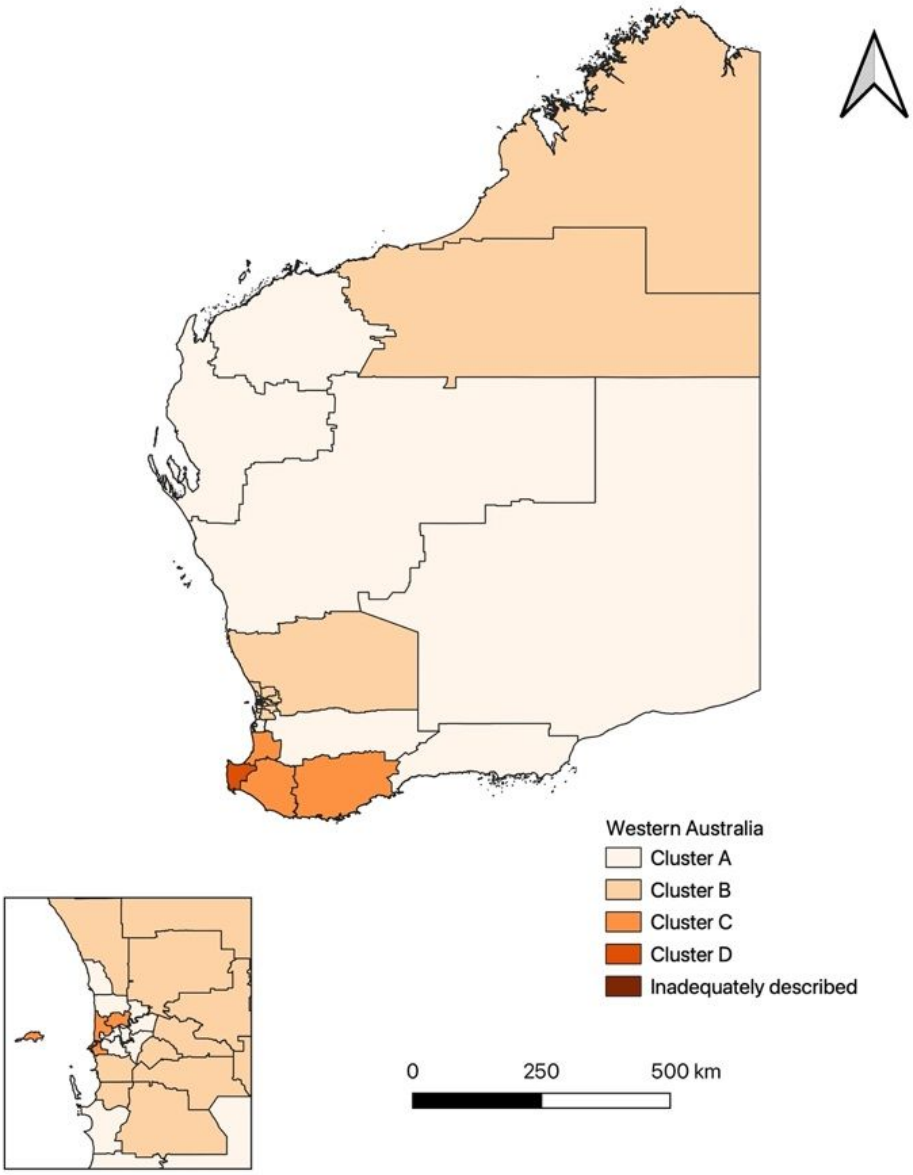

Figure 9

Employment trajectory clusters, Western Australia (Perth inset)

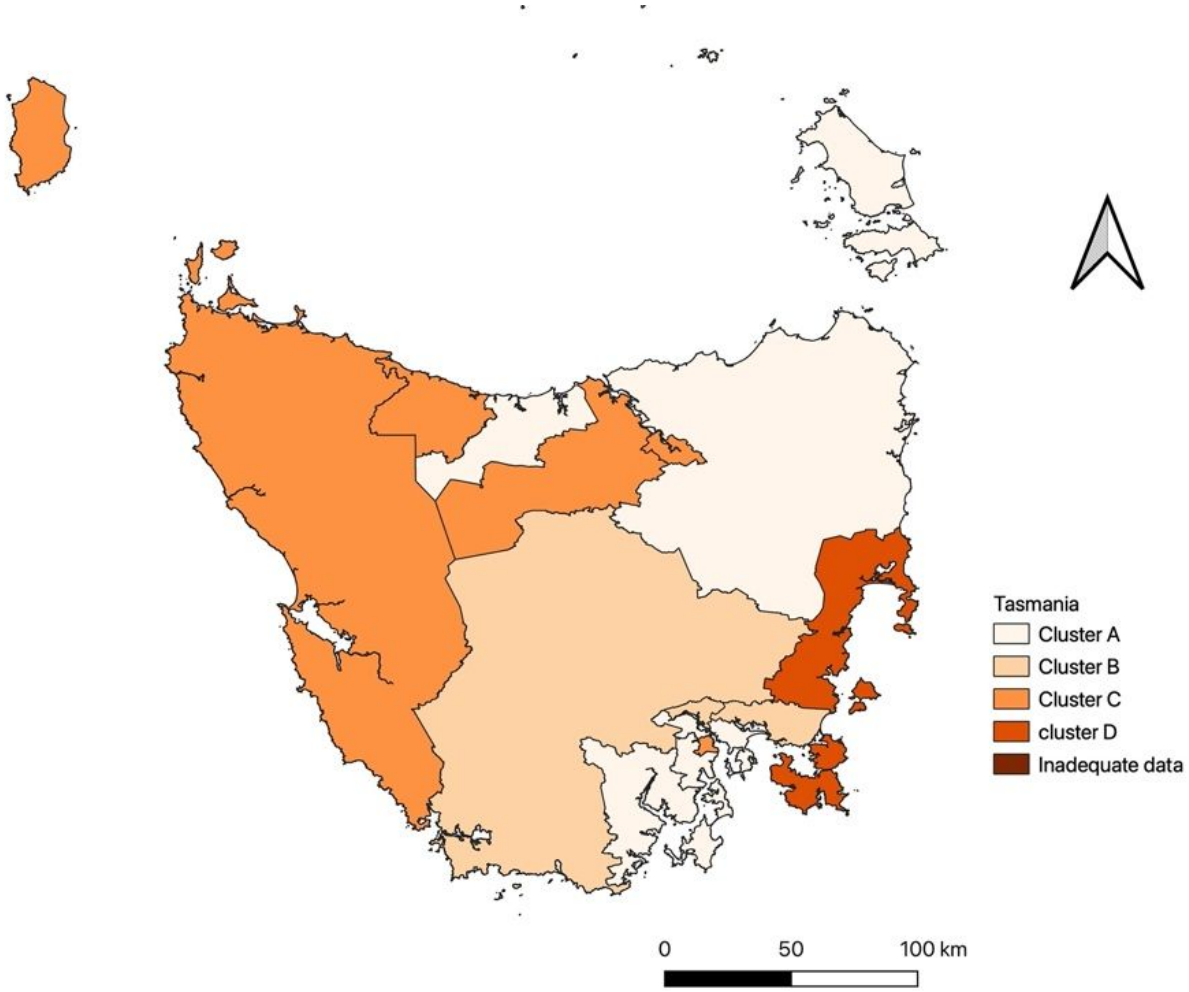

Figure 10

Employment trajectory clusters, Tasmania

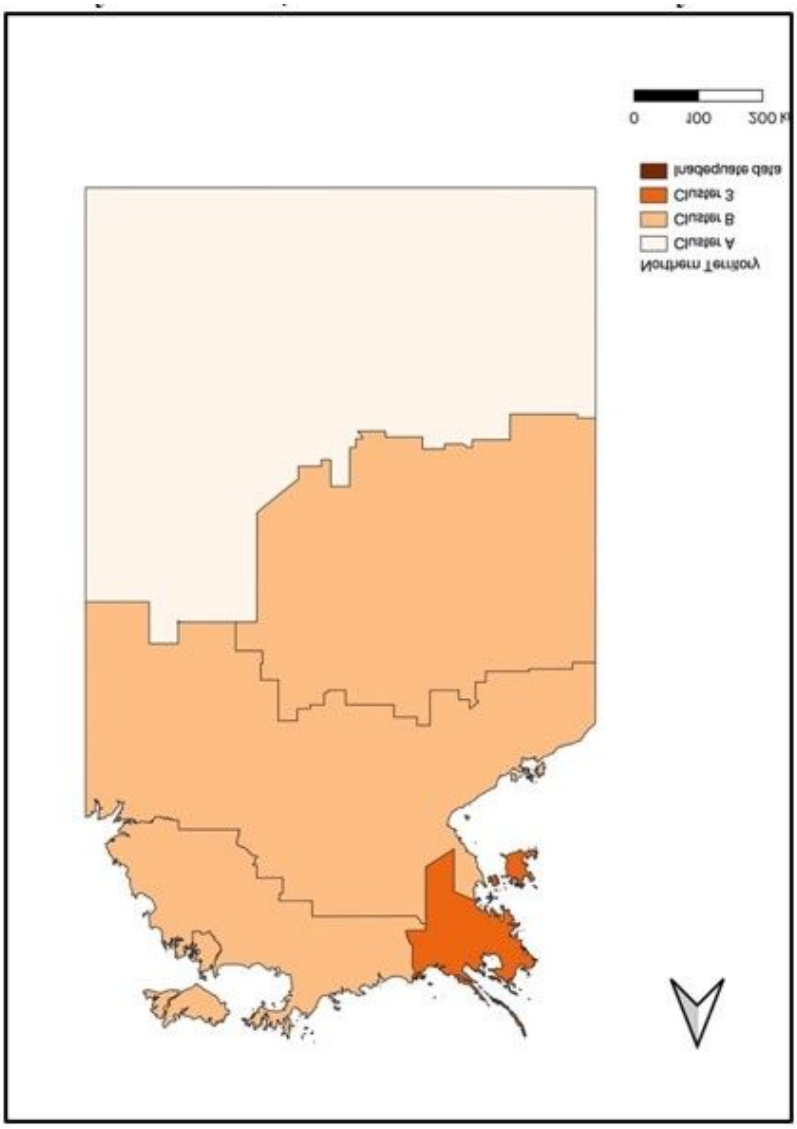

Figure 11

Employment trajectory clusters, Northern Territory

Figure 12

Employment trajectory clusters, Australian Capital Territory