Economic Complexity of Australian Regions

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0.1. Introduction

0.2. Literature Review

[1] introduced the concept of economic complexity as a means of quantifying and explaining differences in the economic development trajectory of different countries. Their method used bilateral trade data to identify the network structure of countries and the products they export and built on the concept of relatedness introduced in [2]. Economic complexity has been shown to be a positive predictor of Gross Domestic Product (GDP), and GDP growth. Increasing economic complexity has also been shown to decrease unemployment and increase employment [3], reduce green house gas emissions [4] and reduce income inequality [5].

Relatedness has since been applied across industry [6], research areas [7], occupation [8] and technology (patents) [9].

The relatedness approach has also been used to quantify economic complexity across cities, states, and regions, using employment data[10, [11], [12]], business counts[13], patent classifications [14], and interstate and international trade data [15].

Despite differences in data sources, the method for calculating economic complexity in the literature is relatively standard. The presence of an activity in a region is often identified using a location quotient method, such that an activity is said to be present in a region if:

$$\frac{X_a^r / \sum_a X_a^r}{\sum_r X_a^r / \sum_{r,a} X_a^r} \geq 1$$

Where X is the measure of an activity a in region r - such as the level of employment in an occupation in a city, or the number of businesses classified in

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an industry in a province, or the value of exports of a product from a country. The location quotient method creates a binary matrix M with a rows and r columns.

0.2.1. Regional economic complexity of small areas

The location quotient method can be unreliable due to the discontinuity at 1. This is especially relevant when economic complexity is calculated in regional areas where either X_a^r or $\frac{\sum_r X_a^r}{\sum_{r,a} X_a^r}$ are small. In these cases, small changes, or measurement error in X_a^r can significantly change the location quotient.

The choice of region size and activity classification is important. In a study of the economic complexity of US regions, [10] use metropolitan areas as the basis for calculations. Metropolitan areas in the United States are defined such that jobs within a given area are held by residents who live in that area.Metropolitan areas have a population of at least 50,000 people. The smallest MSA was estimated to have a 2023 population of 57,700 (about 0.015% of US population). They find a poor correlation between ECI calculated at higher level aggregated industry classifications indicating the importance of a high degree of disaggregation to provide as much information to the model as possible [10].

In New Zealand, [11] use weighted correlations of local employment shares. Regions range from a population of 1,434 to 573,150 with a mean population of 29,947 and median population of 6,952. Employment is measured as an industry-occupation pair.

- Differences in relationship between complexity and relatedness on indicators may be entirely context dependent.

0.3. Data & Methods

0.3.1. Data

- Calculate economic complexity indicators for Australian regions using employment data from the 2021 Census.
- Regions classified by Statistical Areas Level 3 (SA3)
- Economic activity classified by ANZSIC industry division and ANZSCO major group

Source: Article Notebook

- We exclude individuals who identify their place of work as a Migratory - Offshore - Shipping region or as No Fixed Address. Employment in these regions totals 497,913 or about 4% of the total sample.
- Following [11], employment is aggregated into industry-occupation pairs, allowing for differentiation between, for example, managers working in agriculture, forestry, and fishing, and managers working in retail trade.

- Dataset covers 340 regions and 152 industry-occupations. Figure 1 shows the presence of any level of employment within a region and industry-occupation. As can be seen, there is a high level of employment density across our data, with 88.5% of all combinations of region, industry, and occupation.

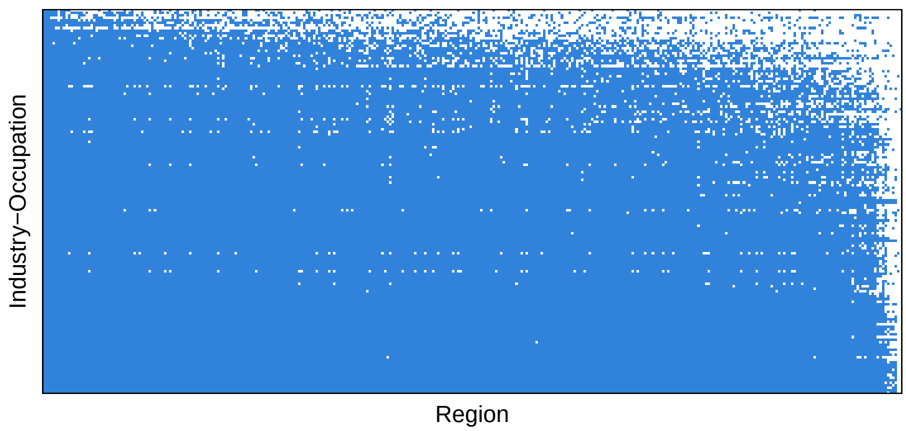

Figure 1: Presence of employment across regions and industry-occupations.

Source: Article Notebook

0.3.2. Method

This section follows the method of [11] using correlations of employment shares rather than a location quotient method.

0.3.2.1. Relatedness.

Activities are related based on the weighted correlation between the local activity share of employment, weighted by each regions share of total employment.

- First calculate the weighted covariance

$$cov_{aa} = \sum_{c \in C} (\frac{E_c^{a_i}}{E_c} - \frac{E^{a_i}}{E})(\frac{E_c^{a_j}}{E_c} - \frac{E^{a_j}}{E})$$

- Divide the weighted covariance by the city share-weighted standard deviations of the local activity shares to get the weighted correlation.

- Map the correlation to the interval $[0, 1]$ such that:

$$r_{aa} = \frac{1}{2}(cor(a_i, a_j) + 1)$$

City relatedness is calculated symmetrically such that:

$$r_{cc} = \frac{1}{2}(cor(c_i, c_j) + 1)$$

0.3.2.2. Complexity.

Activity complexity is defined by the second eigenvector of the matrix r_{aa} and city complexity is defined by the second eigenvector of the matrix r_{cc}. The sign of activity complexity is set such that it is positively correlated with the weighted mean size of cities that contain activity a, and the sign of city complexity is set such that it is positively correlated with the local share-weighted mean complexity of activities in city c

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0.4. Results

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Figure 2 shows the regional complexity of SA3 regions in Australian Greater Capital City Areas based on 2021 Census data. Complexity is highest in capital cities and surrounding regions.

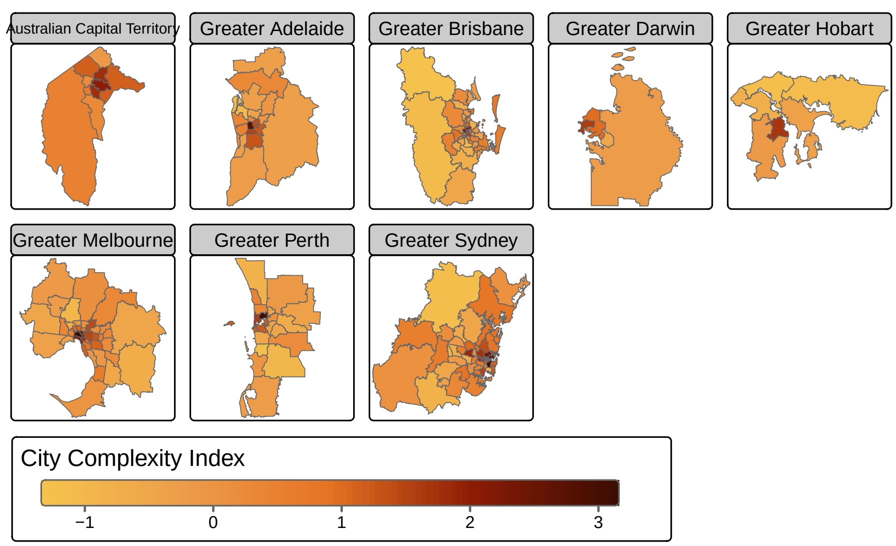

Figure 2: Complexity of Australian Greater Capital City Areas

Source: Article Notebook

0.4.1. Regression

$ECI_r = CC + log(employment) + log(population) + log(income_{hh}) + log(business_{entries}) + business_{share}$

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0.4.2. Spatial Correlation

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Based on Figure 2, it looks like there are clusters of complexity, centred around capital cities.

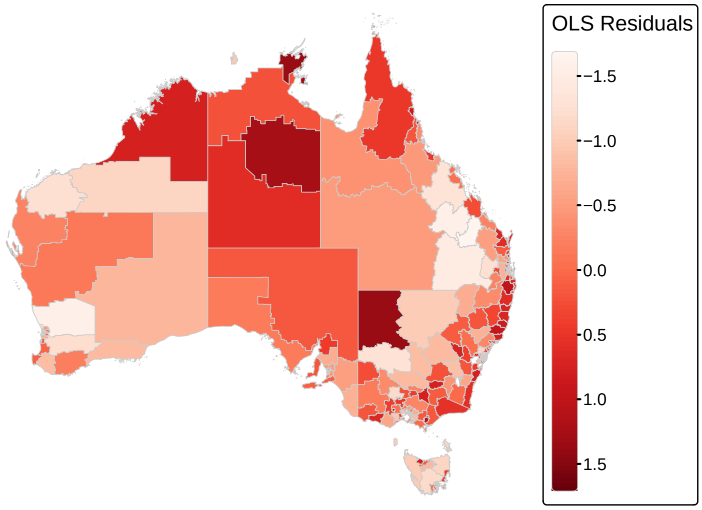

Figure 3: Residuals from linear regression

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The residuals from the linear regression are shown in Figure 3 which also shows that the distribution of the residuals appears non-random.

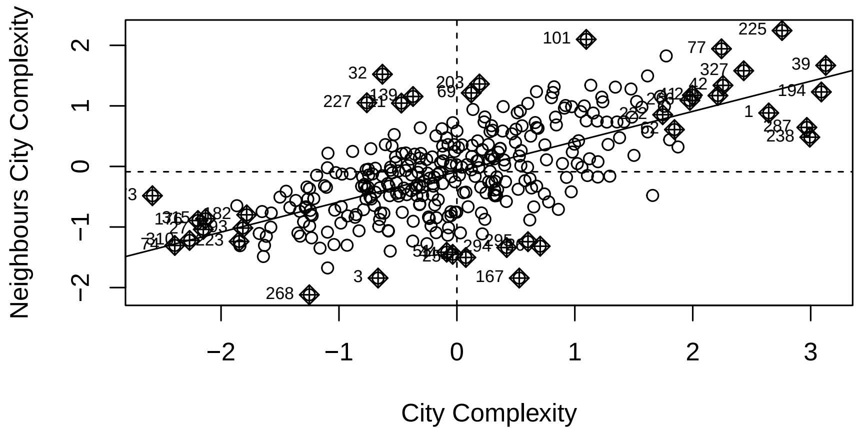

Figure 4: Moran Scatterplot for City Complexity in Australia

Source: Article Notebook

The correlation between complexity and lagged complexity is shown in Figure 4 which also shows a dependency. Finally, we observe a global Moran's I of 0.498499 with a p.value of 0. As such, the data appear to be spatially autocorrelated, so a lagged AR or lagged error model should be estimated instead.

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0.5. *Hot spots*

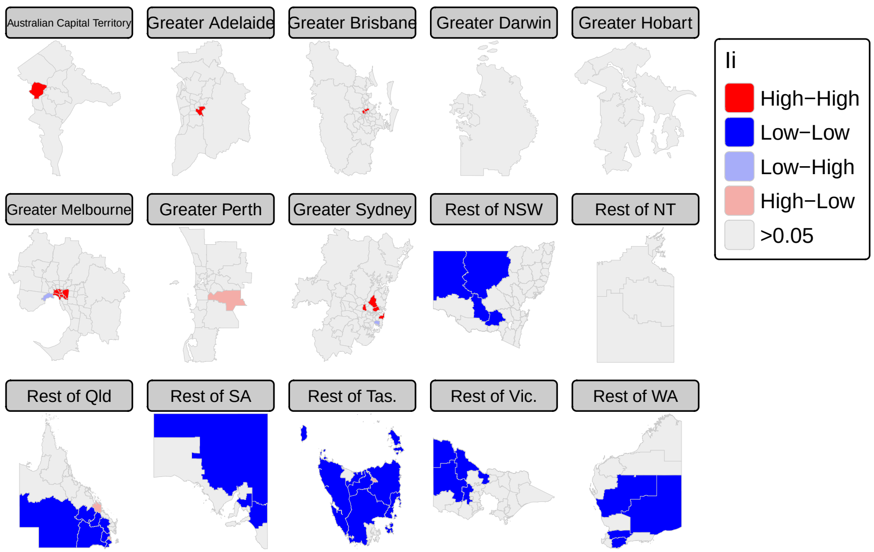

Figure 5: City Complexity hot spots (based on local Moran's I p.values)

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0.6. *Conclusion*

0.7. *Appendix*

Regional economic complexity can be calculated using other data, including employment by industry and employment by occupation.

0.7.1. *Other Employment Indicators*

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Employment density is much sparser when using 4-digit industry of employment data. Only 48 of the industry class-region combinations contain any level of employment.

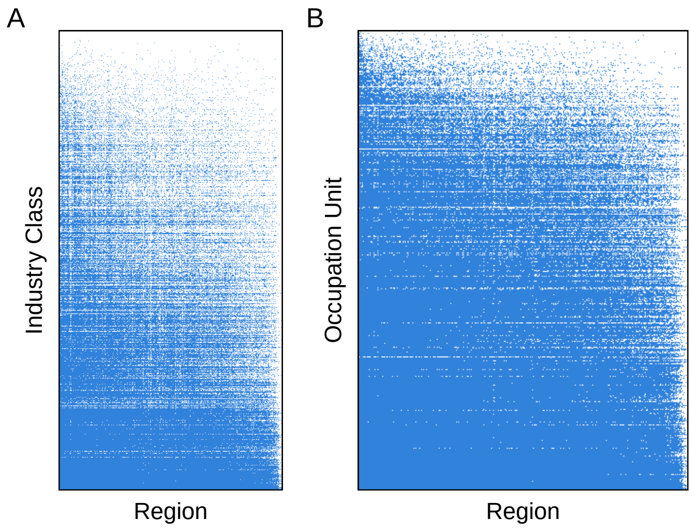
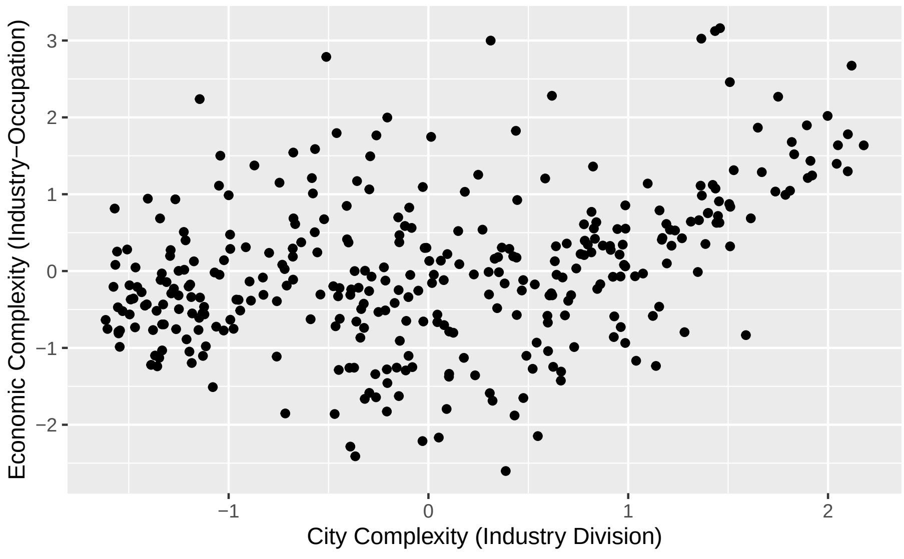


Figure 6: Employment density, SA3 regions: (A) ANZSIC industry class, (B) ANZSCO occupation unit

Source: Article Notebook



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0.7.2. Smaller Areas

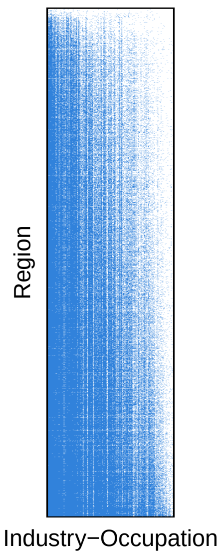

Figure 7: Employment density, Industry-occupation, SA2 regions

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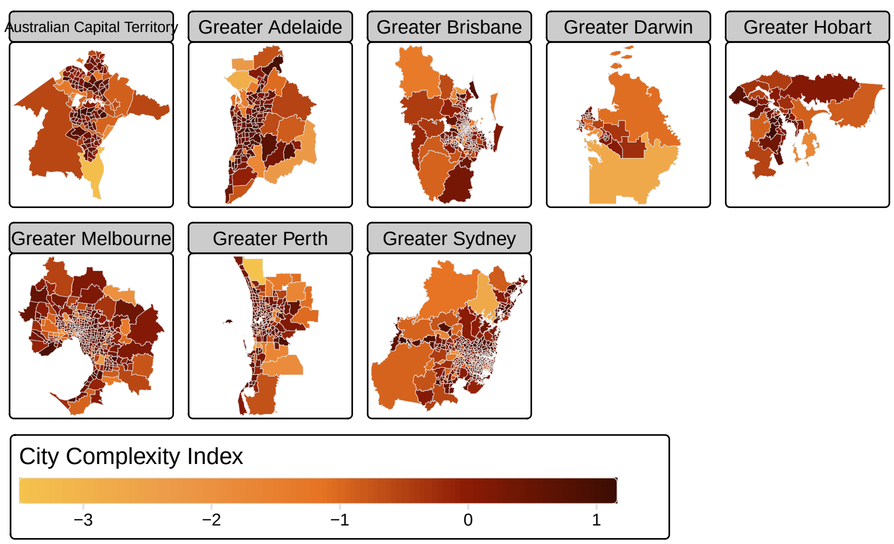

Source: Article Notebook

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	OLS	Spatial AR	Spatial Error
(Intercept)	-17.224 ***	-13.830 ***	-16.581 ***
	(3.417)	(3.351)	(3.561)
log_total_businesses_no	-0.102	0.063	-0.114
	(0.230)	(0.221)	(0.254)
log_total_business_entries_no	0.028	-0.060	-0.037
	(0.409)	(0.389)	(0.395)
log_total_business_exits_no	0.937 *	0.650	0.939 *
	(0.431)	(0.416)	(0.420)
turnover_greater_2m_share	0.491	-0.083	-0.220
	(1.748)	(1.668)	(1.721)
log_total_persons_employed_aged_15_years_and_over_no	-1.691 **	-1.382 **	-1.793 **
	(0.517)	(0.500)	(0.565)
log_estimated_resident_population_persons_no	1.208 *	1.096 *	1.430 *
	(0.511)	(0.490)	(0.565)
business_share	4.280 ***	4.457 ***	4.371 **
	(1.206)	(1.149)	(1.415)
log_median_equivalised_total_household_income_weekly	2.213 ***	1.669 ***	2.097 ***
	(0.283)	(0.294)	(0.321)
rho		0.273 ***	
		(0.060)	
lambda			0.360 ***
			(0.066)
N	330	330	330
R2	0.528	0.560	0.574
logLik	-346.835	-338.084	-335.202
AIC	713.669	698.168	692.403

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.