Economic Complexity of Australian Regions

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0.1 Introduction

0.2 Literature Review

César A. Hidalgo & Hausmann (2009) 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 C. A. Hidalgo et al. (2007). Economic complexity has been shown to be predictor of

Relatedness has since been applied across industry (Neffke & Henning, 2012), research areas (Guevara et al., 2016), occupation (Muneepeerakul et al., 2013) and technology (patents) (Kogler et al., 2013).

The relatedness approach has also been used to quantify economic complexity across cities, states, and regions, using employment data[Fritz & Manduca (2021); @ecnz; Chávez et al. (2017)], business counts(Gao & Zhou, 2018), patent classifications (Balland & Boschma, 2021), and interstate and international trade data (Reynolds et al., 2018).

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 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.

- In a study of the economic complexity of US regions, Fritz & Manduca (2021) 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).
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0.2.1 Small (n) areas

- In New Zealand, Davies & Maré (2021) 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.

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- C. A. Hidalgo et al. (2007) and others have focused on the co-occurrence of revealed comparative advantage indices, derived from a location quotient. The location quotient is measured as:

$$LQ = \frac{X_r^a / X_r}{X^a / X}$$

- As such, small values of $\frac{X^a}{X}$ can exacerbate any measurement error in the numerator. Additionally, the binary nature of measuring revealed comparative advantage when the location quotient is greater than 1, results in a discontinuity at $LQ = 1$.

- 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 Davies & Maré (2021), 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.

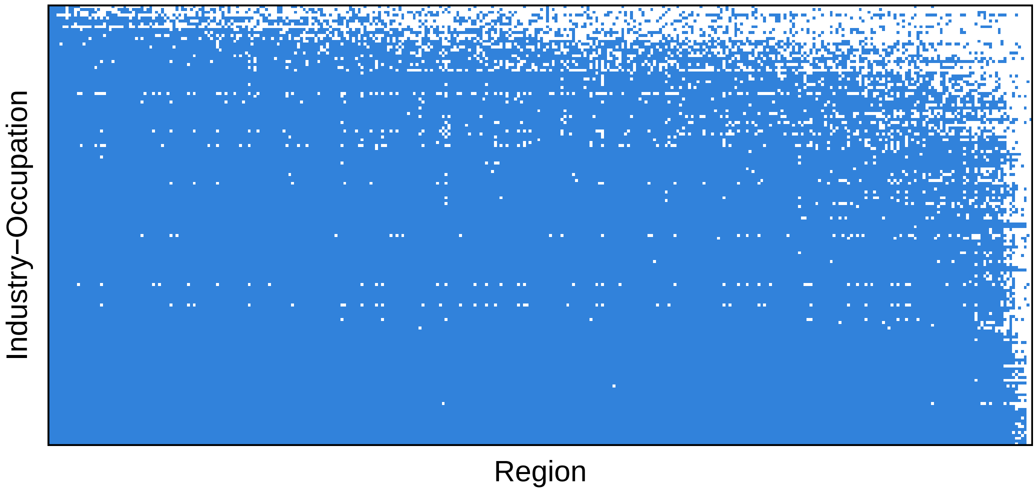

Figure 1: Presence of employment across regions and industry-occupations.

Source: Article Notebook

0.3.2 Method

This section follows the method of Davies & Maré (2021) 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

Source: Article Notebook

0.4 Results

Source: Article Notebook

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.

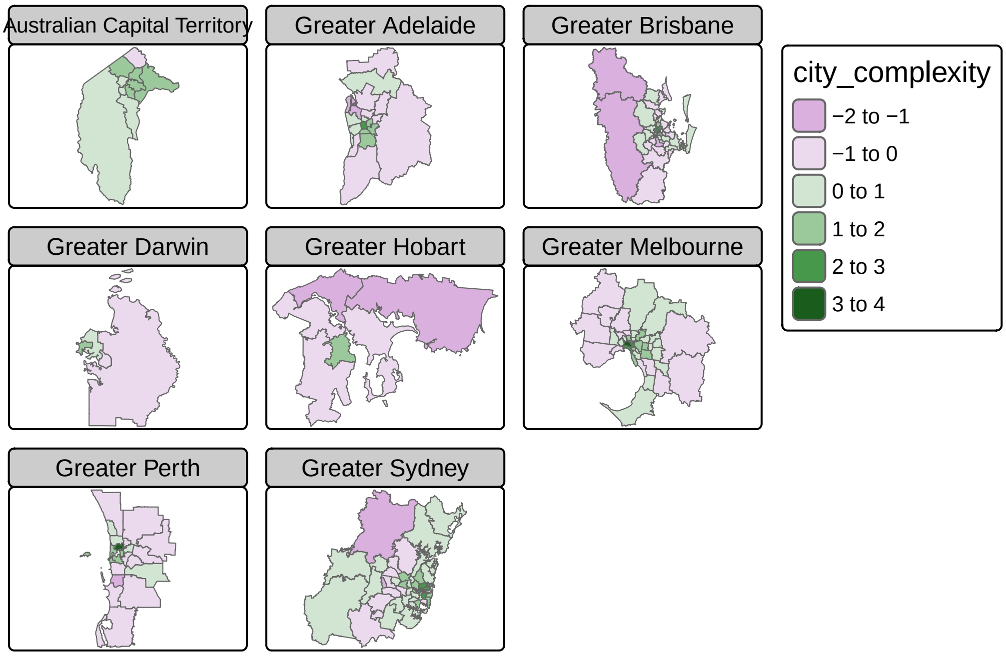

Figure 2: Complexity of Australian Greater Capital City Areas

Source: Article Notebook

0.4.1 Spatial Correlation

- Is economic complexity correlated across space?

Source: Article Notebook

- Global Moran's I = 0.5007756 with a p.value of 0.

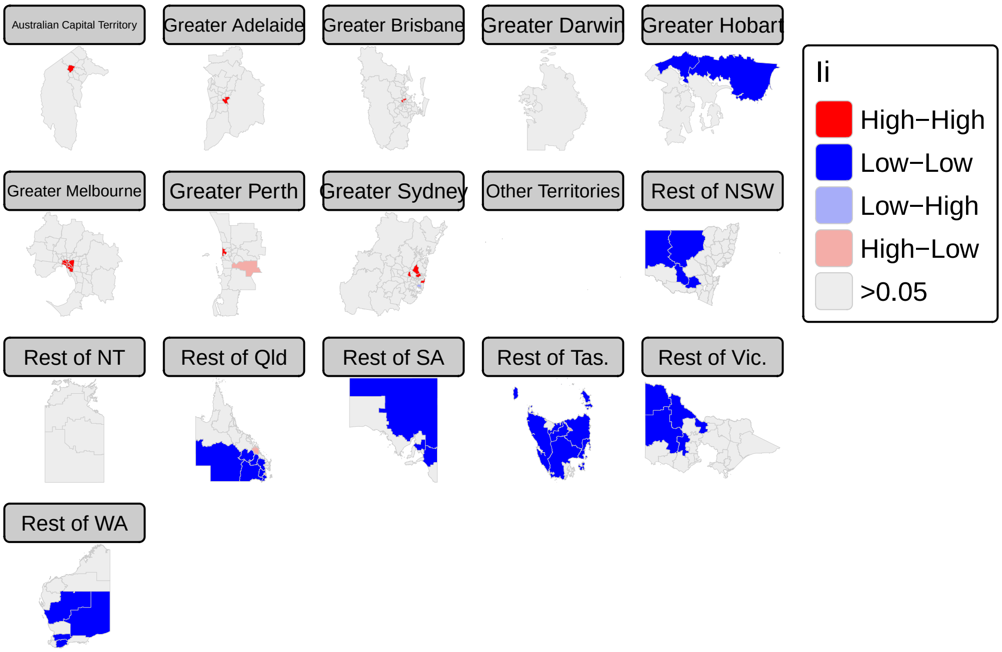

Figure 3: City Complexity hot spots (based on local Moran's I p.values)

Source: Article Notebook

0.5 Conclusion

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