MONASH University

Sub-Sectoral Employment Dynamics in Australia

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1 Introduction

The COVID-19 pandemic has caused a massive effect on economies around the world. Across different countries, millions of workers were furloughed or even lost their jobs as businesses struggled to survive (Lewis & Hsu, 2020). Same situation happened in Australia, due to more restrictions, many businesses closed their doors, while employees were working with less hours or being dismissed by companies. As a result of the the continuous "lockdown" periods in 2020, the estimates made by the Australian Bureau of Statistics (ABS, 2021) concluded that 72% of business generated less revenue and the underemployment rate hit historically high with 13.8% by the end of April, at the time only one month after the COVID-19 outbreak.

Our research is motivated by the lack of knowledge about the employment of sub-sector knowledge in Australia,as many studies now focusing on aggregated employment rate. Meanwhile, a general problem of aggregated researches is the lack of hierarchical information, which may result in a biased conclusion or "a illusion of employment prosperity". Thus, a focus on the sectoral employment and even different sub-sectors has responded to the COVID-19 will overcome this problem, giving us a better scope to evaluate the influences of COVID-19 in Australia while keeping the original hierarchical structure of the data.

2 Research aim and questions

This research will extend the work done by Anderson et al. (2020) based on the new availability of "post-covid" data, and provide a model for the sub-sectors to evaluate the long run effect and the COVID-19 post-impacts. We will also provide an contrafactual analysis based on the assumption "if there is no pandemic". Subsectoral data will generally provide us more information and preserve the hierarchical structures, which will particularly assist the employment analysis in Australia.

The overall research aim is to provide estimates of subsectoral employment based on historical data. Specifically, we seek to answer the following questions.

1. What were the initial effects of the COVID-19 pandemic on employment? How strongly does it affect our life at present (long-term influence)?
2. Have the government policies done well in helping the recovery of COVID-19?
3. Which sub-sectors have experienced less shock and "survived" the poor employment situation during the pandemic period?
4. Can we build up an accurate model that precisely forecasts the 87 sub-sectors to support our contrafactual analysis?

3 Review of literature

Our review of literature mainly focuses on two areas:

1. The COVID-19 sectoral impacts and modelling to Economies.

2. Modelling of large numbers of time series.

3.1 Sectoral Impact for COVID-19 to Economies

Most studies are now focusing on the evaluation of sectoral impacts that COVID-19 have to large economies such as the US and Europe. Ludvigson, Ma, and Ng (2020) developed a disaster series to translate the macroeconomic impact of costly and deadly disasters in recent US history and modelled as sectoral shock to predict COVID-19, concluding that the shock would lead to a cumulative loss of 20% in industrial production, 39% in service sector and also reduce the US GDP by 12.75 per cent at the end of 2020. Gregory, Menzio, and Wiczer (2020) conducted simulations under different scenarios via a search theoretic model using US data and found the recovery in US is L-shaped, with employment remaining lower than the pre-covid for a long period. They also extended their studies at disaggregated level, showing that "arts and entertainment" and "accommodation and food services" sectors would have the biggest shock during the pandemic.

In Australia, Anderson et al. (2020) developed a multivariate time series for 19 main sector in Australia (as a small open economy) using a Bayesian VARX model. Their research concluded that "Manufacturing" and "Construction" have highest positive spillovers for the aggregate economy. Meanwhile, they also applied a "Conditional Forecasting" method proposed by Waggoner and Zha (1999) to simulate different scenarios for pandemic in Australia. However, this research is limited by the lack of hierarchical information of the most disaggregted level in Australia (sub-sectors of main jobs), which can be extremely useful in macroeconomic analysis.

3.2 Modelling

3.2.1 Baysian VAR

Literature of Multivariate, Hierarchical and large-size data tend to rely on Bayesian Vector Autoregression model(BVAR) (e.g. Anderson et al., 2020; Litterman, 1986; Bańbura, Giannone, & Reichlin, 2010). The BVAR model is attractive because (a) it is a scientific method that can be evaluated on its own without any judgmental adjustments. (b) it generates a complete and multivariate probability distribution, which appears to be more realistic than other similar methods (Litterman, 1986). (c) BVAR allows variables to have unit roots without influencing the inference of the parameter of the model (Woźniak, 2016).

In order to utilize the Bayesian VAR estimators and decrease the weight of hte lagged variable with the lag length, Litterman et al. (1979) proposed the Minnesota Prior by forcing the means of parameters 'centered' as a random walk. The mean on its first own lag is set to unity and the rest are set to zero so that (a) the most recent lag should provide more information than distant lags. (b) own lags should explain more than the lags of other variables.

3.2.2 Improvement of BVAR

The Literature suggests that a significant improvement can be made for the large BVAR dynamic model by imposing a stronger shrinkage to the Bayesian estimators (Bańbura, Giannone, & Reichlin, 2010; Litterman, 1986). Robertson and Tallman (1999) and Kadiyala and Karlsson (1997) proposed a normal inverted Wishart prior which retains the principal of Minnesota prior. Meanwhile, Bańbura, Giannone, and Reichlin (2010) suggested an easier way to apply the Minnesota prior via adding dummy observations in the BVAR system.

4 Data collection and exploratory analysis

4.1 Process

Our data is gained from the ABS Employment by industry subdivision of main job (ABS, 2022), which records employment (measured in $'\mathbf{000}$) by the ANZSIC industry sub-division of their main jobs from $1984:Q4$ to $2022:Q2$. Our data structure is provided via Figure 4.

Although seasonally adjusted data is available in (ABS, 2022), we still work with original data to capture any possible changes. Before we construct our model, we apply an seasonal differencing to the logarithm of the original series in order to make it stationary, which will make us easier to conduct further steps.

4.2 Priliminary Exploratory Data Analysis

Main Sub-Sectors with highest and lowest difference in 2020:Q2 compare with Q1

Date	Industry	Top five	Industry	bottom five
2020 Q2	30 Building Construction	30.7	91 Sports and Recreation Activities	-58.8
2020 Q2	81 Tertiary Education	29.6	69 Professional, Scientific and Technical Services (Except Computer System) Design and Related Services)	-59.2
2020 Q2	01 Agriculture	27.0	42 Other Store-Based Retailing	-65.1
2020 Q2	26Electricity Supply	23.4	89 Heritage Activities	-93.1
2020 Q2	34 Machinery and Equipment Wholesaling	12.9	45 Food and Beverage Services	-255.4

Figure 1: *The Highest and lowest five sub-sectors' employment change ('000) in 2020:Q2*

Figure 2 illustrates the changes of raw data for 19 sectors in a more disaggregated manner. Due to the closedown of businesses and travel bans on 2020:Q2, we can observe that the number dropped substaincially (from around 13200 to 12200 on $2020 : Q2$). Most industries behaved similarly with significant changes shown in Figure 2 . Comparing with the previous data of these industries, Accommodation&Food, Media&telecom and Administrative industries have experienced a severe loss of employment and have not fully recovered to the pre-covid level. However, industries like Financial and Electricity, Gas show an continuously increase trend as before. This maybe due to the government subsidy in the Financial area and the rise of household demand of electricity during lockdown.

Meanwhile, at 87 sub-sector level (the most disaggregated) in Figure 1, we can conclude that the Food and Beverage Service experienced a severe shock after the lockdown, following by Heritage Activities and Other Store-Based Retailing.Figure 3 demonstrates the performance of each industry in the most disaggregated level, we can see sub-sectors we mentioned before have shown a hugh decreasing in employment people. It further proves that the employment decreases hughly in those sub-sectors mentioned before.

Nevertheless, there is a draw back of sectoral employment by comparing Figure 2 and Figure 3, that is subsectoral performance may not be homogeneous with their sectoral level (upper-level). For some industries in these two figures, the hugh changes usually driven by some dominant sub-sectors. For example, in 19 sectoral level we may believe that all of the Accommodation & Food subsectors experienced a large shock by only looking their aggregated performance for Construction sector. (see Figure 2). However, the reality is while Construction sector is decreasing, its sub-sectors 20.Building Construction and and 31.Heavy and civil engineering Construction increased(see Figure 3). This means that not all sub-sectors suffered from the COVID-19 even the overall industry got influenced.

5 Methdology

5.1 Proposed Model

At the moment, we plan to use a Bayesian VARX model based on a method proposed by Anderson et al. (2020). In the model, each sector is affected by the lags of sectoral growth and a lag of the total employment growth, where the lag of aggregated employment act as an economy-wide factor which will affect each sector.

Under the assumption that the structure of Australian economy will not change during the COVID-19, we suggest the BVAR model as

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \mathbf{A}_3\mathbf{y}_{t-3} + \mathbf{A}_4\mathbf{y}_{t-4} + \mathbf{\Gamma x_{t-1}} + \mathbf{u_t}$$

where $\mathbf{y_t}$ is an 87×1 vector of subsectoral employment growth rate at time t and $\mathbf{x_{t-1}}$ is the 4×1 vector of 4 lags of the aggregated employment (this vector of variables are predetermined at time t), $\mathbf{c}$ is a vector of constants, $\mathbf{A_{1,2,3,4}}$ are 87×87 parameter matrices. $\mathbf{\Gamma}$ is a 87×4 matrix and $\mathbf{u_t}$ is a vector of reduced form errors with the mean equals to zero and independent variance $\mathbf{u_t} \sim (\mathbf{0}, \mathbf{\Sigma})$. (see Appendix)

5.2 Prior and shrinkage

We plan to estimate the VARX using Bayesian methods by specifying a Minnesota prior (e.g. Anderson et al., 2020; Litterman, 1986; Robertson & Tallman, 1999) at this stage. In order to set up the Minnesota prior in our BVAR model, Bańbura, Giannone, and Reichlin (2010) suggestes that we can specify a nature conjugate Normal-Wishart prior and apply shrinkage to the VAR slope coefficients using a Minnesota-type prior.

$$E[a_j^{jk}] = E[\gamma_i^j] = 0$$

$$Var[a_j^{jk}] = \begin{cases} \frac{\lambda^2}{i^2}, & j = k \\ \frac{\lambda^2}{i^2}\frac{\sigma_j^2}{\sigma_k^2}, & otherwise \end{cases}$$

$$Var[\gamma_i^j] = \frac{\lambda^2}{i^2}\frac{\sigma_j^2}{\sigma_e^2}$$

Bańbura, Giannone, and Reichlin (2010) stated that the natural conjugate Normal-Inverse-Wishart posterior moments can be calculated either analytically or though adding the dummy observations. In our study, we will use dummy observations to estimate the BVAR e.g.(Bańbura, Giannone, & Reichlin,

Table 1: *Completed work*

Timeline	Tasks
Week 2	Background reading about Multivariate VAR model
Week 3	Collect Sub-sectoral data from ABS website
	Prepare materials reltaed to subsectoral employment evaluations
Week 4	Prepare literature review related to BVAR model and setting priors
	Analysis about the MATLAB code done by Andereson et al. (2020)
Week 5	Read articles about Conditional Forecasting
Week 6	Prepare the conditional forecasting coding and hierarchical forecasting
Week 7	Exploratory data analysis on sectoral and subsectoral data
Week 8	Select suitable plots and test softwares to prepare the proposal
week 9	Write research proposal and prepare the first presentation

Table 2: *Research plan*

Timeline	Tasks
June - July	Modelling of subsectoral employment
August	Train the model using pre-covid data with different univariate models
September	apply foreecasts for quarters between 2020 to 2022
October	Write my thesis and prepare for the second presentation

2010; Anderson et al., 2020; Woźniak, 2016). An example completed by Anderson et al. (2020) will be given in the Appendix. After the estimation of Bayesian VAR and then amounts to conducting least squares, we can draw our VAR coefficients by solving the posterior mode and mean.

6 Timeline and expected outcome

Table 1 summarises the work done to date. Table 2 maps out the plan for completing the thesis research.

It is expected that we will have an accurate multivariate BVAR model to forecast the scenario without COVID-19 based on the data of 87 sub-sectors before 2019. Then we have some

7 Acknowledgement

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8 Appendix

Here is an example of the BVAR estimation done by Anderson et al. (2020).

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2 + \cdots + \mathbf{A}_4\mathbf{y}_{t-4} + \mathbf{\Gamma}_1\mathbf{x}_{\mathbf{t-1}} + \mathbf{u}_\mathbf{t} \tag{1}$$

$$= \begin{bmatrix} c_1 \\ \vdots \\ c_2 \end{bmatrix} + \begin{bmatrix} a_1^{11} & \cdots & a_1^{1n} & \cdots & a_4^{11} & \cdots & a_4^{1n} & \gamma_1^1 & \cdots & \gamma_4^1 \\ \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ a_1^{n1} & \cdots & a_1^{nn} & \cdots & a_4^{n1} & \cdots & a_4^{nn} & \gamma_1^n & \cdots & \gamma_4^n \end{bmatrix} \begin{bmatrix} \mathbf{y}_{\mathbf{t-1}} \\ \vdots \\ \mathbf{y}_{\mathbf{t-4}} \\ x_{t-1} \\ \vdots \\ x_{t-4} \end{bmatrix} \tag{2}$$

$$+ \begin{bmatrix} u_{1,t} \\ \vdots \\ u_{n,t} \end{bmatrix} \tag{3}$$

$$\tag{4}$$

where $E(\mathbf{u}_\mathbf{t}\mathbf{u}_\mathbf{t}') = \mathbf{\Sigma}$ and $E(\mathbf{u}_\mathbf{t}\mathbf{u'}_{\mathbf{t-1}}) = \mathbf{0}$. Here the n represent the number of sectors (or in our case will be 87) and $c$represents the vector of constants. There are 4 lags included for the total employment $(x_{t-1}, \cdots, x_{t-4})$ as predetermined variable at time t.

Here is an Minnesota prior example done by Anderson et al. (2020):

The Normal-Wishart prior distribution take the form of

$$vec(\beta|\Sigma) \sim N(vec(\beta_0), \mathbf{\Sigma} \otimes \mathbf{\Omega_0}) \textbf{ and}$$

$$\Sigma \sim \mathbf{IW}(S_0, a_0)$$

where we set the prior parameters and a_0 based on the prior setting. The expectation of Σ being $diag(\sigma_1^2, \cdots, \sigma_n^2$. Then we implement our VAR by defining dummy observations

$$Y_d = \begin{pmatrix} \mathbf{0_{np+p,n}} \\ \mathbf{diag}(\sigma_1, \cdots, \sigma_\mathbf{n}) \\ \mathbf{0_{1\times n}} \end{pmatrix}$$

$$X_d = \begin{pmatrix} \mathbf{J_p} \otimes \mathbf{diag}(\frac{\sigma_1}{\lambda} \cdots \frac{\sigma_\mathbf{n}}{\lambda}, \frac{\sigma_\mathbf{e}}{\lambda}) & \mathbf{0_{(np+p)\times 1}} \\ \mathbf{0_{n,np+p}} & \mathbf{0_{n\times 1}} \\ \mathbf{0_{1,np+p}} & \epsilon \end{pmatrix}$$

where

$$\mathbf{J_p} = \mathbf{diag}(\mathbf{1}, \cdots, \mathbf{p})$$

$$\mathbf{S_0} = (\mathbf{Y_d} - \mathbf{X_d} \times \mathbf{B_0})'(\mathbf{Y_d} - \mathbf{X_d}\mathbf{B_0})$$

$$\mathbf{B_0} = (\mathbf{X_d'}\mathbf{X_d})^{-1}\mathbf{X_d}\mathbf{Y_d},\ \mathbf{\Omega_0} = (\mathbf{X_d'}\mathbf{X_d})^{-1}\ \textbf{and}$$

$$a_0 = T_d - np - p - 1$$

where T_d is the number of rows for both $\mathbf{Y_d}$ and $\mathbf{X_d}$.

We can get

$$\mathbf{Y}^* = \mathbf{X}^*\beta + \mu^* \quad \textbf{where :}$$

$$\mathbf{Y}^* = [\mathbf{Y}', \mathbf{Y_d'}]';\ \mathbf{X}^* = [\mathbf{X}', \mathbf{X_d'}]';\ \mu^* = [\mu', \mu_\mathbf{d}']'$$

Then we can estimating the BVAR by conducting an least square regression of Y^* onX^*. The posterior distribution then have the form of

$$vec(\beta)|\Sigma, Y \sim N(vec(\tilde{\beta}), \mathbf{\Sigma} \otimes (\mathbf{X}^{*\prime}\mathbf{X}^*)^{-1})\ \textbf{and}$$

$$\Sigma|Y \sim \mathbf{IW}(\tilde{\Sigma}, T_d + T - np + 2)$$

where $\tilde{\beta} = (\mathbf{X}*' \mathbf{X}*)^{-1}\mathbf{X}^{*'}\mathbf{Y}^*$ and $\tilde{\Sigma} = (\mathbf{Y}^* - \mathbf{X}^*\tilde{\beta})'(\mathbf{Y}^* - \mathbf{X}^*\tilde{\beta})$

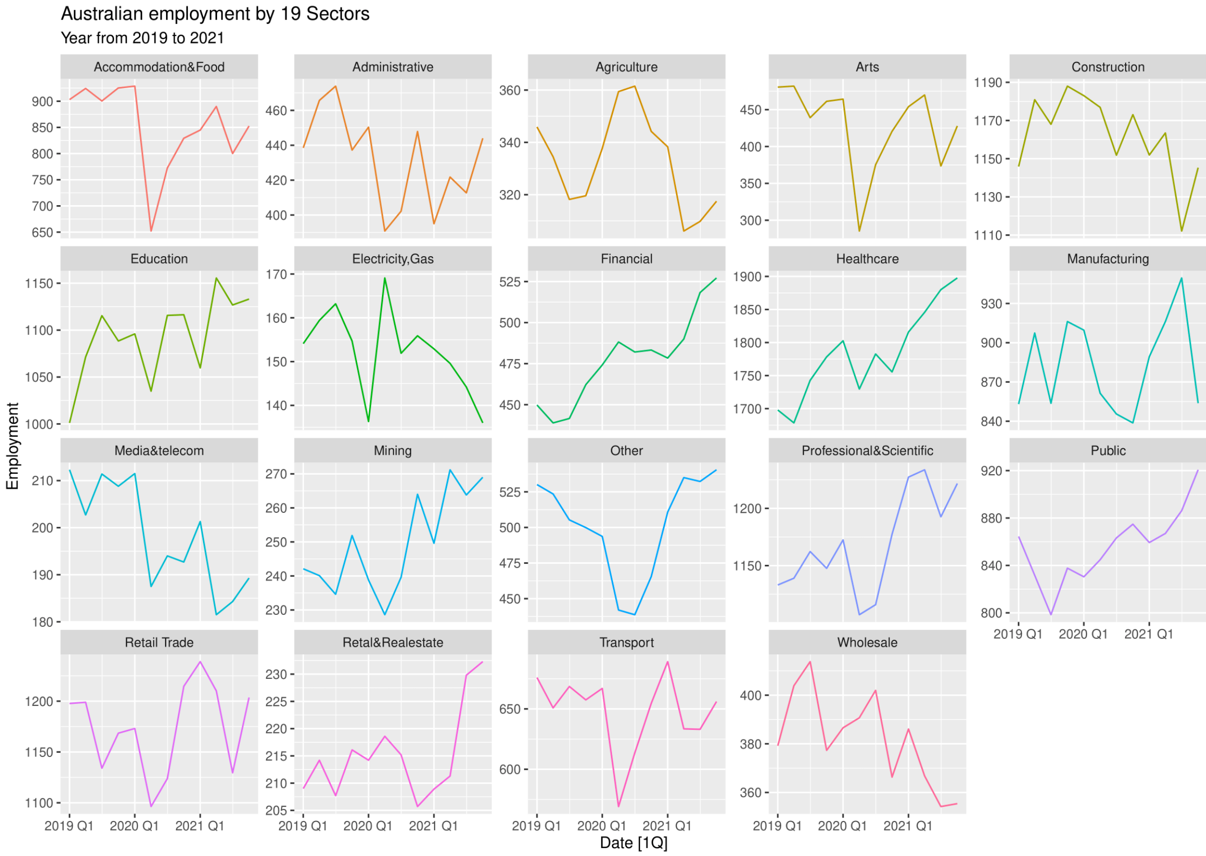

Figure 2: *Employment('000) of 19 sectors in Australia from 2019:Q1 to 2021:Q4*

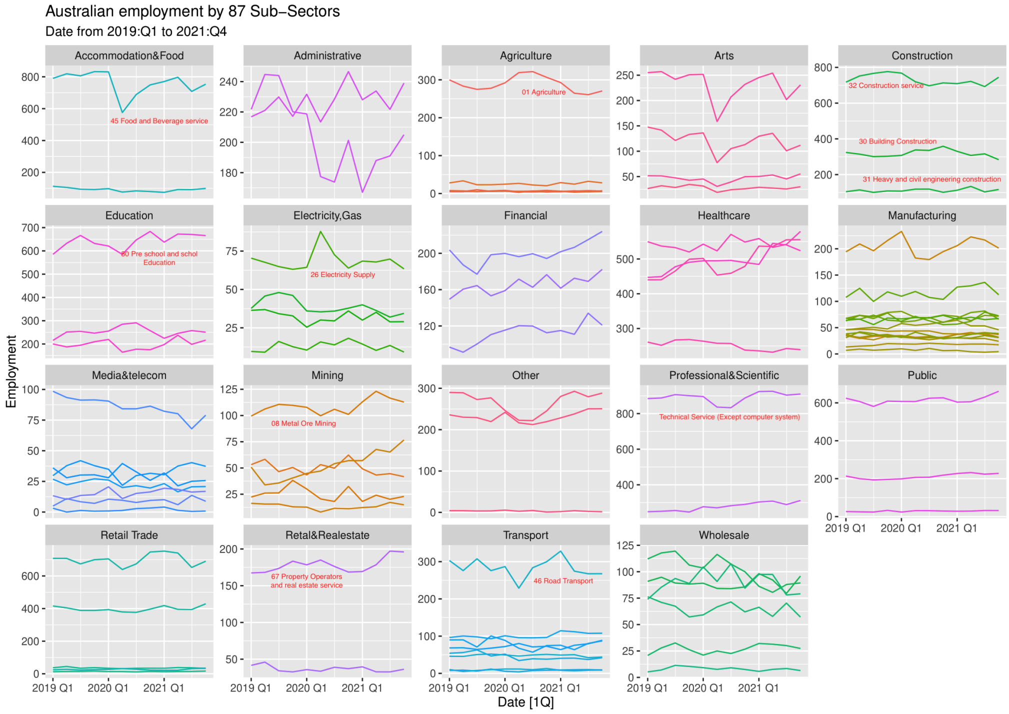

Figure 3: *Employment('000) of 87 sub-sectors in Australia from 2019:Q1 to 2021:Q4*

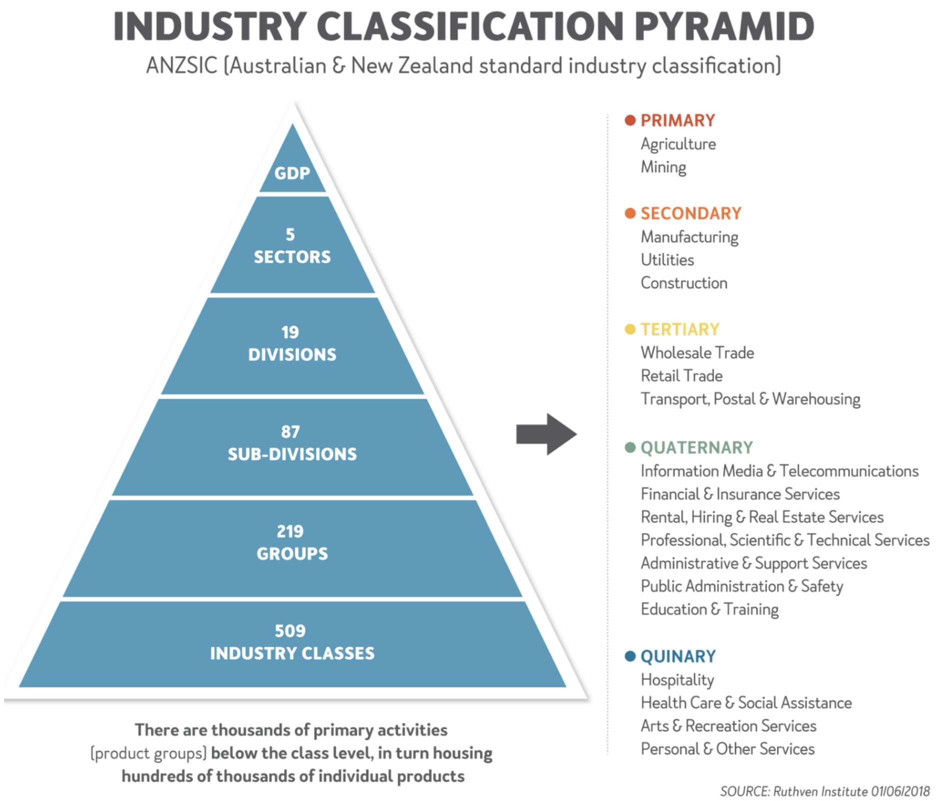

Figure 4: *Australian Industry Pamamid plot by (ANZSIC)*

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