Disaggregated Sectoral Employment Dynamics in Australia

A thesis submitted for the degree of

Bachelor of Commerce (Honours)

by

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Contents

Acknowledgement

I would like to express gratitude to my supervisor Professor Farshid Vahid and my coordinatior Professor Heather Anderson for their selfless support and devoted care along the way.

Declaration

I declare that this thesis contains no material which has been submitted in any form for the award of any other degree or diploma in any university or equivalent institution, and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

– Signature: ***Elvis Zhixiang Yang***

Abstract

I develop a multivariate time series model of employment in Australia at a disaggregated level with 87 sectors in total. I use this model to determine the long run employment spillovers to the total employment at this level. Our findings is that …

Moreover, I provide an interactive shiny app that will give an intuitive visualization of these changes. At the stage of recovering from COVID-19, it will provide more useful information for policymakers on recovering total employment rate more effectively.

Chapter 1

The Australian COVID-19 Pandemic Background

The COVID-19 pandemic has had 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 and Hsu, 2020). The 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 continuous "lockdown" periods in 2020, estimates made by the Australian Bureau of Statistics (ABS, 2021) concluded that 72% of businesses generated less revenue and the underemployment rate hit a historical high of 13.8% by the end of April, 2020, only one month after the COVID-19 outbreak.

Our research is motivated by the lack of quantitative research on the employment of two-digit disaggregated industry sectors in Australia, as many studies have focused on the aggregated employment rate. A general problem of aggregated research is the loss of hierarchical information, which may result in a biased conclusion or "an illusion of employment prosperity". Thus, a quantitative analysis of the sectoral employment will ameliorate this problem, giving us a better scope to evaluate the impacts of COVID-19 in Australia.

1.1 Research Aim and questions

This research will extend Anderson et al. (2020) by using data on 87 two-digit industry sectors instead of 19 sectors that they used. I will develop a model for the two-digit sectors to evaluate the long run effect and the COVID-19 post-impacts. I will also provide a counterfactual analysis based on an optimistic assumption of no pandemic or major events happened. The two-digit sectoral data will provide us with more information, which will assist in getting a better understanding of employment dynamics in Australia on a disaggregated level.

The overall research aim is to provide estimates of two-digit sectoral employment based on historical data. Specifically, my goals are:

1. To construct a time series model of employment in 87 two-digit sectors of the Australian economy.
2. To use this model to conduct a counterfactual analysis.
3. To use this model to determine which two-digit sectors have the highest impact (or positive spillover) on employment growth in the long run.

1.2 Thesis Structure

This thesis focuses on analysing Australian Employment at a disaggregated level, then estimate the long run effects of the COVID-19 to sectoral employment rate in Australia. The remainder of the thesis is structured as follows. First, in chapter 2, I review the existing literature in the relevant fields. Second, in chapter 3, I will provide exploratory data analysis and data resources. Then, I will propose our selected model in chapter 4. After we selected our model, I will conduct analysis to evaluate the damages of COVID-19 and provide useful insights on key beneficial industries after COVID-19 in chapter 5. Eventually, I will provide policy implementations and discussions in chapter 6.

Chapter 2

Review of literature

Our review of literature mainly focuses on two areas:

1. The COVID-19 sectoral impacts and modelling of the economy.
2. Modelling of large numbers of time series.

2.1 Sectoral Impact of COVID-19.

Most existing studies have focused on the evaluation of the impacts of COVID-19 on broad sectors of 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 model them as sectoral shocks to predict COVID-19. They concluded that the shock would lead to a cumulative loss of 20% in industrial production, 39% in public services and also reduce the US GDP by 12.75 per cent by 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 the US is L-shaped, with employment remaining lower than pre-covid for a long period. They also extended their studies at a disaggregated level of 20 sectors, 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 model for 19 main sectors in Australia (as a small open economy) using a Bayesian VARX model. Their research concluded that "Manufacturing" and "Construction" have the 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 the pandemic in Australia. However, their research does not use a finely disaggregated level in Australia (two-digit subsectors of main sectors), which can be extremely useful in macroeconomic analysis.

2.2 Baysian VAR

The Bayesian Vector Autoregression model (BVAR) is commonly used in the literature for multivariate data (e.g. Anderson et al., 2020; Litterman, 1986; Bańbura, Giannone, and Reichlin, 2010). The BVAR model is attractive because it allows us to estimate a large number of parameters, when the sample size is not large, in a statistically coherent way.(Litterman, 1986; Woźniak, 2016).

In order to utilize the Bayesian VAR estimators Litterman et al. (1979) proposed the Minnesota Prior, which decreases the weight of the lagged variables with the lag length. The prior mean on the 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; and *(b)* own lags should explain more than the lags of other variables.

2.3 Improvement of BVAR

The literature suggests that a significant improvement can be made in large BVAR dynamic models by imposing a stronger prior assumption (Bańbura, Giannone, and Reichlin, 2010; Litterman, 1986). Robertson and Tallman (1999) and Kadiyala and Karlsson (1997) proposed a Normal-inverse-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 into the BVAR system.

Chapter 3

Data collection and exploratory analysis

3.1 Data Introduction and wrangling

The data I use in this thesis come from the Australia Bureau of Statistics (ABS), involving 87 industry sub-division of main jobs. The ABS records the employment (measured in *thousands*) from $1984 : Q4$ to $2021 : Q4$ with a structure provided via Figure B.5.

Although seasonally adjusted data is available in (ABS, 2022), the method of seasonal adjustment used by ABS is unknown. Therefore, I choose to work with the original data to capture any possible changes in seasonal patterns instead of the seasonally adjusted data provided by Australian Bureau of Statistics.

Since the original data from ABS is not tidy. In this thesis, I use the Excel to extract both the employment for both two-digit disaggregated level and the total employment. Then, I take the following modifications to deal with zeros, meanwhile, keeping the data structure coherent. The cleaned data can be seen in *ABSemp.xlsx* file at (`https://github.com/elvisssyang/Disaggregated_Employment`).

- Merge the two-digit subsector *57- Internet Publishing and Boardcasting* and *54- Publishing(except internet)* to be come *54 Publishing and boadcasting*.

- Merge the *96 Private Households Employing Staff and Undifferentiated Goodsand Service Producing Activities of Households for Own Use* and *95 Personal and Other Services* to become *95 Personal and other services (include activities for own use)*.
- I will also not address the non-classified series in this thesis due to the data contains many zeros and hard to be distributed into specific sectors (we cannot effectively trace the source of them). To make the forecasts coherent (sum to the total employment) and analysis universal, I will not consider them in our analysis.

Without any zeros, a log transformation can be applied to interprete the percentage change of the employment. The VAR model decided to fit the data requires stationary. As a result, I will further apply a seasonal difference to eliminate the seasonality (i.e. nonstationarity).

3.2 Preliminary Exploratory Data Analysis

Figure B.1 illustrates the changes in the raw data for 19 main sectors in Australia during the pandemic. Due to the closedown of businesses and travel bans on 2020:Q2, we can observe that the total employment number dropped substantially (from around 13,200,000 to 12,200,000 on $2020:Q2$). Most industries behaved similarly with significant changes shown in Figure B.1 . 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, some industries like "Financial" and "Electricity & Gas" showed a continuously increasing trend as before.

Nevertheless, there is a drawback of considering the 19 board sectors only; because the two-digit subsectoral dynamics of these sectors may not be homogeneous with their aggregated sectoral changes. For example, when observing the aggregated performance of the "Manufacturing" and "Mining" sectors from the 19 sectoral level (see Figure B.3), we may believe that their corresponding subsectors should illustrate the same pattern. However, the reality is that while there is a decreasing trend in the "Manufacturing" sector or an increasing trend in the "Mining" sector, some of their two-digit subsectors are performed differently (see Figure B.4). This means that not all two-digit subsectors follow the same pattern with the aggregated sectoral level.

Table 3.1 shows the top five and bottom five two-digit subsectors in terms of their employment growth during the pandemic. From 3.1 we can conclude that the "Forestry and Logging"

Date	Sector	Percentage Changes
2020:Q2	27 Gas Supply	50.48%
2020: Q2	57 Internet Publishing and Broadcasting	44.44%
2020: Q2	56 Broadcasting	41.43%
2020: Q2	26 Electricity Supply	36.34%
2020: Q2	20 Non-Metallic Mineral Product Manufacturing	32.37%

Date	Sectors	Percentage Changes
2020: Q2	03 Forestry and Logging	-55.88%
2020: Q2	96 Private Households Employing Staff	-49.09%
2020: Q2	60 Library and Other Information Services	-46.60%
2020: Q2	02 Aquaculture	-44.58%
2020: Q2	91 Sports and Recreation Activities	-43.71%

Table 3.1: *The highest and lowest five two-digit subsectors' employment percentage change for 2020:Q1 to 2020:Q2*

experienced a severe shock after the lockdown happened on 2020:Q2, followed by "Private Households Employing Staff" and "Library and Other Information Services". Figure B.2 demonstrates the performance of each industry at a more disaggregated two-digit subsectoral level, we can observe that many two-digit subsectors have also shown huge decreases in employment in 2020:Q2.

Chapter 4

Methdology

4.1 Proposed Model

I 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 lag of sectoral growth and a lag of the total employment growth. The lag of aggregate employment growth acts as an economy-wide factor which will affect each sector.

Conventionally, lags are selected correspond to the patterns of the time series (i.e. seasonality, cycle or trend). That is, for quarterly employment data, four lags are preferred in general (see Anderson et al. (2020) and Stock and Watson (2001)). However, in concern of the dimensionality in my case. In large Bayesian VAR, distant lags can be shrunk by assigning a specific prior distribution. This will make the similar amount information provided by either four lags or one lag. Thus, given I will replace the four lags with one lag on both 84 sectors and the total employment because one lags can effectively avoid overfitting while provide sufficient information.

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

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{y}_{t-1} + \mathbf{\Gamma} x_{t-1} + \mathbf{u_t}$$

where $\mathbf{y_t}$ is an 84×1 vector of two-digit subsectoral employment growth rate at time t and $\mathbf{x_{t-1}}$ is a 1×1 vector stands for one lag on the growth rate of the total employment (this vector of variables are predetermined at time t), $\mathbf{c}$ is a vector of constants, $\mathbf{A_1}$ are 84×84 parameter matrices. $\mathbf{\Gamma}$ is a 84×4 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 for details)

4.2 Prior and shrinkage

Bayesian VAR helps to overcome the curse of high dimensionality via the imposition of prior beliefs on the parameters (Bańbura, Giannone, and Reichlin, 2010). I will estimate the dynamics using Bayesian VAR model by specifying a Minnesota prior (e.g. Anderson et al., 2020; Litterman, 1986; Robertson and Tallman, 1999). In order to set up the Minnesota prior in our BVAR model, Bańbura, Giannone, and Reichlin (2010) suggests a Minnesota-type prior that applies shrinkage to the VAR slope coefficients as follows:

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

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

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

where the degree of shrinkage is governed by λ, $\frac{1}{i^2}$ to down-weight more distant lags and the $\frac{\sigma_j^2}{\sigma_k^2}$ adjusts for different scale of the data. σ_e^2 is the variance after fitting an AR model on total employment growth.

Bańbura, Giannone, and Reichlin (2010) also suggested that a natural conjugate Normal-Inverse-Wishart which retains the principle of Minnesota prior will help in adding Minnesota prior to the Bayesian VAR system. Its posterior moments can be calculated either analytically or through adding the dummy observations. I will use dummy observations to estimate the BVAR (Bańbura, Giannone, and Reichlin, 2010). More details are provided in the Appendix.

4.3 An new approach to select hyperparameter in Minnesota prior

Specifically, the Minnesota type prior have the following beliefs about the variances:

$$Var[a_i^{jk}] = \begin{cases} \frac{\lambda^2}{i^2}, & j = k \\ \frac{\lambda^2}{i^2}\frac{\sigma_j^2}{\sigma_k^2}, & otherwise \end{cases} \cdots (4.3.1)$$

$$Var[\gamma_i^j] = \frac{\lambda^2}{i^2}\frac{\sigma_j^2}{\sigma_e^2} \cdots (4.3.2)$$

where λ is a hyperparemeter here we need to specify based on how far we will shrink the estimator and $\frac{\sigma_j^2}{\sigma_k^2}$ adjusts for the different scale of the data. To effectively scale the estimator on total employment growth γ, I will fit an AR(1) to on the total employment growth as mentioned in *Chapter 4.1*

In equation 4.3.1, we can see as i (number of estimators) increases, the $Var[a_i^{jk}]$ will then decrease in both cases, which preserved the structure of Minnesota Prior to weight down more distant lags.

As the Minnesota prior described from the above equation (4.3.1 and 4.3.2), the hyperparameter λ controls the overall tightness (variance) of the prior distribution (Bańbura, Giannone, and Reichlin, 2010). If $\lambda = 0$, we can see that the prior have no variance, which means the posterior equals the prior and the data have no influence on the estimates. On the contrary, if $\lambda = \infty$, the posterior expectations will be same as ordinary least squares (OLS) estimates. In practice, we tend to shrink the forecasts to the mean value, which is an valid method for many macroeconomic data, which have mean reversion pattern. Therefore, a small λ shrink the posterior mean towards the zero will greatly benefit the forecasting.

Admittedly, the selection of hyperparameter λ is important in improving forecast accuracy by controlling the degree of shrinkage. For example, Bańbura, Giannone, and Reichlin (2010) point out that a gain in efficiency could be made by applying an Bayesian shrinkage in estimating large multivariate VAR models. Moreover, they also conclude that large vector autoregressions (VARs) with shrinkage are credible to conduct structural analysis. Nonetheless, the main problem that encountered is to set an appropriate value for λ as models become larger (i.e. how far it will shrink the estimators). Based on applied experiences, Litterman concluded that the shrinkage estimate $\lambda = 0.2$ is indeed sufficient to deal with many empirical cases (Litterman, 1986). Apart from this, the data size is also an essential basis to be considered when deciding the degree of shrinkage (Bańbura, Giannone, and Reichlin, 2010). Unlike the one-digit level (19 sectors) did by Anderson et al. (2020), the two-digit level (87 sectors) employment in Australia is more complex and have more variables. Thus, a new shrinkage parameter λ should be specified particularly for this case.

In concern of the size of industries, different two-digit disaggregated sectors may have different sizes and on different scales. It is quite obvious that traditional scaled dependent error measurements (e.g. MAE, MSE) will no longer holds. Even though MAPE being unit-free, it is not appropriate because a tiny change in forecasts in a small disaggregated industry will have significant effects on its MAPE. Accordingly, I will aggregate all sectors to the total employment to handle this problem. Consequently, we will only need to minimise the forecast error of total employment in our case to select the optimal λ.

To simulate forecasting performance, I conduct an out-of-sample forecasting experiment. Here,I denote H as our longest forecast horizon to be evaluated, and by T_b and T_e the beginning and the end of the testing sample, respectively. Under a given forecast horizon h, lambda value λ and model m, for each given period between T_b and T_e, we computer h-step-ahead forecasts.

Out-of-sample forecast accuracy is measured in terms of the mean squared forecast error (**MSFE**).

$$MSFE_{i,h}^{(\lambda),m} = \frac{1}{T_e - T_b} \Sigma_{T=T_b+H-h}^{T_e-h} (y_{i,T+h|T}^{(\lambda,m)} - y_{i,T+h})$$

where $y_{i,T+h|T}^{(\lambda,m)}$ is defined as the hth steps ahead forecast given the information up to time T and $y_{i,T+h}$ is the actual data for the hth steps ahead forecast.

In this section, I will provide an effective searching algorithm to evaluate the optimal shrinkage estimator λ. For our purposes, we want to provide accurate forecasts based on the scenario where no covid happened to support our counterfactual analysis. Therefore, the pre-covid data (before 2020 Quarter One) is split into training/test with a training set of length $n = 120$ as T_b and test set of length $n = 22$ as T_e. As a consequence, I will set the $H = 22$ being equal to the length of test set, $h = 1$ for one step experiment, Here is a brief description of our proposed algorithm:

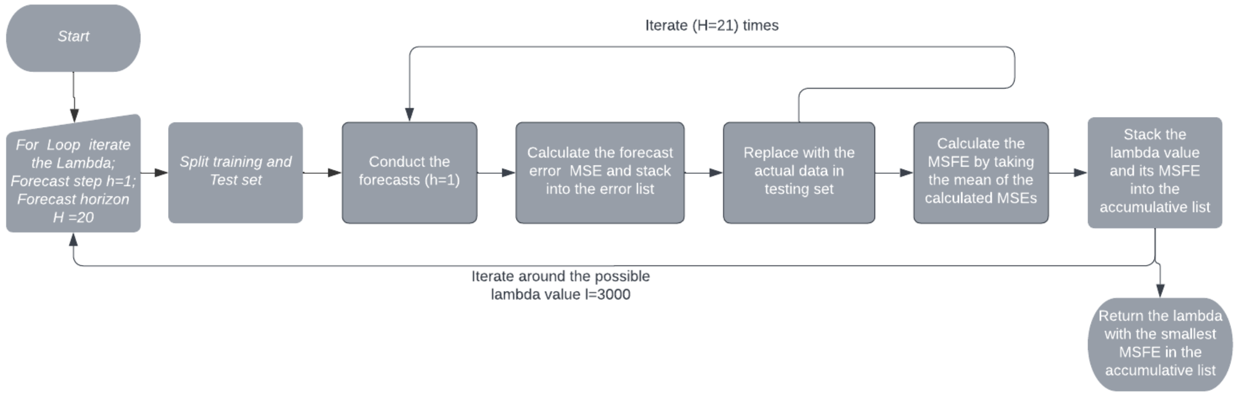

Figure 4.1: *Proposed algorithm of selecting optimal λ*

To mitigate the impact of high-dimensionality. I designed algorithm starting from 0.0001, with a step of 0.0001 and will stop at 0.3. There are 3000 different lambdas are considered and it will automatically return the lambda with minimum MSFE (see Matlab code in my github [Link https://github.com/elvisssyang/Disaggregated_Employment/tree/main/Matlab]).

In summary, we prefer the value of λ that has the lowest MAFE for our total employment. From the return value of our searching algorithm (see Figure 4.1). The estimated hyperparameter $\lambda = 0.0808$ has the lowest mean scaled forecast error (MSFE). Therefore, we conclude that the hyperparameter $\lambda = 0.0808$ outperforms other values in our training steps, which will be applied into our Minnesota prior.

Chapter 5

Sectoral Employment Analysis

5.1 Evaluations after COVID-19

5.2 Long-run Multiplier Analysis

Due to the reason that industries are interdependent, we should notice that the change of one sector may have influences on both total employment and other sectors. In this thesis, I will use the structure of multivariate BVAR to capture the dynamics of sectoral employment for each disaggregated sector.

This analysis is based on the estimated BVAR model and the 87 two-digit disaggregated data.

At each time period, we have :

$$GR_T = \sum_{j=1}^{87} w_j \times GR_j$$

where w_j is the share of employment of two-digit subsector j in the total employment, GR_T is the growth rate in total employment and GR_j is the growth rate in employment of two-digit subsector j.

In particular, if there is a one percent increase in sector i, the total employment will increase by sector i's share simultaneously. Nonetheless, given the increase in total employment in sector i may also have indirect effects to other sectors in consecutive periods, especially for sectors with similar economic pattens. Therefore, I define the long-run employment multiplier as the effect of initial increase in sector *i* onto the total employment in the long-run , which follow the definition stated in Anderson et al. (2020). Admittedly, if the long-run effect is larger than the immediate effect for this sector, then stimulate this sector will have positive spillover effect onto the total employment.

I use the estimated BVAR model to simulate the long-run employment multiplier for each specific sector with the horizons of one year, two year and ten years. Subsequently, the differences between the simulated five year multipliers and the initial shares are the spillovers of the two-digit subsectors.

Compare the long-term multipliers with the shares of sectors, we can find that `Furniture and Other Manufacturing`, followed by `Broadcasting (except Internet)`, `Agriculture, Forestry and Fishing Support Services` generate the strongest positive spillover to the total economy. They belongs to the `Manufacturing`, `Agriculture` and `Information, Media & Telecom` respectively.

A very interesting fact

Chapter 6

Discussions and conclusion

6.1 Policy Implications

6.2 Limitation and possible extensions

Appendix A

An Example of Bayesian VAR Prior

The VARX model is:

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

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

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

$$\tag{A.4}$$

where $\mathbb{E}(\boldsymbol{u}_t\boldsymbol{u}_t') = \boldsymbol{\Sigma}$ and $\mathbb{E}(\boldsymbol{u}_t\boldsymbol{u'}_{t-1}) = 0$. Here the n represent the number of sectors (in our case this will be 87) and $\boldsymbol{c}$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.

Then we implement our VAR by defining $(np + n + 1)$ dummy observations.

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

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

where

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

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

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

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

where T_d is the number of rows for both $\boldsymbol{Y}_d$ and $\boldsymbol{X}_d$.

We can get

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

$$\boldsymbol{Y}^* = [\boldsymbol{Y'}, \boldsymbol{Y_d'}]';\ \boldsymbol{X}^* = [\boldsymbol{X'}, \boldsymbol{X_d'}]';\ \boldsymbol{\mu}^* = [\boldsymbol{\mu'}, \boldsymbol{\mu_d'}]'$$

Then we can estimating the BVAR by conducting least squares regression of $\boldsymbol{Y}^*$ on$\boldsymbol{X}^*$. The posterior distribution then has the form of

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

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

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

Appendix B

Graphs

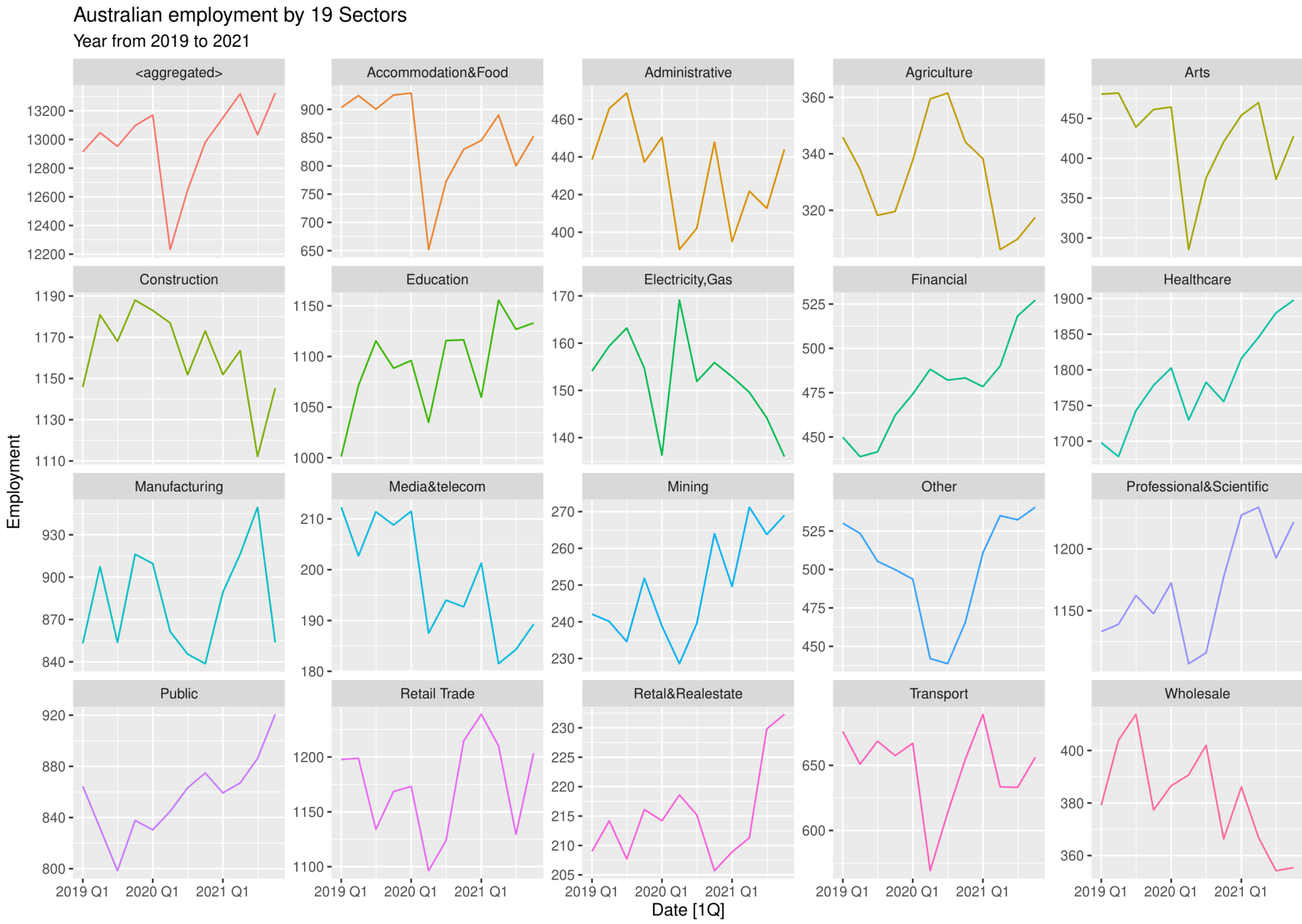

Figure B.1: *Employment('000) of 19 sectors in Australia from 2019:Q1 to 2021:Q4*

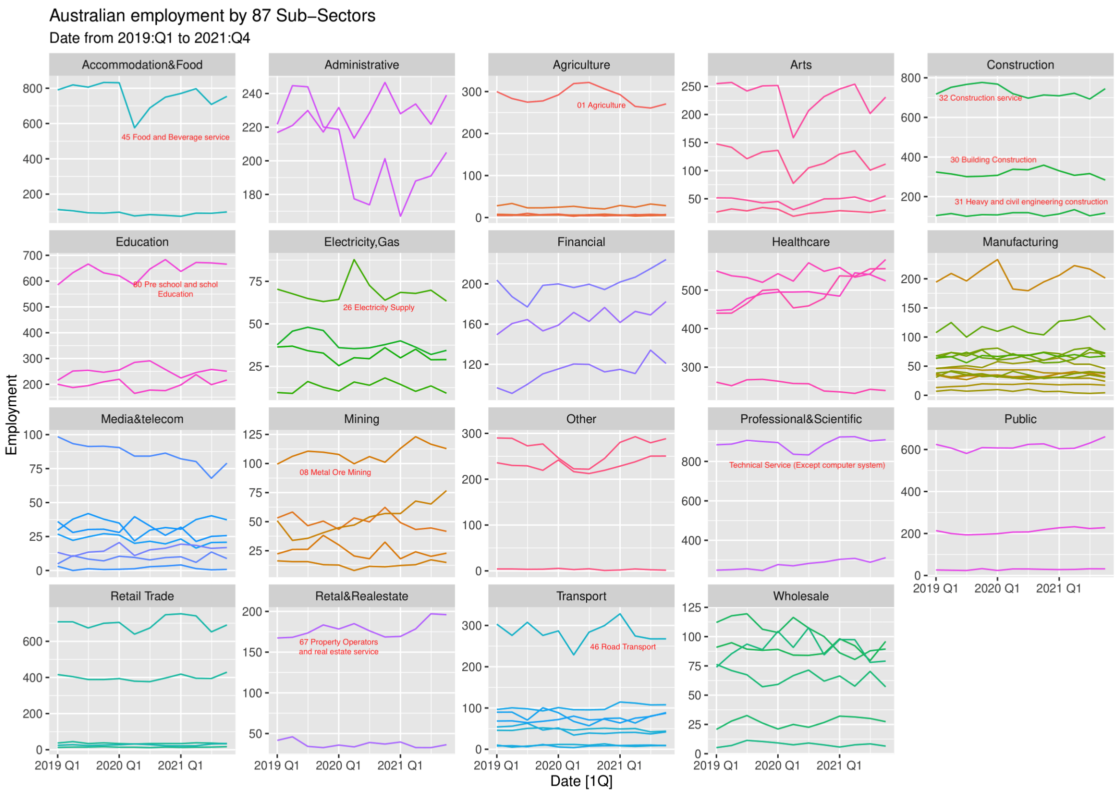

Figure B.2: *Employment('000) of 87 two-digit subsectors in Australia from 2019:Q1 to 2021:Q4*

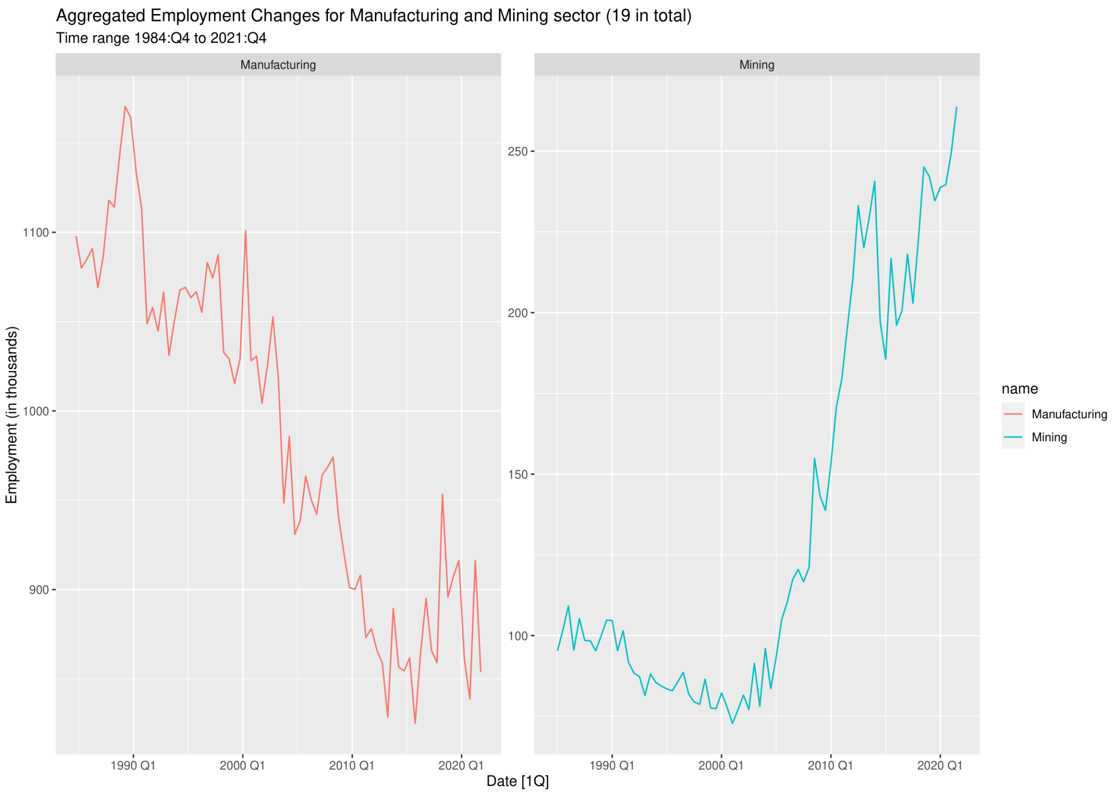

Figure B.3: *Aggregated Employment(in thousands) for Manufacturing and Mining sector in Australia from 1984:Q4 to 2021:Q4*

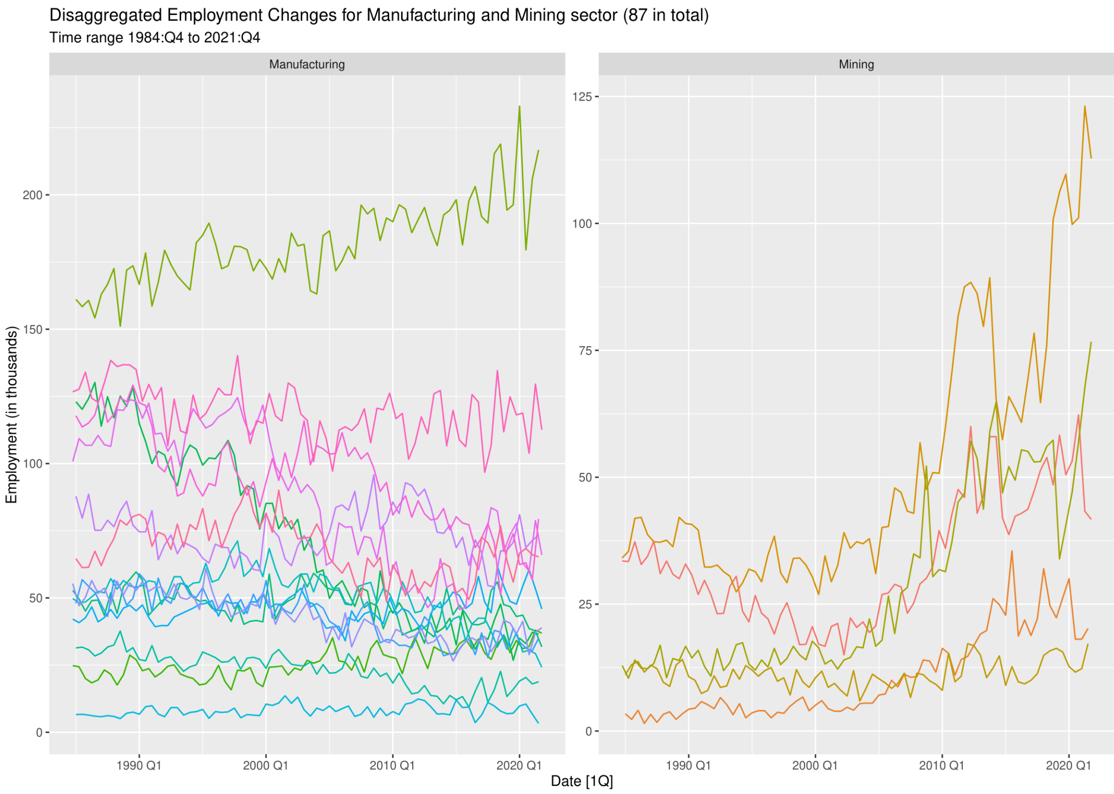

Figure B.4: *Disaaggregate Employment(in thousands) of 87 two-digit subsectors in Manufacturing and Mining sector from 1984:Q4 to 2021:Q4*

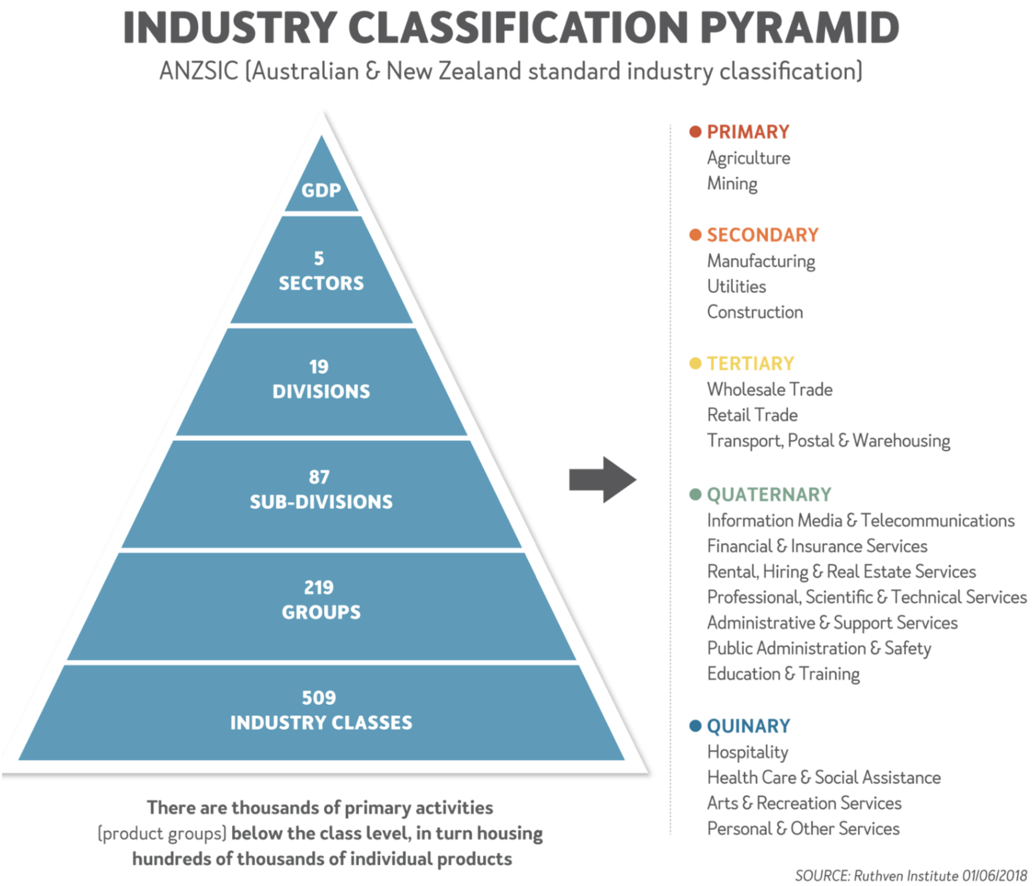

Figure B.5: *Australian Industry Pamamid plot by (ANZSIC)*

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