Disaggregated Sectoral Employment Dynamics in Australia

A thesis submitted for the degree of

Bachelor of Commerce (Honours)

by

Zhixiang Yang

30306396

Department of Econometrics and Business Statistics

Monash University

Australia

October 2022

Contents

Acknowledgement

I would like to express gratitude to my supervisor Professor Farshid Vahid and my coordinator Professor Heather M Anderson for their selfless support and devoted care along the way. I would also like to thank my family and Xiefei Li for their continuous supports and encouragement.

`Matlab version. 2022a` codes are used to generate the estimated coefficients for the proposed Bayesian VAR model. The author would like to thank Benjamin Wong for providing the MATLAB packages.

`R 4.1.2 "Bird Hipple"` (R Core Team, 2021a) and Rstudio `2022.07.1+554 "Spotted Wakerobin"` (RStudio Team, 2020) are used for data analysis in this thesis.

R package used and their versions in this research include `matrixStats 0.61.0` (Bengtsson, 2021), `ggplot2 3.3.5` (Wickham, 2016), `zoo 1.8.9` (Zeileis and Grothendieck, 2005), `tidyverse 1.3.1` (Wickham et al., 2019), `dplyr 1.0.8` (Wickham et al., 2022), `stats 4.1.2` (R Core Team, 2021b), `readr 2.1.2` (Wickham, Hester, and Bryan, 2022), `pracma 2.3.8` (Borchers, 2022), `lubridate 1.8.0` (Grolemund and Wickham, 2011), `fpp3 0.4.0` (Hyndman, 2021), `ggpubr 0.4.0`(Kassambara, 2020). (*Note: In no particular order above*)

This thesis is produced using the R package `bookdown 0.25` (Xie, 2016) with the Rmarkdown template package `monash 0.0.0.9000` for the honours thesis in the Department of Econometrics and Business Statistics, Monash University (Tanaka and Hyndman, 2022)

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 investigate the performance of Australian employment at a disaggregated level and compare the actual situation with the no-COVID situation, generated via a series of appropriate forecasting methods. A multivariate time series model is developed to determine the long run employment spillovers to the total employment at this level. My results suggest that in the two-digits subsectoral level, `Other Store-Based Retailing`, followed by `Administrative Services`, `Furniture and Other Manufacturing` will generate the strongest positive spillovers to the total economy. One of the main contributions of this paper is that the government can stimulate these high and positive spillovers to recover the total employment rate effectively and efficiently.

Moreover, I evaluate the impacts of COVID-19 on the Australian labour market with the conterfactual analysis. The outcomes demonstrate that the pandemic has a long-lasting effect on the economy. Besides, I point out the main reason behind the lowest unemployment rate record and uncover the underlying problems. The spillover analysis together with the evaluation, thus, provide another aspect for policymarkers to improve the Australian economy.

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, while 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 more information, which will assist in getting a better understanding of employment dynamics in Australia on a more 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 counterfactual 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 a brief conclusion and discuss the limitations of our works and possible future extensions 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. Bayesian VAR 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 U.S. 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 typical 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 informative in macroeconomic analysis.

2.2 Baysian VAR

The Bayesian Vector Autoregression model (BVAR) is commonly used in the literature for high-dimensional multivariate modelling (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 Setting Minnesota Prior with shrinkage

The literature suggests that a significant improvement in the predicting performance of large BVAR dynamic models can be made by more careful choice of prior assumptions (Bańbura, Giannone, and Reichlin, 2010; Litterman, 1986). Moreover, in setting the Minnesota Prior in our estimated model, Robertson and Tallman (1999) and Kadiyala and Karlsson (1997) proposed a Normal-inverse-Wishart prior which retains the principal of Minnesota prior. Particularly, Bańbura, Giannone, and Reichlin (2010) suggested an easier way to apply the Minnesota prior via adding dummy observations into the BVAR system (see Appendix for details).

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 86 industry sub-division of main jobs. The ABS records the employment (measured in thousands people ($'000$)) from $1984:Q4$ to $2021:Q4$ with a structure provided via Figure 3.1.

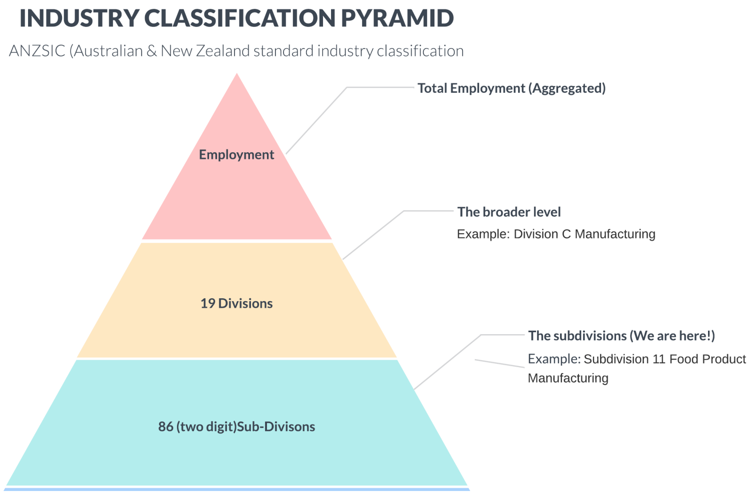

Figure 3.1: *Australian Industry Pamamid plot by (ANZSIC)*

Although seasonally adjusted data is available in (ABS, 2022a), however, the seasonal adjustment of post-COVID data is problematic due to the shocks caused by lockdowns would impact the post-covid seasonality. Hence, I use the original data to capture any possible changes in seasonal patterns instead of the seasonally adjusted data provided by Australian Bureau of Statistics.

In this thesis, I downloaded only the data from 1984 Quarter 4 to 2022 Quarter 2. Moreover, I use the Excel to extract both the employment for both two-digit disaggregated level and the total employment. Note that some of the data are zero, which is not feasible for a log transformation, so I will making the following modifications to remove them while keeping the structure of data coherent. Then, I take the following modifications to remove 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 a new combined subsector called *54 Publishing and boadcasting*.
- Combine the *96 Private Households Employing Staff and Undifferentiated Goodsand Service Producing Activities of Households for Own Use* and *95 Personal and Other Services* as *95 Personal and other services (include activities for own use)*.

It is notice that there are few non-classified series (nfd) in ABS employment data. However, I will not address these series in this thesis because there are no further details provided by ABS. If this is put into the model, it will influence the sectoral dynamics. To make the forecasts coherent (sum to the total employment) and analysis universal, I will not consider them in this thesis. As a result, my total employment data is not same as the published total employment data. The largest discrepancy, however, is only a small portion of the real total employment. Accordingly, this will not significantly affect 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).

Finally, in **Chapter 6**, I have also combine the following data to further support our conterfactual analysis:

- Total Labour Force: Gained from ABS website (see ABS (2022a))
- Unemployment Rate: Gained from ABS website (see ABS (2022b))

3.2 Preliminary Exploratory Data Analysis

Figure B.1 illustrates the changes in the raw data for 19 main sectors in Australia from 2010 to 2022. 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 "Arts" industries have experienced a severe loss of employment and have not fully recovered to the pre-covid level. However, some industries like "Financial" and "Healthcare" has barely changed and showed a continuously increasing trend as the pre-COVID period.

Nevertheless, there is a drawback of considering the 19 broad 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 year-on-year growth rate of "2022 Q2". From Table 3.1, we can see that "Other Transport" experienced a severe shock after the lockdown happened on "2020 Q2", followed by "Non-Metallic Mineral Mining and Quarrying" and "Sports and Recreation Activities". However, not all subsectors suffered a lot on "2020 Q2". Here, we can see that both "Water Transport" and "Gas Supply" had a remarkable increase, followed by "Broadcasting (excerpt Internet)" and "Exploration and Other Mining Support Services".

Date	Sector	YoY growth rate
2020: Q2	48 Water Transport	81.01%
2020: Q2	27Gas Supply	55.14%
2020: Q2	56 Broadcasting (except Internet)	34.49%
2020: Q2	10 Exploration and Other Mining Support Services	32.87%
2020: Q2	63 Insurance and Superannuation Funds	27.78%

Date	Sectors	YoY growth rate
2020: Q2	50 Other Transport	-78.98%
2020: Q2	09 Non-Metallic Mineral Mining and Quarrying	-66.92%
2020: Q2	91 Sports and Recreation Activities	-60.48%
2020: Q2	55 Motion Picture and Sound Recording Activities	-55.19%
2020: Q2	03 Forestry and Logging	-54.40%

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

Chapter 4

Methdology

4.1 Proposed Model

I plan to use a Bayesian VARX model based on the method used in Anderson et al. (2020). The VARX model is especially useful in modelling dynamic behaviours of the relationships between variables (Warsono et al., 2019). In the model, each sector is affected by the lags of sectoral growth and a lag of the total employment growth. The lag of total employment growth is included to act as an economy-wide factor.

In many time series models, the number of lags are selected according to the patterns of the time series (i.e. seasonality, cycle or trend). For quarterly data, four lags are usually used (see Anderson et al. (2020) and Stock and Watson (2001)). However, because of the high-dimensionality and relatively small sample size in my case, I will use one lag of 84 sectors and one lag of the total employment.

Therefore, the suggested BVAR model is:

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

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 84×1 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)

In the proposed model, the use of seasonality unadjusted data allows the estimates to be coherent (i.e. the sum of subsectoral employments equals to total employment). Moreover, the share of each subsector change endogenously as the varying employment over time. Therefore, even we have one lag of the growth rate of total employment, there is no multicollinearity because the shares of subsectors change over time.

4.2 Prior and Shrinkage

Bayesian VAR helps to overcome the curse of high dimensionality by imposing the prior beliefs on the parameters (Bańbura, Giannone, and Reichlin, 2010). I will estimate the employment dynamics using Bayesian VAR model by specifying a Minnesota type prior (e.g. Anderson et al., 2020; Litterman, 1986; Robertson and Tallman, 1999), which is defined 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 in the proposed model (see **Chapter 4.1**), the number of lag is $i = 1$. Therefore, the a_1^{jk} and γ_1^{jk} are j, k^{th} of A_1 and Γ_1 matrices, degree of shrinkage is governed by λ, $\frac{1}{i^2}$ down-weights the 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 suggest a natural conjugate Normal-Inverse-Wishart prior, which retains the principle of Minnesota prior. This will greatly simplify the steps of adding Minnesota prior to the Bayesian VAR model. 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 Selecting the hyperparameter of Minnesota Prior

Specifically, the Minnesota type prior has the following beliefs about the variances in our estimated one lag BVAR model:

$$Var[a_1^{jk}] = \begin{cases} \lambda^2, & j = k \\ \frac{\lambda^2 \sigma_j^2}{\sigma_k^2}, & otherwise \end{cases} \cdots (4.3.1)$$

$$Var[\gamma_1^j] = \frac{\lambda^2 \sigma_j^2}{\sigma_e^2} \cdots (4.3.2)$$

where λ is a hyperparemeter specified 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 γ_1^j and a_j^{jk}, I obtain σ_n^2 by fitting an AR(4) model on the n-th variable using least squares, which is commonly used in many literatures(Anderson et al., 2020; Bańbura, Giannone, and Reichlin, 2010; Koop, 2013).

As the Minnesota prior defined from the above equations (see 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 $\lambda \to 0$, we can see that the prior assumption is influential, which means that the posterior getting closer to the prior, so the data have no influence on the estimates. On the contrary, if $\lambda \to \infty$, the posterior expectations will approach to ordinary least squares (OLS) estimates. In many macroeconomic VAR forecasting, data are presented in a large dimension. As the dimension increases, we want to shrink more in order to avoid the over-fitting (De Mol, Giannone, and Reichlin, 2008).

Admittedly, the hyperparameter λ plays an important role 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. They also conclude that large bayesian vector autoregressions (BVARs) with shrinkage are credible to conduct structural analysis.

Based on applied experiences, Litterman concluded that the shrinkage estimate $\lambda = 0.2$ is sufficient to deal with many empirical cases (Litterman, 1986). More importantly, the data size also needs to be considered as an essential basis when deciding the degree of shrinkage (Bańbura, Giannone, and Reichlin, 2010). Unlike the one-digit level (19 sectors) done by Anderson et al. (2020), the two-digit level (84 subsectors) employment in Australia is more complex with many variables. Thus, $\lambda = 0.2$ may not be suitable for this multivariate case. Here, I will provide a detailed analysis of the approach I used to select the optimal λ.

Due to the reason that the size of disaggregated subsectors have different scales, the commonly used scale-dependent error measurement (e.g. MAE, MSE) will fail when comparing forecast accuracy between subsectors. Even though MAPE is unit-free, it is not robust in sectors that have relatively small shares. When y_t is close to zero, MAPE will likely have extreme values or become undefined. Accordingly, I will sum all sectors to the total employment and minimise the forecast error of total employment to select the optimal λ.

The error measurement I will use is the root mean squared forecast error RMSFE. It is calculated via an out-of-sample forecasting experiment, which is a similar practice in many empirical cases (Bańbura, Giannone, and Reichlin, 2010; Koop, 2013). Here, I denote H as the longest forecast horizon to be evaluated, both T_b and T_e as the end of training set and testing set, respectively. Give the forecast horizon h, hyperparameter λ and model m, for each given period between T_b and T_e ($T = T_b, \cdots, T_e - h$), we computer h-step-ahead forecasts $y^{(\lambda,m)}_{i,T+h|T}$, using only the information up to time T. And then minus the actual data $y_{i,T+h}$ to calculate the forecast error.

Then, out-of-sample forecast accuracy is measured in terms of the root mean squared forecast error (**RMSFE**) as:

$$RMSFE^{\lambda}_{h} = \sqrt{\frac{1}{T_e - T_b - h} \Sigma^{T_e - h}_{T=T_b} (y^{\lambda}_{T+h|T} - y_{T+h})^2}$$

where $y^{\lambda}_{T+h|T}$ is defined as the h-th steps ahead forecast given the information up to time T and y_{T+h} is the actual data for the h-th steps ahead forecast. Here, m and λ stands for the evaluated RMSFE, conditioned on a specific model and the hyperparameter λ.

In this section, I will set up an effective searching algorithm to search for the optimal shrinkage estimator λ. For our purposes, we want to provide accurate forecasts of total employment based on the scenario where no covid happened to support our counterfactual analysis. Therefore, the pre-covid total employment data (before 2020 Quarter 2) is split into training and test with a training set of length ($n = 120 = T_b$) and a test set of length ($n = 22 = T_b + H - h = T_e - h$). As a consequence, I will set the $H = 22$ to be the length of test set, $h = 1$ for one step experiment and m is the BVAR proposed earlier in **Chapter 4**.

Here is a brief description of the proposed algorithm:

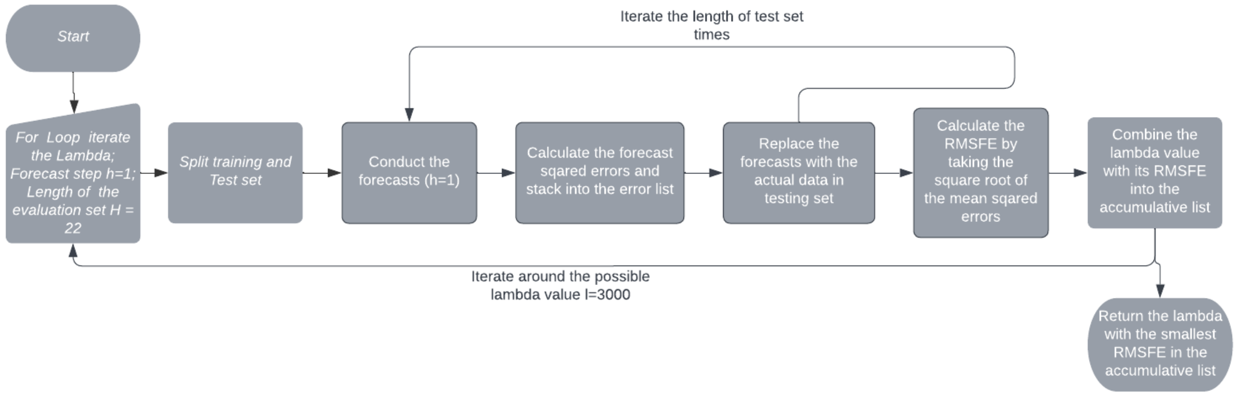

Figure 4.1: *Proposed algorithm of selecting optimal λ*

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

From the return value of our searching algorithm (see Figure 4.1). The estimated hyperparameter from the algorithm is $\lambda = 0.0808$, which certainly has the lowest mean scaled forecast error (RMSFE) as designed. Based on this, we choose $\lambda = 0.0808$ for subsequent analysis.

Chapter 5

Sectoral Employment Analysis

5.1 Long-run Multiplier Analysis

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

The following analysis is based on the estimated BVAR model and 87 two-digit disaggregated data. It is also under the assumption that the structure of Australian economy will not change after the COVID-19 happens.

At each time point, the relationship is defined as:

$$GR_T = \sum_{i=1}^{87} w_i \times GR_i$$

where w_i is the share of subsector i, GR_T is the growth rate of the total employment and GR_i is the growth rate in employment of subsector i.

In particular, if there is a one percent increase in employment of subsector i, the total employment will increase by the corresponding share(w_i) simultaneously. In addition, given an increase in the total employment, it may also have indirect effects to other sectors in consecutive periods, especially for sectors with close economic ties. Therefore, I define the employment long-run employment multiplier as the effect of initial increase in sector i on the total employment in the long-run, which follows the definition in Anderson et al. (2020). If the subsector has a larger long-run effect on the total employment than its immediate effect, then stimulate this sector will lead a positive spillover effect onto the total employment.

I use the estimated BVAR model to simulate the long-run employment multiplier for each sector with the horizons of one year, two years and ten years. Subsequently, the differences between the simulated ten-year multipliers and the initial shares are the spillovers of the disaggregated subsectors. I abstract the top 10 subsectors with strong positive spillovers in Table 5.1. The full list is available in Appendix B (see Table B.2).

Table 5.1: *Disaggregated Sub-Sectoral Long-run Employment Multipliers*

Sector/ Sub-sector	M10-M0	Sector/ Sub-sector	M10-M0
75 Admin/ Public Administration	-0.0356327	42 Retail/ Other Store-Based Retailing	0.01773361
80 Educ/ Preschool and School Education	-0.0320646	72 Admin/ Administrative Services	0.01339419
81 Educ/Tertiary Education	-0.0215685	25Manu/ Furniture and Other Manufacturing	0.01141447
84 Health/ Hospitals	-0.016484	39 Retail/ Motor Vehicle and Motor Vehicle Parts Retailing	0.00966318
85 Health/ Medical and Other Health Care Services	-0.0112633	56 Info/ Broadcasting (except Internet)	0.00736334
82 Educ/ Adult, Community and Other Education	-0.0109159	18 Manu/ Basic Chemical and Chemical Product Manufacturing	0.00674883
46 Trans/ Road Transport	-0.0108955	33 Wholesale/ Basic Material Wholesaling	0.00646865
58 Info/Telecommunications Services	-0.0084901	13 Manu/ Textile, Leather, Clothing and Footwear Manufacturing	0.00619223
11 Manu/ Food Product Manufacturing	-0.0082163	52 Trans/ Transport Support Services	0.00617277
01 Agri/ Agriculture	-0.0076574	94 Other/ Repair and Maintenance	0.00583089

Note: M10 is the 10-year long-run total employment spillovers and M0 is the shares of each sector. ;The M10-M0 are sectors with high spillover effects.; The M10/M0 are the spillover relative the size of sector.

Comparing the long-term multipliers with the shares, we find that `Other Store-Based Retailing` [1] will generate the strongest positive spillover to the whole economy, followed by `Administrative Services`[2], `Furniture and Other Manufacturing`. They belongs to the `Retailing`, `Administrative and Support Services` and `Manufacturing` sectors in the broadest level respectively. These results imply that if there are exogenous increases of employment in these sectors, total employment increases over and above the initial increase in these sectors.

[1] This subsector contains the following groups: 421. Furniture, Floor Coverings, Houseware and Textile Goods Retailing; 422. Electrical and Electronic Goods Retailing; 423. Hardware, Building and Garden Supplies Retailing; 424. Recreational Goods Retailing; 425. Clothing, Footwear and Personal Accessory Retailing; 426. Department Stores; 427. Pharmaceutical and Other Store-Based Retailing

[2] This subsector contains the following groups: 721. Employment Services; 722. Travel Agency and Tour Arrangement Services; 729. Other Administrative Services.

It's also worth noticing that some small subsectors (see Table B.2 for sizes) have relative huge changes from Table 5.1. This may be caused by their small shares in the total employment. Thus, a shock in small subsectors (e.g. `Fishing, Hunting and Trapping`) will have a significant change relative to the size of this subsector.

There are a few interesting points to be noticed here. First, the spillover effect is not just related the size of subsectors. For instance, `Fishing, Hunting and Trapping` is the smallest sector (see Table B.2). However, it generates positive spillovers. On the contrary, both the `Professional, Scientific and Technical Services`, which are a large subsectors but generate negative spillover in the long run.

Second, I find that subsectors in the `Construction` sector[3] will not bring strong positive spillovers. The `Construction services` subsector even generates a negative spillover. This is in contrast to the result of Anderson et al. (2020) at the broadest level, where they discover that the `Construction` sector has a strong positive spillover. Although the total spillovers of the `Construction` sector is still positive[4], individual subsectors may not have positive spillovers, like the `Construction Service` subsector. This also proves the importance of extending the research to a finer partition (more disaggregated level).

Third, both `Teritiary Education` and `Adult, Community and Other Education` generate negative spillovers, which implies that education industry will reduce the labour force participation in the long run. This is mainly because one decides to persuade an postgraduate degree or a certificate, then the focus will be removed from working/finding jobs. The finding is also consistent with the research of broadest level (19 sectors) done by Anderson et al. (2020).

5.2 Evaluations after COVID-19

5.2.1 Losses of Total Employment

It is now commonly known that COVID-19 can be rigorously prevented by vaccines, face masks and social distancing. We can never fully stop transmission of the virus or from being infected unless there is no interaction among people. Thus, it is expected that the COVID-19 has caused

[3] Construction Sector contains three subsectors: 30. Building Construction; 31. Heavy and Civil Engineering Construction;32. Construction Services

[4] The Spillover for the `Construction` sector is equal to the sum of all its subsectors (-0.0004619 + 0.00271218 +0.00066987 = 0.00292015)

massive losses to the Australian labour market and these negative impacts will be persistent in the long run. In order to prove my idea and raise the awareness of COVID-19, I will conduct a counterfactual analysis by evaluating the total employment with and without pandemic. In this section, I use the estimated model to provide a counterfactual analysis for total employment after the pandemic. Similar as Anderson et al. (2020), I will consider a no pandemic case ("no-COVID" scenario). Other kinds of scenarios are not considered since the pandemic has already happened. Recent data will help to compare and evaluate the impact of COVID-19 on the labour market.

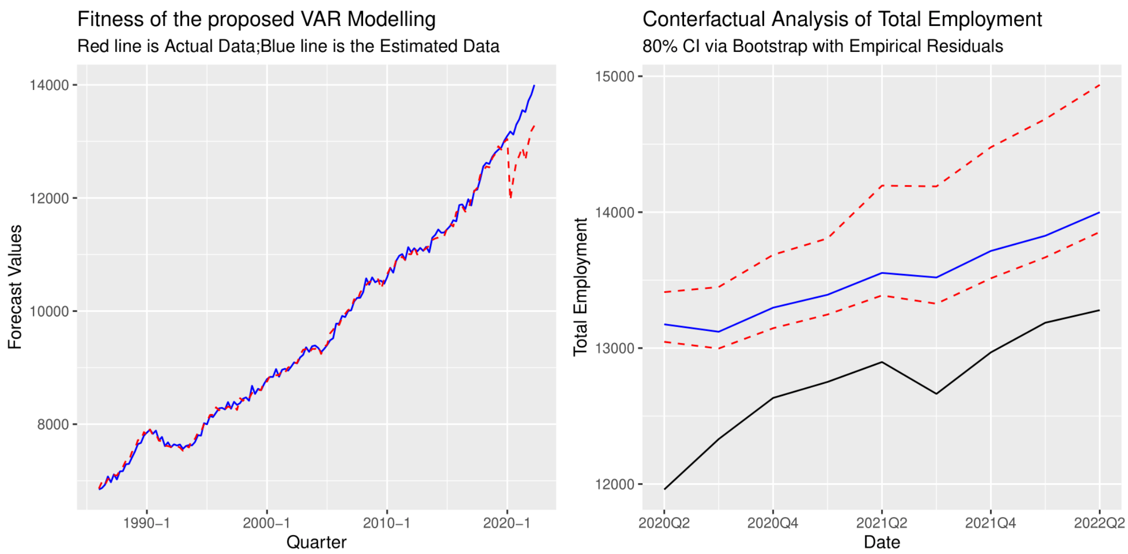

Figure 5.1: *Conterfactual analysis of total employment(in thousands) with confidence interval generated via bootstrap*

The Figure 5.1 displays the COVID-19 has caused a continuous structural shock of the total employment in Australia since the outbreak of the COVID-19. Based on the point forecasts together with a 80% confidence interval (via bootstraping), our model suggests that employment losses remained about 750,000 persons below where it would have been without the pandemic (see the differences in Figure 5.1). As a result, by comparing the trend of the "no pandemic" scenario and that of the actual data, the essentially parallel trend revealed that we may not expect the total employment reach the forecasts under no-COVID case at this stage. That is, the COVID-19 has a long lasting impacts on the economy even after 2 years, starting from the first lock down in "2020 Quarter 2".

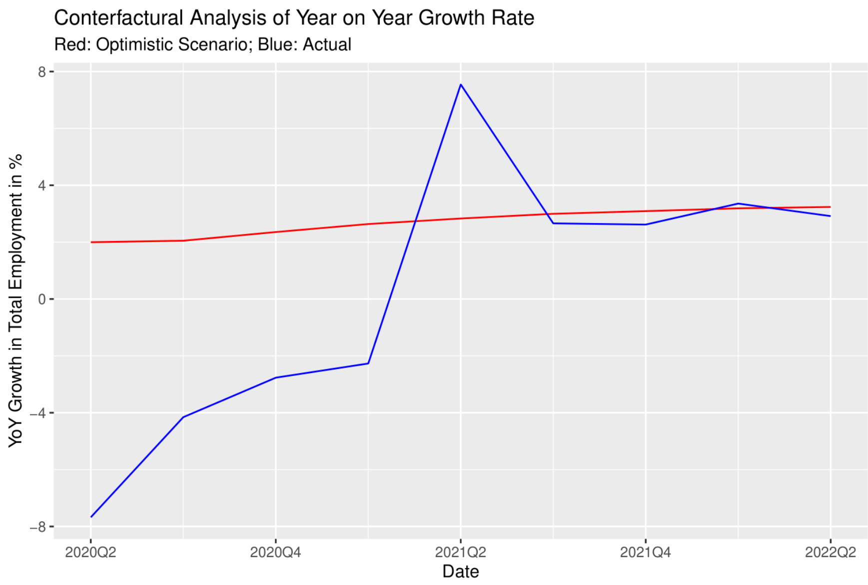

Figure 5.2: *Conterfactural analysis of Year-on-Year growth rate with forecasts generated via the estimated BVAR model*

I have also considered the Year-on-Year growth for quarterly total employment data from 2020 Q2 to 2022 Q2 (up-to-date at the time of collecting). From the Figure 5.2, the actual employment growth was far away from the expected growth, especially at 2020 Q2, where Australia was experiencing the first lockdown. Although the year-on-year growth rate gradually recovered to normal after that, the total employment is still lower than it ought to be under the no-covid situation. Again, the has emphasize the finding above as "We may not expect the employment number to reach the estimated no-COVID level in a short period." Therefore, based on the conterfactual analysis of both employment and the year-on-year growth rate, it is reasonable to believe that the COVID-19 has indeed a significant impact in the labour market in the short run as well as in the long run.

5.2.2 Empirical Example: The historically lowest unemployment rate:

In June 2022, Australia has reached the lowest unemployment rate since August 1974 (ABS (2022b)). Then one may want to know the underlying reason of this extremely low unemployment rate. Is it the stimulus policies during the COVID-19 has contributed the most for the unemployment rate? In answering this question, I will provide a conterfactual analysis of the unemployment rate to exploit what would the unemployment be without the pandemic case.

To give an accurate interpretation of the low unemployment rate, the answer should refer to the definition, which is the percentage who are in the labour force but are unemployed. Mathematically, it can be:

$$\text{Unemployment Rate} = \frac{Total\ Labour\ Force - Number\ of\ Employed\ People}{Total\ Labour\ Force}$$

Clearly, the unemployment rate depends on both total labour force and the number of employed people. Since the estimated BVAR model suggested that employment is less than what is would have been without COVID. Therefore, given the low unemployment rate and lower employed people than no-COVID scenario, the reason must be a significant decline in the total labour force after the pandemic.

To further support our assumption, I use quarterly labour force data from ABS from "1984 Q4" to "2022 Q2" (ABS, 2022a). Moreover, a stepwise `ARIMA` model (Hyndman, 2021) is used to fit the "no-COVID" data between "1984 Q4" to "2020 Q1" to forecast the total labour force under the "no-COVID" scenario (see Figure 5.3). Compare it with the actual data, it is clear that the real total labour force is below its no-COVID forecast the unemployment rate is the lowest historically. Therefore, the main reason of low unemployment is in fact the decline of the total labour force rather than a huge increase in the number of employed people.

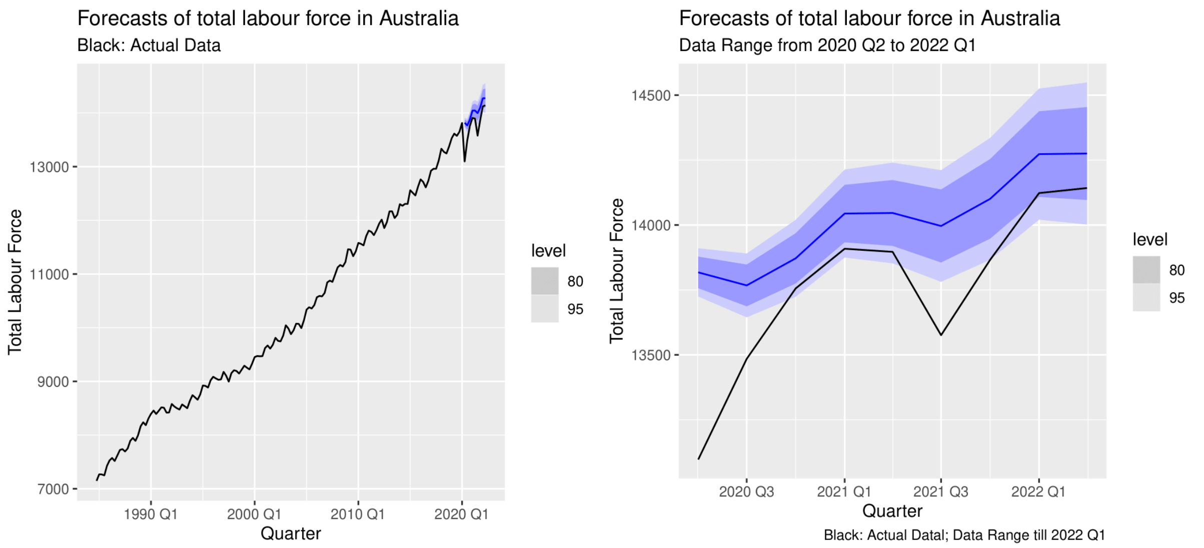

Figure 5.3: *Conterfactual analysis of the total labour force*

After examining the underlying reason of the low unemployment rate, I have also studied the unemployment rate performance under the no-COVID scenario. The forecasts of no-COVID unemployment rate is the difference between the total labour force and employment rate over the total labour force under the no-COVID scenario. It is noticeable that the expected unemployment rate (under no-COVID scenario) is still achieve or close to the lowest record and with more labour force and total employment.

Overall, the findings suggest that we would have experienced the historically low unemployment rate even in the absence of COVID-19. This further assures us that the policies directed at stimulating employment during the pandemic (e.g. Jobkeeper program) are not likely to be responsible for the current low unemployment rate.

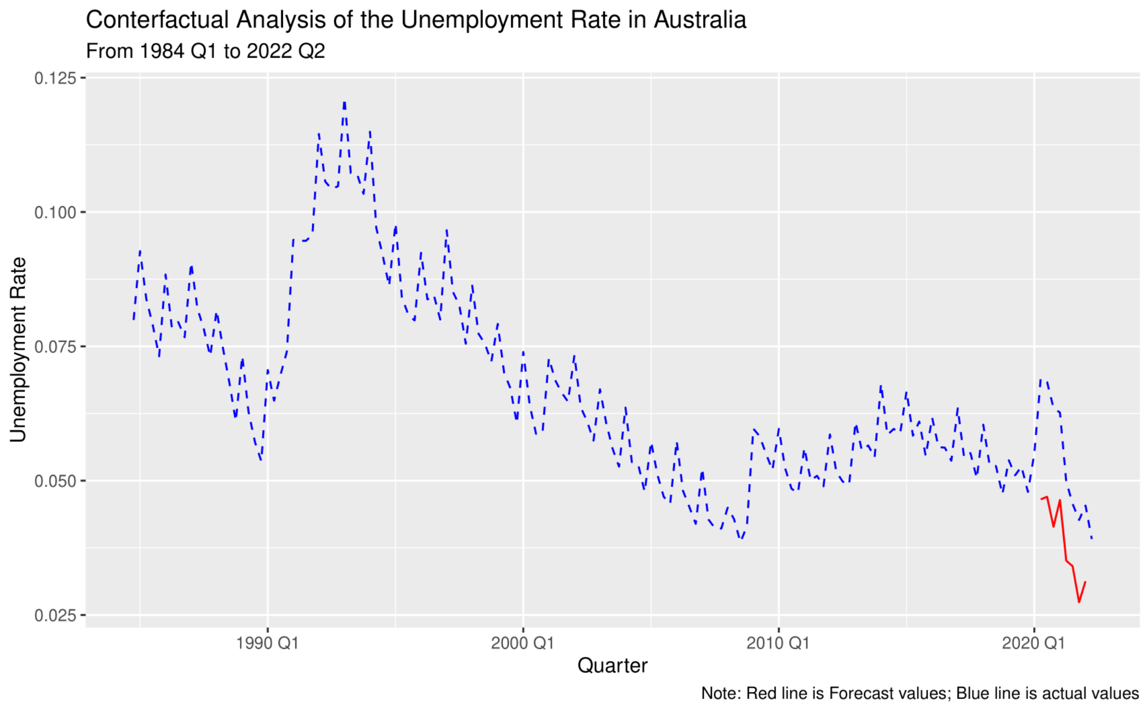

Figure 5.4: *Conterfactual analysis of the employment rate in Australia*

Chapter 6

Discussions and conclusion

In conclusion, I have developed a dynamic Bayesian VAR system for analysis the two-digit employment dynamics in Australia, which provides a new idea of analysing the employment by different industries in the Australian labour market. We conducted the spillover analysis, concluding that in the subdivision level, `Other Store-Based Retailing`, followed by `Administrative Services`, `Furniture and Other Manufacturing` will generate strong positive spillovers to the total economy. By stimulating these sectors, the total employment will increase more steadily.

6.1 Limitation and possible extensions

6.1.1 Limitations on Data.

In this research, the Non-classified data have not been taken into consideration in our research. This because it will influence our sectoral dynamics if I distribute these data by the shares of two-digit subsectors. Instead, I aggregate the existing disaggregated data to be our total employment in order to make our forecasts coherent. A possible future direction will be considering an advanced classification algorithm to effectively cluster these non-classified data into the groups. Apart from this, the details of job keepers or how did the subsidies flow into each disaggregated subsectors are also unclear due to the lack of resources.

Moreover, we only consider the ANZSIC subdivision in our case (two-digit sectors) only. In the future, it will be great to consider adding the Division level (the broadest level) and the group and classes (the finest level) using the hierarchical forecasting.

6.1.2 Limitations on Assumption

The predictions we examined are based on the assumption that the both the dynamics and structure of the sectoral employment will not change before and after COVID-19. Therefore, a further research area could consider to justify whether the dynamics or structure of the industries has changed after the COVID.

6.1.3 Advanced algorithm in hierarchical forecasting

In this research, the Bayesian VAR modelling method has provided us a great analysis of employment dynamics in Australia. However, when there are more data and hierarchies are considered, the VAR modelling may also be inefficient. Therefore, a more efficient machine learning method can be considered in the application of hierarchical forecasting.

To improve the forecast accuracy, we use machine learning to give a new way designed for accurate and interpretable forecasts. First, pick up the common features or data types from the data and cluster them into groups based on them. Second, conduct the group-based forecasting for each new cluster. Then, we can reconcile them to be coherent, which will benefit the decision and policy implementation processes.

Here, I will given an example of the machine learning algorithm.

1. Cluster bottom level data based on common features (e.g. domain-specific features, time series characteristic etc.) via possible machine learning algorithms (e.g. manifold learning, k-means).

2. Develop a model to forecast each time series in the same cluster. It looks restrictive but two points should be helpful in improving flexibility. First, the choice of model is flexible and can be complex. There are many types of model to choose, depending on the domain-types and time series patterns. Moreover, the types of model are not limited, which can be either a single model (e.g. univariate, multivariate and ML) or a combined model (e.g. Weighted

average of various forecasting methods). Second, forecasting methods can be different for different clusters of the data, due to some unique patterns in time series.

3. Reconcile our forecasts to make them coherent. To get more interpretable results, reconciliation is required to fit all forecasts produced in our program into the original structure of the data (i.e. original groups).

Appendix A

An Example of Bayesian VAR Prior

The VARX model is:

$$
\begin{aligned}
\boldsymbol{y}_t &= \boldsymbol{c} + \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \boldsymbol{\Gamma}_1 \boldsymbol{x}_{t-1} + \boldsymbol{u}_t \\
&= \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} + \begin{bmatrix} a_1^{11} & \cdots & a_1^{1n} & \gamma_1^1 \\ \vdots & \ddots & \vdots & \vdots \\ a_1^{n1} & \cdots & a_1^{nn} & \gamma_1^n \end{bmatrix} \begin{bmatrix} \boldsymbol{y}_{t-1} \\ x_{t-1} \end{bmatrix} \\
&+ \begin{bmatrix} u_{1,t} \\ \vdots \\ u_{n,t} \end{bmatrix}
\end{aligned}
$$

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 85) and $\boldsymbol{c}$represents the vector of constants. There is one lags included for the total employment (x_{t-1}) as predetermined variable at time t.

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

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

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

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

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

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

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

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

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

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

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

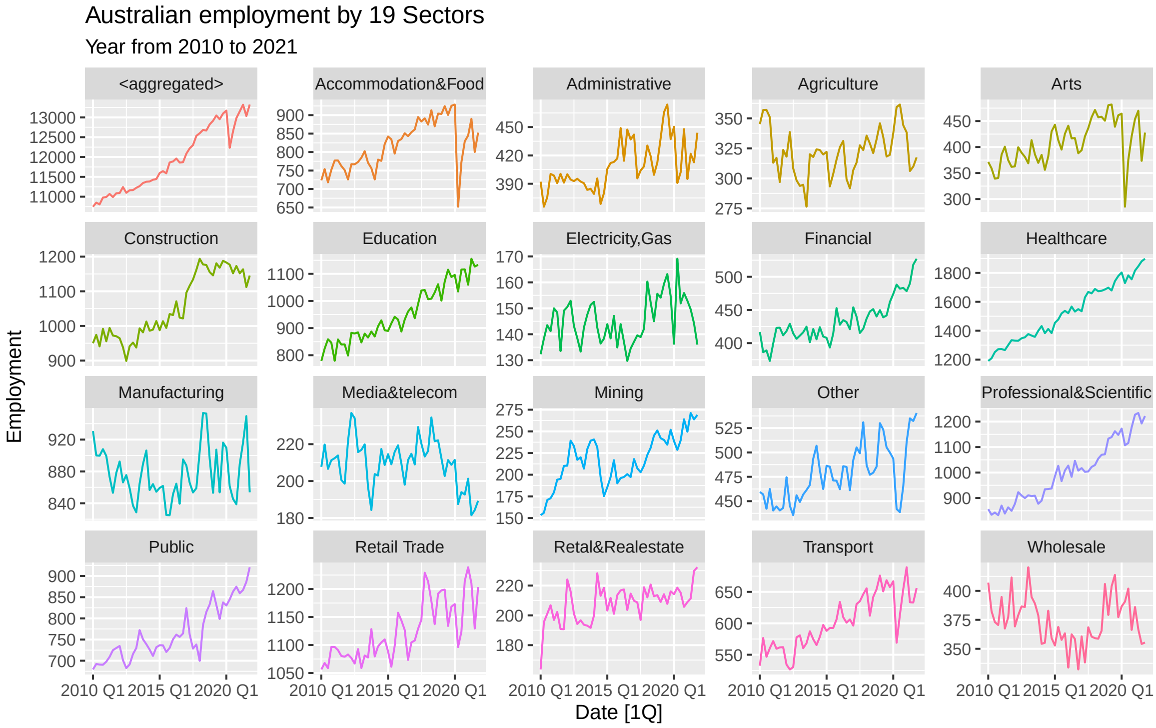

Figure B.1: *Employment('000) of 19 sectors in Australia from 2010:Q1 to 2021:Q4*

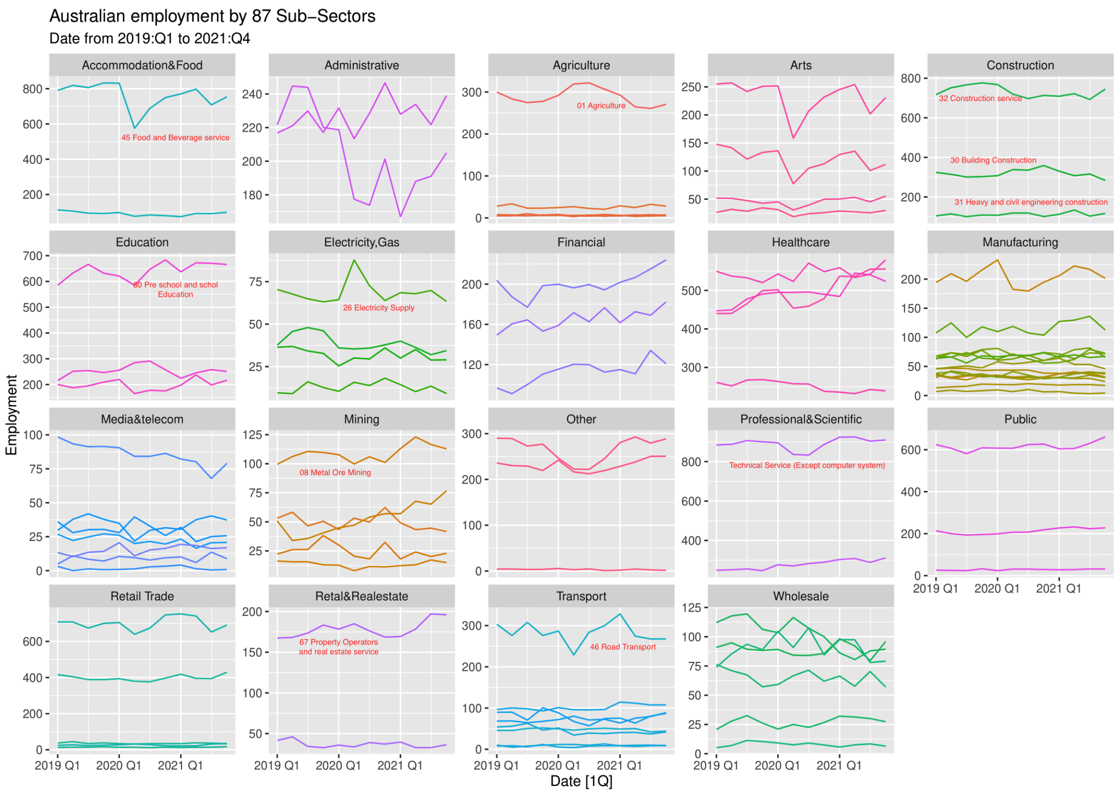

Figure B.2: *Employment('000) of 87 two-digit subsectors in Australia from 2019:Q1 to 2021:Q4*

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

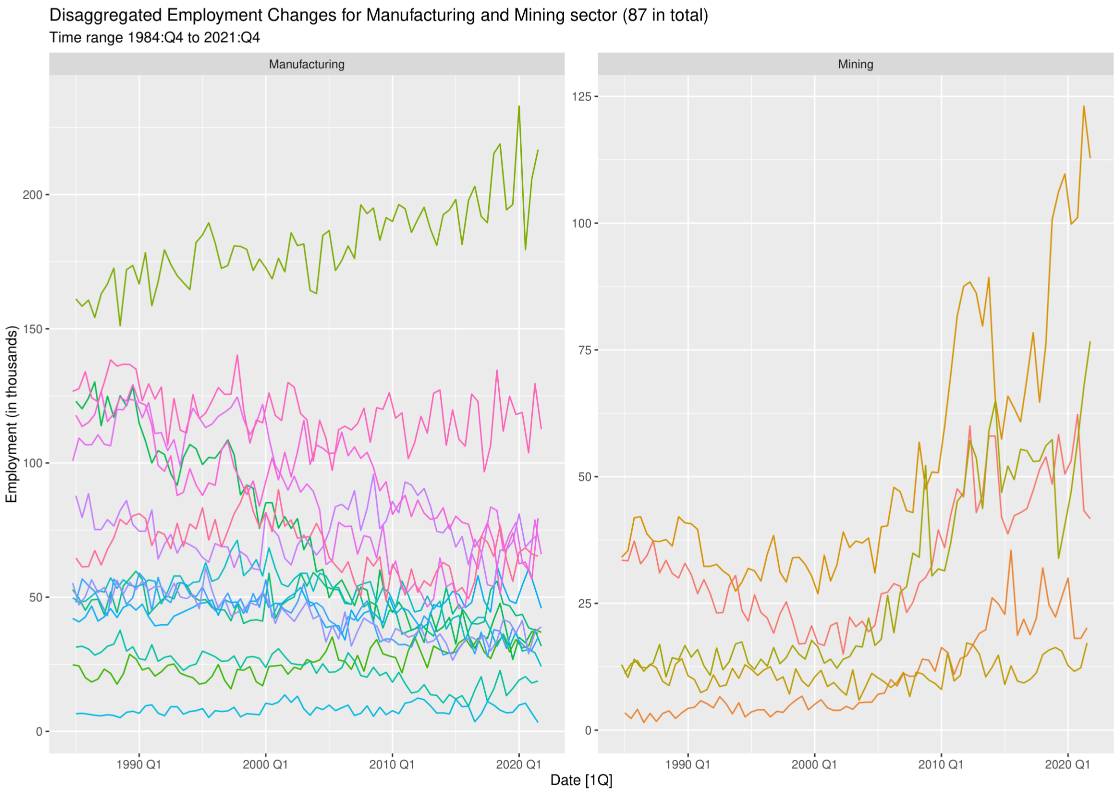

Figure B.4: *Disaaggregate Employment(in thousands) of 87 two-digit subsectors in Manufacturing and Mining sector from 1984:Q4 to 2021:Q4*

Table B.1: *The long run Employment Multipliers Analysis (84 Disaggregated Sectors) Sorted by Shares of Subsectors*

Sub-Sector	Shares	1 Year	2 Years	5 Years	10 Years	M10/M0	M10-M0
69 Professional, Scientific and Technical Services (Except Computer System) Design and Related Services)	0.06931674	0.0485337	0.062318	0.06666942	0.06671967	0.96253315	-0.0025971
45 Food and Beverage Services	0.06348661	0.04693738	0.06311697	0.0666367	0.06668314	1.05034955	0.00319652
32 Construction Services	0.05913525	0.04299346	0.05568259	0.05863971	0.05867338	0.99218952	-0.0004619
42 Other Store-Based Retailing	0.05378582	0.04963343	0.06655111	0.07145667	0.07151944	1.32970786	0.01773361
80 Preschool and School Education	0.0492665	0.02091953	0.01855257	0.01721796	0.01720194	0.34916098	-0.0320646
75 Public Administration	0.04641708	0.01553789	0.01250828	0.01080403	0.01078435	0.23233592	-0.0356327
85 Medical and Other Health Care Services	0.04116996	0.02431334	0.02916687	0.02989798	0.02990662	0.72641828	-0.0112633
84 Hospitals	0.0369132	0.01785159	0.0199097	0.02042347	0.02042915	0.55343755	-0.016484
87 Social Assistance Services	0.03680509	0.02207106	0.02929537	0.0311832	0.03120476	0.84783798	-0.0056003
41 Food Retailing	0.03040546	0.01923095	0.02775936	0.03134743	0.0313965	1.03259348	0.00099102
30 Building Construction	0.02365835	0.01966493	0.02362512	0.02432029	0.02432822	1.02831441	0.00066987
46 Road Transport	0.02212746	0.01012106	0.01115604	0.01122802	0.011232	0.50760455	-0.0108955
01 Agriculture	0.02177417	0.00998719	0.01235378	0.01409829	0.01411674	0.64832471	-0.0076574
95 Personal and other services (include activities for own use)	0.02127031	0.0127474	0.01505848	0.01597865	0.01599074	0.75178666	-0.0052796
86 Residential Care Services	0.02028961	0.0108231	0.01516439	0.01583014	0.0158379	0.78059125	-0.0044517
70 Computer System Design and Related Services	0.01989965	0.01064273	0.01220485	0.0126649	0.01267126	0.63675763	-0.0072284
81 Tertiary Education	0.01945371	0.00166075	-0.0015457	-0.0021075	-0.0021148	-0.1087109	-0.0215685
72 Administrative Services	0.01790544	0.02068182	0.02911507	0.03127308	0.03129963	1.74805115	0.01339419
94 Repair and Maintenance	0.0177703	0.01434611	0.02128838	0.02357418	0.0236012	1.32812526	0.00583089
73 Building Cleaning, Pest Control and Other Support Services	0.01736876	0.01180556	0.01573853	0.01716652	0.01718243	0.98927169	-0.0001863
11Food Product Manufacturing	0.01649038	0.00702254	0.00846642	0.00827582	0.00827409	0.50175246	-0.0082163
82 Adult, Community and Other Education	0.01566605	0.00554203	0.00471415	0.00475267	0.00475016	0.30321348	-0.0109159
77 Public Order, Safety and Regulatory Services	0.01521818	0.00871417	0.01309719	0.01440524	0.01442184	0.94767203	-0.0007963
62 Finance	0.01472397	0.00857652	0.01062002	0.0110417	0.01104891	0.75040274	-0.0036751
67 Property Operators and Real Estate Services	0.01358111	0.00573538	0.00632144	0.00644085	0.00644122	0.47427795	-0.0071399
64 Auxiliary Finance and Insurance Services	0.01229925	0.00710233	0.00875331	0.00932324	0.00933078	0.75864648	-0.0029685
91 Sports and Recreation Activities	0.01027608	0.00887835	0.01209347	0.01274308	0.01275193	1.24093321	0.00247585
24Machinery and Equipment Manufacturing	0.0087394	0.00384771	0.00486625	0.00522805	0.00523156	0.59861717	-0.0035078
34 Machinery and Equipment Wholesaling	0.00863129	0.00463038	0.00550646	0.00586781	0.00587311	0.68044432	-0.0027582
39Motor Vehicle and Motor Vehicle Parts Retailing	0.00844596	0.01088201	0.01646315	0.01809008	0.01810914	2.14411792	0.00966318
08 Metal Ore Mining	0.00838419	0.00574686	0.00556897	0.0053132	0.00530956	0.6332827	-0.0030746
31 Heavy and Civil Engineering Construction	0.00832434	0.00731709	0.01027104	0.01102691	0.01103652	1.32581315	0.00271218
63 Insurance and Superannuation Funds	0.00805214	0.00443011	0.00497832	0.00501181	0.00501281	0.62254327	-0.0030393
51 Postal and Courier Pick-up and Delivery Services	0.00757723	0.00121361	0.00131748	0.00140896	0.00141185	0.18632811	-0.0061654
44 Accommodation	0.00753476	0.0032441	0.00545	0.00634005	0.00635098	0.84289032	-0.0011838
37 Other Goods Wholesaling	0.0071892	0.00459914	0.00631193	0.00661623	0.00662058	0.92090624	-0.0005686
58 Telecommunications Services	0.00707916	0.00011311	-0.001374	-0.0014087	-0.001411	-0.1993137	-0.0084901
33 Basic Material Wholesaling	0.00697878	0.00828557	0.01222171	0.01343315	0.01344743	1.92690232	0.00646865
52 Transport Support Services	0.00675677	0.00753772	0.01162295	0.01291333	0.01292955	1.91356851	0.00617277
21Primary Metal and Metal Product Manufacturing	0.0058726	0.00462923	0.00499628	0.00494162	0.00494054	0.84128732	-0.0009321
22Fabricated Metal Product Manufacturing	0.00538804	0.0066765	0.00944416	0.01058564	0.01059958	1.96724154	0.00521154
53 Warehousing and Storage Services	0.00527028	0.00263016	0.00272967	0.00287253	0.00287296	0.54512411	-0.0023973
23Transport Equipment Manufacturing	0.00514673	0.00299308	0.00469464	0.00556819	0.0055781	1.08381385	0.00043137
26Electricity Supply	0.00502125	0.00491081	0.00586741	0.00563882	0.005636	1.12243022	0.00061475
25Furniture and Other Manufacturing	0.00496526	0.00907029	0.01434533	0.01635773	0.01637974	3.29886584	0.01141447
36 Grocery, Liquor and Tobacco Product Wholesaling	0.00491893	0.00061785	-0.0006336	-0.0008216	-0.0008238	-0.1674704	-0.0057427
49 Air and Space Transport	0.00419885	0.00350454	0.00513191	0.00542985	0.00543509	1.29442326	0.00123624
18 Basic Chemical and Chemical Product Manufacturing	0.00395754	0.00606204	0.00950461	0.01069071	0.01070637	2.70531007	0.00674883
06 Coal Mining	0.00383591	0.00383353	0.00407393	0.00408138	0.00408139	1.06399293	0.00024547
47 Rail Transport	0.00381661	0.00126166	0.00105419	0.00112838	0.00112925	0.29587899	-0.0026874
90 Creative and Performing Arts Activities	0.00360425	0.00468914	0.00613651	0.00651375	0.00651912	1.80872881	0.00291486
14Wood Product Manufacturing	0.00347877	0.00302624	0.00302602	0.00331986	0.00332296	0.9552116	-0.0001558
29Waste Collection, Treatment and Disposal Services	0.00339383	0.00565936	0.00756816	0.0078664	0.0078681	2.31835492	0.00447427
89 Heritage Activities	0.00301159	0.00369792	0.0051636	0.00528106	0.00528232	1.7539992	0.00227074
10 Exploration and Other Mining Support Services	0.00299228	-0.0006873	-0.0017035	-0.0019049	-0.0019072	-0.6373821	-0.0048995
55 Motion Picture and Sound Recording Activities	0.00294209	0.00032963	-0.0005498	-0.0005605	-0.0005605	-0.1905091	-0.0035026
40 Fuel Retailing	0.00291506	-0.0012046	-0.0024966	-0.0027078	-0.0027087	-0.9292227	-0.0056238
66 Rental and Hiring Services (except Real Estate)	0.00287066	0.003369	0.00341671	0.00336895	0.00336725	1.17298563	0.00049658
19Polymer Product and Rubber Product Manufacturing	0.00283012	0.00233992	0.00331413	0.00359534	0.00359859	1.27153097	0.00076847
20Non-Metallic Mineral Product Manufacturing	0.00277221	0.00357344	0.00319618	0.0030411	0.0030398	1.0965273	0.00026759
16Printing (including the Reproduction of Recorded Media)	0.00262163	-0.000264	0.00122375	0.00182629	0.00183417	0.69963121	-0.0007875
12Beverage and Tobacco Product Manufacturing	0.00252896	0.00277597	0.00231169	0.00223403	0.00223473	0.88365682	-0.0002942
28Water Supply, Sewerage and Drainage Services	0.00249614	0.00282008	0.00239868	0.00201716	0.0020111	0.80568129	-0.000485
13Textile, Leather, Clothing and Footwear Manufacturing	0.00244016	0.00487731	0.00773749	0.00862047	0.00863239	3.53763202	0.00619223
92 Gambling Activities	0.00243437	0.00430809	0.00667533	0.00741282	0.00742126	3.04853477	0.00498689
07 Oil and Gas Extraction	0.00232626	-0.0017933	-0.0034336	-0.0039433	-0.0039495	-1.6977721	-0.0062757
56 Broadcasting (except Internet)	0.00225097	0.00562035	0.00883845	0.00960654	0.00961432	4.27118764	0.00736334
35 Motor Vehicle and Motor Vehicle Parts Wholesaling	0.00208109	0.00130996	0.0019761	0.0022859	0.00228915	1.09997643	0.00020806
76 Defence	0.00203668	0.00108328	0.00081797	0.00081458	0.00081483	0.40007524	-0.0012219
05 Agriculture, Forestry and Fishing Support Services	0.00201545	0.00410222	0.00612542	0.00684863	0.00685748	3.40246046	0.00484203
54 Publishing and Broadcasting	0.00199035	0.00146161	0.00254755	0.00299741	0.00300331	1.50893341	0.00101296
43 Non-Store Retailing and Retail Commission Based Buying and/or Selling	0.00198842	0.00008765	-0.0006368	-0.0010072	-0.0010108	-0.5083429	-0.0029992
15Pulp, Paper and Converted Paper Product Manufacturing	0.00134556	0.00088098	0.00127857	0.00145108	0.00145231	1.07933418	0.00010675
60 Library and Other Information Services	0.00113321	0.00262681	0.00408402	0.00438669	0.00438973	3.8737221	0.00325652
09 Non-Metallic Mineral Mining and Quarrying	0.00109846	0.00030124	0.00035283	0.00047586	0.00047618	0.43350017	-0.0006223
27Gas Supply	0.00093436	0.00119372	0.00200704	0.00226239	0.00226542	2.42456061	0.00133106
38 Commission-Based Wholesaling	0.00073359	0.00117105	0.00148834	0.00157279	0.00157404	2.14566446	0.00084045
59 Internet Service Providers, Web Search Portals and Data Processing Services	0.00071236	-0.0002143	-0.0006387	-0.0006332	-0.0006331	-0.8887063	-0.0013454
48 Water Transport	0.00067182	-0.0003845	-0.0003261	-0.0002884	-0.0002886	-0.4295098	-0.0009604
17Petroleum and Coal Product Manufacturing	0.00066795	0.00026082	-0.0002759	-0.0005609	-0.0005649	-0.8457507	-0.0012329
50 Other Transport	0.00062162	0.00128362	0.00155246	0.00160919	0.00160982	2.58970933	0.0009882
03 Forestry and Logging	0.00053668	-0.0012108	-0.0017314	-0.0018066	-0.0018077	-3.3683565	-0.0023444
02 Aquaculture	0.00050193	-0.0001496	-0.0003808	-0.0004863	-0.0004873	-0.9709079	-0.0009893
04 Fishing, Hunting and Trapping	0.00046139	0.00209291	0.00329398	0.00352863	0.00353112	7.65320735	0.00306973

Note: The long run employment multiplier for subsector i is the effect of a 1% increase in employment of subsector on the total employment in the long run.
M10 is the long term multiplier; M0 is the initial responses of the total employment (i.e. the shares of subsector i).
M10-M0 is the spillover of the subsector i.
M10/M0 is the spillover of the subsector i relative to the share of it.

Table B.2: *Disaggregated Sectoral Long-Run Employment Multipliers: Full list of 84 sectors*

Bibliography

ABS (2021). *One year of COVID-19: Aussie jobs, business and the economy*. https://www.abs.gov.au/articles/one-year-covid-19-aussie-jobs-business-and-economy (visited on 04/29/2022).

ABS (2022a). *Labour Force, Australia, Detailed, March 2022*. https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release (visited on 04/29/2022).

ABS (2022b). *Unemployment rate falls to 3.5 percent*. https://www.abs.gov.au/media-centre/media-releases/unemployment-rate-falls-35 (visited on 10/01/2022).

Anderson, HM, G Caggiano, F Vahid, and B Wong (2020). Sectoral Employment Dynamics in Australia and the COVID-19 Pandemic. *Australian Economic Review* **53**(3), 402–414.

Bańbura, M, D Giannone, and L Reichlin (2010). Large Bayesian vector auto regressions. *Journal of applied Econometrics* **25**(1), 71–92.

Bengtsson, H (2021). *matrixStats: Functions that Apply to Rows and Columns of Matrices (and to Vectors)*. R package version 0.61.0. https://CRAN.R-project.org/package=matrixStats.

Borchers, HW (2022). *pracma: Practical Numerical Math Functions*. R package version 2.3.8. https://CRAN.R-project.org/package=pracma.

De Mol, C, D Giannone, and L Reichlin (2008). Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components? *Journal of Econometrics* **146**(2), 318–328.

Gregory, V, G Menzio, and D Wiczer (2020). Pandemic recession: L-shaped or V-shaped. *Covid Economics* **88**.

Grolemund, G and H Wickham (2011). Dates and Times Made Easy with lubridate. *Journal of Statistical Software* **40**(3), 1–25.

Hyndman, R (2021). *fpp3: Data for "Forecasting: Principles and Practice" (3rd Edition)*. R package version 0.4.0. https://CRAN.R-project.org/package=fpp3.

Kadiyala, KR and S Karlsson (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics* **12**(2), 99–132.

Kassambara, A (2020). *ggpubr: 'ggplot2' Based Publication Ready Plots*. R package version 0.4.0. https://CRAN.R-project.org/package=ggpubr.

Koop, GM (2013). Forecasting with medium and large Bayesian VARs. *Journal of Applied Econometrics* **28**(2), 177–203.

Lewis, B and T Hsu (2020). *The Collateral Damage of Coronavirus*. https://www.nytimes.com/2020/05/09/business/economy/coronavirus-unemployment.html (visited on 04/29/2022).

Litterman, RB et al. (1979). *Techniques of forecasting using vector autoregressions*. Tech. rep.

Litterman, RB (1986). Forecasting with Bayesian vector autoregressions—five years of experience. *Journal of Business & Economic Statistics* **4**(1), 25–38.

Ludvigson, SC, S Ma, and S Ng (2020). *COVID-19 and the macroeconomic effects of costly disasters*. Tech. rep. National Bureau of Economic Research.

R Core Team (2021a). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/.

R Core Team (2021b). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/.

Robertson, JC and EW Tallman (1999). Vector autoregressions: forecasting and reality. *Economic Review-Federal Reserve Bank of Atlanta* **84**(1), 4.

RStudio Team (2020). *RStudio: Integrated Development Environment for R*. RStudio, PBC. Boston, MA. http://www.rstudio.com/.

Stock, JH and MW Watson (2001). Vector autoregressions. *Journal of Economic perspectives* **15**(4), 101–115.

Tanaka, E and R Hyndman (2022). *monash: Consolidated tools and templates for staff at Monash University*. R package version 0.0.0.9000.

Waggoner, DF and T Zha (1999). Conditional forecasts in dynamic multivariate models. *Review of Economics and Statistics* **81**(4), 639–651.

Warsono, W, E Russel, W Wamiliana, W Widiarti, and M Usman (2019). Vector autoregressive with exogenous variable model and its application in modeling and forecasting energy data:

Case study of PTBA and HRUM energy. *International Journal of Energy Economics and Policy* **9**(2), 390–398.

Wickham, H (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, H, M Averick, J Bryan, W Chang, LD McGowan, R François, G Grolemund, A Hayes, L Henry, J Hester, M Kuhn, TL Pedersen, E Miller, SM Bache, K Müller, J Ooms, D Robinson, DP Seidel, V Spinu, K Takahashi, D Vaughan, C Wilke, K Woo, and H Yutani (2019). Welcome to the tidyverse. *Journal of Open Source Software* **4**(43), 1686.

Wickham, H, R François, L Henry, and K Müller (2022). *dplyr: A Grammar of Data Manipulation*. R package version 1.0.8. https://CRAN.R-project.org/package=dplyr.

Wickham, H, J Hester, and J Bryan (2022). *readr: Read Rectangular Text Data*. R package version 2.1.2. https://CRAN.R-project.org/package=readr.

Woźniak, T (2016). Bayesian vector autoregressions. *Australian Economic Review* **49**(3), 365–380.

Xie, Y (2016). *bookdown: Authoring Books and Technical Documents with R Markdown*. ISBN 978-1138700109. Boca Raton, Florida: Chapman and Hall/CRC. https://bookdown.org/yihui/bookdown.

Zeileis, A and G Grothendieck (2005). zoo: S3 Infrastructure for Regular and Irregular Time Series. *Journal of Statistical Software* **14**(6), 1–27.