AUSTRALIAN JOURNAL OF LABOUR ECONOMICS
VOLUME 23 • NUMBER 2 • 2020

Measuring the impacts of COVID-19 on job postings in Australia using a reweighting-estimation-transformation approach

Kailing Shen Australian National University
Bledi Taska Burning Glass Technologies

Abstract

We propose a reweighting-estimation-transformation (RWET) approach to estimate the impacts of COVID-19 on job postings in Australia. Contrary to the commonly used aggregation-based method on counting data, our approach can be used in a relatively 'thin' market, such as Australia. In a thin market, the number of job postings is relatively small, and the share of empty cells increases substantially when aggregating the data into finer categories. Using Australian job postings collected by Burning Glass Technologies and the RWET approach, our empirical evidence shows that the overall labour demand in Australia as of July 2020 is slowly recovering from its lowest 45 per cent dip at the beginning of May. Our results also suggest that the impacts of the pandemic are relatively evenly distributed across skill levels, but vary substantially across states, industries and occupations. Our findings of the dynamics on the demand side of the labour market suggest that skill-targeted policies might not be as effective as policies targeted at the state and industry levels to facilitate economic recovery.

JEL Codes: J21, J63, C55
Keywords: Job Posting; COVID-19; Thin Market

Corresponding author: Kailing Shen, kailing.shen@anu.edu.au
We would like to thank Mikal Skuterud for sharing the sample size data of the Canadian Labour Force Survey. We also thank the editors for providing very helpful comments. The online appendix can be accessed at https://github.com/Discovery666/BGANZ_Paper

1. Introduction

Many countries have been abruptly shaken by COVID-19 in 2020. Although in most cases, lives and health are considered top priorities, it remains essential to monitor the economy. Robust and prompt information of the economy is critical for policymakers, who might consider the optimal approach to support sections affected the most or to facilitate recovery post-pandemic. Job postings data can be particularly useful in such a context.

We compare job postings and other forms of data in detail later. Briefly, compared with survey or administrative data, job postings data have several advantages. These data are a rapid, cheap and precise reflection of the demand side of the labour market. In other words, they are collected nearly real-time at minimum cost and with little misreporting, and thus can facilitate quick and solid policymaking.

These features of job postings data can be especially important in a pandemic. Economic downturn due to a pandemic is such a rare event, and there is little ex ante understanding of it. Policies that have been proved effective in the past, such as in the Global Financial Crisis (GFC), might not be appropriate in the present situation. With near-real-time, high-frequency data on the labour market, policies can be tailor-made and adjusted quickly.

It can be challenging to analyse job postings data in high frequency for a small economy such as Australia. If we follow the commonly adopted method by aggregating the data into cells, more and more cells will be empty for small economies as the level of granularity of these cells becomes higher and higher. There simply are not many job postings for a 'thin' market. This limits the depth of the analysis.

Therefore, we propose a reweighting-estimation-transformation (RWET) approach that overcomes the small sample size problem. Our approach makes it possible to compare the size and composition of two comparable datasets, such as for two time periods and/or two geographic regions. The key idea here is to construct a weighting variable to 'rebalance' the two datasets. Once the datasets are reweighted, we can then use a linear probability model to examine the differences between the two. For ease of interpretation, the delta method can then be used to transform the estimated coefficients into the predicted size and composition differences.

It is worth noting, different from the aggregation-based counting data approach, that the RWET approach only compares two datasets/periods at a time. However, because the RWET approach operates at the micro-level, the identification of the model uses all observations at once. This is different from the aggregation-based approach on counting data, which effectively are censored at zero for empty cells. In particular, the small sample size will not cause data censoring when RWET is applied; rather, it leads to vaguely identified coefficients, which is merely a reflection of the lack of information contained in the data as in any other regression model.

Besides methodological contributions, we provide an empirical analysis of the impacts of the pandemic on the labour demand in Australia by using the RWET approach. The data used here are provided by Burning Glass Technologies (BGT), a Boston-based company that has been collecting and analysing job postings data worldwide since 2007.

Our empirical evidence shows that the overall labour demand in Australia as of July 2020 is slowly recovering from its lowest 45 per cent dip at the beginning of May. Our results also suggest that the impacts of COVID-19 are relatively even across different skill levels. Such similarity also applies across job postings according to various experience levels. These results are robust whether or not we control for composition changes. Further, they differ notably from the patterns of past economic recessions, where workers with more education and experience were affected less (e.g., Rosen 1968; Clark and Summers 1981; Jaimovich and Siu 2009; and Hoynes, Miller and Schaller 2012).

Finally, our empirical evidence shows that COVID-19's impacts on the labour market vary substantially across states, industries and occupations. The two largest states of Australia, New South Wales and Victoria, have both suffered significantly in terms of job postings but in July, 2020 all other states and territories were recovering consistently. As an example of cross-industry variations, in July 2020 the job postings for the health care and social assistance industry actually increased 15 per cent relative to the 2019 level, while those for the accommodation and food services industry were still 29 per cent less than the 2019 level. Across broad occupation categories, sales workers and clerical and administrative workers have been most affected, while labourers and machinery operators and drivers have been least affected. In July, the job postings for both labourers and machinery operators and drivers have even increased by 26 per cent and 35 per cent relative to the 2019 level, respectively.

These patterns are largely intuitive as they match the lockdown policies. However, they do suggest that the nature of the economic recession is of a very different nature from any past recessions. It is not the least skilled workers that are disproportionately affected. As the RWET approach used here allows us to control for composition changes in job postings, these patterns are identified with minimal confounding effects (e.g., variations in education or experience requirements across industries or occupations).

The rest of this paper is organised as follows: section 2 provides a literature review; section 3 discusses the job posting data used here; section 4 explains the RWET approach; section 5 discusses the empirical findings, and section 6 concludes with further discussions.

2. The literature on recessions and the labour market

There has been a long history of studies on the differential impacts of economic recessions on workers of different demographic characteristics. In general, less educated, less experienced, young and unskilled workers are found to be affected most during recessions.

For example, Rosen (1968) shows that skilled workers in the railroad industry experience less employment cyclical variation than unskilled workers. Clark and Summers (1981) suggest that economic recessions affect young workers disproportionately more than others. More recently, Jaimovich and Siu (2009) find that for all G7 countries, there is an empirical regularity between the individual's age and the cyclicality of their employment and hours worked. In particular, prime-age workers have the most acyclical employment, while teenagers and individuals over 60 have more procyclical employment. Similarly, using the Current Population Survey microdata, Hoynes, Miller and Schaller (2012) show that since 1979, the employment and unemployment cyclicality differences across gender, race, age and education have been 'remarkably stable'. In particular, male, black and Hispanic, youth and low-educated workers were affected much more than others during recessions.

Different from the above studies, Kahn, Lange and Wiczer (2020) examine the impact of COVID-19 on the job postings and initial UI claims in the United States. They find that job postings are affected significantly regardless of whether the industries or occupations have the work-from-home capability. Kahn, Lange and Wiczer (2020) suggest that the impact of COVID-19 on labour demand is similar on jobs that can be performed remotely and those that cannot. If we consider jobs that can be performed remotely to be high-skill jobs, then their results suggest that perhaps the impact of COVID-19 on labour demand is not mainly on unskilled jobs. Conversely, Bai *et al*. (2020) found that firms with more capability to work-from-home showed more resilience in the pandemic than did firms with lower capability. More recently, Chetty *et al*. (2020) argue that their empirical study using various real-time data suggests that traditional macroeconomic tools might not be effective with constrained demand due to pandemic health concerns.

In summary, the economic downturn in 2020 may be of a different nature compared with past recessions.

3. Job postings data: Burning Glass Technologies ANZ Job Feed

The dataset used in this study is created by BGT and is formally known as the NOVA™ ANZ Job Feed, referred to as BGT-ANZ hereafter. The data cover from 1 January 2012 to 31 July 2020. BGT collect job postings data from a broad range of sources in Australia in real-time.

Broadly, job postings data differ significantly from more traditional data sources, such as survey data and administrative data. Most survey data have months or years of time lags due to questionnaire design/data collection/data processing. Further, current evidence suggests that the respondents might find it difficult or be reluctant to respond to surveys during lockdowns. For example, online appendix Figure A1 and Figure A2 show the monthly sample size of the Current Population Survey of the United States and the Labour Force Survey of Canada. Both figures show a dramatic drop in sample size since the pandemic started.

Most administrative data can be timely and cost-effective. However, they capture outcomes rather than intentions. Because of legal reasons, administrative data often only have minimal information about individuals' demographic information, such as age, gender and education, whereas such information could be important for us to understand the causes of people's behaviour. Different from administrative data, job postings data are rich in information and provide the true intention of employers. There is little incentive for employers to misreport, and the data reflect employers' expectations of future product market demand.

Job postings data do come with their own limitations, mostly data quality and representativeness. Raw job postings data need to be processed and deduplicated for analytical usage. Such data quality issues apply to most internet-generated big data in general. For example, BGT takes comprehensive steps to remove duplicate postings, scams (e.g., pyramid schemes) and international jobs (e.g., for nurses to move to the United Kingdom). It is common for duplicates to occur both within and across different sources, with job boards showing the highest rate of duplicates. BGT has also found cases of recruiters posting a job multiple times with different regions listed to increase views, and this is particularly prevalent with international jobs. BGT's algorithms to identify these and other issues results in the removal of more than half of the postings on average.

Korbel (2018) shows that the BGT-ANZ data are largely representative in Australia. For instance, the National Skills Commission of the Australian Government produces its Internet Vacancy Index (IVI) based on SEEK, CareerOne and Australian JobSearch. In 2018, the IVI suggests a figure of 2,187,223 job postings, while BGT-ANZ covers more than 2,200,000 for the same period. Therefore, BGT-ANZ provides a robust representative dataset for the labour demand in Australia.

The representativeness of job postings data could be an issue more specific for economic research. In particular, job postings data only reflect a selected sample of the total vacancies. Employers always have multiple channels, such as social networks, to communicate their job vacancy information to the other side of the labour market. These channels differ in terms of various factors, such as cost, time efficiency and communication effectiveness. There have been substantial shifts in employers' choices in recent decades, and we might continue to observe such changes in the coming years as technology evolves. For the purpose of this study, there is sufficient understanding of how such selection might affect the usage of such data as a measure of labour demand.

Finally, job postings data are an expression of employers' intention to hire; it is beyond such data as to whether and what kinds of worker–employer matches are made. In April 2020, the Australian Bureau of Statistics announced that it will release weekly statistics based on employers' reported data through the Australian Taxation Office Single Touch Payroll system. This type of data describes the stock of the employed population. Job postings data are considered more informative for a better understanding of the employers' demand for new hires. In short, the BGT-ANZ data have unique advantages for us to examine the dynamics of the labour demand in this unprecedented period.

The full BGT-ANZ dataset has several components; besides the main data, it contains detailed information on skill requirements, degree requirements, etc. For the purpose of this study, we shall only use the main data. However, the application of our RWET approach to more detailed categories is relatively straightforward.

Table 1: Characteristics of Job Postings in Australia, 2012–2020

	2012–2014	*2015–2017*	*2018*	*2019*	*2020*
# calendar days	1,096	1,096	365	365	213
# job postings/day	2,116	2,561	2,718	2,857	2,230
# job postings	2,319,063	2,806,711	992,058	1,042,685	475,016
Education requirement					
If valid					
10–12	1.1%	1.2%	1.4%	1.6%	1.5%
13–14	11.1%	10.9%	11.3%	10.2%	10.8%
15	16.9%	17.9%	17.0%	17.5%	18.2%
16	54.8%	54.7%	54.4%	54.5%	52.2%
17	12.1%	10.6%	11.1%	10.5%	10.4%
18	2.6%	3.2%	3.2%	4.2%	5.3%
21	1.3%	1.6%	1.5%	1.4%	1.6%
Missing	76.8%	74.7%	73.8%	76.7%	76.9%
Experience requirement					
If valid					
1	14.6%	15.4%	14.7%	14.1%	14.2%
2	20.4%	22.3%	22.5%	21.5%	21.3%
3	20.2%	20.9%	20.9%	21.3%	20.4%
4–5	28.8%	27.9%	28.2%	29.0%	29.1%
6–8	8.0%	7.1%	7.3%	7.3%	7.5%
9–10	6.0%	5.0%	4.9%	5.2%	5.8%
11–15	1.9%	1.4%	1.4%	1.6%	1.7%
Missing	80.8%	80.3%	80.9%	83.4%	83.6%
Minimum annual wage offered					
If valid					
Less than 50K	17.9%	12.2%	7.6%	8.0%	6.3%
50k–70K	27.4%	30.8%	29.9%	28.1%	28.4%
70k–90K	20.4%	21.6%	21.6%	21.9%	23.0%
90K–110K	13.8%	15.5%	17.8%	16.2%	18.0%
110K–130K	9.2%	9.0%	11.6%	13.1%	11.9%
130K–150K	4.3%	4.1%	4.7%	4.4%	5.2%
150K–200K	7.0%	6.9%	6.8%	8.3%	7.3%
Missing	73.0%	75.5%	75.6%	73.9%	75.0%
State					
New South Wales	37.6%	39.7%	39.3%	38.4%	34.7%
Victoria	22.4%	23.5%	26.1%	24.6%	22.1%
Queensland	17.6%	17.4%	16.9%	16.4%	19.6%
Western Australia	11.6%	7.4%	6.5%	7.9%	9.5%
South Australia	4.0%	4.6%	4.1%	4.5%	4.5%
Australian Capital Territory	3.9%	4.4%	4.3%	5.0%	5.9%
Northern Territory	1.9%	1.6%	1.5%	1.7%	1.8%
Tasmania	1.1%	1.3%	1.2%	1.5%	1.7%
Industry					
Health care and social assistance	15.7%	17.7%	17.9%	18.6%	21.2%
Public administration and safety	13.3%	17.5%	16.4%	15.7%	17.8%
Mining	10.7%	4.0%	6.0%	4.7%	5.3%
Professional, scientific and technical services	9.9%	10.0%	9.7%	10.6%	9.9%
Accommodation and food services	8.2%	7.6%	6.5%	7.2%	6.0%
Financial and insurance services	7.8%	7.0%	6.2%	7.0%	6.9%
Education and training	6.5%	7.9%	10.3%	10.7%	9.4%
Retail trade	6.4%	7.8%	6.8%	6.6%	6.3%
Manufacturing	3.9%	3.6%	3.2%	3.4%	3.5%
Construction	3.2%	2.2%	1.9%	1.6%	1.9%
Rental, hiring and real estate services	2.3%	2.6%	1.9%	2.0%	1.9%
Information media and telecommunications	2.3%	2.6%	2.3%	2.4%	2.3%
Transport, postal and warehousing	2.0%	1.3%	3.0%	2.4%	1.2%
Electricity, gas, water and waste services	1.8%	1.2%	1.2%	1.3%	1.2%
Wholesale trade	1.7%	1.7%	1.6%	1.5%	1.2%
Arts and recreation services	1.5%	2.1%	1.9%	1.4%	1.2%
Other services	1.4%	1.6%	1.9%	1.6%	1.6%
Administrative and support services	1.2%	1.2%	0.9%	1.1%	1.0%
Agriculture, forestry and fishing	0.2%	0.2%	0.2%	0.2%	0.3%
Missing	58.6%	53.4%	48.8%	46.9%	48.3%
Occupation					
Professionals	37.1%	37.5%	39.4%	40.8%	40.7%
Clerical and administrative workers	15.1%	15.5%	14.4%	14.1%	13.2%
Managers	14.8%	14.3%	13.9%	15.5%	15.1%
Technicians and trades workers	12.0%	10.5%	11.5%	9.8%	10.0%
Sales workers	9.3%	9.6%	7.8%	7.8%	7.0%
Community and personal service workers	4.7%	5.1%	4.8%	4.9%	5.2%
Labourers	3.9%	4.4%	4.3%	3.9%	4.8%
Machinery operators and drivers	3.2%	3.2%	3.9%	3.3%	4.2%
Missing	13.4%	15.4%	16.2%	17.5%	17.2%

Table 1 provides a summary of the BGT-ANZ data used in this study. As the table shows, average number of job postings per day increased from 2012 up to 2019, and then dropped significantly in 2020. Among job postings with various education requirements, those requiring 16 years of education dropped the most, and among job postings with various experience requirements, those requiring 3 years of experience dropped the most. Overall, the patterns in Table 1 do not suggest that COVID-19 affects less skilled jobs more.

4. Aggregation-based approach versus reweighting-estimation-transformation approach

4.1 Aggregation-based approach

Before analysis, we aggregate our job postings into date- and covariate-specific cells. The number of postings in each cell can then be used as a measure of labour demand. This is an aggregation-based approach.

4.1.1 Overall impact of COVID-19 on the number of postings

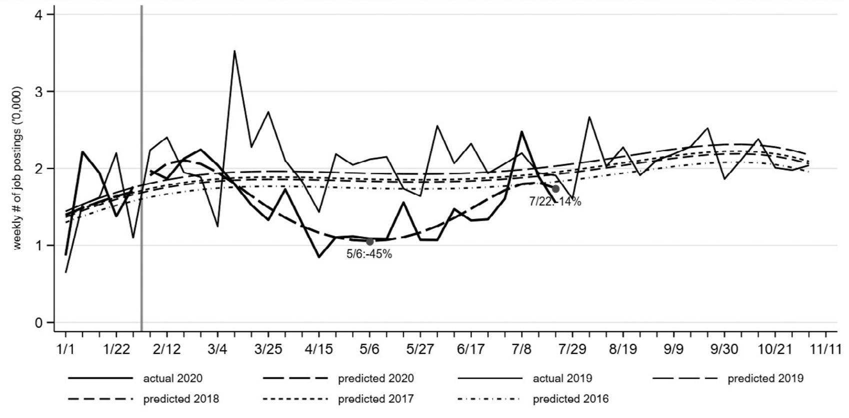
To examine the impacts of COVID-19 on the number of job postings at the aggregate level, we group all the job postings by posting date. In particular, let $n_{w,y}$ be the number of job postings for week w of year y; we then estimate the impacts of COVID-19 at the aggregate level as follows:

$$ln(n_{w,y}) = \alpha_0 + \sum_{s=1,\dots,5}(\alpha_s w^s) + \sum_{t=1,\dots,5}\beta_t \cdot 1(y \equiv 2020) \cdot 1(w \geq 6) \cdot (w-6)^s + \gamma_y + \mu_{w,y} \quad (1)$$

In other words, our baseline includes both year fixed effects and the common quintic time trend. The impacts of COVID-19 are captured to such a baseline from week six of 2020, the week start from 5 February 2020, also using quintic terms. The number of job postings drops substantially at December of each year. Thus, we only keep the first 45 weeks' data for each year, which correspond to early November.

The predicted weekly number of postings and the raw number of postings for the years 2019 and 2020 are presented in Figure 1. As the figure shows, there is a general increasing trend of job postings from January forward, which is common for each year. The impact of COVID-19 started in early March of 2020 in Australia. The number of job postings dropped consistently from March to the beginning of May, when the impact reached its highest level of 45 per cent. From May 2020, the number of postings actually increased slowly and steadily. In the last whole week of our study period, the period from 22 July to 28 July, the impact of COVID-19 on the number of job postings in Australia is estimated to be -14 per cent.

Figure 1: Number of Job Postings in Australia, 2016–2020



Note: The GBT-ANZ job postings data from 2012 to 28 July 2020 are used for the estimation of the model as specified in equation (1). The last week of July is dropped here as it only contains 3 days.

It is worth noting that although our data do not cover the total job postings in Australia, the estimation of the impact of COVID-19 here would only be biased if the selection of job postings into the GBT-ANZ changes over time. For example, if during COVID-19, conditional on having job vacancies, fewer employers choose to publish their job openings in one of the many sources used by BGT, perhaps as they can easily find someone through the social network, then our estimation will be biased down. In that scenario, the actual impact of COVID-19 would be less severe than estimated here. In contrast, if during COVID-19, conditional on having job vacancies, more employers choose to publish their job openings in our sources, perhaps as they would like to take advantage of the larger and more productive pool of potential applicants, then the actual impact of COVID-19 would be more severe than our estimation.

4.1.2 Overall impact of COVID-19 with skill composition controlled

The overall impact of COVID-19 estimated in section 4.1.1 could be biased if as the result of COVID-19 there are more job postings with lower education and experience requirements. That is, even though the total number of postings might not have dropped much, the composition of the job postings in terms of education and experience requirements might have shifted towards the lower end of the distribution. In this case, our estimation of the impact of COVID-19 on the labour demand could be biased up without controlling for education and experience requirements.

Therefore, to incorporate the composition shifts in our analysis, we group the job postings by week of the year, education requirement and experience requirement. Let $n_{w,y,d,p}$ be the number of job postings for week w of year y of education requirement d and experience requirement p; we can then estimate the impacts of

COVID-19 as follows:

$$Y_{w,y,d,p} = \alpha_0 + \sum_{s=1,\ldots,5}(\alpha_s w^s) + \sum_{m=2,\ldots,6}\delta_m \cdot 1(y \equiv 2020) \cdot 1(month\ of\ week\ w \geq m) + \gamma_y + a_d + b_p + \mu_{w,y,d,p} \quad (2)$$

For ease of presentation, we choose to estimate the changes in job postings in monthly frequency here. In particular, δ_m captures the changes in $Y_{w,y,d,p}$ for February, March, April, May, June and July 2020 from the previous month. These monthly coefficients are the effects of COVID-19 while holding the composition of education and experience constant. The year, education and experience fixed effects are captured by γ_y, a_d and b_p, respectively.

Panel A of Table 2 illustrates the extent of empty cells in our data. When the 7,635,533 job postings are grouped into week x 8 education categories x 8 experience categories cells, there are 100 (1 - 21,195/25,024) = 15.3 per cent cells empty. Four different specifications are compared in panel A. The raw number of postings is used in columns (1) and (2), while the log form is used in columns (3) and (4).

Given a substantial share of the cells are empty, columns (2) and (4) use a Tobit model, while columns (1) and (3) use ordinary least squares with observations of empty cells excluded. As a comparison between columns (1) and (2), or columns (3) and (4), suggests, the results are sensitive to the presence of empty cells, even when we only have two sets of covariates, education and experience. Further, panel A illustrates that the results from the log form are easier to interpret.

Panel B of Table 2 examines the impacts of COVID-19 on the number of postings when we take education and experience requirements into consideration. Among the four columns, column (8) is our preferred specification. It suggests that the number of postings dropped 40.6 per cent in April relative to March and increased 29.5 per cent in July relative to June, and that other month-to-month changes in 2020 are not statistically significant once education and experience are controlled. If we compare the estimated coefficients of April across the columns of panel B, it is interesting that the estimated coefficients decrease from -40.6 per cent to -47.3 per cent, or the estimated coefficient is biased down when education and experience controls are omitted. Based on the omitted variable bias formula, this negative sign of the bias suggests that the drop in job postings is more pronounced for the levels of education and experience with more postings originally. In other words, as panel A suggests, job postings for the 16-year education group and 4–5 years of experience are most affected by COVID-19. Conversely, the estimated coefficients of July increase from 29.5 per cent to 36.1 per cent when education and experience controls are omitted. This positive sign of the bias suggests that the increase in job postings is more pronounced for the levels of education and experience with more postings originally.

Table 2: Impacts of COVID-19 on the Number of Job Postings, using Aggregate-Counting Approach

	A. without COVID-19 controls			
	(1)	*(2)*	*(3)*	*(4)*
Dep variable:	*# of posting of education*experience*date cells*		*# of posting of education*experience*date cells (ln)*	
Approach	OLS	Tobit	OLS	Tobit
Education requirement (default group 10-12)				
13–14	249.4***	655.3***	1.079***	1.843***
15	298.9***	740.7***	1.395***	2.234***
16	506.5***	994.5***	2.721***	3.677***
17	277.9***	760***	1.308***	2.25***
18	195.2***	555***	.519***	1.19***
21	-14.79	-51.61	.0385**	-.0718***
Missing	1855***	2343***	3.677***	4.634***
Experience requirement (default group 1)				
2	43.23	79.91**	.2771***	.3503***
3	44.26	93.86***	.2802***	.3846***
4–5	75.98**	122.8***	.5053***	.5943***
6–8	-82.07**	-175.2***	-.3699***	-.5253***
9–10	-108.6***	-227.2***	-.5415***	-.7189***
11–15	-218.2***	-518***	-1.173***	-1.624***
Missing	1740***	1868***	2.61***	2.912***
# of observations	21,195	25,024	21,195	25,024
R^2	0.283	0.028	0.895	0.439
	B. with COVID-19 controls			
	(5)	*(6)*	*(7)*	*(48*
Dep variable:	*# of posting of education*experience*date cells (ln)*			
Approach	Tobit			
2020 Feb and afterwards	.1612	.1509	.1524	.1481***
2020 March vs. Feb	-.0582	-.0422	-.0497	-.0489
2020 April vs. March	-.4727**	-.4393**	-.4289***	-.4063***
2020 May vs. April	-.0693	-.0717	-.0681	-.0643
2020 June vs. May	.0896	.0540	.0509	.0480
2020 July vs. June	.3611*	.312	.3052**	.2946***
Year F.E. and weekly quintic controls		Y	Y	Y
Education requirement			Y	Y
Experience requirement				Y
# of observations	25,024	25,024	25,024	25,024
R^2	0.000	0.000	0.167	0.440

Note: *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Let the set of properties for job postings, $i \in I$, be x_i. For our BGT-ANZ data, x_i contains posting date $(jdate_i)$, education requirement (edu_i), experience requirement (exp_i), wage offered $(wage_i)$, state of the job vacancy $(state_i)$, industry of the employer (ind_i), occupation (occ_i), etc. The problem of empty cells will only worsen if we want to consider all of these properties. Thus, we propose an RWET approach instead.

4.2 Reweighting-estimation-transformation approach

There are three steps in our RWET approach proposed here.

4.2.1 Step 1. Construction of weight variable, w_i

Let D_0 be the number of calendar days covered in the benchmark dataset of job postings. Let D_1 be the number of calendar days covered in the investigation dataset of job postings. In our case, we use BGT-ANZ data for the year 2019 as the benchmark dataset. Thus, D_0 is 365. Without loss of generality, we can use BGT-ANZ data for March 2020 as the investigation dataset. Thus, D_1 is 31.

Then, we can pool the benchmark dataset with the investigation dataset to examine the changes in the job postings when the composition is held constant. Because these two datasets cover a different number of days, we need to construct a weight variable to make them comparable. In particular, the weight for job posting i, w_i, is:

$$w_i = \begin{cases} 1 & \text{if } i \in \text{investigation dataset} \\ D_1/D_0 & \text{if } i \in \text{ benchmark dataset} \end{cases}$$

In our example, the weight variable for job postings in our benchmark dataset will be 31/365 ≈ 0.0849.

If these two datasets have exactly the same number of job postings per day and the same composition of job postings, then, after weight is considered, any observation of the combined dataset will have exactly 50 per cent likelihood to come from either 2019 or March 2020. If the compositions of these two datasets are exactly the same while the 2019 dataset has more job postings per day than the March 2020 dataset, then, after weight is considered, the probability of a random observation of the combined dataset to come from 2019 will be higher than 50 per cent, and vice versa. This is the intuition of our strategy here.

4.2.2 Step 2. Regression with the constructed weight variable

Here, we can use a linear probability model on the combined dataset with weight considered and the dummy for March 2020, the investigation dataset, as our dependent variable. By using a linear probability model rather than Probit or Logit, we can consider fixed effects if required:

$$y_i = \beta_0 + \alpha \cdot X_i + \mu_i$$

In this study, X_i includes dummies for education requirement categories, experience requirement categories, minimum wage offered categories, job location states, employer industries and occupations.

4.2.3 Step 3. Transformation

For ease of interpretation, we can use the estimation results to predict the likelihood of any job postings to come from March 2020. Let the covariate of a job posting be X, then $\widehat{y(X)} = \widehat{\beta_0} + \hat{\alpha} \cdot X$ is the likelihood of this job posting coming from March 2020 rather than from 2019. The likelihood of this same job posting coming from 2019 is $1 - \widehat{y(X)}$.

Define $\widehat{d(X)} \equiv \frac{\widehat{y(X)} - (1 - \widehat{y(X)})}{(1 - \widehat{y(X)})} = \frac{\widehat{y(X)}}{1 - \widehat{y(X)}} - 1$. This is the change of this job posting's likelihood to come from 2019 versus March 2020. If we set X at the mean of 2019, then $\widehat{d(X)}$ gives the change of the likelihood of a typical job posting in 2019 to appear in March 2020.

The standard error can be calculated using the delta method. In particular:

$$var(\widehat{d(X)}) = \left[\frac{1}{1 - \widehat{y(X)}} + \frac{\widehat{y(X)}}{(1 - \widehat{y(X)})^2}\right] \cdot var(\widehat{y(X)}) \cdot \left[\frac{1}{1 - \widehat{y(X)}} + \frac{\widehat{y(X)}}{(1 - \widehat{y(X)})^2}\right]$$

Obviously, there is no empty cell problem in our RWET approach. Further, it is straightforward to estimate the change of any specific job postings. For example, by keeping all other covariates at their 2019 mean, we can set the education requirement of the hypothetic job postings to 10–12 years. Using the estimation results of March 2020 versus the year of 2019, we can then obtain, for this specific education level, the composition-adjusted percentage change of the number of job postings.

5. Main findings

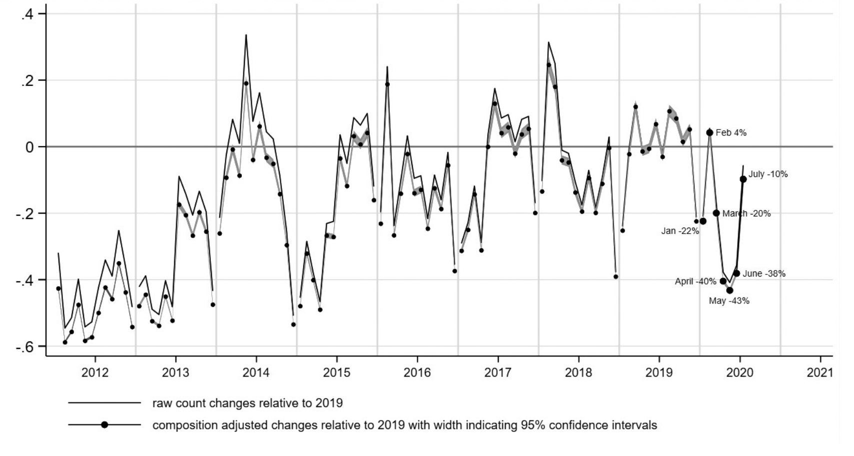
The empirical results based on our RWET approach are presented in Table 3 and Figures 2–3 and Figure A4 of the online appendix.

For each month from January 2012 to July 2020, we run a separate RWET process. Then, we present the estimated percentage change of job postings numbers for a typical 2019 job at these months. Such composition-adjusted estimations of job postings numbers, as well as 95 per cent confidence intervals, are shown in Figure 2.

As the figure shows, the composition-adjusted estimates are very similar to the raw job postings count changes. The differences between the two curves are larger for earlier years, perhaps because of the gradual change in the composition of the job postings over time.

Figure 2 also shows that the drop in job postings is quite significant in March and April 2020. By July, there has been some significant recovery of the number of job postings, composition-adjusted or not. Further, the composition-adjusted drop is shown to be slightly higher than the raw data, which implies that the type of jobs that are more representative in 2019 dropped more significantly as a result of the COVID-19 shock.

Figure 2: Percentage Changes of Number of Job Postings Relative to 2019, Jan 2012 to July 2020



Note: The GBT-ANZ job postings data from 2012 to 28 July 2020 are used for the estimation of the model as specified in equation (1). The last week of July is dropped here as it only contains 3 days.

The composition-adjusted change in job postings numbers, together with statistical significance levels, are presented in the first row of Table 3 for the first 7 months of 2020. The rest of Table 3 then presents the composition-adjusted change in job postings numbers for the same months, while keeping all other covariates at the 2019 average. For example, for job postings with an education requirement of 10–12 years, and all other covariates at the 2019 average, the number of job postings dropped by 25.13 per cent in January 2020; increased by 11.94 per cent in February 2020; and dropped by 1.37 per cent, 59.85 per cent, 51.45 per cent, 41.4 per cent and 18.8 per cent in March, April, May, June and July, respectively.

These estimated changes are also illustrated in Figures 3 in the online Appendix. As a comparison, online appendix Figure A3 provides graphs of the raw changes for each month. While the estimated changes are very similar to the raw changes, indicating little changes in the composition of the job postings from their 2019 benchmark set, we do have the advantage of knowing the statistical significance of each of these changes by using RWET, as the 95 per cent confidence intervals are indicated by the solid lines in these estimated bars. As the figures show, many of the small increases are not statistically significant.

Table 3: Impacts of COVID-19 on the Number of Job Postings, using Reweighting-Estimation-Transformation (RWET) Approach

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	January	*February*	*March*	*April*	*May*	*June*	*July*
For typical 2019 job postings	-0.2242***	0.0422***	-0.1999***	-0.4046***	-0.4323***	-0.3811***	-0.0979***
Education requirement							
If valid							
10–12	-0.2513***	0.1194	-0.0137	-0.5985***	-0.5145***	-0.4140***	-0.1811**
13–14	-0.1720***	0.0330	-0.0842**	-0.4367***	-0.4254***	-0.4519***	-0.2348***
15	-0.0690**	0.0995**	-0.0928***	-0.4837***	-0.5104***	-0.3675***	-0.0932***
16	-0.1944***	0.0211	-0.1546***	-0.4487***	-0.4729***	-0.4341***	-0.2106***
17	-0.1261***	0.0542	-0.1744***	-0.4466***	-0.4792***	-0.4448***	-0.1923***
18	0.0031	0.2610**	0.0195	-0.2520***	-0.3091***	-0.2028***	0.1382
21	-0.2383***	0.0335	-0.1778*	-0.0042	-0.2330***	-0.0818	0.5650*
Missing	-0.2433***	0.0398***	-0.2200***	-0.3923***	-0.4214***	-0.3712***	-0.0746***
Experience requirement							
If valid							
1	-0.1650***	0.0690	-0.0599	-0.4531***	-0.5064***	-0.4589***	-0.1918***
2	-0.0959***	0.0979**	-0.0795**	-0.4860***	-0.4481***	-0.4729***	-0.2438***
3	-0.1172***	0.0453	-0.1561***	-0.4701***	-0.4898***	-0.4705***	-0.1764***
4–5	-0.0744***	0.1104***	-0.1647***	-0.4435***	-0.4364***	-0.4257***	-0.1907***
6–8	-0.0778	0.0998	-0.1915***	-0.3212***	-0.4777***	-0.3585***	-0.1286**
9–10	-0.0953	0.2237*	-0.1264**	-0.3522***	-0.3751***	-0.3919***	0.1273
11–15	-0.2198**	-0.0139	-0.1156	-0.3188***	-0.5162***	-0.3416***	0.2823
Missing	-0.2461***	0.0329***	-0.2133***	-0.3963***	-0.4262***	-0.3682***	-0.0817***
Minimum annual wage offered							
If valid							
Less than 50k	-0.3781***	-0.2127***	-0.4339***	-0.6874***	-0.5108***	-0.5554***	-0.3810***
50k–70k	-0.1204***	-0.0031	-0.1504***	-0.4853***	-0.4570***	-0.4753***	-0.2240***
70k–90k	-0.0596**	0.0862**	-0.1199***	-0.5279***	-0.4519***	-0.4496***	-0.2303***
90k–110k	0.1222***	0.2681***	-0.1775***	-0.5017***	-0.4073***	-0.4374***	-0.2701***
110k–130k	-0.1838***	0.0958*	-0.3091***	-0.5884***	-0.4793***	-0.5367***	-0.4179***
130k–150k	0.1250	0.3947***	-0.1203**	-0.4286***	-0.3849***	-0.4353***	-0.2025***
150k–200k	-0.3282***	-0.1037**	-0.2312***	-0.5400***	-0.5223***	-0.5711***	-0.3692***
Missing	-0.2598***	0.0376***	-0.1992***	-0.3544***	-0.4229***	-0.3406***	-0.0214**

Note: *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 3: Impacts of COVID-19 on the Number of Job Postings, using Reweighting-Estimation-Transformation (RWET) Approach (continued)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	January	*February*	*March*	*April*	*May*	*June*	*July*
State							
New South Wales	-0.2913***	-0.0299**	-0.2915***	-0.4111***	-0.4965***	-0.4540***	-0.1535***
Victoria	-0.1729***	0.0498***	-0.2988***	-0.5119***	-0.5266***	-0.4632***	-0.2475***
Queensland	-0.1822***	0.2158***	0.2293***	-0.2987***	-0.2728***	-0.3036***	-0.0189
Western Australia	-0.0803***	0.1390***	-0.1080***	-0.3384***	-0.2430***	-0.2525***	0.3406***
Southern Australia	-0.2499***	-0.0542*	-0.2745***	-0.4101***	-0.4089***	-0.2751***	0.0264
Australian Capital Territory	-0.2282***	0.0798**	-0.1611***	-0.2641***	-0.2339***	-0.0298	0.1137***
Northern Territory	-0.2295***	-0.0716	-0.2563***	-0.3365***	-0.3167***	-0.0476	0.0583
Tasmania	-0.3013***	-0.0784	-0.0743	-0.2477***	-0.3129***	0.0844	0.2190**
Occupation							
Professionals	-0.2261***	0.0366**	-0.2344***	-0.3922***	-0.4375***	-0.3763***	-0.0750***
Clerical and administrative workers	-0.2057***	0.0457*	-0.1723***	-0.4900***	-0.4787***	-0.4475***	-0.2262***
Managers	-0.2181***	0.0610**	-0.2021***	-0.3674***	-0.4510***	-0.3710***	-0.1585***
Technicians and trades workers	-0.2372***	0.0308	-0.1957***	-0.3518***	-0.3995***	-0.3208***	-0.0085
Sales workers	-0.1871***	0.0334	-0.2155***	-0.5320***	-0.5781***	-0.4612***	-0.1592***
Community and personal service workers	-0.1795***	-0.0317	-0.1885***	-0.3916***	-0.2474***	-0.3991***	-0.0923***
Labourers	-0.1857***	0.0961*	-0.0754**	-0.2266***	-0.2431***	-0.2093***	0.2631***
Machinery operators and drivers	-0.2447***	0.1617***	0.0088	-0.3045***	-0.2024***	-0.1915***	0.3590***
Missing	-0.2575***	0.0364*	-0.1978***	-0.4149***	-0.4327***	-0.3979***	-0.1335***

Continued over page

Note: *, ** and *** indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 3: Impacts of COVID-19 on the Number of Job Postings, using Reweighting-Estimation-Transformation (RWET) Approach (continued)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
	January	*February*	*March*	*April*	*May*	*June*	*July*
Industry							
Health care and social assistance	-0.2266***	-0.0732***	-0.1605***	-0.2676***	-0.2821***	-0.1702***	0.1511***
Public administration and safety	-0.2895***	0.1635***	-0.2263***	-0.3929***	-0.2113***	-0.1591***	0.1178***
Mining	-0.3040***	-0.0354	-0.3452***	-0.3481***	-0.4963***	-0.4394***	-0.2192***
Professional, scientific and technical services	-0.2515***	0.0642*	-0.2252***	-0.4365***	-0.5640***	-0.5518***	-0.2138***
Accommodation and food services	-0.2205***	-0.0992***	-0.4437***	-0.7023***	-0.6268***	-0.4902***	-0.2851***
Financial and insurance services	-0.0886***	0.1415***	-0.1284***	-0.4957***	-0.5114***	-0.4086***	-0.0420
Education and training	-0.3899***	0.1145***	-0.3171***	-0.6564***	-0.4484***	-0.4609***	-0.2338***
Retail trade	-0.0814**	-0.0645*	-0.2118***	-0.4821***	-0.5691***	-0.4890***	-0.1000***
Manufacturing	-0.2497***	0.1484**	-0.2297***	-0.3804***	-0.5407***	-0.4497***	-0.1439***
Construction	-0.1869***	0.1360	-0.0866	-0.4317***	-0.4612***	-0.3782***	-0.0011
Rental, hiring and real estate services	-0.3313***	-0.0728	-0.2053***	-0.4670***	-0.4674***	-0.3322***	0.0173
Information media and telecommunications	-0.0577	0.0718	-0.1895***	-0.4414***	-0.5955***	-0.5156***	-0.2292***
Transport, postal and warehousing	-0.4981***	-0.4256***	-0.6313***	-0.8374***	-0.7447***	-0.6658***	-0.4699***
Electricity, gas, water and waste services	-0.2293***	-0.1983***	-0.2575***	-0.4981***	-0.4615***	-0.5452***	-0.3108***
Wholesale trade	-0.2986***	0.0882	-0.3363***	-0.5593***	-0.6445***	-0.6011***	-0.3236***
Arts and recreation services	0.1707	0.4525**	-0.2294***	-0.8781***	-0.8756***	-0.7106***	-0.5652***
Other services	-0.2811***	0.1025	-0.2039***	-0.5392***	-0.5219***	-0.3887***	-0.0659
Administrative and support services	-0.2349***	0.1394	-0.2271***	-0.7116***	-0.6096***	-0.4674***	-0.4262***
Agriculture, forestry and fishing	-0.1647	0.0442	-0.1345	-0.4693***	-0.4855***	-0.3022***	-0.0499
Missing	-0.1967***	0.0627***	-0.1376***	-0.3060***	-0.3958***	-0.3686***	-0.0903***

Note: *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Figures A3.1-A3.4 in the online Appendix suggest that the impacts of the pandemic are relatively evenly distributed across skill levels. For example, the impacts are similar in terms of timing and intensity across different education, experience and minimum annual wage categories. The impacts are also similar across temporary and permanent job postings.

Figures A3.5-A3.7 in the online Appendix suggest that the impacts of the pandemic vary substantially across states, industries and occupations. In these three figures, categories are sorted in descending order according to the share of total postings in each category. For example, in Figure A3.5, there are more job postings for New South Wales than for any other state; in Figure A3.6, there are more job postings in the health care and social assistance industry than in any other industry, and in Figure A3.7, there are more job postings for professionals than for any other occupation.

Obviously, we can use much finer categories of geographic regions, industries and occupations. In Figure A4 of the online appendix, we present a set of results for the impacts of COVID-19 across industries within each state. These results are based on estimations for each state. As these graphs show, the impacts also differ across states. For example, arts and recreation services are affected the most in New South Wales, Victoria, Queensland and Western Australia, but not in South Australia and Australian Capital Territory. The results presented here do illustrate broader patterns. In these broader patterns, the results suggest that the impacts of this pandemic vary across regions, industries and occupations.

6. Discussion

This paper proposes a new approach to estimate the changes of job postings that could be used for a relatively thin market. This RWET approach allows the analysis at a higher granularity than the commonly used aggregation-based approach. On the basis of this approach, we examine the impact of COVID-19 on the Australian labour market by using job postings data provided by BGT. The empirical evidence shows that the overall labour demand in Australia as of July 2020 is slowly recovering from its lowest 45 per cent dip at the beginning of May. Our results also suggest that the impacts of the pandemic are relatively evenly distributed across skill levels, but vary substantially across states, industries and occupations.

Australia is a small open economy. The economic development levels across the country are relatively uniform. During a ‘normal’ economic downturn, one would expect the impacts to be similar across geographic regions and, as discussed, less competitive firms to be affected most. Therefore, more educated, more experienced and highly paid workers would be affected less as they are more likely to be working with more competitive firms. Moreover, as Hershbein and Kahn (2018) note, in the US the firms in the hardest hit regions tended to increase their skill requirements more after the GFC. These patterns, supported by past empirical studies, all justify skill-upgrading types of policies during a ‘normal’ economic downturn.

However, the economic downturn due to COVID-19 has obviously not been ‘normal’ from the beginning. Under lockdown measures, competitiveness hardly helps firms; nor do skills help workers. Therefore, we suggest that appropriate economic policies have to be matched with relaxation of lockdown measures and these have to be gradual to allow firms and workers to recover from the 'coma'. The usual concern of skill-mismatch due to technology upgrading also seems unreasonable as it is unlikely that surviving firms will update their capital investment immediately after COVID-19. Of course, if government policies provide capital-upgrading incentives intentionally, matters may be different. Thus, if employment is the focus of recovery policies, then our findings suggest that skill-targeted policies might not be as effective as policies targeted at the state and industry levels.

This paper sets a prototype of possible research on job postings as a measure of labour market activities. There are more and more near-real-time administrative data on the labour market that could complement job postings data nowadays. Many of these new data could be utilised further using the RWET approach proposed here. In other words, the RWET approach can be used much more broadly than only on job postings data.

The BGT data also have various additional information categories, which could be used to understand the dynamics of labour demand over time. For example, there is detailed information on skills, degrees, subjects and majors. Analysing this information is beyond the scope of this study but could be the focus of future research.

References

Bai, J., Brynjolfsson, E., Wang, J., Steffen, S. and Wan, C. (2020), 'The Future of Work: Work from Home Preparedness and Firm Resilience During the COVID-19 Pandemic'. Retrieved from: https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M. and the Opportunity Insights Team (2020), 'Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data'. Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3616893

Clark, K. B. and Summers, L. H. (1981), 'Demographic Differences in Cyclical Employment Variation', *Journal of Human Resources*, 16, 61–79.

Hershbein, B. and Kahn, L. B. (2018), 'Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings', *American Economic Review*, 108, 1737–1772.

Hoynes, H., Miller, D. L. and Schaller, J. (2012), 'Who Suffers During Recessions?', *Journal of Economic Perspectives*, 26(3), 27–48.

Jaimovich, N. and Siu, H. E. (2009), 'The Young, the Old, and the Restless: Demographics and Business Cycle Volatility', *American Economic Review*, 99, 804–826.

Kahn, L. B., Lange, F. and Wiczer, D. G. (2020), *Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims*, National Bureau of Economic Research Working Paper No. 27061.

Korbel, P. (2018), Internet Job Postings: Preliminary Skills Analysis, NCVER Technical Paper. Retrieved from: https://www.ncver.edu.au/research-and-statistics/publications/all-publications/internet-job-postings-preliminary-skills-analysis

Rosen, S. E. (1968), 'Short-Run Employment Variation in Class-I Railroads in the U.S., 1947–1963', *Econometrica*, 36, 511–529.