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Just How Efficient is The Australian Labour Market.

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ABSTRACT

Efficiency, in the context of labour markets, can be thought of as being a measure of how successful the labour market is at matching available jobseekers to available jobs. In this research, a Stochastic frontier approach is used to obtain estimates of how efficient this production system is operating across geographical regions in Australia. The relevance of the work stems from the additional insights it provides into how different labour markets within Australia operate, and consequently, the ability of decision makers to design appropriate policies for those labour markets.

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Key words: Labour supply, labour demand; occupational market, public policy, immigrants

JEL classification codes: J22; J23, J62, J38, J61

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Just How Efficient is the Australian Labour Market?

I. Introduction

There are several 'frictions' in the labour market arising from imperfect information, policy-led distortions, and the heterogeneous nature of the workforce. Consequently, matching workers to jobs and jobs to workers is challenging despite attempts by policymakers to reduce the rate of unemployment and its duration by improving access to education and training, and embarking on labour market reforms and apprentice support programs etc. To improve our understanding of the workings of labour market and the sources of frictions Peter Dimond, Dale Mortensen and Christopher Pissarides have developed a labour market search and matching model.[1] It is essentially based on the production function concept with the numbers of unemployed (supply) and vacancies (demand) are taken as 'inputs' and the flow of newly matched worker-employer pairs as the 'output'. The resulting matching function describes the rate at which successful job matches 'output' are created from the stocks of 'inputs' [i.e., jobseekers and job vacancies]. As Fahr and Sunde (2004, page 410) argue "the empirical results have a clear and intuitive interpretation, providing information on the relative strength of supply and demand in the job creation process, on the overall efficiency (or speed) of the matching process, as well as its structure with respect to scale effect" . These insights can offer useful policy insights for designing labour market policies to influence labour demand and supply as well as the factors influencing the efficiency of labour market.

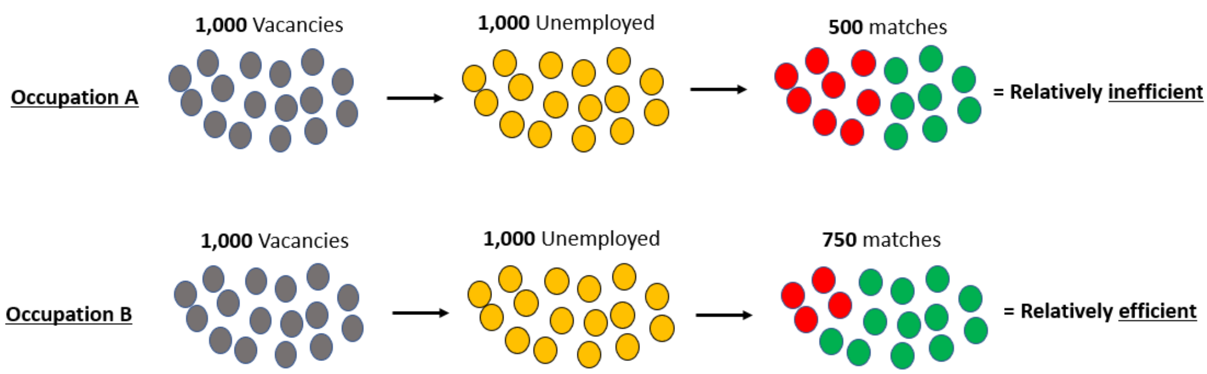
Despite these potential benefits, as yet no occupational level search and matching study is undertaken in Australia, while the available few studies, based on aggregated data, are dated back to the early 2000.[2] This is not surprising as occupational level analysis requires significant amount of disaggregated data, which are not readily available or have been historically unavailable. Fortunately, we have access to these data from government records and files as well as from publicly available sources, enabling us to develop a database for this research. Furthermore, recent emergence of new data sources (such as new administrative data and

[1] The roots of search and matching model go back to the pioneer work in this area by Diamond-Mortensen-Pissarides over the past several decades who were awarded Nobel prize in economics in 2010.

[2] The existing search and match studies based on Australian data can be grouped into two groups. First group of studies have used the econometric framework. These include, Beggs and Chapman (1990), Mumford and Smith (1999;2000), Stromback (2012), Leeves (2000) and Wesselbaum (2014). The second group of research applies a general equilibrium job matching model for the Australian economy and assess the impact of shocks on long-term unemployment and macroeconomic variables (see, for example, Herbert and Leeves, 2003).

linked data assets) has facilitated the analysis of detail occupational level job matching now than ever before, enabling researchers to shed light on the emerging trends in occupational level job matching efficiency.[3] As labour market dynamics can differ between regions or occupations, the investigation of matching function based on occupational (or regional data) can capture variations across occupations (or regions). For example, the factors that influence matching efficiency can vary from professional occupations, to trades, to lower skilled occupations. By disaggregating the matching function such differences can be observed and analysed. Understanding occupational level labour market dynamics is important at least for three reasons. Firstly, to address labour supply issues (through targeted migration program, training subsidies, etc). Secondly, to influence labour demand (through programs such as employer subsidies, wage subsidies, etc). Finally, to tackle labour market frictions by improving and facilitating job matching process between jobseekers and firms (through targeted employment services, employment facilitators, etc). The Seach and matching framework provides another way to conceptualise labour market efficiency as can be seen from figure 1 below:

Figure 1: Conceptualising labour market efficiency



The aim of this research is to shed light on these issues by estimating the matching function using broad occupational level data. We do this in two stages. In the first stage, we estimate a

[3] Matching function has a strong link with the Beveridge curve and labour market tightness (v/u). Changes in matching efficiencies shifts the position of Beveridge curves. A decline in efficiency shifts the curve outward pointing higher unemployment for the same level of vanacy, while an improvement in efficiency shifts the curve inward (Hall and Schulhofer-Wohl, 2017).

matching function for the Australian labour market (i.e., by pooling data across all one-digit Australia New Zealand Standard Classification of Occupations (ANZSCO)) and obtain the relative strength of demand and supply in the job creation and matching. This analysis will also provide an average picture for benchmarking the performance of each one-digit occupation in terms of job matching efficiency.[4] In the next stage, we investigate the drivers of efficiency, using insights from the theoretical and empirical literature. From policy perspective, it would be important to know how efficient/ inefficient matching is, and what causes them.

Following this brief introduction, section II presents a framework for estimating matching efficiency and discusses their drivers. In section III, emerging trends in labour demand, supply, job matching, and its efficiency is analysed, while estimation procedures and empirical results are reported in section IV. The paper concludes with policy remarks in section IV.

II. Framework for Modelling Job Matching Efficiency and their Drivers

(a) Modelling Matching Efficiency

We rely on econometric procedures to model matching efficiency. Within econometric framework matching efficiency can be modelled using the OLS and/or the Stochastic Production Frontier (SPF) analysis.[5] In the first, we deploy the SPF analysis to estimate matching efficiency across all ANZSCO occupations, while in the second stage we use pool OLS to investigate the drivers of efficiency.

In any moment in time there is the coexistence of unemployment and vacancies due to prevalence of frictions in labour market. Workers often search good jobs and firms also search good workers. Unemployed workers are matched in the vacant positions through matching with the firms, which is not instantaneous. The matching model assumes that at each moment in time, a proportion of existing filled jobs are destroyed, and new vacancies are created, so firms have positions to be filled. Thus, in equilibrium, there is a constant inflow into unemployment and the model predicts an equilibrium unemployment rate that is strictly greater than zero. The

[4] Matching efficiency is also dubbed as the 'speed of matching' by Fahr and Sunde (2004:410) and Lindeboom et al (1994: 48). In this paper both terms are used synonymously.
[5] Further discussion on this can be found in Petrongolo and Pissarides, 2001; Fahr and Sunde, 2001 and Ilmakunnas and Pesoal, 2003 and literature cited therein.

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larger the number of active unemployed (*U*) and the more vacancies (*V*) the more matches *M* (hires) are generated. Its general form is given as:

$$M = F\,(U, V) \tag{1}$$

Following the standard practice, we retain the Cobb-Douglas representation of the matching function.

$$M = F\,(U, V) = \mathrm{A}U^{\alpha}V^{\beta} \tag{2}$$

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As before *M* represents total matches or hires, while α and β are the elasticities of matching with respect to *U* and *V*, respectively.[6] In the standard labour market matching context, *A*, captures the overall matching efficiency, which can be interpreted as the speed in which new matches are formed, holding the numbers of *U* and *V* unchanged (see, Fahr and Sunde, 2004: 410; Lindeboom et al, 1994: 48). As noted earlier, α and β represent the elasticities of job matching with respect to unemployed (*U*) and vacancies (*V*) and their coefficients also imply the relative contribution of unemployed (supply) and vacancies (demand) in creating new matches, respectively. For example, labour markets with a small β but a large α tend to suggest that to create more job matches increasing the stocks of job seekers is more responsive than vacancies.

As Ilmakunnas and Pesola (2003:418) argue to estimate the Cobb-Douglas matching function as a frontier one can use stochastic frontier analysis, which explicitly include inefficiency as shown below:

[6] Theoretically, in the Cobb Douglas framework a matching function exhibits constant returns to scale, implying that the combined elasticities of job seekers (α) and job vacancies (β) are equal to 1, although empirical studies have allowed for flexible functional forms (Fahr and Sunde, 2004). Blanchard and Diamond (1989a, p. 13) argue the 'plausibility of increasing returns to scale come from the idea that active, thick, markets may lead to easier match'. In a survey of the literature Petrongolo and Pissarides (2001) have documented that these elasticities can be greater or less than unity.

$$M_{ot} = AU_{ot}^{\alpha}V_{ot}^{\beta}\omega^{\tau} + \varepsilon_{ot} - R_{ot} \tag{3}$$

Here, as before M refers to job matching, A is the total matching productivity, α and β are parameters to be estimated, τ is a liner time trend. Subscripts $_{ot}$ after the variables refer to occupation and time. ε_{ot} is an error term, while R_{ot} represents technical inefficiency in the job matching process. In frontier analysis, the matching function represents the maximum achievable matches from the stocks of unemployed and vacancies. Occupations can deviate from the best practices by having few matches, allowing the estimation of inefficiencies.

The matching function as a frontier analysis can be estimated as:

$$\ln M_{ot} = C + \alpha \ln U_{ot} + \beta \ln V_{ot} + \varepsilon_{ot} - R_{ot} \tag{4}$$

Here, C is a constant term and other notations are as noted earlier. Once occupational level job matching efficiency is estimated, we proceed with the investigation of the drivers of efficiency.

(b) The Drivers of Efficiency

In this section, based on theoretical and empirical literature, we advance some hypotheses below to investigate the drivers of efficiency in the next section.

Does wage rates (WAGE) influence the speed of job matching? On theoretical grounds, one would expect a positive relationship between wage rates and matching efficiency as attractive wages—by increasing the search intensity of workers—result in vacancies being filled quickly (Heijdra, 2009).[7] In contrast, substantially lower potential wages may discourage workers from search activity, thereby reducing the speed of job creation. So, the effect of wage rates on the job matching efficiency is unknown.

On theoretical grounds, one would expect that the inflow of motivated skilled migrants (MIGR) help improves labour supply and thereby facilitate the speed of job matching. However, it is possible to argue that skilled migrants qualified overseas may also be hard to match because of

[7] It has been argued that by lowering the discrepancy between the government welfare payments and the actual wage search activity of unemployed job seekers can be increased.

the non-transferability of country-specific skills, limited knowledge of local labour market institutions, in addition to language and cultural differences (Webster, 1998). This line of argument is very similar to Coates et. al, (2022) who question Australia's ability to address skills shortages through the skill migration program. Hence, the effects of skilled migrants (MIGR) on the speed of job matching must be investigated empirically.

As demonstrated by Mortensen and Pissarides (1994) a high density of labour union (UNION) discourages hiring and reduces job flows as firms anticipate the higher layoff costs when creating and filling a position. This lowers both the flows out of unemployment (by increasing hiring costs) and the flow out of employment (by increasing firing costs). Accordingly, we expect a lower efficiency with a higher density of labour union and a negative sign for the coefficient of UNION variable is predicted.

Does part-time female workforce (PTFEM) have any effect on the speed of job matching? While we are not aware of any study investigating this issue, it is plausible to argue that the greater the share of part-time female workforce, the lower the labour market efficiency as employers can view them unreliable source of labour supply due to the possibility of high absenteeism. On the other hand, it is also possible to argue that the higher share of part-time female workforce, the greater the flexibility to firms and hence the higher the matching efficiency. So, the effect of part-time female labour force (PTFEM) on job matching efficiency is unknown and must be investigated empirically.

How does the location impact the speed of job matching? Since urban centres have a large pool of labour—due to better amenities and opportunities for job seekers and their families—the speed of job matching is faster in these centres compared to regional locations which are charactered by the lower density of vacancies and job seekers, underdeveloped infrastructure and less skilled workforce. Subsequently, matching workers to jobs and jobs to workers can be daunting. On these grounds, we expect a negative sign for the coefficient of regionality (REGION) variable.

Jobs matching is relatively easier at the time of GDP growth, so we expect a positive sign for the coefficient of per capita GDP growth (PGDP) variable. As Li et. al, (2015) argue that the prevalence of underemployment (UNDEREMP) is a sign of labour market inefficiency which often results in the erosion of skills. Consequently, underemployed jobseekers may not be preferred candidates by employers (see, for example, Van Ours, 1991). Accordingly, a negative sign for the coefficient of UNDEREMP is expected.

An emerging trend in Australia and elsewhere is that an increasing employment flow is taking place from people not in labour force (NILF) category than from unemployed labour force.[8] This is not surprising given that most of these people already have some kind of prior work experience, making them attractive for employers. On this ground, one would expect that the higher the share of hires from the NILF, the greater the speed of job matching. Subsequently, we expect a positive sign for the coefficient of NILF variable.

What effect does the occupation transition (OCCTRANS)—the movement of people from one occupation to another occupation— has on the speed of matching? While little evidence is available on this issue, it has been documented that people are making more transitions, more frequently across the boundaries of occupations, industries, functional areas, countries, and the labour market (Sullivana and Ariss, 2021). So, how does these transitions affect the speed of job matching? It is plausible to argue that the larger the share of people moving from one occupation to another the lower the speed of job matching because of the possibility of time-consuming recruitment negotiations and screening process. On the other hand, it is also possible to argue that when the share of such workforce is higher, the speed of matching is quicker because these jobseekers already have prior work-related skills and experience, resulting in quicker recruitment negotiations. So, the effect of occupation transition rate on the speed of matching is unknown and must be investigated empirically.

Does the Award coverage (AWARDCOV)—which outlines the minimum wage and employment conditions under the Fair Work Ombudsman Act—improves or deteriorates the speed of job matching? Although empirical evidence on this issue is not yet available, it is plausible to argue that by outlining employment terms and conditions the Award coverage provides greater certainty to jobseekers and employers, and thereby facilitates the speed of matching. On these grounds, one would expect that the higher the Award coverage rate the better the speed of job matching. Accordingly, a positive sign for the coefficient of AWARDCOV variable is expected.

The above discussions lead to the following specification of the model. The expected signs of the coefficients are given below the equation in parentheses. What does a positive or negative

[8] In Australia, about two thirds of the employment flows is from NILF, which include retirees, people taking career break and full-time students (Anderson and Richardson, 2023, p. 21). Sullivana and Ariss (2021) note that in Canada about 47% of male and in US about 29% of the male and female are in workforce after their retirement.

coefficient mean? The positive coefficients can be interpreted as an increase in efficiency, resulting from the respective variables. The opposite is true for the negative coefficients.

$$\ln EFFICI_{ot} = C + \underset{(?)}{\xi \ln WAGE_{ot}} + \underset{(?)}{\theta \ln MIGRAT_{ot}} + \underset{(-)}{\text{ჳ} \ln UNION_{ot}} + \underset{(?)}{\text{Ƹ} \ln PTFEM_{ot}} + \underset{(-)}{\lambda \ln REGION_{ot}}$$
$$+ \underset{(+)}{\phi \ln PGDP_{ot}} + + \underset{(-)}{\Psi \ln UDEREMP_{ot}} + \underset{(+)}{\pi \ln NILF} + \underset{(?)}{\text{ӎ} \ln OCCTRANS_{ot}} + \underset{(+)}{\text{ж} \ln AWARDCOV}$$
$$+ \text{Є}_{ot} \qquad (5)$$

EFFICI = Occupation specific matching efficiency.

WAGE = median wage, measured by one-digit ANZSCO occupation specific median wage growth rate.

MIGRAT = skilled migrants. It is proxied by skilled migrants (arriving in Australia in the last two years) as a proportion of total occupational employment.

UNION = density of labour union, defined as percentage of union members in each occupation.

PTFEM = part-time female workers (aged 24-45), proxied by the proportion of part-time female employees as percentage of total occupational employment.

REGION= regionality, captures the influence of regional locations on matching efficiency. It is measured by the proportion of occupational employment that is found in regional areas.

PGDP = per capita GDP growth, measured by quarterly growth in seasonally adjusted per capita GDP.

UDEREMP = underemployment rate, measured by the number of underemployed in each occupation as a proportion of total employment in that occupation.

NILF = NILF hire rate. It is measured by the ratio of total hires from NILF in each occupation as a proportion of total occupational employment.

OCCTRANS = occupation transition rate. It is proxied by the movement of people from one occupation to another occupation in the last three months as a proportion of total employment in that occupation.

AWARDCOV= award coverage rate, defined as the proportion of workers covered under the Award in each occupation.

θ is an error term.

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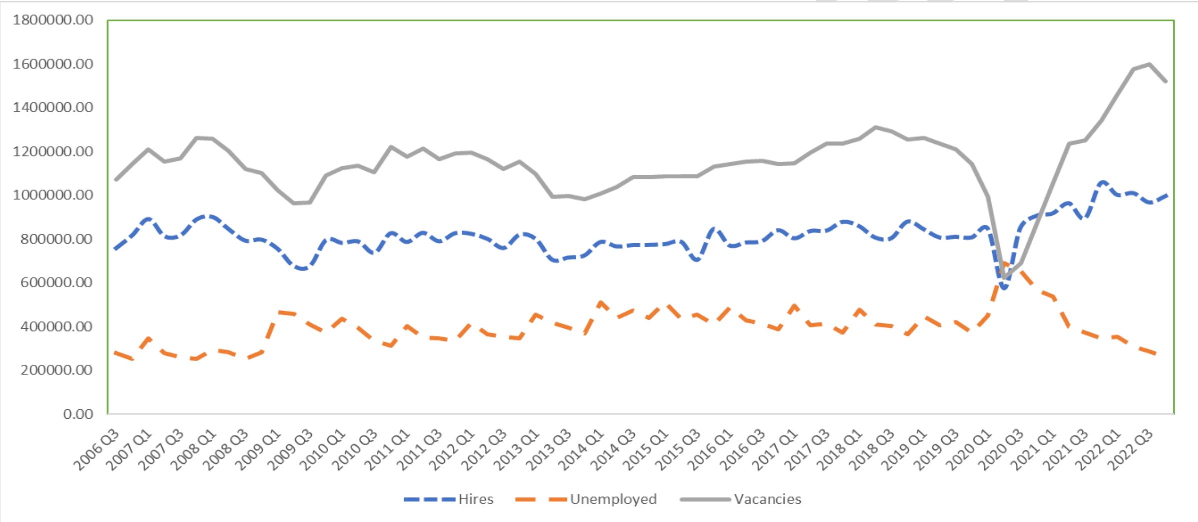
As mentioned earlier, *o*, is occupation and *t* is time period.

Appendix Table I presents variable names, expected signs and data sources for estimating matching function and drivers of efficiency models.

III. Trends in Labour Demand, Supply, Job Matching and Matching Efficiency

In this section we present an overview of the emerging trends in labour demand (vacancies), supply (unemployed), job matching (hires) and the efficiency of matching. Figure 3 presents aggregate trends in hires, vacancies and unemployed for 2006 Q3 to 2022 Q4 periods.

Figure 3: Hires, vacancies and unemployed: 2006 Q3 to 2022 Q4.



Few points worth noting from the above figure (Figure 3). First, over the years there has been a sharp increase in both the number of vacancies and hires compared to the number of unemployed (except for 2020 when unemployment surged but hires and vacancies declined sharply due to the COVID-19 pandemic). Second, both the number of vacancies and hires have reached its recorded level by the end of 2022, while the number of unemployed has dramatically declined, thanks to a tight labour market. Third, there is a significant gap between the number of hires and vacancies—except for 2020—and the gap is widening. The number of vacancies is substantially higher than the hires, and only about two-third of the vacancies are being filled. What does this tell us? This points to the prevalence of skills shortages in a wide range of sectors, including IT, health, construction etc. Forth, the number of hires exceed the number of unemployed. This is because new hires include not just unemployed but also those not in labour force (NILF) as well as people moving between jobs. Anderson and Richardson (2023) estimate that about two thirds of employment flows in Australia is from NILF while only one third come from unemployed labour force. This figure is substantially higher than the overseas experience. For example, Blanchard and Diamond (1989a) estimate that in US about 45 percent of new hires originates from unemployed labour force, while the remaining 40 percent and 15 percent come from NILF and people moving between jobs respectively.

Occupational level trends in hires, unemployed and vacancies is presented in figure 4, while matching efficiency is presented in figure 5. Trends in hires, vacancies, and unemployed varies significantly between the occupations (figure 4). For instance, in comparison with other occupations, Managers (ANZSCO 1) and Professional (ANZSCO 2) occupations have more vacancies than the number of hires. In other words, all advertised positions in these occupations are not being filled, indicating the lack of relevant skills among potential employees, which naturally requires more time to find a suitable match. This finding is consistent with JSA's Recruitment Experiences and Outlook Survey (REOS) which consistently shows high recruitment difficulties in these occupations. Occupations like Community and personal service workers (ANZSCO 4) and Machinery operators and drivers (ANZSCO 7) exhibit hardly any gap between vacancies and hires, indicating quicker job matching. Access to temporary visa holders and international students appears to have facilitated job matching in Community and personal service.

There are significant variations in job matching efficiency between the occupations (see, figure 4). Matching efficiency is consistently higher in Community and personal services (ANZSCO 4) and lower in Managers (ANZSCO 1). Higher efficiency in Community and personal services appears to be due to the availability of jobseekers in this occupational group—particularly access to temporary visa holders who could be trained quickly—resulting in quicker job matching, while opposite is true for Managers. Lower job matching efficiency for Managers (ANZSCO 1) seems to be linked with a low number of potential employees with relevant skills. Job matching efficiency in all other occupations are lower in comparison with Community and personal services, except for Managers (figure 5).

Average trends in job matching efficiency is presented in figure 6. There have been fluctuations in matching efficiency between the periods although a small improvement is seen since the mid-2000 despite significant drop in 2009 and 2020 due to the global financial crisis and the COVID-19 pandemic, respectively.

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Figure 4: Trends in Hires, Unemployed and Vacancies in one-digit ANZSCO Occupations: 2006Q3-2022Q4

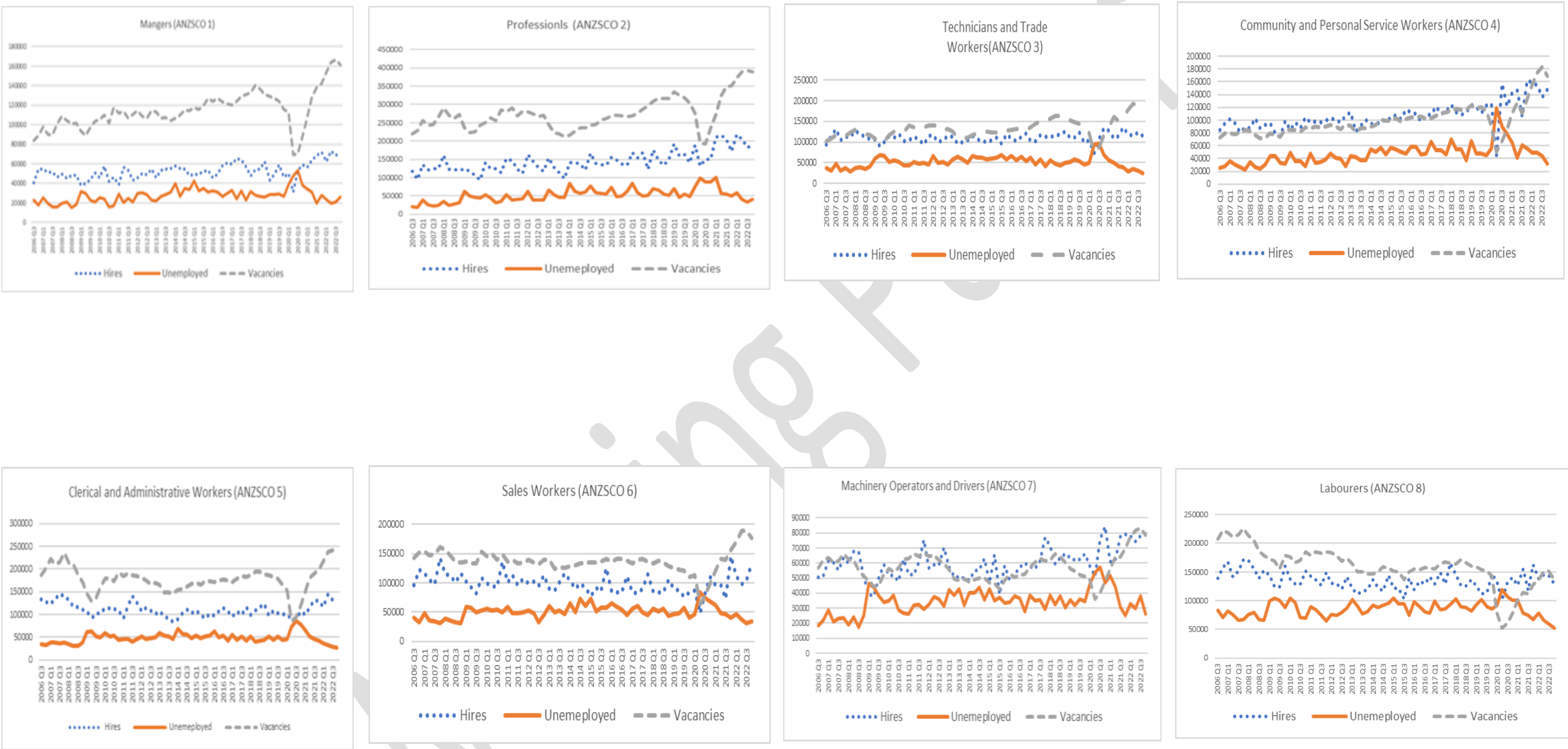
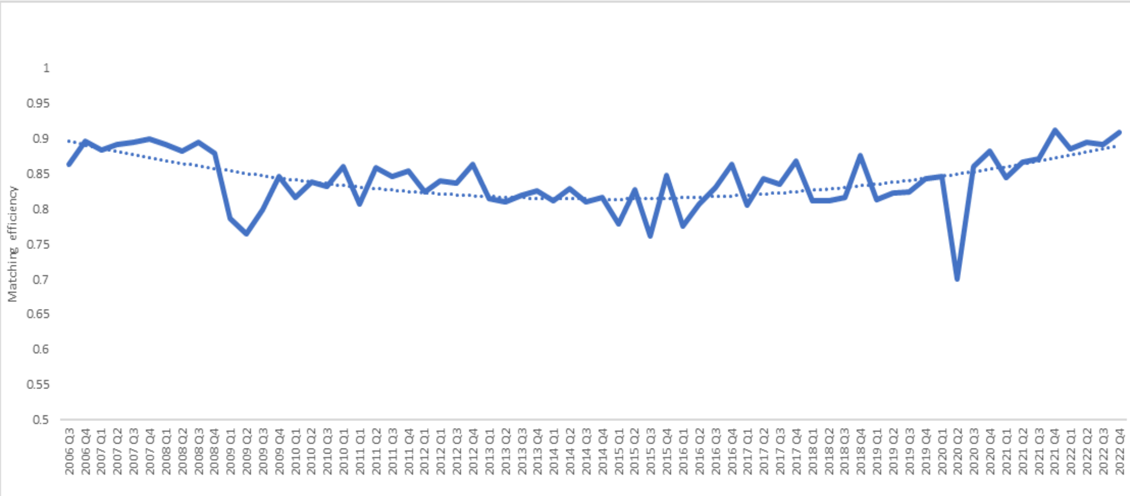


Figure 5: Matching efficiency in one-digit ANZSCO Occupations: 2006Q3-2022Q4

Figure 6: Average matching efficiency across all occupations: 2006 Q3-2022 Q4



IV. Estimation Procedures and Results

In this section we discuss the model estimation procedures and report the results. The models specified earlier are estimated in two stages. In the first stage, we estimate the matching function for total employment across all occupations (equation 4). This is done by pooling cross-section and time series data for all one-digit occupations, using the stochastic production frontier analysis. Estimated matching function provides information on the relative strength of demand and supply in job creation as well as the efficiency of job matching (or the speed of matching). In the second stage, drivers of efficiency are investigated (equation 5).

The results for the matching function across all occupations are reported in Table 1.

Across all occupations, estimated coefficients for the elasticity of matches with respect to vacancies (labour demand) is 45 percent, while for unemployed (labour supply) it is about 33 percent. Both elasticities are statistically significant and, as expected, have positive signs. The higher elasticity for vacancies than unemployed suggest that policies aimed at increasing the stock of job vacancies by 1 percent is much more responsive in creating new matches than the stock of jobseekers by 1 percent. For example, 10 percent increase in job vacancies can create just over 4 matches, while 10 percent increase in jobseekers can only create about 3 matches, underlining the importance of policies aimed at increasing the stock of vacancies. These may

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include labour market reforms and/or vacancies subsidies programs etc. Overall, job matching efficiency over the entire study period is 84 percent.

<u>Table 1: Estimates of Matching Function using Stochastic Production Frontier Analysis: 2006 Q3-2022 Q4, Panel results</u>

Dependant variable: Log of matches

Term	Model 1
Constant	2.863 (0.363) ***
Log Vacancies (*V*)	0.450 (0.02) ***
Log Unemployed (*U*)	0.326 (0.026) ***
Efficiency	0.841
Sigma Squared (σ^2)	0.229 (0.21)
Gamma (γ)	0.907 (0.078) ***
Mu (μ)	-0.787 (1.291)
Log likelihood	64.239

Note: t-ratios are given in parenthesis. Significant levels are: ***=1%, **=5% and *=10%

It should be noted that our estimates regarding the relative importance of labour demand and supply in job creation are different from the overseas studies by Fahr and Sunde (2002) for West Germany, and Ilmakunnas and Pesoal (2003) for Finland, who have applied the same methodology as ours. For instance, they observed a higher elasticity of matching with respect to unemployed (labour supply) than vacancies (labour demand) , while our findings suggest the other way round. The differences in results could be linked to the level of disaggregation and the differences in industrial relations environment. For instance, labour union is relatively less intense in Australia compared to Germany and Finland.[9] This may be the reason as to why

[9] OECD (2023) notes that the percentage of employees covered by trade union in Australia is lower (13.7 % in 2018) compared to 16.3% and 58.8% (in 2019) in Germany and Finland respectively.

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demand plays an important role in creating more matches. Table 2 presents job matching efficiency for one-digit ANZSCO occupation and their ranking.

Table 2: Ranking of job matching efficiency for one-digit ANZSCO occupations

ANZSCO one-digit occupation	Speed/Efficiency of job matching	Ranking of occupation
Community and Personal Service Workers (ANZSCO group 4)	0.92	1
Technicians and Trades Workers (ANZSCO group 3)	0.89	2
Labourers (ANZSCO group 8)	0.87	3
Professionals (ANZSCO group 2),	0.87	4
Clerical and Administrative Workers (ANZSCO group 5),	0.85	5
Machinery Operators and Drivers (ANZSCO group 7),	0.84	6
Sales Workers (ANZSCO group 6)	0.83	7
Managers (ANZSCO group 1)	0.66	8

Source: Authors estimates based on equation 4. Ranks are based on average efficiency over 2006 Q2-2022 Q4.

The efficiency of job matching across all occupations is about 84 percent (see, Table 1). Using this figure as a benchmark, we note that Managers (ANZSCO group 1) and Sales workers (ANZSCO 6) exhibit the lowest job matching efficiency, possibly due to the small number of firms and jobseekers in these occupations, while large occupational labour markets such as, Community and personal service workers (ANZSCO group 4), Technicians and trade workers (ANZSCO group 3), and Labourers (ANZSCO group 8) show the higher matching efficiency. It appears that the larger the respective labour market, the better the speed of job matching, perhaps in such markets both firms and jobseekers meet each other promptly— a finding similar to Fahr and Sunde (2004) for the West German, and Coles and Smith (1996) for England and Wales.

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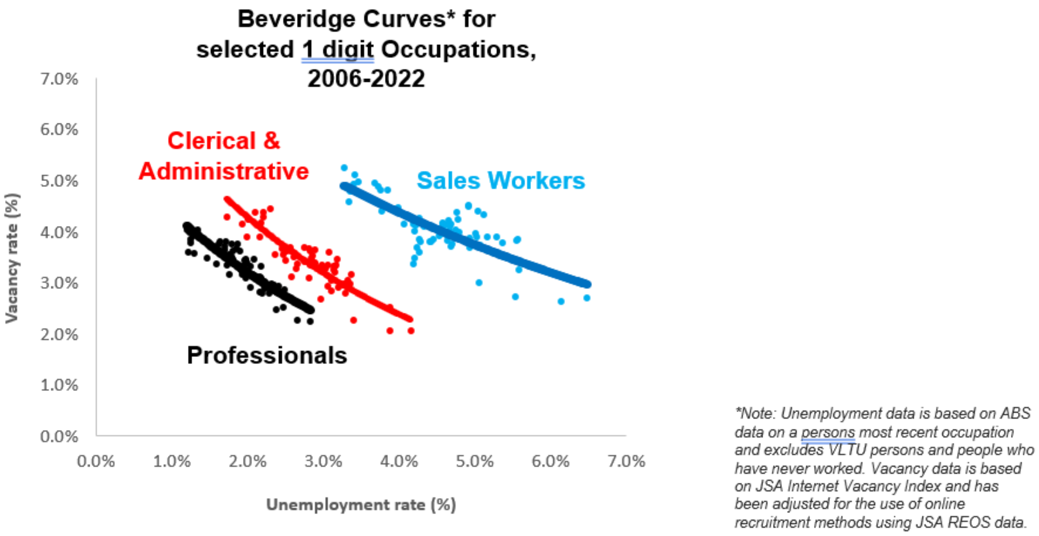
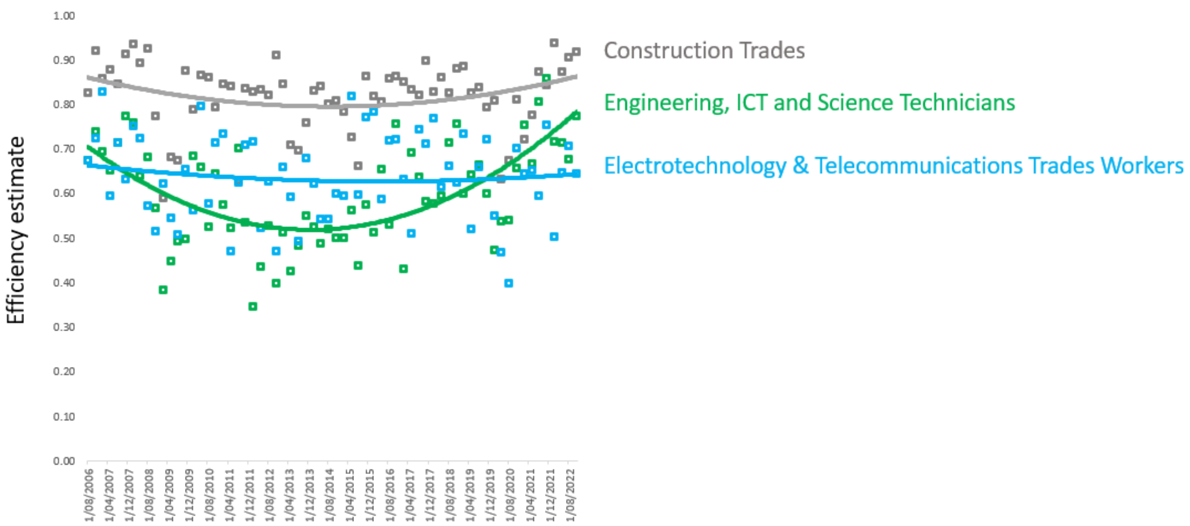
Our estimate of matching efficiency is very similar to the Beveridge Curve which is also used to examine labour market efficiency as shown in figure 7 below:

Figure 7: Beveridge Curve for selected one-digit occupations



Our preliminary examination of job matching efficiency shows variations in matching efficiency between the occupations within a one-digit occupation as shown in figure 8.

Figure 8: Occupation comparisons within one-digit occupation



Why does efficiency vary across the occupations? We examine this issue using OLS by pooling cross-sectional and time series data for all eight one-digit ANZSCO occupations (equation 5). Before estimating the final model, presented below, several diagnostic tests, including F-test, were performed. Our specified model passes the F-test. Multi-collinearity between variables was also checked to ensure they are not highly corelated with each other. At the experimental stage, we tried several specifications of the model by adding or deleting variables, using first difference and fixed effect models. These do not alter our results.[10] The results for the preferred model of the drivers of efficiency are presented in Table 3.

Table 3: OLS Results- Drivers of Efficiency across all Occupations:2006 Q2-2022 Q4

Dependant variable: Matching Efficiency

Intercept	0.610 (0.029) ***
Median wage growth (WAGE)	0.042 (0.111)
Skilled migrants (MIGRAT)	0.013 (0.003) ***
Labor union density (UNION)	-0.003 (0.001) ***
PT female workers rate (PTFEM)	-0.002 (0.001) **
Regional employment rate (REGION)	-0.314 (0.091) ***
Per capita GDP growth (PGDP)	0.004 (0.003) *
Underemployment rate (UNDEREM)	-0.016 (0.002) ***
NILF hire rate (NILF)	0.035 (0.006) ***
Occupation transition rate (OCCTRANS)	0.056 (0.014) ***
Award coverage (AWARDCOV)	0.007 (0.001) ***
R^2	0.55
Adjusted R^2	0.54
F	63.68 ***
No of Observations	536

Significant levels are: ***=1%, **=5% and *=10%.

[10] These can be obtained from the authors on request. Due to space consideration, they are not present here.

We do not find any statistical evidence to support or reject the hypothesis that growth in median wage rate (WAGE) has any effect in job matching efficiency although its coefficient has a positive sign. However, in a study of the efficiency of the Australian labour market, using the Beveridge Curve for the late 1960s to late 1990s macro data, Groenewold (2003) finds that the higher real wage, in fact, pushes the Beveridge Curve outward, indicating a deterioration in efficiency.

The coefficient of skilled migrants (MIGR) variable is highly significant and has a positive sign, suggesting that the inflows of skilled migrants improve job matching efficiency. This result is not surprising given that skilled migrants tend to have high participation rates, and they bring skills that are not readily available in Australia, particularly in health, IT, education, and engineering occupations (NSC, 2021). This finding points to the importance of allocating skilled migration visa to the occupations that have skills shortages. However, in an analysis of the extended Beverage Curve for Australia Webster (1999) finds that immigration has no effect in labour market efficiency.

We find statistical evidence to support the hypothesis that a higher density of labour union (UNION) lowers matching efficiency, although its impact is marginal. For instance, a 10 percent increase in the density of labour union lowers the efficiency only by 0.30 percent. How does labour union affect labour market efficiency? It appears that in the presence of a high density of union, unless essential, firms are reluctant to create and fill positions because of the anticipated higher hiring and firing costs (OECD, 2020). This naturally reduces flow out of employment and flow into employment, lowering the efficiency of labour market.

The coefficient of part-time female workforce (PTFEM) variable is statistically significant and has a negative sign, although its impact is negligible. This tends to suggest that a 10 percent increase in part-time female workers leads to less than a quarter of a percent decline in efficiency, perhaps because employers view them an unreliable source of labour supply and perceive they possess limited skills. One possible way to address this would be to create designated part-time female positions, especially in the medium and large size businesses, and incentive them to undertake micro credentials courses.

We provide further evidence in support of the view that regional labour markets (REGION) are less efficient in matching jobs to people and people to jobs. Why would this be the case? There are at least two possible explanations. First, regional labour markets are characterised by

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small number of employers and job seekers—mainly due to the lack of efficient physical infrastructure—resulting in time consuming matching and negotiation process. Second, these labour markets tend to have the domination of less skilled and older workforces, who may be lacking emerging skills brought about by technological revolution. These contribute to slow job creation and matching in regional areas. To enhance job matching in these locations will require improved connectivity between cities and regional centres and better education and training facilities in regional areas. Coles and Smith (1996) also find similar results for England and Wales.[11]

As expected, per capita GDP growth (PGDP) has a positive impact on the speed of matching, but the relationship is not very robust (significant only at 10% level).

The statistically significant and a negative coefficient for the underemployed (UNDEREMP) variable suggests that a higher share of such workforce is detrimental to the speed of job matching, perhaps due to skills erosion among these workers, making them less competitive. One possible way to address this may include incentivising them to undergo micro credential courses.

Our finding provides strong support for the hypothesis that hires from NILF could be one of the major drivers of efficiency. For instance, a 10 percent increase in hires from NILF could contribute to 3.5 percent rise in efficiency. However, motivating NILF cohort to participate in labour market remains a challenge unless policy around age pension and other welfare benefits is liberalised. Also, offering generous childcare assistance to families with small children, together with free skills upgrading training would be helpful.

The coefficient of occupation transition rate (OCCTRANS) variable is statistically significant and has a positive sign, suggesting that the greater the movement of people between occupations the better the job matching efficiency, perhaps these cohort already have prior work-related skills, making them attractive for employers.

As expected, the coefficient of the Award coverage (AWARDCOV) variable is statistically significant with a positive sign, but its impact is marginal. A 10 percent increase in the Award coverage can improve job matching efficiency by 0.7 percent, suggesting some efficiency can be gained in labour market by increasing the Award coverage.

[11] Coles and Smith (1996) who use a geographic area variable to capture the density effect of jobseekers and vacancies on job matching, find a decline in the speed of matching in smaller locations (ie, matching rate declines as dispersion increases).

V. Concluding Remarks

Despite the importance of matching workers to jobs and jobs to workers, which determines the duration of unemployment, a detail analysis of occupational level job matching in the search and matching framework for the Australian labour market is limited. This is not surprising given that such analysis requires a large number of data, which are not readily available. Fortunately, we have developed a database from government records/ files, and publicly available sources to shed light on this issue to improve our understanding of the functioning of labour market.

Our experimental search and matching model show that labour market efficiency is broadly consistent across most occupational groups (with only slight variations), except for Managers and Sales workers, which exhibit matching efficiency below the national average. It appears that in the large occupational labour markets, such as Community and personal services, job matching efficiency is higher, perhaps due to the high density of both firms and jobseekers in such markets.

The examination of the drivers of efficiency indicates the importance of mobilizing NILF in labour market, targeting skilled migration program in the area of skills shortages, and widening the Award coverage. This demands for a wide range of reforms, particularly in the area of age pension and welfare payments as well as industrial relations. Improved access to short-term micro credential and VET courses to NILF, and underemployed and part-time workforce would also help improve job matching efficiency. Our findings also point to the importance of improved connectivity between urban and regional/rural centres to attract potential employers and employees to create jobs and expedite job matching in regional locations.

While these findings are interesting, they must be interpreted with cautions. For example, our measure of occupation-specific skilled migrants variable (MIGRAT)─the ratio of skilled migrants to total occupation employment variable─ is based on the gross skilled migration data in the absence of occupation-specific skilled migration flows. This may have caused some bias in our results. Further analysis at the two- and three-digit occupations will be required to confirm some of these results, given the variation in efficiency between occupational groups at the one-digit level. In the future, it will also be useful to undertake similar analysis by State and Territory and/or industry to capture region- and/ or industry- specific variations in job matching efficiency. Despite these, our results do provide useful policy insights to a wide range of users including, education and training providers, officials responsible for subsidising

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training courses and policymakers responsible for mobilising NILF and deciding the size of skill migration program.

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Appendix I: Variable names, measurement of variables, expected signs and data sources for estimating matching function and drivers of efficiency

Matching function (Equation 3)		
Variable names	*Expected sign*	*Measurement and data sources*
Flow of hires/ matches (M)		Flow of hires includes those employed with job tenure less than 3 months. Data source: computed from ABS DataLab.
Stock of unemployed (U)	+	Number of unemployed by most recent occupation. Data source: Longitudinal Labour Force Survey, ABS.
Stock of vacancy (V)	+	Number of job vacancies. Internet vacancy index (IVI) was the main source of data, which was adjusted using insights from REOS. This was important as IVI only covers about 65 percent of the vacancies (REOS, JSA). Since many small businesses and businesses in rural areas rarely place online job advertisements, and IVI does not cover all online platforms, adjusting IVI data was necessary to better reflect the complete flow of vacancies. Data sources: JSA
Drivers of efficiency (Equation 5)		
Variable names	*Expected sign*	*Measurement and data sources*
Median wage growth rate (WAGE)	?	Data sources: Employee Earnings, Benefits and Trade Union Membership, ABS (Cat. no. 6310).
Proportion of skilled migrant workforce (MIGRAT)	?	Skilled migrants by ANZSCO occupations are not available, so the number of total skilled migrants was divided by each

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		one-digit ANZSCO occupational employment to identify occupational distribution of skilled migrants. Data source: Department of Home Affairs
Density of union (UNION)	-	It is defined as percentage of union members in each occupation. Data Source: Employee Earnings, Benefits and Trade Union Membership, ABS (Cat. no. 6310).
Proportion of part time female workforce (PTFEM)	?	It is proxied by the part-time female employees (aged 24-45) as percentage of total occupational employment. Data Source: Longitudinal Labour Force Survey, ABS DataLab.
Regionality (REGION)	-	Proportion of employment found in regional areas. Data Source: NERO, JSA.
Growth in per capita GDP (PGDP)	+	Data Source: Australian National Accounts: National Income, Expenditure and Product, Table 1: key National Account Aggregates, ABS (Cat. No. 5206.0).
Proportion of unemployed workforce (UNDEREMP)	-	Data Source: Longitudinal Labour Force Survey, ABS DataLab.
Proportion of hires from NILF (NILF)	+	Data Source: Longitudinal Labour Force Survey, ABS DataLab.
Occupation transition (OCCTRANS)	?	It was proxied by the movement of people from one occupation to another occupation in the last three months as a proportion of total employment in that occupation Data Source: Longitudinal Labour Force Survey, ABS DataLab.

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Proportion of workforce covered by Award (AWARDCOV)	+	Data Source: Employee Earnings and Hours, ABS (Cat. No. 6306.0).

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