How efficient is the Australian labour market? Analysing job matching efficiency for regions, occupations and industries

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Abstract

In an efficient labour market, employers fill vacancies in a timely manner, and those who are unemployed do not remain out of work for long. However, this is not always the case. During an economic downturn, workers who are laid off may possess different skills to those required in sectors that remain strong. As a result, the unemployed may remain unemployed for longer, because they are unable to find work. In addition, the remaining vacancies may go unfilled, as suitable workers cannot be obtained from the unemployment pool. In such circumstances, poor labour market efficiency is at play, and the economic and social costs can be substantial. Consequently, Jobs and Skills Australia (JSA) has been researching this topic by examining the question 'for a given level of vacancies (demand) and unemployment (supply), how many hires should be occurring in the labour market?'. Using data from both JSA and the Australian Bureau of Statistics (ABS), experimental insights into labour market efficiency for regions and occupations have been derived, paving the way for further research that may provide opportunities to inform economic and labour market policies. Our results tend to suggest that efficiency of the labour market in matching unemployed persons with jobs is currently relatively high and has broadly improved in recent years.

JEL Codes: J22; J23, J62, J38
Key words: Labour supply, labour demand; occupational market, public policy

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Introduction

This study provides an insight into the efficiency of Australian labour market at regional, occupational and industry level using disaggregated data. The understanding of the labour market efficiency is important because at any given point in time, there are typically hundreds of thousands of vacant jobs in the market[1] and yet also hundreds of thousands of unemployed persons. If there are so many jobs available, why do we still see unemployment? And conversely, if there are so many unemployed persons, why do vacancies still go unfilled? Clearly, the answer lies in understanding labour market efficiency, and in particular 'frictions' in the labour market. Such frictions hinder how quickly available workers can be matched to available jobs, and can arise from imperfect information, skills mismatch, geographic mismatch and policy-led distortions (among other things). Given this, analysing labour market efficiency may help inform policy responses – whether they be labour market policy, economic policy or education and skills policy levers.

Jobs and Skills Australia (JSA) has been researching this topic by examining the question *'for a given level of vacancies (demand) and unemployment (supply), how many hires should be occurring in the labour market?'*. In this context, the aim of this study is to understand how labour market efficiency varies across Australia. As such, we set out to estimate labour market matching efficiency in Australia for occupations, regions and industries. Using data from both JSA and the Australian Bureau of Statistics (ABS), experimental insights on labour market efficiency for regions, occupations and industry have been derived, which we termed the *MUVER model*.

The Model

Background to the Model

The roots of labour market efficiency analysis go back to the Search and Matching model.[2] 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

1 Warranted, there were periods following the onset of COVID-19 that the level of vacancies fell to very low levels. However, this is considered an atypical period.

2 The pioneer work in this area was done by Diamond-Mortensen-Pissarides (DMP) over the decades, resulting in the Nobel prize in economics for their 'fundamental contributions to search and matching theory' in 2010. Extensive discussion of this literate can be found in Petrongolo and Pissarides (2001). Also see, Blanchard and Diamond (1989) for the discussion on this topic.

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' and the relative weights of each input (labour demand and supply) in job matching process (see, Coles and Smith, 1996).

To help understand labour market efficiency in simpler terms, let us consider an example. Suppose there are two regions, both of which currently have one hundred vacancies and one hundred unemployed persons. Hypothetically, a perfectly efficient labour market would see the available workers (unemployed persons) quickly matched to the available jobs (vacancies), clearing the market leaving no structural or long-term unemployment or unfilled vacancies (shortages). However, suppose that in one region, we see eighty matches occur, and in another region, we see twenty matches occur. In this simplistic scenario, the difference in the number of matches can be thought of as a result of matching efficiency, or frictions.

Model Specification

In frontier analysis, the matching function represents the maximum achievable matches from the stocks of unemployed and vacancies as shown in figure 1 below. In the context of the Cobb-Douglass production function, we adopt the stochastic frontier analysis approach (SFA)[3], namely:

$$m_{it} = A u_{it}^{\alpha} v_{it}^{\beta} e^{\varepsilon_{it} - z_{it}} \tag{1}$$

With technical change, the matching function in equation (1) can be rewritten in a linear form as shown in Fahr and Sunde (2002;2004) and Ilmakunnas and Pesoal (2003) via logarithmic transformation as:

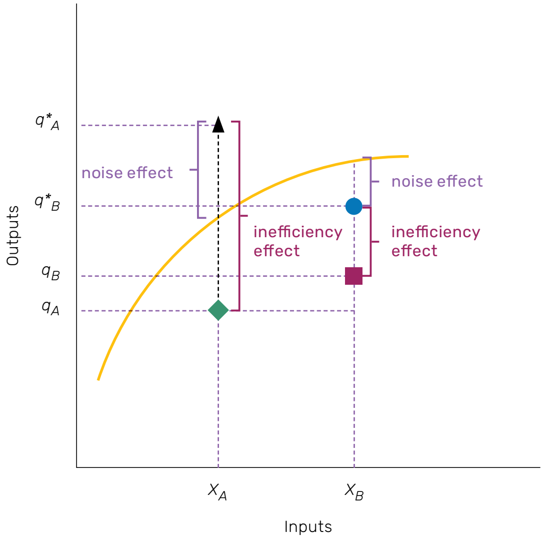
$$\log(m_{it}) = c + \beta \log(v_{it}) + \alpha \log(u_{it}) + wt + \varepsilon_{it} - z_{it} \tag{2}$$

Here, m_{it} refers to job matching, v_{it} refers to vacancies, u_{it} refers to unemployment, c is a constant term, t refers to a time trend, and α, β and w are parameters to be estimated. Subscripts it after the variables refer to occupation/region or industry and time. $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$ is an error term, while $z_{it} \sim N^{+}(0, \sigma_z^2)$ represents technical inefficiency in the job matching process. The stochastic frontier model is estimated by an econometric maximum likelihood estimation, which requires distributional assumptions of the error terms ε and -z. The technical efficiencies are defined as the ratio between the observed output and the stochastic frontier output i.e. $TE = e^{-z}$ (see, e.g. Coelli *et al.*, 2005, p. 244). The algorithm re-parameterizes the variance parameter of σ_{ε}^2 and the scale parameter of the inefficiency term σ_z^2 and estimates $\gamma = (\sigma_z^2 / \sigma_z^2 + \sigma_{\epsilon}^2)$.

3 See, Bauer (1990), Warren (1991), and Coelli *et al.*, (1998) for extensive surveys of the literature.

Using the model specified above, the new experimental model developed by Jobs and Skills Australia to estimate labour market efficiency for occupations, regions and industries is termed the *MUVER model*.

Figure 1. Visualisation of SPF analysis of efficiency



The Data

Analysis of labour market efficiency under the search and matching framework is predicated on obtaining appropriate data on matches, unemployment and vacancies. Given our interest in examining variations in efficiency at detailed levels, such data was required at disaggregated levels of occupation, region and industry. Developing this database was a major task and took considerable amount of time and resources. Recent developments in the availability of detailed labour market data makes this possible.

Table 1 below provides details of the relevant data underpinning the model, including the relevant coverage of the model and the relevant definitions utilised.

Table 1. Definition of data, coverage and sources

Focus	Occupational Model	Regional Model	Industry Model (validation)
Data availability			
Disaggregation	ANZSCO 2 digit	All capital cities & regional SA4s	ANZSIC 1 digit
Coverage[4]	41 of 46 series[5]	All series	18 of 19 series[6]
Frequency	Quarterly	Quarterly	Quarterly
Starting period	February 2006	May 2010	November 2009
Definitions			
Matches	Quarterly count of employed persons who report that they have worked for the current employer/business for less than three months		
Unemployment	Based on most recent occupation of employment	Based on place of usual residence	Based on most recent industry of employment
Vacancies	Estimated total number of new vacancies (flow) that arose during the quarter		Count (stock) of vacancies that exist at the survey reference date
Data sources			
Matches	ABS Labour Force Survey – Detailed (accessed via ABS Datalab)		
Unemployment	ABS Labour Force Survey – Detailed (accessed via ABS Datalab)		
Vacancies	JSA Internet vacancy Index adjusted using insights from JSA Recruitment Experience and Outlook Survey (see the snapshot summary below)		ABS Job Vacancy Series

Of note is the definition of matches used in our analysis. To utilise a consistent method across occupation, region and industry analysis, the definition of matches adopted for our analysis is *'the quarterly count of employed persons who report employment of less than three months'.* The logic of this definition is that since our data is quarterly, all persons who report employment of less than three months can thus be assumed to be a new hire (match) for that period.[7] Given the data available to us, this was considered the

4 Please note that where appropriate, missing values are imputed to support analysis and modelling using common imputation techniques. Where imputation was not possible (due to insufficient data), the series was excluded from the model coverage.

5 Some 2-digit occupations within the same 1-digit group were combined to enable modelling.

6 The ABS Job Vacancy Series does not include vacancy data for the Agriculture, Forestry and Fishing industry.

7 A review of the ABS Labour Force Survey methodology indicates that the respondents were asked how many months they have worked for the current employer/business (LFS questions 80 and 81). As such, employment data obtained from the ABS LFS may represent either the respondent's tenure

most appropriate approach for our analysis.

Regarding unemployment, the measures of unemployment by occupation and industry relate to the occupation and industry of employment *prior* to becoming unemployed. Similarly, regional unemployment is based on a person's current usual place of residence. By using these measures of unemployment, our model inherently assumes that the unemployed are seeking to return to their most recent occupation and industry, and in the case of our regional model, are looking for work within their current region. While we know transitions between occupations and regions occur in the labour market, this assumption is considered reasonable given the available data. Further research to expand the definition of supply in our model would be a worthy exploration.

Finally, for our vacancy measure, the JSA Internet Vacancy Index (IVI)[8] was adjusted using insights from the JSA Recruitment Experiences and Outlook Survey (REOS)[9] to take into account the fact that not all job vacancies are advertised online. By combining these two sources of labour market information, JSA has developed a new estimate of the total number of new vacancies each quarter. This measure was utilised in our modelling of labour market efficiency (matching efficiency) for occupations and regions. As the JSA IVI does not include industry data, data on industry vacancies was obtained from the ABS Job Vacancy Series, with the industry model predominantly acting as a point of validation for the regional and occupational results.

Results and discussion

The model specified above is estimated separately for occupations, regions and industries. Results are reported in Table 2 below.

in employment (if they were NILF or unemployed prior to commencing in the position) or tenure with an employer (if they were employed with another employer/business prior to commencing in their current position). In this way, the data effectively captures both movements into employment from unemployed/NILF and also between-firm movements in employment (for example, employer A in quarter 1 and then employed with employer B in quarter 2).

8 See https://www.jobsandskills.gov.au/data/internet-vacancy-index for further information about the JSA IVI.

9 See https://www.jobsandskills.gov.au/data/recruitment-experiences-and-outlook-survey for further information about the JSA REOS.

Table 2. Estimates of matching efficiency for occupations, regions and industries

JSA MUVER model
Estimates of Job Matching Efficiency for Australia[10]
Dependant variable: Log of matches

Disaggregation	Occupation	Region	Industry (validation)
Focus	3 digit ANZSCO	SA4 with GCCSAs for capital cities	1 digit ANZSIC
Period	2006 to 2022	2010 to 2023	2009 to 2022
Constant	2.983 (0.124)***	2.331 (0.07)***	1.326 (0.117)***
Log Vacancies (V)	**0.223** (0.01)***	**0.304** (0.008)***	**0.231** (0.015)***
Log Unemployed (U)	**0.536** (0.016)***	**0.429** (0.009)***	**0.744** (0.017)***
Time (t)	-0.011 (0.003)***	-0.004 (0.001)***	0.06 (0.008)***
Efficiency	**0.829**	**0.744**	**0.807**
Sigma Squared (σ^2)	0.183 (0.019)***	0.23 (0.033)***	0.101 (0.009)***
Gamma (γ)	0.429 (0.061)***	0.604 (0.058)***	0.234 (0.069)***
Log likelihood	-751.338	-1,126.291	-185.237

As seen in Table 2, the estimated SFA function is monotonically increasing in v_{it} and u_{it}. The matching elasticity of vacancies is 0.22, 0.30 and 0.23, while the elasticity of unemployment is 0.54, 0.43 and 0.74 for occupation, region and industry models respectively (the elasticity of scale, obtained from the sum of the coefficients for v_{it} and u_{it}, is 0.76, 0.73 and 0.98 for occupation, region and industry models respectively). The estimates of efficiency are broadly consistent, ranging from 0.829 for the occupation model to 0.744 for the regional model and 0.807 for the industry model.

The Gamma parameter γ lies between zero and one, indicating the importance of the inefficiency term in the model.[11] As the estimate of γ is 0.429, 0.604 and 0.234

10 Differences in the model results are to be expected given the differing time periods, data sources and levels of disaggregation (for example, for the industry model, there are eighteen underlying industries whereas there are forty-one series in the occupation model).

11 If γ is zero, the inefficiency term z_{it} is irrelevant and the results should be equal to OLS results. In contrast, if γ is one, the noise term ε_{it} is irrelevant and all deviations from the production frontier are explained by technical inefficiency.

for occupation, region and industry models respectively we can conclude that the inefficiency term is important for explaining deviations from the production function. The time trend indicates very little technical change (negative) -1.1 per cent and -0.4 per cent for occupation and region models respectively, while it is positive 6 per cent for the industry model.

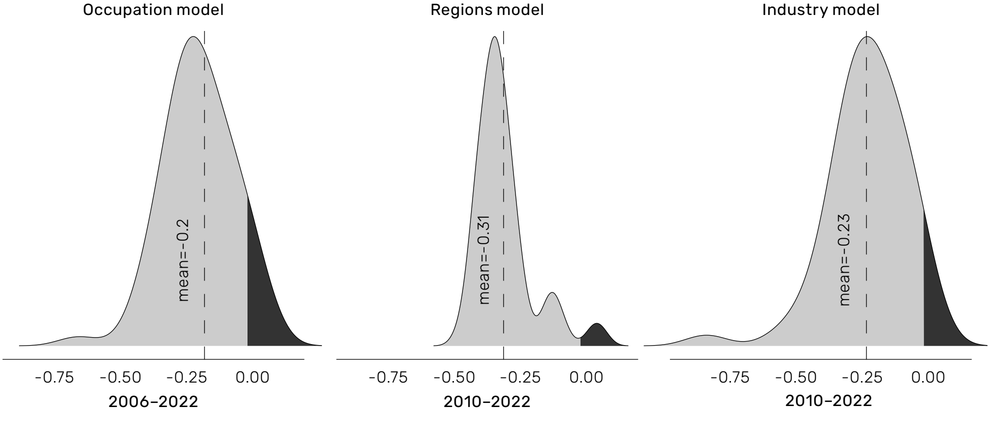
It is important that when examining the model outputs, we also analyse the results of the subsequent likelihood ratio test (Table 3). Under the null hypothesis (no inefficiency, only noise), the test statistic asymptotically follows a mixed χ^2-distribution (Coelli, 1995). The small P-value indicates that the data clearly reject the OLS model in favour of the stochastic frontier model, i.e. there is significant technical inefficiency.

Table 3. Results of Likelihood ratio test run on the JSA experimental MUVER model

Model 1: OLS (no inefficiency)	Occupation	Region	Industry (validation)
Model 2: Error components frontier	**(2 digit)**	**(SA4)**	**(1 digit)**
Likelihood ratio test result	167(0.0000)***	393(0.0000)***	167(0.0000)***

A well-known result due to Waldman (1982) also states that, in the standard normal/half-normal SFA model, estimated technical inefficiency will be zero if the OLS residuals are positively skewed. Such a result might cast doubt on the specification of the stochastic frontier model (Greene, 1990). By contrast, a negative skewness means that the residuals are left-skewed (negative), and in our case this would mean that it is likely that not all occupations/regions are fully technically efficient. In the case of our models, testing results show the residuals of the three models are indeed left-skewed (negative) as expected (see Figure 2).

Figure 2. Residuals of JSA experimental MUVER models

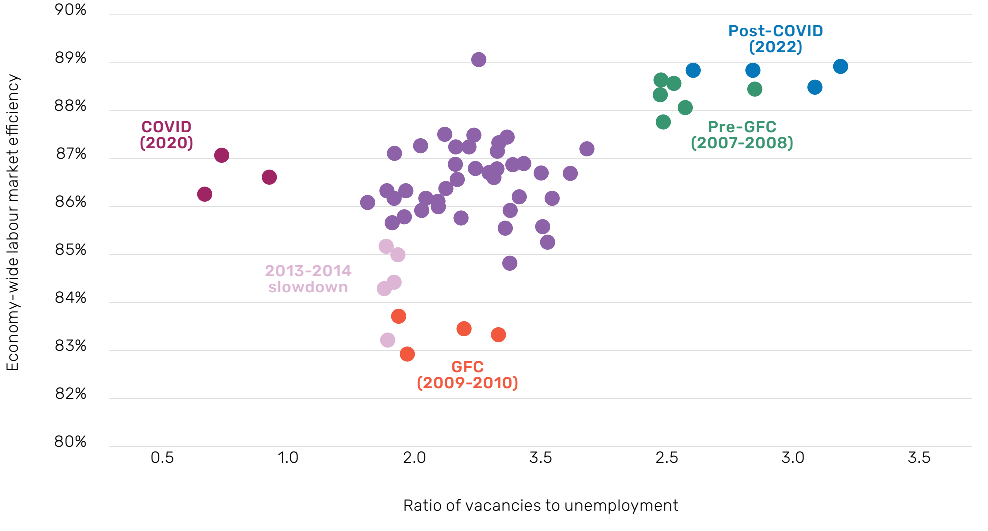


Sources: Based on JSA MUVER models.

Headline national results for Australia

Examining the average (mean) results from the modelling can provide an indication of trends in national matching efficiency across Australia. When we estimate the model by occupation, we can pool the results to obtain an average of matching efficiency for Australia over time (from 2006 to 2022). As demonstrated in Figure 3 (which compares the matching efficiency with the prevailing rate of vacancies to unemployment), matching efficiency for Australia has varied considerably over time. Following the height of COVID-19 in 2020, we found that matching efficiency remained relatively stable, despite a rapid decline in the vacancy rate (see maroon dots). This is in stark contrast to the GFC period (see red dots) and the slowdown in the labour market in 2013-14 (lilac dots), when economy wide matching efficiency appears to have declined. By contrast, in 2022, labour market efficiency reaches a similar point to that of the pre-GFC strength of 2007-08, with both the vacancy rate and matching efficiency very high. This suggests that during the very tight labour market conditions of these periods, the labour market became more efficient in matching unemployed persons to vacant jobs, potentially due to employers having to change their preferences or tastes to job suitability to fill positions (for example, by taking on workers who are only partially suitable for a job). This may suggest that in the short term, a tight labour market may actually support improved matching between unemployed workers and vacant positions.

Figure 3. Average matching efficiency for Australia compared with the vacancy rate, over time

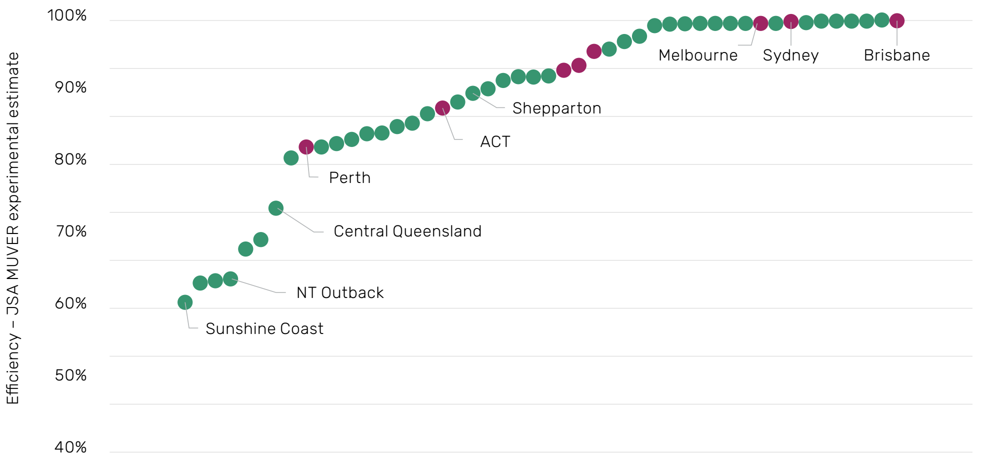


Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA experimental estimates of total vacancies and ABS Labour Force Survey unemployment estimates.

Detailed estimates of efficiency by region

When examining the estimates of matching efficiency by region (SA4 regions), we see the efficiency of the labour market in matching unemployed persons with job vacancies varies by region. As demonstrated in Figure 4, efficiency varies by region, with a number of regions effectively acting as "frontier" regions, where the labour market of the region is functioning efficiently. Metropolitan areas are identified by the maroon dots, with Melbourne, Sydney and Brisbane acting as aforementioned frontier regions. By contrast, Perth and ACT are less efficient.

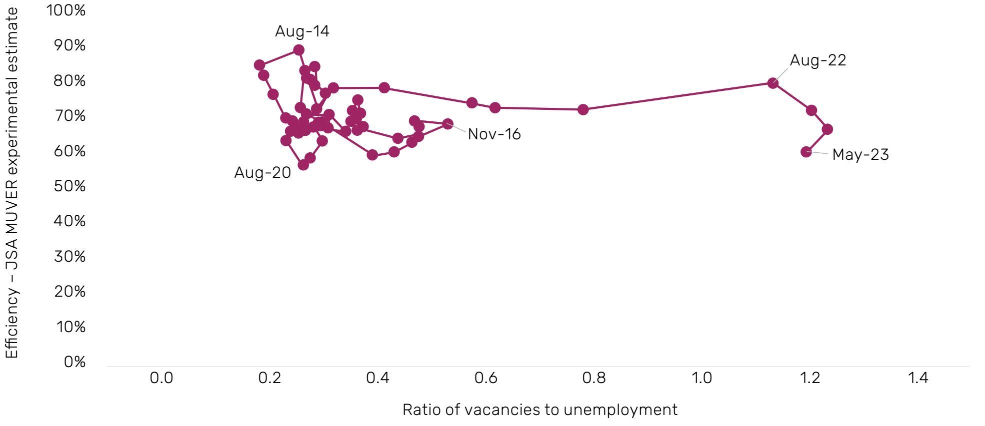
Figure 4. Estimates of matching efficiency by region – JSA experimental MUVER model, May 2023



Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency.

The model outputs of efficiency also enable the analysis of changes in efficiency over time. Examining the model's efficiency estimate relative to the ratio of vacancies to unemployment for the Sunshine Coast in Figure 5 shows that efficiency in the region particularly started to decline in late 2022. In addition, the level of efficiency in the Sunshine Coast also never reached the heights of August 2014, despite the very high vacancy ratio, perhaps indicating an emerging shortage of workers (or suitable workers) to fill available vacancies in the region, indicating efficiency may decline as labour market tightness persists.

Figure 5. Estimates of matching efficiency and ratio of vacancies to unemployment – Sunshine Coast



Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA experimental estimates of total vacancies and ABS Labour Force Survey unemployment estimates.

Combining estimates of regional labour market efficiency with JSA analysis of relative regional labour market strength (RLMI)[12] may also help categorise regional labour markets into types, helping to inform possible policy responses. Using this approach, and as detailed in Figure 5, we can classify each region into four distinct categories.

12 JSA's Regional Labour Market Indicator (RLMI) combines key indicators of spare labour market capacity, from both an employee and employer perspective, into a single, and easy to interpret, summary measure (with regions grouped into distinct categories of overall labour market performance, ranging from 'poor' to 'strong') which provides an accurate and reliable view of labour market performance. Factors included in the RLMI include the working age (15-64) employment rate, the unemployment rate, the JobSeeker income support rate, the underemployment rate and the vacancy fill rate. Further information about the JSA RLMI can be found at: https://www.jobsandskills.gov.au/data/regional-labour-market-indicator

Table 4. Approach to combining estimates of regional matching efficiency and regional relative labour market strength to categorise regions

Categorisation	Matching efficiency (JSA MUVER)	Relative labour market strength (JSA RLMI)	Description
'Frontier' regions	High	Strong	Experiencing good conditions and efficient rate of matching.
'Mismatched' regions	Low	Strong	Strong conditions, but lower matching efficiency. May reflect local unemployed persons being overlooked for candidates from other nearby regions (such as cities), either due to employer preferences or a mismatch in suitability.
'Job deficit' regions	High	Weak	A relatively high rate of matching is occurring. Vacancies are filled quickly, but there's insufficient vacancies to sufficiently reduce or clear unemployment.
'Challenging' regions	Low	Weak	Weak conditions, but also lower matching efficiency when a vacancy arises.

Helpfully, by identifying and classifying regions in such ways the associated possibilities for policy responses can be more directly targeted. This may include the targeting of wage subsides (for employers in 'mismatched' regions), training subsidies (for unemployed persons in 'mismatched' regions), job creation policies (for 'job deficit regions') and more comprehensive responses for 'challenging regions'. While experimental, this framework certainly provides a case for further interrogation and analysis of the methodology.

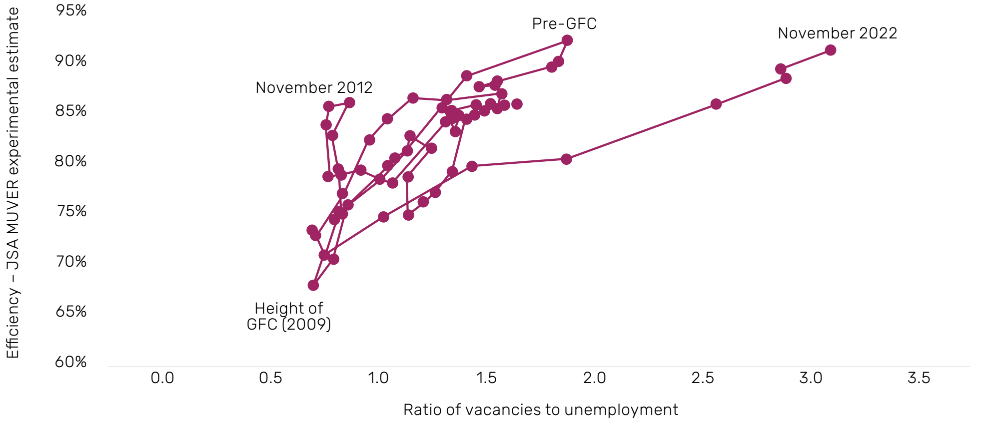
Figure 6. Comparison of regional efficiency estimates and relative labour market strength – JSA MUVER model and JSA RLMI

Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA RLMI estimates of Relative Labour Market Strength.

Detailed estimates of efficiency by occupation

Similar to the regional results highlighted in Figure 5, the model outputs of efficiency also enable the analysis of changes in efficiency over time for occupations. For instance, as per Figure 7, we can examine the model estimates of the matching efficiency for Construction Trades over time. This shows that efficiency of Construction Trades in matching unemployed persons (based on their most recent occupation) and job vacancies was particularly high in late 2022, on par with the results achieved prior to the onset of the GFC. By contrast, during the height of the construction downturn in the GFC of 2009, matching efficiency dropped rapidly. This was likely because the vacancy rate was very low, and those employers could be more selective when determining which available workers they wished to form a match with. This demonstrates the type of occupational analysis such model results may enable.

Figure 7. Estimates of matching efficiency and labour market tightness (ratio of vacancies to unemployment) over time – Construction Trades occupation



Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA experimental estimates of total vacancies and ABS Labour Force Survey unemployment estimates.

Estimates of matching efficiency by occupation may also be informative in considering the prevalence of shortages across the labour market. It may be that persistent shortages arise from frictions that hinder the efficiency matching of unemployed workers to available jobs, such as due to a skills mismatch. However, in the short term, it may be that shortages – while costly for businesses – may prompt employers to change their preferences and tastes, such that they become more likely to take on unemployed persons who are partially suitable for a role and may otherwise be overlooked in more neutral labour market conditions. This, in turn, could lead to labour market efficiency increasing in the short term when shortages arise.

Conclusion, limitations and areas for further Research

Limitations and areas for further research

There are a number of limitations and gaps in the analysis that are worth noting. These provide opportunities for further examination in due course as the model is continuously improved by Jobs and Skills Australia. Particular limitations worth noting include:

- **Transitions in the labour market are difficult to measure.** While we selected the most appropriate measure of matches/hires we could identify (based on quarterly data of persons who are employed with a job tenure of less than three months), there are some hires and matches that are difficult to observe (such as internal within-in firm movements and promotions) and data quality can vary.
- **Unemployment is arguably a narrow definition of labour supply.** Given a large number of movements into employment also come from those not in the labour force, further research to consider expanded definitions of potential labour supply may be warranted, potentially including incorporating controls for different types of jobseekers.
- **The analysis does not attempt to evaluate the quality of a match.** Instead, the model focusses on the level (or rate) of matching occurring. As such, the quality of the match (including measuring labour productivity, job satisfaction, job tenure, wages, etc.) is not captured.
- **Understanding the drivers – or determinants – of matching efficiency has proven difficult.** Potential influencers of matching efficiency include wages, migration, unionisation rates, gender-based labour market segregation and other factors. While this is a strong area of interest, such analysis has proven challenging due to conceptual challenges in determining whether modelled associations are genuine causal relationships, as well as data limitations at disaggregated levels (among other factors). However, further work could be done to evaluate the incorporation of such drivers into our model as adjustment factors, as has been attempted in various literature.

Conclusion

JSA's experimental MUVER model uses a well-established labour market search and matching framework to provide a range of insights that improve our understanding of the functioning of the Australian labour market among geographic regions, industries and occupations. Our results tend to suggest that efficiency of the labour market in matching unemployed persons with jobs is currently relatively high and has broadly improved in recent years. Given the labour market has recently been very tight, this likely reflects employers becoming more willing to take on unemployed persons to fill their vacancies. In fact, generally speaking, the labour market appears to be more efficient in matching unemployed persons to vacancies when there is an elevated level of shortages. This is because shortages – while costly for businesses – may prompt employers to take on unemployed persons who are 'partially suitable' for a job, and who may otherwise be overlooked in less tight labour market conditions. However, persistent shortages may nonetheless lead to an eventual decline of matching efficiency.

Combining estimates of regional labour market efficiency with analysis of relative labour market strength also helps identify several types of regional labour markets, while occupational analysis may also be useful for a range of policy applications. As JSA's new model of matching efficiency is experimental in nature, and subject to further review and development, further work is needed to validate and confirm these initial findings. JSA welcomes feedback and suggestions on how the analysis could be improved in the future.

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