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The labour market matching efficiency in Australian regions

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Abstract
We advance the literature on estimating job matching functions in two ways. Scholars acknowledge that past matching efficiency affects current job search and posting behaviour (i.e. tightness is endogenous); however, they so far ignore that forecast (lead) matching efficiency may also affect tightness. We specify a model that accommodates lagged and lead efficiency to address both endogeneity channels. Scholars also acknowledge that matching efficiency may be region-specific; however, a test to formally evaluate matching heterogeneity is missing, for which we develop a χ^2-distributed test statistic. Using regional Australian data, we (i) demonstrate that lead matching efficiency indeed endogenizes labour market tightness, and (ii) confirm matching heterogeneity in the Australian regional context. Both innovations have policy relevance, and their application will improve matching efficiency estimates and provide policymakers with a tool to test whether region-specific labour market policy is warranted.

KEYWORDS
geographic separation, labour market tightness, matching efficiency, matching function estimation

JEL CLASSIFICATION
J63; J64; E24.

1 | INTRODUCTION

The labour market matches unemployed jobseekers with vacancies posted by firms. Economists use a matching function to capture this process, where the inputs are job vacancies and unemployed jobseekers, and the output is the flow of matched worker–employer pairs (see Petrongolo and Pissarides (2001) for a survey of the literature). Akin to a production function from which one can compute productivity, researchers calculate a matching efficiency from the matching function, which measures frictions in the labour market.

Understanding the labour market matching efficiency is of importance both academically and policy-wise. Academically, the matching efficiency informs on how well the labour market is functioning in allocating scarce resources, with ramifications for unemployment and vacancy duration (Laureys 2021; Bassier *et al.* 2023). Policy-wise, knowledge of the labour market matching efficiency can help policymakers to fine tune their policies targeted at reducing labour market frictions. Due to their importance, researchers have estimated the matching function and matching efficiency in different institutional contexts: for example, Coles and Smith (1996) for the UK, Yashiv (2000) for Israel, Ilmakunnas and Pesola (2003) for Finland, and Barnichon and Figura (2015) and Sedláček (2016) for the USA.

In estimating a matching function, the observed data are market equilibrium outcomes, where market tightness (ratio of vacancies to unemployed jobseekers) is a function of matching efficiency. That is, in addition to a direct effect, the matching efficiency also indirectly affects the job finding rate by influencing firms' incentives to post job vacancies (Borowczyk-Martins *et al.* 2013). This equilibrium effect implies that market tightness is endogenous.

To address this endogeneity concern, Borowczyk-Martins *et al.* (2013) decompose matching efficiency into three terms: a constant, a seasonal dummy and an unobserved component. Assuming that the unobserved component follows an autoregressive moving average (ARMA) process, they transform the matching function to include lags of the dependent and independent variables. Their empirical specification is akin to a type of autoregressive distributed lag (ARDL) model, where the coefficients of the lead terms are constrained to zero (i.e. only the coefficients of lags are estimated) and the error term is autocorrelated.

However, with knowledge of the ARMA process of matching efficiency, firms are likely to forecast into the future and respond accordingly, resulting in current market tightness depending on not only past but also future efficiency. Therefore to capture potential endogeneity more fully, it is necessary to include lead terms in the estimations. Hence the first contribution of this study is to extend the framework of Borowczyk-Martins *et al.* (2013) to address the potential endogeneity of market tightness, for which we specify an ARDL model to estimate the matching efficiency in Australian regional labour markets. We will demonstrate that current labour market tightness indeed depends on future efficiency for some of these labour markets, validating our modelling choice to address endogeneity.

Subsequently, we examine both the short-run dynamics and long-run equilibrium of the matching process—our second contribution. That is, we use the estimates of the ARDL model to compute the coefficients for the long-run equilibrium, by imposing a steady-state restriction. We expect that the matching rate is more sensitive to changes in the number of unemployed jobseekers and/or vacancies in the long run when labour market agents have had time to adjust.

Our study focuses on Australia, which is composed of eight states and territories, all of which exhibit institutional and industrial make-up differences. Manning and Petrongolo (2017) argue that the intrinsic attractiveness of a job in one area for persons in another area decreases as the distance between two areas increases. Such a decline of job attractiveness by distance implies that labour markets have a regional dimension. Australia has a large territory, where the distance between the capitals of two states is great. In light of this geographical distance between states and the regional dimension of labour markets, we treat labour markets in different regions as separate markets. Since different states and territories have different institutional and industrial make-ups, one may expect these labour markets to exhibit regional heterogeneity.

Existing studies have observed such regional heterogeneity. Dixon *et al.* (2012) and Bodman (1999) suggest that the matching processes in Australian states and territories are not likely to be homogeneous. For example, in the mining state of Western Australia, vacancies for casual work in hospitality can be difficult to fill because mines usually outcompete other employers for workers by offering much better conditions, a scenario not commonly reflected in Australia's more metropolitan states/regions (Lynch 2023). From an institutional perspective, state support for vocational education and training (VET) qualifications has affected workers' willingness to accept vacancies; in the case of the mid-north coast of New South Wales, a lack of local technical and further education (TAFE) positions has led to hard-to-fill vacancies in the region (Hansen 2022).

Despite Dixon *et al.* (2012) and Bodman (1999) providing some supporting evidence that the matching process is not homogeneous across states, they did not formally test this hypothesis. We estimate the ARDL models for each state and territory (from here on called regions), and develop a test to formally evaluate the hypothesis—our third contribution. Briefly, with the estimates of ARDL models, and conditional on a region chosen as the benchmark, we compare the estimates of the other regions with those of the benchmark region, by computing a Euclidean distance between two sets of estimates, normalized by their variance/covariance. The test statistic is χ^2-distributed, and under the null hypothesis of homogeneous labour markets, the value of the test statistic will be small. To the best of our knowledge, our study is the first attempt to formally test the heterogeneity of labour market matching processes across regions.

The rest of the paper is organised as follows: Section II briefly reviews the related literature, focusing on Australia. Section III presents the analytical framework and discusses the estimation strategy. Section IV covers the data. Section V discusses the results, robustness checks and research implications. Section VI concludes our paper.

2 | RELATED LITERATURE

The estimation of matching functions has a history going back several decades. A large portion of this research has considered the Cobb–Douglas matching function, with the number of vacancies and unemployed jobseekers as inputs, multiplied by an efficiency term, and the number of matches as the output (Petrongolo and Pissarides 2001). As is the case for the production function, researchers have sought to establish the elasticities of outputs with respect to inputs, and estimate the efficiency and its determinants, using country- or region-level data.

The estimated elasticities for unemployment and vacancies vary from country to country. Ilmakunnas and Pesola (2003) estimate the matching function for Finland. They establish the range of elasticity estimates for unemployment as 0.73–0.95, and vacancies as 0.1–0.39. Barnichon and Figura (2015) find similar results for the USA. In contrast, for Israel, Yashiv (2000) finds elasticities 0.05–0.48 and 0.61–1.12 for unemployment and vacancies, respectively.[1] Across-country heterogeneity can arise due to institutional variation, such as the labour market laws, and differences in the industrial make-up across country borders.

Besides cross-country heterogeneity, regions within the same country can also exhibit differences in the matching functions. Bennett and Pinto (1994) estimate the matching function for local areas in Britain. They find a 'remarkable degree of homogeneity', despite not testing it formally. However, upon inspection, their estimates indicate that elasticities do vary within the UK. They also acknowledge that several regions lie outside their specified range of homogeneity, and suggest that these regions may be outliers because of the prevalence of the coal mining industry (dominant industry) or commuting behaviour (Bennett and Pinto 1994).

Researchers frequently include additional explanatory variables in regressions to explain regional differences in matching efficiency. These variables include the number of long-term unemployed jobseekers, percentage of female participation and percentage of unemployed jobseekers over or under a certain age (Coles and Smith 1996; Ibourk *et al.* 2004; Ilmakunnas and Pesola 2003). Researchers also attempt to control for unobserved regional differences in matching efficiency, using region fixed effects in the panel data context (Ilmakunnas and Pesola 2003; Kano and Ohta 2005). These studies assume that the coefficients for additional explanatory variables are homogeneous across regions. Since the body of country-level studies suggests that the effect of these factors on efficiency is not universally homogeneous (Coles and Smith 1996; Ilmakunnas and Pesola 2003; Ibourk *et al.* 2004; Antczak *et al.* 2019; Mumford and Smith 1999), it is likely that one will need to accommodate such differences in regional studies as well.

In Australia, two papers have challenged the assumptions of homogeneous elasticities and homogeneous effects from determinants of matching efficiency, though not in the matching function framework. Bodman (1999), conducting a Beveridge curve analysis, adopts the framework of Warren (1991), namely a function describing the maximum potential change in employment (the maximum potential matches minus separations from employment) for a given period, to analyse labour market inefficiency in Australia and its states. Bodman (1999) assumed that the matching and separation rates can be adequately modelled as linear functions of the difference between actual and desired wages. Whilst not estimating the matching function directly, his results suggest that there are regional differences in efficiency, in both its time-invariant component and the set of variables that significantly affect matching efficiency. Similarly, Dixon *et al.* (2012) attempt to estimate the matching efficiency and infer elasticities of unemployment and vacancies for Australian states and territories using the Beveridge curve analysis. They find evidence of differences in both elasticities and matching efficiency across regions. It is worth mentioning that neither paper provides theoretical motivation for the implicit assumption of differences in the matching process that would have motivated the research, and they defer this discussion to results sections. However, it is known, and data are readily available that can demonstrate, that these regions are both (mostly) self-contained labour markets, and with different industry and demographic compositions.[2] These facts likely motivated the hypothesis of Bodman (1999) and Dixon *et al.* (2012).[3]

The derivation of the Beveridge curve relation assumes that the number of unemployed jobseekers is stable over time, requiring that the number of separations must equal the number of matches in each period (Elsby *et al.* 2015). This assumption is restrictive and unlikely to hold, hence why it is preferable to directly estimate the matching function rather than the (indirect) Beveridge curve analysis. In doing so, inputs in the matching function are endogenous due to the equilibrium effect (Borowczyk-Martins *et al.* 2013). Borowczyk-Martins *et al.* (2013) note that in equilibrium, firms are incentivized to post more vacancies when there is greater matching efficiency. This results in potential endogeneity that may in turn bias parameter estimates. To address this source of endogeneity, Borowczyk-Martins *et al.* (2013) assume that the error term, which contains the matching efficiency, follows an ARMA process, and transform the estimation equation to include lags of the dependent and explanatory variables. Their method of dealing with endogeneity has since been implemented by authors such as Şahin *et al.* (2014), and adapted for use by Barnichon and Figura (2015). However, if the unobserved component of efficiency follows an ARMA process, and this process is known to firms, then they can forecast the future values of efficiency, and incorporate these forecasts in their (labour market) decision-making. The result is that future values of efficiency may affect current market tightness, which necessitates an ARDL model for the estimation task at hand.

In summary, there is a lack of studies that compensate for regional heterogeneity in the labour market matching processes. To fill this gap, we estimate the matching efficiency in Australian regional labour markets, and formally test whether heterogeneity exists. Simultaneously, we extend the Borowczyk-Martins *et al.* (2013) method to an ARDL model to account for endogeneity emanating from future market efficiency. In addition, we compute the long-run equilibrium coefficients from the short-run dynamic estimates, which previous studies, to the best of our knowledge, have not explored.

3 | ANALYTICAL FRAMEWORK

In the labour market, firms post vacancies and unemployed jobseekers look for jobs in each period. The aggregate outcome (number of matched workers) is described by a Cobb–Douglas matching function, namely $M = m(U, V) = AU^{1-\eta}V^{\eta}$, where M, U and V represent the number of matches, unemployed jobseekers and vacancies, respectively. Here, A is the matching efficiency; and as is typical in the literature, we impose the Cobb–Douglas functional form and constant returns to scale (CRTS) condition in the second equality, that is, $\eta \in (0, 1)$.

We define labour market tightness in the typical way as $\Theta \equiv V/U$. With CRTS, one can rewrite the matching function as $F = A\Theta^{\eta}$, where $F \equiv M/U$ is the job-finding rate. Under the assumption of random matching (i.e. each unemployed jobseeker/vacancy is randomly assigned to a vacancy/unemployed jobseeker), F is an unemployed jobseeker's probability of finding a job in the market. Similarly, the probability of a vacancy being filled is $M/V = A\Theta^{\eta-1}$.[4]

To post a vacancy, firms incur cost C. Once the vacancy is filled, it has value Π, namely the present value of all future profits associated with the filled vacancy. In equilibrium, due to free entry and exit, the cost of posting a vacancy equals the expected value of filling the vacancy, that is, $C = A\Theta^{\eta-1}\Pi$. Therefore in equilibrium, market tightness depends on the matching efficiency (A), resulting in market tightness endogeneity when one proceeds with estimating the matching function.

To address the endogeneity of market tightness due to the equilibrium effect, Borowczyk-Martins *et al.* (2013) decompose the matching efficiency as $a_t = \mu + s_t + \varepsilon_t$, where $a = \ln(A)$, the subscript t indexes time, μ is a constant term, s_t captures seasonality as they use monthly time series data, and ε_t follows an ARMA(p, q) process, namely $P(L)\,\varepsilon_t = Q(L)\,\omega_t$, where L is the lag operator, $P(L)$ and $Q(L)$ are polynomial functions of L of orders p and q, respectively, and ω_t is a serially uncorrelated disturbance. With this decomposition, Borowczyk-Martins *et al.* (2013) then establish an estimation equation as $f_t = \nu + \sum_{l=1}^{p} \rho_l f_{t-l} + \eta\theta_t - \sum_{l=1}^{p} \lambda_l \theta_{t-l} + P(L)\,s_t + Q(L)\,\omega_t$, where $f = \ln(F)$, $\theta = \ln(\Theta)$, and ν, ρ, η and λ are parameters to estimate. They utilize the moment conditions implied by the exogeneity of ω_t for the purpose of estimation.

Since ε_t follows an ARMA process, rational firms are likely to be sufficiently informed to forecast into the future. For example, firms can recognize patterns in the labour market through their experience, and form expectations about future market conditions (both efficiency and market tightness). In doing so, their job posting behaviour is likely to depend on the expected future market tightness and efficiency. Subsequently, current-period market tightness depends on expected future market tightness and efficiency, resulting in a correlation with current-period efficiency (causing endogeneity) via the correlation between expected future efficiency and market tightness and current-period efficiency. To illustrate, consider a firm with an $(H + 1)$ planning horizon $\{t, t + 1, \ldots, t + H\}$, where t is the first period in which the firm can post a vacancy, and $H \geq 1$. The firm's problem is to decide first whether to post the vacancy and then when to post, should it decide to post the vacancy. The optimal decision on whether to post a vacancy is described by an indicator function $\chi_t = \mathbf{1}\left(\max_{0\leq\tau\leq H} \left\{E_t\left[A_{t+\tau}\Theta_{t+\tau}^{1-\eta}\right]\Pi\right\} \geq C\right)$, where the expectation is conditional on the firm's information set at time t. That is, if there exists a period in its horizon such that the expected value of posting is larger than the cost, then the firm will post the vacancy. Conditional on the decision to post, the optimal posting time is then $t + \operatorname{argmax}_{0\leq\tau\leq H} E_t\left[A_{t+\tau}\Theta_{t+\tau}^{\eta-1}\right]$, where if there are multiple time periods in the argmax, then it is understood that the firm posts in the earliest period. Therefore we can observe that firms' optimal posting behaviour depends on the expected future market tightness and efficiency. In turn, this results in correlation between current-period market tightness and current-period efficiency through correlation between current-period efficiency and expected future efficiency.[5]

In light of this source of endogeneity, we extend the model of Borowczyk-Martins *et al.* (2013) to include lead values of θ_t, as follows:

$$f_t = v + \sum_{l=1}^{p} \rho_l f_{t-l} + \eta\theta_t + \sum_{l=-q\prime}^{q} \lambda_l \Delta\theta_{t-l} + \xi_t, \tag{1}$$

$$f_t = v + \sum_{l=1}^{p} \rho_l f_{t-l} + \eta\theta_t + \sum_{l=-q\prime}^{q} \lambda_l \Delta\theta_{t-l} + \sum_{i=1}^{I} \psi_i z_{i,t} + \sum_{i=1}^{I} \sum_{l=-q\prime}^{q} \alpha_{i,l} \Delta z_{i,t-l} + \xi_t, \tag{2}$$

where $v = \left(1 - \sum_{l=1}^{p} \rho_l\right)\mu$, which is the constant component of efficiency, f_{t-l} is the lagged job-finding rate with coefficients ρ_l, η is the parameter for vacancies in the Cobb–Douglas style model, λ_l is the parameter for the lead and lags of the difference of tightness $\Delta\theta_{t-l}$,[6] and ψ_i are the parameters for the additional explanatory variables $z_{i,t}$, of which there are nine ($I = 9$). We include the difference of these additional explanatory variables, $\Delta z_{i,t-l}$, for which the parameters are $\alpha_{i,l}$.

Equations (1) and (2) are ARDL models, where (1) is the baseline model and (2) has additional explanatory variables z_i. Our models are akin to the specification of Borowczyk-Martins *et al.* (2013), who specify an ARDL model with lead terms constrained to zero. We relax this restriction and utilize a more general ARDL model in our estimations to account for endogeneity arising from the non-inclusion of future market efficiency terms (i.e. potential omitted variable bias). Since our data are de-seasonalized, we do not include the seasonality term in the models. The additional explanatory variables in equation (2) intend to capture factors that influence the matching efficiency. Their inclusion is informed by previous studies.

First, the participation rate (*PART*) may proxy for worker search effort according to Holmes and Otero (2019). The proportion of people younger than 35 in the labour force (*YNGR_35*) and the proportion of people older than 55 in the labour force (*OLDER_55*) are suggested to affect efficiency through search effort and employer preferences according to Ilmakunnas and Pesola (2003). The proportion of females in the labour force (*FEM*) is said to proxy for both discrimination effects and worker search intensity according to Destefanis and Fonseca (2007) and Kunze and Troske (2012). The log of average duration of job search (*AVG_SEARCH*) may affect efficiency through employer ranking and the search intensity of workers according to Destefanis and Fonseca (2007), Mumford and Smith (1999) and Petrongolo and Pissarides (2001). As a measure of the business cycle to account for variations in efficiency from output (Bodman 1999), we use the monthly growth of the S&P New Zealand stock index[7] (*NZX_GRWTH*), which is unlikely to be endogenously determined (simultaneity bias) as opposed to the Australian stock index.[8] The political party in government is also suggested to affect matching efficiency, so we include the indicator variable *STE_GOV*, which takes value 1 when the Labor Party rather than the Liberal Party is in power at the regional level (Bodman 1999), and similarly define *AUS_GOV* for the federal government. In addition to these variables found in the literature, we include a dummy variable for Australia's COVID-19-related international lockdown (*INT_LOCK*), beginning in April 2020 and extending to the end of our time series. April 2020 was the first full month of lockdown, and saw other significant policy changes take place, including a large increase in active labour market policy which may have affected matching efficiency. To control for the effects that this regime shift may have had on the elasticities (matching technology), we additionally estimate equations (1) and (2) with an interaction term for *INT_LOCK* and θ, an approach used by Yashiv (2000) to control for potential differences in elasticities between the 1980s and 1990s.

To estimate equations (1) and (2), we utilize the following procedure. First, we test the stationarity of the time series, using the Dickey–Fuller test, to confirm that the time series are either $I(0)$ or $I(1)$. Second, we choose the lag length using the Bayesian information criterion (BIC). That is, we run regressions iteratively over $(p, q) \in \{1, 2, 3, 4\} \times \{1, 2, 3, 4\}$, and select the values of p and q

that produce the lowest BIC. Finally, with the chosen p and q, we then run regressions to estimate equations (1) and (2). We carry out several diagnostic tests after the regressions, namely the stationarity of residuals using the Dickey–Fuller test, heteroscedasticity using the Breusch–Pagan test, autocorrelation using the Breusch–Godfrey and Durbin alternative tests, and autoregressive conditional heteroscedasticity (ARCH) using Engle's Lagrange multiplier test. If the residuals are subject to autocorrelation or autoregressive conditional heteroscedasticity, then we adjust p and q to those with the next lowest BIC in the second step. If this fails to correct for these issues, then we use heteroscedasticity and autocorrelation-robust (HAC) standard errors. We repeat this process for all regions separately.

These regressions produce the short-run parameter estimates for the matching function. In the long run, the labour markets achieve a steady state. Imposing the steady-state restriction on equations (1) and (2), we can obtain the long-run coefficient. For equation (1), this would imply

$$f = \beta_0 + \beta_1\theta, \tag{3}$$

where.

$$\beta_0 = \frac{v}{1 - \sum_{l=1}^{p}\rho_l} \quad \text{and} \quad \beta_1 = \frac{\eta}{1 - \sum_{l=1}^{p}\rho_l},$$

and we calculate the standard errors of $\hat{\beta}_0$ and $\hat{\beta}_1$, where the hats denote estimates, by the delta method.

With estimates of the long-run coefficients in each region, we then proceed to test whether the estimates are systematically different across regions. If not, then we can conclude that Australian labour markets are integrated across regions; otherwise, they are geographically segmented. Let $\hat{\beta}^j = \left(\hat{\beta}_0^j, \hat{\beta}_1^j\right), j = 1, \ldots, 7$, denote the point estimates of the long-run coefficients in region j, and let $\widehat{\mathrm{Var}}\left(\hat{\beta}^j\right)$ be estimates of their variance–covariance matrix.

We first choose state i as the benchmark, namely conditional on the estimates of region i, and set up the null hypotheses

$$H_0 : \beta^j = \hat{\beta}^i, \quad i,j = 1, \ldots, 7, \; i \neq j,$$

where β^j is the true parameter value of region j, and note that since we are conditioning on region i, $\hat{\beta}^i$ is a vector of constants. The test statistic is

$$T_i^j = \left(\hat{\beta}^j - \hat{\beta}^i\right)' \left[\mathrm{Var}\left(\hat{\beta}^j \middle| \hat{\beta}^i\right)\right]^{-1} \left(\hat{\beta}^j - \hat{\beta}^i\right), \quad i,j = 1, \ldots, 7, \; i \neq j,$$

which is χ^2-distributed.

Later, when implementing the test, we replace $\mathrm{Var}\left(\hat{\beta}^j \middle| \hat{\beta}^i\right)$ by $\widehat{\mathrm{Var}}\left(\hat{\beta}^j\right)$; we denote this test statistic by $\tilde{T}_i^j$. If data are independent across regions, then $\mathrm{Var}\left(\hat{\beta}^j \middle| \hat{\beta}^i\right) = \mathrm{Var}\left(\hat{\beta}^j\right)$ and therefore $\widehat{\mathrm{Var}}\left(\hat{\beta}^j\right)$ is appropriate under the null hypothesis. If instead there exists spatial correlation, then $\mathrm{Var}\left(\hat{\beta}^j \middle| \hat{\beta}^i\right) - \mathrm{Var}\left(\hat{\beta}^j\right)$ is negative semi-definite, and $\widehat{\mathrm{Var}}\left(\hat{\beta}^j\right)$ overestimates $\mathrm{Var}\left(\hat{\beta}^j \middle| \hat{\beta}^i\right)$, which results in a smaller test statistic. Nevertheless, in such a case, if the null hypothesis is rejected when using $\widehat{\mathrm{Var}}\left(\hat{\beta}^j\right)$, then it will be rejected when using $\mathrm{Var}\left(\hat{\beta}^j \middle| \hat{\beta}^i\right)$.

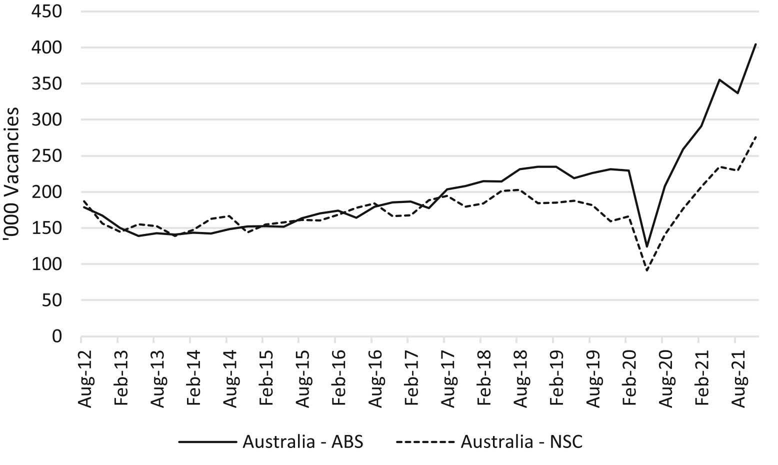

FIGURE 1 Number of vacancies in Australia as measured by the ABS and the NSC.

4 | DATA

To estimate equations (1) and (2), we require data on the number of new hires (M), vacancies (V) and unemployed jobseekers (U), and the additional explanatory variables (z). We source the vacancy data from the National Skills Commission (NSC), which counts newly posted online job advertisements across Australia's three largest online job boards, namely Seek, CareerOne and Workforce Australia, on a monthly basis from June 2012 to December 2021. A caveat is that it under-represents the total number of vacancies because it does not include vacancies advertised elsewhere, and counts only newly posted ads for each month. Such a measurement error can result in estimation bias, if it is correlated with the right-hand-side variables. For example, variables that affect the matching efficiency and subsequently the duration of vacancies can be correlated with the error term, which contains the measurement error. To alleviate such a concern, later in the estimations, we also utilize the quarterly estimates of job vacancies from the Australian Bureau of Statistics (ABS), available on a quarterly basis from November 1983 to November 2021 as a robustness check.[9] The ABS series, compared to the NSC series, has lower frequency, is based on a sample of approximately 5700 companies, and has a five-quarter gap between 2008 and 2009, resulting in fewer observations when coupled with other labour force data used in this analysis. That said, the two series are correlated, as Figure 1 demonstrates.

Additionally, we conduct a two-stage regression of the ABS vacancy series on NSC vacancies (and other variables), then use the predicted values in our matching function estimation. Results of these regressions are reported in the Appendix.[10]

We source the unemployment data from the ABS detailed labour force data publication, produced on a monthly basis since October 1998. It provides estimates of the population above age 14, classified as part-time employed, full-time employed, unemployed and not in the labour force (NILF), with subcategories for age and sex. From the dataset, we also construct most additional explanatory variables (z). We construct regional union density using annual data on union membership from the ABS. We use worker flows between labour force classifications to construct the number of new hires, namely the number of individuals employed in the present month that were either unemployed or NILF in the previous month.[11]

Data from the NSC and the ABS cover all of Australia. However, discrepancies exist in terms of geographical classification (see Figure 2). To reconcile this, we add the 'Australian Capital Territory' (ACT) data to 'New South Wales' (NSW) data to form an amalgamated region NSW-ACT, resulting in a total of seven regions.[12] In addition, the NSC region of Bendigo is

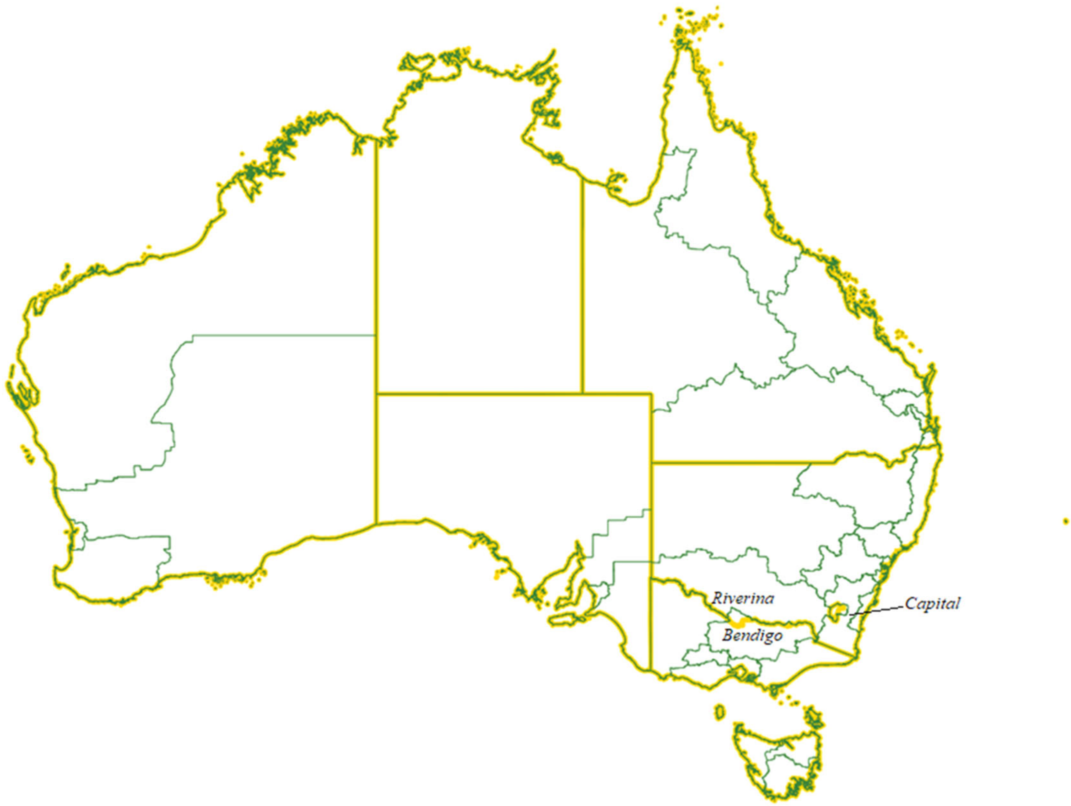

FIGURE 2 State and NSC boundaries.

assigned to 'Victoria', the state where most of its population lives. The other five regions are 'Queensland', 'Tasmania', 'South Australia', 'Western Australia' and 'Northern Territory'.

Aside from Tasmania, all regions have a land border, making commuting across boundaries for work a regular occurrence for some.[13] To assess the degree of such inter-region commuting, we check the 2021 ABS census data. The proportion of the population that commuted across borders for work is low, ranging between 0.7% and 1.9%; that is, inter-region work commuting is not likely to be a concern for our estimations.

We de-seasonalize all time series using X13-ARIMA. Figures 3–6 present summaries of these series. Visually inspecting the series of new hires, the average number of new hires across Australian regions appears to be relatively stable until mid-2020, with the remainder of the time series covering the period coinciding with the COVID-19 pandemic and subsequent economic expansion. The series exhibits a decrease in the first stage of the pandemic, and an increase during the subsequent economic expansion. Such clear and sustained increases are not noticeable prior to 2020, likely because Australia did not experience notable economic expansions or contractions over this period. The standard deviation across regions, indicated by the range markers in Figure 3, appears to decrease (increase) with relatively large decreases (increases) in the average number of new hires.

Turning to the average number of vacancies in Figures 4 and 5 (NSC and ABS, respectively), both series are generally lower than the average number of new hires, indicating that both the NSC and ABS vacancy series underestimate the number of vacancies at any given time. The effect of the COVID-19 economic expansion on vacancy posting is easily observable in both figures. As was the case with new hires, decreases in the average number of vacancies appear to

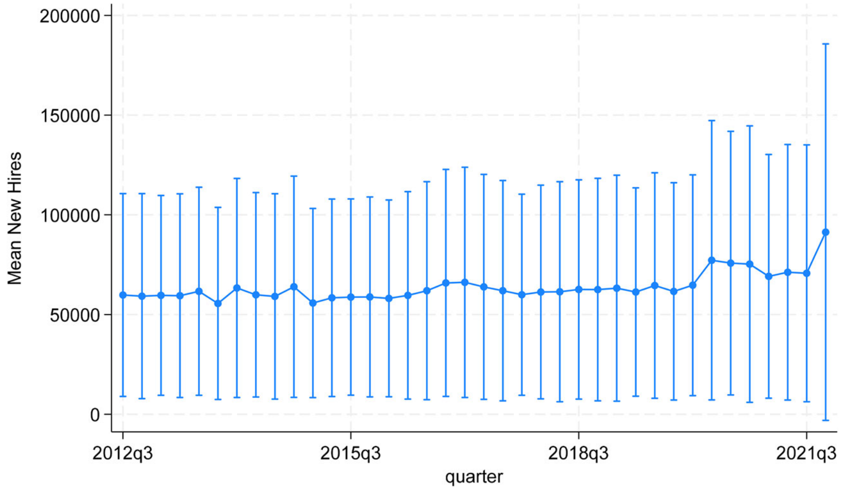

FIGURE 3 Mean number of new hires for all regions.

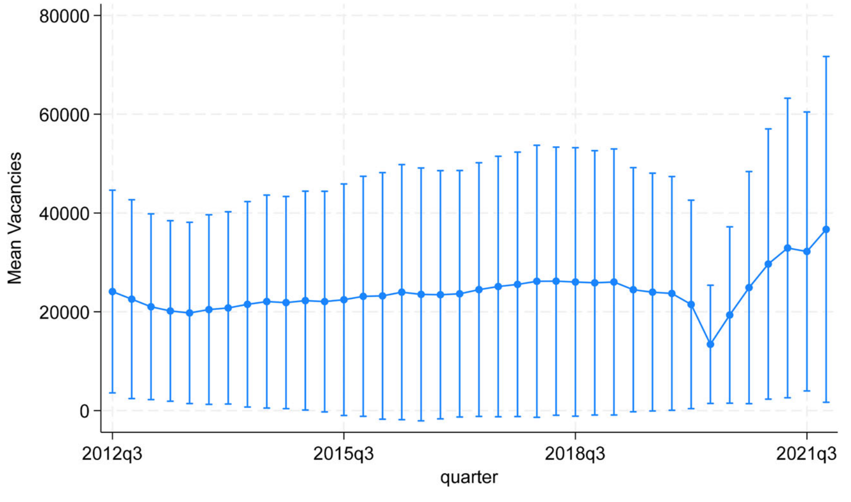

FIGURE 4 Mean number of vacancies recorded by the NSC for all regions.

coincide with decreases in the standard deviation, though there are no clearly observable increases in standard deviation when there are relatively large increases in the series—at least, not until the post-COVID-19 expansion.

The average number of unemployed jobseekers increases at the start of the series and remains relatively stable leading up to the pandemic (see Figure 6). As with the other three series, the effects of the pandemic and subsequent expansion are clear in the series. Unemployment appears to be inversely correlated with vacancies from 2020 onwards, as expected. Again, one can observe that the increase in unemployment results in an increase in the standard deviation. Based on observations of all series, the relation between the standard deviation and large changes is likely explained by these series having a zero lower bound. It is also clear from these four series that the labour market variables vary in size from tens of thousands to hundreds of thousands. In addition, the COVID-19 pandemic appears to affect all time series.

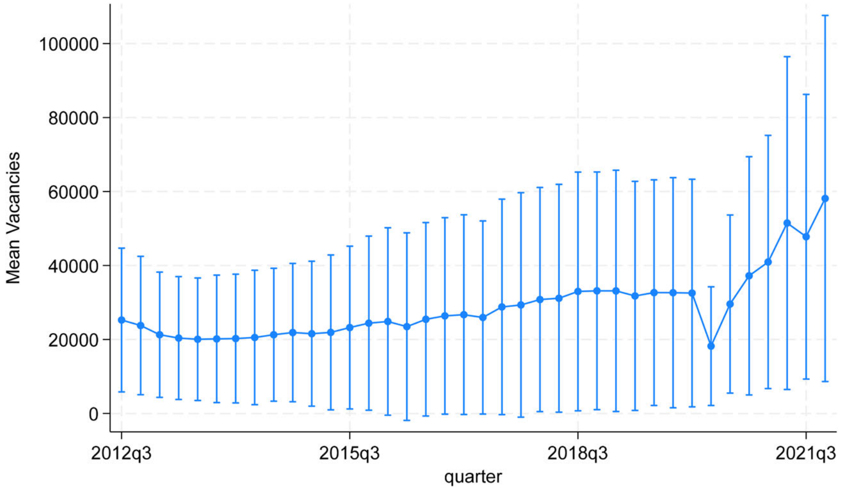

FIGURE 5 Mean number of vacancies recorded by the ABS for all regions.

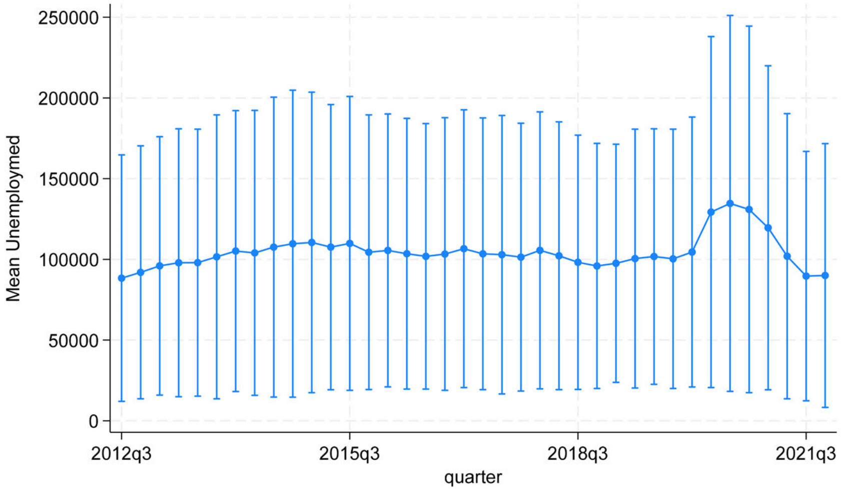

FIGURE 6 Mean number of unemployed jobseekers recorded for all regions.

5 | RESULTS

Following the procedure described in Section 3, we first test stationarity of the time series, with results reported in Appendix Table A1. Several variables were found to be integrated of order 1, $I(1)$, with no variable being $I(2)$ or higher. For example, for most regions, both the NSC and ABS measures of θ were $I(1)$, with the Northern Territory being level stationary. Hence the ARDL models are appropriate.

We then estimate equations (1) and (2), which we term 'baseline' and 'full specification', respectively. As outlined previously, we determine the lag orders p and q by utilizing the BIC whilst accounting for the heteroscedasticity, autocorrelation and ARCH effects in the residuals. For some states, changing the order (p, q) had little or no effect on correcting the heteroscedasticity, autocorrelation and/or ARCH effects, in which case we compute the HAC-robust standard errors.

For the baseline estimations, only Western Australia required HAC-robust standard errors. In the full specification estimations, Queensland, Victoria, Western Australia and South Australia required HAC-robust standard errors.

5.1 | The matching function

Tables 1 and 2 report the short- and long-run estimation results for the baseline and full specifications. In addition, in order to allow for a different matching elasticity in the COVID-19 era, we also conduct estimations with the interaction term $\theta \times INT\_LOCK$, and Tables 3 and 4 report the regression results. Below, in discussing the matching elasticity (the coefficient of θ), we focus first on the short-run estimates (Table 1), then on the long-run estimates (Table 2), and finally, we discuss the results for estimations accommodating for COVID-19 (Tables 3 and 4).

First, in the short run, the estimates of η in the baseline and full specifications are within the range $(0, 1)$ for all regions, in line with the assumption of CRTS. For example, the short-run full specification estimate of η for NSW-ACT is 0.362, so a 1% increase in the number of vacancies results in a 0.362% increase in the number of matches under random matching. Likewise, a 1% increase in the stock of unemployed jobseekers results in a 0.638% increase in matches.

Comparing across different regions, regional variation exists in the elasticity estimates in both the baseline and full specifications. Using the full specification estimation results, the highest point estimate of η is 0.555 in Queensland, with standard error 0.097. In contrast, the lowest point estimate is 0.204 in the Northern Territory, with standard error 0.102. These two estimates are outside two standard deviations of each other. Hence *prima facie* the difference appears to be statistically significant. Such a difference may evidence a systematic difference in the labour markets in different regions, which we will formally test in Subsection 5.4.

Besides, we find that for four (NSW-ACT, Queensland, Victoria and South Australia) of the seven regions, one or more differenced lead values of tightness ($\Delta\theta_{t+l}$) are statistically significant in the ARDL specification.[14] That is, for these four regions, the Borowczyk-Martins *et al.* (2013) strategy to address endogeneity would be insufficient given that the restriction of lead coefficients being equal to zero does not hold. We further investigate the effect of including the leads of market tightness by running regressions without those leads, and comparing the point estimate of market tightness with that of including leads. The regression results are reported in Appendix Table A2, where we can observe that the point estimates with leads are larger.

Second, by imposing the steady-state restriction outlined in Section 3, we obtain the long-run coefficients for each region's matching function, reported in Table 2. Compared with the short-run results of Table 1, two patterns emerge. That is, the matching elasticity estimates continue to fall in the range $(0, 1)$, in line with CRTS, and the results exhibit regional heterogeneity. In addition, the long-run estimates of matching elasticity are typically higher than those of short-run estimates. This is not surprising given that we expect the labour market to be more elastic in the long run as firms and workers have more time to respond to any change in the market.

Third, by including an interaction term, $\theta \times INT\_LOCK$, we allow the matching elasticity to be different in the COVID-19 era, and Tables 3 and 4 report the short- and long-run results, respectively. We observe statistically significant estimates of the interaction term for five regions (NSW-ACT, Queensland, Victoria, Western Australia and Tasmania) both in the short run (Table 3) and in the long run (Table 4), indicating that the changes in labour market conditions in response to COVID-19 changed the elasticities of the matching function. However, since our sample does not cover the whole COVID-19 period, more research is needed to uncover the role of COVID-19 in the labour markets, which we leave for the future.

TABLE 1 Short-run estimation results.

	NSW-ACT		Queensland		Victoria		Western Australia		South Australia		Tasmania		Northern Territory	
Region	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.
f_{t-1}	0.25**	0.007	0.227**	−0.045	0.257***	0.142	0.263***	0.039	0.231**	−0.035	0.222**	0.155	0.36***	0.268**
	(0.098)	(0.112)	(0.094)	(0.045)	(0.093)	(0.146)	(0.095)	(0.08)	(0.096)	(0.085)	(0.102)	(0.125)	(0.09)	(0.107)
f_{t-2}	0.161	–	–	−0.203***	0.292***	–	–	–	–	–	0.006	0.05	0.271***	0.19*
	(0.101)			(0.034)	(0.092)						(0.104)	(0.119)	(0.082)	(0.1)
f_{t-3}	0.092	–	–	–	–	–	–	–	–	–	0.037	−0.066	–	–
	(0.096)										(0.102)	(0.119)		
f_{t-4}	0.094	–	–	–	–	–	–	–	–	–	0.088	–	–	–
	(0.093)										(0.099)			
θ	0.207***	0.362***	0.249***	0.555***	0.119**	0.434***	0.32***	0.508***	0.261***	0.469***	0.394***	0.313**	0.111*	0.204**
	(0.064)	(0.115)	(0.063)	(0.097)	(0.049)	(0.107)	(0.051)	(0.082)	(0.051)	(0.055)	(0.093)	(0.143)	(0.067)	(0.102)
PART	–	−9.452**	–	−8.537***	–	−13.986**	–	−8.079***	–	−16.432***	–	−1.602	–	1.087
		(4.41)		(1.423)		(5.869)		(2.691)		(3.71)		(4.428)		(2.077)
YNGR_35	–	−2.856	–	−9.504***	–	3.021	–	3.161	–	−7.077**	–	−4.594	–	1.526
		(5.278)		(3.405)		(4.668)		(6.756)		(2.814)		(4.446)		(6.152)
OLDER_55	–	20.928**	–	3.787	–	16.062**	–	10.425*	–	−1.854	–	1.408	–	−3.407
		(9.047)		(3.244)		(8.162)		(5.831)		(1.601)		(3.135)		(6.448)
FEM	–	4.004	–	2.371	–	7.424	–	8.03**	–	6.147**	–	1.066	–	2.841
		(7.875)		(3.127)		(4.656)		(3.382)		(2.989)		(5.939)		(4.595)
AVG_SEARCH	–	−0.283	–	−0.081	–	−0.069	–	−0.296***	–	−0.165	–	−0.201	–	0.058
		(0.201)		(0.115)		(0.141)		(0.086)		(0.118)		(0.241)		(0.058)
INT_LOCK	–	−0.176*	–	−0.109***	–	0.124	–	−0.091***	–	−0.085***	–	0.088	–	−0.014
		(0.099)		(0.022)		(0.097)		(0.032)		(0.029)		(0.093)		(0.105)
NZX_GRWTH	–	−2.428*	–	−1.282**	–	−0.191	–	−0.036	–	0.84	–	−2.617*	–	−0.597
		(1.426)		(0.512)		(0.732)		(0.789)		(0.592)		(1.522)		(1.938)

TABLE 1 (Continued)

Region	NSW-ACT		Queensland		Victoria		Western Australia		South Australia		Tasmania		Northern Territory	
	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.
STE_GOV	–	–	–	−0.163***	–	−0.07**	–	−0.183***	–	−0.085***	–	−0.055	–	0.033
				(0.023)		(0.031)		(0.054)		(0.025)		(0.084)		(0.065)
AUS_GOV	–	0.106**	–	0.094***	–	0.089**	–	0.002	–	0.13***	–	0.036	–	−0.107
		(0.047)		(0.021)		(0.04)		(0.033)		(0.041)		(0.088)		(0.076)
$\Delta\theta_{t+l}$	No	No	Yes	Yes	No	Yes	No	No	No	Yes	No	No	No	No
Constant	0.083	2.74	−0.034	8.243***	−0.033	2.132	0.136**	0.205	−0.014	11.34***	0.463**	2.777	0.015	−2.329
	(0.072)	(2.935)	(0.091)	(1.365)	(0.073)	(3.374)	(0.055)	(4.913)	(0.088)	(3.34)	(0.197)	(3.603)	(0.068)	(3.842)
Adj. R^2	0.4240	0.7876	0.3876	0.7639	0.3257	0.6528	0.5934	0.794	0.4945	0.7372	0.2973	0.4255	0.5998	0.5589
$MSE^{1/2}$	0.1214	0.09602	0.1108	0.06848	0.1114	0.09315	0.1172	0.08343	0.1143	0.08202	0.1355	0.12722	0.1903	0.1998

Notes: Standard errors are reported in parentheses. Differences of variables not reported. $\Delta\theta_{t+l}$ indicates whether one of the l differenced lead values of tightness is statistically significant (Yes or No). Definitions of variables can be found in Section 3.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

TABLE 2 Long-run estimation results.

Region	NSW-ACT		Queensland		Victoria		Western Australia		South Australia		Tasmania		Northern Territory	
	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.
θ	0.514***	0.365***	0.322***	0.444***	0.264***	0.506***	0.433***	0.528***	0.339***	0.453***	0.608***	0.364**	0.301*	0.375**
	(0.16)	(0.103)	(0.072)	(0.069)	(0.101)	(0.132)	(0.047)	(0.06)	(0.057)	(0.043)	(0.146)	(0.156)	(0.164)	(0.161)
PART	–	−9.52**	–	−6.841***	–	−16.297**	–	−8.403***	–	−15.869***	–	−1.861	–	2.005
		(4.332)		(1.052)		(6.724)		(2.65)		(2.855)		(5.19)		(3.789)
YNGR_35	–	−2.876	–	−7.616***	–	3.52	–	3.287	–	−6.835**	–	−5.338	–	2.814
		(5.318)		(2.832)		(5.466)		(7.038)		(2.851)		(5.379)		(11.411)
OLDER_55	–	21.079**	–	3.035	–	18.716*	–	10.843*	–	−1.791	–	1.637	–	−6.284
		(9.145)		(2.552)		(9.71)		(6.099)		(1.592)		(3.574)		(11.717)
FEM	–	4.032	–	1.9	–	8.651*	–	8.352***	–	5.937**	–	1.238	–	5.24
		(7.899)		(2.495)		(4.458)		(3.223)		(3.001)		(6.905)		(8.361)
AVG_SEARCH	–	−0.285	–	−0.065	–	−0.08	–	−0.308***	–	−0.16	–	−0.234	–	0.107
		(0.198)		(0.091)		(0.165)		(0.079)		(0.115)		(0.264)		(0.104)
INT_LOCK	–	−0.178*	–	−0.087***	–	0.145	–	−0.095***	–	−0.083***	–	0.102	–	−0.026
		(0.103)		(0.018)		(0.11)		(0.031)		(0.031)		(0.109)		(0.193)
NZX_GRWTH	–	−2.445	–	−1.027***	–	−0.223	–	−0.037	–	0.812	–	−3.042*	–	−1.1
		(1.498)		(0.394)		(0.859)		(0.821)		(0.578)		(1.736)		(3.623)
STE_GOV	–	–	–	−0.13***	–	−0.082**	–	−0.191***	–	−0.082***	–	−0.063	–	0.06
				(0.017)		(0.032)		(0.055)		(0.023)		(0.098)		(0.119)
AUS_GOV	–	0.106***	–	0.075***	–	0.103**	–	0.002	–	0.125***	–	0.042	–	−0.198
		(0.047)		(0.016)		(0.047)		(0.035)		(0.033)		(0.102)		(0.135)
Constant	0.206	2.76	−0.044	6.606***	−0.074	2.484	0.184**	0.213	−0.019	10.952***	0.715**	3.227	0.042	−4.295
	(0.204)	(2.943)	(0.118)	(1.16)	(0.157)	(4.06)	(0.072)	(5.11)	(0.114)	(2.914)	(0.345)	(4.272)	(0.184)	(7.093)
Adj. R^2	0.4240	0.7876	0.3876	0.7639	0.3257	0.6528	0.5934	0.794	0.4945	0.7372	0.2973	0.4255	0.5998	0.5589
$MSE^{1/2}$	0.1214	0.09602	0.1108	0.06848	0.1114	0.09315	0.1172	0.08343	0.1143	0.08202	0.1355	0.12722	0.1903	0.1998

Notes: Standard errors are reported in parentheses. Differences of variables not reported. Definitions of variables can be found in Section 3.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

TABLE 3 Short-run estimation results with interaction term.

	NSW-ACT		Queensland		Victoria		Western Australia		South Australia		Tasmania		Northern Territory	
Region	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.
f_{t-1}	−0.005	0.093	0.248***	−0.088**	0.18*	−0.053	0.217**	0.005	0.259***	−0.047	0.278***	0.136	0.345***	0.297***
	(0.107)	(0.078)	(0.095)	(0.037)	(0.1)	(0.126)	(0.099)	(0.087)	(0.098)	(0.072)	(0.089)	(0.106)	(0.092)	(0.107)
f_{t-2}	0.08	–	–	−0.23***	0.203*	–	−0.109	–	−0.079	–	–	–	0.287***	–
	(0.101)			(0.035)	(0.103)		(0.101)		(0.091)				(0.084)	
f_{t-3}	0.166*	–	–	–	–	–	0.24**	–	–	–	–	–	–	–
	(0.098)						(0.098)							
f_{t-4}	0.082	–	–	–	–	–	–	–	–	–	–	–	–	–
	(0.098)													
θ	0.435***	0.817***	0.264***	0.46***	0.198***	0.753***	0.322***	0.317***	0.293***	0.39***	0.248***	0.034	0.092	0.487***
	(0.087)	(0.102)	(0.065)	(0.063)	(0.058)	(0.144)	(0.068)	(0.07)	(0.059)	(0.07)	(0.053)	(0.254)	(0.075)	(0.174)
$\theta \times INT\_LOCK$	−0.099**	−0.368***	−0.014	0.242*	−0.061*	−0.341**	0.067*	0.399***	−0.005	0.151	−0.021	0.465*	0.059	−0.352
	(0.039)	(0.072)	(0.024)	(0.144)	(0.032)	(0.16)	(0.04)	(0.094)	(0.02)	(0.107)	(0.017)	(0.27)	(0.045)	(0.258)
PART	–	−4.743	–	−8.154***	–	−12.201**	–	−8.199***	–	−20.24***	–	2.064	–	0.781
		(3.436)		(1.69)		(5.612)		(2.972)		(2.964)		(3.266)		(2.195)
YNGR_35	–	−11.242***	–	−11.374***	–	−2.79	–	−2.06	–	−7.712**	–	−5.437*	–	0.318
		(3.544)		(3.452)		(6.265)		(7.461)		(3.214)		(2.931)		(6.287)
OLDER_55	–	7.823*	–	2.954	–	13.809	–	7.007	–	−0.405	–	4.638	–	−4.171
		(4.209)		(3.084)		(8.803)		(6.262)		(1.804)		(2.968)		(6.585)
FEM	–	−3.029	–	4.734	–	5.417	–	2.521	–	6.094**	–	−2.925	–	5.906
		(5.468)		(2.996)		(6.087)		(2.278)		(2.888)		(4.614)		(4.938)
AVG_SEARCH	–	−0.239***	–	−0.139	–	−0.114	–	−0.356***	–	−0.221	–	−0.093	–	0.128*
		(0.071)		(0.135)		(0.185)		(0.073)		(0.142)		(0.178)		(0.069)
INT_LOCK	–	−0.521***	–	0.222	–	−0.449*	–	0.492***	–	0.176	–	0.927	–	−0.543
		(0.113)		(0.236)		(0.262)		(0.139)		(0.169)		(0.561)		(0.379)

TABLE 3 (Continued)

	NSW-ACT		Queensland		Victoria		Western Australia		South Australia		Tasmania		Northern Territory	
Region	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.
NZX_GRWTH	–	−1.06	–	−0.81*	–	−0.614	–	0.584	–	0.964	–	0.303	–	−0.761
		(0.752)		(0.488)		(0.89)		(0.735)		(0.634)		(1.179)		(2.091)
STE_GOV	–	–	–	−0.167***	–	−0.143***	–	−0.193***	–	−0.118***	–	−0.137*	–	0.058
				(0.023)		(0.052)		(0.059)		(0.023)		(0.074)		(0.069)
AUS_GOV	–	0.053**	–	0.135***	–	0.064	–	0.074***	–	0.178***	–	0.169**	–	−0.142*
		(0.023)		(0.024)		(0.07)		(0.026)		(0.025)		(0.08)		(0.078)
$\Delta\theta_{t+l}$	Yes	Yes	No	No	No	Yes	Yes	No	No	Yes	Yes	Yes	No	No
Constant	0.222***	9.091***	−0.001	7.792***	−0.009	5.265	0.191**	5.366	0.011	13.764***	0.056	0.906	0.007	−2.88
	(0.078)	(1.78)	(0.098)	(1.434)	(0.073)	(3.188)	(0.083)	(4.659)	(0.095)	(3.333)	(0.075)	(2.811)	(0.074)	(3.981)
Adj. R^2	0.5166	0.7796	0.3959	0.7841	0.3555	0.5700	0.5462	0.8271	0.5088	0.7431	0.4369	0.5033	0.5963	0.5406
$MSE^{1/2}$	0.10947	0.08709	0.11004	0.06549	0.10889	0.10412	0.11131	0.07645	0.11264	0.0811	0.1278	0.12059	0.19116	0.2039

Notes: Standard errors are reported in parentheses. Differences of variables not reported. $\Delta\theta_{t+l}$ indicates whether one of the l differenced lead values of tightness is statistically significant (Yes or No). Definitions of variables can be found in Section 3.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

TABLE 4 Long-run estimation results with interaction term.

Region	NSW-ACT		Queensland		Victoria		Western Australia		South Australia		Tasmania		Northern Territory	
	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.	Baseline	Full spec.
θ	0.642***	0.9***	0.351***	0.349***	0.321***	0.715***	0.494***	0.319***	0.357***	0.373***	0.344***	0.039	0.251	0.693***
	(0.115)	(0.091)	(0.08)	(0.047)	(0.078)	(0.111)	(0.084)	(0.077)	(0.057)	(0.057)	(0.043)	(0.294)	(0.19)	(0.224)
$\theta \times INT\_LOCK$	−0.146***	−0.405***	−0.018	0.183*	−0.099**	−0.324**	0.103	0.401***	−0.006)	0.144	−0.029	0.539*	0.16	−0.501
	(0.046)	(0.085)	(0.032)	(0.107)	(0.042)	(0.144)	(0.068)	(0.076)	(0.024	(0.105)	(0.023)	(0.311)	(0.129)	(0.357)
PART	–	−5.229	–	−6.187***	–	−11.59**	–	−8.239***	–	−19.324***	–	2.389	–	1.111
		(3.517)		(1.25)		(5.253)		(3.072)		(2.438)		(3.779)		(3.122)
YNGR_35	–	−12.396***	–	−8.63***	–	−2.65	–	−2.07	–	−7.363**	–	−6.291*	–	0.452
		(4.463)		(2.652)		(5.972)		(7.406)		(3.168)		(3.374)		(8.945)
OLDER_55	–	8.625**	–	2.241	–	13.117	–	7.041	–	−0.386	–	5.366	–	−5.933
		(4.323)		(2.337)		(8.326)		(6.592)		(1.724)		(3.409)		(9.297)
FEM	–	−3.34	–	3.591	–	5.145	–	2.534	–	5.818**	–	−3.384	–	8.401
		(6.024)		(2.229)		(5.754)		(2.33)		(2.768)		(5.352)		(6.914)
AVG_SEARCH	–	−0.264***	–	−0.106	–	−0.108	–	−0.358***	–	−0.211	–	−0.108	–	0.182*
		(0.066)		(0.101)		(0.175)		(0.055)		(0.135)		(0.204)		(0.094)
INT_LOCK	–	−0.574***	–	0.168	–	−0.427*	–	0.494***	–	0.168	–	1.072*	–	−0.772
		(0.138)		(0.178)		(0.241)		(0.119)		(0.164)		(0.646)		(0.524)
NZX_GRWTH	–	−1.169	–	−0.615*	–	−0.583	–	0.587	–	0.92	–	0.351	–	−1.083
		(0.82)		(0.364)		(0.845)		(0.721)		(0.622)		(1.366)		(2.978)
STE_GOV	–	–	–	−0.126***	–	−0.136***	–	−0.194***	–	−0.113***	–	−0.159*	–	0.083
				(0.017)		(0.047)		(0.054)		(0.022)		(0.085)		(0.097)
AUS_GOV	–	0.059***	–	0.103***	–	0.061	–	0.074***	–	0.17***	–	0.195**	–	−0.202*
		(0.022)		(0.016)		(0.067)		(0.029)		(0.022)		(0.091)		(0.107)
Constant	0.328**	10.023***	−0.001	5.912***	−0.015	5.001*	0.293**	5.392	0.014	13.141***	0.078	1.049	0.02	−4.097
	(0.141)	(1.77)	(0.13)	(1.145)	(0.118)	(3.036)	(0.141)	(4.463)	(0.117)	(3.091)	(0.1)	(3.252)	(0.202)	(5.659)
Adj. R^2	0.5166	0.7796	0.3959	0.7841	0.3555	0.5700	0.5462	0.8271	0.5088	0.7431	0.4369	0.5033	0.5963	0.5406
$MSE^{1/2}$	0.10947	0.08709	0.11004	0.06549	0.10889	0.10412	0.11131	0.07645	0.11264	0.0811	0.1278	0.12059	0.19116	0.2039

Notes: Standard errors are reported in parentheses. Differences of variables not reported. Definitions of variables can be found in Section 3.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

5.2 | Determinants of matching efficiency

The additional explanatory variables (*PART*, *YNGR_35*, *OLDER_55*, *FEM*, *AVG_SEARCH*, *INT_LOCK*, *NZX_GRWTH*, *STE_GOV* and *AUS_GOV*) enter equation (2) through the matching efficiency. Hence their coefficient estimates inform the direction and magnitude of their effects on the matching efficiency. Below, we discuss the long-run effects (Table 2).

The participation rate (*PART*) has a significantly negative effect on the matching efficiency for five of the seven regions. The negative effect contradicts findings by Holmes and Otero (2019), who find that it had a positive effect on matching efficiency in their Beveridge curve analysis. One possible explanation for the negative effect on the matching efficiency is that as participation increases, firms rank fresh unemployed jobseekers (e.g. marginally attached jobseekers) below jobseekers with a recent job history, thus reducing matching efficiency.

The coefficient for the proportion of people younger than 35 in the labour force (*YNGR_35*) is statistically significant and negative for two regions, and not statistically significant in the other regions. That is in line with Destefanis and Fonseca (2007), who attribute negative effect on matching efficiency to discrimination or ranking effects. The coefficient for the proportion of people over 55 in the labour force (*OLDER_55*) is statistically significant and positive for three regions—consistent with Bova *et al.* (2018), who attribute the positive effect to employer preferences for applicants with labour market experience.

The proportion of females in the labour force (*FEM*) has a statistically significant positive effect on the matching efficiency in three of the seven regions (no statistically significant effect in other regions). This is in line with findings from other research (Ibourk *et al.* 2004; Holmes and Otero 2019), which attributes the positive effect to a positive attitude towards women participating in employment (positive discrimination) and/or women's willingness to accept temporary or part-time work.

We find that the average length of job search (*AVG_SEARCH*) reduces matching efficiency in one region, with no statistically significant effects in the other regions. This finding is in line with the expectation that unemployment duration reduces the attractiveness to hire an unemployed jobseeker, adversely affecting matching efficiency.

The dummy variable for Australia's international lockdown and a subsequent period of significant government spending in Australia (*INT_LOCK*) intends to control for possible effects from the COVID-19 pandemic. The coefficient estimate is statistically significant and negative for four regions, but not statistically significant for the remaining regions. Given the multitude of policy interventions that occurred during the COVID-19 pandemic, of which each may have had an impact on the matching efficiency, it is not clear what the aggregate effect of these policy interventions may have been. However, our results validate the inclusion of the dummy variable, given the estimate of its coefficient being statistically significant in several regions.

The growth of the New Zealand stock index (*NZX_GRWTH*) intends to control for the effect of the business cycle on labour market matching efficiency. We proxy the business cycle by the growth of the New Zealand stock market index. On the one hand, conceptually the New Zealand economy is closely related to Australia's, while on the other hand, the labour market matching efficiency in Australia is less likely to affect the business cycle of the New Zealand economy. The coefficient estimates are statistically significant but negative for two regions (Queensland and Tasmania), suggesting that the matching efficiency is countercyclical in these two regions.

The political flavour of the region's government (*STE_GOV*) is statistically significant and negative for four regions. This result indicates that the labour market is less efficient when the Australian Labor Party forms a region's government, a result that largely fits with the Bodman (1999) findings, even though a region's government primarily affects its labour market through fiscal policy and regulations.[15] Interestingly, the indicator for when Labor forms a federal government (the level of government most responsible for industrial relations in Australia) is positive and statistically significant for four regions.

TABLE 5 The mean and variance of matching efficiency.

Region	NSW-ACT	Queensland	Victoria	Western Australia	South Australia	Tasmania	Northern Territory
Mean	1.040	1.179	1.365	1.405	1.244	1.161	1.165
Variance	0.037	0.019	0.059	0.036	0.026	0.031	0.091
Mean pre-COVID-19	1.004	1.178	1.318	1.406	1.243	1.150	1.173
Variance pre-COVID-19	0.014	0.018	0.022	0.029	0.020	0.027	0.096

Comparing the coefficient estimates of these variables, not surprisingly, we can see that the point estimates differ between regions, and while a given estimate may be statistically significant in one region, it may not be significant in another. That said, we still observe that the magnitudes of the coefficients for $PART$, $YNGR\_35$, $OLDER\_55$ and FEM appear to be larger than those of the other variables, suggesting the important roles that these four variables have on the matching efficiency.

5.3 | Labour market matching efficiency

Starting with the matching function $f = a + \eta\theta$, we can write the matching efficiency as $A = e^{f-\eta\theta}$. Hence we can recover the matching efficiency, provided that we know η. Our ARDL estimations provide an estimate of η. Accordingly, we can construct the labour market matching efficiency as $\widehat{A}_t = e^{f_t - \widehat{\eta}\theta_t}$, where the hat denotes an estimate, and $\widehat{\eta}$ is the long-run point estimate from the full specification model.[16]

Table 5 reports the mean and variance of matching efficiency across regions, and Figure 7 presents the time series for each region. Overall, we observe heterogeneity of matching efficiency across different regions (states), which occurs because (i) different states have different values of the determinants of matching efficiency, and (ii) each determinant exerts a different marginal effect on the matching efficiency in different states.

Figure 7 shows that NSW-ACT, Queensland, Victoria, Western Australia, South Australia and the Northern Territory all experienced a sharp increase in matching efficiency in May 2020. At approximately this time—more specifically, from April 2020 to March 2021—the Australian federal government implemented the JobKeeper programme, which subsidized pre-COVID-19 employment arrangements (Bishop and Day 2020). It is not until October 2020 that the Australian federal government started providing subsidies for hiring new employees as part of the JobMaker programme. One expects policies that encourage hiring to have a larger effect on matching efficiency than a policy preventing separations. The large increase in matching efficiency observed in mid-2020 is nonetheless a result of the introduction of the JobKeeper programme, albeit for a more technical reason. That is, the ABS classified workers who were either stood down or lost their jobs during COVID-19 and who were subsequently re-hired by the same employer under the JobKeeper programme as having found a new job. The high levels of efficiency achieved shortly after the implementation of JobKeeper were not sustained.

Table 5 shows that Western Australia has the highest average matching efficiency (1.405), while NSW-ACT has the lowest (1.04). Variance is the highest for the Northern Territory (0.091), while the lowest is Queensland (0.019). For most regions, the COVID-19 period increased the variance of their efficiency, with Victoria, NSW-ACT, South Australia and Western Australia having the largest increases in variance. These four regions, especially Victoria, had significant government interventions throughout this period.[17]

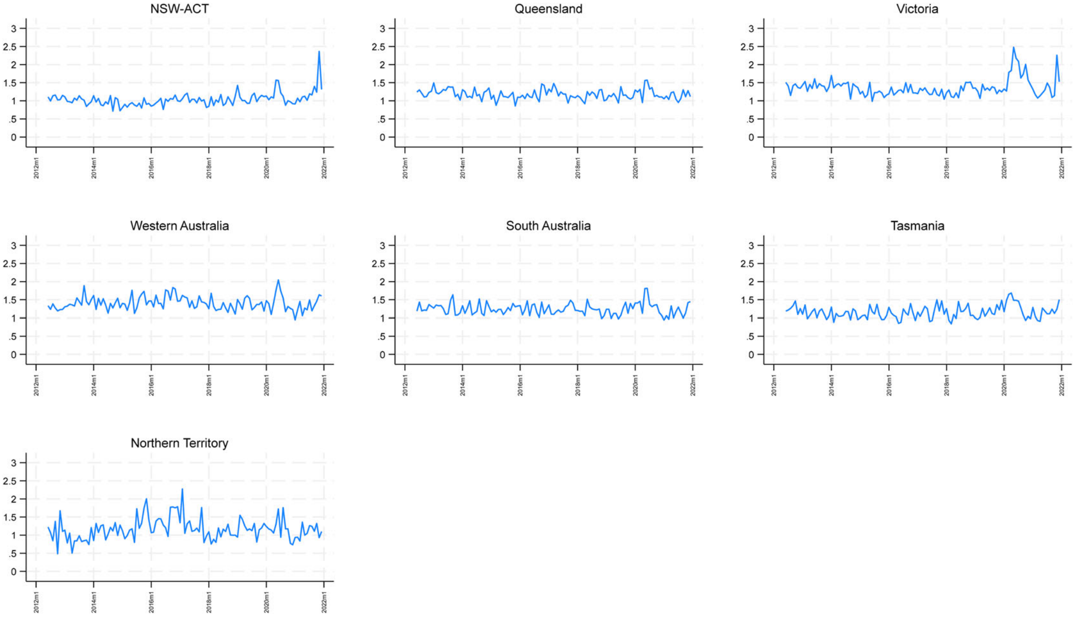

FIGURE 7 Matching efficiencies of Australian regions.

The innate efficiency of a region, represented by the constant term in our regression results (see Table 2), appears not to be a major determinant of the ranking of regions' efficiency, with the two regions that have a statistically significant constant having only the third and fourth highest average efficiencies. This is not entirely explained by the impacts of the pandemic on matching efficiency, as can be seen in Table 5, where average matching efficiency pre-COVID-19 had the same rank order. This appears to be caused by the negative effect that *PART* and, in particular, *YNGR*_35 have on efficiency in Queensland and South Australia, whereas *YNGR*_35 has no effect on efficiency in Victoria or Western Australia. At the same time, *FEM* and *OLDER*_55 have a significant, positive impact on efficiency in Victoria and Western Australia, whereas these variables have a lesser or no effect in Queensland and South Australia.[18] This leads us to believe that the average efficiency of a region is predominantly determined by innate efficiency, *PART*, *YNGR*_35, *OLDER*_55 and *FEM*.

5.4 | Geographical separation of labour markets

As outlined in Section 3, we can also test whether the labour market is regionally separated, namely whether the long-run coefficient estimates are systematically different across regions. Table 6 presents our test statistics $\tilde{T}_i^j$ for the baseline model with each region used as a benchmark, and Table 7 reports the test statistics for the full specification model. Since the test requires conditioning on the parameter estimates of a particular region (i.e. the chosen benchmark region), it is likely that using different benchmarks results in different test statistics. Hence we present the results from using each region as a benchmark. In case the test statistic is small under one benchmark and big under another, we can still reject the null hypothesis.

For the baseline regressions, the pair of regions for which the null hypothesis could not be rejected at the 5% level is South Australia and Queensland. However, when considering the full specification estimates, the null is evidently rejected also for this region pairing. For the other

TABLE 6 Test of geographical separation of labour markets—baseline model.

Benchmark region	NSW-ACT	Queensland	Victoria	Western Australia	South Australia	Tasmania	Northern Territory
NSW-ACT	–	29.85	25.60	47.84	89.28	184.05	3.58
Queensland	1.50	–	6.55	17.67	0.52	19.00	4.94
Victoria	4.06	23.48	–	11.63	47.48	6.91	2.44
Western Australia	7.98	13.87	2.82	–	3.80	32.49	0.65
South Australia	1.21	0.10	7.02	16.94	–	24.76	4.40
Tasmania	182.01	479.10	133.61	295.90	217.46	–	52.26
Northern Territory	15.02	78.11	6.29	23.69	94.59	10.49	–

Notes: 2 degrees of freedom, $\chi^2 = 6$ at $\alpha = 5\%$.

TABLE 7 Test of geographical separation of labour markets—full specification model.

Benchmark region	NSW-ACT	Queensland	Victoria	Western Australia	South Australia	Tasmania	Northern Territory
NSW-ACT	–	11,410.78	2341.11	11,548.75	30,529.52	4651.15	884.62
Queensland	484.40	–	202.90	2066.47	13,021.89	1352.21	253.88
Victoria	997.97	9684.10	–	14,959.40	59,946.74	6064.42	1290.36
Western Australia	2942.47	4222.96	5075.03	–	35,182.72	2512.98	134.39
South Australia	1163.23	18,970.50	9585.19	35,109.61	–	240.44	1536.74
Tasmania	307.76	4532.43	3135.07	3509.22	276.48	–	130.27
Northern Territory	781.64	7479.86	8878.49	2239.68	11,551.40	1860.24	–

Notes: 10 degrees of freedom, $\chi^2 = 18.31$ at $\alpha = 5\%$.

regions, it is clear in Tables 6 and 7 that the parameter estimates are systematically different across regions. Therefore our region-by-region estimations are appropriate.

The results from Tables 6 and 7 provide statistical evidence in support of the Bodman (1999) and Dixon *et al.* (2012) claims that the matching functions of Australian states and territories are heterogeneous, at least to some degree. To further illustrate this regional heterogeneity, we run additional estimations, assuming homogeneity across regions. The results are reported in Table 8, where we can observe that these estimates are quantitatively different from many of the regional estimates. For example, the long-run estimate of matching elasticity (columns 'Without $\theta \times INT\_LOCK$' of Table 8) is 0.354 with standard error 0.085. In contrast, that of Western Australia is 0.528 with standard error 0.06 (columns 'Western Australia' of Table 2). Bodman (1999) and Dixon *et al.* (2012) suggest that such a heterogeneity is likely due to differences in industrial composition, demographics, and institutional and administration/government policies.

5.5 | Robustness to alternative measure of vacancies

In our previous estimations, we used monthly NSC vacancy data from June 2012 to December 2021. As a robustness check, we re-estimated the full specification model, using the quarterly ABS vacancy data from November 1998 to November 2021.[19] The ABS data are published on a quarterly basis, aligning with the frequency of several other macroeconomic data items published by the ABS, for example gross state product (GSP). Using these data, we construct a variable to

TABLE 8 Short- and long-run estimation results using NSC vacancy data for Australia.

	With $\theta \times INT\_LOCK$		Without $\theta \times INT\_LOCK$	
Australia	Short-run	Long-run	Short-run	Long-run
f_{t-1}	0.022	–	0.017	–
	(0.106)		(0.104)	
f_{t-2}	–	–	–	–
f_{t-3}	–	–	–	–
f_{t-4}	–	–	–	–
θ	0.29**	0.296**	0.348***	0.354***
	(0.128)	(0.123)	(0.097)	(0.085)
$\theta \times INT\_LOCK$	0.167	0.17		
	(0.14)	(0.144)		
PART	−14.844***	−15.183***	−16.234***	−16.506***
	(4.104)	(3.68)	(3.838)	(3.402)
YNGR_35	−15.578**	−15.932**	−19.561***	−19.889***
	(6.403)	(6.515)	(5.664)	(5.854)
OLDER_55	15.896**	16.258**	14.657*	14.904**
	(7.87)	(7.807)	(7.618)	(7.531)
FEM	−7.412	−7.581	−7.172	−7.292
	(9.055)	(9.291)	(9.053)	(9.229)
AVG_SEARCH	0.115	0.118	0.178	0.181
	(0.231)	(0.239)	(0.224)	(0.233)
INT_LOCK	0.003	0.003	−0.242***	−0.246***
	(0.223)	(0.228)	(0.071)	(0.07)
NZX_GRWTH	−0.547	−0.56	−0.734	−0.746
	(0.534)	(0.552)	(0.52)	(0.54)
AUS_GOV	0.173***	0.177***	0.15***	0.153***
	(0.045)	(0.046)	(0.043)	(0.043)
$\Delta\theta_{t+l}$	No	–	No	–
Constant	15.971***	16.335***	18.433***	18.743***
	(4.63)	(4.447)	(4.199)	(4.022)
Adj. R^2	0.7842	0.7842	0.7767	0.7767
$MSE^{1/2}$	0.05847	0.05847	0.05949	0.05949

Notes: Standard errors are reported in parentheses. Differences of variables not reported. $\Delta\theta_{t+l}$ indicates whether one of the l differenced lead values of tightness is statistically significant (Yes or No). Definitions of variables can be found in Section 3. Data are aggregated over all regions in Australia in the estimations.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

control for business cycle effects, namely the growth in the average GSP of every region excluding the region for which we fit the matching function (*CYCLE*). As opposed to the NSC data, the ABS data also cover the Global Financial Crisis, so we include an indicator variable for the period from May 2007 to February 2009 (*GFC*).

Given the difference in data frequency and study period, we do not expect to find similar point estimates; rather, we look for broad confirmation of the analysis using NSC vacancy data. The results are presented in Tables 9 and 10. We repeated the procedure outlined in Section 3, which resulted in a different order of the ARDL model compared to the estimates produced using NSC vacancy data.

TABLE 9 Short-run estimation results using ABS vacancy data.

Region	NSW-ACT	Queensland	Victoria	Western Australia	South Australia	Tasmania	Northern Territory
f_{t-1}	0.021	0.054	−0.033	0.186	0.063	0.101	−0.036
	(0.132)	(0.13)	(0.143)	(0.132)	(0.05)	(0.147)	(0.139)
f_{t-2}	–	−0.053	–	–	–	–	–
		(0.127)					
f_{t-3}	–	0.345***	–	–	–	–	–
		(0.113)					
f_{t-4}	–	–	–	–	–	–	–
θ	0.372***	0.29***	0.303**	0.414***	0.209*	0.412**	0.483***
	(0.09)	(0.091)	(0.123)	(0.088)	(0.109)	(0.161)	(0.168)
PART	2.122	−5.304*	1.282	−2.824	−3.926	−0.916	9.428*
	(3.483)	(2.885)	(4.621)	(4.008)	(3.92)	(4.753)	(5.139)
YNGR_35	−9.361*	−2.807	−10.548**	−0.028	−11.67	−8.639*	−4.57
	(4.726)	(7.67)	(5.117)	(3.698)	(7.729)	(4.728)	(10.438)
OLDER_55	−0.357	4.773	−7.668**	−1.73	−2.155	−1.914	−14.853
	(3.944)	(5.844)	(3.459)	(2.066)	(2.354)	(3.433)	(9.097)
FEM	−13.543**	−16.553**	6.397	−2.144	−4.752	−8.578	7.288
	(6.567)	(8.174)	(6.314)	(4.326)	(8.003)	(9.037)	(7.73)
AVG_SEARCH	0.241	0.008	−0.134	−0.064	−0.153	−0.087	0.417**
	(0.199)	(0.14)	(0.232)	(0.143)	(0.166)	(0.213)	(0.167)
INT_LOCK	0.0	−0.051	−0.049	−0.127	−0.001	−0.002	−0.09
	(0.055)	(0.073)	(0.076)	(0.092)	(0.049)	(0.157)	(0.211)
CYCLE	6.079**	−1.518	−2.191	1.4	4.56*	−0.427	−13.218*
	(2.379)	(3.456)	(2.771)	(3.292)	(2.526)	(3.914)	(7.084)
GFC	0.012	0.174**	0.059	0.009	0.1***	0.118	0.034
	(0.049)	(0.067)	(0.056)	(0.081)	(0.032)	(0.131)	(0.147)
STE_GOV	0.008	−0.018	−0.003	0.034	−0.043	−0.077	0.034
	(0.063)	(0.05)	(0.04)	(0.06)	(0.028)	(0.136)	(0.113)
AUS_GOV	−0.139***	−0.058	−0.113**	−0.159**	−0.029	−0.042	0.126
	(0.045)	(0.052)	(0.046)	(0.068)	(0.044)	(0.099)	(0.111)
$\Delta\theta_{t+l}$	No	No	No	No	No	No	No
Constant	7.824**	11.642**	2.297	3.601	9.892	8.64	−4.164
	(2.967)	(4.46)	(4.213)	(2.854)	(6.62)	(6.204)	(3.926)
Adj. R^2	0.4732	0.7645	0.4112	0.7562	0.694	0.4076	0.4031
$MSE^{1/2}$	0.08172	0.09497	0.09953	0.123	0.09482	0.16574	0.27519

Notes: Standard errors are reported in parentheses. Differences of variables not reported. $\Delta\theta_{t+l}$ indicates whether one of the l differenced lead values of tightness is statistically significant (Yes or No). Definitions of variables can be found in Section 3.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

When using the ABS vacancy data, estimates of η in the baseline and full specifications are still within the range $(0, 1)$ for all regions, in line with the assumption of CRTS.[20] Comparing the estimates of η (elasticity of vacancies) in Tables 1–4, 9 and 10, the short- and long-run NSC estimates of η are larger than the ABS estimates in NSW-ACT, Victoria and South Australia, but smaller in Western Australia, Tasmania and the Northern Territory. Short-run estimates are larger when using the NSC vacancy series in Queensland, but smaller for long-run estimates.

Long-run estimates of η, derived from using the ABS vacancy series, are generally larger than short-run estimates (with the exception of Victoria and the Northern Territory—see Table 10)

TABLE 10 Long-run estimation results using ABS vacancy data.

Region	NSW-ACT	Queensland	Victoria	Western Australia	South Australia	Tasmania	Northern Territory
θ	0.38***	0.444***	0.293***	0.509***	0.223*	0.458***	0.466***
	(0.073)	(0.099)	(0.11)	(0.103)	(0.12)	(0.176)	(0.143)
PART	2.168	−8.115	1.241	−3.467	−4.19	−1.019	9.1*
	(3.583)	(5.074)	(4.473)	(4.983)	(4.194)	(5.286)	(4.821)
YNGR_35	−9.563**	−4.295	−10.214**	−0.035	−12.454	−9.605*	−4.412
	(4.551)	(11.715)	(4.977)	(4.541)	(8.41)	(5.174)	(10.093)
OLDER_55	−0.365	7.302	−7.425**	−2.124	−2.3	−2.129	−14.338*
	(4.027)	(9.36)	(3.322)	(2.537)	(2.501)	(3.724)	(8.586)
FEM	−13.834**	−25.325*	6.194	−2.633	−5.071	−9.538	7.035
	(6.52)	(14.819)	(6.095)	(5.27)	(8.649)	(10.496)	(7.399)
AVG_SEARCH	0.246	0.012	−0.13	−0.079	−0.163	−0.097	0.403***
	(0.197)	(0.215)	(0.223)	(0.174)	(0.174)	(0.235)	(0.152)
INT_LOCK	0.0	−0.078	−0.048	−0.155	−0.001	−0.002	−0.086
	(0.056)	(0.108)	(0.073)	(0.114)	(0.052)	(0.175)	(0.205)
CYCLE	6.21***	−2.323	−2.122	1.719	4.866*	−0.475	−12.76*
	(2.382)	(5.161)	(2.703)	(4.064)	(2.621)	(4.337)	(6.668)
GFC	0.012	0.266***	0.057	0.011	0.106***	0.131	0.033
	(0.049)	(0.103)	(0.053)	(0.099)	(0.034)	(0.139)	(0.142)
STE_GOV	0.008	−0.027	−0.003	0.042	−0.046	−0.086	0.033
	(0.064)	(0.075)	(0.038)	(0.073)	(0.031)	(0.15)	(0.109)
AUS_GOV	−0.142***	−0.088	−0.109***	−0.196**	−0.031	−0.046	0.122
	(0.041)	(0.08)	(0.042)	(0.082)	(0.048)	(0.11)	(0.107)
Constant	7.992***	17.812**	2.225	4.422	10.557	9.607	−4.02
	(2.72)	(8.445)	(4.08)	(3.527)	(7.242)	(7.133)	(3.734)
Adj. R^2	0.4732	0.7645	0.4112	0.7562	0.694	0.4076	0.4031
$MSE^{1/2}$	0.08172	0.09497	0.09953	0.123	0.09482	0.16574	0.27519

Notes: Standard errors are reported in parentheses. Differences of variables not reported. Definitions of variables can be found in Section 3. ***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

but are within one or two standard deviations of each other. Hence there is no clear evidence that long-run elasticities are higher than short-run elasticities. The absolute difference between the highest and the lowest long-run estimates of η (0.509 for Western Australia versus 0.223 for South Australia) together with the standard errors of these estimates suggests that Australia's regional labour markets are diverse, which confirms findings from the analysis based on the NSC vacancy data.

Parameter estimates for several variables said to affect matching efficiency have the opposite sign to what was found in the previous NSC regressions, though for the most part, the sign of these parameters did not switch for any particular region. For example, *FEM* in the NSC regression for South Australia was positive, but in the ABS regressions it was not statistically significant; however, it was statistically significant and negative for NSW-ACT and Queensland. This might be best explained by the difference in time periods covered and how discrimination effects may have changed over time. The variable that appears most inconsistent with prior regressions is *AUS_GOV*, now having a negative coefficient. This might be explained by the Australian Labor

TABLE 11 Test of geographic difference in estimates—full specification regressions using ABS vacancy data.

Benchmark region	NSW-ACT	Queensland	Victoria	Western Australia	South Australia	Tasmania	Northern Territory
NSW-ACT	–	43.87	118.12	127.64	680.85	124.85	7324.37
Queensland	800.08	–	152.56	279.43	9237.69	869.90	13,671.59
Victoria	57.14	37.27	–	42.98	1391.47	138.27	3484.19
Western Australia	208.95	52.11	147.12	–	856.00	103.30	12,945.55
South Australia	802.51	305.75	862.16	360.73	–	105.53	5820.21
Tasmania	383.91	191.07	544.62	89.86	588.99	–	12,408.78
Northern Territory	33,042.05	10,030.47	19,523.25	10,968.14	144,254.40	5746.09	–

Notes: 12 degrees of freedom, $\chi^2 = 21.03$ at $\alpha = 5\%$.

Party forming government not long after the global financial crisis started, and approximately half of their time in government being spent as a minority government.[21]

Repeating our test statistics $\tilde{T}_i^j$, the results in Table 11 show that we reject the null of geographically homogeneous matching function for all regions using the ABS vacancy data, which confirms findings using the NSC vacancy data.

5.6 | Policy implications

Our formal test for labour market matching heterogeneity provides policymakers with a tool to evaluate the need for region-specific labour market policy. We confirm matching heterogeneity across Australia's regions. Forced by data limitations, we do so at a relatively high aggregation level, producing large geographies made up of diverse regions (typified in Australia). Our analyses suggest that further disaggregation of labour market data is important in order to understand regional labour markets and policy impacts on those labour markets.

In addition, policymakers should note that the determinants of matching efficiency vary in magnitude and direction across regions, meaning that a one-size-fits-all approach to labour market policy on the national level may work for some regions, but have adverse effects in others.

For the participation rate and the proportion of people younger than 35 in the labour force, all statistically significant effects on matching efficiency (regardless of time horizon and vacancy data source) are uniform (and negative). Both effects are likely a result of jobseeker ranking. In light of the negative effects, policymakers should not rely solely on measures encouraging labour force participation, but rather should offer increased support to those (re)transitioning into the labour force in conjunction. Also, policy aimed at improving the competitive position of young people in the labour market has the potential to improve the functioning of the labour market. The weak labour market position of youngsters may be a result of relatively low human capital or limited work experience, in which case policymakers should consider rolling out training/education programmes or apprenticeship opportunities, respectively.

6 | CONCLUSION

In this paper, we extend the Borowczyk-Martins *et al.* (2013) framework by recognizing that firms may forecast matching efficiency and act in response by changing the timing of vacancy posting and therefore changing the current number of vacancies posted. To address this source of potential endogeneity, we specify a more general ARDL model, by incorporating lead terms of labour market tightness in the model specification. Using Australian labour market data for seven regions from 2012 to 2021, we find evidence in support of the forecasting hypothesis in the form of statistically significant parameter estimates for lead terms for four of the seven regions. Additionally, the ARDL model allows for analysis of the short-run dynamic and long-run equilibrium parameter estimates. Findings from these estimates indicate that vacancies generally have, as expected, modestly higher elasticities in the long run.

The results of regional matching function (Beveridge curve) analyses have led many authors, particularly in Australia, to hypothesize that matching functions are systematically different across regions, namely regional separation of labour markets—a claim that, to the best of our knowledge, has lacked robust statistical supporting evidence. We construct a test statistic to evaluate this hypothesis, which can be used in other similar contexts. The test results confirm regional separation of labour markets in Australia.

Our analyses for Australian regions produce estimates of elasticity of vacancies with respect to matches, η, within $(0, 1)$—consistent with the CRTS assumption. Additionally, we find evidence in support of the notion that η changed during the COVID-19 pandemic, though this change did not occur in all regions, and the direction of the change was not uniform. Several explanatory variables are found to exert statistically significant effects on matching efficiency, in line with the existing literature. However, the effect of these variables is not uniform across geography; our results show that the sign and magnitude differ across regions. Notably, we find that the participation rate has a negative effect on matching efficiency for two regions, contradicting previous findings by Holmes and Otero (2019).

The analyses confirm regional matching heterogeneity across Australian regions, suggesting that regional-level policies (customized to regional idiosyncrasies) rather than a monolithic national-level policy are more likely to be effective. In short, for the Australian context, we would argue that policymakers need to tailor their policy-setting region-by-region to achieve better outcomes.

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ENDNOTES

[1] For a more comprehensive international comparison of elasticities, see Petrongolo and Pissarides (2001).

[2] If one takes the two-digit employment industry by place of work from the past two censuses, and calculates the Krugman Index for each region, then it is clear that there are specializations in each region, with some regions being more similar than others.

[3] It would, in fact, be better to study the matching functions of Australia's functional economic regions as defined in Stimson *et al.* (2016), which are generally contained within the state boundaries; however, we are restricted by data availability from undertaking this research.

[4] Note that our modelling focuses on the steady state implicitly. We abstract away from a rigorous mechanism of including the leads and lags in the modelling.

[5] In the literature of estimating the production function, similarly, the inputs can be correlated with the productivity, resulting in an endogeneity issue. Researchers have endeavoured to address such a potential endogeneity issue. For example, see among others Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg *et al.* (2015). Later in our ARDL model, we include lag and lead terms to absorb the potential correlation between the market tightness and matching efficiency (see Stock and Watson 1993). That said, we acknowledge that the lag and lead terms may not absorb all the potential correlation, resulting in estimation bias.

[6] Note that λ here is not comparable to a similar parameter found in Borowczyk-Martins *et al.* (2013).

[7] S&P/NZX All Index.

[8] GDP and GSP are not available on a monthly basis, hence are used only in the robustness check.

[9] Since the ABS started the collection of detailed labour force data (including some of the additional explanatory variables that we include in our analysis) in October 1998, this additional analysis is limited to November 1998 to November 2021.

[10] The results of these regressions fit with the findings of the other sets of regressions broadly, i.e. CRTS assumption validated, point estimates of parameters being more than two standard deviations apart for different regions, estimates of η generally being less than two standard deviations apart when comparing regression estimates from the two different sets of vacancy data, and the signs and significance of all other explanatory variables (variables that might affect efficiency) being consistent with the estimates from regressions using NSC data directly, etc. We report these results in the Appendix as an additional robustness check.

[11] The dataset published by the ABS is constrained in that it is not possible to measure job-to-job flows. This method of calculating new hires is, to the authors' knowledge, the best available estimate for Australia.

[12] The Australian Capital Territory is geographically located within New South Wales.

[13] Ilmakunnas and Pesola (2003) find that cross-boundary commuting had a significant effect on the matching function of Finnish regions.

[14] In NSW-ACT, it was the interaction term that had a statistically significant lead.

[15] We omitted the variable *STE_GOV* for NSW-ACT, because New South Wales had no change in government over the study period.

[16] All other variables, including $\Delta\theta_{t\pm l}$, are factors that affect the matching efficiency.

[17] Western Australia attempted, with early success, 'COVID zero' policies that allowed for a relatively rapid 'return to normal' for intrastate travel.

[18] Note the trend of an ageing workforce.

[19] We use the X13-ARIMA package to simulate the data for the five-quarter gap between 2008 and 2009.

[20] Estimates of $\Delta\eta$ were insignificant for all regions, so regressions without the interaction term are reported and used in tests of geographic separation.

[21] The equivalent of a congressional minority for the President's party in the USA.

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APPENDIX A

Table A1 reports the tests for stationarity, and Table A2 presents the short-run estimation results with and without leads.

We regress the ABS vacancy series against the NSC vacancy series, a trend variable, an interaction term between the trend variable and the NSC vacancy series and a constant, to attempt to predict values of the ABS series on a monthly basis. Tables A3 and A4 include additional regression estimates when $\widehat{\Delta\eta}$ is no longer statistically significant, using the estimated ABS vacancy series to produce θ. Comparing these regression results with regression results in Tables 1–4 shows that estimated parameters are generally quite similar, particularly for estimates of η in both the short and long run.

TABLE A1 Dickey–Fuller tests for stationarity.

Variables	Level	First difference	Order of integration	Level	First difference	Order of integration	Level	First difference	Order of integration	Level	First difference	Order of integration
	NSW-ACT			Queensland			Victoria			Western Australia		
f	−5.758***	−17.379***	$I(0)$	−7.377***	−16.445***	$I(0)$	−6.101***	−17.285***	$I(0)$	−4.854***	−15.492***	$I(0)$
θ	−1.85	−8.568***	$I(1)$	−1.716	−8.817***	$I(1)$	−1.495	−9.303***	$I(1)$	−1.728	−8.158***	$I(1)$
θ (ABS)	−1.978	−9.005***	$I(1)$	−2.679*	−10.508***	$I(0)$	−2.089	−9.786***	$I(1)$	−1.682	−10.134***	$I(1)$
PART	−3.064**	−9.096***	$I(0)$	−3.596***	−11.257***	$I(0)$	−2.498	−11.568***	$I(1)$	−3.178**	−10.953***	$I(0)$
YNGR_35	−1.956	−11.085***	$I(1)$	−2.505	−15.509***	$I(1)$	−1.597	−14.455***	$I(1)$	−0.592	−16.175***	$I(1)$
OLDER_55	−1.023	−10.645***	$I(1)$	−0.536	−14.354***	$I(1)$	−1.412	−15.701***	$I(1)$	−1.089	−15.462***	$I(1)$
FEM	−2.298	−14.514***	$I(1)$	−1.978	−15.348***	$I(1)$	−2.471	−16.235***	$I(1)$	−1.263	−16.464***	$I(1)$
AVG_SEARCH	−4.804***	−14.467***	$I(0)$	−2.864**	−16.162***	$I(0)$	−4.883***	−14.628***	$I(0)$	−2.139	−12.128***	$I(1)$
NZX_GRWTH	−10.472***	−16.964***	$I(0)$									
CYCLE	−8.658***	−15.187***	$I(0)$	−10.237***	−15.709***	$I(0)$	−10.362***	−17.142***	$I(0)$	−9.783***	−15.125***	$I(0)$

Variables	South Australia			Tasmania			Northern Territory		
f	−6.063***	−14.902***	$I(0)$	−5.684***	−16.608***	$I(0)$	−9.092***	−22.166***	$I(0)$
θ	−0.96	−9.073***	$I(1)$	−0.694	−11.645***	$I(1)$	−3.905***	−17.296***	$I(0)$
θ (ABS)	−2.172	−11.478***	$I(1)$	−2.004	−10.749***	$I(1)$	−3.943***	−11.117***	$I(0)$
PART	−4.927***	−13.836***	$I(0)$	−4.457***	−12.941***	$I(0)$	−3.853***	−12.757***	$I(0)$
YNGR_35	−3.942***	−11.712***	$I(0)$	−4.272***	−12.168***	$I(0)$	−3.262**	−18.597***	$I(0)$
OLDER_55	−2.208	−13.844***	$I(1)$	−1.751	−13.633***	$I(1)$	−2.478	−14.659***	$I(1)$
FEM	−2.871**	−14.592***	$I(0)$	−2.877**	−14.296***	$I(0)$	−3.581***	−17.584***	$I(0)$
AVG_SEARCH	−4.342***	−15.26***	$I(0)$	−5.753***	−17.262***	$I(0)$	−6.367***	−16.874***	$I(0)$
NZX_GRWTH	−10.472***	−16.964***	$I(0)$						
CYCLE	−9.693***	−15.468***	$I(0)$	−9.674***	−15.459***	$I(0)$	−9.675***	−15.484***	$I(0)$

Notes:
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

TABLE A2 Short-run estimation results with and without leads.

Region	NSW-ACT		Victoria		South Australia	
	Leads	No leads	Leads	No leads	Leads	No leads
f_{t-1}	0.093	−0.084	−0.053	0.155	−0.035	0.212*
	(0.078)	(0.111)	(0.126)	(0.13)	(0.085)	(0.124)
f_{t-2}	–	–	–	–	–	–
f_{t-3}	–	–	–	–	–	–
f_{t-4}	–	–	–	–	–	–
θ	0.817***	0.739***	0.753***	0.54***	0.469***	0.316***
	(0.102)	(0.208)	(0.144)	(0.14)	(0.055)	(0.088)
$\theta \times INT\_LOCK$	−0.368***	−0.279	−0.341**	−0.309	–	–
	(0.072)	(0.221)	(0.16)	(0.192)		
PART	−4.743	−5.47	−12.201**	−5.394	−16.432***	−6.805
	(3.436)	(3.55)	(5.612)	(5.86)	(3.71)	(5.219)
YNGR_35	−11.242***	−12.44**	−2.79	−7.181	−7.077**	−7.943*
	(3.544)	(5.613)	(6.265)	(4.483)	(2.814)	(4.69)
OLDER_55	7.823*	10.098	13.809	5.867	−1.854	−1.338
	(4.209)	(7.85)	(8.803)	(7.726)	(1.601)	(3.76)
FEM	−3.029	4.426	5.417	4.461	6.147**	6.636**
	(5.468)	(7.111)	(6.087)	(4.752)	(2.989)	(3.216)
AVG_SEARCH	−0.239***	−0.241*	−0.114	−0.007	−0.165	−0.255
	(0.071)	(0.144)	(0.185)	(0.137)	(0.118)	(0.172)
INT_LOCK	−0.521***	−0.471*	−0.449*	−0.465*	−0.085***	−0.1**
	(0.113)	(0.275)	(0.262)	(0.243)	(0.029)	(0.049)
NZX_GRWTH	−1.06	−1.691*	−0.614	−0.901*	0.84	−0.771
	(0.752)	(0.992)	(0.89)	(0.484)	(0.592)	(0.915)
STE_GOV	–	–	−0.143***	−0.089**	−0.085***	−0.058
			(0.052)	(0.044)	(0.025)	(0.047)
AUS_GOV	0.053**	0.079	0.064	0.025	0.13***	0.066
	(0.023)	(0.051)	(0.07)	(0.056)	(0.041)	(0.067)
Constant	9.091***	6.008*	5.265	3.828*	11.34***	5.551
	(1.78)	(3.338)	(3.188)	(2.051)	(3.34)	(3.908)
Adj. R^2	0.7796	0.7071	0.5700	0.6356	0.7372	0.5546
$MSE^{1/2}$	0.08709	0.10277	0.10412	0.09798	0.08202	0.10168

Notes: Standard errors are reported in parentheses. Differences of variables not reported.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.

TABLE A3 Short-run estimation results for estimated ABS vacancy series.

	NSW-ACT	Queensland		Victoria		Western Australia	South Australia	Tasmania	Northern Territory
Region	Interaction	Interaction	No interaction	Interaction	No interaction	Interaction	No interaction	No interaction	No interaction
f_{t-1}	−0.303*	−0.096***	−0.072	−0.1	0.062	0.014	−0.044	0.106	0.272***
	(0.159)	(0.035)	(0.045)	(0.124)	(0.133)	(0.098)	(0.085)	(0.121)	(0.085)
f_{t-2}	–	−0.249***	−0.231***	–	–	−0.194***	–	0.036	0.188***
		(0.033)	(0.035)			(0.045)		(0.119)	(0.036)
f_{t-3}	–	–	–	–	–	−0.088	–	–	–
						(0.069)			
f_{t-4}	–	–	–	–	–	–	–	–	–
θ	0.907***	0.512***	0.577***	0.654***	0.465***	0.247***	0.475***	0.41***	0.228***
	(0.193)	(0.077)	(0.1)	(0.114)	(0.095)	(0.051)	(0.053)	(0.143)	(0.079)
$\theta \times INT\_LOCK$	−0.542**	0.139	–	−0.222	–	0.521***	–	–	–
	(0.266)	(0.139)		(0.147)		(0.075)			
$PART$	−6.81	−7.982***	−8.79***	−10.192*	−12.167**	−13.413***	−17.55***	−0.624	1.107
	(6.619)	(1.711)	(1.456)	(5.157)	(5.228)	(3.406)	(3.567)	(4.217)	(1.567)
$YNGR\_35$	−12.114	−11.606***	−9.119***	−8.662	−1.96	−1.511	−7.393***	−9.3*	2.079
	(7.314)	(3.535)	(3.448)	(6.272)	(4)	(7.728)	(2.62)	(4.679)	(4.163)
$OLDER\_55$	−5.163	0.927	2.134	6.34	10.759*	10.306*	−2.813	−2.186	−3.71
	(13.548)	(3.421)	(3.01)	(8.039)	(5.856)	(5.992)	(1.92)	(3.229)	(2.715)
FEM	0.989	−0.405	−2.984	−1.423	0.954	−1.658	5.145	−0.873	1.194
	(10.229)	(2.772)	(2.995)	(6.191)	(4.609)	(1.96)	(3.143)	(5.841)	(3.418)
AVG_SEARCH	−0.263	−0.186	−0.178	−0.105	−0.1	−0.551***	−0.245**	−0.196	0.051
	(0.257)	(0.135)	(0.129)	(0.174)	(0.12)	(0.109)	(0.112)	(0.212)	(0.045)
INT_LOCK	−0.677**	0.013	−0.12***	−0.344	0.015	0.42***	−0.126***	0.053	−0.003
	(0.272)	(0.192)	(0.022)	(0.213)	(0.093)	(0.063)	(0.029)	(0.095)	(0.064)
NZX_GRWTH	1.803	−0.613	−0.973*	−0.52	−0.265	1.034	0.939	−2.452	−0.511
	(1.932)	(0.506)	(0.537)	(0.848)	(0.697)	(0.865)	(0.611)	(1.488)	(1.176)

TABLE A3 (Continued)

	NSW-ACT	Queensland		Victoria		Western Australia	South Australia	Tasmania	Northern Territory
Region	Interaction	Interaction	No interaction	Interaction	No interaction	Interaction	No interaction	No interaction	No interaction
STE_GOV	–	−0.182***	−0.177***	−0.164***	−0.104***	−0.213***	−0.069***	−0.048	0.0
		(0.022)	(0.022)	(0.051)	(0.028)	(0.066)	(0.023)	(0.081)	(0.043)
AUS_GOV	0.158***	0.121***	0.093***	0.076	0.089**	0.075***	0.162***	0.039	−0.071
	(0.048)	(0.025)	(0.018)	(0.067)	(0.037)	(0.028)	(0.041)	(0.085)	(0.043)
$\Delta\theta_{t+l}$	Yes	No	Yes	Yes	Yes	No	Yes	No	No
Constant	11.16**	10.787***	11.422***	10.604***	7.035*	10.379**	12.993***	5.59	−1.811
	(4.423)	(1.563)	(1.275)	(3.649)	(3.721)	(4.514)	(3.298)	(3.794)	(2.097)
Adj. R^2	0.7545	0.7884	0.77	0.605	0.6858	0.8332	0.7422	0.4459	0.6913
$MSE^{1/2}$	0.078	0.06482	0.06759	0.0998	0.0886	0.07352	0.08124	0.12494	0.1664

Notes: Standard errors are reported in parentheses. Differences of variables not reported. $\Delta\theta_{t+l}$ indicates whether one of the *l* differenced lead values of tightness is statistically significant (Yes or No).
***, **, * indicate *p*-values ≤1%, ≤5%, ≤10%, respectively.

TABLE A4 Long-run estimation results for estimated ABS vacancy series.

	NSW-ACT	Queensland		Victoria		Western Australia	South Australia	Tasmania	Northern Territory
Region	Interaction	Interaction	No interaction	Interaction	No interaction	Interaction	No interaction	No interaction	No interaction
θ	0.696***	0.381***	0.443***	0.594***	0.496***	0.195***	0.455***	0.477***	0.422***
	(0.125)	(0.058)	(0.065)	(0.083)	(0.095)	(0.043)	(0.038)	(0.155)	(0.108)
$\theta \times INT\_LOCK$	−0.416**	0.103	–	−0.202	–	0.411***	–	–	–
	(0.198)	(0.102)		(0.13)		(0.039)			
PART	−5.227	−5.938***	−6.746***	−9.269**	−12.966**	−10.571***	−16.817***	−0.726	2.051
	(4.97)	(1.243)	(1.005)	(4.64)	(5.216)	(2.679)	(2.75)	(4.918)	(2.742)
YNGR_35	−9.298*	−8.633***	−6.999**	−7.877	−2.089	−1.191	−7.084***	−10.832*	3.851
	(5.343)	(2.664)	(2.815)	(5.705)	(4.263)	(6.029)	(2.694)	(5.6)	(7.815)
OLDER_55	−3.963	0.69	1.638	5.766	11.466*	8.122	−2.696	−2.546	−6.874
	(10.45)	(2.542)	(2.277)	(7.32)	(6.438)	(5.075)	(1.904)	(3.793)	(4.853)
FEM	0.759	−0.301	−2.29	−1.294	1.016	−1.307	4.93	−1.017	2.211
	(7.848)	(2.063)	(2.287)	(5.629)	(4.813)	(1.511)	(3.111)	(6.805)	(6.163)
AVG_SEARCH	−0.202	−0.139	−0.136	−0.096	−0.107	−0.434***	−0.234**	−0.228	0.095
	(0.197)	(0.1)	(0.095)	(0.157)	(0.129)	(0.054)	(0.108)	(0.236)	(0.087)
INT_LOCK	−0.519***	0.009	−0.092***	−0.313*	0.016	0.331***	−0.121***	0.062	−0.006
	(0.193)	(0.142)	(0.017)	(0.189)	(0.099)	(0.04)	(0.031)	(0.111)	(0.118)
NZX_GRWTH	1.384	−0.456	−0.747*	−0.473	−0.283	0.815	0.9	−2.856*	−0.947
	(1.5)	(0.375)	(0.402)	(0.771)	(0.745)	(0.684)	(0.595)	(1.708)	(2.252)
STE_GOV	–	−0.136***	−0.136***	−0.149***	−0.111***	−0.168***	−0.067***	−0.056	0.0
		(0.016)	(0.014)	(0.043)	(0.027)	(0.046)	(0.022)	(0.095)	(0.08)
AUS_GOV	0.121***	0.09***	0.071***	0.069	0.095**	0.059**	0.155***	0.046	−0.131
	(0.032)	(0.018)	(0.014)	(0.06)	(0.039)	(0.025)	(0.033)	(0.098)	(0.085)
Constant	8.566***	8.024***	8.767***	9.643***	7.497*	8.18***	12.45***	6.511	−3.356
	(3.14)	(1.191)	(1.029)	(3.235)	(4.167)	(3.067)	(2.867)	(4.458)	(3.648)
Adj. R^2	0.7545	0.7884	0.77	0.605	0.6858	0.8332	0.7422	0.4459	0.6913
$MSE^{1/2}$	0.078	0.06482	0.06759	0.0998	0.0886	0.07352	0.08124	0.12494	0.1664

Notes: Standard errors are reported in parentheses. Differences of variables not reported.
***, **, * indicate p-values ≤1%, ≤5%, ≤10%, respectively.