

# Is there regional lock-in of unemployment rates in Australia?

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## Abstract

*This paper assesses the persistence of unemployment rates across Australian regions to see if there is evidence of sustained disadvantage for some Australian regions. Using Australian labour market data for statistical area level 4 regions over 1999–2018, the paper finds that lagged regional unemployment rates have substantial explanatory power for current regional unemployment rates. This effect lasts at least 19 years, even after controlling for factors such as average income levels and the industry structure of each region. There is strong persistence in the male unemployment rate across regions, a weaker effect for the female unemployment rate, and no observable effect for the youth unemployment rate. Lock-in effects are even stronger for participation rates. The results suggest that there is a potential role for well-designed place-based policies to combat persistent labour market disadvantages in some regions.*

*JEL* Codes: E24, J60, R10, R38

Keywords: unemployment, participation; region, lock-in

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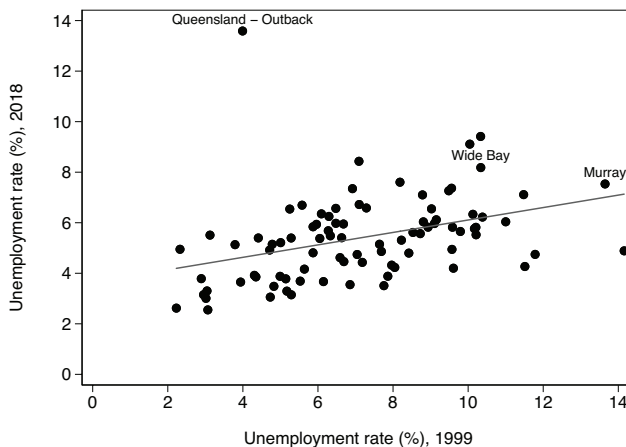
Note: The online code is available from the authors.

## 1. Introduction

2019 saw Australia enter its 28th consecutive year without a technical recession, a run unprecedented among developed economies. Since 1998, the national unemployment rate has continuously remained below 8 per cent, averaging 5.6 per cent. Most Australians in the labour force have been able to find work. Yet Australia's labour market performance has not benefited regions uniformly. Among statistical area level 4 (SA4) regions, in 2018 Australia's annual average unemployment rates ranged from 2.6 per cent in Sutherland (Sydney) to 13.6 per cent in the Queensland Outback (ABS, 2019a). If there are persistent differences in unemployment rates across Australian regions, this would provide motivation for a renewed focus on how best to address regionally-concentrated pockets of disadvantage.

Relatively high persistence in unemployment rates across Australian regions is visible in Figure 1, which shows one dot for each of 87 Australian regions. The upward-sloping line of best fit shows a positive relationship between unemployment rates in 87 Australian regions measured nearly two decades apart, suggesting that there is a degree of geographical 'lock in' of unemployment rates. For some regions, such as the Murray region (New South Wales) and Wide Bay (Queensland), unemployment rates were relatively high in both 1999 and 2018. Only one region – Queensland Outback – has shifted markedly between relatively low and relatively high unemployment rates.

Figure 1: Annual average unemployment rates in 1999 and 2018 for the 87 statistical area level 4 (SA4) regions in Australia



Source: Based on ABS (2019a) data.

This paper examines the existence and size of lock-in effects in SA4-level labour market outcomes in Australia. The principal focus is whether relatively high regional unemployment rates persist over time, as would occur if they follow a long-

run autoregressive process. Strong lock-in would reflect geographical agglomeration of disenfranchised members of the working age population.<sup>1</sup> The analysis controls for a range of other factors that could affect regional unemployment rates.

In the 1970s, persistently high unemployment in Europe led to the study of the concept of hysteresis in unemployment: that the effects of previous shocks persist due to relatively fast increases, but slow declines, in unemployment rates. Blanchard and Summers (1986) suggested that unemployment hysteresis can result from disenfranchisement, and that wage adjustment often works to maintain the jobs of those currently employed rather than to bring unemployed labour into employment. Australian studies using national and state data find some evidence of hysteresis in unemployment rates, despite real wage flexibility (Flatau *et al.* 1991; Karunaratne 1995; Smyth 2003).

Large negative shocks have been found to lead to long-term unemployment, which reduces employability, raises welfare dependence, and may increase the social acceptability of being unemployed (Blanchard and Katz 1997; Martin 2012). Shocks from factors such as natural disasters have been found to have persistent economic impacts in other countries in the past (Cavallo *et al.* 2013; Best and Burke 2019). Long-term unemployment began to receive greater attention as a policy priority in Australia in the early 1990s (Chapman 1993a, Chapman 1993b; Lewis 1994). Long-term unemployment could contribute to regional lock-in of unemployment.

The extent of regional lock-in of unemployment rates in Australia is of relevance to debates about managing local economic transitions and about industry, population, and migrant settlement policy. The federal government, and state and territory governments, have made a number of disparate attempts to support regions experiencing high unemployment (Productivity Commission 2017). These have included support for local worker retraining and structural adjustment packages, as well as direct subsidies to encourage firms to remain in areas perceived to be at risk of high unemployment. For example, the Victorian government established a Latrobe Valley Authority following the 2017 closure of the Hazelwood coal-fired power station, and was joined by the federal government in various local spending initiatives (Burke *et al.* 2019). While this paper does not attempt to determine the effectiveness of such interventions, understanding the degree of lock-in in regional unemployment can inform decisions about the extent to which persistent regional disadvantage remains an issue under current policy settings.

Section 2 of this paper provides context and a framework to account for differences in regional unemployment. Section 3 describes the data and regression methodology. Section 4 presents the initial regression results, which are extended in section 5 by adding a series of control variables. Section 6 considers alternative labour market dependent variables. Section 7 provides analysis of subsets of regions

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1 'Lock-in' is a term often used in the technology literature, for example lock-in of certain types of electricity generation technologies as a result of persistence emerging from institutions, technological systems, and natural resources (Unruh 2000). The labour economics literature also focuses on the characteristic of persistence when referring to lock-in, often specifically in relation to employment status following implementation of training programs (Fitzenberger and Speckesser 2007; Biewen *et al.* 2014; Doerr *et al.* 2017; Kruppe and Lang 2018).

and a brief case study of Wide Bay in Queensland, an area with a persistently high unemployment rate. Section 8 is the conclusion.

## 2. Context

### *International studies*

Blanchard and Katz (1992) examined how long it takes for state unemployment rates to converge back to the national average following local employment shocks in the United States (US). Using a model that assesses joint fluctuations in rates of participation, employment, and unemployment, they found that effects of shocks typically dissipate over a period of five to seven years (Blanchard and Katz 1992). They concluded that this does not primarily occur because of recovery in the local economy but because workers leave the state in pursuit of employment opportunities elsewhere. In contrast, the effects of labour demand shocks on regional unemployment in Europe tend to disappear within four years, with changes in participation rates being a dominant adjustment mechanism (Decressin and Fatás 1995). If there is rapid shock dissipation, relatively short-term effects can be seen to be temporary deviations from long-run equilibrium.

Barriers to equilibrium adjustment processes would slow the process. For instance, Blanchflower and Oswald (2013) found that higher home ownership in US states is associated with a higher unemployment rate, possibly on account of reduced labour mobility. Existing residents may also have economic or social ties that slow movement and contribute to lock-in (Glaeser 2007). Dao *et al.* (2017) found that US interstate mobility in response to labour demand variation is not as high as previously thought, with declines in mobility since the early 1990s. Lower mobility should lead to heightened variation in unemployment rates across states. In contrast, Amior and Manning (2018) found evidence that high persistence of employment-population ratios across US regions is due to persistence in labour demand shocks rather than a lack of migration.

### *Australian context*

Some studies have considered regional unemployment at the state/territory level in Australia. Using the Household Income and Labour Dynamics in Australia (HILDA) survey, Kishi and Kano (2017) found a negative relationship between state unemployment rates and the probability of finding permanent employment. Dixon and Shepherd (2011) analysed unemployment rate trends and found that Australia's larger states (Victoria, New South Wales, Queensland, South Australia, and Western Australia) have had similar labour market cycles. Tasmania, Northern Territory, and the Australian Capital Territory have exhibited more independent fluctuations in unemployment rates, as might be expected given that they are smaller jurisdictions. Around half or less of the variation in unemployment in Australian states is due to national effects (Shepherd and Dixon 2002), which leaves substantial scope for studies that focus on lower levels of aggregation. Dixon *et al.* (2001) found a negative correlation between the national unemployment rate and the relative dispersion of state unemployment rates, which suggests that regional variation may be of particular concern when national unemployment rates are low.

Studies of Australian states have found some evidence of persistence in unemployment rates. For example, Groenewold (1997) found that there are long-run equilibrium differences in unemployment rates across Australian states, and that only around half of the adjustment after a shock happens within the first five years. The study by DeBelle and Vickery (1999) found evidence of persistent differences between state unemployment rates and that most of the interstate migration in response to labour demand differences occurs within the first four years. The implication of persistence in unemployment rates across Australian states is that there might be scope for greater government involvement to address ongoing labour market imperfections (Smyth 2003). However, a regionally-differentiated fiscal policy from the federal government could cause the unemployment rate to rise in regions receiving federal assistance if there is substantial migration to those regions (Groenewold and Hagger 2008).

Analysis of state-level unemployment rates does not address the issue of unemployment rate lock-in across Australian regional labour markets. Possible regional lock-in of unemployment rates could be caused by labour market adjustment channels (migration, for example) not being strong enough to make the effects of shocks uniformly dissipate over space. For context, statistical area level 4 mobility is approximately 6 per cent per annum, based on the average of departures divided by population in 2017 (ABS 2019b).

There are also some studies that focus on regional lock-in and related issues across regions within individual Australian states. Plummer and Tonts (2013) found evidence of persistence in regional unemployment rates in a study of Western Australia over 1984–2011 that split the state into 13 regions. Trendle (2002) found persistence in unemployment rates across Queensland regions. McGuire (2001) noted that there has been substantial migration to regions with high unemployment rates in Queensland, which highlights the importance of factors other than local labour market opportunities for migration decisions. These are likely to include climatic conditions and local amenities. In contrast to these studies, section 3 details how this paper analyses all 87 regional labour markets ('SA4 regions') across Australia.

### ***Other contributing factors***

The sectoral composition of regional economies could influence labour market dynamics. For instance, industrial specialisation could contribute to more efficient labour markets if close proximity of many firms within an industry promotes transmission of knowledge. Alternatively, diversity could spur greater innovation (Beaudry and Schifffauerova 2009). Bradley and Gans (1998) found a negative effect of the government employment share on labour force growth. Whilst the authors noted that this effect could be limited to their period of investigation (1981–1991), it does confirm that sectoral employment composition can be important for labour market outcomes. Employment changes in cyclical sectors such as mining can exacerbate shortages of skilled labour in boom periods (Garnett 2012). There can be either positive or negative indirect effects on employment in non-mining sectors (Fleming *et al.* 2015).

Industries demanding more highly educated workers may have more stable employment patterns, which is one of the reasons why higher education may be

associated with lower unemployment rates (Elhorst 2003). Kishi (2014) found positive effects of education on a binary employment variable in Australia. Similarly, Trendle (2002) found that Queensland regions that have a higher proportion of their population holding at least a bachelor degree have lower rates of unemployment. Other socio-demographic characteristics – such as the proportion of Indigenous Australians – may also affect regional labour market differences (Altman and Daly 1995; Biddle and Hunter, 2006).

Vega and Elhorst (2016) note that analyses of regional unemployment rates may need to account for spatial dependence and control for common factors to avoid biased inference. This approach is used in this paper. Section 3 goes on to explain the estimation approach, including the use of a spatial autoregressive model and climate zone binary variables as controls. The focus is on the dependence of SA4 unemployment rates on their medium-run lagged values.

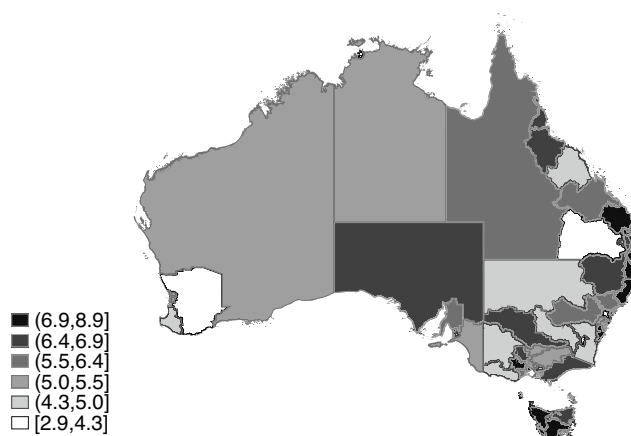
### 3. Data and methodology

#### *Data*

The primary dataset analysed in this paper is the December 2018 release of the ABS Labour Force Survey (ABS 2019a). This is a survey of around 26,000 dwellings conducted each month by the ABS. Data organised by statistical area level 4 (or SA4) region are used. Each region tends to have between 100,000 and 500,000 residents: between 100,000 and 200,000 in regional areas and between 300,000 and 500,000 in metropolitan areas. SA4 labour force data are based on where people live, not where they work. Regional boundaries have been designed by the ABS (2011) to ensure that a large proportion of people live and work within the same SA4 region, especially outside large cities. The sample period is 1999–2018, as the SA4 unemployment rates are available from October 1998.

Figure 2 provides a map of Australia's SA4 regions, showing average unemployment rates over January 1999–December 2018. SA4 regions in regional areas tend to be large in geographic area. The map suggests some degree of clustering of high-unemployment regions. There have been relatively high average unemployment rates in Tasmania and areas including coastal regions of northern New South Wales and southern Queensland. Most states have regions with low unemployment rates, such as Sydney – Baulkham Hills and the Hawkesbury region (New South Wales), Melbourne – Outer East (Victoria), Darling Downs – Maranoa (Queensland), and the Wheat Belt (Western Australia). At any point in time there is a wide divergence in unemployment rates within Australian states. For example, year-2018 annual average unemployment rates in NSW ranged from 2.6 per cent in Sydney – Sutherland to 9.1 per cent in Coffs Harbour – Grafton. Variation within states motivates analysis at the regional level.

Figure 2: Average unemployment rate for each SA4 region, January 1999–December 2018



*Notes:* Based on ABS (2019a) data. SA4 boundaries are based on 2011 definitions, which match the boundaries for the unemployment rate data.

## Methods

The primary method is ordinary least squares (OLS) regression using an SA4 region's early-period unemployment rate to explain its current unemployment rate. In addition, a generalised spatial two-stage least squares approach is used to control for potential spatial correlations. The basic form of the estimation model is:

$$U_L = c + \alpha U_E + X' \beta' + \varepsilon$$

where  $U_L$  is an SA4's later-period unemployment rate,  $c$  is a constant,  $U_E$  is its early-period unemployment rate,  $X$  is a vector of controls, and  $\varepsilon$  is an error term.

The intuition behind this model is that the coefficient on  $U_E$  will measure the extent to which regions that had relatively high unemployment rates in year  $E$  (the early year) continue to have relatively high unemployment rates in year  $L$  (the later year). This measures the 'lock-in' effect. In a bivariate regression with no controls,  $\alpha = 1$  would imply complete lock-in, meaning the unemployment rate in each region in year  $L$  is exactly equal to the year- $E$  unemployment rate plus the average SA4-level change in the unemployment rate (given by  $c$ ).  $\alpha = 0$  would imply no lock-in, that is no observable relationship between a region's unemployment rate in years  $E$  and  $L$ .

If consecutive years were selected for analysis, one could expect a strong relationship between lagged and current unemployment rates, indicated by a relatively large coefficient on  $U_E$ . The consideration of longer periods allows more opportunity

for adjustments to any initial unemployment rate differential to occur. Blanchard and Katz's (1992) vector auto-regression findings for the US suggest one might not expect a statistically significant coefficient when years  $E$  and  $L$  are more than around five years apart.

The  $X$  control vector includes industry structure percentages from the ABS 'Data by region' portal (ABS 2019b). Industry structure variables are important in part because technological progress has made it more difficult to get a job in some low-skill industries in Australia over recent decades (Garnett 2018). Regions that have a large number of people employed in the same sector may experience different degrees of lock-in (for example because of different skillsets among workers). The industry structure variables include the percentages of the labour force employed in each of the five largest sectors: health care, retail trade, manufacturing, construction, and education. State binary variables are included in the  $X$  vector to control for state-level heterogeneity (for example due to legal or institutional arrangements).

The paper also explores the use of socio-economic controls. These include the log average income in the region, the share of the population with post-school education, and the region's early-year labour force participation rate (ABS 2019a).<sup>2</sup> Robustness tests also include other variables, including the log of the mean sale price of detached dwellings so as to control for wealth effects. These controls help to reduce the risk of omitted variable bias. Further, differences in effects for Greater Capital City Statistical Areas according to the 2011 Australian Statistical Geography Standard can be assessed. There are 46 capital city SA4s and 41 non-capital city SA4s in the dataset.

While SA4 regions were designed by the Australian Bureau of Statistics (ABS) to represent regional labour markets, in urban areas there is considerable commuting across SA4 boundaries for work. This paper also uses generalised spatial two-stage least squares estimation to consider unobserved correlated factors that vary across neighbouring SA4s. Specifically, a spatial-autoregressive approach is used for some estimates to control for unemployment rates in neighbouring SA4s. The spatial weighting matrix gives an equal positive weight on the neighbouring SA4 unemployment rate for all contiguous spatial regions.

The cross-sectional approach adopted in this paper is suitable for the primary aim of testing for long-term persistence in labour market outcomes. The method allows us to assess long-term impacts without the risk of short-term noise in the data being influential. It also avoids time-series problems of serial correlation in error terms that may arise when using annual data. Correlation of error terms over time is not possible in cross-sectional models, as error terms only exist for single time periods.

The labour force survey data are based on a multi-stage area sample of persons aged 15 or more from the Australian civilian population. Households are surveyed for eight months, with one-eighth of the sample being replaced each month. The use of flexible survey collection techniques helps the ABS to reduce the risk of spatial correlations in the measurement error as a result of non-participation in some areas,

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<sup>2</sup> Post-school education includes all educational attainments other than pre-primary, primary, or secondary education. Examples include Bachelor Degrees, Diplomas, and Certificate Level IV (ABS 2019b).



with information being obtained from participants by either self-completion online or by telephone. Any measurement issues related to specific individuals would thus have only a temporary effect, and would tend to be averaged out. The Australian Labour Force survey has a response rate of approximately 92 per cent, higher than in many other countries (ABS 2019c).

In line with ABS advice, the use of annual averages of unemployment rates in this paper helps to reduce the risk of unrepresentative surveys in particular months. Nevertheless, it is not possible to fully rule out the case that regional lock-in effects at least in part pick up persistence in region-level measurement error in the ABS Labour Force Survey (2019a). The results should be interpreted with this caveat.

#### 4. Initial results

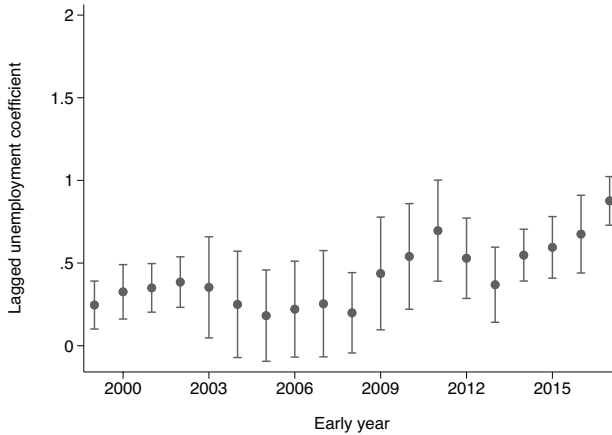
The initial specification is a simple regression that explains the unemployment rate in each SA4 region in 2018 ( $U_{2018}$ ) using the region's unemployment rate in 1999 ( $U_{1999}$ ) and no controls:

$$U_{2018} = c + \alpha U_{1999} + \varepsilon$$

This initial regression returns an estimated coefficient of  $\alpha = 0.25$  (standard error 0.075), which is statistically different from zero at the 1 per cent level. The regression  $R^2$  is 0.14. This simple regression suggests a lock-in effect over a period of 19 years, longer than the time-frame in the state-level study of Blanchard and Katz (1992) for the US.

To test whether this effect exists more generally, the initial regression is repeated by varying the early year, holding the late year at 2018. The estimation coefficients and 95 per cent confidence intervals are plotted in Figure 3. The regression coefficient is similar for all years until 2008, and increases noticeably for the period 2009–2018. These results suggest that there is a lock-in effect lasting up to two decades or longer, with the effect being strongest for more recent years. It is possible that the global financial crisis (GFC), which was most acute in 2009, could have influenced this story, although the GFC was less pronounced in Australia compared to many other developed countries.

Figure 3: Regression coefficients and 95 per cent confidence intervals



*Notes:* The dependent variable is the unemployment rate in 2018. The independent variable is the unemployment rate in each early year.

## 5. More fully-specified estimates

### *Addition of controls*

This section considers the addition of variables to the regression equation to control for unobserved factors that may affect regional unemployment rates. Model 2 includes state dummies, and the industry structure variables are included in model 3.<sup>3</sup> Model 4 also includes socio-economic variables such as the log of average income and the share of the regional population with post-school qualifications, as well as the year-1999 participation rate.

The socio-economic and industry structure variables are measured as at 2011, the earliest available date for the SA4 level. Ideally, all control variables would be measured at the initial time of 1999, but unfortunately data are not available for some variables in this early year. However, additional robustness tests (see online code) consider the effect of different timings of these variables. Using income and education variables measured as at the 2016 census does not have a major impact on the results, suggesting that the precise timing of these variables may not be crucial.

The unemployment rate results are again estimated using 1999 as the early year and 2018 as the later year when including the additional controls, such as the industry structure variables. Table 1 displays the results. Robustness tests in the online code control for other key sectors that vary substantially across SA4 regions, such as agriculture and mining.

<sup>3</sup> State-specific dummy variables also cover territories. All states/territories except the ACT contain more than one SA4 region, with NSW having the most at 28.

Table 1: Regression results explaining 2018 unemployment rate

	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
1999 unemployment rate	0.246*** (0.075)	0.240*** (0.077)	0.205*** (0.059)	0.143* (0.072)
New South Wales		0.891*** (0.242)	0.160 (1.063)	0.370 (1.243)
Victoria		0.670** (0.254)	-0.160 (1.288)	0.055 (1.408)
Queensland		2.431*** (0.627)	1.860 (1.405)	1.811* (1.085)
South Australia		1.039** (0.437)	0.043 (1.354)	0.052 (1.240)
Western Australia		2.047*** (0.423)	1.546 (1.016)	1.613 (1.186)
Tasmania		1.229*** (0.308)	0.617 (1.150)	0.191 (1.095)
Northern Territory		1.239** (0.613)	1.236 (0.757)	0.078 (0.714)
Health			0.047 (0.147)	0.092 (0.173)
Retail			0.079 (0.309)	-0.365 (0.465)
Manufacturing			0.075 (0.099)	0.025 (0.140)
Construction			-0.117 (0.115)	0.015 (0.164)
Education			-0.153 (0.164)	-0.045 (0.151)
Log income				-1.590 (2.402)
Post-school education				-0.067 (0.087)
Participation rate, 1999				-0.043 (0.050)
<i>R</i> <sup>2</sup>	0.143	0.315	0.340	0.419

*Notes:* \*\*\*, \*\*, \* show statistical significance at 1, 5 and 10 per cent level respectively. Robust standard errors are in brackets below the coefficients. Coefficients are not shown for constants. The state/territory variables are binary. The industry structure variables are the percentages employed in each industry in 2011, the earliest year available at the SA4 level. Model 1 and 2 have 87 observations. Model 3 and 4 have 86 observations based on availability of census data.

In model 2, each of the state binary variables are significantly different from the omitted variable for the Australian Capital Territory at the 5 per cent level. In model 3, none of the industry share coefficients are statistically significant. The 1999 unemployment rate coefficient is still positive and significant at the 1 per cent level for

models 2–3 with additional controls, and with a similar magnitude to model 1. This suggests the results are not substantially influenced by state-specific factors or the industry structure in particular regions. The unemployment rate coefficient declines in magnitude and significance when controlling for socio-economic variables in model 4, but remains positive and significantly different from zero at the 10 per cent level.

### **Further robustness tests**

Results are similar in a number of robustness tests, including approaches to address possible spatial correlations. For instance, similar results are obtained using generalised spatial two-stage least squares estimates instead of ordinary least squares, as shown in Table 2. Models 1–3 show positive coefficients for the spatial autoregressive terms (that is, higher unemployment rates for neighbours having a positive effect), although these are not statistically significant. An alternative approach of controlling for seven climate zone variables also does not have a substantial effect on the lock-in relationship (results available in the online code). Results are also similar when controlling for outward migration divided by population in 2017, the log of average house price (excluding attached dwellings), and when using 2016 data for income and education rather than 2011 data. Further robustness tests in the online code account for population size. The unemployment-rate lock-in coefficients from Table 1 are similar when controlling for the log of the working-age population size.

Table 2: Spatial-autoregressive regression results using the 2018 unemployment rate

	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
1999 unemployment rate	0.249*** (0.064)	0.242*** (0.062)	0.197*** (0.076)	0.155* (0.083)
Spatial autoregressive term	0.097 (0.093)	0.122 (0.086)	0.092 (0.088)	-0.101 (0.104)
State dummies	No	Yes	Yes	Yes
Industry structure	No	No	Yes	Yes
Socio-economic variables	No	No	No	Yes

*Notes:* \*\*\*, \*\*, \* show statistical significance at 1, 5 and 10 per cent level respectively. Standard errors are in brackets below the coefficients. Coefficients are not shown for constants. There are 86 observations in each case. The spatial autoregressive term shows the effect of the unemployment rate in neighbouring SA4s in 2018 on the dependent variable based on a weighting matrix that assigns the same positive weight to each contiguous SA4 and zero otherwise.

To test whether lock-in effect exists for different sub-groups, separate regressions were conducted for the male unemployment rate, female unemployment rate, and the youth (under 25) unemployment rate. The results are presented in Table 3, and suggest that effects are particularly sizeable for the male unemployment rate.

The larger lock-in effect for males might be because other groups (female or youth) are more likely to move in and out of the labour force. The youth cohort may also be more mobile. The standard errors are largest for the youth unemployment rate, indicating estimates that are less precise.

Table 3: 1999 unemployment rate coefficient for male, female, and youth groups

<i>Group</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
All	0.246*** (0.075)	0.240*** (0.077)	0.205*** (0.059)	0.143* (0.072)
Males	0.252*** (0.070)	0.270*** (0.077)	0.279*** (0.068)	0.215*** (0.080)
Females	0.224*** (0.080)	0.200** (0.079)	0.088 (0.067)	0.046 (0.081)
Youth	0.126 (0.100)	0.073 (0.103)	-0.092 (0.102)	-0.140 (0.098)
State dummies	No	Yes	Yes	Yes
Industry structure	No	No	Yes	Yes
Socio-economic variables	No	No	No	Yes

*Notes:* \*\*\*, \*\*, \* show statistical significance at 1, 5 and 10 per cent level respectively. Robust standard errors are in brackets below the coefficients. Coefficients are not shown for constants. These are separate regressions for each group. The dependent variable is the respective unemployment rate in 2018.

Lock-in effects may differ between major cities and the rest of the country. If people in urban areas find it easier to travel across SA4 boundaries and/or relocate to a different region in order to find work, lock-in effects for these areas may be smaller. However, if there are entrenched inequalities within urban areas, lock-in effects may instead be larger. Restricting the sample to only the 46 capital-city regions results in a finding of positive and significant lock-in effects for models 1–3 in Table 4, although not model 4. The equivalent non-capital city coefficients are positive but not significant. The online code also shows that an interaction term between the capital city binary variable and the lagged unemployment rate is positive and significant for models 1–3 in a full sample estimate. Lock-in effects thus seem to be larger across SA4 regions in major urban centres.

Table 4: 1999 unemployment rate coefficient for capital city and non-capital city sub-samples

<i>Sub-sample</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
Capital cities	0.530*** (0.064)	0.456*** (0.079)	0.215** (0.105)	0.104 (0.121)
Non-capital cities	0.031 (0.125)	0.053 (0.139)	0.153 (0.152)	0.162 (0.224)
State dummies	No	Yes	Yes	Yes
Industry structure	No	No	Yes	Yes
Socio-economic variables	No	No	No	Yes

*Notes:* \*\*\*, \*\*, \* show statistical significance at 1, 5 and 10 per cent level respectively. Robust standard errors are in brackets below the coefficients. Coefficients are not shown for constants. These are separate regressions for both the 46 capital-city regions and the 41 non-capital-city regions.

## 6. Alternative dependent variables

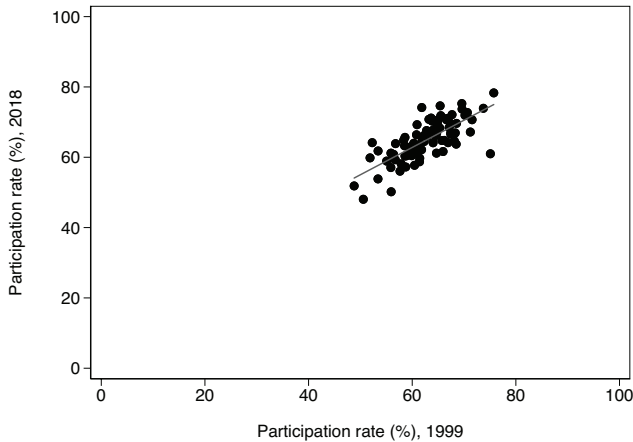
There are strong reasons to expect a regional lock-in effect for the labour force participation rate. A key one is that it is possible that those who are less committed to labour force participation choose locations based more on amenity and cost of living rather than expected wages. Sources of amenity are likely to include nice weather and coastal frontages. Coastal locations have indeed been associated with strong population growth (Garnett and Lewis 2007). There might also be demographic differences that themselves persist and that cause persistent differences in participation rates.

Using the same functional form, the results for the labour force participation rate are:

$$P_{2018} = 16.24 + 0.78P_{1999}$$

The coefficient on  $P_{1999}$  has a standard error of 0.10 and the regression has an  $R^2 = 0.55$ . The data points and the fitted regression function from the initial regression are plotted in Figure 4.

Figure 4: SA4 annual average participation rates in 1999 and 2018



Source: Based on ABS (2019a) data.

Consistent with expectations, there is a much stronger regional lock-in effect for participation rates than unemployment rates. Table 5 gives the results for participation rate lock-in effects, using 1999 as the early year. The magnitude of the lagged participation rate variables declines when the extra controls are added, but remains at 0.6 or above. Results are similar when controlling for climate zone. Lagged participation rates remain positive and significant at the 1 per cent level for each early year from 1999–2017 when controlling for state and industry structure variables, along with log income and the post-school education share.

Table 5: 1999 participation rate coefficients explaining 2018 participation rate

	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>
1999 participation rate	0.776*** (0.100)	0.758*** (0.118)	0.698*** (0.120)	0.623*** (0.130)
State dummies	No	Yes	Yes	Yes
Industry structure	No	No	Yes	Yes
Socio-economic variables	No	No	No	Yes

Notes: \*\*\*, \*\*, \* show statistical significance at 1, 5 and 10 per cent level respectively. Robust standard errors are in brackets below the coefficients. Coefficients are not shown for constants. The state/territory control variables are binary. The industry structure variables are the percentages employed in each industry. Model 1 and 2 have 87 observations. Model 3 and 4 have 86 observations based on availability of census data.

Repeated regressions with the participation rate for each early year from 2000–2017, again holding 2018 as the later year, show results for all years being consistent with those for 1999 (lagged participation-rate coefficients at or above 0.5), and the coefficients approaching one as the early year approaches 2018. The proportion of variation explained by the lagged participation rate is high and relatively consistent for each early year, and becomes even higher over the five most recent years (see the online code). The high proportions of explained variation suggest that unobserved differences may not be a major concern.

There are also similar results to those in Table 1 using a dependent variable measured as the number of unemployed persons divided by the population (using data for the civilian population aged 15 and over). This is in contrast to the primary approach of using the size of the labour force as the denominator.

## 7. Subset and case-study analysis

This section focuses on comparing regions with a persistently high unemployment rate with regions with a persistently low unemployment rate. The section also considers a case study of the Wide Bay statistical area in Queensland. The motivation for these analyses is to go deeper than what the full-sample analysis allows.

### *Subset analysis*

Regions can be classified as:

- Those with a persistently high unemployment rate: regions that had an unemployment rate that was above the median for SA4 regions in every year from 1999–2018.
- Those with a persistently low unemployment rate: regions that had an unemployment rate that was below the median for SA4 regions in every year from 1999–2018.
- Others.

Using these definitions, six of the 87 SA4 regions have had a persistently high unemployment rate (Table 6). These six regions were distributed across five states. Four were in greater capital city areas, while two were elsewhere. Eight other regions have had unemployment rates above the median in at least 18 out of the 20 years. This includes four in greater capital city areas and four outside of greater capital city areas.



Table 6: SA4 regions with unemployment rates above or below the median in each of the 20 years to 2018

<i>Above-median unemployment rates in every year from 1999–2018</i>	<i>Below-median unemployment rates in every year from 1999–2018</i>
Sydney – South West	Sydney – Baulkham Hills and Hawkesbury
Melbourne – West	Sydney – Eastern Suburbs
Logan – Beaudesert	Sydney – North Sydney and Hornsby
Wide Bay	Sydney – Northern Beaches
Adelaide – North	Sydney – Sutherland
Tasmania – West and North West	Melbourne – Inner South
	Melbourne – Outer East
	Brisbane – Inner City
	Darwin
	Australian Capital Territory

*Notes:* There are also 8 regions that had unemployment rates above the median in at least 18 of 20 years. These regions were: Central Coast, Mid North Coast, Richmond – Tweed, Melbourne – North West, Moreton Bay – North, Sunshine Coast, Mandurah, and Launceston and North East.

There were 10 regions with a persistently low unemployment rate. These were predominantly in the large cities of Sydney and Melbourne. The list includes regions in the inner-city (Melbourne – Inner South, for example) as well as city-fringe areas (Sydney – Baulkham Hills and Hawkesbury, for example). There were also regional and remote areas that had unemployment rates below the median in at least 18 of 20 years (Darling Downs – Maranoa and Western Australia – Wheat Belt).

Table 7 compares characteristics of the two types of regions. The regions with a persistently high unemployment rate over 1999–2018 had a faster average rate of population growth, consistent with the idea that good employment prospects are not the only reason for driving regional population growth differentials. The level of income was substantially higher in the regions with persistently low unemployment rates on average. Public-sector and education-sector employment levels are lower in the regions with persistently high unemployment rates compared to regions with persistently low unemployment rates. Income growth and net migration levels are quite similar between the two types of regions.

Table 7: Characteristics of locked-in regions

<i>Characteristic</i>	<i>Persistently high unemployment rate</i>	<i>Persistently low unemployment rate</i>
Unemployment rate 1999	10.2	4.1
Unemployment rate 2018	7.0	3.4
Population growth	43.4	30.7
Income level 2016 (\$'000)	51.2	80.1
Income growth	17.3	19.0
Inward migration	6.2	8.6
Outward migration	5.1	7.6
Public-sector employment 2011	6.1	9.6
Public-sector employment 2016	5.7	9.1
Education employment 2011	6.8	8.5
Education employment 2016	7.6	9.1

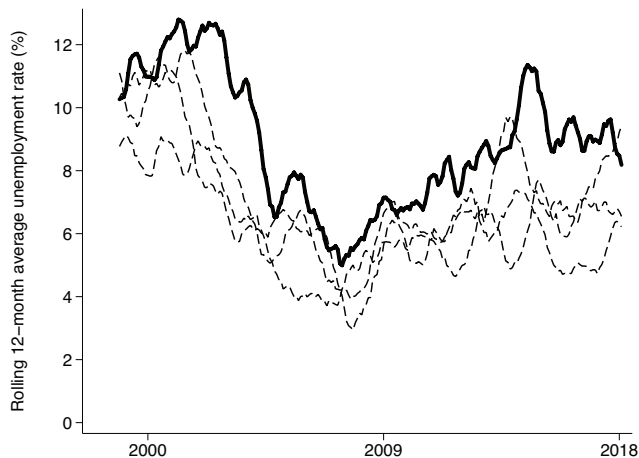
*Notes:* Values are percentages except for income level, which is in thousand dollars. Income growth is from 2011–2016. Population growth is from 1999–2018. Migration is a share of the total population in 2017. There were six regions with a persistently high unemployment rate and 10 with a persistently low unemployment rate, as listed in Table 6. Data are from the ABS (2019a; 2019b).

### **Case study: Wide Bay statistical area**

Wide Bay is the statistical area to the north of the Sunshine Coast in Queensland. It includes the regional centres of Bundaberg, Maryborough, and Hervey Bay. Major industries of employment are health, retail, and agriculture. The region has a lower share of people in the 20–44 age group compared to the state and national averages, but an above-average proportion in the age group of 45 and above (Neville 2013).

There has been consistently high unemployment in Wide Bay over the last few decades. Wide Bay was the single worst performing labour market region in 5 of the 20 years since 1999 and has been in the quintile of worst-performing regions in every year except one. Figure 5 shows that the rolling 12-month unemployment rate has usually been above the corresponding rates in the nearby regions of Fitzroy (Gladstone and Rockhampton), the Sunshine Coast, and Moreton Bay – North.

Figure 5: Rolling 12-month average unemployment rate for Wide Bay and nearby regions



*Notes:* Rolling 12-month average unemployment rate for Wide Bay (bold and solid line) and regions near Wide Bay: Fitzroy (Gladstone and Rockhampton), the Sunshine Coast, and Moreton Bay – North (dashed lines). Based on ABS (2019a) data.

There are a number of possible explanations for persistently high unemployment rates in Wide Bay. There have been pockets of high population growth in the region, despite the high unemployment rate. Population growth has been fast among the 45 years and above age group (Neville 2013). Wide Bay is one of a number of coastal areas that has above-average durations of job search along with high population growth, suggesting that people often choose the area for reasons other than job prospects (Garnett 2018). Another possible contributing factor is its large Indigenous population, which at 4.7 per cent of the population in 2016 was substantially above the national average of 2.8 per cent. The tendency to migrate to other regions can be lower for Indigenous Australians (Taylor and Stanley 2005).

The Wide Bay region is known as a hotspot of youth unemployment (Brotherhood of St Laurence 2018). Key areas in Wide Bay have high rates of disengagement – defined as people not working or studying – among young adults (Neville 2013). Fewer local tertiary education options are one possible explanation. Young people are also more likely to be unemployed if they live in a household where no one else is employed (Biddle 2007), which is more likely in Wide Bay due to its high overall unemployment rate.

## 8. Conclusion and policy implications

This paper examined whether lock-in effects exist among Australian regional labour market outcomes, with a focus on unemployment rates. The analysis found evidence of an unemployment-rate lock-in effect lasting at least 19 years. Strong lock-in effects

also exist for participation rates. These findings are based on concise econometric approaches that directly address the question of labour lock-in across regions. The results show a higher degree of persistence in regional differentials in unemployment rates than implied by the findings of most previous studies, for example the study of Blanchard and Katz (1992) for the US.

The results are robust to a number of model variants. This includes addition of state binary variables, industry structure percentages, socio-economic controls, and a spatial autoregressive term. Robustness tests in the online code using climate zone variables also help to control for unobserved heterogeneity at the regional level.

The existence of an unemployment-rate lock-in effect could be explained by a number of factors. These include constraints to worker relocation – potentially due to a lack of ability to move, and/or an unwillingness to leave because of personal connections. High amenity and low living costs could also compensate some people sufficiently for their unemployment status in some regions. However, robustness tests in the online code still reveal an unemployment-rate lock-in effect when accounting for migration, low house prices, and climate zone. Part of the unemployment-rate lock-in effect thus likely represents some form of persistent regional disadvantage.

The paper's results support the notion that place-based policies are relevant to consider in addressing persistent regional disadvantage (Partridge *et al.* 2015). For example, targeting of retraining initiatives and employment generation schemes in regions such as Wide Bay could be considered. This could include public sector employment. Diagnosis of a problem is different to identifying the best available cure, however. Both Glaeser and Gottlieb (2008) and the Productivity Commission (2017) warn that regionally-focused initiatives risk being inefficient, and Freebairn (2003) concluded that region-specific policies are often inferior to economy-wide policies for reducing unemployment. Another possibility is efforts to reduce barriers to mobility, such as reductions in stamp duty on home purchases.

Program design that facilitates ongoing monitoring and evaluation of policy effectiveness would allow evidence-based assessments of the value of specific place-based policies (Productivity Commission 2017). This could include further evaluation of past programs to address unemployment, such as recent funding for the Latrobe Valley, the Regional Growth Fund in Victoria, or the Royalties for Regions program in Western Australia. Identifying optimal approaches for overcoming region-based unemployment rate lock-in is an important area for future research.

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