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What drives long distance commuting into Australian regions?
A spatial panel model approach

Abstract: Impacts of long distance commuting (LDC) on a host region have been a topic of research interest for some time. Recently, however, criticisms have surfaced about the validity of studies which address this topic. Specifically, temporal variability and spatial interaction have rarely been considered. This article argues that a single model which jointly incorporates these two aspects can improve the predictive power of LDC impacts. Using spatial panel modelling, 516 Local Government Areas (LGAs) across Australia over two census periods (2006 and 2011) were used to explore drivers of LDC. It was found that local labour market characteristics had minimal influence on recruitment strategies of firms that typically use LDC. Housing affordability does not impact on the decision of non-resident workers to either migrate into a region or adopt LDC into that region. However, local service provision and the availability of rental accommodation reduces the uptake of LDC. In addition, higher turnover of the resident population erodes social capital in host regions, which reduces the attractiveness of the local area and leads to increased use of LDC.

Keywords: long distance commuting, mining, Australia, regions, spatial analysis

1. Introduction

Long distance commuting (LDC) and its socio-economic impact on regions that host LDC workers continues to be a topic of interest in academia (Chapman et al., 2015; Haan et al., 2014; Misan and Rudnik, 2015; Silin, 2015). LDC is characterised by a cyclical nature of travelling to a work region, spending several days in the work region, followed by returning to the region of residence for leisure. Travel between a work region and region of residence is predominantly conducted through Fly-in Fly-out (FIFO) and Drive-in Drive-out (DIDO). Nicholas and Welters (2016) demonstrate that mining is an important industry in the LDC workforce in Australia, even though it is not the only industry adopting LDC practices (see also Skilton (2015)). Consequently, research which investigates the impacts of LDC has typically been situated in a mining context.

Mining in Australia predominantly occurs in rural/remote regions whose economies depend on a limited number of industries (Kotey, 2015; Tonts et al., 2013). As a result, the opportunities for the mining industry to build local backward and forward industry linkages and hence contribute to the growth and diversification of the local economy are restricted. Instead, the region becomes a resource bank to other regions from which the mining industry sources its input requirements – typically urban regions (MacKinnon, 2013; Rolfe and Kinnear, 2013; Tonts et al., 2013). The adoption of LDC into a region – whether related to mining or otherwise – only reinforces this tendency. LDC workers do not spend (or only disperse limited amounts of) their wages in the host region, which gives rise to the hollow economy syndrome (McKenzie, 2010). Furthermore, LDC might contribute towards fractionalisation of the community (Storey, 2010; Tonts and Plummer, 2012) and social disorder (Carrington et al., 2012).

It is against this backdrop that research exploring the impact of LDC into a region or mining in general on the socio-economic wellbeing of host regions is conducted. This body of research has highlighted the displacement of non-mining related industries (Fleming and Measham, 2015a), increased income (Hajkowicz et al., 2011), increased income inequality (Fleming and Measham, 2015b; Reeson et al., 2012), increased housing cost (Haslam McKenzie et al., 2013) or more general increased cost of living (Lawrie et al., 2011). In addition, the diversity of the commodity base was found to be a driver of socio-economic outcomes (Tonts et al., 2012).

However, this body of research has recently drawn criticism from two ends. First, Chapman et al. (2015) show that the impact of drivers of socio-economic wellbeing in resource rich regions is highly variable both across time and space. Hence, results from studies that explore the impacts of LDC or mining in a particular region (Chapman et al., 2015; Tonts et al., 2013) or studies that compare impacts across regions, but not simultaneously across time (Fleming and Measham, 2015a; Hajkowicz et al., 2011; Haslam McKenzie and Rowley, 2013; Reeson et al., 2012; Tonts et al., 2012) are difficult to reconcile. Studies that account for both time and space are rare (Fleming and Measham, 2015b). Second, Nicholas and Welters (2016) show the importance of spatial interaction in explaining the extent of LDC in a host region, which is arguably an important driver of impacts on regional socio-economic wellbeing. Spatial interaction occurs if the extent of LDC into a region not only depends on circumstances in the region, but also on circumstances in other regions. They argue that this is likely the case given the relatively undeveloped economic structure of host regions. This implies mining industries in the region must interact with other regions to source capital input (the resource bank argument) and labour input (the LDC argument).

Not controlling for spatial interaction may lead to biased model results. Yet, none of the above studies controls for spatial interaction – though Fleming and Measham (2015b) and Rolfe and Kinnear (2013) demonstrate the importance of spatial spill over effects.

This study builds on the Chapman et al. (2015) and Nicholas and Welters (2016) studies. That is, Chapman et al. (2015) account for time and space but not spatial interaction, whereas, Nicholas and Welters (2016) control for space and spatial interaction but not time. To address this gap, the current study incorporates all three elements: space, spatial interaction and time. The addition of temporal effects to the Nicholas and Welters (2016) study is not only likely to increase the accuracy of the model, but also to address issues of causality. That is, without controlling for time, only correlation (not causality) between the extent of LDC into a region and regional characteristics can be detected. The analysis presented here establishes both correlation and causation; thus, a much stronger evaluation of the determinants which influence the extent of LDC in a host region can be achieved, and hence, firmer policy implications can be suggested.

To do this, data from the 2006 and 2011 Australian Censuses for 516 regions are utilised. Findings from the study confirm that spatial interaction is present; hence, consideration of this element does indeed improve the accuracy of the model. Researchers interested in explaining the extent of LDC or the impacts of LDC on the wellbeing of regions should endeavour to incorporate spatial interaction in their analysis next to space and time. Furthermore, local service provision and the availability of rental accommodation rather than the tightness of the labour market or housing affordability reduce the uptake of LDC into a region. Lastly, population transience increases LDC into a region.

2. Long distance commuting in rural/remote Australia

Spatial interaction occurs if economic activity in a region uses inputs which are not sourced locally. With respect to labour requirements, this will typically happen in thin labour markets; these markets cannot accommodate substantial additional labour demand – not even if significant wage premiums are offered. Thin labour markets are found in rural and remote regions of Australia. Hence, if firms require workers, they must entice them to migrate to the region or commute to the region either on a daily basis or less frequently through LDC. In the case of the mining industry, which typically operates in rural/remote Australia, this was illustrated by SCRA and Windsor (2013, 25) "resource companies prefer to engage with local workers where possible; however, this pool is very quickly exhausted particularly in regards to skilled workers".

Traditionally, mining workers would relocate (i.e. migrate) to the host region at least for the duration of their contract. Subsequent increased demand for housing and other services combined with miners' significant purchasing power have, however, led to inflationary pressures on the local housing market. These pressures have caused concerns around housing affordability (Haslam McKenzie et al., 2013) and cost of living in general (Lawrie et al., 2011). In some regions with extraction firms, the cost of living can rival that of cities (McKenzie, 2010). Windle and Rolfe (2013) argue that high prices discourage permanent migration into the region, which serves as the main justification used by mining companies to adopt LDC (Lawrie et al., 2011). High cost of living also encourages local residents to sell their house while the price is high and to relocate to lower cost regions. Some of these former residents then utilise LDC practices to work in their original region (Basson and Basson, 2012).

Nonetheless, the notion that mining firms use LDC as a recruitment strategy of last resort is contested. McKenzie (2010) argues that LDC workers are more mobile and provide mining firms more flexibility to move workers between smaller extraction sites. As a result McIntosh (2012, 233) argues that "nowadays, however, workers are hired by contracting companies and essentially all new recruits are FIFOs/DIDOs". Regardless of the motives, the use of LDC in Australia, particularly in rural/remote Australia, is widespread and not confined to mining (Nicholas and Welters, 2016; Skilton, 2015). Accordingly, spatial interaction could distort research findings if not appropriately controlled for in the Australian context. In subsequent sections, the idea of 'regions' will be defined followed by the provision of the working definition of LDC adopted in this article; these definitions are employed to build a spatially inclusive model which explores the determinants of the extent of LDC into a region.

3. Defining a region in the Australian context

In this study, 'region' represents a spatial unit where areas are grouped together based on similar economic, social and geographic characteristics (Garnett and Lewis, 2007). Overall, three demarcation strategies are commonly employed to define regions. Firstly, population-based demarcations use pre-established government defined regions. These areas are determined based on administrative needs indirectly influenced by population size. Up until 2011, the Australian landscape was divided by Statistical Local Areas (SLAs) and Local Government Areas (LGAs). Population-based demarcations are employed extensively in government data collections such as the Australian census. Regions do not overlap and the entirety of Australia is covered in this approach. Secondly, place-based demarcations use the borders of towns, cities or mining sites to determine regions. This form of demarcation is particularly useful when investigating specific points of interest which need to avoid influences from surrounding areas. Thirdly, activity-based demarcations use commuting behaviour to inform regional boundaries. That is, if the share of people who both live and work in a region surpasses a critical level, the area is considered to be self-contained and a region is declared (Mitchell and Stimson, 2010).

Due to the desire to encompass Australia in its entirety, place-based strategies are inappropriate. An activity based-demarcation strategy, on the other hand, holds value in that it can demarcate regions based on economic activity. Two main factors, however, determined this strategy to be a non-viable albeit preferred option. Firstly, shifts in economic activity may lead to shifts in regional boundaries over time. As this study employs a temporal component to the spatial analysis, changes to regional boundaries over time are undesirable. Secondly, activity-based demarcation strategies produce few – and therefore geographically large – regions in rural/remote areas. The majority of LDC workers commute to/from rural/remote areas; thus, an activity-based demarcation runs the risk of obscuring LDC workers, who are identified in the current work through the difference between their region of residence and region of work (see Section 4). Population-based demarcation strategies that currently exist do not suffer from – or experience to a lesser degree – the above problems. Hence, we adopt a population-based demarcation strategy using Local Government Areas (LGAs). LGAs can be populated with ABS census data; this is the only database which provides the necessary scope (i.e. nationwide) and level of detail (i.e. regional) that is required to complete a spatial panel dataset.

We use data for all 670 Australian LGAs in 2006 and 562 LGAs in 2011. We remove 31 regions from the analysis because their low population sizes lead to inconsistent data[i]. An inherent problem arose during data collection due to population changes and the repositioning of the 2011 LGA boundaries particularly for regions in Queensland and the Northern Territory. In 2008, the Queensland government amalgamated 158 LGAs into 74. The majority of these amalgamations were between regions with the same outside boundary. Furthermore, the Northern Territory underwent a restructuring that altered regions for a majority of the territory. Pink (2012) suggested that conversions into different regions achieved better results when a number of smaller regions were converted into larger ones. Therefore, to maintain regional consistency, we introduced the amalgamations evidenced in the 2011 census into the 2006 census data for this study. In case there were no common boundaries between the years, we group regions occupying the same location to form mega-regions. Figure 1 depicts the 516 LGA regions (spanning 2006 and 2011) that we include for further analysis.

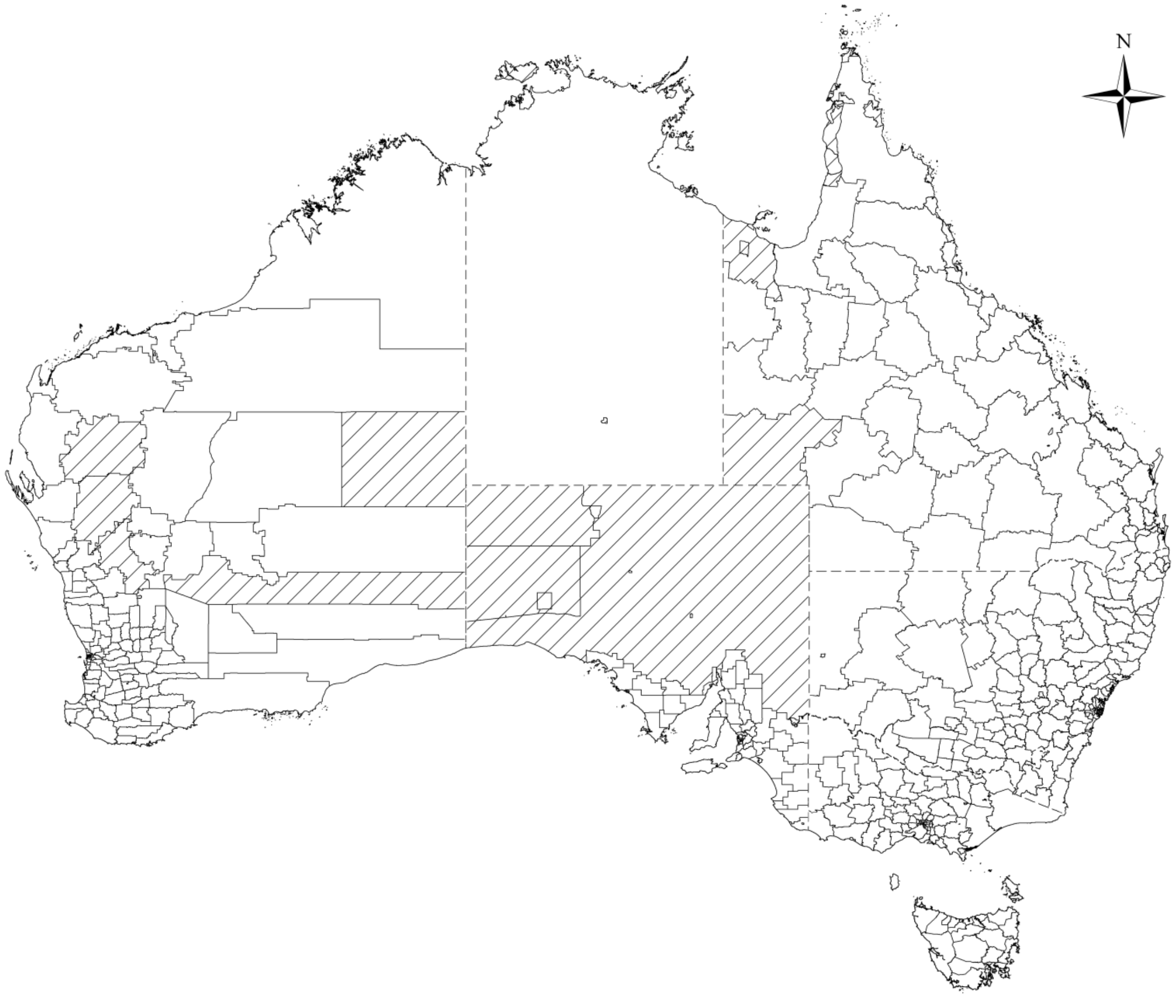

Figure 1: Australian map of selected LGA regional demarcations, shaded areas = regions removed from analysis

4. Defining a long distance commuter

For this study, we use a measurement of the proportion of the workforce in a region that apply LDC to commute to work (proportion of LDC in the workforce) as our dependent variable. To establish the proportion of LDC in the workforce, we use Place of Work and Place of Enumeration data from the 2006 and 2011 ABS censuses for each LGA region in Australia. ABS data are, however, not designed to capture LDC (McKenzie, 2010; SCRA and Windsor, 2013). Hence, there is no definitive way of empirically defining an LDC worker. All methods to define an LDC worker impose that an LDC worker must work in a different region than where they reside. The problem with that definition is that it may falsely classify daily commuters as long distance commuters. This is the case for daily commuters who live close to a regional boundary but work on the other side of the boundary, which is especially relevant for densely populated, hence geographically small, regions. KPMG (2013) therefore imposes an additional requirement, which is that population weighted centres of the two regions need to be at least 200km apart. Skilton (2015) questions whether that distance is far enough to exclude daily commuting and suggests it should be at least 400km.

In this article, an alternative approach developed by Nicholas and Welters (2016) is employed, who instead of distance imposed an additional criteria related to the region's Accessibility/Remoteness Index (ARIA+) (provided free online by the Australian Department of Health at: https://www.adelaide.edu.au/apmrc/research/projects/category/aria.html) to filter out daily commuting. Using road distance from the nearest service town, the ARIA+ produces an index from 0 (high accessibility) to 15 (high remoteness). To control for daily commuters, we classified regions into four categories; Cities, Rural Centres, Rural Areas and Remote Areas, depending on their remoteness index. Each of these categories has different criteria to control for daily commutes (refer to the Appendix). The key difference between the approach of this article and that of Nicholas and Welters (2016) is that we adopt a more detailed regional classification (i.e. 516 regions versus 325 regions). This reduces the risk of not considering LDC workers particularly in rural/remote regions.

5. Potential drivers of long distance commuting

The independent variables (i.e. hypothesised drivers of the proportion of LDC in the workforce) in this study align with the decision making process of companies in search for workers and – if the company decides to recruit outside the region - the locational decision of the recruited worker. It is hypothesised that (1) local labour market conditions influence the company's decision to recruit locally, and (2) residential attractiveness of the region influences the recruited worker's decision to either relocate or instead become a long distance commuter (Nicholas and Welters, 2016; Storey, 2010).

5.1 Local Labour Market

SCRA and Windsor (2013) found that the labour market within a host region is important because companies look locally first before using LDC. However, that view is contested both for the mining industry (McIntosh, 2012) and the health care industry (Perkins, 2012). To test whether local labour market conditions influence the extent of LDC into a region, we include the official unemployment rate and the non-participation rate as measures of local labour market tightness. We include the latter to capture discouraged workers who may present themselves for work if it becomes available (Mitchell et al., 2014). Utilisation of a spatial panel model will facilitate the establishment of causality, not just correlation, unlike the analysis provided by Nicholas and Welters (2016).

To accommodate the mining industry’s preference to recruit from employees (specifically in the agriculture and construction industries) rather than the unemployed (Blackman et al. (2014), we follow Nicholas and Welters (2016) and include a variable which captures the proportion of labour that would be attractive for the mining firms to raid (which is the proportion of construction and agriculture workers in the total labour force). New is the inclusion of the average age of the regional workforce. SCRA and Windsor (2013) found that mining companies predominantly employ younger individuals even if skilled (older) labour is present within a region.

5.2 Residential attractiveness of the region

To proxy the residential attractiveness of a region, the themes that Nicholas and Welters (2016) include in their analysis have been built upon. They employed a housing market theme (McKenzie, 2010; SCRA and Windsor, 2013) and a local service provision theme (Chapman et al., 2015; Sharp et al., 2002) to capture the residential attractiveness of the region. This study additionally considers themes around alternative employment opportunities in the region as well as regional population transience.

Relocation to a region of work becomes more attractive if alternative employment opportunities exist outside of the recruiting industry. This is because the worker’s accompanying family might require employment or the worker themselves may require another position in case they lose their new job (Randall and Ironside, 1996; Tonts et al., 2012). Therefore we include a Herfindahl type employment industry concentration index. The higher the index, the more concentrated the industry landscape in the region is, which increases the employment vulnerability of the region while decreasing the attractiveness of the region as a residential location. In addition, two more indicators of alternative employment opportunities related to alternative wages form part of the analysis in this article. If alternative employment opportunities exist, but at significantly lower wages than the job for which the worker considers relocating, the region loses its attractiveness to reside. Exploiting the fact that the occupation ‘Machinery Operator and Driver’ is the dominant occupation in the mining industry, we include the average wage earned for that occupation in the mining industry relative to the average wage a worker with that occupation can earn outside the mining industry in the region. The higher this relative wage is, the less attractive alternative work is in terms of pay. Similarly, we include average income in the mining industry relative to average income outside the mining industry in a region.

Lovell and Critchley (2010) argue that long-term residents of a region which exhibits population churn (for example because of the cyclical nature of mining) gradually develop an ‘emotional fatigue’ toward building relationships with newcomers which instils hesitancy when an opportunity to build new friendships presents itself (Ooi et al., 2014). As the social networks between long-term and temporary residents break down so does their trust (Bertotti et al., 2012). For long-term residents concepts like ‘outsider’ are increasingly used to describe temporary residents, which further alienates them (SCRA and Windsor, 2013). With the lack of close friendships and support networks within their region of work, the region itself becomes a less attractive place to move to (Lovell and Critchley, 2010). To capture population transience, we include the share of residents of a region who have lived in the region for at least five years. An increase in population transience is predicted to increase LDC into the region.

The housing market is represented using rental prices and mortgage repayments per bedroom – both are measures of housing affordability. It is expected that reduced affordability will increase LDC (Hajkowicz et al., 2011). Thus we include the proportion of unoccupied dwellings in the region as a measure of housing market tightness.

Given the limited lifespan of the mine and/or construction project (SCRA and Windsor, 2013), workers who are considering a relocation to the region of work might prefer temporary accommodation (i.e. rental houses) over buying a house. That is, it is expected that a negative relationship will exist between the proportion of rental properties to LDC.

We include three variables in the analysis to proxy regional service provision: the average number of teachers (full time equivalent) per student, average number of medical practitioners (MPs) (full time equivalent) per resident and the proportion of dwellings in the region with internet. All three measures are expected to increase the residential attractiveness of the region, hence reduce uptake of LDC (Poortinga, 2012).

5.3 Composition of LDC

Within Australia, the mining industry is typically associated with the use of LDC, hence mining and LDC impacts seem mutually inclusive (Carrington et al., 2012). While this perception has some merit, other industries such as health care (Hussain et al., 2014) and construction (McKenzie, 2010) also use LDC to service rural communities. Skilton (2015) using 2011 census data showed that only 21% of LDC in Australia was a direct result of mining, with 52% completely unrelated. Accordingly, we include variables measuring the employment industry shares of mining and construction – two prominent adopters of LDC – in this analysis.

5.4 Composition of Population

Aboriginal and Torres Strait Islander (ATSI) communities make up a higher proportion of the population within rural regions compared to urban regions in Australia. Lawrence (2005) and Tonts and Plummer (2012) have found that training programs which allow workers to enter the mining workforce have had limited success – potentially suggesting that where shares of ATSI peoples are high, LDC rises. Furthermore, we include regional population size as a control for residual daily commutes. LGAs represent the area of influence for local councils, which are centred on a town. Typically, LGAs in metropolitan areas have higher population sizes than LGAs in rural/remote Australia. Since the risk of incorrectly assigning LDC status to daily commuters is higher in geographically smaller LGAs, the inclusion of LGA population size will control for so far non-captured daily commuting.

6. Exploratory Data Analysis

We use balanced panel data from the Australian Bureau of Statistics' (ABS) census for 2006 and 2011 to populate our model for all variables included in Section 5. To prevent the identification of people due to small cell numbers, the ABS randomises cells. This process creates an artificially introduced error; therefore, this study employs the same method as Mitchell et al. (2007) who changed all cell counts of six or less into zero. A preliminary analysis of the data indicates that not all variables are normally distributed. Furthermore, the dependent variable (proportion of LDC in the workforce) and Herfindahl Index have the form of a Poisson distribution. We use a two-step procedure to transform the data. Firstly, we add 0.05 to all data points to allow log transformation, and secondly, we log transform the data. This produces variables with distributions closer to normal when compared to other transformation options. The validity of the estimation technique and the model specification technique are maintained with these newly transformed variables. Table 1 contains the descriptive statistics of the raw data variables employed in this study.

Table 1: Summary Statistics (N = 1032, n=516, T=2)

		Mean	**S.D.**
Dependent Variable:			
Proportion of Long Distance Commuters in Workforce		0.02	0.07
Independent Variables:			
Local Labour Market			
Local Unemployed Pool:	Unemployment Rate	5.01	1.98
	Non-Participation Rate	60.34	6.61
Local Employed Pool:	Proportion of Labour Attractive for	0.23	0.16

	Average Age of Workers	41.53	2.36
Regional Attractiveness			
Local Housing Market:	Rental Price per Bedroom	58.01	33.16
	Mortgage Price per Bedroom	420.08	199.46
	Proportion of Rental Properties	0.29	0.11
	Proportion of Unoccupied Dwellings	0.16	0.09
Population Transience:	Proportion of Long-term Residents	0.61	0.08
Local Service Provision:	Teachers per Students	0.08	0.05
	Medical Practitioners per Person	0.01	0.01
	Proportion of Dwellings with Internet	0.65	0.12
Alternative Employment Opportunities:	Herfindahl index	1257.0	792.09
	Ratio of Drivers and Machinery Income inside and outside Mining	0.96	0.07
	Ratio of income inside and outside of Mining	1.06	0.11
Composition of LDC:	Mining Employment Share	0.03	0.10
	Construction Employment Share	0.06	0.03
Composition of Population:			
Population:	Proportion of ATSI Persons	0.04	0.07
	Population	40,392	72,364

Note: Data source: 2006 and 2011 Australian censuses. S.D. = Standard Deviation.

According to this study's methodology, the overall number of LDC workers has decreased from 96,614 in 2006 to 77,822 in 2011, a decline of 24 per cent. Interestingly, Australia's total workforce increased by eight per cent over the same time period. While no other national survey exists for direct comparison, state-wide and regional LDC counts have been undertaken, which are summarised in the government inquiry in SCRA and Windsor (2013). The Queensland Office of Economic and Statistical Research (QOESR) provided estimates of LDC workers for select regions to the inquiry. In 2012, these estimates were 25,035 workers in Bowen Basin (Queensland) and 6,445 workers in Surat Basin (Queensland). The Chamber of Minerals and Energy of Western Australia made a submission to the government inquiry and estimated that LDC consisted of 52 per cent of the mining industry or 46,800 LDC workers in Western Australia alone. It seems estimates of LDC counts in the current study are conservative compared to existing literature. Figure 2 visually represents LDC across Australia.

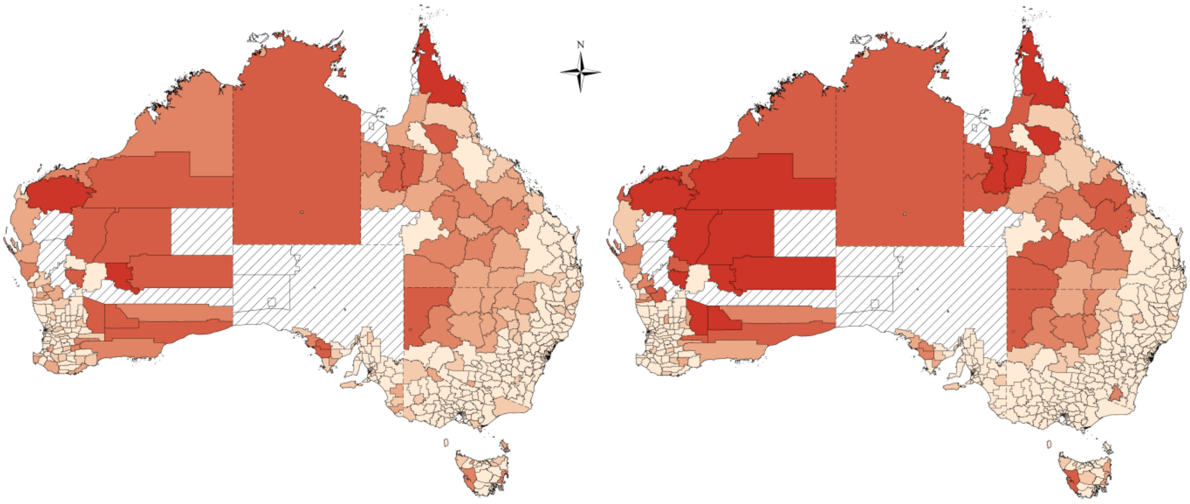

Figure 2: Long Distance Commuting across Australia for 2006 (left) and 2011 (right). Data range between: less than 1% (pale yellow) to 30% and higher (maroon)

We use 'ArcMap10' software to test for the presence of spatial interaction between the regions for which we conduct a global Moran I test on all variables for 2006 and 2011 (see Table 2). In addition, we conducted a local Moran I test for the dependent variable (proportion of LDC in workforce) for years 2006 and 2011 (see Figure 3). All Moran I tests use inverse (Euclidean) distance matrices with row standardisation and the False Discovery Rate (FDR) correction[ii].

Table 2: Global Moran I test for 2006 and 2011

	2006	**2011**
Dependent Variables:		
Proportion of Long Distance Commuters in Workforce	0.15	0.26
Independent Variables:		
Local Labour Market		

Local Unemployed Pool:	Official Unemployment Rate	0.19	0.09
	Non-Participation Rate	0.11	0.09
Local Employed Pool:	Proportion of Labour Attractive for	0.29	0.30
	Average Age of Workers	0.17	0.19
Regional Attractiveness			
Local Housing Market:	Rental Price per Bedroom	0.42	0.39
	Mortgage Price per Bedroom	0.41	0.34
	Proportion of Rental Properties	0.18	0.17
	Proportion of Unoccupied Dwellings	0.17	0.26
Population Transience:	Proportion of Long-term Residence	0.19	0.16
Local Service Provision:	Teachers per Student	0.08	0.06
	Medical Practitioners per Person	0.36	0.36
	Proportion of Dwellings with Internet	0.24	0.21
Alternative Employment Opportunities:	Herfindahl Index	0.32	0.30
	Ratio of Drivers and Machinery Income inside and outside of Mining	0.09	0.13
	Ratio of Income inside and outside of Mining	0.0	0.02
Composition of LDC:			
	Mining Employment Share	0.17	0.17
	Construction Employment Share	0.13	0.07
Composition of			
	Proportion of ATSI persons	0.35	0.35
	Population	0.38	0.36

Note: All coefficients are significant at 1 per cent

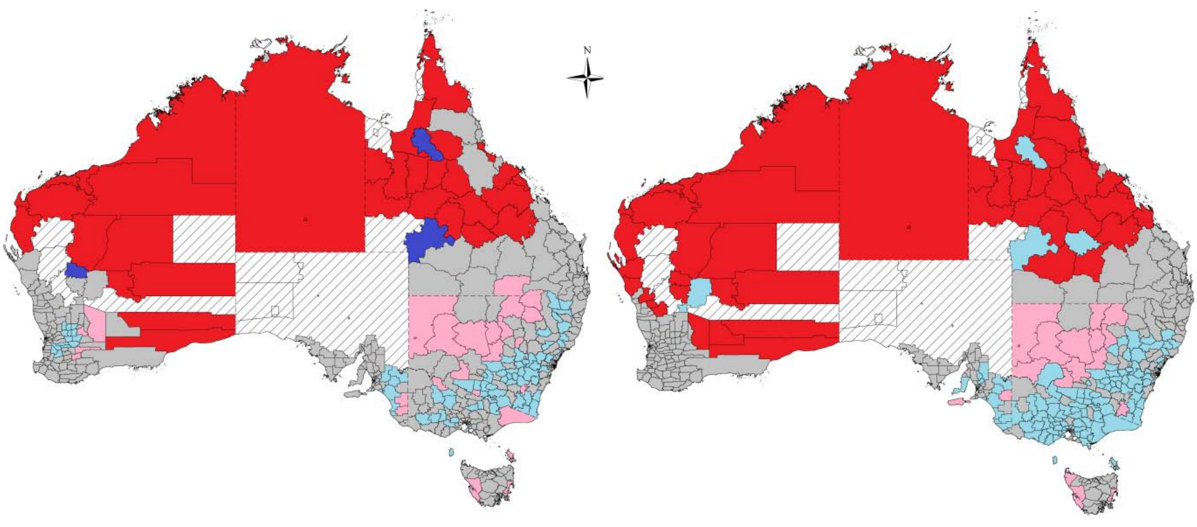

Figure 3: Local Moran I cluster map of long distance commuting practices across Australia in 2006 (left) and 2011 (right). *Note*. Individual colours represent degree of clustering. Red = high

to high clustering; pink = high to low; light blue = low to high; dark blue = low to low; grey = no significance.

Global Moran I results in Table 2 indicate that the values of all variables both in 2006 and 2011 were spatially correlated. The presence of spatial correlation, be it positive (similar values in nearby regions) or negative (dissimilar values in nearby regions), violates the assumption that data are randomly distributed across the sample area (Australia) and thus needs to be taken into account. To provide context for this spatial correlation, we produce local Moran I maps for the dependent variable (see Figure 3). For both years we note significant positive spatial correlation in the northern and western regions of Australia (similar high values in nearby regions shown in dark red; similar low values in nearby regions shown in dark blue). Further, we note significant negative spatial correlation predominantly in south-eastern regions of Australia (high values which contrast with low values in nearby regions shown in pink; low values which contrast to high values in nearby regions shown in light blue). Grey areas indicate no spatial correlation.

Some care needs to be taken when interpreting the results from the local Moran I maps. These tests are two-tailed with the assumption of normality for the analysed variable. In this study, the assumption of normality is not met because the proportion of LDC in the workforce (dependent variable) exhibits a skewed distribution (even after being log transformed). This means the Moran I test has a higher chance of a type 1 error for clustering significance (right-hand tail) and type 2 error for dispersion significance (left-hand tail). To minimise the chance of these errors, we use the FDR correction and implement a distance cut-off point to the inverse distance matrix so regions can only have a maximum of eight neighbours. For regions that have dispersion significance, the Moran I will report an insignificant result. Consequently, an insignificant Moran I does not indicate a lack of spatial correlation, but rather a failure of the statistical technique to identify dispersion patterns. Nevertheless, despite the inability to detect all spatial correlations, the Moran I maps clearly show that spatial interactions are present within this panel data set.

7. Model Estimation

We use statistical package Stata 13 to determine where spatial interactions occur within the data set. We use maximum likelihood estimators for both fixed and random effects for each of the spatial panel models described in this section, using the command xsmle[iii]. Further, we use software package 'Geoda' to create a spatial weight matrix, specifically a second order queen contiguity matrix. This matrix models the spatial interactions between regions over time. We used the Bayesian Information Criterion (BIC) as a model specification test to select the appropriate model, which is a spatial autocorrelation panel model with fixed effects[iv].

We present the results of the spatial autocorrelation panel model with fixed effects in Table 4. Only one local labour market variable is significant: average age of the workforce and LDC exhibit a positive relationship. Secondly, seven regional attractiveness variables exhibit a statistically significant relationship with LDC in a region. The state of the housing market, population transience and local service provision all matter for the extent of LDC in a region – although three statistically significant relationships (mortgage price per bedroom, unoccupied dwellings and proportion of dwellings with Internet) display directions which oppose original expectations. Alternative employment opportunities in the region have no significant bearing on the uptake of LDC. Variables measuring the composition of LDC variable, both mining and construction variables are significant. In terms of the composition of population, the ATSI population variable is statistically insignificant. LGA population is significantly positive which indicates that residual daily commuting is still present in the data despite attempts to control for it in the measurement of LDC.

Table 4: Estimation of the spatial autocorrelation panel model with spatial and time fixed effects using heteroskedasticity corrected consistent estimates

		Coeff.	**(Std**
Independent Variables:			
Local Labour Market			
Local Unemployed Pool:	Official Unemployment Rate	-0.01	(0.04)
	Non-Participation Rate	0.33	(0.26)
Local Employed Pool:	Proportion of Labour Attractive for	-0.29	(0.20)
	Average Age of Workers	4.15	(1.29)***
Regional Attractiveness			
Local Housing Market:	Rental Price per Bedroom	0.08	(0.12)
	Mortgage Price per Bedroom	-0.29	(0.10)***
	Proportion of Rental Properties	-0.70	(0.22)***
	Proportion of Unoccupied Dwellings	0.39	(0.06)***
Population Transience:	Proportion of Long-term Residence	-1.54	(0.30)***
Local Service Provision:	Teachers per Student	-0.09	(0.04)**
	Medical Practitioners per Person	-0.51	(0.25)**

	Proportion of Dwellings with Internet	1.30	(0.25)***
Alternative Employment Opportunities:	Herfindahl Index	-0.09	(0.16)
	Ratio of Drivers and Machinery	-0.10	(0.20)
	Income inside and outside of Mining		
	Ratio of Income inside and outside of Mining	-0.27	(0.21)
Composition of LDC:			
	Mining Employment Share	0.22	(0.04)***
	Construction Employment Share	0.05	(0.03)
Composition of			
	Proportion of ATSI persons	0.05	(0.06)
	Population	0.95	(0.18)***
Model Information:			
	Spatial Rho	0.08	(0.01)***
	Spatial Lambda	-0.04	(0.02)*
	Sigma	0.03	(0.00)***
	Observations	1032	
	Groups	516	
	Time periods	2	

* significance 10 per cent
** significance 5 per cent
*** significance 1 per cent

8. Discussion

8.1 Study Design

We considered the spatial autocorrelation panel model with fixed effects the most efficient model for this study. Using a fixed effect model controls for all non-dynamic factors, these include remoteness, distance and resource reservoirs all of which are strong determinants of LDC. Significant spatial rho and lambda results indicated that spatial interactions exist both within the spatially-lagged dependent variable and within the error term. Circumstances surrounding the introduction of LDC practices were influenced not only by the local region's characteristics but also by characteristics of neighbouring regions. Consequently, this study adds to the growing body of work in mining and LDC studies that highlights the need to account for spatial interactions within econometrics modelling over space (Elhorst, 2014; McDonald et al., 2012; Nicholas and Welters, 2016; Perdue and Pavela, 2012; SCRA and Windsor, 2013; Tonts et al., 2012).

The significant positive relationship between regional population and the extent of LDC into a region in the regression analysis suggests that our method to distinguish long distance commuting from daily commuting among employees whose place of residence does not equal place of work is imperfect – especially for city regions (regions with large populations). The inclusion of the regional population in the regression accounts for this imperfection in the analysis. Nonetheless, we call for direct measures of long distance commuting status in future surveys, to resolve the problem of having to estimate the LDC status of a worker (SCRA and Windsor, 2013).

8.2 Local Labour Market

The state of the local labour market has only limited impact on the extent of LDC into a region. Results from this study found no evidence that the availability of unemployed or discouraged workers reduces the uptake of LDC into the region, which is in line with (McIntosh, 2012; Nicholas and Welters, 2016; Perkins, 2012). With respect to the regional workforce, it was found that an increase in the average age of the regional workforce increases the uptake of LDC into the region – presumably because the mining industry prefers to recruit from relatively younger segments of the labour market. Relevant work experience in the local workforce tends to reduce the adoption of LDC into the region, however, this effect is not statistically significantly different from zero.

8.3 Residential attractiveness of a region

Residential attractiveness of a region has a significant influence on the extent of LDC into a region. This finding is similar to Nicholas and Welters' (2016) results – although some of the impacts are more complex than initially thought.

Variables expected to indicate tightness in the housing market (mortgage price per bedroom [positive] and proportion of unoccupied dwellings [negative]) reduce the uptake of LDC into the region, i.e. encourage workers to relocate to the work region. High wages (e.g. at least paid in the mining industry) perhaps ensure that workers who consider relocating do not see low housing affordability as a concern, as they have the purchasing power to succeed in such circumstances, as opposed to local residents. Further, the proportion of rental in total properties in a region indeed reduces LDC into the region, which suggests it increases the residential attractiveness of the region. Given the limited lifespan of mine and/or construction projects (SCRA and Windsor, 2013), employment in the region will be temporary, which may explain the popularity of rental accommodation. The availability of rental subsidies may further promote the use of rental accommodation (United Research Services, 2012).

Population transience increases the extent of LDC into a region. This is in line with Lovell and Critchley (2010) and Ooi et al. (2014) who argue that population churn reduces the appetite of long-term residents to connect with newcomers. An unwelcome environment may stop workers from relocating to a region of work. Instead, they become long distance commuters.

Quality service provision, measured by teachers per students and medical practitioners per person, increases the residential attractiveness of a region, as it reduces the extent of LDC into the region (Tonts et al., 2012). Contrary to expectation, the proportion of dwellings with internet increases the extent of LDC into a region. Perhaps internet availability is not only an indicator of residential attractiveness, but also a solution to the communication problem that arises as a result of LDC, making LDC less problematic.

8.4 Alternative employment opportunities

Finally, alternative employment opportunities in the region do not influence the decision to relocate to the region of work or instead adopt LDC into the region.

9. Conclusions

Impacts concerning long distance commuting (LDC) have been well researched as LDC is increasingly introduced to meet labour requirements in rural and remote communities. Current research, however, shows no consistency or consensus in how regions may be impacted. Chapman et al. (2015) argue that regional and temporal differences may explain inconsistent results and argue for research that is space and time inclusive. Nicholas and Welters (2016) argue that extra regional differences (causing spatial interaction) may explain inconsistent results and argue for research that controls for spatial interaction. Accordingly, this study represents the first to control for time, space and spatial interaction simultaneously to explain the determinants of the extent of LDC into a region.

Overall, we found that the share of people available but currently without work in the labour force in a region plays no role in the recruitment strategy of firms that typically rely on LDC workers. There is some evidence that such firms include the regional workforce in their recruitment strategies; this study found that an increase in the average age of the workforce increases the uptake of LDC into a region (the mining industry prefers to recruit from relatively younger cohorts). In addition, tight conditions in the regional housing market do not deter workers from relocating to such a region. We argue that their high purchasing power favours them in the housing market relative to local residents. The availability of rental accommodation also increases the residential attractiveness of a region to workers who are aware that their employment in the region is of temporary nature, hence do not want to commit to buying a house. We also confirm that population churn erodes social capital in regions, which make them less attractive to relocate to. Finally, the residential attractiveness of a region increases if education and health provision improve.

Consequently, if the goal is to convince workers to migrate rather than adopt LDC into a host region (and as a result reduce the hollow economy syndrome), policymakers should aim to improve local service provision and/or increase rental accommodation in the host region. The current study further shows that tightness of the labour market and housing affordability are unrelated to the uptake of LDC into a region; hence, should not be priority areas for policymakers who wish to reduce LDC.

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[i] These regions are Anangu Pitjantjatjara, Aurukun, Burke, Cherbourg, Diamantina, Doomadgee, Hope Vale, Kowanyama, Lockhart River, Mapoon, Maralinga Tjarutja, Menzies, Mornington, Murchison, Napranum, Ngaanyatjarraku, Northern Peninsula Area, Palm Island, Pormpuraaw, Tiwi Islands, Torres Strait Island, Unincorporated Queensland, Unincorporated South Australia, Unincorporated Tasmania, Unincorporated Victoria, Unincorporated Western Australia, Upper Gascoyne, Woorabinda, Wujal Wujal, Yalgoo and Yarrabah.

[ii] False Discover Rate (FDR) correction is a process developed by Benjamini and Hochberg (1995) to control for the growing probability of type 1 errors when multiple regions are tested for spatial interaction.

[iii] An alternative estimation procedure used by previous studies focused in regional Australia (Fleming et al., 2015) is the geographically weighted regression (GWR). Both these techniques are valid but have different purposes. The advantage of a GWR is the ability to control for the spatial heterogeneity that might be present in spatial data, whereas the advantage of spatial panel models is the ability to test for and specify where the spatial interactions are in the model.

[iv] The Spatial Panel Autocorrelation Model with spatial and time fixed effects has the most efficient estimators (BIC: -1106.17). Post estimate tests reveal, however, that residuals do not

follow a normal distribution (Shapiro-Wilk test 0.966, $p < 0.001$) due to either autocorrelation and/or heteroskedasticity. With the panel data only containing two time periods, the likelihood of autocorrelation is remote, although heteroskedasticity remains a possibility. To test for heteroskedasticity, we perform a Chi-square test. The test statistic (χ^2 (19) = 216.72, $p < 0.001$) indicates the presence of heteroskedasticity and/or unusualness in the data. Logged data combined with a non-normally distributed dependent variable support the assumption of unusual data indicated through the Chi-square analysis. Tests for heteroskedasticity do not provide any insight into the nature of non-normal residuals. Therefore, this study will assume that heteroskedasticity is present within the model and apply robust estimates to compensate.