DO STATE BORDERS EFFECT COMMUTING FLOWS – A CASE STUDY OF THE QUEENSLAND AND NEW SOUTH WALES BORDER ALONG THE TWEED RIVER

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ABSTRACT: This paper explores the impact of State borders on commuting flows. Barriers exist when the commuting frequency at a cross-border link is below the expected level given other characteristics, such as origin and destination size and distance. Work here applies spatial interaction modelling techniques to census 2016 Journey to Work data for the SA2s of the Richmond-Tweed region of New South Wales and the Gold Coast region of Queensland. The study is particularly relevant, with border closures the instrument of choice of State leaders hoping to restrict the spread of Corona Virus Disease-2019. The analysis uncovers evidence of barriers to cross border commutes using 2016 data. This finding is surprising, given that Australian States and Territories share the same language and culture, along with a constitution prohibiting trade barriers between the states.

KEYWORDS: Commutting; journey to work; spatial interaction modelling.

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1. INTRODUCTION

National borders, or borders created by language differences, have been found to create barriers to commuters, truncating labour market flows (Olson, 2002; Persyn and Torfs, 2016). Less is known about the effect of State borders within a nation with a homogeneous language and culture like Australia, Canada or the United States (US), though Agrawal and Hoyt (2014) identify large effects on commuting times for workers in US Metropolitan Statistical Areas (MSAs) in which taxes are based on the state of residence. However, overall border effects between states seem unlikely, or certainly less likely than in the case of national borders. In the latter case, flows are likely to be affected by language barriers, or legislation restricting access of foreign workers to employment opportunities within a foreign labour market.

The effect of State or Territory borders on commuting patterns is of interest for a number of reasons. Firstly, in the Australian context, the constitution indicates that trade between the States shall be absolutely free[1]. For this reason, a finding that State borders act as a barrier will be of some interest to national policymakers. In more recent times, the impact of State borders has likely been more pronounced, with several State and Territory Governments restricting access to their territories by closing borders in an attempt to control the spread of Corona Virus Disease-2019 (COVID-19).

The focus of this paper is the possible effects of State and Territory borders on labour market flows and labour market outcomes. Commuting is an important equilibrating mechanism in the regional labour market. In a standard closed-economy labour market model, commuting reduces differences in regional labour market outcomes, such as unemployment rates and wages and brings aggregate welfare gains (Borjas, 2001).

Commuting is, however, not without cost. These costs may be directly related to commuting distance and include travel expenses or the opportunity cost of lengthy daily commutes. Additionally, there may be substantial costs when a worker commutes to a different region. Persyn and Torfs (2016) note that these costs may include factors like informational deficiencies, linguistic barriers, or a regional cultural divide. Their existence may explain the difference between the expected commuting flows between regions based on purely economic and geographic factors and observed commuting flows. The same authors note that a finding of less than expected commutes also suggests an inefficient spatial allocation of labour, implying welfare gains from policies aimed at removing these barriers. Policies which may achieve

- [1] Section 92 of the Constitution of Australia, states, '... *trade, commerce, and intercourse among the States, whether by means of internal carriage or ocean navigation, shall be absolutely free.*'

this, include improving information exchange related to interregional job search or adjusting the regional skill structure.

Policymakers have the authority to make policies for their own jurisdictions and a finding that a State border acts as a barrier also implies that State policy may impact on local labour market conditions while their impacts, i.e., higher or lower unemployment rates, may not be diminished through the equalising impact of increased cross border commuting (Marston, 1985). This is potentially good news when policies have detrimental effects on local economic conditions, but means that sound economic management will be penalized if no border effects exist.

While there are a number of implications of border effects, if they exist, a brief search of the regional science literature indicates a paucity of research on this topic in Australia. Thus this paper addresses an important research gap of interest for a number of different reasons. This study uses census 2016 Journey to Work flows from Statistical Area Level 2 (SA2s) within the larger SA4s of the Richmond and Tweed of Northern New South Wales and the Gold Coast of South East Queensland (QLD) to explore the effect of the New South Wales - Queensland border on commuting flows. This data is outlined in the next section, while section 3 outlines the methodology adopted to measure the impact of the border on commuting flows. Section 4 briefly outlines the methodology adopted to analyse the data and also presents the modelling results. A brief conclusion is presented in section 5.

2. DATA

All data used in this study is drawn from the 2016 Australian Bureau of Statistics (ABS) Census of Population and Housing and has been extracted using ABS table builder. It relates to the 70 SA2s within the Gold Coast and Richmond-Tweed SA4s. While these SA4s lie adjacent to each other, they straddle the New South Wales - Queensland border, with the Gold Coast north of the Tweed river in Queensland, and the Richmond-Tweed SA4 within New South Wales (NSW).

The data extracted include Journey to Work, Origin-Destination flow matrices, showing work commutes on census day, in August 2016. These have been extracted by the 1st division Australianand New Zealand Standard Classification of Occupations (ANZSCO)occupational division as well as for total employment. Besides providing details of the flows between SA2s, this data has been used to derive estimates of the size of the origin and potential destination regions (in terms of the numbers of employed people), both of which are variables frequently incorporated in spatial interaction models. The distance between SA2s has been calculated as the Euclidian distance, derived using the X-Y coordinates of the centroids from each pair of SA2s.

Department of Infrastructure and Regional Development (2015) notes that average commutes for Gold Coast and Tweed Heads fall in the 15-20 km band. Table 1 below presents an aggregated flow matrix for the Tweed-Richmond and Gold Coast SA4s. Across the row of this table, we see the place of work or residents from the region in question, so that the first row shows the place of work of residents of the Tweed-Richmond SA4. For this region, 78,495 or 81.4% both live and work in the region, while another 8,597 or 8.9% commute to the Gold Coast for work. Census data indicates that there were 96,431 employed persons in the Tweed-Richmond SA4 at census time 2016 while 85,786 persons worked within this region. In contrast, there were 266,906 employed persons residing in the Gold Coast SA4. Of these, census data indicates that 207,865 or 77.9% worked on the Gold Coast, while a further 5,398 (2.0%) worked in the Richmond-Tweed SA4.

Table 1. Census 2016 Journey to Work Flows between the Richmond-Tweed and Gold Coast SA4s.
Source: ABS Census of Population and Housing (2016).

	Tweed SA4	Other NSW	Gold Coast SA4	Other QLD	Other Australia	Total
Tweed SA4	78,495	6,667	8,597	1,979	693	96,431
Other NSW	1,132	3,227,510	580	5,351	49,022	3,283,595
Gold Coast SA4	5,398	1,718	207,865	49,747	2,178	266,906
Other QLD	654	6,592	21,678	1,827,847	12,569	1,869,340
Other Australia	107	29,549	501	6,460	5,129,738	5,166,355
Total	85,786	3,272,036	239,221	1,891,384	5,194,200	10,682,627

The difference in incomes (*Income_Diff*), represents the wage premia for working in a specific SA2 and is derived by first calculating the average weekly income of persons working in each SA2 (by each of the eight 1st division occupational categories along with total employment). In contrast, the difference in occupational structure between origin and destination regions (*Occ_Diff*), is derived as the mean absolute percentage difference in employment by occupation of workers residing in the origin region, compared to the occupational structure of persons employed in potential destination regions. This variable takes the value of 0 when origin employment and potential destination region's employment structure is identical and increases with increasing dissimilarity in regions. *Occ_Diff* is calculated using the 135 ANZSCO 3-digit, Minor groups occupational categories. In the tables of the appendix, model results for the 1st division ANZSCO categories are presented. In the models presented in these tables, the Minor groups which form the 1st digit category are used to derive the measure of *Occ_Diff*.

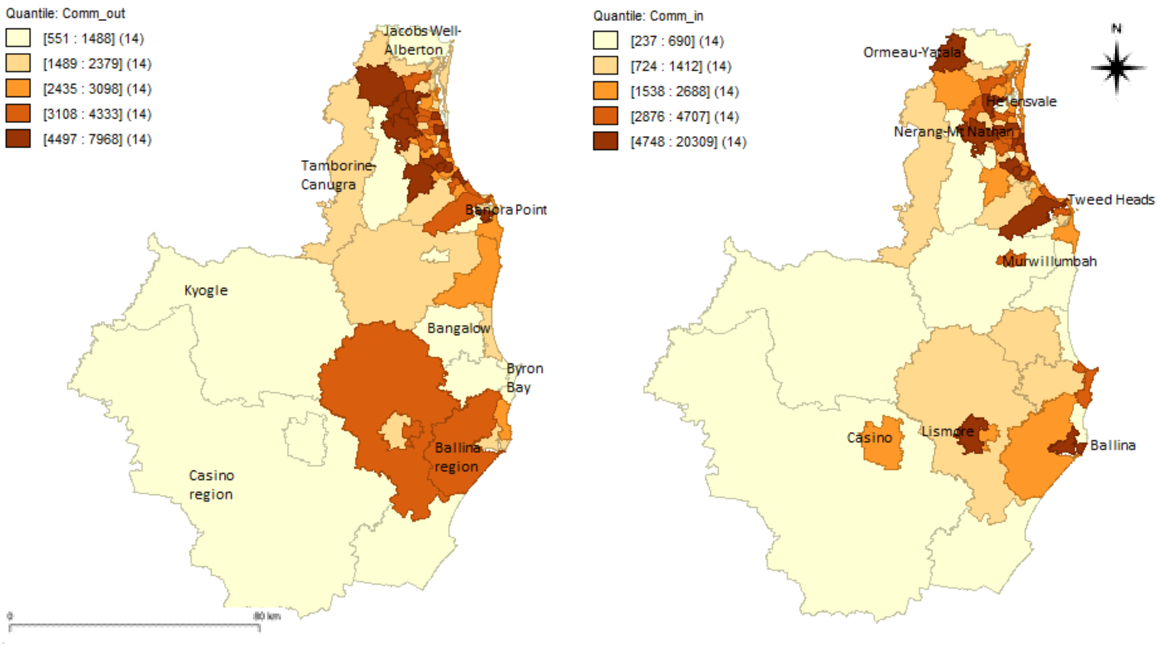

Figure 1a. Quintile Map of Outflows Figure 1b. Quintile Map of Inflows

Figure 1. Regional Inflows and Outflows. Source: ABS Census of Population and Housing (2016).

Figure 1 provides quintile maps of in- and out-flows of commuters, with each quintile comprising 14 SA2s. The maps show large out-flows of workers from regions to the west of the Gold Coast in South-East Queensland and to a lesser extent around the hinterlands of Lismore and Ballina. In contrast, Lismore and Ballina are in the highest quintile of in-flows as is the Tweed Heads SA2. North of the NSW Border, SA2s in the highest quintile for inflows of commuters include those around Nerang and Helensvale.

Details of the regional distribution of average weekly wages at Place of Usual Residence (PUR) and Place of Work (POW) can be found in Figures 2a and 2b. Figure 2a shows the average weekly income by POW. SA2s in the highest quintile tend to be clustered in the Gold Coast region, with the only SA2 in this quintile in the Tweed SA4 being Ballina. In contrast, when looking at incomes by PUR, SA2s in the highest quintile again include Ballina and a cluster of areas at the northern end of the Gold Coast (around Hope Island), and further south at Burleigh Heads and Kingscliff and Fingal Head.

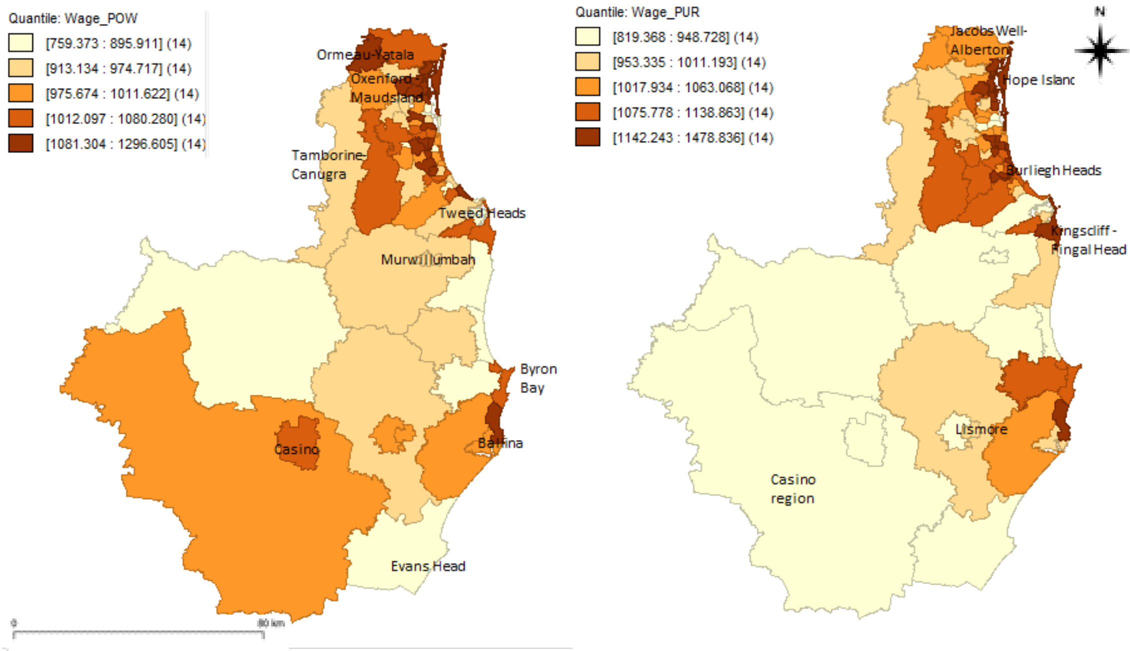

Figure 2a. Quintile Map - Wage at Place of Work

Figure 2b. Quintile Map - Wage at Place of Residence

Figure 2. Wages and Place of Work and Place of Residence. Source: ABS Census of Population and Housing (2016).

In the study of regional labour markets, it is generally assumed that, all else being equal, high wages make a region attractive. There is likely to be more competition for jobs, thus high wages are likely to be associated with relatively high in-commutes, all else being equal (Nowotny, 2010).

3. METHODOLOGY

In this section, the concept of barriers, along with the potential impacts of commuting barriers on the functioning of regional labour markets are discussed. The motivation for the modelling approach adopted is also outlined. Examples of work exploring the impact of barriers to spatial interaction include Batten and Törnqvist (1990) and Nijkamp *et al.*, (1990). Barrier theory has been applied to a variety of topics. For example, the barrier concept was used in an analysis of international trade by Bröcker and Rohweder (1990) and of communication by Rietveld and Janssen (1990) and Rossera (1990). Olsson (2002) and Persyn and Torfs (2016) provide examples of labour market applications. Generally, barriers are considered to exist where some form of interaction is unexpectedly low and, or where interaction costs increase sharply (Batten and Törnqvist, 1990).

A spatial barrier in a regional labour market is recognised by a lower than expected commuting flow between two regions (SA2s in the current study). Although some interaction may exist across the barrier, most of the labour force is geographically constrained. Olsson (2002) notes that in the presence of barriers, workers look for jobs and firm workers, in spatially constrained areas. The existence of a spatial barrier makes it less likely that a worker will find the job that suits them, while employers will be less likely to find the most suitable employee. For this reason, Olson (2002) and Persyn and Torfs (2016) note that the existence of barriers will reduce both labour productivity and total production.

A simple schema for the open gravity model estimated here is presented in equation (1). In the open gravity approach, interaction (in this study commutes) depends on origin, destination, and network attributes (Persyn and Torfs, 2016). The commuting flow from one region to another depends on many things, but the sizes of the regions, and the commuting time between them, are naturally important explanatory variables.

Following Olsson (2002), the commuting data consists of the number of workers that commute from region i to region j, i.e., C_{ij}. The data provide information about the number of workers that reside in a region, i i.e., O_i, as well as the number of persons working in a region (SA2), j, i.e., E_j. Olsson (2002) notes that O_i can be interpreted as the realised labour supply in the origin region i and E_j as the realised labour demand (Employment) in the destination region j. Additional data required for spatial interaction modelling include commuting time, or distance (D)

between region i and j, as used in this study. In this work, only inter-regional commutes are analysed, i.e. $j \neq i$.

$$C_{ij} = \alpha O_i^{\beta 1} E_j^{\beta 2} + \varepsilon^{-\lambda D + \varepsilon ij} \tag{1}$$

The larger the region of residence (measured by the number of workers living there), the larger the number of expected out-commuters. Similarly, the number of workers that commute to a region is expected to increase with the number of jobs in that region. In contrast, commuting distance is expected to have a negative impact on the number of commuters, as it is expected that the farther apart two regions are located, the fewer workers are expected to commute between them. Long commuting time makes a workplace unattractive, at least if alternatives exist.

This relationship is illustrated as the smoothly declining expected level of commuting, C_{ij} in Figure 3. In this study, a barrier is said to exist if commuting between two SA2s is lower than the expected level, i.e. lower than the level predicted by the model (without a barrier specification). If a barrier is present, the curve will shift downward at the border. The size of the shift is a measure of the size of the barrier.

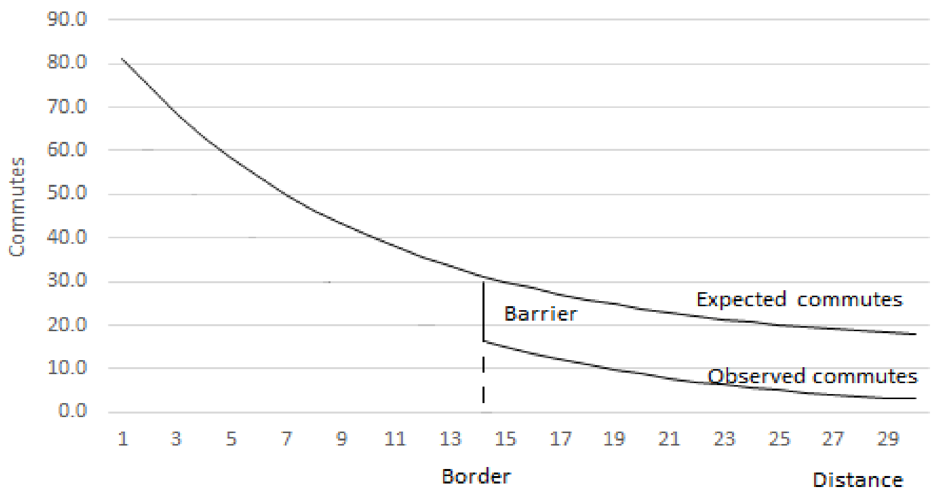

Figure 3. The Barrier Effect on Commuting. Source: Author's Calculations.

The second version of the open gravity model used in the analysis is introduced in equation (2). The barrier dummy B_{ij} is set to one if the commuter flow passes a border, and zero if not.

$$C_{ij} = \alpha O_i^{\beta 1} E_j^{\beta 2} + \varepsilon^{-\lambda(Dij + \gamma Bij) + \varepsilon ij} \quad (2)$$

In this specification, the estimated barrier parameter, γ, provides a way of representing and measuring the barrier effect. This formulation renders a barrier parameter expressed in the commuting distance dimension. Olsson (2002) notes that there are likely many causes for low interaction, such as the established choice and search behaviour, newspaper circulation resulting in information loss outside the circulation region and so on. The same author also notes that removal of the barrier (or barriers) is expected to generate a proportional increase in commuting, equal to $\varepsilon^{\lambda\gamma} - 1$, since:

$$(\overline{C}_{ij} \mid B_{ij} = 0) / (\overline{C}_{ij} \mid B_{ij} = 1) = e^{\lambda\gamma} \quad (3)$$

In other words, $\delta = \lambda\gamma$ is also an estimate of the effect of the barrier.

4. ESTIMATION

A number of alternative approaches have been developed to estimate gravity models. For example, a log-linearized version of the gravity equation (2) could be estimated by OLS. However, Silva and Tenreyro (2006) note that this approach has at least two limitations: first, in the presence of heteroskedasticity, log-linear transformations will result in the error term becoming correlated with the covariates. Second, by log-transforming equations 1 and 2, all observations with a commuter flow equal to zero are dropped from the analysis. This is the case for between 43% of our sample using total employment. Furthermore, this type of censoring may result in sample selection bias (Wölwer *et al.*, 2018).

To overcome these issues, this study treats commuter flows as count data. Count models explicitly allow for zero as a possible outcome and do not suffer from bias in the presence of heteroskedasticity (a situation where the residual of the estimated relationship displays unequal variability (scatter) across the dataset). Initial modelling indicated that overdispersion was a significant problem in models estimated using the Poisson distribution (variation was higher than expected). Test results for overdispersion from the Poisson versions of all models are included in all regression diagnostics. To address this issue, the study first used a negative binomial model that allowed the variation of the count variable to exceed its mean (overdispersion). However, additional diagnostics, specifically the Voung-test results (Voung, 1989), indicated that with the data used in this analysis, the zero-inflated version of the negative binomial model was the most appropriate approach to use and only results derived using this estimation technique are presented in the following tables. The authors note that this approach does not address the potential problems that may be caused by the existence of spatial autocorrelation (the presence of systematic spatial variation in the residuals of the estimated equations), however, it is also recognised that software to estimate count data models with both excessive zeros and spatial autocorrelation is not readily available.

Table 2 provides results from three models applied to Total employment. Model 1, in the first two columns is the base model. In this version of the model, there is no dummy variable included to capture the impact of cross-border flows. In contrast, columns 3 and 4 provide estimation results of Model 2, which includes a single dummy variable (*Cross_State_DV*), which takes the value of 0 when the flow is within the same state as the origin SA2 and 1 if the flow crosses a state border. The final two columns present the results of model 3. In this version of the model, two cross-border dummy variables are included, the first (*NSW_QLD_DV*) takes the value of 1 if the flow is from NSW to QLD and 0 otherwise, the second (*QLD_NSW_DV*) takes the value 1 if the flow is from QLD to NSW and 0 otherwise.

Details in the lower panel of Table 2 provide model diagnostics and summary information. Data here indicates that 4,830 observations were used in model estimation, with only the flows within each SA2 being dropped. The use of the count data approach to estimate the models means that an additional 2,075 zero flows are incorporated in the model for total employment. The overdispersion test statistics (which ranges from a high of 59.491 in model 1 to a low of 48.443 in model 2) is highly significant at normal levels in all models. This supports the use of the negative binomial version of the count data model applied here rather than the Poisson version. The Voung-statistic is also highly significant in all three models (as indicated by the extremely low p-values), suggesting that the data accessed here favours the application of the zero-inflated version of the model.

The middle panel of Table 2, with the title, *Zero-inflation model coefficients*, presents the models the probability of membership to each group, i.e. flows with a zero or non-zero value. In all three versions of the model, all three included coefficients are significant. Further, in all models the coefficients for *Ln_Origin* and *Ln_Dest*, the natural logs of the sizes of the origin and destination SA2 respectively, are negative, indicating that the larger are origin and destination size, the less likely the flow is to be a zero flow. In contrast, the coefficient estimates of *Ln_Dist*, the distance between origin and destination SA2s, is positive in all three versions of the model, indicating that the probability of a zero flow between origin and destination regions increases with the distance between SA2s.

Table 2. Model Estimation Results, Total Employment. Source: ABS Census of Population and Housing (2016) and Author's Calculations.

	Model 1		Model 2		Model 3	
Negative binomial model explaining flows from origin to destination SA2s						
(Intercept)	-6.869	0.000	-6.798	0.000	-6.911	0.000
ln_Origin	0.804	0.000	0.803	0.000	0.800	0.000
ln_Dest	0.765	0.000	0.755	0.000	0.770	0.000
ln_Dist	-0.829	0.000	-0.785	0.000	-0.780	0.000
Inc_diff	-0.396	0.002	-0.411	0.001	-0.499	0.000
Occ_diff	1.748	0.000	1.600	0.000	1.558	0.000
Cross_State_DV			-0.725	0.000		
NSW_QLD_DV					-0.880	0.000
QLD_NSW_DV					-0.528	0.000
Log(theta)	0.103	0.001	0.144	0.000	0.156	0.000
Zero-inflation model coefficients (binomial with Logit link)						
(Intercept)	4.215	0.000	4.415	0.000	4.260	0.000
ln_Origin	-1.112	0.000	-1.108	0.000	-1.096	0.000
ln_Dest	-0.937	0.000	-0.954	0.000	-0.937	0.000
ln_Dist	3.399	0.000	3.364	0.000	3.345	0.000
No. Obs	4,830		4,830		4,830	
No. zeros	2,075		2,075		2,075	
% 0's	43%		43%		43%	
Function evaluations						
Number of iterations in BFGS optimization	1		1		1	
Log-likelihood (13 df)	-14,880		-14,780		-14,780	
Df	11		12		13	
Young statistic (AIC)	24.866		20.608		20.473	
p-value	0.000		0.000		0.000	
Overdispersion test	59.491		48.443		48.467	
p-value	0.000		0.000		0.000	

Turning to the coefficient estimates of the negative binomial model explaining commuting flows presented in the top panel of Table 2, the results are unsurprising in most instances. The coefficient of the natural log of the number of jobs in the Origin region (*Ln_Origin*) and the natural log of the number of jobs in the Destination region (*Ln_Dest*) are both positive in all three models presented in Table 2. This is a common finding in spatial interaction modelling. Flows from larger regions are larger, while flows to large employing regions are also larger. There are no surprises with this result.

In this type of analysis, distance is generally interpreted as a deterrent, suggesting that greater distances are associated with a lower volume of commutes. This is consistent with the parameter estimates from the three versions of the model presented here. In all cases, distance is highly significant (low p-value of the z-statistic) and the estimate is negative, indicating that as distance increases, the magnitude of flows declines. Interestingly, as we step from model 1 to model 2 to model 3, we see marginal declines in the absolute size of the parameter estimate for *Ln_Dist*, suggesting that excluding the effect of the border, via the dummy variables, results in an over-estimate of the deterrent effect of distance.

Further, the estimates of *Inc_diff* (the income difference) and the *Occ_diff,* (the difference in occupation structure between the origin and destination region) are as expected. For *Inc_diff,* which is derived as the income of the origin region, less the income of the destination region, a negative sign is expected, suggesting that workers are attracted to regions with incomes above that of their home region. This idea is supported by the coefficient estimates from all three versions of the model presented in Table 2, with all versions yielding a negative and statistically significant estimate of *Inc_diff*.

The value of *Occ_Diff* (the mean absolute percentage difference in occupational structures of workers residing in a region, compared to the occupational structure persons working in potential destination regions), runs from 0 for regions where the occupational structure of the workforce of an origin region is identical to that of a destination region, to 1 for regions with the most different occupation structure. The positive coefficient is a little surprising, flows are to SA2s that are more different in occupational structure. This outcome might be occurring because workers leaving a region are not representative of the region and for this reason, are less likely to find work in the place of residence and more likely to commute out of the SA2.

The next three coefficient estimates refer to the dummy variables included to capture the effect of cross-border flows. Perhaps surprisingly, in all instances, these coefficient estimates are statistically significant and negative. This result indicates that the NSW-QLD border acts as a deterrent to commuting flows.

Following the discussion around equations (2) and (3) in section 3, the impact of the border can be calculated as $\delta = \lambda\gamma$, where γ = estimated parameter of border dummy and λ = the parameter estimate for distance. For the second model, the results indicate that the removal of the border effect will increase commuting flows by 56.9% for Total employment, while in model 3, the removal of the border effect will see flows form NSW to QLD increase by 68.6% and flows from QLD to NSW increase by 41.2%. These estimates seem unreasonably high and might be better interpreted as evidence of some significant impediments to cross-border commutes at the NSW-QLD border.

A possible approach to allow the derivation of more reasonable estimates of the impact of the border might be to disaggregate total employment and instead, estimate separate models for each first division ANZSCO occupational category. The results of adopting this strategy for models 2 and 3 are presented in Tables A1 and A2, respectively in the appendix. While there is some variability in the model results when comparing the models for the individual occupations to the models for total employment, it is noted that the state dummy variables are negative in all models, while the coefficient estimates for *Ln_Origin*, the natural log of the number employed in the origin region, *Ln_Dest*, the natural log of the number employed in the destination region and *Ln_Dist*, the natural log of the distance between the origin and destination regions are also the same sign in all models. For the version of the model with only 1 state dummy variable (model 2) for the individual ANZSCO occupations, 68.7% of the signs of the estimated coefficients are the same as in the model for total employment. This increases to 78.6% for the model that has cross border flows disaggregated according to the direction of the flow (model 3).

Figure 4 presents the estimated effects of the removal of the cross-state border effects by individual occupation derived from the models in Table A1. This effect is estimated for all flows, i.e., they are not dependent on the direction of the flows (equivalent to model 2 of Table 2). While the estimate of the impact of removing the border on commutes is a 56.9% increase in cross-border commutes in the model for Total employment, the average estimate across the eight individual occupations is only

24.2%, with the lowest estimate being a 15.7% increase in cross-border commutes for Machinery Operators, to a high of 30.7% for sales workers.

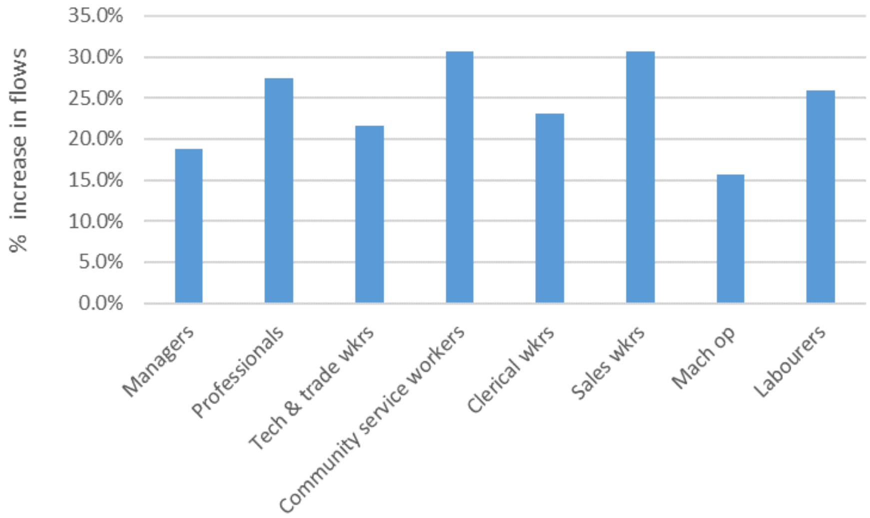

Figure 4. Proportional Effect of Removal of Border - by Occupation.
Source: ABS Census of Population and Housing (2016).

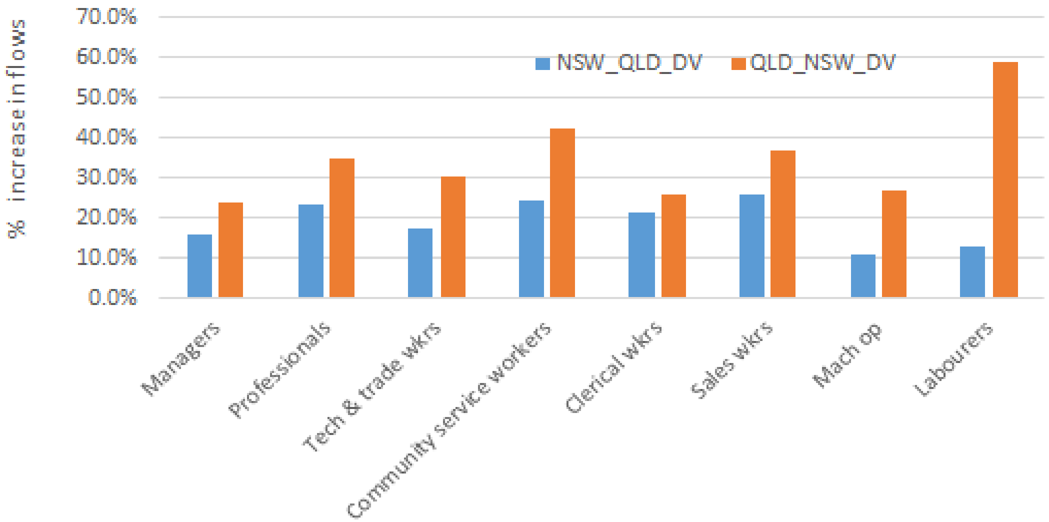

Figure 5. Proportional Effect of Removal of Border - Two Way Flows.
Source: ABS Census of Population and Housing (2016).

Figure 5 graphically presents estimates of the effect of the removal of the border for individual occupations from model 3 (presented in Table A2 of the appendix). The model results presented in this figure indicate that on average, flows from QLD to NSW would increase by an average of 34.9% with the removal of the impediment associated with the state border, while flows from NSW to QLD would increase by an average of 18.8%. For all occupations, the removal of the effect of the state border would be greater for QLD commuters.

5. CONCLUSION

In this study, three versions of a model explaining commutes between the SA2s within the SA4s of the Richmond-Tweed and Gold Coast SA4s have been estimated. These models move from a simple model that does not incorporate a border effect (Model 1 of Table 2). This is extended to a model having a single dummy variable to capture the effect of the state border on commutes (Model 2). Finally, a model with two dummy variables to determine if the state border has different effects on commutes from NSW to QLD and QLD to NSW (Model 3) is estimated.

The results are surprising on three counts. First, the model estimates yield many parameter estimates of the expected sign. These signs are consistent across all versions of the model and across the models of individual occupational categories. For example, *Ln_Dist*, the natural log of straight line distance between each pair of SA2s, is negative and significant in every version of the model. This is a common finding in spatial interaction models (Lourens *et al.*, 2020; Persyn and Torfs, 2016). A similar result holds for *Ln_Origin* and *Ln_Dest*, the natural log of employment size of the origin and destination regions respectively. These variables have positive and significant parameter estimates in all versions of the model.

The second surprising result is that the state border is found to have an effect on cross-border commutes. This is surprising because the homogeneity of language and culture throughout much of Australia naturally leads to the conclusion that state borders should have no effect. However, this does not seem to be the case for the NSW-QLD border at the Tweed. Finally, the effect of the border does not appear to vary systematically by occupation or skill level. There is no trend in the estimated impacts of removing the borders as we move from Managers through to the less skilled Labourers occupational category (see Figure 3). However, the border effect uncovered in this work is found to have more of an impact for QLD workers commuting into NSW than it does for NSW workers travelling north.

The reason for the results uncovered are unclear, particularly given that parts of the border run through an urban area in the Tweed-Coolangatta SA2s, where the state border runs down an urban thoroughfare. A number of factors may be at play. First, it may not so much be the border as geography that is producing the finding. In some situations, straight-line distances may be a poor proxy for the cost of commutes. In the current situation, the Tweed river, Border ranges, river valleys which are prone to flooding and the layout of the road network, all act to constrain commutes in the study area. However, the study area itself is a predominantly narrow north-south band compressed between the Pacific Ocean and the Great Dividing Range. This suggests that straight line distance should provide a reasonable approximation and it is difficult to see that the use of road network information will alter the findings by much. And if a decision is made to use road network information, then decisions must also be made about which point (settlement) in each SA2 the distances are measured between.

Further, the effect of the recent border closures remains to be seen. It is likely that interstate commutes in both directions have been reduced, with the introduction of border passes by the Queensland government along with the occasional closing of the border, acting to lengthen the duration of commutes and reduce the incentive to cross the border for employment. This extra ‘cost’ of commuting (longer durations) due to regulations introduced during a health crisis, may have effects that take some time to work through. Whether this has had a greater effect on NSW commuters travelling to QLD, or Queenslanders working in the Tweed is uncertain. However, there is likely to be some detrimental impact on commutes in both directions and in a recent study of the NSW-Victorian border closures, Spennemann (2021) noted short term impacts on workers from local communities, while Bernard *et al.*, (2020) noted that the impacts on internal migration of border closures are expected to be short-lived.

It might be thought that this result augers well for regional labour market policy in south-east QLD and northern NSW. With the border acting as an impediment to commuting flows, commuting may not have the equalizing effect expected in regional labour market theory (Marston, 1985). In this case, policies aimed at improving local labour market conditions in South-East QLD, for example, may not be washed away by in-commutes from northern NSW and vice-versa. In this situation, labour market programs may be effective in reducing unemployment in these two regional labour markets.

This finding needs to be tempered by the conclusion that missing interregional commuting suggests an inefficient spatial allocation of labour, implying that welfare gains can be obtained by removing these barriers (Borjas, 2001; Persyn and Torfs, 2016). These policies may comprise the improvement of information exchange related to assist in regional job search, adjustments to regional skill structure and improvements in the ease of commuting through infrastructure investments. Put simply, these impacts will occur on both sides of the border, with lower unemployment rates in one region attracting labour from the other, improving job matching, raising the productivity of firms, easing skill shortages and reducing inflationary pressures resulting from a constrained labour market with commutes supplementing the local labour supply.

REFERENCES

Agrawal, D. and Hoyt W. (2014). State tax differentials, cross-border commuting, and commuting times in multi-state metropolitan areas. CESifo Working Paper Series 4852, CESifo. Online version accessed October 2021, https://aysps.gsu.edu/files/2016/11/AgrawalHoyt.pdf

Batten, D. F. and Törnqvist, G. (1990). Multilevel network barriers: the methodological challenge. *The Annals of Regional Science*, 24, pp. 271-287.

Bernard, A., Charles-Edwards E, Alvarez, M., Wohland, P., Loginova, J, and Kalemba S. (2002). Anticipating the impact of Covid-19 on Internal migration. Centre for Population Research Paper, The Australian Government, Canberra.

Borjas, G. J. (2001). Does immigration grease the wheels of the labor market?. *Brookings Papers on Economic Activity*, 2001, pp. 69-133.

Bröcker and Rohweder (1990). Barriers to International Trade, Methods of Measurement and Empirical Evidence. *Annals of Regional Science*, 24, pp. 289-305.

Department of Infrastructure and Regional Development (2015). Australia’s commuting distance: cities and regions. Department of Infrastructure and Regional Development. Online version accessed October 2021, https://www.bitre.gov.au/sites/default/files/is_073.pdf.

Broersma L., Edzes A. and van Dijk J. (2020). Commuting Between Border Regions in The Netherlands, Germany and Belgium: An Explanatory Model. *Journal of Borderlands Studies*, DOI:10.1080/08865655.2020.1810590.

Marston, S. T. (1985). Two views of the geographical distribution of unemployment. *Quarterly Journal of Economics*, 100, pp. 57-79.

Nijkamp, P., Rietveld, P. and Salomon, I. (1990). Barriers in spatial interactions and communications - A conceptual exploration. *The Annals of Regional Science*, 24, pp. 237-252.

Nowotny, K. (2010). Commuting, Residence and Workplace Location Attractiveness and Local Public Goods. *Working paper no. 359, Austrian Institute of Economic Research* (WIFO), Vienna, DOI:http://hdl.handle.net/10419/128896.

Olsson, M. (2002). Chapter 5, Spatial Barriers in Labour Market Commuting. In Olsson, M. *Studies of Commuting and Labour Market Integration*, Jönköping International Business School, Jönköping University.

Persyn, D. and Torfs, W. (2016). A gravity equation for commuting with application to estimating regional border effects in Belgium. *Journal of Economic Geography*, 16, pp. 155-175.

Rietveld, P. and Janssen, L. (1990). Telephone Calls and Communication Barriers, The Case of the Netherlands. *Annals of Regional Science*, 24, pp. 307-318.

Rossera, F. (1990). Discontinuities and Barriers in Communications, The Case of Swiss Communities of Different Language. *Annals of Regional Science*, 24, pp. 319-336.

Santos Silva, J. M. C. and Tenreyro, S. (2006). The Log of Gravity. *The Review of Economics and Statistics,* 88, pp. 641-658.

Spennemann, D. (2021). “No Entry into New South Wales”: COVID-19 and the Historic and Contemporary Trajectories of the Effects of Border Closures on an Australian Cross-Border Community. *Land*, 10, p. 610, DOI: 10.3390/land10060610.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica*, 57, pp. 307-333.

Wolwer, A., Burgard, J. and Breßlein, M. (2018). Gravity models in R. *Austrian Journal of Statistics*, 47, pp. 16-38.

APPENDIX

Table A1. Parameter Estimates and Goodness of Fit Statistics of Negative Binomial Version of Model with Cross-Border Dummy. Source: ABS Census of Population and Housing (2016) and Author's Calculations.

	Managers	Professionals	Tech & trade workers	Community service workers	Clerical workers	Sales workers	Mach op	Labourers
Count model coefficients								
Intercept	-4.253	-1.731	-4.507	-3.130	-3.580	-2.197	-2.163	0.052
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.738
Ln_Dist	-0.506	-0.443	-0.460	-0.551	-0.462	-0.586	-0.351	-0.573
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ln_Origin	0.581	0.404	0.579	0.503	0.451	0.330	0.492	0.483
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ln_Des	0.726	0.516	0.764	0.653	0.732	0.685	0.540	0.302
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Inc_Diff	0.314	-0.244	0.427	0.080	0.902	0.226	0.181	-0.132
	0.000	0.000	0.018	0.572	0.000	0.009	0.144	0.214
Occ_Diff	-0.430	2.558	-0.893	-0.257	-0.964	-1.078	-0.634	0.384
	0.164	0.000	0.001	0.362	0.000	0.009	0.179	0.313
Cross border_DV	-0.372	-0.618	-0.470	-0.556	-0.499	-0.523	-0.448	-0.453
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log (Theta)	1.154	0.138	1.093	0.859	0.921	0.715	1.241	0.632
	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Zero-inflation model coefficients								
Intercept	11.325	-0.854	9.779	5.218	8.794	6.644	5.448	0.503
	0.000	0.131	0.000	0.000	0.000	0.000	0.000	0.137
ln_Origin	-1.407	-0.685	-1.402	-1.078	-1.215	-0.916	-0.971	-1.037
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ln_Dest	-2.088	-0.479	-1.736	-1.300	-1.707	-1.540	-1.356	-0.862
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ln_Dest	3.032	2.308	2.793	2.922	2.861	2.702	2.184	2.803
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	Managers	Professionals	Tech & trade workers	Community service workers	Clerical workers	Sales workers	Mach op	Labourers
Theta	3.170	1.148	2.982	2.360	2.512	2.045	3.458	1.8805
No. Obs	4,830	4,830	4,830	4,830	4,830	4,830	4,830	4,830
No. zeros	3,078	2,739	2,925	3,068	3,100	3,280	3,853	3,304
% 0's	63.7%	56.7%	60.6%	63.5%	64.2%	67.9%	79.8%	68.4%
Function evaluations								
Number of iterations in BFGS optimization:	1	1	1	1	1	1	1	1
Log-likelihood (12 df)	-6,984	-9,577	-7,669	-7,403	-7,236	-6,713	-4,113	-6,555
Voung statistic (AIC)	25.281	26.784	25.213	23.414	24.152	22.764	20.553	21.940
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overdispersion test	54.879	63.219	47.224	48.628	27.121	43.4823	59.1445	60.2844

Table A2. Parameter Estimates and Goodness of Fit Statistics of Negative Binomial Model with 2 Cross Border Dummy Variables. Source: ABS Census of Population and Housing (2016) and Author's Calculations.

	Managers	Professionals	Tech & trade workers	Community service workers	Clerical workers	Sales workers	Mach op	Labourers
<u>*Count model coefficients*</u>								
Intercept	-4.271	-1.687	-4.521	-3.092	-3.598	-2.185	-2.135	0.083
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.589
Ln_Dist	-0.506	-0.450	-0.461	-0.553	-0.461	-0.584	-0.359	-0.581
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ln_Origin	0.582	0.396	0.574	0.498	0.451	0.327	0.485	0.471
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ln_Dest	0.729	0.522	0.772	0.654	0.735	0.686	0.545	0.313
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Inc_Diff	0.289	-0.261	0.290	0.112	0.876	0.203	0.156	-0.124
	0.001	0.000	0.122	0.431	0.000	0.021	0.210	0.247
Occ_Diff	-0.472	2.361	-0.939	-0.316	-0.982	-1.124	-0.734	0.199
	0.127	0.000	0.001	0.261	0.000	0.007	0.121	0.600
NSW_QLD_DV	-0.308	-0.513	-0.371	-0.435	-0.458	-0.439	-0.307	-0.219
	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.020
QLD_NSW_DV	-0.466	-0.777	-0.660	-0.762	-0.555	-0.628	-0.749	-1.015
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log (Theta)	1.153	0.137	-0.371	-0.435	-0.458	-0.439	-0.307	-0.219
	0.000	0.001	0.000	0.000	0.000	0.000	0.002	0.020
<u>*Zero-inflation model coefficients*</u>								
Intercept	11.323	-0.808	9.792	5.248	8.799	6.660	5.452	0.558
	0.000	0.154	0.000	0.000	0.000	0.000	0.000	0.101
ln_Origin	-1.407	-0.692	-1.404	-1.081	-1.215	-0.919	-0.967	-1.037
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ln_Dest	-2.086	-0.476	-1.735	-1.300	-1.707	-1.539	-1.355	-0.865
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ln_Dest	3.029	2.301	2.789	2.917	2.860	2.701	2.172	2.781
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Theta	3.169	1.146	2.981	2.362	2.511	2.048	3.437	1.879

	Managers	Professiona ls	Tech & trade workers	Community service workers	Clerical workers	Sales workers	Mach op	Labourers
No. Obs	4,830	4,830	4,830	4,830	4,830	4,830	4,830	4,830
No. zeros	3,078	2,739	2,925	3,068	3,100	3,280	3,853	3,304
% 0's	63.7%	56.7%	60.6%	63.5%	64.2%	67.9%	79.8%	68.4%
Function evaluations								
Number of iterations in BFGS optimization	1	1	1	1	1	1	1	1
Log-likelihood (13 df)	-6,983	-9,575	-7,665	-7,399	-7,236	-6,712	-4,110	-6,543
Voung statistic (AIC)	30.774	28.247	25.072	23.334	24.135	22.823	20.536	22.115
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overdispersion test	55.275	63.234	47.338	48.550	27.216	43.5388	59.363	60.089