Activity Centre Policy Effects on Employment Clustering: A Spatial Study of Job Density in Melbourne, Australia

Jennifer Day¹, Sophie Sturup², Yiqun Chen³, Matthew Budahazy¹, Amy Wu¹, Lu Fan³

¹Faculty of Architecture, Building and Planning, The University of Melbourne
²Department of Urban planning and Design, Xi’an Jiantong – Liverpool University
³Faculty of Engineering, The University of Melbourne

Abstract: This paper considers the spatial relationship between Victorian Government activity centre (AC) policies between 2001 and 2011, and employment clusters that have formed in the same period. The core inquiry is into whether employment clusters have developed in response to urban spatial plans, and more generally, whether urban spatial planning has been able to guide job growth in Victoria. The alternative is that urban spatial planning has not been successful in directing activity to ACs, nor stimulating the creation of nearby employment clusters. To address this query, we use an innovative clustering analysis tool that we developed for the Australian Urban Research Infrastructure Network (AURIN). This tool allows us to identify employment clusters at the intra-urban scale for each census year. We then observe changes in job densities against ACs as they have been defined in government policy across the same period. The analysis both demonstrates the power of the clustering analysis tool and provides spatial evidence to support the efficacy of AC policies.

1. Introduction

This paper seeks to evaluate whether activity centre (AC) policies in Victoria have been associated with increases in the density of employment in urban sub-centres in Melbourne. Strategic spatial planning (SSP) is an urban planning mechanism that allows policymakers to align land use and urban form to a city’s vision for future development (Albrechts, 2006). One element of strategic visioning is the designation of non-CBD sub-centres, also referred to as employment clusters or ‘activity centres’ (ACs), which function as concentrated nodes of economic activity that are geographically dispersed across the metropolitan area (DTPLI, 2014). In undertaking this evaluation we are seeking to understand the efficacy of AC policy and considerations outside whether the continuation of ineffective policies is appropriate is outside the scope of this paper.

Since 1981, metropolitan SSP in Victoria has attempted to develop a regional hierarchy of ACs in order to influence the spatial geography of employment. This dispersal of social and economic activity is intended to support a polycentric city structure that promises to boost local employment, while contributing to overall State and national economic development (McNabb, 2001; Pfister et al., 2000). For example, Plan Melbourne’s (DTPLI, 2014) National Employment Clusters, located in Parkville, Monash, Dandenong South, La Trobe, East Werribee and Sunshine, promise to ‘provide high job concentrations in suburban locations’ (p.10). However the theoretical reasoning provided for why or how they will do so varies, and the evidence that such policies actually produce job concentrations is sparse. This is partly attributable to a lack of suitable data for analysis. This paper uses a new software tool, as described in Day (et al., 2013a, 2013b), that downward-projects data at the appropriate scale.

In developing the paper, we reviewed the AC policies in Victorian SSP documents from 1981 to 2014 and established the logic behind the designated hierarchy and location of ACs. Using Census Journey to Work (JTW) data from 2006 and 2011 we then compared job growth in these geo-located ACs with job growth in other areas. Our results suggest that AC policies are not producing the concentrations they promise.

The following sections demonstrate our research framework, which is based on recent methods in evaluation of suburban sub-centres and employment density. We commence with a brief review of the
empirical literature. We then outline the data and method employed, including an overview of the innovative clustering tool and the econometrics models employed. Lastly, the outputs from the analysis will be discussed in line with policy implications for future strategic plans in Melbourne.

2. Literature review

Porter (1998) popularised the notion that regional economic development could be stimulated through policies that encourage firms to cluster. That is, forming a ‘critical mass’ of economic activity in which participant industries and entities compete and cooperate (Porter, 1998, p. 78). The logic underpinning this theory is that the geographic concentration of firms generates agglomeration economies i.e. the productivity bonus associated with the spatial co-location of firms (Porter, 1990). Agglomeration economies are the productivity benefits that firms receive from being located in close proximity to concentrations of firms and people. They are often differentiated into two sub-categories, urbanization economies and localization economies. Urbanization economies are the productivity effects of being in a large labour market featuring a large concentration of readily accessible firms across a variety of sectors, while localization economies are the productivity benefits associated with being near firms that are involved in similar or complementary industries.

In Australia, the political enthusiasm for cluster effects has manifested in the State-directed promotion of ACs, whose economic leverage is associated with the concept of agglomeration economies (Boddy, 2000). Although these policies have been pursued as part of a desire to develop polycentricity in Australian cities, critics suggest that government policy is limited to the simple identification of existing ACs rather than strategically leading AC development (Freestone and Murphy, 1998; Pfister et al., 2000). In Melbourne, O’Connor (2012) identified a geographic structure comprised of five areas of relatively self-contained socio-economic activity, however, growth in these suburban centres is attributable to neo-liberal market forces rather than government policy (similar findings are discussed by Pfister et al., 2000). Likewise, Birrell’s (et al., 2005) critique of Melbourne 2030 (Dol, 2002) alludes to the over-designation of ACs that ignores the reality of job location in the metropolitan area.

There is significant evidence that agglomeration occurs outside of designated ACs, which makes analysis of these policies crucial. For instance, Gordon and Richardson (1996) found that most of the job growth in Los Angeles during the 1970s-80s occurred outside major employment centres. Fujita and Ogawa’s (1982) seminal work attributed sub-centre formation to increasing population and traffic congestion, later corroborated by McMillen and Smith (2003) and Wheaton (2004). Likewise, the relevance of AC policy is questioned by Fujita et al. (1999), whose numerical simulations suggest that a diversified economy will ‘[self-organise]’ into a hierarchical urban system. However zealously sub-centre policies have been pursued by Victorian governments, little analysis exists which tests their efficacy, i.e. whether or not the policies have actually resulted in dense, jobs-rich urban sub-centres. Day (et al., 2014) conclude that this is the result of insufficient data available at a fine-enough resolution for urban-scale analysis.

In Australia, there is a body of literature exploring the mechanisms that cause clusters to form. For example, Enright & Roberts (2001) consider several cases of regional development policy lead by economic cluster development. The economic clusters are each related to specified value chains rather than generalised job increases (as indicated in AC policies), which are driven by specific and large scale policy investment. Likewise, Nathan and Overman (2013) analysed regional clusters in the US and UK, concluding that local policies seeking cluster-level outcomes should limit their scope to a specific set of sectors. Other examples include Beaudry and Schifmanu (2009) and Duranton and Puga (2004), both of whom explored the mechanisms of specialisation versus diversification in cluster formation.

There is limited literature evaluating how ACs impact on subregional employment growth in Australia. Following studies from the United States (US) (Gordon and Richardson, 1996), job density, commute time and distance from the CBD are used as proxies or thresholds for conceptualising AC impacts (Parolin, 2005; O’Conner, 2006). Other studies criticise SSP and suggest that local planning mechanisms work against densification and job growth in ACs (Woodcock et al., 2011; Birrell et al., 2005). For instance, Pfister’s (et al., 2000) statistical analysis of Sydney’s spatial structure suggests that despite two decades
of planning for a metro ‘centres policy’ (p. 432), there has been a ‘recentralisation’ (p. 440) of employment that undermines any positive relationship between State-designated ACs and employment growth.

Work from other contexts, particularly the US, provides the primary justification for our work and research framework. Researchers such as McDonald and Prather (1994) sought to identify ‘major suburban employment centres’ in Chicago, through statistical tests that utilised 1980 US JTW Census data. The statistical identification of employment centres suggests a significant departure from a monocentric employment density pattern. Moreover, we follow some analysts that investigate the impact of AC type and distance from them on concentrations of job growth. In Los Angeles, Guiliano and Small (1999) aggregate employment, population and area within and outside of non-CBD sub-centres. They conclude that in both instances, distance from the highest density employment zone is strongly correlated with employment density. Parolin (2005) draws similar conclusions in Sydney. Based on a nonlinear-least-squares estimate of a simple exponential density function, they find that 69% of zonal employment density is explained by distance from the CBD (Guiliano and Small, 1999, p. 167). The CBD’s dominant influence on employment density, either alone or in combination with other centres was corroborated by Griffith (1981a), Gordon and Richardson (1996), and McDonald and Prather (1994). Interestingly, researchers also found that distance between sub-centres was an influential determinant of job growth, independent of distance from the CBD (see, McMillen and McDonald, 1998).

Analysts have also sought to empirically identify sub-centres rather than accept government definitions. McDonald (1987) argues that gross employment density (employment per square mile, all land uses included) is a reasonable measure for employment sub-centre identification because the intent is to identify sites that influence employment location in a wider area. However, that analysis is focused on the language of the policies and the empirical evidence focuses on residential densities and transport accessibility rather than employment increases in the centres. Our approach in this paper is to test whether government-defined sub-centres see more growth than the surrounding non-designated areas.

3. Activity centres in Melbourne’s spatial plans (1981-2014)

Since 1981, a hierarchical designation of ACs has characterised SSP in Victoria. The Metropolitan Strategy Implementation (MMBW, 1981) was the first strategic plan that focused on developing ACs, and was followed by Living Suburbs (DPD, 1995), Melbourne 2030 (DoI, 2002) and Plan Melbourne (DTPLI, 2014). AC policy is grounded in the pursuit of polycentric city structure (MMBW, 1981), integrating transport and land use, particularly at transport nodes (DPD, 1995), reducing travel to the city centre, promoting firm-location in employment clusters (DoI, 2002), and development of compact communities, whereby goods and services (and preferably employment) are accessible within 20 minutes of where people live (DTPLI, 2014). ACs have been variously classified in different plans e.g., Expanded Central City, National Employment Clusters, Metropolitan Activity Centres, State-significant Industrial Precincts, Health and/or Education Precincts, Activity Centres, and Neighbourhood Centre (DTPLI, 2014). As we describe below, part of our task was to create a hierarchical classification system that is applicable to all plans.

4. Data and Methods

This section describes the data and methods used to frame the analysis. We start with a software tool developed by Day (et al., 2013a, 2013b), which parses available data into spatial units suitable for metropolitan analysis.

Data

This paper uses Census Journey to Work (JTW) data for 2006 and 2011, which measures respondents reported travel to work on Census day. Originally, our ambitions were to generate a longer panel of evidence dating back to the original 1981 spatial plan. However, sufficient data were not available to run the analysis software. JTW tables from the ABS Census data facilitate comprehensive analysis of changes in the distribution of employment. These data record the number of people employed and the employing industry (among other variables) for each Census Destination Zone (DZN). We focus on job
numbers because JTW data is the best available dataset that reflects employment at a spatially-representative level. No other datasets in Victoria provide this level of detail. This is an unavoidable shortcoming that could be remedied by the Victorian government sharing more data on firm size and productivity with researchers (Day et al., 2014).

Although industry of employment is provided down to four-digit Australian and New Zealand Industrial Classification (ANZSIC) codes, three-digit ANZSIC codes provide a sufficient level of detail for an analysis of ACs. Therefore, we selected 143 three-digit ANZSIC codes to include in the analysis, based on the spatial plans’ specifications for the types of jobs that AC policies attempt to concentrate. These are generally service-related and include activities such as retail, entertainment, accounting and law services, and government offices.

Data parsing

Census JTW data, given in DZN geographies, is provided at a coarse spatial scale. These zones are too large and contain too many varied land uses, including residential land uses, to be useful in urban analysis. Day (et al., 2013a, 2013b) and Day (et al., 2014) develop a downward-projection process wherein JTW data reported at DZN geographies can be merged with land use zoning data; jobs in that DZN are allocated to smaller polygons based on land use zones. This downward projection process provides data on jobs and job densities in polygon format at a suitable scale for analysis of urban densities. The tool, and the polygon base map are open-source and available via the AURIN portal (see <http://aurin.org.au/>).

The data parsing tool applied to our 143 ANZSIC codes results in 5,965 polygons, which form this paper’s unit of analysis. Figure 1 shows the polygons.

Figure 1. Polygons generated by AURIN Employment Polygon Parsing Tool
Activity centre identification, classification, and influence Areas

The locations of designated ACs from each strategic plan were recorded in a spreadsheet. Since the 1995 plan (DPD, 1995), ACs have been classified in a hierarchy ranging from centres of very local to national importance (McDougall and Finney, 2013). We developed a master classification system that could accommodate the classification systems of all plans since 1981. This resulted in four AC ranks:

- Rank 1: ACs of national importance (e.g. National Employment Cluster)
- Rank 2: ACs of metropolitan importance (e.g. Expanded Central City)
- Rank 3: ACs of sub-metropolitan importance (e.g. Major Activity Centre)
- Rank 4: ACs of local importance (e.g. Activity Centre)

Most of the spatial plans describe the ACs generally with reference to their suburb, but do not provide precise locations or boundaries. To geo-code the ACs, we first found the centroid coordinates for each relevant suburb and then chose the closest most logical location for the AC. This was performed by manual review, guided by the relevant state government publications that local authorities use when planning for ACs.

The next step was to operationalise each AC's influence area. Influence areas are those areas where we expect AC policies to have an effect. The core tests we employ in this paper are into whether the 5,965 polygons generated by the software tool show increased jobs and jobs densities if they are within an AC influence area, and which type of AC produces the largest increases.

We operationalise influence areas according to each strategic plan’s AC hierarchy. To reflect the different designations and sizes of ACs expressed in the policy, different buffers were applied to the centroids. A key consideration in structure planning for ACs is walkability. For instance, PPN58 (DPCD, 2010) notes
that planning for activity centres should include opportunities to provide for and improve walkability within 400 to 800 metres from the centre’s core. We draw from the town centre typologies and influence used in similar density analysis (McDougall and Finney, 2013). Figure 2 shows the AC locations and influence areas. The following scale was used to determine the buffer for each rank of AC:

### Table 1. AC ranks and influence areas

<table>
<thead>
<tr>
<th>Rank</th>
<th>Buffer (m)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2,000</td>
<td>National Employment Cluster/ Large centre without a category (e.g. Melbourne Airport)</td>
</tr>
<tr>
<td>2</td>
<td>1,000</td>
<td>Expanded Central City</td>
</tr>
<tr>
<td>3</td>
<td>800</td>
<td>Major Activity Centre</td>
</tr>
<tr>
<td>4</td>
<td>400</td>
<td>Activity Centre</td>
</tr>
</tbody>
</table>

**Analytical framework**

We use two different units of analysis in this paper. We first use the polygons described in Figure 1. Second, we collapse the data within each LGA. There are 36 LGAs, and each LGA has the possibility of five types of areas relevant to our analysis. The first type is those areas comprised of polygons that are within the influence area of a Rank 1 AC. The next types are those areas within the influence area of a Rank 2, 3, and 4 AC, respectively. Finally, there are those polygons that are outside the influence areas of all ACs.
The AC buffer zones provide a useful framework wherein we measure job increases and job densities, and changes in those measures over time. Within an LGA, some polygons fall outside the influence area of an AC. The observation of higher densities or faster growth within the ACs, as opposed to outside of them, suggests that AC policies have been associated with increases in job numbers or densities.

There are threats to validity of these tests; neither of these measurements are perfect indicators. If we conclude that 2011 job numbers or densities are higher inside of ACs than outside them, this could be the result of ACs being designated in areas where job numbers or densities were already high. In some cases, a higher magnitude of jobs or densities could reflect the placement of ACs in already-dense, jobs-rich areas. A longer analysis timeframe would address this threat to the validity of the findings. This is a task of future work, as additional historical Census data becomes available.

We also measure the change in job numbers and densities between 2006 and 2011. Again, these measurements do not provide conclusive evidence that the ACs existence is the reason for differential job growth nearby and further from ACs. Again, ACs could have been designated in places where job growth was known to be occurring. However, temporal comparisons remove some threats to validity. Some of the temporal analyses we describe below allow us to control for whether an AC was established and already dense in the earlier year of the analysis period, thus removing this as a threat to validity. As we will see in the results section, this turns out to be an important control.
**Statistical tests**

We use t-tests and linear regression analysis to evaluate the hypothesis. We start by running simple t-tests on AC-influenced middle polygons in the metropolitan area versus areas not influenced by ACs. This allows for a high-level inquiry into whether jobs and job densities are increasing faster in the AC-influenced areas within the metropolitan area. This would provide some evidence – tempered by the caveats mentioned above – that the AC policy is associated with increased job concentrations.

We move on to more-complex t-tests that control for spatial factors at the LGA unit of analysis. Specifically, we examine changes within suburbs, querying whether polygons within the AC influence areas grow faster in terms of jobs than areas in the same LGA but outside the AC influence area.

Finally, the regression analyses work with the middle polygons to test whether a polygon’s job growth and job density growth are influenced by the particular type of AC, the distance from each type of AC, and whether the AC was established in 2006. We model our results with ordinary least squares (OLS) estimators.

5. Results

This section summarises the results of our statistical tests and discusses the significance of those results to the policy analysis. Overall, we find that there is very little evidence to support the efficacy of AC policies.

**t-tests without LGA control**

Table 2 shows the results of the simple statistical tests on all polygons, metropolitan-wide, without controlling for LGA. Our null hypothesis is that the mean number of jobs in all AC influenced polygons is equal to the mean number of jobs in polygons outside AC influenced areas. We test this for 2006 and 2011 and then against the percentage change between both years. We conduct a single tailed test, thus, as the table indicates with the ‘significance’ column, a significant test statistic (yes, in the column) will reject the null hypothesis and conclude that there is a difference in the indicators, i.e. the mean number of jobs in all AC influence areas are greater than the mean number of jobs outside AC influence areas.

These results point to an interesting contradiction. The first five tests support the conclusion that in terms of absolute job numbers, jobs density, and jobs growth, ACs are associated with more jobs and higher concentrations of jobs. This suggests that AC policies are working as intended. However, the last two tests seriously undermine that conclusion. The results suggest that there has been no relative change in job densities, either on an absolute or percent basis, between 2006 and 2011. That is, there is no statistical evidence to suggest that job density has grown faster in AC-influenced areas than outside them. This is perplexing because absolute job numbers appear to be growing. However, it must be accounted for given that density rather than absolute job numbers comprise the key indicator for this analysis. This is because the concentration of jobs, or the creation of job density, is the primary goal of AC policies.

These results are not likely to be measurement errors or sampling biases because we have an effective census of polygons numbering more than 5,000. This is perplexing because the AC-influenced areas are relatively small compared with the areas not influenced by ACs. Given the difference in areas, it would be more likely that the number of jobs outside of the ACs would be large, and that the jobs-based tests would fail to be significant. However, exactly the opposite has happened: the absolute jobs-based tests are significant, and the density-based tests are not.
Furthermore, the data suggest that, in both 2006 and 2011, the average number of jobs in AC-influenced polygons was higher than the average number of jobs outside of the AC influence areas. In 2006, the mean jobs count in AC-influenced polygons was 157, versus 59 outside of the AC areas. In 2011, it was 177 versus 62. Job density is also higher in the AC areas in 2006 and 2011. Average density (jobs per square metre) was 0.00671 in 2006 and 0.00691 in 2011, versus 0.00493 and 0.00497 outside of the AC areas in 2006 and 2011. These differences are all statistically significant (see Table 2 above). We control for this apparent contradiction below, after observing that the pattern does not persist after adding LGA controls.

**t-tests with LGA control**

In order to observe whether the particular characteristics within LGAs account for some of the patterns we see in the t-tests above, we next collapse our small-polygon data to the LGA as the unit of analysis. This method allows us to observe and compare the job numbers and densities inside and outside of ACs within a particular LGA. This method controls for LGA-specific features, such as distance to the CBD and density. Therefore, if any of the above analysis is related to unobserved spatial variation in the small polygons, analysis with LGA control should eliminate those factors.

Table 3 shows the results of t-tests with LGA control. After controlling for LGA effects, some of the significances disappear. While job numbers are higher within ACs than outside, densities and density changes are not significant. This further supports the hypothesis that AC policies had little effect on job concentration in ACs between 2006 and 2011. These t-tests also resolve the contradiction discussed above, where densities appear to be stagnant while job numbers are growing. This contradiction does not exist when LGA is controlled for.
Regressions without LGA control

Two sets of OLS models were estimated, both of which have the dependent variable set as job density change in the small, tool-derived polygons between 2006 and 2011. The results are presented in Table 4. The variable called ‘touch_r1_2006_dummy’ indicates that the polygon touched (i.e. was in the influence area of) a Rank 1 AC in 2006. The variable called ‘touch_r2_2006_dummy’ indicates that the polygon touched a Rank 2 AC. The suppressed category is ‘no_touch,’ representing those polygons that touched no AC in 2006. The variable ‘density_2006’ indicates the density of the polygon in 2006.

These OLS estimations provide a more nuanced picture than the t-tests. They allow us to see the effect of different types of ACs, and the effect of past densities of ACs on their 2006-11 growth. Table 4 shows that in comparison to the mean job density change in all polygons outside AC influence areas, only those polygons in Rank-2 AC influence areas have experienced a significantly greater change in job density i.e. 0.008 jobs per square meter difference. Also, within AC influence areas, the higher job density a polygon was in 2006, the smaller change in job density was found in 2011 (relative to non-AC influence areas). This is expected, as higher-density areas have less capacity to grow in density due to their advanced starting points.

Most importantly, these results suggest that being near a Rank 1, 3, or 4 AC is not associated with any change in job density. In the next section, we query whether this result holds when LGA is controlled for.

Table 3. Statistical tests for all polygons with LGA control

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>Null Hypothesis</th>
<th>Mean X</th>
<th>Mean Y</th>
<th>Degrees of Freedom</th>
<th>p-value</th>
<th>Significance (5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jobs</td>
<td>Across all LGAs, the mean number of jobs within AC-influenced areas are equal to the mean number of jobs outside AC-influenced areas, 2006</td>
<td>133.75</td>
<td>59.00133</td>
<td>36.9</td>
<td>0.0000</td>
<td>Yes</td>
</tr>
<tr>
<td>Density</td>
<td>Across all LGAs, the mean job density within AC-influenced areas is equal to the mean job density outside AC-influenced areas, 2006</td>
<td>0.00540</td>
<td>0.00454</td>
<td>56.5</td>
<td>0.4720</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Across all LGAs, the mean job density within AC-influenced areas is equal to the mean job density outside AC-influenced areas, 2011</td>
<td>0.00544</td>
<td>0.00455</td>
<td>63.5</td>
<td>0.3829</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Across all LGAs, the mean job density difference between within and outside AC-influenced areas in 2011 is equal to its counterpart in 2006</td>
<td>0.00042</td>
<td>0.00038</td>
<td>60.7</td>
<td>0.9776</td>
<td>No</td>
</tr>
</tbody>
</table>

NOTE: Jobs densities are in units of jobs per square meter, N=36

Regressions without LGA control

Two sets of OLS models were estimated, both of which have the dependent variable set as job density change in the small, tool-derived polygons between 2006 and 2011. The results are presented in Table 4. The variable called ‘touch_r1_2006_dummy’ indicates that the polygon touched (i.e. was in the influence area of) a Rank 1 AC in 2006. The variable called ‘touch_r2_2006_dummy’ indicates that the polygon touched a Rank 2 AC. The suppressed category is ‘no_touch,’ representing those polygons that touched no AC in 2006. The variable ‘density_2006’ indicates the density of the polygon in 2006.

These OLS estimations provide a more nuanced picture than the t-tests. They allow us to see the effect of different types of ACs, and the effect of past densities of ACs on their 2006-11 growth. Table 4 shows that in comparison to the mean job density change in all polygons outside AC influence areas, only those polygons in Rank-2 AC influence areas have experienced a significantly greater change in job density i.e. 0.008 jobs per square meter difference. Also, within AC influence areas, the higher job density a polygon was in 2006, the smaller change in job density was found in 2011 (relative to non-AC influence areas). This is expected, as higher-density areas have less capacity to grow in density due to their advanced starting points.

Most importantly, these results suggest that being near a Rank 1, 3, or 4 AC is not associated with any change in job density. In the next section, we query whether this result holds when LGA is controlled for.
Table 4. OLS model of job density change in small polygons, 2006 and 2011, without LGA control

| Coefficient      | Estimate | Std. Error | t-statistic | Pr(>|t|) |
|------------------|----------|------------|-------------|---------|
| (Intercept)      | 0.0012267| 0.0001954  | 6.279       | 3.65E-10*** |
| touch_r1_2006_dummy | 0.0005203| 0.0009802  | 0.531       | 0.596   |
| touch_r2_2006_dummy | 0.007971 | 0.0011638  | 6.849       | 8.19E-12*** |
| touch_r3_2006_dummy | 0.0006702| 0.0009532  | 0.703       | 0.482   |
| touch_r4_2006_dummy | -0.0005756| 0.0004023 | -1.431      | 0.153   |
| density_2006     | -0.2234949| 0.0062724  | -35.631     | < 2e-16*** |

Signif. codes: 0.001 **** 0.01 *** 0.05 ** 0.1 *

Residual standard error: 0.01273 on 5959 degrees of freedom
Multiple R-squared: 0.1785 Adjusted R-squared: 0.1778
F-statistic: 258.9 on 5 and 5959 DF, p-value: < 2.2e-16

Regressions with LGA control

Finally, we run the same regression as above, but this time, including dummy variables for each LGA. This controls for some of the spatial variation in density introduced by LGAs. For space reasons, the location-specific dummy variables are not shown in Table 5 below. The results are qualitatively the same as above: Rank 2 ACs are associated with higher levels of density growth, and density in 2006 is negatively correlated with density growth. Interestingly, these results suggest that Rank 4 ACs are associated with density decline.

Table 5. OLS model of job density change, 2006 and 2011, with LGA control

| Coefficient      | Estimate | Std. Error | t-statistic | Pr(>|t|) |
|------------------|----------|------------|-------------|---------|
| (Intercept)      | 0.001954 | 0.001503   | 1.3         | 0.1938  |
| touch_r1_2006_dummy | 0.0003745| 0.001045   | 0.358       | 0.7202  |
| touch_r2_2006_dummy | 0.007271 | 0.001741   | 4.176       | 0.0000301*** |
| touch_r3_2006_dummy | 0.00113  | 0.001021   | 1.107       | 0.2685  |
| touch_r4_2006_dummy | -0.0009221| 0.0004186  | -2.214      | 0.0269 *|
| density_2006     | -0.2253  | 0.006334   | -35.565     | < 2.00E-16*** |

Signif. codes: 0.001 **** 0.01 *** 0.05 ** 0.1 *

Residual standard error: 0.01273 on 5924 degrees of freedom
Multiple R-squared: 0.1827 Adjusted R-squared: 0.1772
F-statistic: 33.12 on 40 and 5924 DF, p-value: < 2.2e-16

6. Discussion and Conclusion

The findings presented above suggest with remarkable consistency, across a range of approaches, that AC policies are not significantly associated with higher jobs densities in the AC influence areas, with the notable exception of our Rank 2 ACs. Something is different about Rank 2 ACs.

The findings of this research cast doubt on the efficacy of the current incarnation of AC policy in increasing employment density. While we accept that policy implementation is not a linear process, it would be reasonable to expect that over a 10 year period some reflection of a successful policy would be apparent in the urban fabric. Current AC policies appear to be focused on designation rather than supporting the clusters beyond designation. Indeed if employment is considered a proxy for economic activity, it casts doubt on the policy’s ability to stimulate more activity. Our findings support others
(O'Connor, 2012; Pfister et al., 2000; Birrell, 2005) who have suggested that AC policy tends to follow economic development, rather than leading it.

A distinction can be drawn between ACs and employment clusters, where the latter have focused more on ‘the linkages and interdependencies among actors in value chains’ (Enright & Roberts, 2001, p. 66). At its core, AC policy is about developing polycentric urban forms, or at least reducing trips to central activity districts, and most recently, creating the circumstances for a ‘20 minute city’ (DTPLI, 2014). It could be argued that this objective can be achieved without increasing either economic activity or employment. Such an argument ignores the relative importance of JTW as a variable in the production of sustainable cities. It would also have to ignore the relative attraction of larger, more prosperous centres over smaller, weaker ones. Consequently, we suggest that if AC policy is to be considered successful, it must be found to act on increasing both job density and economic activity in the designated centres. Although outside the scope of this research, there may be value in shifting AC policy toward a more solid engagement with the findings of employment cluster literature, with effective policy action moving beyond the simple designation of ACs as a SSP tool. Closer observation of Rank 2 ACs may provide further evidence or support in the development of effective AC policy.

Others have pointed out that AC policy has tended to follow the market, and designate centres of activity where activity is already occurring. It could be observed that as a strategic policy, designating ACs is more about decreasing statutory planning barriers to the expansion of ACs, rather than explicitly generating new centres. This presents the policy as more passive than progressive and alludes to the limited ability of government to influence the geography of economic activity (Birrell et al., 2005). If this is the case, expectation management is required regarding the designation of AC in places such as Beveridge in far north Melbourne, as policy may create distortions in property values.

There are considerable difficulties associated with using JTW data as a proxy for economic activity. JTW data is not an accurate picture of employment. It is a proxy that does not reflect the employee’s employment status (full time or part time), the company’s productivity, number of employees, or other measures that are relevant to the study of agglomeration economies. We focus on job numbers because JTW data is the best available dataset reflecting employment at a spatially-representative level. No other datasets in Victoria provide this level of detail. This is an unavoidable shortcoming which could be remedied by governments sharing more data on firm size and productivity with researchers (Day et al., 2014).

A further limitation on our findings is that the data we have used as comparison reflects only 5 years of development. It could be that the impact of AC policy is not felt until ACs are many years old. This is something for further study, however if true, it provides another justification for a longer term approach to planning matters. For instance, if the designation of ACs takes 10 years or more to be effective, then ACs must be designated with at least a 10 year expectation of continuation. Constant fiddling with these policies is probably not productive.

We note that this lack of evidence of increasing density does not necessarily suggest that AC policies cannot achieve density increases. The period between the 2002 implementation and the 2011 Census (around two years and 10 months, given that Census data is collected late in the Census year) is not a sufficiently long period within which structural change occurs in urban development patterns. It is worth continuing to monitor these results as new data become available in future Censuses and other data sources.
References


DPD (Department of Infrastructure) (2002) Melbourne 2030: Planning for Sustainable Growth (Melbourne: Department of Infrastructure)

DPCD (Department of Planning and Community Development) (2008) Melbourne 2030 – A Planning Update: Melbourne @ 5 Million (Melbourne: Department of Planning and Community Development)

DPD (2010) Structure planning for activity centres, Practice Notes (Melbourne: Department of Planning and Community Development).


