Student number: 201434271

1. Introduction

In recent years we can see changes in Liverpool, including dynamic flows of people which is important to address. Rae (2017) states, there is a visible growth in transport in the North of England and Liverpool is 1% of all travels to work in England and Wales. Data from this paper also show 41.2% of journeys to work are below 5km distance. This paper explores main commuting patterns, where those flows are the largest, how employability affects that, and how important are factors in explaining commuting flows.

2. Methods

The report is based on the Census 2011. Everything was done in the R Studios. Data used include Middle Layer Super Output Areas and employment, health, boundary data. MSOAs show us the flows between small areas of Liverpool. Employment data was implemented as it has a significant impact on flow patterns and earnings (Bergantino and Madio, 2019, Hincks et al., 2018). Moreover, longer commuting patterns tend to influence the health of employees (Kunn-Nelen, 2016). Health, which originally came in 5 categories was regrouped into two groups to help with conciseness.

3. Analysis and Discussion

Figure 1 represents the main commuting patterns. The map suggests that most of the flows are within the city centre however, there is also a connection with the north and south Liverpool areas. This includes Speke and Garston areas where Liverpool John Lennon Airport is placed and through the years areas' main priority was regeneration (Carey and Sutton, 2004).

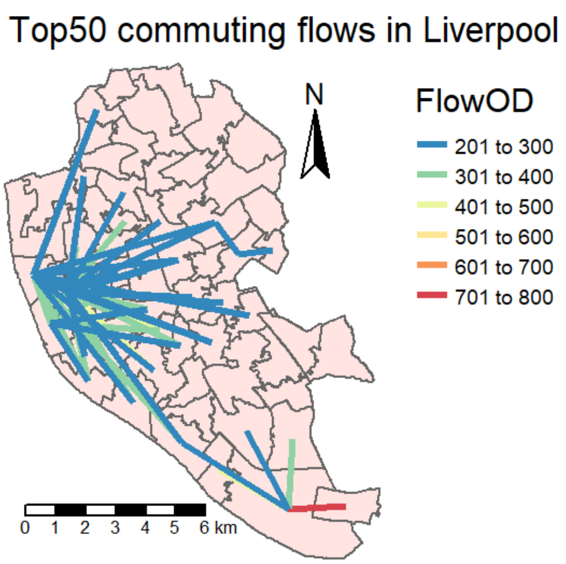

Figure 1 Top 50 commuting flows (source: Census, 2011)

Hincks et al. (2018) research the geodemographic clusters of work-based commuting and indicate that different groups have diverse flow distributions. Figure 2 represents the area of residence of the flow population.

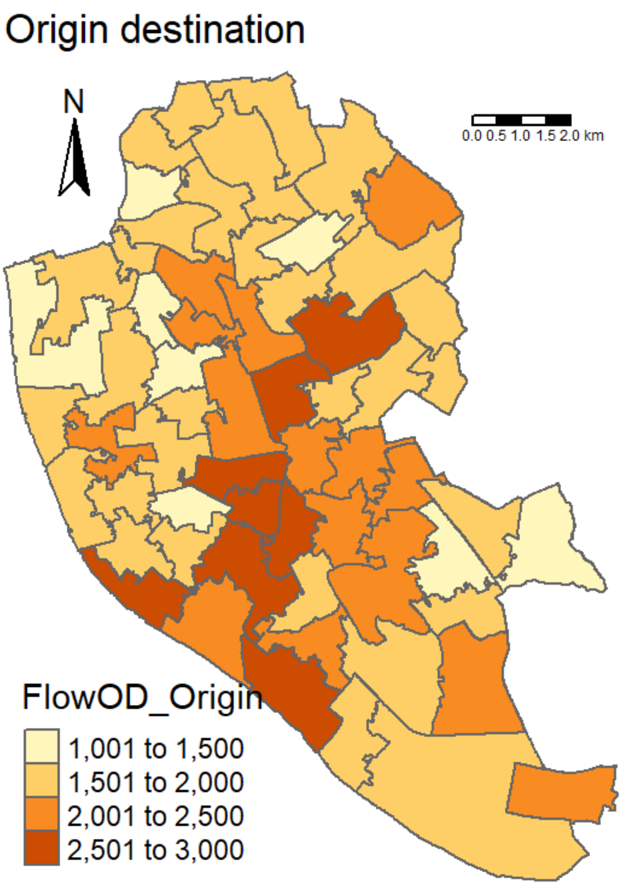

Figure 2 Area of residence - origin destination (source: Census, 2011)

According to Bill et al. (2006) increase in employment revealed the adjustment in the commuting flows which was partly caused by an inflow of high-skilled workforce. It may suggest that flows to Liverpool city centre are caused by a lot of high-tech headquarters. Moreover, unemployment seems also to have an impact on that topic, which is represented in Figure 3. The majority of areas with the most unemployed are not represented by any flows.

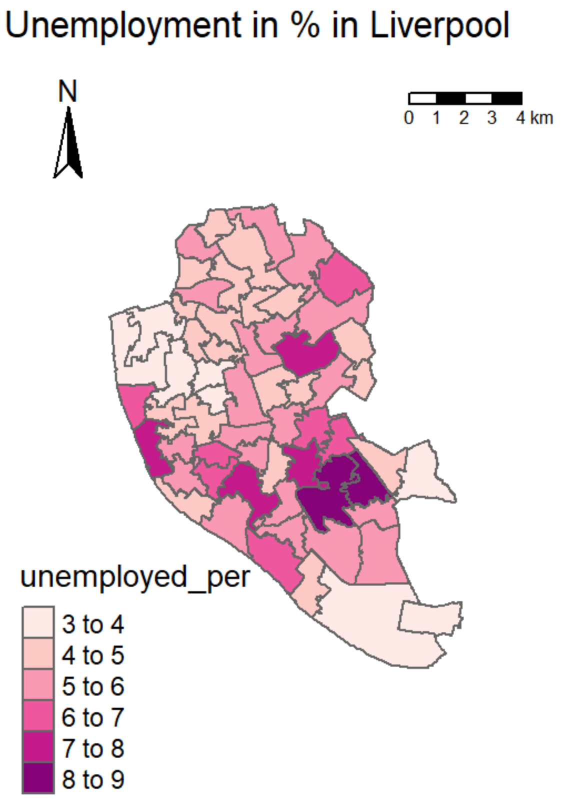

Figure 3 Unemployment in percentages (source: Census, 2011)

Figure 4 represents the distribution of people stating bad health, which supports the thesis of Kunn-Nelen (2016) and shows slightly worse health further from the centre.

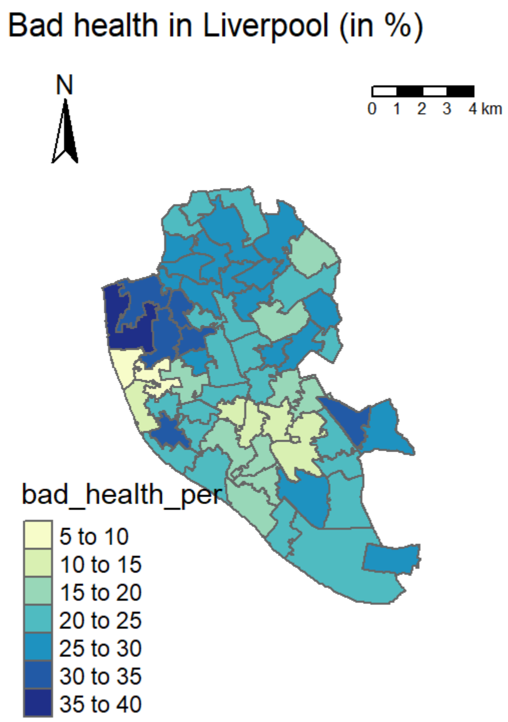

Figure 4 Bad health in percentages (source: Census, 2011)

Table 1 shows the results of the Poisson Regression models. Included variables like length and D_employed are constantly negative and O_employed positive which corresponds with the Hincks et al. (2018) evaluation of supergroups flows and maps. O_employedPT in Model 6 is slightly significant and in model 4 not significant. Bad health, on the other hand, has a positive effect on flows in Model 3 and a negative in own thresholds. The AIC from the baseline model decreases what indicated good model fit.

Table 1 Poisson Regression

Variables	Model [1]	Model [2]	Model [3]	Model [4] (10 flows+)	Model [5] (20 flows+)	Model [6] (30 flows+)
Length	-1.514e-04 (<2e-16)***	-1.534e-04 (<2e-16)***	-1.537e-04 (<2e-16)***	-4.924e-05 (<2e-16)***	-2.262e-05 (<2e-16)***	-1.968e-05 (<2e-16)***
O_employed	3.119e-04 (<2e-16)***	3.192e-04 (<2e-16)***	3.157e-04 (<2e-16)***	1.535e-04 (<2e-16)***	1.504e-04 (<2e-16)***	1.469e-04 (<2e-16)***
D_employed	-5.456e-04 (<2e-16)***	-5.479e-04 (<2e-16)***	-5.481e-04 (<2e-16)***	-6.202e-04 (<2e-16)***	-6.130e-04 (<2e-16)***	-6.114e-04 (<2e-16)***
O_employedPT		-3.693e-04 (<2e-16)***	-4.917e-04 (<2e-16)***	-5.745e-07 (0.987)	1.669e-04 (7.3e-06) ***	9.140e-05 (0.0225) *
O_total_bad_health			5.212e-05 (3.26e-06) ***	-5.745e-07 (<2e-16)***	-1.586e-04 (<2e-16)***	-1.827e-04 (<2e-16)***
AIC:	157926	157598	157578	93379	58286	37098

Significance Levels:

*: slope coefficient estimate is mildly significant.

**: slope coefficient estimate is moderately significant.

***: slope coefficient estimate is highly significant.

4. Conclusion

Commuting flows are visible in Liverpool and suggest where people are employed. Indicators like unemployment and bad health also have a significant effect on them. However, according to Rae (2017), there is a limitation of errors included in big datasets that need to be addressed.

Word count:499

References:

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