Are the benefits of public transport greatly exaggerated?

> "An advanced city is not one where poor residents use cars, but one where rich residents use public transport"

What inequalities persist in the face of large levels of public transport investment? If the above statement from the former mayor of Bogota, Enrique Penalosa, is true, there should be an inverse relationship between accessibility to public transport and inequality. How can this hypothesis be tested in the capital of one of the most developed countries in the world?

East London has seen rapid change in its public transport network as a result of the 2012 Olympic Games, with the construction of stations at the new Westfield Stratford City shopping centre, and a new Docklands Light Railway line from Stratford to Canning Town. We decided to investigate how this change in public transport accessibility could have influenced measures of inequality in the area.

Transport for London freely offers? their Public Transport Accessibility Level (PTAL) data, which combines a number of metrics including the walking network, travel times, frequency of services and waiting times for both the bus and rail systems for the entire capital. Every important aspect of going to catch a bus or train is captured. Initially, this data is calculated at the level of 100x100m squares, which allows for some very pleasing visualisations as seen below. A higher score implies higher levels of accessibility, so it makes sense that Central London and the areas surrounding major rail stations are darker in colour here.

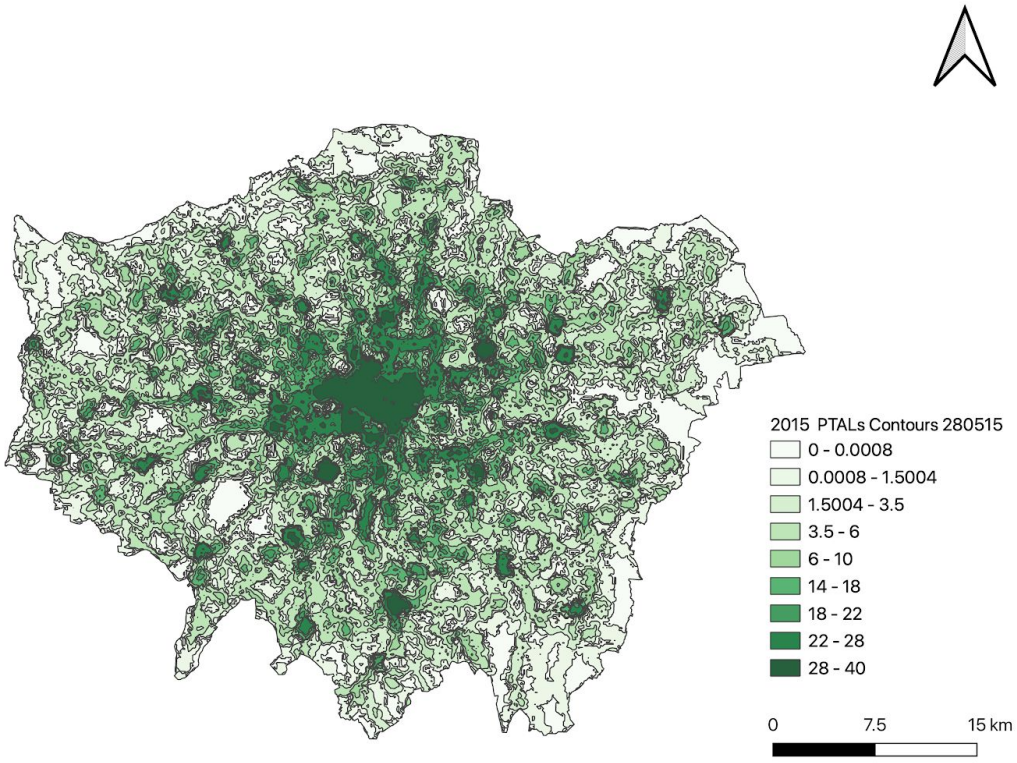

Figure 1

We combine this data with that on a number of other indicators from the Indices of Multiple Deprivation, as well as the median incomes, mean house prices and demographics of the region, all at the Lower Super Output Area level. These are statistical regions, redrawn each census year with an aim of a mean population of 1500.

We can then work on visualising the data and attempting to draw some conclusions. We use QGIS, an open-source geographical information system, to create maps. First, we import and combine our data, then clip it to ensure that only our 7 chosen boroughs are included.

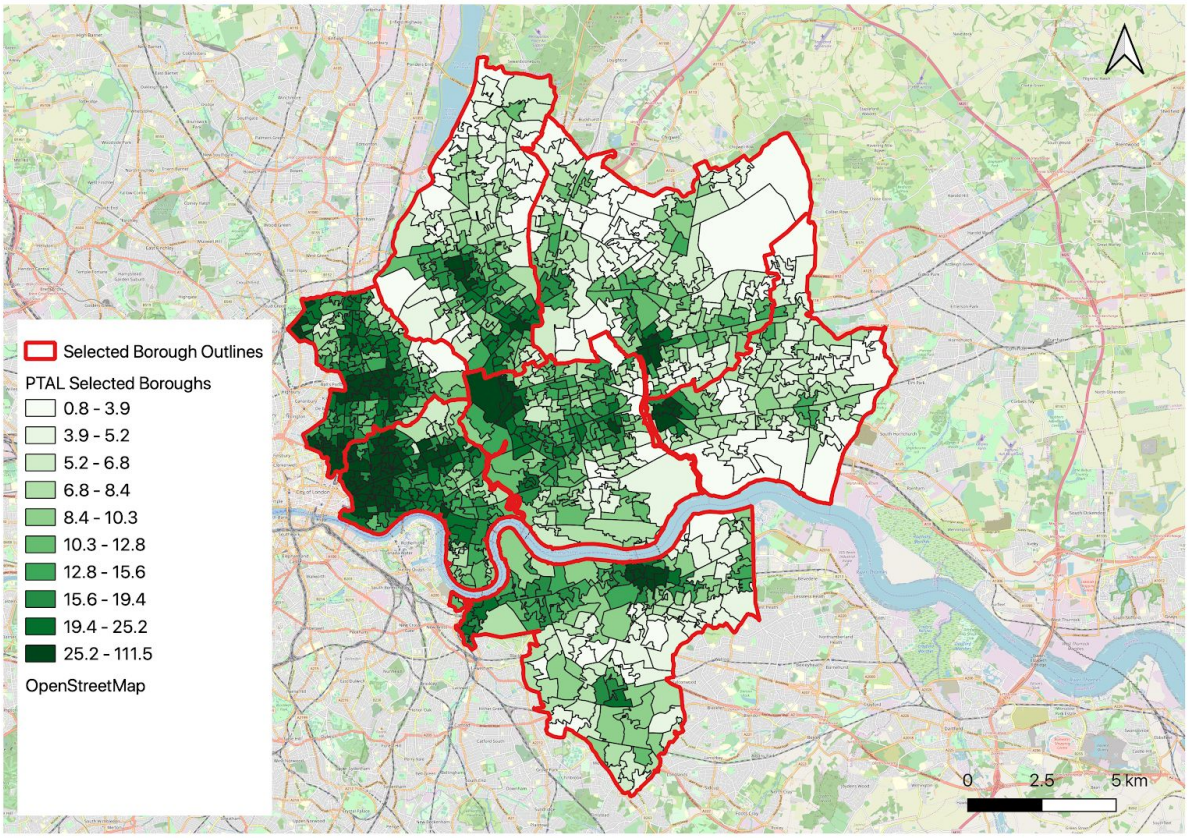
Selected Borough Outlines
PTAL Selected Boroughs
0.8 - 3.9
3.9 - 5.2
5.2 - 6.8
6.8 - 8.4
8.4 - 10.3
10.3 - 12.8
12.8 - 15.6
15.6 - 19.4
19.4 - 25.2
25.2 - 111.5
OpenStreetMap
0
2.5
5 km

Figure 2

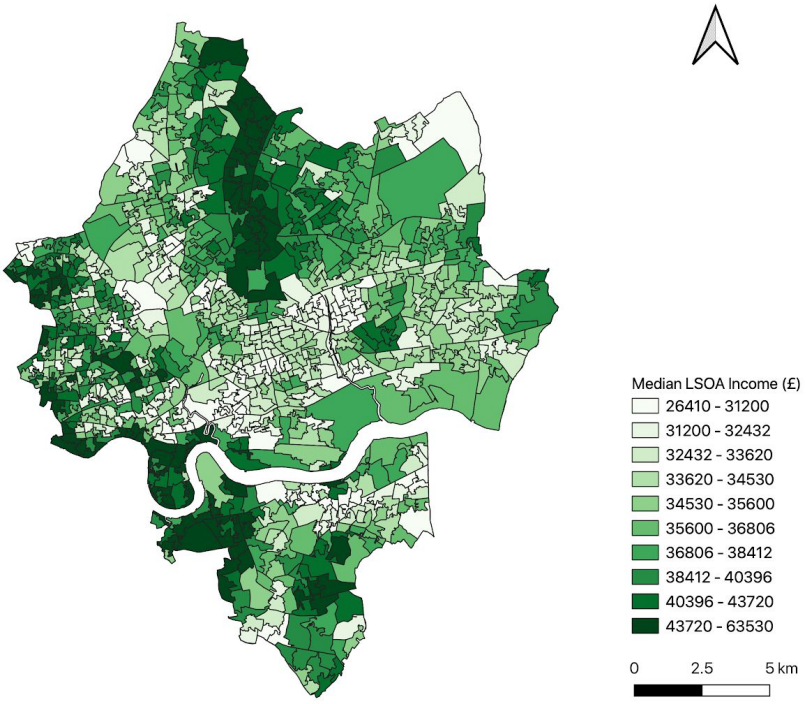
Median LSOA Income (£)
26410 - 31200
31200 - 32432
32432 - 33620
33620 - 34530
34530 - 35600
35600 - 36806
36806 - 38412
38412 - 40396
40396 - 43720
43720 - 63530
0
2.5
5 km

Figure 3

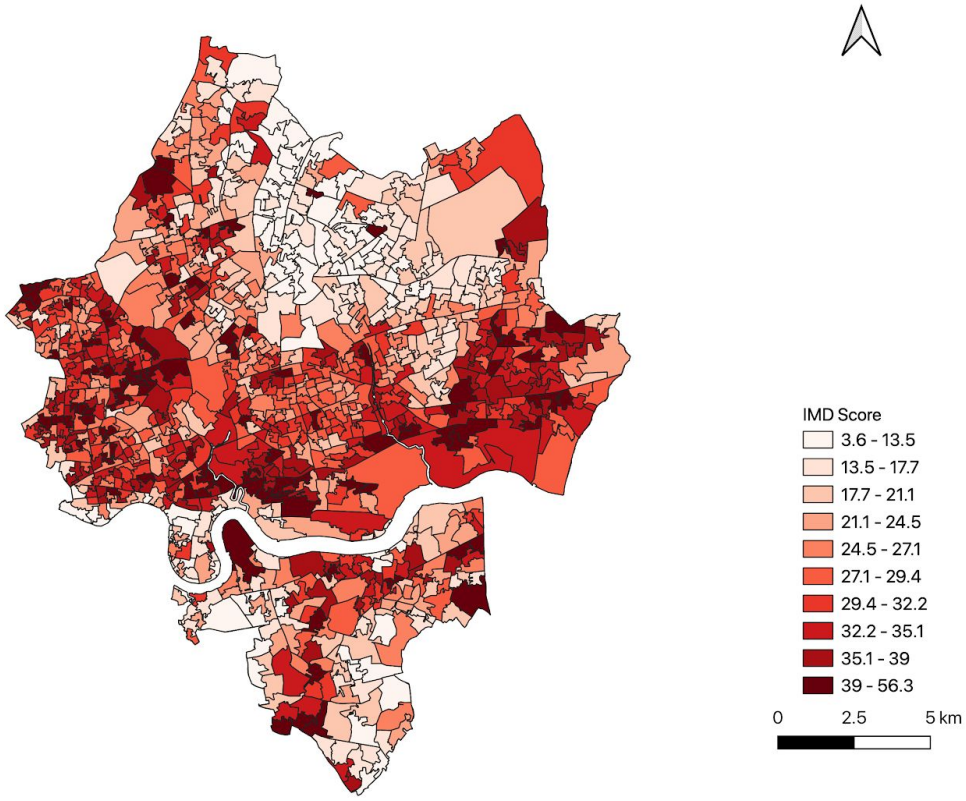
IMD Score
3.6 - 13.5
13.5 - 17.7
17.7 - 21.1
21.1 - 24.5
24.5 - 27.1
27.1 - 29.4
29.4 - 32.2
32.2 - 35.1
35.1 - 39
39 - 56.3
0
2.5
5 km

Figure 4

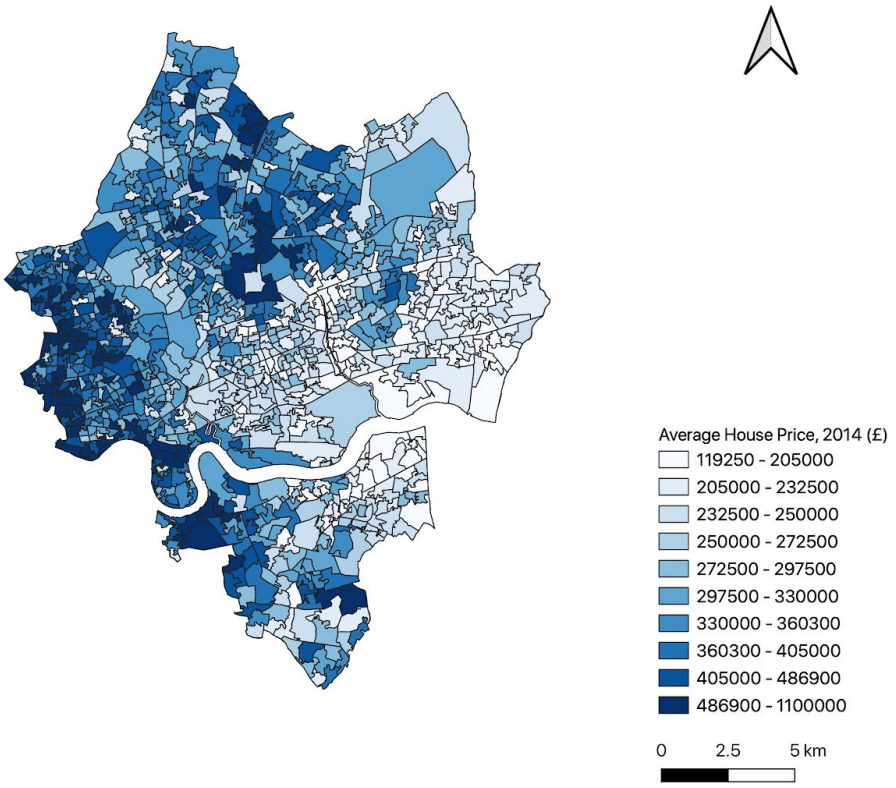

Figure 5

There is no obvious conclusion to be drawn here, aside from the clear difference for the borough of Redbridge, with higher house prices and incomes and lower levels of deprivation. So, we then decide to use further spatial methods to see if we can identify anything else. This requires two other software applications: GeoDa and R.

Spatial analysis needs us to identify precisely where each of our data points is. In QGIS, we plot the LSOAs as polygons on a map, where each polygon is attached to data in a table. There is no relationship between the polygons or the data points, which is what we need in order to carry out spatial analysis. We can fix this problem in GeoDa by creating spatial weights, a matrix for each observation that identifies its neighbours. We use queen contiguity, which ensures that neighbours on both edges and corners are detailed, although given the shape of our polygons this choice is largely irrelevant. We use the spatial weights to generate spatial correlations and run

spatial regressions and process the statistics these generate. In order to find autocorrelation, we applied Moran's I law. According to Anselin (2018), the statistics of Moran I are perhaps the most frequently used indicator of global spatial auto-correlation.

The inconclusive nature of our early analysis continues.

However, we do have a few interesting observations.

- there is a positive association between public transport accessibility and health closer to London- meaning more people may have used health services because of the public transport may have enabled this.
- We could not see any connection between the education of people and their access to public transport; in other words, we cannot say what role education has to play in public transport accessibility.
- Also, there is a connection between barriers to housing and accessibility.
- The boroughs with more whites population had more access to public transport as opposed to the BAME population

Our results can't identify a causal relationship by definition since the factors influencing transport expansion are wide-ranging, so we can't say that accessibility has no influence on inequality or vice versa. However, the relationships identified do support some further analysis. A key flaw is that we can't identify who is using public transport, only how easy it is for them to access it. This creates problems in that we can draw false conclusions such as a borough with poor accessibility but high incomes- could this be the result of car use? Redbridge's suburbia tentatively suggests this, and we suggest alternative costly methods such as passenger surveys, or even automatic fare collection data, which could be more effective.

References:

Anselin, L. (2018) Global Spatial Autocorrelation Moran Scatter Plot and Spatial Correlogram Available at https://geodacenter.github.io/workbook/5a_global_auto/lab5a.html (viewed: 25 Dec 2019)