# How do socio-economic and spatial characteristics influence fire brigade response times and fire risk in London?

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## 1. Research question

Resources are finite, yet there is a consistent demand for efficient public services. Facing budget constraints, public organizations have sought ways to enhance productivity to deliver improved services without increasing resource levels (Cook and Hughes, 2009b). In particular, local governments often encounter substantial challenges in allocating these limited resources effectively. For instance, fire stations are essential for urban infrastructure and serve as key responders during emergencies (Murray and Grubesic, 2007). The effectiveness of fire services in an area is largely influenced by the number of fire stations, locations, and logistical capabilities (Johnson, 2008). It is challenging to allocate fire stations optimally due to the varying sociodemographic contexts, population density, and service area across different regions. These differences in location-specific conditions can lead to uneven workloads among fire stations, with some fire stations facing excessive demands that may compromise public service quality. This research aims to assess two hypotheses empirically:

### 1.1. The relationship between sociodemographic factors and fire incidents:

We hypothesize that variations in educational attainment, income levels, and unemployment rates across regions are associated with differences in the frequency of fire incidents.

### 1.2. Fire incidents, area, and response times:

We hypothesize a positive correlation between the number of fire incidents and response times. Specifically, as the volume of incidents increases and the size of boroughs' area, fire stations face higher workloads, and in the absence of sufficient staffing, longer response times may result.

This research does not focus on using algorithms for resource allocation. It aims to analyze the relationship between socio-economic factors, response times, and fire risk to uncover the issue of unequal resource distribution within the London Fire Brigade and rescue service.

## 2. Literature Review

Before conducting the data analysis, we must gather supporting evidence for the hypotheses and identify appropriate data to apply in the research. Existing research supports the first hypothesis, which highlights fire incidents in high-rise buildings are concentrated in areas with high population density, lower social status, and higher unemployment, and waste fires are prevalent in city centers and panel housing areas (Popelínský, Vachuda, and Veselý, 2017). These findings underline the importance of socio-economic and spatial factors in shaping fire risks and response demands. To support the second hypothesis, the Open Data Institute developed the London Fire Brigade tool (2013), which analyzes the average response time and combines it with footfall data to estimate the risk factor for each borough. This analysis shows boroughs in outer London have higher risk and average response time than the city centre. Also, Uddin and Warnitchai (2020) value the size of areas in their location-allocation model revealing service area is a commonly used metric for evaluating fire station performance and is closely linked to travel time, with larger service areas typically resulting in longer travel times. Taylor (2017) further demonstrates the applicability of spatial survival analysis in modeling emergency response times. This study of the London Fire Brigade revealed delays following the 2014 station closures, with 44% of response times exceeding the six-minute target in affected areas. This indicates that the density of fire stations significantly impacts response times. Moreover, the London Fire Brigade website shows that multiple fire stations are allocated within each borough. However, cross-borough support cannot be ruled out in certain situations (London Fire Brigade, n.d.). Building on this foundation, our research seeks to extend these findings by applying multiple regression models to analyze the relationships between socio-economic variables, response times, and fire incidents.

## 3. Data

This study utilizes London Fire Brigade Incident Records from 2018 to October 2024, initially containing 783,134 rows. After excluding incidents related to "Aircraft," "Boat," and "Rail Vehicle," and removing rows with missing property category data, the dataset was reduced to 781,624 rows. Missing response time data (44,238 rows) were excluded, and average response times were calculated for each borough. The number of unique fire stations in each borough was also considered to account for variability. Socio-demographic data on median income (2022), population (2023), unemployment rates (Q2 2023 and Q2 2024), and educational attainment (2021) were sourced from the London Datastore and Trust for London. Median income was used to minimize outlier effects. Despite varying collection years, the data's proximity ensures consistency and reduces potential temporal biases. A detailed summary of all variables is provided in **Table 1**.

**Table 1** Key variables

| Variable | Type | Description |
|---|---|---|
| Number of fire incidents (Depedent variable) | Numeric | Total fire-related incidents recorded in each borough (2018–Oct. 2024). |
| Income | Numeric | Median annual income of taxpayers in 2022. |
| Unemployment rate | Numeric | Average unemployment rate for Q2 2023 and Q2 2024. |
| Educational attainment | Numeric | Percentage of residents with a degree or equivalent (2021). |
| Response time | Numeric | Average fire service response time per borough (2018–Oct. 2024). |
| Size of boroughs | Numeric | The geographic area of each borough ($km^2$). |
| Number of fire stations | Numeric | Fire stations serving each borough. |
| Population | Numeric | Total population per borough (2023). |

## 4. Methodology

The large variation in borough scales presents significant challenges in interpreting spatial regression results. So, we adopt the multiple regression combined with the k-means clustering method. This approach allows us to analyze how each independent variable influences the number of fire incidents and subsequently use the key variables to cluster boroughs, providing deeper insights into each group. Before conducting the multiple regression analysis, we tested the correlation between variables for robustness. The Pearson Correlation Coefficient **(Figure 1)** shows that the number of fire incidents positively correlates with fire station count (0.58), population (0.36), and unemployment rate (0.39), indicating areas with more incidents tend to have higher fire station density, larger populations, and greater unemployment. Unexpectedly, it negatively correlates with response times (-0.36), suggesting high-incident areas may have more resources. Median income strongly correlates with educational attainment (0.80) and negatively with both unemployment rate (-0.71) and population (-0.71), indicating wealthier areas tend to have lower unemployment and smaller populations. Response time positively correlates with borough size (0.79), aligning with the expectation that larger areas result in longer response times. A Variance Inflation Factor (VIF) analysis revealed that most variables have VIF values below 5, with no significant multicollinearity, though median income's VIF of 5.68 warrants attention.

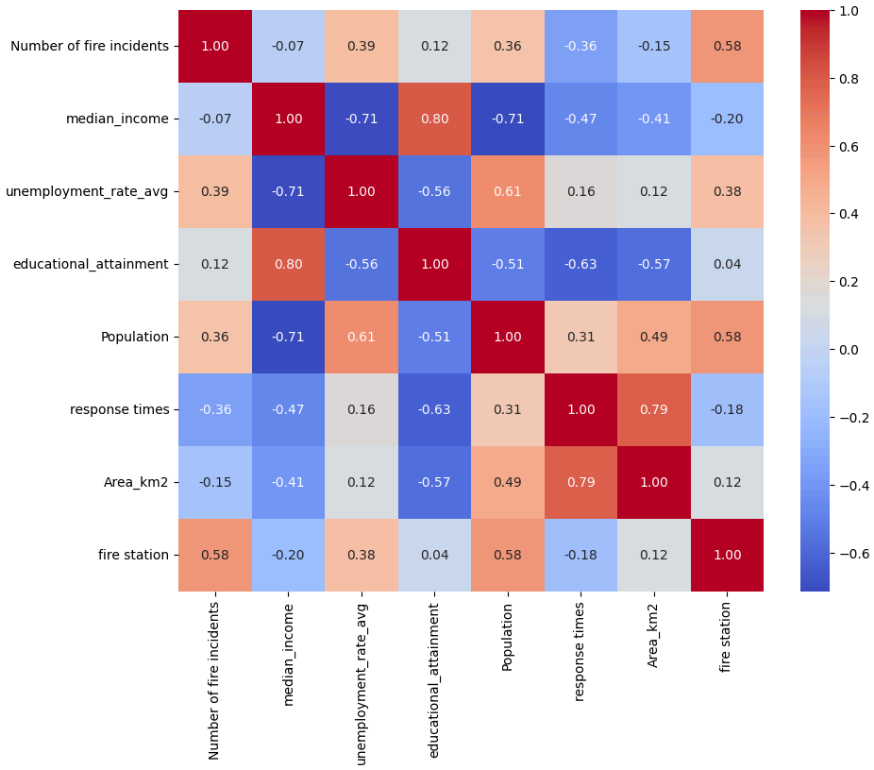


**Figure 1** Correlation Matrix of select Variables

The initial multiple regression analysis yielded an R-squared of 0.514, indicating moderate explanatory power, with an Adjusted R-squared of 0.378, suggesting the presence of redundant variables. The model was statistically significant, as shown by the F-statistic (3.777) and its p-value (0.006). However, the Q-Q Plot **(Figure 2)** revealed a clear outlier data point of Westminster which can be excluded to improve model reliability.

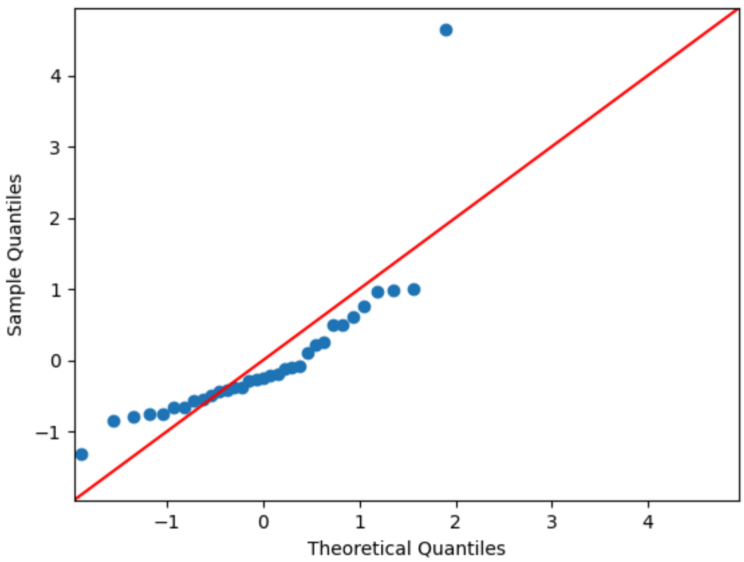


**Figure 2** Fire Incident Model Residuals Q-Q Plot with Outlier

After iterations of the multiple regression model, we found that educational attainment and median income had high p-values, indicating statistical insignificance, likely due to multicollinearity with the unemployment rate. These variables were excluded from the model. The final model shows a strong fit though there is still potential for refinement in **Figure 3**. Explaining 79.2% of the variance (R-squared = 0.792) and adjusted R-squared of 0.752 confirms robust explanatory power, and the F-statistic of 19.80 with a p-value of 4.00e-08 underscores the model's overall significance.

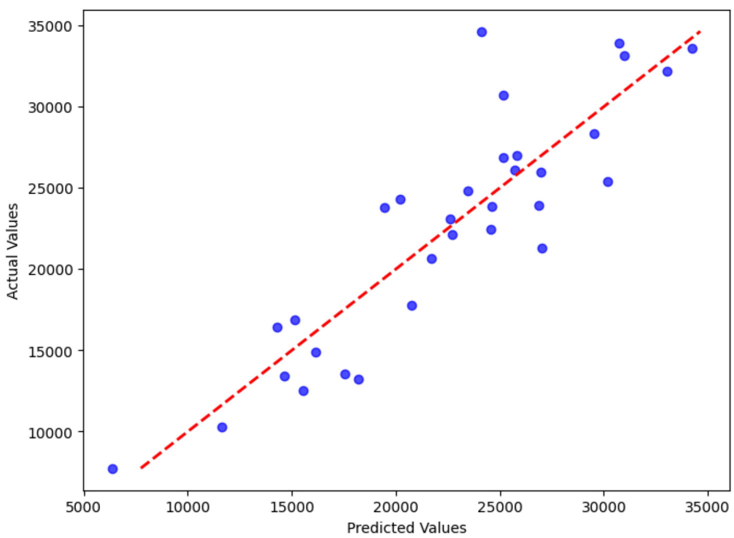


**Figure 3** Analysis of Multiple Regression Outcomes

## 5. Results

This regression analysis reveals key insights into fire incident predictors. The model's constant is 58674.87, indicating the baseline incident count. Significant predictors include the unemployment rate ( $p = 0.0333$) and population ( $p = 0.0221$), both positively correlated with incidents. Response time is inversely related ($p = 0.0002$). Fire stations and borough size show positive but non-significant effects($p > 0.05$). The model equation is:

$$\textit{Number of fire incidents} = 58674.87 + 1867.43 \times \textit{Unemployment rate} + 0.0349 \times \textit{Population} \\ - 197.22 \times \textit{Response Time} + 668.86 \times \textit{fire Stations} + 60.02 \times \textit{borough size}$$

The model supports hypothesis one, as fire incidents show a passive relationship with sociodemographic factors. However, hypothesis two is unsupported, as fire incidents negatively correlate with response time, indicating the government has allocated resources in high-incident boroughs. Subsequently, we removed the insignificant variables for k-means clustering and segmented the data into four groups, with means calculated for each **(Table 2)**. The City of London and Westminster emerged as outliers. Group A showed higher fire incidents, unemployment rates, and population density, with shorter response times than Group B, aligning with the multiple regression results. Interestingly, the clustering map **(Figure 4)** highlights strong spatial correlations, suggesting fire incidents might be influenced by urban-rural spatial characteristics.

**Table 2** Mean of K-Means Clustering Groups

| Cluster | fire incidents | unemployment rate | response times | population density(km²) |
|---|---|---|---|---|
| City of London | 7744.00 | 0.00 (no data) | 285.42 | 4274.44 |
| Westminster | 56548.00 | 4.70 | 305.95 | 9600.89 |
| Group A | 28563.62 | 4.91 | 291.87 | 10608.43 |
| Group B | 19222.44 | 4.76 | 338.73 | 4972.28 |

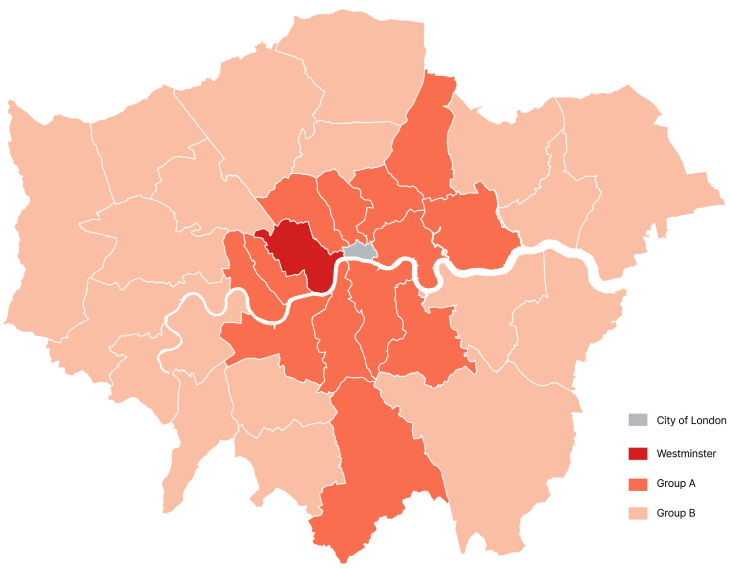


**Figure 4** Map of K-means Clustering

## 6. Discussion and Conclusions

In this study, we've used multiple regression and K-means clustering to test two hypotheses, but there are still some limitations and areas for improvement. First, since our study is cross-sectional, it lacks a temporal dimension, which limits how we can explore changes over time. For example, it's reasonable to assume that response times might vary depending on the time of day, especially because of traffic congestion and local demand for fire services (Taylor, 2017). Also, we did not consider the accessibility of the road network or cross-district support from fire stations. A more detailed analysis, using methods like Voronoi diagrams and buffer zones, could provide a better understanding of how accessible urban fire stations are within communities (Yu et al., 2022). This approach would allow us to look into detail at each fire station's capacity to serve the area, rather than just analyzing data at the borough level. In conclusion, the study shows that areas with higher incidences of fires are predominantly influenced by factors such as unemployment rates and population density. The London Fire Brigade has already allocated significant resources to the city centre (Group A), which results in relatively lower response times in these areas. In contrast, suburban regions (Group B), due to their larger geographic areas, may require improved coordination strategies or enhanced accessibility of the road network to optimize response times.

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