# Potential Causes of Fly-tipping in London

***This study investigated the relationships of waste collection by authorities, cars registered, landfill tax and socio-economic and demographic attributes with fly-tipping in London. Waste collection, employment rates, population density and landfill tax were found to have notable relationships with fly-tipping.***

***Keywords: fly-tipping, waste collection, socio-economic attributes, demographic attribute, London boroughs, vehicles registered, landfill tax.***

## I. Introduction

Fly-tipping is defined as the illegal dumping of waste and it occurs around the world; for example, it is frequently observed in Brazil [1], Hong Kong [2] and Israel [3]. It was estimated the investigation and remediation of fly-tipping incidents costs the UK £100-£150 million per annum [4]. In addition to financial consequences, fly-tipping contributes to water pollution [5], wildlife deaths [6] and can cause negative effects on the wellbeing of those in the area [4], among many other consequences.

Commonly, fly-tipping occurs when waste collection services are insufficient or there is financial motivation, such as avoiding landfill tax [6]. Massari and Monzini identified that some businesses seek to save money on waste disposal by fly-tipping, allowing them to undercut competition [7]. Governments have dedicated significant resources to reduce fly-tipping [8] and used measures such as harsher punishments [9]. However, fly-tipping is currently very prevalent, especially in England where over 1.13 million fly-tipping incidents were recorded from 2020 to 2021 [10].

The motivation behind this study is to be able to identify and investigate potential causes or deterrents for fly-tipping in London. Specifically, this study investigates and attempts to reason the relationships between fly-tipping and the number of vehicles registered in a borough, landfill tax rates, waste disposal by local authorities and socio-economic/demographic factors. The choice of these factors was informed by the literature referenced [4, 6]. The results of this investigation will increase understanding of the factors contributing to fly-tipping and consequently enable more informed strategies to be developed when attempting to combat fly-tipping in London.

## II. Analytical Questions

**1.** Is there a difference in the repercussions given against fly-tipping in Inner London boroughs compared to Outer London boroughs and does this impact the number of fly-tipping incidents (NFTI)?

**2.** Is there a relationship between the NFTI and the waste collection provided by local authorities in London? Authorities can ascertain whether increasing waste collection would significantly decrease fly-tipping incidents.

**3**. Given most instances of fly-tipping occur with the use of cars [6], is there a positive correlation between the number of vehicles registered in London and the NFTI? Vehicle restrictions could be implemented to reduce fly-tipping.

**4**.Does higher landfill tax lead to a greater NFTI? Landfill tax was introduced to encourage recycling [6], however, it may not be worth the cost of increased fly tipping.

**5**.Is the NFTI per capita in a borough correlated to any of its demographic or socio-economic attributes? This would potentially identify further areas to investigate when trying to reduce fly-tipping.

## III. Data

**1.** The main dataset used was the Fly-tipping Incidents dataset and it was required for answering all analytical questions [11]. This contained the number of fly-tipping incidents and number of each type of action taken against fly-tipping in each London borough, every year from 2011 to 2020.

**2.** The Local Authority Collected Waste Management, London dataset provided the total waste collected (TWC) by London authorities from 2011 to 2020 [12]. TWC served as a measure of waste collection provided by local authorities.

**3.** The Number of Licensed Vehicles dataset contained the total number of private or light goods vehicles (PLGV) registered in each London borough every year from 2011 to 2020 [13].

**4.** Landfill tax rates from 2011 to 2020 were manually extracted from the gov.uk website [14]. Comparisons of the changes in landfill tax to the changes in mean fly-tipping incidents over time provided insights which addressed AQ 4.

**5.** The London Borough Profiles dataset contained socio-economic and demographic attributes for each London borough at given years [15].

**6.** The 2016 Mid-Year Estimates dataset [16] was used to investigate the relationship between the population of a borough and its NFTI, informing on whether normalisation of the NFTI by population was necessary to allow valid comparisons of fly-tipping between boroughs. Normalising would assume people mostly fly-tip in their own borough.

## IV. Analysis

This section provides an overview of the analysis undertaken in the corresponding jupyter notebook.

### *A. Missing Values*

The Fly-tipping Incidents dataset contained fifteen missing values; they were addressed individually. As there were only 32 London boroughs, which is a small number of instances for each year, replacing missing values was more favourable than removing the corresponding rows. For the affected boroughs, variation in the attributes with the missing value over time were visualised to inform the missing value replacement process. For example, in the 2017-2018 and 2018-2019 years, no values of total incidents were recorded in Redbridge. However, when visualised in Fig. 1 the total incidents appeared to be increasing linearly over time, except for immediately after the 2014-2015 year. Consequently, linear interpolation was used to generate values for these years.

When there was no clear trend in the attribute over time, the missing value was replaced using the mean value of the two neighbouring years. This dataset also contained anomalous values; in 2015-16 year, Croydon reported 0 total incidents despite recording 1707 actions taken against fly-tipping including 73 prosecutions, suggesting this was a missing value. These values were replaced using the same approach as for missing values. The London Borough Profiles dataset also required replacement of missing values. Only missing values in attributes of interest were replaced; the mean values across all boroughs were used to replace them.

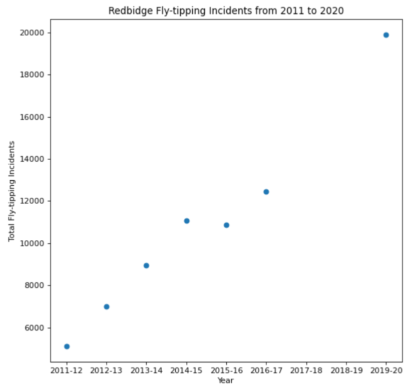



*Figure 1. Redbridge NFTI from 2011 to 2020.*

### B. Normalising the Number of Fly-tipping Incidents

New data frames were generated from the fly-tipping data for each year from 2011 to 2020 as data from individual years were treated individually at points during the investigation.

It was necessary to check whether the NFTI in a borough needed normalisation by being divided by population to enable valid comparisons between boroughs. The 2016 Mid-Year Estimates dataset contained London borough population estimates for 2012, 2013, 2014, 2015 and 2016. The fly-tipping data frames for the corresponding years were merged with the population estimates data, creating five new data-frames. Scatter plots of total fly-tipping incidents in a borough against its population indicated the presence of outliers. Therefore, Spearman's rank which is more robust to outliers than Pearson's correlation was used to determine the correlation between the two variables. Table 1. shows for two out of five years, there was statistically significant weak correlation between population and fly-tipping incidents, however, this was not convincing enough to decide to normalise NFTI data over all years. Therefore, whether to normalise the NFTI or not was decided on a year-by-year basis when answering the AQs.

TABLE 1. The correlation between population and mean NFTI in a borough.

| Year | Spearman's Rank Correlation Coefficient | p-value |
|---|---|---|
| 2012 | 0.24 | 0.19 |
| 2013 | 0.21 | 0.27 |
| 2014 | 0.43 | 0.02 |
| 2015 | 0.34 | 0.07 |
| 2016 | 0.44 | 0.02 |

### C. Approaches to Answering the Analytical Questions

To answer AQ 1**,** it was necessary to add an additional column to the Fly-tipping Incidents dataset which defined each borough as Inner or Outer London. The NFTI were not normalised as London borough population data was not available for all years from 2011 to 2020. Pie charts were used to enable comparisons of the of the proportion of each type of action taken in Inner and Outer London boroughs from 2011 to 2020. The mean NFTI over boroughs for Inner and Outer London were calculated and compared.

There was no available individual data for the masses of waste collected by each borough's local authority; only the summative value of TWC by all London authorities for each year from 2011 to 2020 was available. Consequently, for each year the mean NFTI was calculated using all boroughs since boroughs could not be treated individually. A new data frame was created using the mean NFTI values, TWC values and year. The variations of each variable over time were compared to identify potential relationships, answering AQ 2. If TWC for individual boroughs was made available, these results could be further validated by investigating the relationship between TWC and NFTI in boroughs for individual years.

To answer AQ 3, the means of total PLGV across all boroughs were calculated for each year and its variations from 2011 to 2020 were compared to the variation in the previously calculated mean NFTI values. It has been identified most instances of fly-tipping occur with the use of cars [6], further validating any positive correlation found.

The variation in landfill tax was compared to the variation in mean NFTI from 2011 to 2020 to answer AQ4.

Following the replacement of missing values in the London Borough Profiles dataset and conversion of values to the numeric datatype, attributes were separated by year and combined with the fly-tipping data for the corresponding year. The attributes of interest were recorded in 2015 and 2017.

Table 1. shows in 2015 population was weakly correlated and statistically significantly to NFTI. Therefore, a new attribute of NFTI per capita was calculated by dividing the NFTI by the corresponding population for each borough.

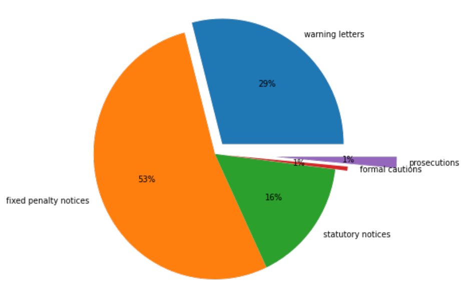
The London Borough Profiles dataset contained the London borough population estimates for 2017. No strong correlation or statistical significance was found between population and the NFTI, therefore the NFTI was not normalised.

Spearman's rank correlation coefficient was calculated to identify correlations between the NFTI/ NTFI per capita and the socio-economic and demographic attributes of interest in 2017 and 2015 respectively.

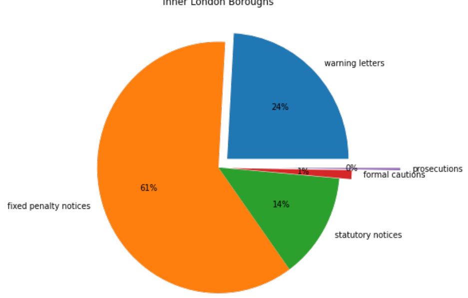
## IV. FINDINGS, REFLECTIONS AND FUTURE WORK

Fig. 2 illustrates that there were not significant differences between the proportion of each type of action against fly-tipping in Inner London boroughs and Outer London boroughs; suggesting measures against fly-tipping are enforced in a uniform way across London. Despite this, the mean NFTI value in Inner London boroughs is greater by over 2000 when compared to Outer London boroughs, suggesting the proportion of each type of action was not a significant factor in deterring the fly-tipping.

Fig. 3 illustrates a relationship between the variations of TWC and mean NFTI over time. The variables were mostly positively correlated until after the 2017-18 year. As the TWC decreases, NFTI increases suggesting fly-tipping is caused by inadequate waste collection which has previously been identified as a contributor to fly-tipping [6], further validating the causal relationship. Authorities could assess whether the cost of increasing waste collection services would be sufficiently compensated by reduced fly-tipping.




*Mean number of fly-tipping incidents in an Outer London borough from 2011-2020: 8635*




*Mean number of fly-tipping incidents in an Inner London borough from 2011-2020: 11122*

*Figure 2. A comparison of the proportion of each type of action taken in Inner London vs Outer London Boroughs from 2011 to 2020.*

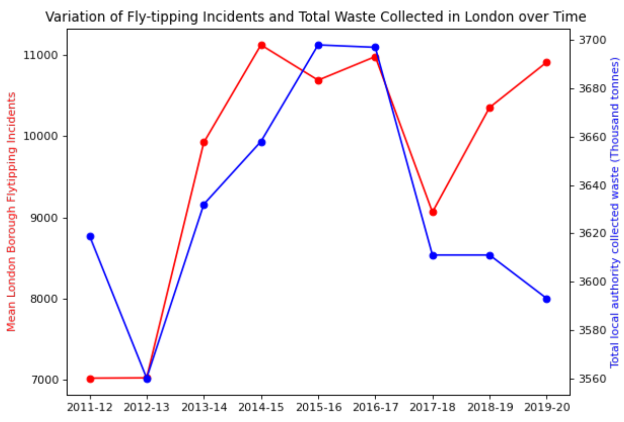



*Figure 3. Variation of fly-tipping incidents and total waste collected in London from 2011 to 2020*

Fig 4. highlights a weak relationship between the mean NFTI and mean PLGV registered in London over time. From 2012 to 2015, there was a sharp increase in the mean NFTI as PLGV increased, suggesting more people had the ability to fly-tip using a PLGV.

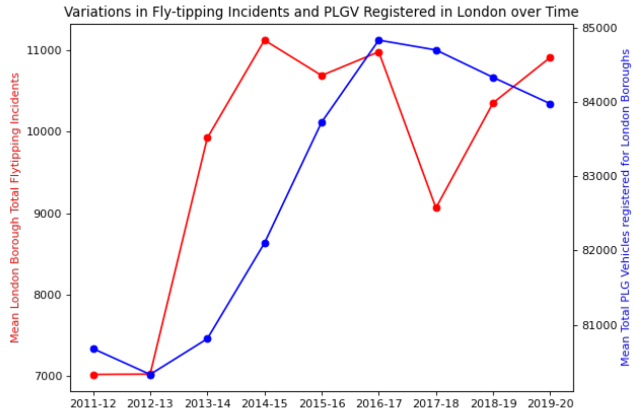



*Figure 4. Variation of fly-tipping incidents and mean PLGV in London from 2011 to 2020*

Landfill tax was introduced to encourage recycling [6], however, alternatively it may have led to an increase in fly-tipping. Fig. 5 shows as the landfill tax rates were increasing at a relatively high rate until 2015; the mean NFTI also increased at a relatively high rate. However, when the rate of increase of landfill tax rates slowed after 2015, the NFTI stopped increasing. A potential explanation is that when landfill tax increases at a high rate, people are more likely to start fly-tipping as there is a more significant difference in their money spent whereas they would dismiss smaller changes. This could be further validated by investigating the trend for NFTI in individual boroughs each year compared to Landfill Tax.

Table 2. shows the only statically significant correlations were for employment rate, net internal migration and population density. Employment rate was negatively correlated to NFTI, suggesting that an additional incentive for authorities to increase employment could be the reduction in the NFTI. Net internal immigration was negatively correlated to NFTI; however, this is unlikely to be a causal relationship as it would suggest as more people left a borough, the NFTI

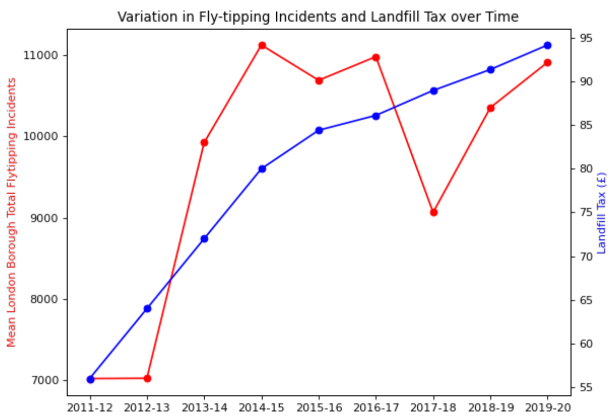



*Figure 5. Variation of fly-tipping incidents and landfill tax in London from 2011 to 2020*

increased. Higher population density may mean less disposal available per person and thus, more fly-tipping. This speculation could be further investigated if the attribute data for other years was released.

Investigating the relationships discussed in this investigation within other cities could help to further validate the patterns observed in London.

TABLE 2. The correlation between borough attributes and NFTI in a borough.

| Attribute | Spearman's Rank Correlation Coefficient | p-value |
|---|---|---|
| Net internal migration (2015) | -0.44 | 0.02 |
| Employment rate (2015) | -0.42 | 0.02 |
| Youth unemployment rate (2015) | 0.15 | 0.44 |
| Proportion of working age or equivalent and above (2015) | 0.16 | 0.40 |
| Mean age (2017) | -0.24 | 0.17 |
| Population density (per hectare) (2017) | 0.35 | 0.04 |

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