Night tubes and crime - outline

Jacob McLoughlin

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1 Idea Outline

Over the second half of 2016, Transport for London phased in the Night Tube over a number of lines. This was an extension of a line's regular tube service through the night on Fridays and Saturdays, rather than ending at 12am and restarting the next morning at 5am. Table 1 shows the staggered nature of the rollout - to this day, many lines still do not have a Night Tube.

The purpose of the Night Tube was to allow Londoners to spend more time enjoying London's night-time economy, but as a consequence it means many people are walking around tube stations in the dark, often alone, and often without their full mental capacity. In fact, in the eyes of a criminal, the areas around tube stations become hotspots for these vulnerable targets, seemingly presenting a perfect opportunity to commit a crime. This is dangerous, and determining whether criminals acted upon this possibility will have significant implications on urban crime policy, as well as giving information on how criminals behave. I am therefore interested in determining the effect the opening of a night-tube line had on the prevalence and nature of crime in the areas surrounding the stations.

The British Transport Police patrolled the night tube stations (Zhang et al, 2022). As such, the crime effect directly next to the station may not change as much as we expect (i.e. our estimate will likely be an underestimate). However, from a policing perspective, it is very interesting to understand the effect in areas around the stations - how far away from the stations do we have to go for any effect to phase out? These questions are interesting from the perspective of understanding criminal behaviour, and also to suggest the extent of complimentary policies to urban transport expansions.

My questions of interest are therefore the following:

- Did the introduction of the night tubes have an effect on crime frequency and nature in areas surrounding the stations?
- How does this effect vary according to distance from the station?

Table 1: Night Tube introduction month and year by London Tube line

Line	**Introduction Date**
Bakerloo	Not introduced
Central	August 2016
Circle	Not introduced
District	Not introduced
Hammersmith & City	Not introduced
Jubilee	October 2016
Metropolitan	Not introduced
Northern	November 2016
Piccadilly	December 2016
Victoria	August 2016
Waterloo & City	Not introduced

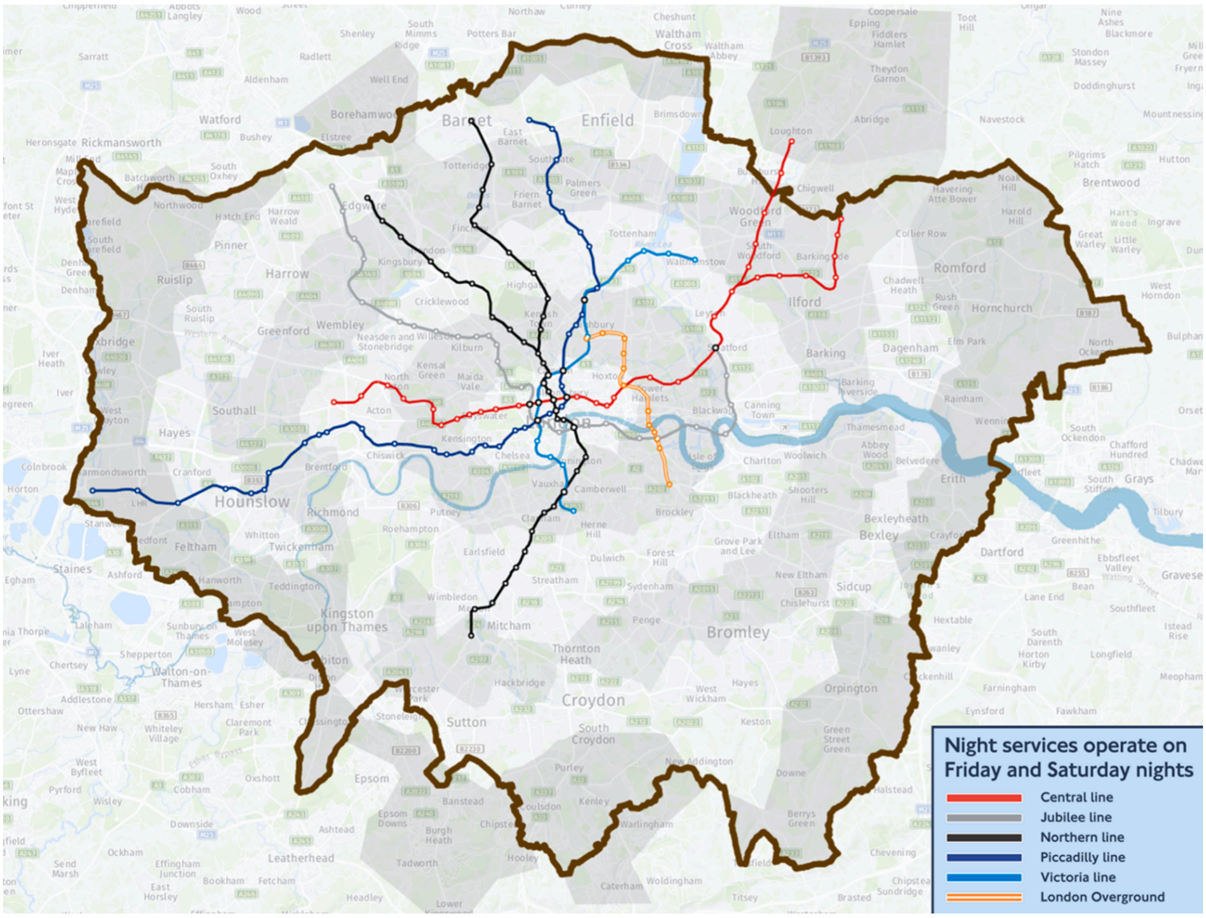


Figure 1: Geographically accurate treated lines (from Zhang et al (2022))

2 Literature

Useful papers include:

Zhang et al (2022):

- Most relevant paper: examines the introduction of the night tube on a variety of social outcomes, including crime
- Issue: it groups at LSOA level, and only uses a simple 2×2 DiD (so no allowing for staggered treatment or dynamics of the effect - biased). It then goes into using debiased DiD with ML
- It also gives evolution of rates for crimes on tubes, overground, buses, but this isn't really that useful
- They define an LSOA as being treated if its centroid is within 800m of a night-tube station, and their control region is the LSOAs with centroids further than 2km from any night-tube station (again biased - parallel trends isn't going to hold as these regions are far more rural)

Jackson and Owens (2011):

- Examines the effect of public transportation expansions on alcohol-related crime and road accidents
- The treatment is expansion in time, almost exactly like the night tube introduction, though they don't have as granular geographic data
- Not directly relevant, but a good paper in a good journal
- READ THROUGH METHODOLOGY IN MORE DETAIL

Becker (1968):

- Sets up the canonical model of criminal behaviour: conceptualised as 'arising from comparison of the expected risk-adjusted returns of legal and illegal activities' (Braakmann)

Braakmann et al (2024):

- Shows that 'temporal variations in the expected returns to crime affect the location of property crime'
- Outlines the Becker model, and the optimal foraging theory of criminal behaviour: 'criminals aim to maximise the proceeds of crime and minimise the time spent searching for a suitable target, committing the crime and the risk of being caught'

Billings et al (2011):

- Did the announcement and opening of Charlotte's light rail system increase crime near stations on the line?
- Treatment distance = 0.5 miles, with a few justifications (most people walk from no further, used in the literature, used by city planners)
- However, they only compare crime counts within this 0.5 mile buffer round each station, and they also hypothesise different mechanisms (e.g. construction leads to gentrification)

MacDonald (2015):

- Reviews the literature explaining why stations tend to be hotspots of crime
- More work on how variation in the built environment around stations is associated with crime, rather than whether the stations actually cause crime

Useful methodological papers include:

Butts (2023): This paper examines how to estimate treatment effects of a point-based policy using a rings-based DiD, but focuses on the case of one point at which there is treatment (so ignores the fact that I have untreated stations). May be useful as a robustness check.

Ahlfeldt et al (2019): This paper examines the effect of proximity to (and exposure to noise from) metro rail in Berlin. They examine spatial decay in the distance effect by using mutually exclusive dummies for distance bands.

Currie et al (2015): This paper examines the effect of air pollution from power plants on house prices and infant health. They examine regions close to plants vs regions further away, and vary the 'close to' distance - the issue is in my context, parallel trends will quickly fail as we compare urban vs less urban.

Eppelsheimer et al (2022): This paper estimates distance decay in the form of spillover functions, using functional regressions. Maybe a useful alternative, but unclear how to incorporate event-studies into this framework.

LOOK FOR OTHERS!

3 Data

I have data on all crimes recorded by the Met Police between 2015 and 2017. In particular, each crime is recorded alongside its month of occurrence, its nature, and its location. The locations are given in terms of coordinates, but to preserve identification of the crime, the exact coordinates can't be given. Instead, the Police keep a set of anonymous map points (e.g. half way down a street, the centre of a car park, etc), and they assign a crime the coordinates of the nearest map point. There are roughly 60,000 of these in my London data; the implicit polygons which each point represents is therefore very small, creating no issues with analysis according to distance from a station. I will use these locations as my unit of observation. I have the crime count at each one from 2015-01 to 2017-12, giving me a rich panel of crime data in London.

I can also disaggregate the crime count into counts of different types of crime, which will be useful to investigate the effect in more detail. Certain types of crime are far more likely to rise than others, if my hypothesised mechanism is correct.

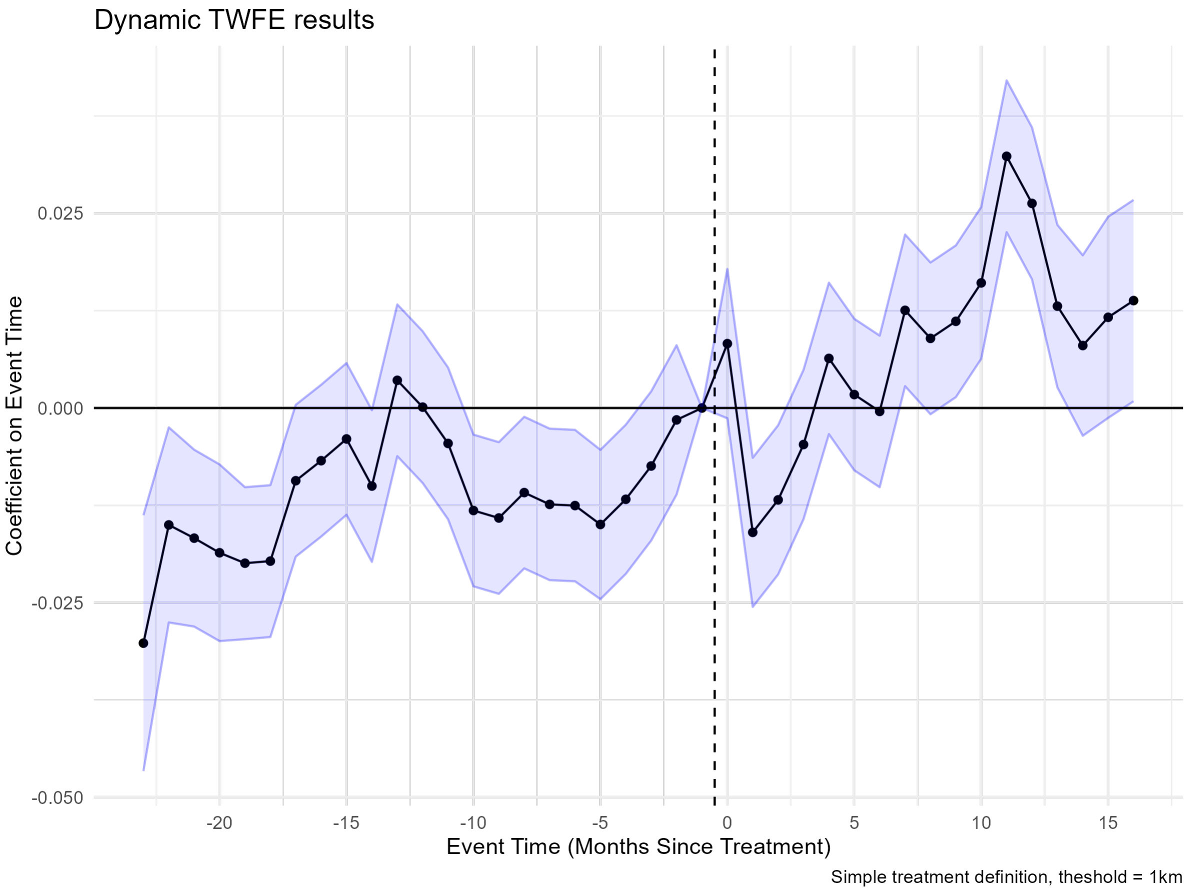
I also work out the planar distance from each location to each tube station less than 2km away from it. I also record the lines that go through that station. As such, for each location I can infer whether it is being treated, as defined below.

4 Identification

Let y_{it} be the log of crime count (+1, to avoid log(0)) at location i in month t. Define treatment first as an indicator for whether the distance from the nearest active night-tube station is less than 1km: $D_{it} = \mathbb{1}\{mindist_{it} \leq 1\}$. Then let s_i be the period of first treatment: $s_i = \min\{t | D_{it} = 1\}$.

Baseline TWFE OLS:
Simple OLS estimation of the most basic regression:

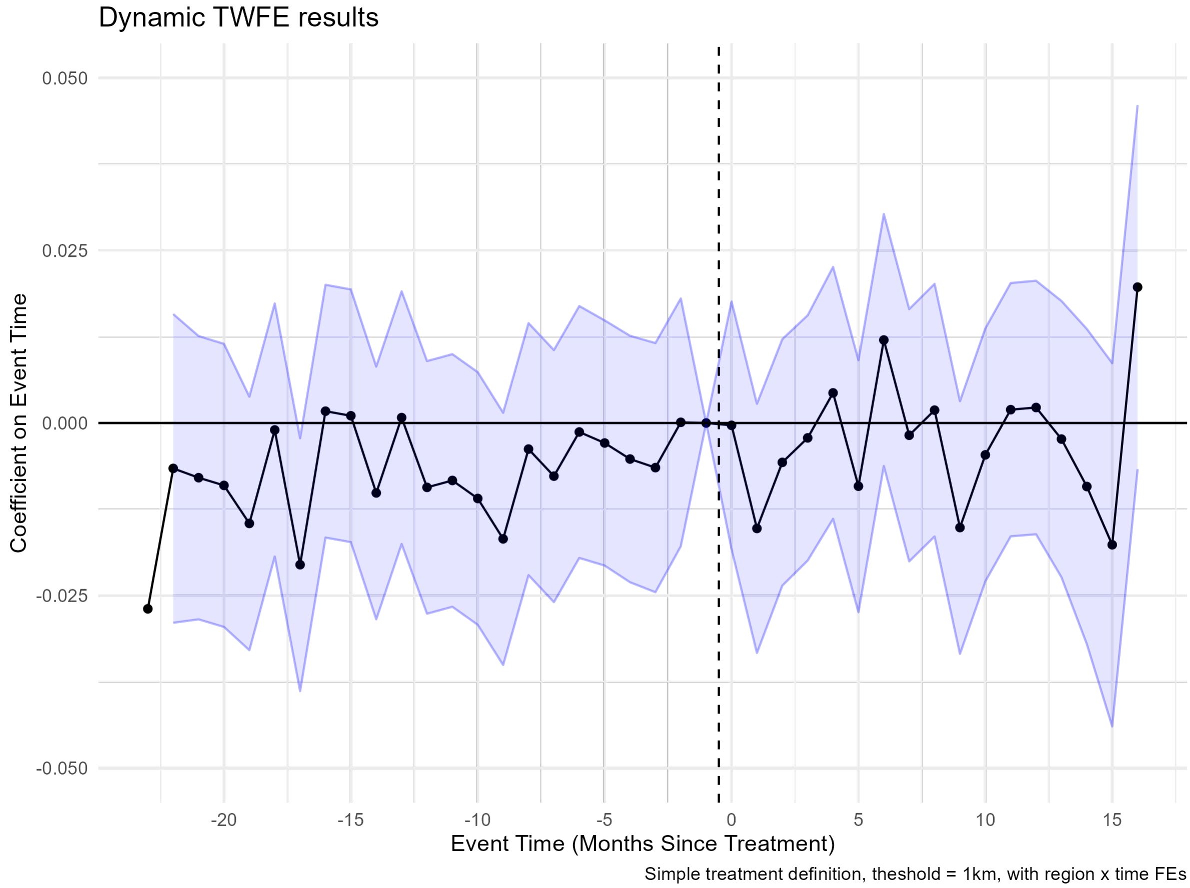
$$y_{it} = \alpha_i + \delta_t + \sum_{k \neq -1} \beta_k \mathbb{1}\{t - s_i = k\} + \epsilon_{it}$$



No controls cause problems here, and so does the TWFE bias with heterogeneous TEs and staggered treatment. If there is an effect it looks likely to be positive, but on the whole, not very convincing at all.

More FEs and controls:
Treatment is determined at the location $\times$ month level, but less granular interactions can be added. Let r be the region of location l - then we can add region by month FEs. Also, include any time-varying (and possibly time-invariant, after interacting with time dummies and leaving one out for collinearity) covariates in the vector $\mathbf{X}_{irt}$. Then we can run the following:

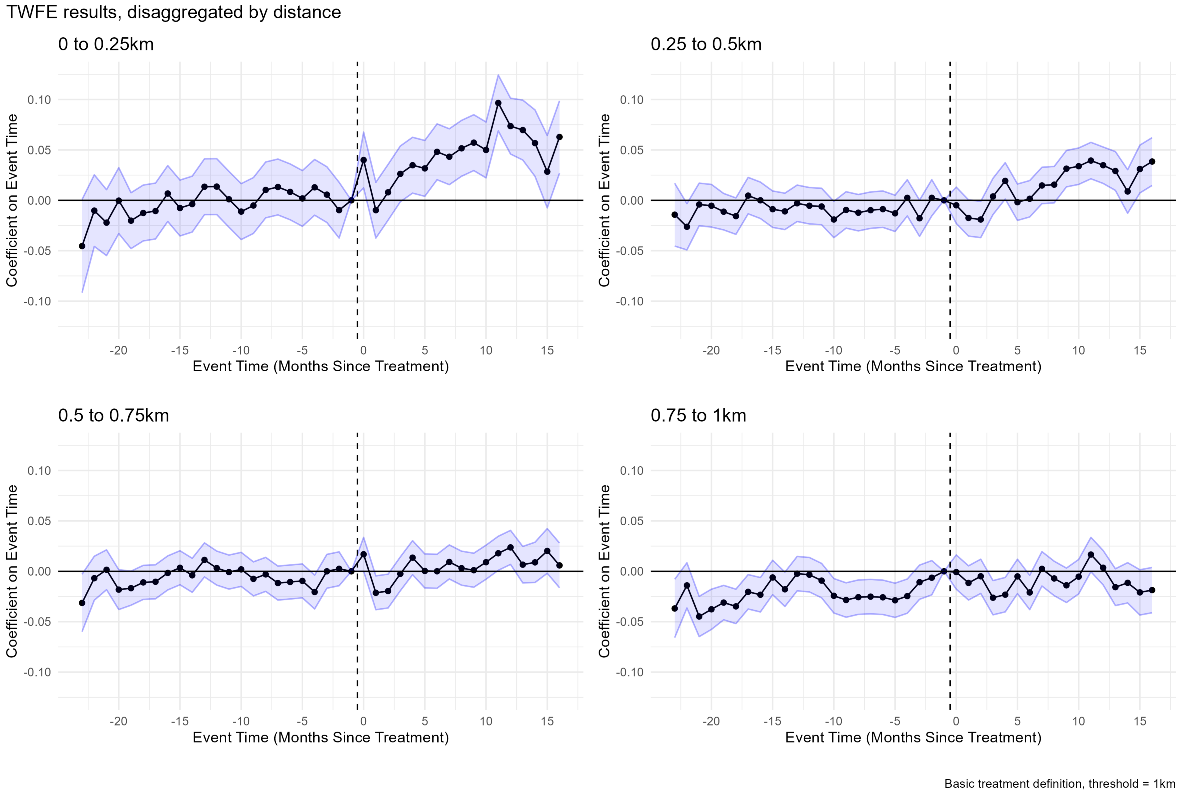
$$y_{irt} = \alpha_i + \delta_t + \gamma_{r\times t} + \sum_{k\neq -1} \beta_k \mathbb{1}\{t - s_i = k\} + \lambda \mathbf{X}_{irt} + \epsilon_{irt}$$



At the moment the regions are too granular: they are at the ward level, which are very small areas. Region $\times$ month FEs therefore absorb a lot of the treatment effect, and this is also probably why the standard errors are larger here than before. I also have no controls yet. This will be redone with broader region FEs, and controls as well.

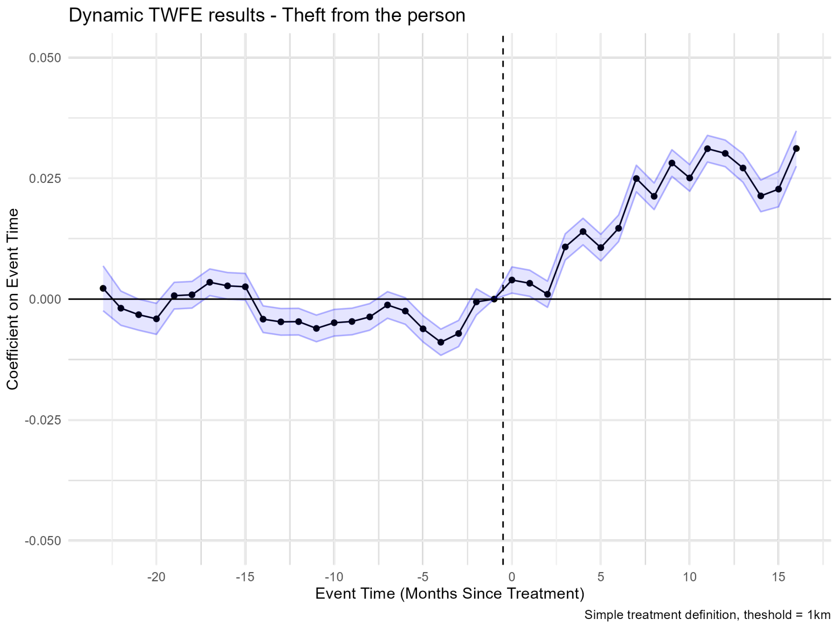
Interaction with distances:
Let $dist_i$ be the shortest distance from location i to an active night-tube station. Divide the interval $[0,1]$ up into N distance bands $\{b_1, ..., b_N\}$. Then we can get distance-specific ATT evolutions.

$$y_{irt} = \alpha_i + \delta_t + \gamma_{r\times t} + \sum_{n=1}^{N} \sum_{k\neq -1} \beta_k^n \mathbb{1}\{t - s_i = k\}\mathbb{1}\{dist_i \in b_n\} + \lambda \mathbf{X}_{irt} + \epsilon_{irt}$$

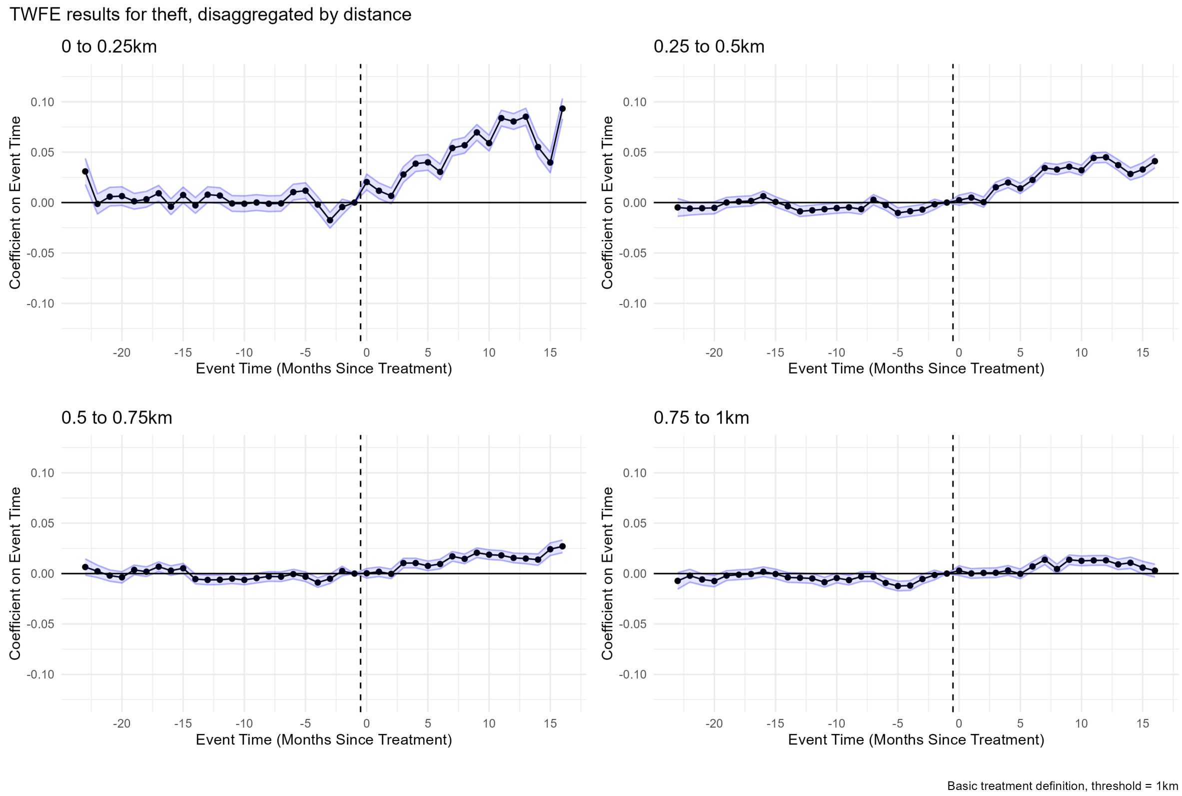


This is the result using no controls, no region × month FEs. They look better than before. There also appears to be a decay in the effect size as we go further from the station.

Disaggregate by crime type:
Do the above regressions using only counts of crimes of a certain type, to really understand how criminals respond to exogenous shocks that should theoretically make some crimes easier and not others. First theft from the person:



(a) Baseline TWFE



(b) TWFE disaggregated by distance

Results look good: we see an increase, as we would expect given the hypothesised mechanism. There is also a clear decay to near zero in the effect as we move further from the station. Unclear why the standard errors are so much smaller than before though.

Treatment intensity:
Define treatment in a continuous way, by summing the reciprocals of distances from all active tube stations. Define $dist_{is}$ to be the planar distance between location i and station s. Then define $T_{it} = \sum_{s \in S_t} \frac{1}{dist_{is}}$ as the sum of the reciprocals of the distances between location i and all stations in the set S_t of stations with night tubes running through them at time t. Then we can run a continuous version of the regression above (allowing for flexibility in the effect through higher order terms):

$$y_{irt} = \alpha_i + \delta_t + \gamma_{r \times t} + \beta_1 T_i + \beta_2 T_i^2 + \beta_3 T_i^3 + \lambda \mathbf{X}_{irt} + \epsilon_{irt}$$

We could also make this dynamic - let s now be the period of first treatment, August 2016. Then (possibly allowing for flexibility as above) we can run the following:

$$y_{irt} = \alpha_i + \delta_t + \gamma_{r \times t} + \sum_{k \geq 0} \beta_k \mathbb{1}\{t - s_i = k\} T_i + \lambda \mathbf{X}_{irt} + \epsilon_{irt}$$

Do everything above properly!
Other things to do:

- Estimate the above with estimators robust to the heterogeneous treatment effects and staggered treatment bias
- Vary sample selection (inner/outer? Just use observations around stations?)
- Vary treatment definitions more
- Matched DiD? Could match locations/regions beforehand
- Determine in the first case the response to the opening: were people using the night tubes? There will be data on this presumably
- Look at comparing only with regions around nearby stations: look at lines going out of London and get rings round just those
- We have to be careful that we aren't using as control the regions in which people would be going to if there was no night tube (i.e. no GE effects/SUTVA violations), and also nearby areas that experience spillover effects
- Triple differences - near vs far from the station, before vs after treatment, treated vs non-treated. Can we even do triple differences with staggered treatment?
- When measuring the decay of the effect over distance from the station, maybe residualise and then run a kernel regression of distance on the residuals
- Maybe use the log of treatment intensity
- What else?