In and around: Identifying predictors of theft within and near to major mass underground transit systems

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Abstract This paper identifies factors that encourage or reduce pick-pocketing at underground rail stations through a case study analysis of the London Underground. Negative binomial Poisson regression models found possible predictor variables of pick-pocketing selected from the internal characteristics of stations, and features of their nearby surroundings. Factors that increased risk were those associated with; greater congestion inside stations including lifts, waiting rooms and fewer platforms; and, increased levels of accessibility near stations, more paths and roads. Features that reduced risk were those likely to encourage detection and guardianship; stations with more personal validators, staffing levels, and shop rentals; and, the presence of more domestic buildings nearby. Station type was also influential; those that were 'attractors' of crime and those frequently used by tourists were at greater risk. The findings suggest a transmission of theft risk between the internal settings of underground stations and their nearby surroundings.

Keywords: Underground mass transit; theft; interstitial crime analysis, pick pocketing.

Introduction

This study analyses theft of personal property offences on the London Underground (LU). This major mass transit system carries over 1,000 million passenger per year, and experienced 5,063 theft offences in financial year 2011/2012 (BTP, 2013). Whilst this represents a rate of only four thefts per million passenger journeys, theft is a key offence type on the LU. Indeed, as a proportion of all offences, over half were for theft. This paper examines a specific type of theft offence, what Smith (2008) termed stealth crimes, for example pick-pocketing. It excludes snatching and other theft types. For these stealth offences, victims are often unaware items are stolen, only discovering them missing at a later date, on transit journeys usually somewhere else on the transit line. As the location of many of these thefts is unknown, an innovative methodology is used to better estimate the locations of theft on transit stations. This is termed Interstitial Crime Analysis (ICA) and is described in detail by Newton *et al* (2014).

This research builds on the Newton *et al* (2014) study into the spatial patterns of theft on the LU that found; theft was concentrated at a small number of stations; positive correlations existed between theft at three settings, ‘below ground’, ‘at’ stations; and, in ‘nearby’ surroundings of stations; and, that these correlations were most prominent at peak travel times. A key question that arose in the previous study which this paper attempts to address is: What are the explanations for these patterns of theft observed on the LU?

This paper aims to identify predictor variables of theft on the LU at two distinct settings; within underground rail stations; and, in the nearby surroundings of stations.

The key questions are; what predictor variables influence theft on the LU; and, is there any evidence of a transmission of theft risk between these internal and external settings?

Theoretical explanations and previous studies (for overviews see Smith and Clarke, 2000; Smith and Cornish, 2006; Newton, 2014) suggest three possible inter-related explanations for theft on transit systems; the presence of transit systems are themselves a system cause of theft; stations act as generators/attractors of theft; and, stations serve as a type of 'risky facility'.

Theoretical background

The presence of transit systems may help shape the crime patterns of urban areas (Piza and Kennedy, 2003). Stations act as a focal point, the entrances and exit to the system, and the interchanges connecting different journeys. During peak travel times they concentrate a number of persons together in small spaces, at other times stations are isolated with fewer users. The presence of a transit station may create opportunities for offending at particular locations at certain times of the day. Therefore, the first question is whether the transit system itself creates opportunities for theft, driven by passenger movement and passenger journeys.

Attractors and generators

Stations may serve as attractors or generators of crime (Brantingham and Brantingham, 1995). Crime attractors are places offenders visit due to known expected opportunities for crime, for example liquor stores, pawn brokers, drug-treatment centres, homeless shelters, and liquor clubs (Rengert *et al*, 2005; McCord *et al*, 2007). Generators are settings whereby a number of persons are channelled together, resulting in unplanned but favourable conditions for crime, for example high schools, football stadiums and parks (Groff and McCord 2012). Kurland (2013) states for football stadiums (although this could equally apply to underground stations) that they may act as; mostly a crime attractor; mostly a crime generator; or simultaneously as a crime generator/crime attractor. However, attractors and generators are difficult to quantify, a point returned to later in this paper. The second question to be explored is therefore whether stations act as an attractor or generator of theft, or both?

Stations may also act as 'risky facilities', a term used to describe similar land features such as bars or hospitals, or in this case underground rail stations, whereby, most of the crime at these facilities occurs at only a minority of them (Eck *et al*, 2007). Explanations for the presence of risky facilities are centred on the mobility of urban areas, determined by the geometry and patterns of crime (Brantingham and Brantingham, 1993). Offenders and victims have daily movement patterns termed routine activities (Felson and Cohen, 1980), and movement is concentrated at favourite activity nodes, for example based on work, leisure, or recreation activities. Risky facilities are often located at these activity nodes. Travel between nodes occurs along distinct routes (paths) constrained by obstacles (barriers) to movement, and offenders increase knowledge of suitable opportunities to offend during their routine activities. On transit systems there are may be certain nodes (stations) and paths (railway lines) that users favour. It is suggested that the presence or absence of certain features along these paths and at these nodes may encourage or deter offenders. A third question is therefore; what characteristics of stations and their nearby surroundings influence opportunities for theft?

All three theoretical standpoints propose that high crime stations will be located in high crime areas, and low crime stations in low crime areas. This suggests crime is a product of its wider environment, and Block and Block (2000) usefully term these nearby surroundings the ‘environs’ of rapid transit. However, the research evidence here is unclear. Not all stations in high crime areas experience high crime levels. Some studies suggest a well-designed transit station can insulate itself from crime in the wider environment (Clarke *et al*, 1996; La Vigne 1996); others argue high crime stations are situated in high crime areas (Block and Block, 2000; Loukaitou-Sideris *et al*, 2002; Ceccato *et al*, 2013, Newton *et al*, 2014). Few studies have examined this explicitly for theft. La Vigne’s (1996) study found Part I offences (including the subcategory of theft) were not correlated with their external environment. However, theft could not be isolated here from other Part I crimes thus findings here for theft alone may be skewed by other crime types.

Bowers (2013) examined whether crime risk transfers between the internal and external settings of risky facilities, and hypothesised risky facilities may act; as radiators of crime, the primary driver of risk radiating risk to the nearby surroundings; or, as absorbers of crime, soaking up crime from the surrounding environment. The study found risky facilities were more likely to act as radiators although did not include transit facilities in the analysis. Underground stations are a unique type of risky facility, a ‘true’ radiator, connected by underground lines (pipes) that can be entered and exited from their external environs, or underground via a different station. A final research question is therefore whether there is a transfer of theft risk between the internal settings of underground stations and their surrounding environs, and vice versa. The following research questions were devised for this study:

1. What are the predictor variables of theft on the LU?
2. Is theft on the LU influenced by both internal design characteristics (within stations) and the external settings near to stations (external features)?
3. Is there evidence of a transmission of theft risk between the internal settings of underground rail stations and their nearby external environs?

Theft on transit systems

Theft on underground stations has been shown to be non-uniform in time and space, concentrated at particular stations and peak times of the day (Loukatiou-Sideris *et al*, 2002; Ceccato *et al*, 2013; Newton, 2014). Theft concentrates at busy stations during the early morning and afternoon rush hour periods. However, high passenger numbers and nearby high theft levels alone do not provide a sufficient explanation of theft. Additional predictor variables present both inside stations (internal characteristics) and in their nearby surroundings (external features) are required to better explain theft levels on underground transit systems, and previous literature on potential mechanisms of theft on transit systems identified a number of possible predictor variables of theft.

Newton *et al* (2014) summarised a number of mechanisms that may act as predictor variables for theft at transit stations. For this study, these are grouped into the following classifications; high densities of people clustered together in small spaces; a lack of user knowledge about the system; the ease of passenger distraction; the accessibility and ease of access to and exit from stations; anonymity of offenders; barriers to movement between and within stations; and, staffing, protection and guardianship. These are not mutually exclusive, for example, high passenger density offers natural anonymity and reduced likelihood of detection. Moreover, individual predictor variables such as paid control gates, better lighting, or the presence of CCTV may impact on more than one of the above classifications.

Stations may act as a crime generator or attractor although few have attempted to quantify the differences between these. Perhaps a useful starting point here is offered by Clarke and Eck (2003); crime generators are defined as having a high count of crime but a low rate per population; and crime attractors as experiencing a high count and rate of crime, a point returned to later in this paper.

This is further complicated as additional features near to a station may also be a crime attractor or generator. Whilst some studies have examined attractors and generators near to risky facilities (Groff *et al*, 2010), few have examined this specifically for transit stations. Bernasco and Block (2011) investigated the influence of crime generators, crime attractors, and offender anchor points on robbery near to rail stations and found; pull factors such as crime generators increased the transient population of an area and therefore increased risk; blocks with attractors/generators of crime elevated crime risk in adjacent blocks; and, push factors such as the presence and proximity of a motivated offender's anchor point increased risk. Again, the authors did not distinguish between features that served as crime attractors and those that were crime generators.

Groff and McCord (2012) examined generators around parks and found; elevated levels of crime near to parks increased risk inside parks; that both the internal and external settings of parks influenced risk; and that features serving as activity generators inside parks reduced crime. Parks with more activity generators, generally the larger parks, had more legitimate users, more capable guardians, and therefore less crime. However, not all activity generators increase legitimate users. At transit stations more activity generators may not reduce theft. Increased numbers of users may actually increase targets but also disguise offenders. Loukatiou-Sideris *et al* (2002) term this a second level population density; as passenger levels increase, a certain density (first level) may be reached that encourages some violent crimes; beyond this, even higher passenger densities (second level) may actually promote some lower level crimes such as pick-pocketing.

Outside of parks, Groff and McCord found increased levels of mixed land use near parks reduced crime levels by increasing 'eyes on the street', consistent with the work of Jacobs (1961). However as discussed by Browning *et al* (2010) mixed land use may also increase crime prevalence due to territorial impacts, reducing informal levels of social control, consistent with Newman (1973). For this paper land use near to stations will be tested as an external predictor variable of theft, as this may serve to increase or potentially reduce theft levels.

Data and methodology

This study uses data from a range of sources, including data on theft within and near to stations, and possible predictor variables of theft, both inside stations (internal characteristics) and near to stations (the external environment).

Crime data

On the LU, stations are policed by the British Transport Police (BTP) and their external environs by the Metropolitan Police Service (MPS) and City of London Police (CoLP). Data was obtained from all three organisations for the 12 month period 1st April 2011 to 31st March 2012 for the following codes; Home Office (HO) codes shoplifting (HO classification 46); theft person (HO classification 39); and theft other (HO Classification 49); and BTP codes theft luggage (J02), theft personal property (J03), theft from the person (J04) and shoplifting (J22).

Theft data was captured for the internal setting, within stations, and the external environs near to stations. For theft at stations, the BTP theft data was separated into thefts 'at' stations with a known location, and theft that happens as part of a transit journey (with an unknown location). The latter was measured using the ICA measure to estimate likely locations of underground theft during transit journeys. A 400m buffer zone around stations was used for the external environs near to stations, a distance shown from previous studies to be appropriate (Newton *et* al, 2014). Additional crime data for other crime types which may influence theft levels were captured at census ward level as it was not available within the 400m buffer for this study.

Interstitial Crime Analysis (ICA)

A difficulty in analysing pick-pocketing offences is that time and location are often unknown; theft may have occurred at or between several stations traversed during a transit journey. The innovative ICA technique (Newton *et al*, 2014) generates probability estimates of the likely locations of theft on underground journeys using the following procedure.

Taking a hypothetical model; if pick-pocketed passenger 'X' travels from station A to station C, and changed at station B, then there are five 'sections' of this journey where theft may have occurred (station A; segment A to B; station B; segment B to C; and station C). The risk at each of the five sections is assigned a value of 0.2. If a second victimised passenger 'Y' travels from station A to C and did not change at B the risk is

0.25 at each section of the journey (station A; segment A to B; segment B to C; station C). If passenger ‘Z’ travels from station A to B, the risk at each section is 0.33 (station A; segment A to B; and station B). The ICA then generates a cumulative risk for each station and for each segment, based on the possible pick-pocketing offences for passengers X, Y, and Z combined. For this paper an ICA score was calculated for each station and station segment using 5063 theft offences on the LU. An ICA score for each station was generated. This was further standardised as a rate (ICA adj*), by dividing the ICA score by the number of annual passenger journeys at each station.

Predictor Variables

A range of station features were selected as potential ‘internal’ predictor variables of theft including; station age and depth, gates and validators, ticket machines, lifts and escalators, amenities, staffing levels and number of platform (Table One). An OLS regression model revealed these variables were highly correlated with each other, and therefore some variables were removed to avoid multicollinearity errors (Table 1). A second OLS regression model confirmed those selected for further analysis were within acceptable statistical levels (VIF< 3.5, Tolerance >0.25).

Table 1

A range of potential ‘external’ predictor variables for theft were identified from the environs of stations including; socio-demographic data, accessibility measures based on roads and paths, nearby crime levels, and local land use (Table Two). An OLS regression model was again used to remove any highly correlated variables. As a final stage, a third OLS model combining both the internal and external predictor variables was generated, and any highly correlated variables were removed before further analysis. The variance inflation factor and tolerance scores revealed variables selected for further modelling were appropriate.

Table 2

A third possible theft predictor variable of theft, in addition to the internal and external predictor variables is ‘station type’ and this was captured and classified using three methods. The first was based on fare zone ranging from zone 1 to zone 6; stations in zone 1 are in the centre of the LU network, those in zone 6 on the outskirts. The second was a TfL classification of primary usage and location, namely; ‘City’; ‘Inner Suburb’; ‘Outer Suburb’; ‘Shopping’; ‘Terminus’; and ‘Tourist’. The third method was an attractor/generator index (AGI) developed specifically for this paper.

Preliminary analysis found considerable variation when comparing stations which experienced high counts of theft, and those stations which had high rates of theft (per million passenger journeys). Only ten stations were in the top twenty of all LU stations for both theft counts and theft rates. Furthermore, there was also considerable spatial variation in high risk stations by time of the day. Therefore the AGI was developed to separate stations into possible crime attractors (with high counts and rates of theft) and potential crime generators (with high counts of theft only). These were also subdivided further by those that experienced; high rates of theft at all times of the day; high theft rates but only at certain times of the day; and, low theft rates.

Theft offences were broken down into six time periods; early (02.00-06:59); morning peak (07.00-09:59); inter-peak (10.00-15:59); afternoon peak (16.00-18:59); evening (19.00-21:59); and late (22.00-01:59). For all stations ICA and ICA adj* scores were calculated, across each of the six time periods. The AGI score devised was then used to classify stations into six types; AGI_1, high theft counts at all time periods; AGI_2, high theft rates at all time periods; AGI_3, high theft counts and high theft rates at all time periods; AGI_4, intermittently high theft counts and rates (at some but not all times of the day; AGI_5, intermittent medium theft rates and counts; and AGI_6, low risk of theft counts and rates.

Modelling

A series of negative binomial Poisson regression models were constructed. The dependent variable was theft at stations measured using the ICA, and this was regressed against a series of potential internal and external predictor variables. Preliminary analysis of the distribution of the ICA scores based on cumulative count data revealed this was highly skewed and over dispersed. Therefore negative binomial Poisson regression models were deemed appropriate (Hilbe, 2011) as used in a number of studies (Osgood, 2000; MacDonald and Lattimer, 2010; Bernasco and Block, 2011).

Six models were constructed; model 1 considered internal characteristics, model 2 external features, and model 3 combined internal and external variables. Three additional models were generated (4-6) to incorporate station type into the analysis, using fare zone, TfL classification, and the AGI score.

The negative binomial Poisson models use theft counts rather than rates. The population at risk is accounted for through the use of an exposure measure, the offset variable. In this analysis, annual per million passenger journey counts at each station were used as the offset variable. Therefore passenger levels which may influence theft levels (Ceccato *et al*, 2013; Newton *et al* 2014) are included in the model but not as a direct predictor variable. The procedure for generating each model was; enter each predictor variable one at a time, significant variables are kept, and none significant variables are removed at each iteration stage. This was repeated for all predictor variables. At the end of this procedure, none significant variables are re-entered into the model to check if they influence the final model and re-included if significant.

Results and Discussion

Model 1 examined internal predictors of theft (Table 3) and variables found to have a statistically significant positive relationship with theft were; the number of lifts that are primary means of access to platforms; and the number of waiting rooms. Negative relationships were found for; station depth; the number of electronic gates; and, the number of platforms. In model 2 (Table 3) external variables found to positively influence theft were; the percentage of roads and paths near to stations; and high levels of theft nearby. Negative relationships were found between theft and; more domestic buildings nearby; and, high levels of violence against the person near to stations. The log likelihood, BIC and AIC values in models 1 and 2 showed they were both better predictors of theft than the baseline model 0 (stations offset by passenger numbers with no predictor variables).

Table 3

Model 3 combined both internal and external predictor variables of theft into a single model (Table 3). The log likelihood, AIC and BIC scores revealed model 3 was a better predictor of theft than models 1 and 2. There were some differences in identified predictor variables. In model 3, variables found to have a negative correlation with theft included; station depth; the number of personal validators; staffing levels; the number of platforms; and, more domestic buildings nearby. Variables shown to significantly increase theft were; the number of lifts which are primary access to platforms; waiting rooms; the percentage of roads and paths in nearby environs, and increased theft levels in the surrounding area.

Models 4 to 6 incorporated station classification into the analysis. Fare zone was found to be none significant and removed. Model 4 analysed the TfL classification of station type and model 5 examined the AGI values. Model 6 combined TfL classification and AGI values (Table 4). In model 4 a significant positive relationship was found between theft and stations classed as 'tourist', and a negative relationship with 'terminus' stations. In model 5 a positive relationship was found between theft and AGI_3 stations (possible crime attractors), and a slightly negative relationship with AGI_5 stations (with intermittent medium levels of theft only at some times of the day). AGI_1 stations (possible crime generators) were also slightly positively correlated with theft. The final model (6) combined all three measures, the internal and the external predictor variables and station typology. The log likelihood, ACI and BCI scores revealed model 6 was a better predictor of theft than all previous models.

Table 4

From model 6 it was evident that predictor variables that reduce the risk of theft are; higher numbers of staff, personal validators, platforms, and shop rentals; more domestic buildings nearby; and stations classified as terminus stations. Potential explanations here are; that validators may reduce offender anonymity; increased staffing levels may increase possible detection and reduce anonymity of offenders; more platforms at stations may disperse passengers throughout the station and therefore victims are less concentrated; and, nearby domestic buildings might encourage more guardianship, or users may be familiar with the station and use it regularly thus be more aware of suspicious offender activity.

Factors that increased the risk of theft below ground included; the number of lifts which are primary means of access to platforms; the number of waiting rooms; theft ‘at’ stations; the percentage of roads and paths in the nearby environs; nearby levels of theft; and stations identified as crime attractors. Potential explanations here are that; lifts and waiting rooms may concentrate persons in confined spaces; more roads and paths may increase accessibility and, or, increase the movement of persons to and away from an area; and, high levels of theft nearby, consistent with Newton *et al*, (2014) indicate a likely transmission of risk from inside a station to its external environs, and vice versa. Moreover, model 6 which incorporated internal characteristics, external variables, and station typology, was a better predictor of theft than other models, suggesting there is an interaction between the internal and external features that influence theft, and, therefore, it is argued that a transmission of theft risk does exist between underground stations and their nearby environs.

There are a number of potential limitations with this analysis. The ICA technique may not accurately estimate likely locations of risk as it assumes that the risk at a segment between two stations, and the risk at a station are equal. Suggestions for future refinement of the ICA method are provided by Newton *et al*, (2014). The AGI index could also be further refined and tested. The predictor variables used may not include all relevant variables, and external predictors are aggregated using census wards which may not representative of station environs. Recorded crime data is subject to under-reporting, although it is contended under-reporting of theft is likely to be a universal problem across the entire LU, not skewing the ICA scores by individual stations. The analysis is based on the LU network and there may be errors due to spatial auto-correlation. However, although the ICA scores are subject to a high degree of spatial auto-correlation, an examination of the ICA adj* (standardised per million passenger journeys) did not find such errors. The negative binomial Poisson regression models are offset by the passenger data thus it is not thought spatial autocorrelation errors are present.

Conclusion

This paper examined potential predictor variables of theft selected from the 'internal' settings of stations and their nearby 'external' environs. It combined the use of the innovative ICA measure for predicting underground theft at unknown locations and times, with negative binomial Poisson regression models to identify predictor variables of theft on the LU. Factors found to increase risk of theft were those that may encourage congestion of passengers within stations (lifts and waiting rooms), and those that increased levels of accessibility and access to stations (more paths and roads nearby). In contrast those that reduce theft were those likely to decrease anonymity and increase potential guardianship and offender detection (higher levels of staffing, personal validators, shop rentals, and more domestic buildings nearby), and those that disperse passengers throughout the station and avoid congestion (more platforms). Stations with higher theft levels in their surrounding environs, those identified as crime attractors (high theft counts and high theft rates), and stations with high levels of tourist use were at greater risk. Terminus stations were at lower risk.

Policy implications and future avenues

The evidence presented in this paper suggests offenders operate both inside the LU and near to underground stations. Indeed, even if different offenders are in operation at these two settings, at peak travel times this elevated risk occurs both within and near to high risk stations, thus deployment of resources, joint operations and shared intelligence between BTP, MPS and CoLP should be encouraged. The ICA technique can assist in identifying the location and times of high risk stations, and deployment at these times and places should focus on both settings, within stations and in their nearby environs, as both are subject to elevated risk levels.

This paper presents evidence of a transmission of theft risk between the internal and external environments and vice versa, and therefore it is likely that barriers to movement between these settings (for example paid access gates) are perhaps not effective at deterring pick-pocketing offenders. An explanation offered by Newton *et al*, (2014) is that offenders are able to travel 'unregistered' on the LU using Oyster cards (plastic pre-paid travel cards) and all day travel cards, which can be bought with cash at automated machines. These travel cards are inexpensive for all day travel, and the price of travel may be small compared to the potential rewards of successful and undetected theft activity.

The findings of this paper present a range of potential design solutions, for example increased accessibility outside stations and increased congestion within stations increases theft risk. However, any design alterations such as restricting accessibility may increase other crime types on the LU, or indeed impact negatively on user's experience and feelings of safety. Moreover, features that increase or reduce theft risk are present both within the internal settings and in the nearby environs of stations, thus measures that address only internal or only external risk factors in isolation may not be effective in reducing theft.

Further avenues for research

The ICA technique should be further refined to better assign risk at stations and segments, for example based on journey time, platform length, carriage capacity, or other possible weightings of risk. A number of additional variables not currently captured could be incorporated into the model, for example line of sight, visibility, lighting, and CCTV. Better measures of nearby predictor variables could also be captured, for example within 250m of a station as opposed to entire census ward areas. Accessibility and congestion could be modelled using CCTV data for example to compare high and low risk stations for theft by different times of the day. The AGI index should also be refined, to develop better measures of crime attractors and crime generators for studies that examine crime at risky facilities.

The ICA technique allows identification of stations that experience high and low levels of theft. This could be used to identify stations for further fieldwork, capturing information on the individual settings within a station, for example on platforms, on stairwells and escalators, to advance knowledge of which sections within a station are more at risk, and at which time of the day or day of the week. The ICA technique could also be used to evaluate the impact of prevention activity, for example deployment of plain clothed and uniform officers could be monitored and compared. The analysis presented here considers two settings, inside and near to stations. Stations could be further subdivided, for example Ceccato *et al* (2013) identified the following; the immediate vicinity; exits and entrances; lounges; transition areas; and platforms; and

Newton *et al*, (2014) identified four alternative settings; near to but outside a station; inside a station but before the paid barrier control, within a station inside the paid barrier control including platforms, escalators and lounges; and on carriages themselves. It may be useful to examine theft against these more detailed settings in a refined model.

Finally this study does not consider the items stolen. It may be useful to study theft offences by the type of property, as the increasing use of mobile technology and smart phones may be attractive to offenders, as a primary or secondary target as opposed to wallets, purses and their contents. There may be different patters observed by type of product stolen. Additionally changes to the network may impact on theft, for example current proposals on the LU to close three out of four ticket offices, extend services to 24 hours, and increase Wi-Fi coverage on the network may actually impact on theft, and or other crime levels. Careful consideration should be given to the management of stations if such changes are introduced.

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Table One: Potential predictor variables of theft – Internal station settings

Predictor	Influence	Selection
Supplied by TfL		
Passenger journey (per million passengers)	CD	Offset Variable
N electric gates (new version)	BM	Y
N pneumatic gates	BM	NMC
N electric gates (old version)	BM	NMC
N manual gates	BM	NMC
N manual gates (1 off type)	BM	Y
N wide aisle gates	BM	NMC
N passenger validators	BM	Y
N ticket halls	FCG	Y
N waiting rooms	FCG	Y
N cash machines	FCG	Y
N shop rentals	FCG	Y
N kiosk rentals	FCG	Y
Station age (years)	FCG	Y
Cycle racks (Yes/No)	FCG	Y
Control room visible to passengers (Y/N)	FCG	Y
Toilets (Y/N)	FCG	NNS
N lifts where primary access	CA	Y
N lifts where secondary access	A	Y
N non-station lifts	A	NNS
N stair lifts	A	NMC
N escalators	A	Yes
N passenger conveyors	A	NMC
Station depth: average platform depth (m)	A	Y
N tube platforms	CA	NMC
N surface platforms	CA	Y
N sub-surface platforms	CA	Y
N island platforms	CA	NMC
Estimated staffing levels (number)	D	Y
Supplied by BTP		
At station theft personal property: J04	OA	Y
At station shoplifting: J03	OA	Y
At station theft other: J22	OA	Y

Predictor: N=Number of
Influence: CD=Congestion/Detection; BM=Barrier to Movement; FCG=Facilities/Congestion/Guardianship; CA=Congestion/Accessibility; A=Accessibility; DG=Detection/Guardianship; OA=Offender Activity
Selection: Y=Yes; NNS= No, not significant, NMC= no, multi-collinearity

Table Two: Potential predictor variables of theft – external nearby settings

Predictor	**Source** GLUD unless stated	**Influence**	**Selection**
Crime			
Nearby station shoplifting (<400m)	MPS/CoLP	OA	Y
Nearby station other theft (<400m)	MPS/CoLP	OA	Y
Theft and handling rate (census ward)		OA	NNS
Robbery rate (census ward)		OA	NNS
VAP rate (census ward)		OA	Y
SES characteristics (census ward)			
Population density		DC	NNS
Average house prices		SES	NNS
Index of Multiple Deprivation Score	ONS	FCG	NNS
LU- % domestic buildings		FCG	Y
LU- % domestic gardens		FCG	NMC
LU-% non-domestic buildings		FCG	NMC
LU- % green space		FCG	NMC
LU-% roads		A	Y
LU- % rail		A	NMC
LU % paths		A	Y
LU - % other land use		FCG	Y
% claiming incapacity benefits		FCG	NMC
% claiming income support		FCG	Y
% of Unauthorised school absence		FCG	Y
% of young persons (<16)		M	Y
% working persons		M	NMC
% old		M	Y

Predictor: LU = Land Use
Source: MPS=Metropolitan Police Service; CoLP=City of London Police; GLUD=Generalised Land Use Database; ONS=Office National Statistics
Influence: CD=Congestion/Detection; BM=Barrier to Movement; FCG=Facilities/Congestion/Guardianship; CA=Congestion/Accessibility; A=Accessibility; DG=Detection/Guardianship; OA=Offender Activity
Selection: Y=Yes; NNS= No, not significant, NMC= no, multi-collinearity

Table Three: Regression analysis: Internal and external characteristics of stations and theft

	Model 1: Internal Only			Model 2: External			Model 3: Internal and External		
Predictor variable	B	SE	Sig	B	SE	Sig	B	SE	Sig
Approximate age	0	0.002					-	-	
Station depth	-0.01	0.003	***				-0.006	0.003	**
Electronic gates	-0.036	0.009	***				-	-	
Manual gates	-1.53	0.844	*				-1.14	0.793	
Personal validators	-0.031	0.018	*				-0.036	0.017	**
Lifts (primary access)	0.118	0.049	**				0.111	0.045	**
Lifts (secondary access)	0.063	0.042					0.04	0.036	
Staff levels (estimated)	-0.008	0.007					-0.016	0.005	***
Sub surface platforms	-0.168	0.06	***				-0.107	0.054	**
Surface platforms	-0.167	0.049	***				-0.136	0.046	***
Ticket halls	-0.054	0.13					-	-	
Waiting rooms	0.151	0.08	*				0.141	0.079	*
Shop rentals	-0.005	0.011					-0.013	0.011	
Kiosk rentals	-0.054	0.062					-	-	
Cycle racks	-0.192	0.107	*				-	-	
Control room	-0.127	0.104					-	-	
At station thefts	-0.005	0.007					0.001	0.006	
Domestic buildings				-0.047	0.015	***	-0.031	0.012	***
Road				0.043	0.014	***	0.039	0.012	***
Path				0.22	0.062	***	0.247	0.055	***
Other land uses				-0.017	0.012		-0.011	0.011	
Children				0.003	0.017		0.013	0.014	
Elderly				0.008	0.023		0.028	0.019	
% Claim income support				-0.034	0.032		-0.026	0.025	
% Unauthorised school Absence				-0.037	0.187		-	-	
Violence rate				-0.002	0.001	**	-	-	
Shoplifting <250m				-0.009	0.009		-0.007	0.008	
Theft person < 250m				0.013	0.007	**	0.011	0.006	*
Other theft < 250m				0.002	0.01		-0.006	0.008	
Constant	1.125	0.373		-0.968	0.59		-0.607	0.632	
minus 2*LOG(lh)		1024.97			1023.42			944.258	
AIC		1170.532			1120.520			1031.237	
AICC		1173.313			1122.213			1036.149	
BIC		1172.56			1165.158			1106.779	

***99% significance; **95% significance, * 90% significance

Table Four: Regression analysis: Internal and external characteristics of stations, station classification and theft

	Model 4			Model 5:			Model 6		
Predictor variable	B	SE	Sig	B	SE	Sig	B	SE	Sig
Station depth	-0.003	0.003		-0.005	0.003	*	-0.003	0.003	
Manual gates	-1.218	0.766		-1.002	0.771		-1.107	0.753	
Personal validators	-0.025	0.016		-0.035	0.016	**	-0.027	0.015	*
Lifts (primary access)	0.103	0.041	**	0.084	0.044	*	0.07	0.04	*
Staff levels	-0.018	0.005	***	-0.013	0.004	***	-0.016	0.004	***
Sub surface platforms	-0.109	0.056	**	-0.147	0.052	***	-0.094	0.053	**
Surface platforms	-0.101	0.044	**	-0.111	0.045	**	-0.087	0.043	**
Waiting rooms	0.128	0.075	**	0.139	0.077	*	0.13	0.074	*
Shop rentals	-0.011	0.009		-0.027	0.01	***	-0.02	0.009	**
At station thefts	-0.001	0.005		0.017	0.007	**	0.012	0.006	**
Domestic buildings	0.033	0.016	**	-0.028	0.012	**	-0.018	0.01	*
Roads	0.014	0.011		0.033	0.012	***	0.021	0.011	**
Paths	0.138	0.052	***	0.217	0.052	***	0.131	0.049	***
Other land uses	-0.005	0.01		-0.016	0.011		-0.009	0.011	
Children	0.007	0.011		0.016	0.011		-0.011	0.011	
Elderly	-0.008	0.011		0.257	0.183		0.023	0.019	
Shoplifting <250m	-0.014	0.008	**	-0.004	0.008		-0.009	0.007	
Theft Person < 250m	0.012	0.005	***	0.009	0.006		0.01	0.005	**
Other Theft < 250m	-0.007	0.007		-0.012	0.008		-0.013	0.007	*
AGI1	0.304	0.181	*	-	-		0.207	0.174	
AGI2	0.066	0.174		-	-		0.064	0.169	
AGI3	0.91	0.151	***	-	-		0.811	0.147	***
AGI4	0.083	0.14		-	-		0.079	0.134	
AGI5	-0.219	0.118	*	-	-		-0.21	0.117	*
Tourist				0.246	0.181		0.351	0.163	**
Shopping				0.021	0.203		0.088	0.181	
Inner suburb				0.027	0.196		0.271	0.18	
Outer suburb				-0.286	0.23		-0.001	0.22	
Terminus				-0.955	0.297	***	-0.55	0.276	**
Constant	-0.855	0.602	-1.42	-0.689	0.636		0.057	1.125	0.050
minus 2*LOG(lh)	893.594			919.17			868.13		
AIC	964.9068526			989.283			947.472		
BIC	1050.749903			1075.126			1050.484		

***99% significance; **95% significance, * 90% significance