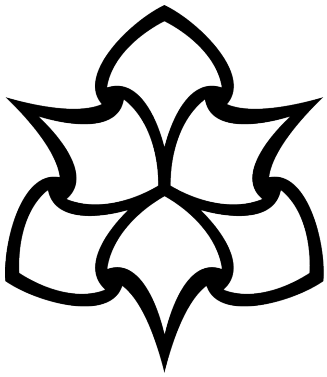

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# The influence of intra-daily activities and settings upon weekday violent crime in public space in Manchester, UK

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| **Abstract:** | People ebb and flow across the city. The spatial and temporal patterning of crime is, in part, reflective of this mobility, of the scale of the population present in any given setting at a particular time. It is also a function of capacity of this population to perform an active role as an offender, victim or guardian in any specific crime type, itself shaped by the time variant activities undertaken in, and the qualities of, particular settings. To this end, this paper explores the intra-daily influence of activities and settings upon the weekday spatial and temporal patterning of violent crime in public spaces. This task is achieved through integrating a transient population dataset with travel survey, point-of-interest and recorded crime data in a study of Great Manchester (UK). The research deploys a negative binomial regression model controlling for spatial lag effects. It finds strong and independent, but time variant, associations between leisure activities, leisure settings and the spatial and temporal patterning of violent crime in public spaces. The paper concludes by discussing the theoretical and empirical implications of these findings. |
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# The influence of intra-daily activities and settings upon weekday violent crime in public spaces in Manchester, UK

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**Abstract**
People ebb and flow across the city. The spatial and temporal patterning of crime is, in part, reflective of this mobility, of the scale of the population present in any given setting at a particular time. It is also a function of capacity of this population to perform an active role as an *offender, victim or guardian* in any specific crime type, itself shaped by the time variant activities undertaken in, and the qualities of, particular settings. To this end, this paper explores the intra-daily influence of activities and settings upon the weekday spatial and temporal patterning of violent crime in public spaces. This task is achieved through integrating a transient population dataset with travel survey, point-of-interest and recorded crime data in a study of Great Manchester (UK). The research deploys a negative binomial regression model controlling for spatial lag effects. It finds strong and independent, but time variant, associations between leisure activities, leisure settings and the spatial and temporal patterning of violent crime in public space. The paper concludes by discussing the theoretical and empirical implications of these findings.

**Key words**: Routine activities, Exposed population-at-risk, Transient population, Interpersonal variability, Trip purpose, Violent crime in public spaces.

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# The influence of intra-daily activities and settings upon weekday violent crime in public spaces in Manchester, UK

**Abstract**

People ebb and flow across the city. The spatial and temporal patterning of crime is, in part, reflective of this mobility, of the scale of the population present in any given setting at a particular time. It is also a function of capacity of this population to perform an active role as an *offender, victim or guardian* in any specific crime type, itself shaped by the time variant activities undertaken in, and the qualities of, particular settings. To this end, this paper explores the intra-daily influence of activities and settings upon the weekday spatial and temporal patterning of violent crime in public spaces. This task is achieved through integrating a transient population dataset with travel survey, point-of-interest and recorded crime data in a study of Great Manchester (UK). The research deploys a negative binomial regression model controlling for spatial lag effects. It finds strong and independent, but time variant, associations between leisure activities, leisure settings and the spatial and temporal patterning of violent crime in public spaces. The paper concludes by discussing the theoretical and empirical implications of these findings.

**Key words**: Routine activities, Exposed population-at-risk, Transient population, Interpersonal variability, Trip purpose, Violent crime in public spaces.

# 1. Introduction

There is longstanding recognition of the necessity to calculate population denominators with reference to specific crime types (Boggs 1965). Failure to do so may serve to inflate or deflate the crime rate (Song et al. 2018), disguising the true nature of the crime problem and impeding its effective address. To this end, Haleem et al. (in this issue) introduced the concept of the exposed population-at-risk, defined as the mix of residents and non-residents who may play an active role as an offender, victim or guardian in a specific crime type, present in a spatial unit at a given time. The exposed population-at-risk, therefore, requires not only the quantification of population present but also the qualification of what they are doing with whom, enabling delineation of whether they can perform an active role in relation to a specific crime type. In this paper, which examines violent crime in public spaces, and reflective of the data qualities at our disposal we identify the transient (mobile) population as the best measure of the exposed population-at-risk, i.e., excluding those at home, who would be unable to perform an active role in public spaces. We return to this issue in detail, below (A conceptual model of likelihood of violent crime in public spaces).

To date, limited attention has been given to a consideration of the intra-daily influence and interplay of activities and settings upon the propensities of the population to perform active roles as offenders, victims or guardians (Hipp 2016; Song et al. 2018). Identifying a falling exposed population-at-risk count to be associated with a rise in late evening violent crime in public spaces, Haleem et al. (in this issue) postulated that it was a likely function of the shifting propensities of that population to perform particular active roles in the setting of the night-time-economy (NTE). To further elucidate this issue, we examine the influence of time variant activities, or the interpersonal variability of population activity patterns (Dharmowijoyo et al. 2014; Moiseeva et al. 2014; Pas and Koppelman 1986), and the characteristics of settings upon the spatial and temporal patterning of violent crime in public spaces on weekdays. Specifically, the research addresses the following questions:

- To what extent do the intra daily activities of the exposed population-at-risk influence the likelihood of violent crime in public spaces?
- To what extent to the characteristics of settings influence the likelihood of violent crime in public spaces?
- Does violent crime in public spaces in one neighbourhood influence the likelihood of violent crime in public spaces in adjacent neighbourhoods?

To achieve this task the research deploys a mobile phone dataset, capable of distinguishing the origin and destination of population trip chains (McGuckin and Murakami 1999), enabling exclusion of those at home, to calculate the exposed (i.e., transient) population-at-risk of violent crime in public spaces. Here, public spaces are defined as comprising streets, alleys, parks and open spaces as well as private spaces to which the citizenry are granted access (e.g., pubs, shops and nightclubs). The paper utilises data derived from travel surveys to qualify the time variant activities embedded in transient population trip chains and point of interest data to define and quantify the characteristics of trip destinations. These data are integrated with fine grained recorded crime data, capable of delineating the Cartesian and temporal coordinates of each crime and the setting in which it took place. This research employs a negative binomial statistical modelling approach, controlling for spatial lag effects in the dependent variable, to estimate the influence of the routine activities

embedded in intra-daily population flows and the characteristics of settings upon the likelihood of violent crime in public spaces taking place.

The paper is structured in the following manner. In the next section, a brief literature review is presented in order to establish a conceptual model of how the interplay of time variant activities and settings serve to shape likelihood of violent crime in public spaces. In section three, the data deployed in this research are described. In section four, the analytical strategy of the research is presented. In section five, the modelling estimated results are presented and described. Finally, we discuss the theoretical and empirical implications of the research findings.

## 2. Background

Crime is over-dispersed in space and time. It concentrates in certain areas (Sherman et al. 1989; Weisburd 2015; Weisburd et al. 2012) at particular moments in time (Brunsdon et al. 2007; Newton 2015; Townsley 2008). The volume of crime in any area at a given time is, at least in part, a function of the scale of the population present. Recognising the daily rhythms of the city, the ebb and flow of the citizenry as they undertake routine activities, multiple endeavours (see Malleson and Andresen (2016) for a review) have been made to capture an ambient population-at-risk count (Andresen 2011), the mix of residents (the static population) and non-residents (the transient population) present in an area at a given time. Haleem et al. (in this issue), however, challenge the appropriateness of applying ambient (i.e., total) population counts. Instead, they argue that an exposed population count, defined as the mix of residents and non-residents who may play an *active* role as an offender, victim or guardian in a specific crime type, present in a spatial unit at a given time, to be a more theoretically relevant population denominator. In these terms, an emergent challenge is that of assessing the propensity, or shifting spatial and temporal propensities, of the exposed population-at-risk to perform an active role as an offender, victim or guardian.

Routine activities theory (Andresen and Jenion 2010; Cohen and Felson 1979) proposes that for a crime to occur it is necessary that a motivated offender and a suitable victim (or target) must hold co-presence in the absence of a capable guardian. However, the likelihood of an individual performing a specific role and the cumulative balance of offenders, victims and guardians present in a spatial unit at a given time may vary (Hipp 2016). Crime pattern theory (Brantingham and Brantingham 1993), building on the concepts and mechanisms of routine activity theory (Bernasco 2014), explains the spatial and temporal concentration of crime as an outcome of the interplay between the flow of the population along specific travel routes (paths) and their confluence in specific locations (nodes) associated with a multitude of activity types (e.g., in-home, work, leisure, schooling). In this vein, Summers and Johnson (2017) have sought to explain the location of outdoor serious violence according to the configuration (or space syntax) of street networks. Anchor points (Rossmo 2000; Townsley et al. 2016; Townsley and Sidebottom 2010) emerge, locations in which people spend longer periods of time. In such locations, crime can be understood as a function of the characteristics of the residential and transient population (Felson and Boivin 2015), depending on the crime type under investigation, and of the qualities of the urban environment (Kinney et al. 2008). In effect, of course, these factors are inter-related.

The ebb and flow, or space-time geography (Hägerstraand 1970; Miller 2005), of the citizenry is shaped by physical limitations to movement (capability constraints), the requirement to undertake mandatory societal roles (e.g., work, education) in specific locations and at particular times (coupling constraints), and by the accessibility of specific locations (authority constraints). Thus, an individual's space-time geography is a reflection of the interplay between the attainment of required and desired goals, framed by a set of spatial and temporal constraints (Arentze and Timmermans 2004). The emergent sequential-activity-travel patterns, or trip chains (McGuckin and Murakami 1999), are "often habitual and shaped by repeated travel between the same locations" (Bernasco 2014, p. 3). In aggregate, the daily routines of the citizenry generate a constant churn of population groups with different motivations and characteristics. The balance between residents (static) and non-residents (transient) in any given spatial unit will vary across time. In situations where there is a high relative prevalence of transient groups, it is plausible that propensity towards guardianship will decline (Boivin 2018).

An individual's social, demographic and lifestyle characteristics affect where they go, what they do and how long they take to do it (Hasan et al. 2013; Lemieux and Felson 2012), as well as their likelihood of performing offending, victimisation and guardianship roles (Curiel and Bishop 2018). The perception of the risk of victimisation may or may not, through choice or constraint, alter their presence or duration at specific locations (Hipp 2016). Examining the exposure risk to violent crime, Lemieux and Felson (2012) calculated a time-adjusted rate measure – the *person hour*, to compare the association between different types of daily activity and the risk of victimisation. They identified that 'attending school' and 'leisure activities away from home' were associated with a high risk of victimisation, though 'travelling to or from work' and 'travelling to or from school' presented the highest risk of victimisation. They concluded that transit activities were considerably riskier than the premise (setting).

The use of transportation data is increasingly prevalent in research seeking to explore crime patterning and is deployed to quantify population flows and qualify the activities (trip purposes) embedded in them (Boivin 2018; Boivin and D'Elia 2017; Boivin and Felson 2018; Felson and Boivin 2015). In overview, these researches make clear that the scale of the transient population and its motivation serve to shape the *daily* patterns of both property and violent crime types. There are, however, a number of data limitations associated with these existing studies, as recognised by the researchers, centred on the spatial and temporal granularity of the transportation and crime data utilised. Of keynote, given the ambition of the current study, these analyses are not capable of distinguishing the scale and nature of activities (trip) purposes at different times of the day, nor are they capable of distilling the temporal qualities of crime patterning.

The land use features, of any given spatial unit, hold a significant impact on the volume of crime that takes place in that spatial unit (Taylor and Gottfredson 1986; Wo 2019). Particular land use types act as crime generators in that they serve to draw in population groups and / or as crime attractors in that they serve to draw in offenders (Brantingham and Brantingham 1995). In other words, *risky facilities* (Bowers 2014) and *magnetic places* (Boivin and D'Elia 2017), such as alcohol-licensed premises (Conrow et al. 2015; Grubesic and Pridemore 2011; Hadfield et al. 2009; Snowden 2016), attract population groups with a heightened propensity to act as offenders or victims and a lowered propensity to act as a guardians, shaping the spatial patterning of crime (Haleem et al., in this issue).

Furthermore, the influence of the land use of any given location may vary through time, due to institutional constraints (e.g., opening hours), impacting upon the temporal patterning of crime . Thus, a city centre may hold mixed land use during the day, serving as a place of work, shopping, education and leisure activities, but at night it might act principally as the locus of the leisure activities. By implication the scale, characteristics and behavioural propensities of the population in the city centre will be time-dependent (Bichler et al. 2011), with the predominant land use and population mix affecting the 'mood' of the area (MacDonald 2015).

## *A conceptual model of likelihood of violent crime in public spaces*

The exposed population-at-risk of violent crime in public spaces, by necessity, comprises those people traversing and occupying that space, but not those for whom the locality represents an end destination (i.e., home). In other words, when at home, residents are unlikely to perform an active role in violent crime in public spaces[1]. In these terms, (and given the qualities of the data at our disposal, see below) the transient population can be established as the best measure of the exposed population-at-risk. Haleem et al. (in this issue) note that this definition may serve to overestimate the exposed population-at-risk at particular times of the day, particularly in periods when there are a high number of workers occupying private space. Similarly, by excluding those travelling to and from home, as we require to do here, may serve to underestimate the exposed population-at-risk.

Existing research has demonstrated that the spatial patterning of violent crime holds a strong association with the clustering and capacity of licensed premises (Gmel et al. 2016), particularly in city centre locations (Gerell and Kronkvist 2016). Relatedly, the temporal patterning of violent crime is associated with the functioning of the NTE, in which cumulative alcohol consumption increases the likelihood of offending whilst decreasing the likelihood of guardianship (Bellis et al. 2010; Flatley 2016; Hadfield et al. 2009). This may account for why the count of violent crime in public spaces rises over the course of an evening even though the count of the exposed population-at-risk declines. Building upon these insights, Fig 1 provides an illustrative model of the changing proportion of crime, as well as the scale and mix of activities being undertaken by the exposed population-at risk in a city centre setting, across different time periods. Here, the activity categories (work, education, shopping, personal business, recreation (e.g., sports) and leisure (e.g., eating and drinking)), time periods (T1 07:00-10.00, T2 10:00-16:00, T3 16:00-19:00, T4 19:00-07:00), population counts and crime data have been calibrated with reference to the data deployed in the research (see Data, below). The model is reflective of the coupling and authority constraints (Hägerstraand 1970; Miller 2005) that inform the pursuit of intra daily routine activities, shaping who does what with whom, where and when. Thus, and in T1, the majority of people travel to the city centre for work. In T2, the count of the population present in the city centre has grown and shopping becomes the dominant activity. In T3, the count of the population present in the city

[1] In stating this, we recognise an extensive literature inspired by Jane Jacobs (1961) that argues the role of citizens operating as 'eyes on the street' from inside their homes. This has informed approaches to Crime Prevention Through Environmental Design (CPTED) that have sought to promote forms of mixed land-use development and building design that maximise the opportunity for residents to act as visual guardians (Cozens and Hillier, 2012). However, and given that the majority of city centre residential developments appear to be mid or high-rise in nature, we are not convinced that they serve to effectively promote 'eyes on the street'?

centre is at its greatest. Shopping is still the dominant activity but there is an increase in those undertaking recreation and leisure activities. Finally, in T4, the population count in the city centre exhibits a dramatic reduction as people return home. Those undertaking leisure activities also exhibits decline, and is lower than in T3, but leisure becomes the dominant activity. The likelihood of violent crime in public spaces can be hypothesised, therefore, as an outcome of the time sensitive interplay of the activities being undertaken by the exposed population-at-risk in and the characteristics of particular settings. In these terms, the scale, relative preponderance and nature of specific activity types, in any given setting at a particular time, will serve to influence the propensity of that population to perform an active role as an offender, victim or guardian. Examining the proportion of daily recorded violent crime in public spaces, it is striking how this varies across different time periods, seemingly serving to confirm this hypothesis. Further and as the exposed population-at-risk moves through neighbourhoods adjacent to these settings, to undertake or having undertaken particular activities, it is likely that they will influence the likelihood of violent crime in public spaces in these neighbourhoods. Prior to progressing, it is important to recognise (as noted earlier) that social, demographic and lifestyle characteristics will influence activity and travel patterns, as well as the propensity to perform offending, victimisation and guardianship roles. Unfortunately, these data were not captured in the MPOD dataset (see below).

**[Insert Fig 1 here]**

# 3. Data

## *Study area*

The research was conducted in Greater Manchester (GM) in the United Kingdom (UK). GM comprises the local authorities of Bolton, Bury, Manchester, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford and Wigan. Each authority contains one or more centre characterised as a locus for the NTE, though Manchester is the principal NTE. At the 2011 Census GM had a resident population of 2.5 million (Office for National Statistics 2018), making it one of the largest metropolitan areas in the UK. GM possesses a dense road network (Levine and Lee 2013) and an extensive public transport infrastructure (rail, coach, and tram), enabling ease of mobility across the area.

## *Spatial unit of analysis*

The geographical unit used in this research is the Lower Layer Super Output Area (LSOA), which is part of the official census reporting geographies of England and Wales (UK). LSOAs contain areas with similar social and land use characteristics, with their boundaries recognising major physical features on the ground. Each LSOA has a residential population of approximately 1,600 people. The study area is composed of 1,673 LSOAs (ONS Geography 2018).

## *Violent crime in public spaces*

The research uses recorded violent crime data, provided by Greater Manchester Police, for the 2013 calendar year. The data holds the following attributes: the Home Office offence code (Home Office

2013); geographical coordinates (which we allocated to the LSOA geographies of the 2011 Census); two temporal fields (Start date/time and End date/time); and, the location type of the offence. Our violent crime data utilises the Home Office (2020) 'violence against the person' offence categories, specifically violence with physical injury (e.g., wounding, grievous bodily harm) and violence without injury (e.g., threats to kill, common assault), that took place in public spaces (e.g., street, park, alley), inclusive of private spaces to which the population are granted access (e.g., pubs, shops, nightclubs). In contrast, violence against the person offences that took place in private spaces (e.g., houses, flats) and private spaces to which the public are not granted access (e.g., schools, care homes) were excluded from the analysis. Whilst 81.8% of the subsequent dataset included offences with the start and end time occurring in the same hour, the remainder did not. To accommodate these data, and following Ratcliffe (2002), we assigned a fraction (an aoristic value) of the crime count to the hours between the start and end time of the crime. We excluded offences with a time span of greater than four hours. We also exclude crimes that took place on weekend days (between Saturday 07:00 and Monday 06:59) as it was not possible to match time-sensitive trip purpose data to these periods. The resultant weekday violent crime in public spaces study data set comprises 11,800 offences, 11.4% of which took place on Wednesdays in comparison to 20.9% that took place on Saturdays, the day with the highest proportion of violent crime in public spaces. In deploying this data, we appreciate that they are not without limitations. Not all violent crimes are reported to the police. The crime survey of England and Wales (CSEW) reports, for the 12 months to March 2019, that only 44.3% of violence offences were reported to the police (ONS, 2019). Further, there are also issues with the integrity of police crime recording. In 2014, police recorded crime statistics lost their national statistics status (UK Parliament, 2014), with subsequent inspections (HMIC, 2014; HMICFRS, 2018) confirming the continuity of shortfalls in recording practices.

### *The exposed population-at-risk*

A Mobile Phone Origin Destination (MPOD) dataset, provided by Transport for Greater Manchester (TfGM), is used to quantify transient population flows across GM. These are synthesised daily trip chaining data (McGuckin and Murakami 1999). The data were collected over a 19-day period, in May and July 2013, then expanded (to represent an entire) and calibrated with reference to the telecommunication company's market share (approximately 33%), TfGM travel diaries and the demographic characteristics of GM drawn from the 2011 census. This delivers 69 million unique trips and 8.4 million trip chains on an average day. It requires to be assumed that the MPOD dataset is not subject to seasonal influence, despite its recording period. Of key value to this research, the MPOD dataset identifies, on the basis of the first and final trip chain, the end destination (i.e., home neighbourhood) of mobile phone users. Using these data, the violent crime in public spaces exposed population-at-risk is calculated as being those people present in a spatial unit (LSOA) in a given time period (see Activity categories below), excluding those people for which the spatial unit represents a final (home) destination.

As the MPOD dataset was originally generated to support the travel demand modelling of TfGM, the dataset was designed to meet this requirement, whilst also reflecting the mobile phone architecture of GM. Firstly, the MPOD data were temporally aggregated to time bins associated with distinct periods of daily travel (see, activities, below), and to weekdays (Monday to Friday) and weekend days (Saturday and Sunday). Secondly, the MPOD data were geographically aggregated to 631

spatial units (501 within the GM boundary) determined by the spatial patterning of cellular signal towers which are more dense in town and city centre areas and by the homogeneity of area land-use (reflecting an origin or destination of travel demand). In effect, and within town and city centres a MPOD spatial unit equates to a single LSOA, whilst out with town and city centres a MPOD spatial unit equates to approximately three LSOAs. Given that the primary aim of the research is to explore the influence of the time variant activities of the exposed population-at-risk on violent crime in public spaces, which concentrates in town and city centres, the relative weakness of the MPOD dataset in less populated areas is outweighed by its strength in town and city centre areas. We utilised a geographical information system (GIS) to employ a best-fit technique to distribute MPOD data across LSOAs (Office for National Statistics 2012; Ralphs 2011).

### *Activity categories*

The research deploys the National Travel End Model (NTEM) datasets[2] (Department for Transport 2017). The NTEM is used (in travel demand planning) to forecast the number of person trips arising from and ending in a particular modelling zone, during specific time periods on weekdays (Monday to Friday) or on weekend days (Saturday and Sunday), and their activity purpose (McNally, 2000). The time sequences specified in the model reflect distinct periods of daily travel demand (AM peak (07:00 -10:00), Inter-peak (10:00-16:00), PM peak (16:00-19:00) and Non-peak (19:00–07:00) and we utilise these in the subsequent analysis of weekday activities.

Weekend days are excluded because activity category data are not available across the four time periods. Whilst the NTEM is used to forecast the number and timing of person trips, these data are generated from a nationally representative data set. It is for this reason that the research deploys the MPOD dataset (described above), to enable more accurate quantification of the number and timing of person trips in GM. The NTEM is utilised, however, to apportion activities to person trips in GM. In line with previous research (Ectors et al. 2017; Vovsha et al. 2004), we encode NTEM non-home-based trip activity types in to a number of activity classes spanning work, education, shopping, personal business, recreation (e.g., outdoor pursuits, sports) and leisure (e.g., eating and drinking, tourism). The proportional distribution of non-home based trip activity types is used to weight the person trips generated by the MPOD dataset. The NTEM generates trip purposes at the Middle Layer Super Output Area (MSOA) level, which we apportion to the LSOAs which constitute a particular MSOA. This is a potential weakness of our approach, if the end destination of trips vary markedly across the LSOAs comprising a MSOA. However, given that the LSOAs spanning town and city centres comprise settings with comparable characteristics (see

The characteristics of settings below), it is unlikely that this strategy will hold significant effect.

[2] The NTEM datasets are derived from the National Travel Survey, which is based on a face-to-face interview and a 7-day self-completed travel diary. Approximately 16,000 individuals, in 7,000 households, participate in the survey each year (Department for Transport 2019) https://www.gov.uk/government/collections/national-travel-survey-statistics Accessed 08 May 2019.

### *The characteristics of settings*

Ordnance Survey (OS) Points of Interest® (POI) data is categorised according to the activity classes derived from the NTEM dataset (work, education, shopping, personal business, recreation and leisure) and aggregated at the LSOA level as a count (Siła-Nowicka et al. 2016). There are 129,275 POIs across GM, with LSOAs exhibiting significant distinction in their POI profile. That being said, town and city centre LSOAs possess the greatest concentration of work, shopping and leisure POIs. A shortcoming in the POI data is that it does not reflect the authority constraints, or temporal function, of POIs, i.e. when POIs are open and accessible.

## 4. Analytical strategy

In order to assess the influence of the time variant activities of the exposed population-at-risk and the characteristics of settings upon the spatial and temporal patterning of violent crime in public spaces a negative binomial regression model (NBM) is deployed controlling for spatial lag effects. The decision to utilise a NBM followed an assessment of the over-dispersion of violent crime in public spaces on weekdays, which found variance-to-mean ratios ranging from 1.47 to 11.72 across the four time periods studied. NBMs are best suited to manage data exhibiting significant over-dispersion (Kim 2018; Osgood 2000). The NBM uses offset terms to adjust for the varied size of the exposed population-at-risk across the LSOA geography of GM, and in differing time periods, in order to calculate rates of violent crime in public spaces. Finally, the model controls for spatial lag effects, i.e., the potential of the characteristics of neighbouring spatial units to influence the focal spatial unit (Wenger 2018). To do so, the model includes a spatially lagged dependent variable, the average violent crime in public spaces rate in adjacent spatial units in different time periods (see Kearns et al. 2019). Moran's I (Anselin 1988; Moran 1950) is used to assess the spatial autocorrelation of the model's residual value.

Prior to the final models being constructed, an assessment of the degree of multi-collinearity between the independent variables was undertaken (Belsley 1991). This task identified that working activity trips held a high variance inflation factor (VIF) with settings identified as possessing a concentration of work places, i.e., the VIF was greater than 10. The most likely explanation for this finding is that working activity trips can be regarded as obligatory (Ratcliffe, 2006) and are made to settings in which work places concentrate, i.e., there are tight coupling constraints. As a consequence, these variables were excluded from the final models. The model specifications can be expressed as follows: While $V_{iT} \sim \lambda(\mu_{iT})$ denotes the violent crime in public spaces count $V$ exhibiting a Poisson distribution $\lambda$ at location $i$ in specific time-periods $T$, where $T$ =1 to 4.

- ***Model 1****: Settings* - the reference model, $\log(V_{iT}) = X'\beta + \log(E_{iT})$, where $E$ is the exposed population-at-risk offset, $\exp(\beta)$ yields the percentage change in the crime rate derived from a 1 unit change in the explanatory variable $X$, the characteristics of settings, in each LSOA. This can be rewritten as $\log(V_{iT}/E_{iT}) = X'\beta$, where our dependent variable, $\log(V_{iT}/E_T)$, denotes the rate of violent crime in public spaces, calculated with reference to the spatially and temporally variant exposed population-at-risk.
- ***Model 2****: Settings and activities* – here the explanatory variable $X$ incorporates the attributes

of both settings and activities.

- ***Model 3****: Settings, activities and spatial lag effects* **-**The NBM with spatial lag is $\log(V_{iT}) = X'\beta + WV_{iT} + \log(E_T)$.

# 5. Results

This section commences by outlining a set of descriptive statistics, capturing key aspects of the variables deployed in the study, serving to support the interpretation of the NBM. Thereafter, the model performance and its findings are reported. Fig 2 presents a set of time variant kernel density maps. Using Kernel density estimation (KDE) enables assessment of the continuous distribution of violent crime in public spaces from a defined point (Rosser et al., 2017), in our case the centroid of GM LSOAs. KDE produces a smooth surface to fit a two-dimensional spatial probability density function (Gerber, 2014) allowing clear visualisation of the spatial concentration of violent crime in public spaces in and around town and city centres (see Song et al., 2018, for a comparable example of this approach). Table 1 details the spatial and temporal variance of the count of violent crime in public spaces, the exposed population-at-risk (by activity type) and the characteristics of settings (Points of Interest). Finally, Fig 3 presents the proportion of activities (by activity type) undertaken by the exposed population-at-risk in each of the four time periods examined in the study. For reference only, given the analytical strategy adopted, data on work-related activities are also presented in these figures and table.

**[Insert Fig 2, Table 1, and Fig 3 here]**

Examining the spatial and temporal patterning of violent crime in public spaces, two observations stand out. Firstly, and in T4, the kernel density map of the count of violent crime in public spaces holds sharper delineation than in T1-T3. Secondly, the mean and maximum count of violent crime in public spaces is significantly higher in T4 than in T1-T3. Thus, violent crime in public spaces is of a greater scale and spatial concentration in T4 in comparison to T1-T3, when and where it is relatively sparse and dispersed. The exposed population-at-risk, by activity type, also exhibits distinct spatial and temporal variation. Thus, and in comparison to T1-T3, the scale of the exposed population-at-risk and the mean number of education, shopping and personal business activities undertaken are smaller in T4. Whilst the mean number of recreation and leisure activities undertaken are higher in T4 than in T1 and T2, they are substantially lower than in T3. Expressed as proportions, recreation and leisure activities dominate T4, as might be expected given the daily rhythms of the city. Finally, the characteristics of settings vary markedly across space, though not (of course) through time, implying that facilities supporting particular activity types cluster in certain settings. Thus, and for example, the spatial variance in the presence of leisure facilities is far greater than that of recreation facilities.

## *Model performance*

Table 2 presents the results of the various criteria that were used to assess and compare the performance of each model, in each time-period (T1-T4). The smaller log-likelihood (LL), Akaike Information Criterion (AIC) and Bayesian information criterion (BIC) scores achieved by model 3 indicate that it offers the best fit (Hilbe 2011; Lucy W. Mburu and Helbich 2016). The dispersion

parameter (i.e., θ theta) illustrates that the final models are not over-dispersed (0.87 to 1.27, p<0.001), serving to validate the appropriateness of deploying the NBMs (Zuur and Hilbe 2013; Vandeviver et al., 2015). Model 3, which combines setting and activity data with the spatial lagged covariate, exhibits differing performance across T1-T4. Whilst morning peak hours (07:00-10:00) shows the best model fit (i.e., AIC = 2405.42, LL =-1189.71, θ = 1.27, p 0.001), inter-peak hours (10:00-16:00) achieves the best goodness-of-fit (McFadden R2 = 0.079).

Table 2 also displays the incidence-rate ratios (IRR), the exponential form of the regression coefficient generated by the three NBMs, in each of the four time periods studied. The value of the IRR denotes the corresponding multiplicative change of influence arising from a one-unit change in the explanatory variable (Mburu and Helbich, 2016). Thus, an IRR value of 1.5 would imply that an explanatory variable is associated with a 50% increase in the risk of violent crime in public spaces, whilst an IRR value of 0.5 would imply that an explanatory variable is associated with a 50% decrease in the risk of violent crime in public spaces.

**[Insert Table 2 here]**

## *The influence of intra-daily activities and settings upon weekday violent crime in public spaces*

Given that Model 3 affords the best overall fit, the reporting of the key findings of the research is confined to this model. In overview, the activities of the exposed population-at-risk, in different time periods, hold statistically significant associations with weekday violent crime in public spaces. Thus, the nature of the activity being undertaken, remembering that these vary in scale and proportional distribution, serves to either decrease or increase the likelihood of crime. Focussing on the most statistically significant findings, the exposed population-at-risk undertaking education (in T1-T4, p<0.001), shopping (in T1 and T2, p<0.001) and recreation (in T4 p<0.001) activities diminish the risk of weekday violent crime in public spaces. In T4, the presence of those people undertaking education and recreation activities decrease likelihood of violent crime in public spaces by 44% and 39% respectively. In sharp contrast, the presence of the exposed population-at-risk undertaking leisure activities in T4 increase the likelihood of violent crime in public spaces by 59%.

In overview, the characteristics of settings (Points of Interest) hold limited association with the time variant incidence of weekday violent crime in public spaces. In the four time periods studied, statistically significant associations were only found between the presence of shopping facilities (in T2, p<0.001 and T3, p<0.01), personal business facilities (in T2, p<0.01), leisure facilities (in T4, p<0.001) and violent crime in public spaces. Of the more robust associations, the presence of shopping facilities (in T2) and leisure facilities (in T4) increased the likelihood of violent crime in public spaces by 40% and 63% respectively. The spatial lag variable exhibits a positive and statistically significant effect, particularly in T2-T4, i.e., it displays significant positive spatial autocorrelation. In effect, a 1% increase in violent crime in public spaces in any given spatial unit is associated with a 30% to 41% increased likelihood of violent crime in public spaces occurring in adjacent spatial units.

# 6. Discussion

The most striking results of Model 3 occur in T4 (19:00 to 07:00) when leisure activities and leisure settings hold strong and independent influence on the likelihood of weekday violent crime in public spaces, though they are bound by coupling constraints. It is in this period that the count of violent crime in public spaces is at its highest and most spatially concentrated (see Fig 2), a period also in which the exposed population-at-risk is significantly lower than at other times of the day (see Fig 1). In T4, leisure (and recreation) activities dominate, though the scale of the exposed population-at-risk undertaking these activities is smaller than earlier in the day, and are serviced by facilities that cluster in particular settings. Whilst previous literature has highlighted the importance of the scale and trip purpose of the transient population on crime (Boivin 2018; Boivin and D'Elia 2017; Boivin and Felson 2018; Felson and Boivin 2015), we believe that this is the first study to demonstrate the *time variant* nature of its influence.

The results evidence the claims made in existing research exploring the relationship between the NTE and violent crime. Alcohol consumption is the principal leisure activity of the NTE (Hadfield et al. 2009), occurring in a social environment that induces cumulative alcohol consumption (Bellis et al. 2010; Moore et al. 2007). Alcohol consumption is associated with heightened aggression and an increased likelihood of being involved in violence (Finney 2004; Schnitzer et al. 2010), making it plausible that a smaller population denominator is responsible for a higher crime count. The evidence gathered here appears compelling in this regard. Over the duration of a weekday evening, the exposed population-at-risk undertaking leisure activities exhibit an increased propensity to perform the roles of offender and / or victim and a decreased propensity to perform the role of guardian. Further, it is plausible that the absence of population groups undertaking other activities, who might play an active or passive role as a guardian (Felson and Boivin 2015), serves to further heighten the likelihood of violent crime in public spaces. The research found the presence of those undertaking education and recreation activities served to temper violent crime in public spaces in T4. It would appear worthwhile, from a policy perspective, to consider ways to increase the scale of those undertaking these activities in the later evening in city centre areas.

The results confirm the influence of environmental features on crime patterning (Brantingham and Brantingham, 1995; Kinney et al. 2008; Montoya 2015), specifically the role that drinking establishments (e.g., pubs, restaurants and nightclubs) or *risky facilities* (Bowers 2014) when clustered in settings or *magnetic places* (Boivin and D'Elia 2017) hold on the spatial concentration of violent crime in public spaces (Gmel et al. 2016). It is noteworthy, given the discussion of leisure activities associated with the NTE, that the authority constraints (Hägerstraand 1970; Miller 2005) governing access to drinking establishments do not prohibit this activity taking place in other time periods. This being said, premises such as pubs, restaurants and nightclubs tend, reflecting coupling constraints (Hägerstraand 1970; Miller 2005), to upscale their operation in the NTE.

In overview, through adopting a theoretically informed definition of the exposed population-at-risk of violent crime in public spaces, taking the transient population as the best available measure of this, and integrating both intra-daily activity and setting characteristics data, this research delivers substantive contributions to the existing literature. It demonstrates that population scale does not hold a direct relation with crime patterning. Rather, crime patterning (spatial and temporal) is a

function of the routine activities of the transient population and of the characteristics of the settings in which such routines take place. In contrast to previous studies that have been unable to distinguish intra-daily activity patterns, this paper illustrates that weekday violent crime in public spaces is reflective of the time sensitive and independent influence of, and interaction between, the coupling constraints shaping intra daily activities (scale and type) and land use features. The scale and mix of the transient population activities are evidenced to either heighten or lessen exposure to weekday violent crime in public spaces. When leisure activities dominate the use of settings, though smaller in scale than in other moments of the day, exposure to weekday violent crime in public spaces is at its greatest. At these times and in these settings, it is plausible that the balance between those capable of performing the role of victim, offender or guardian shifts, with people likely to hold an increased propensity to perform the roles of victim and/or offender and a decreased propensity to perform the role of guardian. That criminogenic settings, understood as a combination of crime attractors and population generators, also exhibit clustering and / or people pass through neighbouring spatial units to access these settings is no doubt influential in the higher levels of weekday violent crime in public spaces in adjacent spatial units.

# 7. Conclusion

This paper contributes to the emergent body of research examining the influence of the transient population on crime (Boivin 2018; Boivin and Felson 2018; Felson and Boivin 2015; Song et al. 2018). In contrast to these studies, however, it demonstrates that the activities undertaken by the transient population hold intra-daily distinction in their scale and influence on the likelihood of crime. Exploring the influence of intra-daily activities and settings upon weekday violent crime in public spaces, it found leisure activities and settings characterised by leisure facilities to significantly increase the likelihood of crime on weekday evenings but not at other times of the day. In these terms, weekday violent crime in public spaces is a function of what people do, with and without others, where and when. Cumulatively, these elements shape the mix of *active* offenders, victims and guardians in a given spatial unit at a given time. The research was founded on the integration of novel and fine-grained data, enabling quantification of a theoretically informed crime specific exposed population-at-risk (in this instance the transient population), qualification of their activities and of the characteristics of the settings they visited. These data are not without their limitations. Significantly, it was not possible to determine the socio-demographic characteristics of the exposed population-at-risk, recognising that these serve to influence where people go, what they do and how long they take to do it, as well as their likelihood of performing offending, victimisation and guardianship roles. Accessing such data would serve to significantly enhance this research field.

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# Tables and Figures

**Table 1. Weekday violent crime in public spaces, the activities of the exposed population and the characteristics of settings**

| Variable | T1 (morning peak hours: 7:00-10:00) | | | | T2 (inter-peak hours: 10:00-16:00) | | | | T3 (evening peak hours: 16:00-19:00) | | | | T4 (non-peak hours: 19:00-07:00) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Min. | Mean | Max. | SD | Min. | Mean | Max. | SD | Min. | Mean | Max. | SD | Min. | Mean | Max. | SD |
| **Violent crime counts in public spaces** | 0.00 | 0.33 | 9.00 | 0.78 | 0.00 | 1.70 | 56.00 | 3.62 | 0.00 | 1.39 | 61.00 | 2.71 | 0.00 | 3.63 | 222.00 | 9.00 |
| **Exposed population** | | | | | | | | | | | | | | | | |
| **Work** | 4.03 | 143.05 | 4,619.42 | 250.97 | 1.78 | 35.23 | 1,445.35 | 58.62 | 7.75 | 141.83 | 2,636.88 | 163.82 | 1.39 | 33.78 | 1,093.72 | 47.45 |
| **Education** | 5.14 | 121.82 | 1,379.05 | 126.09 | 3.51 | 91.23 | 842.21 | 90.3 | 2.18 | 38.04 | 394.49 | 34.93 | 0.05 | 1.24 | 12.84 | 1.17 |
| **Shopping** | 0.74 | 35.66 | 2,046.86 | 67 | 2.48 | 115.23 | 6,932.13 | 231.47 | 2.83 | 86.14 | 5,835.36 | 190.32 | 0.41 | 14.16 | 888.72 | 25.95 |
| **Personal business** | 0.75 | 21.59 | 330.98 | 29.57 | 1.88 | 45.6 | 798.2 | 54.79 | 1.91 | 34.22 | 720.07 | 41.26 | 0.29 | 5.67 | 56.25 | 5.8 |
| **Recreation** | 0.06 | 8.79 | 331.05 | 18.89 | 0.43 | 27.61 | 1,289.19 | 58.96 | 1.35 | 56.23 | 3,425.7 | 144.47 | 1.65 | 35.56 | 1,462.19 | 52.86 |
| **Leisure** | 0.35 | 9.11 | 292.19 | 13.5 | 1.1 | 23.53 | 628.72 | 29.55 | 3.27 | 63.22 | 1,884.25 | 85.56 | 1.52 | 32.55 | 504.15 | 32.16 |

| Variable | Min. | Mean | Max. | SD |
|---|---|---|---|---|
| **Settings** | | | | |
| **Work** | 3.00 | 34.58 | 899.00 | 47.57 |
| **Education** | 0.00 | 2.15 | 23.00 | 2.16 |
| **Shopping** | 0.00 | 8.02 | 545.00 | 23.28 |
| **Personal business** | 0.00 | 5.90 | 149.00 | 8.78 |
| **Recreation** | 0.00 | 2.85 | 41.00 | 3.19 |
| **Leisure** | 0.00 | 5.51 | 241.00 | 11.29 |

**Table 2. IRRs (Incident rate ratios) and model fit for the negative binomial regression models.**

| Variable | T1 (AM peak 07:00 -10:00) | | | T2 (Inter-peak 10:00-16:00) | | | T3 (PM peak 16:00-19:00) | | | T4 (Non-peak 19:00-07:00) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) |
| **Settings** | | | | | | | | | | | | |
| **Education** | 0.96 (0.06) | 1.00 (0.06) | 0.99 (0.06) | 1.00 (0.04) | 1.05 (0.04) | 1.05 (0.04) | 0.97 (0.04) | 1.03 (0.04) | 1.03 (0.04) | 0.98 (0.04) | 1.04 (0.04) | 1.02 (0.04) |
| **Shopping** | 0.86 (0.07) | 1.08 (0.10) | 1.08 (0.10) | **1.18 (0.07)**** | **1.50 (0.10)***** | **1.40 (0.09)***** | 1.10 (0.07) | **1.29 (0.09)***** | **1.23 (0.08)**** | 0.91 (0.05) | 1.09 (0.07) | 1.08 (0.07) |
| **Personal business** | **1.39 (0.14)***** | 1.06 (0.11) | 1.04 (0.11) | **1.63 (0.11)***** | **1.22 (0.08)**** | **1.20 (0.08)**** | **1.44 (0.10)***** | 1.08 (0.08) | 1.05 (0.07) | **1.53 (0.09)***** | 1.14 (0.07)* | 1.12 (0.07) |
| **Recreation** | 0.94 (0.07) | 1.03 (0.07) | 1.03 (0.07) | **0.89 (0.04)**** | 0.96 (0.04) | 0.96 (0.04) | 0.91 (0.04)* | 1.01 (0.05) | 1.02 (0.04) | **0.90 (0.04)**** | 0.93 (0.04) | 0.95 (0.04) |
| **Leisure** | 1.02 (0.10) | 1.18 (0.11) | 1.18 (0.11) | **0.83 (0.06)**** | 0.98 (0.07) | 1.00 (0.07) | 0.90 (0.07) | 1.07 (0.08) | 1.11 (0.08) | **1.31 (0.09)***** | **1.79 (0.11)***** | **1.63 (0.10)***** |
| **Exposed population** | | | | | | | | | | | | |
| **Education** | - | **0.84 (0.05)**** | **0.84 (0.05)**** | - | **0.72 (0.04)***** | **0.74 (0.04)***** | - | **0.62 (0.04)***** | **0.65 (0.04)***** | - | **0.51 (0.03)***** | **0.56 (0.04)***** |
| **Shopping** | - | **0.72 (0.08)**** | **0.73 (0.08)**** | - | **0.80 (0.04)***** | **0.83 (0.05)***** | - | 0.98 (0.07) | 0.98 (0.07) | - | 1.16 (0.08)* | 1.18 (0.08)* |
| **Personal business** | - | 1.00 (0.05) | 1.00 (0.05) | - | 0.98 (0.04) | 0.99 (0.04) | - | 0.98 (0.05) | 0.99 (0.05) | - | **0.86 (0.04)**** | 0.90 (0.04)* |
| **Recreation** | - | 1.03 (0.06) | 1.03 (0.06) | - | 1.02 (0.05) | 1.02 (0.05) | - | 0.87 (0.07) | 0.88 (0.06) | - | **0.65 (0.05)***** | **0.71 (0.05)***** |
| **Leisure** | - | 0.89 (0.04)* | 0.89 (0.04)* | - | 1.05 (0.05) | 0.98 (0.04) | - | 1.14 (0.10) | 1.08 (0.09) | - | **1.97 (0.15)***** | **1.59 (0.12)***** |
| **Spatial lag** | | | | | | | | | | | | |
| **Average violent crime rates in adjacent areas** | - | - | 1.13 (0.06)* | - | - | **1.30 (0.04)***** | - | - | **1.41 (0.04)***** | - | - | **1.40 (0.04)***** |
| **N** | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 |
| **Log Likelihood** | -1221.76 | -1192.21 | -1189.71 | -2805.95 | -2737.4 | -2701.3 | -2696.74 | -2619.42 | -2568.53 | -3818.5 | -3843.96 | -3723.97 |
| **Deviance** | 1092.63 | 1109.83 | 1110.56 | 1720.33 | 1714.94 | 1610.04 | 1701.32 | 1717.73 | 1723.13 | 1851.45 | 2087.98 | 1824.42 |
| **AIC** | 2457.52 | 2408.41 | 2405.42 | 5625.9 | 5498.8 | 5428.6 | 5407.49 | 5262.83 | 5163.07 | 7650.99 | 7711.92 | 7473.95 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **BIC** | 2495.48 | 2473.48 | 2475.91 | 5663.85 | 5563.87 | 5499.09 | 5445.44 | 5327.9 | 5233.56 | 7688.95 | 7776.98 | 7544.44 |
| **Dispersion parameter (θ)** | 1.66 | 1.30 | 1.27 | 1.16 | 0.98 | 0.89 | 1.33 | 1.00 | 0.87 | 1.20 | 0.97 | 0.90 |
| **Moran's I of residuals** | 0.18 | 0.17 | 0.14 | 0.23 | 0.23 | 0.12 | 0.26 | 0.26 | 0.12 | 0.28 | 0.30 | 0.18 |

**Note: *** (p<0.001), **(p<0.01), and * (p<0.05), IRRs whose p-values are less than 0.01 are marked in bold**.

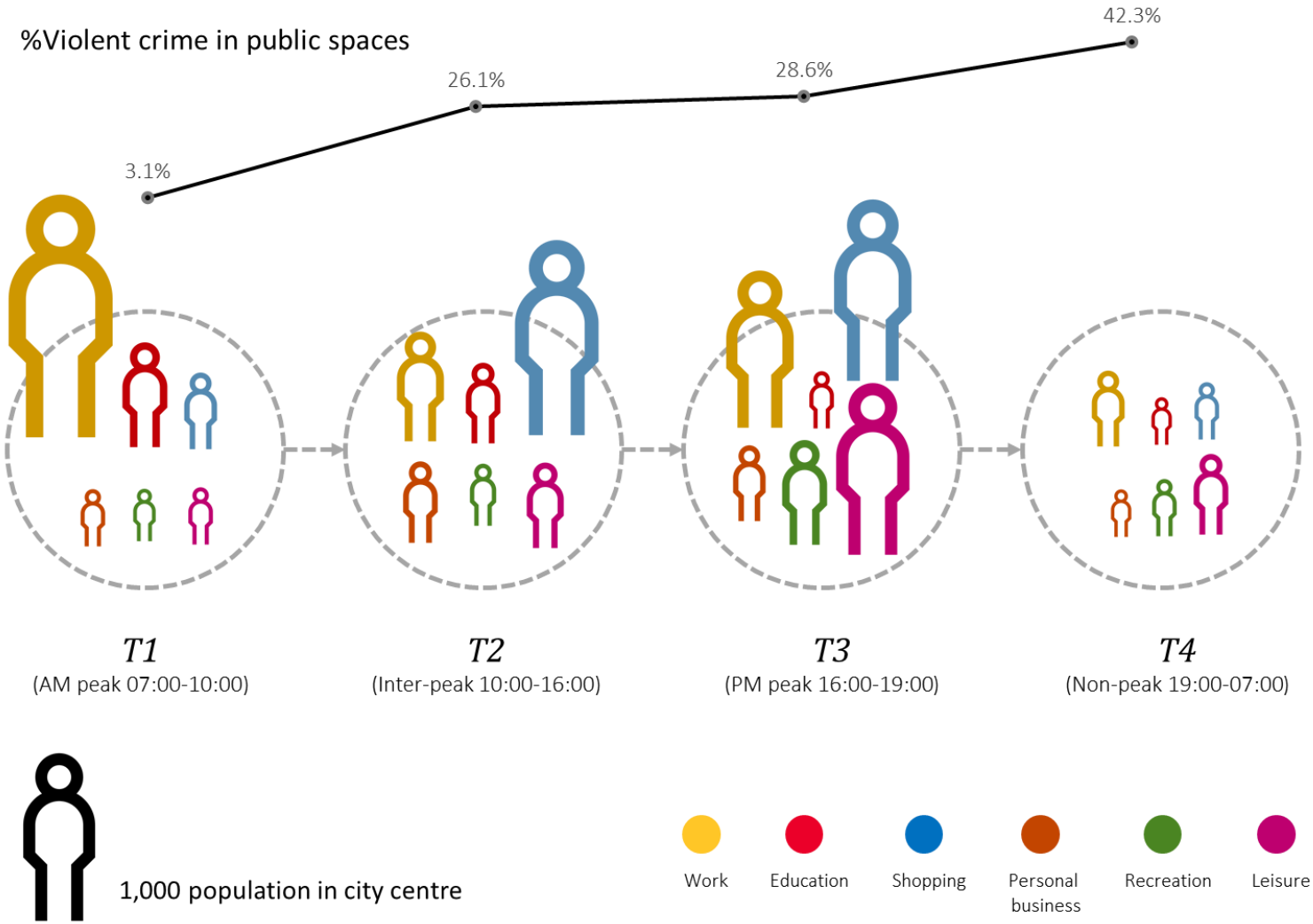
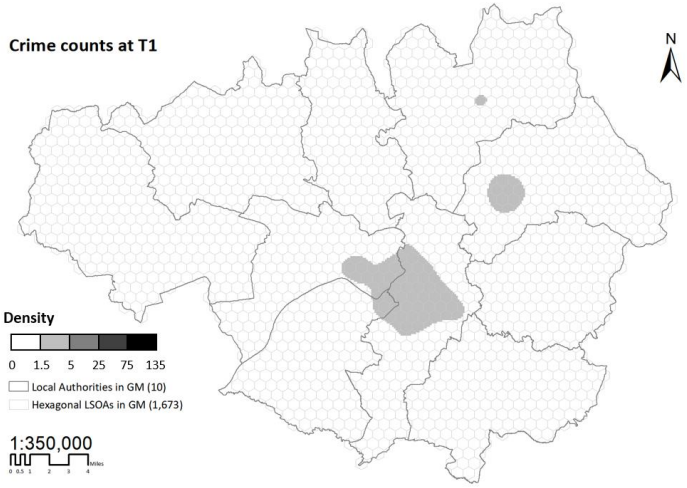
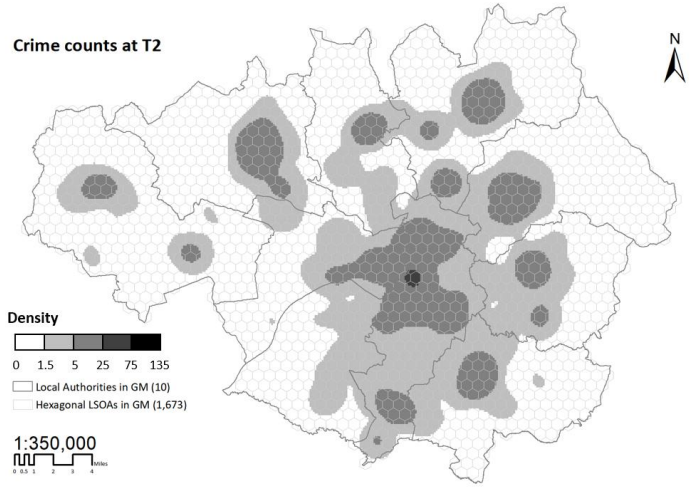


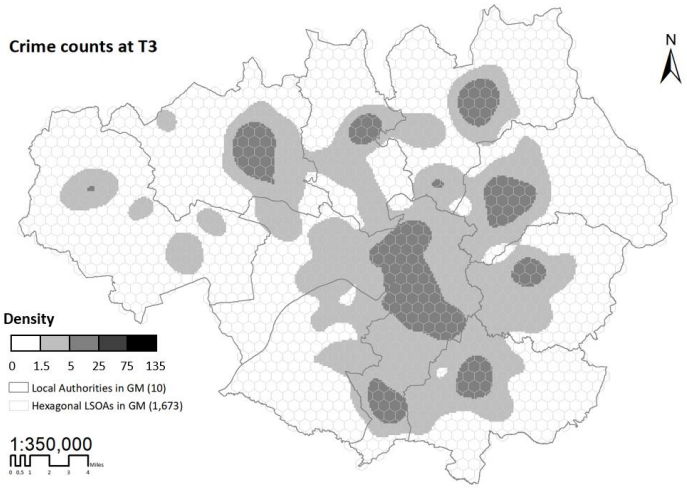

**Fig 1. Illustration of the time-variant scale and activity mix of the exposed population-at-risk in a city centre, and its association with violent crime in public spaces.**



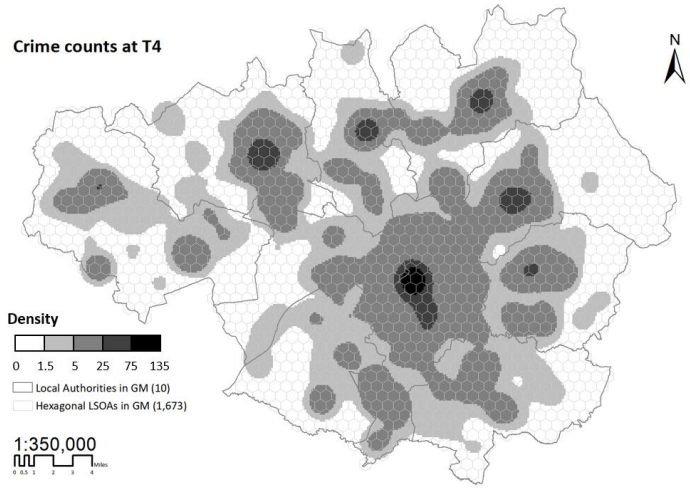

a: Crime counts at T1




b: Crime counts at T2




c: Crime counts at T3




d: Crime counts at T4

**Fig 2. The kernel density estimation of violent crime in public spaces in different time periods**
**(Source: Contains Ordnance Survey Boundary Line; Ordnance Survey data © Crown copyright and database right 2018)**

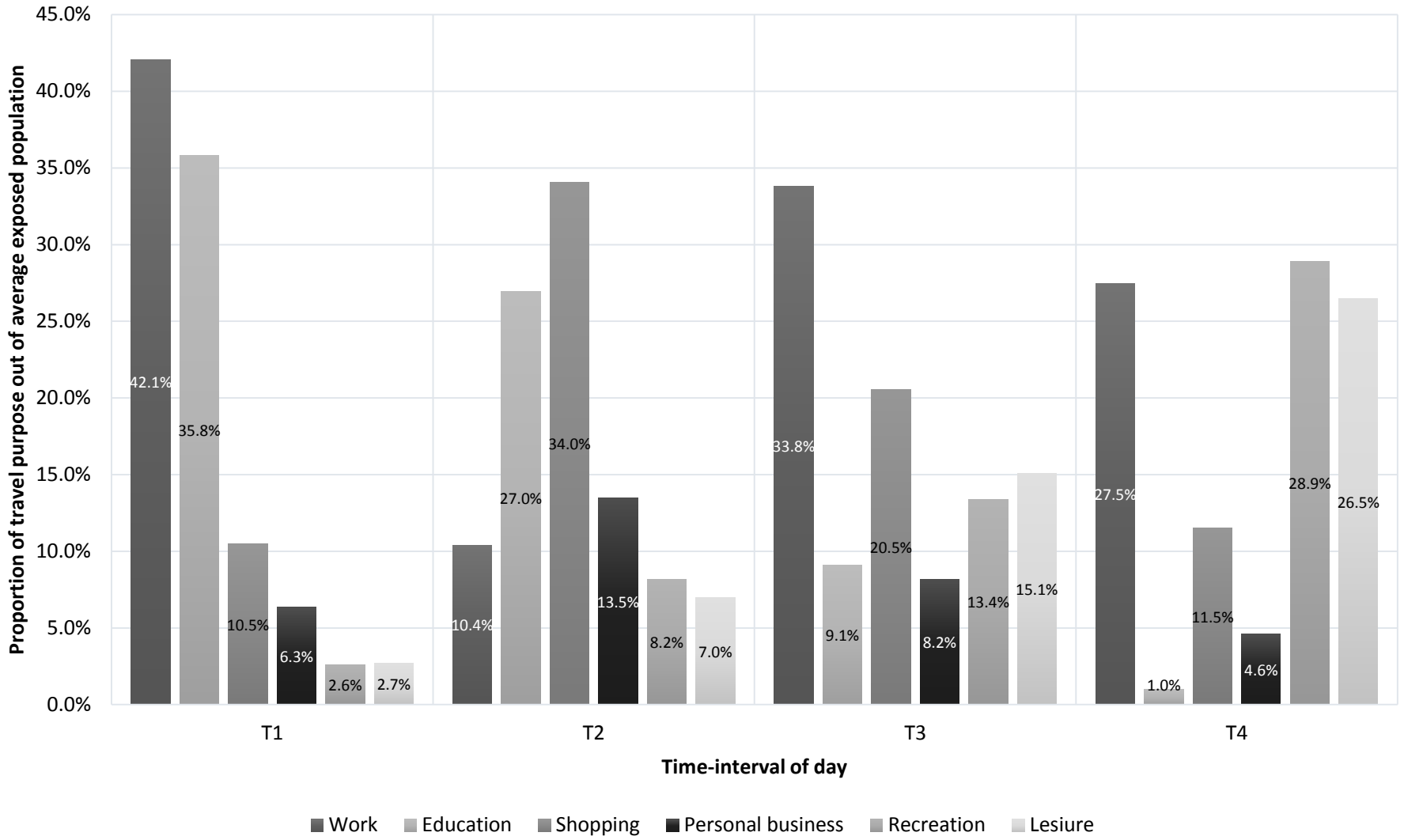



**Fig 3. Average exposed populations by major activity types at time-intervals of day across Greater Manchester.**
**(Source: National Trip End Model data set, TEMPro (The Trip End Model Presentation Program) v.7.2 provided by Department for Transport)**

# The influence of intra-daily activities and settings upon weekday violent crime in public spaces in Manchester, UK

**Abstract**

People ebb and flow across the city. The spatial and temporal patterning of crime is, in part, reflective of this mobility, of the scale of the population present in any given setting at a particular time. It is also a function of capacity of this population to perform an active role as an *offender, victim or guardian* in any specific crime type, itself shaped by the time variant activities undertaken in, and the qualities of, particular settings. To this end, this paper explores the intra-daily influence of activities and settings upon the weekday spatial and temporal patterning of violent crime in public spaces. This task is achieved through integrating a transient population dataset with travel survey, point-of-interest and recorded crime data in a study of Great Manchester (UK). The research deploys a negative binomial regression model controlling for spatial lag effects. It finds strong and independent, but time variant, associations between leisure activities, leisure settings and the spatial and temporal patterning of violent crime in public spaces. The paper concludes by discussing the theoretical and empirical implications of these findings.

**Key words**: Routine activities, Exposed population-at-risk, Transient population, Interpersonal variability, Trip purpose, Violent crime in public spaces.

# 1. Introduction

There is longstanding recognition of the necessity to calculate population denominators with reference to specific crime types (Boggs 1965). Failure to do so may serve to inflate or deflate the crime rate (Song et al. 2018), disguising the true nature of the crime problem and impeding its effective address. To this end, Haleem et al. (in this issue) introduced the concept of the exposed population-at-risk, defined as the mix of residents and non-residents who may play an active role as an offender, victim or guardian in a specific crime type, present in a spatial unit at a given time. The exposed population-at-risk, therefore, requires not only the quantification of population present but also the qualification of what they are doing with whom, enabling delineation of whether they can perform an active role in relation to a specific crime type. In this paper, which examines violent crime in public spaces, and reflective of the data qualities at our disposal we identify the transient (mobile) population as the best measure of the exposed population-at-risk, i.e., excluding those at home, who would be unable to perform an active role in public spaces. We return to this issue in detail, below (A conceptual model of likelihood of violent crime in public spaces).

To date, limited attention has been given to a consideration of the intra-daily influence and interplay of activities and settings upon the propensities of the population to perform active roles as offenders, victims or guardians (Hipp 2016; Song et al. 2018). Identifying a falling exposed population-at-risk count to be associated with a rise in late evening violent crime in public spaces, Haleem et al. (in this issue) postulated that it was a likely function of the shifting propensities of that population to perform particular active roles in the setting of the night-time-economy (NTE). To further elucidate this issue, we examine the influence of time variant activities, or the interpersonal variability of population activity patterns (Dharmowijoyo et al. 2014; Moiseeva et al. 2014; Pas and Koppelman 1986), and the characteristics of settings upon the spatial and temporal patterning of violent crime in public spaces on weekdays. Specifically, the research addresses the following questions:

- To what extent do the intra daily activities of the exposed population-at-risk influence the likelihood of violent crime in public spaces?
- To what extent to the characteristics of settings influence the likelihood of violent crime in public spaces?
- Does violent crime in public spaces in one neighbourhood influence the likelihood of violent crime in public spaces in adjacent neighbourhoods?

To achieve this task the research deploys a mobile phone dataset, capable of distinguishing the origin and destination of population trip chains (McGuckin and Murakami 1999), enabling exclusion of those at home, to calculate the exposed (i.e., transient) population-at-risk of violent crime in public spaces. Here, public spaces are defined as comprising streets, alleys, parks and open spaces as well as private spaces to which the citizenry are granted access (e.g., pubs, shops and nightclubs). The paper utilises data derived from travel surveys to qualify the time variant activities embedded in transient population trip chains and point of interest data to define and quantify the characteristics of trip destinations. These data are integrated with fine grained recorded crime data, capable of delineating the Cartesian and temporal coordinates of each crime and the setting in which it took place. This research employs a negative binomial statistical modelling approach, controlling for spatial lag effects in the dependent variable, to estimate the influence of the routine activities

embedded in intra-daily population flows and the characteristics of settings upon the likelihood of violent crime in public spaces taking place.

The paper is structured in the following manner. In the next section, a brief literature review is presented in order to establish a conceptual model of how the interplay of time variant activities and settings serve to shape likelihood of violent crime in public spaces. In section three, the data deployed in this research are described. In section four, the analytical strategy of the research is presented. In section five, the modelling estimated results are presented and described. Finally, we discuss the theoretical and empirical implications of the research findings.

## 2. Background

Crime is over-dispersed in space and time. It concentrates in certain areas (Sherman et al. 1989; Weisburd 2015; Weisburd et al. 2012) at particular moments in time (Brunsdon et al. 2007; Newton 2015; Townsley 2008). The volume of crime in any area at a given time is, at least in part, a function of the scale of the population present. Recognising the daily rhythms of the city, the ebb and flow of the citizenry as they undertake routine activities, multiple endeavours (see Malleson and Andresen (2016) for a review) have been made to capture an ambient population-at-risk count (Andresen 2011), the mix of residents (the static population) and non-residents (the transient population) present in an area at a given time. Haleem et al. (in this issue), however, challenge the appropriateness of applying ambient (i.e., total) population counts. Instead, they argue that an exposed population count, defined as the mix of residents and non-residents who may play an *active* role as an offender, victim or guardian in a specific crime type, present in a spatial unit at a given time, to be a more theoretically relevant population denominator. In these terms, an emergent challenge is that of assessing the propensity, or shifting spatial and temporal propensities, of the exposed population-at-risk to perform an active role as an offender, victim or guardian.

Routine activities theory (Andresen and Jenion 2010; Cohen and Felson 1979) proposes that for a crime to occur it is necessary that a motivated offender and a suitable victim (or target) must hold co-presence in the absence of a capable guardian. However, the likelihood of an individual performing a specific role and the cumulative balance of offenders, victims and guardians present in a spatial unit at a given time may vary (Hipp 2016). Crime pattern theory (Brantingham and Brantingham 1993), building on the concepts and mechanisms of routine activity theory (Bernasco 2014), explains the spatial and temporal concentration of crime as an outcome of the interplay between the flow of the population along specific travel routes (paths) and their confluence in specific locations (nodes) associated with a multitude of activity types (e.g., in-home, work, leisure, schooling). In this vein, Summers and Johnson (2017) have sought to explain the location of outdoor serious violence according to the configuration (or space syntax) of street networks. Anchor points (Rossmo 2000; Townsley et al. 2016; Townsley and Sidebottom 2010) emerge, locations in which people spend longer periods of time. In such locations, crime can be understood as a function of the characteristics of the residential and transient population (Felson and Boivin 2015), depending on the crime type under investigation, and of the qualities of the urban environment (Kinney et al. 2008). In effect, of course, these factors are inter-related.

The ebb and flow, or space-time geography (Hägerstraand 1970; Miller 2005), of the citizenry is shaped by physical limitations to movement (capability constraints), the requirement to undertake mandatory societal roles (e.g., work, education) in specific locations and at particular times (coupling constraints), and by the accessibility of specific locations (authority constraints). Thus, an individual's space-time geography is a reflection of the interplay between the attainment of required and desired goals, framed by a set of spatial and temporal constraints (Arentze and Timmermans 2004). The emergent sequential-activity-travel patterns, or trip chains (McGuckin and Murakami 1999), are "often habitual and shaped by repeated travel between the same locations" (Bernasco 2014, p. 3). In aggregate, the daily routines of the citizenry generate a constant churn of population groups with different motivations and characteristics. The balance between residents (static) and non-residents (transient) in any given spatial unit will vary across time. In situations where there is a high relative prevalence of transient groups, it is plausible that propensity towards guardianship will decline (Boivin 2018).

An individual's social, demographic and lifestyle characteristics affect where they go, what they do and how long they take to do it (Hasan et al. 2013; Lemieux and Felson 2012), as well as their likelihood of performing offending, victimisation and guardianship roles (Curiel and Bishop 2018). The perception of the risk of victimisation may or may not, through choice or constraint, alter their presence or duration at specific locations (Hipp 2016). Examining the exposure risk to violent crime, Lemieux and Felson (2012) calculated a time-adjusted rate measure – the *person hour*, to compare the association between different types of daily activity and the risk of victimisation. They identified that 'attending school' and 'leisure activities away from home' were associated with a high risk of victimisation, though 'travelling to or from work' and 'travelling to or from school' presented the highest risk of victimisation. They concluded that transit activities were considerably riskier than the premise (setting).

The use of transportation data is increasingly prevalent in research seeking to explore crime patterning and is deployed to quantify population flows and qualify the activities (trip purposes) embedded in them (Boivin 2018; Boivin and D'Elia 2017; Boivin and Felson 2018; Felson and Boivin 2015). In overview, these researches make clear that the scale of the transient population and its motivation serve to shape the *daily* patterns of both property and violent crime types. There are, however, a number of data limitations associated with these existing studies, as recognised by the researchers, centred on the spatial and temporal granularity of the transportation and crime data utilised. Of keynote, given the ambition of the current study, these analyses are not capable of distinguishing the scale and nature of activities (trip) purposes at different times of the day, nor are they capable of distilling the temporal qualities of crime patterning.

The land use features, of any given spatial unit, hold a significant impact on the volume of crime that takes place in that spatial unit (Taylor and Gottfredson 1986; Wo 2019). Particular land use types act as crime generators in that they serve to draw in population groups and / or as crime attractors in that they serve to draw in offenders (Brantingham and Brantingham 1995). In other words, *risky facilities* (Bowers 2014) and *magnetic places* (Boivin and D'Elia 2017), such as alcohol-licensed premises (Conrow et al. 2015; Grubesic and Pridemore 2011; Hadfield et al. 2009; Snowden 2016), attract population groups with a heightened propensity to act as offenders or victims and a lowered propensity to act as a guardians, shaping the spatial patterning of crime (Haleem et al., in this issue).

Furthermore, the influence of the land use of any given location may vary through time, due to institutional constraints (e.g., opening hours), impacting upon the temporal patterning of crime . Thus, a city centre may hold mixed land use during the day, serving as a place of work, shopping, education and leisure activities, but at night it might act principally as the locus of the leisure activities. By implication the scale, characteristics and behavioural propensities of the population in the city centre will be time-dependent (Bichler et al. 2011), with the predominant land use and population mix affecting the 'mood' of the area (MacDonald 2015).

## *A conceptual model of likelihood of violent crime in public spaces*

The exposed population-at-risk of violent crime in public spaces, by necessity, comprises those people traversing and occupying that space, but not those for whom the locality represents an end destination (i.e., home). In other words, when at home, residents are unlikely to perform an active role in violent crime in public spaces[1]. In these terms, (and given the qualities of the data at our disposal, see below) the transient population can be established as the best measure of the exposed population-at-risk. Haleem et al. (in this issue) note that this definition may serve to overestimate the exposed population-at-risk at particular times of the day, particularly in periods when there are a high number of workers occupying private space. Similarly, by excluding those travelling to and from home, as we require to do here, may serve to underestimate the exposed population-at-risk.

Existing research has demonstrated that the spatial patterning of violent crime holds a strong association with the clustering and capacity of licensed premises (Gmel et al. 2016), particularly in city centre locations (Gerell and Kronkvist 2016). Relatedly, the temporal patterning of violent crime is associated with the functioning of the NTE, in which cumulative alcohol consumption increases the likelihood of offending whilst decreasing the likelihood of guardianship (Bellis et al. 2010; Flatley 2016; Hadfield et al. 2009). This may account for why the count of violent crime in public spaces rises over the course of an evening even though the count of the exposed population-at-risk declines. Building upon these insights, Fig 1 provides an illustrative model of the changing proportion of crime, as well as the scale and mix of activities being undertaken by the exposed population-at risk in a city centre setting, across different time periods. Here, the activity categories (work, education, shopping, personal business, recreation (e.g., sports) and leisure (e.g., eating and drinking)), time periods (T1 07:00-10.00, T2 10:00-16:00, T3 16:00-19:00, T4 19:00-07:00), population counts and crime data have been calibrated with reference to the data deployed in the research (see Data, below). The model is reflective of the coupling and authority constraints (Hägerstraand 1970; Miller 2005) that inform the pursuit of intra daily routine activities, shaping who does what with whom, where and when. Thus, and in T1, the majority of people travel to the city centre for work. In T2, the count of the population present in the city centre has grown and shopping becomes the dominant activity. In T3, the count of the population present in the city

[1] In stating this, we recognise an extensive literature inspired by Jane Jacobs (1961) that argues the role of citizens operating as 'eyes on the street' from inside their homes. This has informed approaches to Crime Prevention Through Environmental Design (CPTED) that have sought to promote forms of mixed land-use development and building design that maximise the opportunity for residents to act as visual guardians (Cozens and Hillier, 2012). However, and given that the majority of city centre residential developments appear to be mid or high-rise in nature, we are not convinced that they serve to effectively promote 'eyes on the street'?

centre is at its greatest. Shopping is still the dominant activity but there is an increase in those undertaking recreation and leisure activities. Finally, in T4, the population count in the city centre exhibits a dramatic reduction as people return home. Those undertaking leisure activities also exhibits decline, and is lower than in T3, but leisure becomes the dominant activity. The likelihood of violent crime in public spaces can be hypothesised, therefore, as an outcome of the time sensitive interplay of the activities being undertaken by the exposed population-at-risk in and the characteristics of particular settings. In these terms, the scale, relative preponderance and nature of specific activity types, in any given setting at a particular time, will serve to influence the propensity of that population to perform an active role as an offender, victim or guardian. Examining the proportion of daily recorded violent crime in public spaces, it is striking how this varies across different time periods, seemingly serving to confirm this hypothesis. Further and as the exposed population-at-risk moves through neighbourhoods adjacent to these settings, to undertake or having undertaken particular activities, it is likely that they will influence the likelihood of violent crime in public spaces in these neighbourhoods. Prior to progressing, it is important to recognise (as noted earlier) that social, demographic and lifestyle characteristics will influence activity and travel patterns, as well as the propensity to perform offending, victimisation and guardianship roles. Unfortunately, these data were not captured in the MPOD dataset (see below).

**[Insert Fig 1 here]**

# 3. Data

## *Study area*

The research was conducted in Greater Manchester (GM) in the United Kingdom (UK). GM comprises the local authorities of Bolton, Bury, Manchester, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford and Wigan. Each authority contains one or more centre characterised as a locus for the NTE, though Manchester is the principal NTE. At the 2011 Census GM had a resident population of 2.5 million (Office for National Statistics 2018), making it one of the largest metropolitan areas in the UK. GM possesses a dense road network (Levine and Lee 2013) and an extensive public transport infrastructure (rail, coach, and tram), enabling ease of mobility across the area.

## *Spatial unit of analysis*

The geographical unit used in this research is the Lower Layer Super Output Area (LSOA), which is part of the official census reporting geographies of England and Wales (UK). LSOAs contain areas with similar social and land use characteristics, with their boundaries recognising major physical features on the ground. Each LSOA has a residential population of approximately 1,600 people. The study area is composed of 1,673 LSOAs (ONS Geography 2018).

## *Violent crime in public spaces*

The research uses recorded violent crime data, provided by Greater Manchester Police, for the 2013 calendar year. The data holds the following attributes: the Home Office offence code (Home Office

2013); geographical coordinates (which we allocated to the LSOA geographies of the 2011 Census); two temporal fields (Start date/time and End date/time); and, the location type of the offence. Our violent crime data utilises the Home Office (2020) 'violence against the person' offence categories, specifically violence with physical injury (e.g., wounding, grievous bodily harm) and violence without injury (e.g., threats to kill, common assault), that took place in public spaces (e.g., street, park, alley), inclusive of private spaces to which the population are granted access (e.g., pubs, shops, nightclubs). In contrast, violence against the person offences that took place in private spaces (e.g., houses, flats) and private spaces to which the public are not granted access (e.g., schools, care homes) were excluded from the analysis. Whilst 81.8% of the subsequent dataset included offences with the start and end time occurring in the same hour, the remainder did not. To accommodate these data, and following Ratcliffe (2002), we assigned a fraction (an aoristic value) of the crime count to the hours between the start and end time of the crime. We excluded offences with a time span of greater than four hours. We also exclude crimes that took place on weekend days (between Saturday 07:00 and Monday 06:59) as it was not possible to match time-sensitive trip purpose data to these periods. The resultant weekday violent crime in public spaces study data set comprises 11,800 offences, 11.4% of which took place on Wednesdays in comparison to 20.9% that took place on Saturdays, the day with the highest proportion of violent crime in public spaces. In deploying this data, we appreciate that they are not without limitations. Not all violent crimes are reported to the police. The crime survey of England and Wales (CSEW) reports, for the 12 months to March 2019, that only 44.3% of violence offences were reported to the police (ONS, 2019). Further, there are also issues with the integrity of police crime recording. In 2014, police recorded crime statistics lost their national statistics status (UK Parliament, 2014), with subsequent inspections (HMIC, 2014; HMICFRS, 2018) confirming the continuity of shortfalls in recording practices.

### *The exposed population-at-risk*

A Mobile Phone Origin Destination (MPOD) dataset, provided by Transport for Greater Manchester (TfGM), is used to quantify transient population flows across GM. These are synthesised daily trip chaining data (McGuckin and Murakami 1999). The data were collected over a 19-day period, in May and July 2013, then expanded (to represent an entire) and calibrated with reference to the telecommunication company's market share (approximately 33%), TfGM travel diaries and the demographic characteristics of GM drawn from the 2011 census. This delivers 69 million unique trips and 8.4 million trip chains on an average day. It requires to be assumed that the MPOD dataset is not subject to seasonal influence, despite its recording period. Of key value to this research, the MPOD dataset identifies, on the basis of the first and final trip chain, the end destination (i.e., home neighbourhood) of mobile phone users. Using these data, the violent crime in public spaces exposed population-at-risk is calculated as being those people present in a spatial unit (LSOA) in a given time period (see Activity categories below), excluding those people for which the spatial unit represents a final (home) destination.

As the MPOD dataset was originally generated to support the travel demand modelling of TfGM, the dataset was designed to meet this requirement, whilst also reflecting the mobile phone architecture of GM. Firstly, the MPOD data were temporally aggregated to time bins associated with distinct periods of daily travel (see, activities, below), and to weekdays (Monday to Friday) and weekend days (Saturday and Sunday). Secondly, the MPOD data were geographically aggregated to 631

spatial units (501 within the GM boundary) determined by the spatial patterning of cellular signal towers which are more dense in town and city centre areas and by the homogeneity of area land-use (reflecting an origin or destination of travel demand). In effect, and within town and city centres a MPOD spatial unit equates to a single LSOA, whilst out with town and city centres a MPOD spatial unit equates to approximately three LSOAs. Given that the primary aim of the research is to explore the influence of the time variant activities of the exposed population-at-risk on violent crime in public spaces, which concentrates in town and city centres, the relative weakness of the MPOD dataset in less populated areas is outweighed by its strength in town and city centre areas. We utilised a geographical information system (GIS) to employ a best-fit technique to distribute MPOD data across LSOAs (Office for National Statistics 2012; Ralphs 2011).

### *Activity categories*

The research deploys the National Travel End Model (NTEM) datasets[2] (Department for Transport 2017). The NTEM is used (in travel demand planning) to forecast the number of person trips arising from and ending in a particular modelling zone, during specific time periods on weekdays (Monday to Friday) or on weekend days (Saturday and Sunday), and their activity purpose (McNally, 2000). The time sequences specified in the model reflect distinct periods of daily travel demand (AM peak (07:00 -10:00), Inter-peak (10:00-16:00), PM peak (16:00-19:00) and Non-peak (19:00–07:00) and we utilise these in the subsequent analysis of weekday activities.

Weekend days are excluded because activity category data are not available across the four time periods. Whilst the NTEM is used to forecast the number and timing of person trips, these data are generated from a nationally representative data set. It is for this reason that the research deploys the MPOD dataset (described above), to enable more accurate quantification of the number and timing of person trips in GM. The NTEM is utilised, however, to apportion activities to person trips in GM. In line with previous research (Ectors et al. 2017; Vovsha et al. 2004), we encode NTEM non-home-based trip activity types in to a number of activity classes spanning work, education, shopping, personal business, recreation (e.g., outdoor pursuits, sports) and leisure (e.g., eating and drinking, tourism). The proportional distribution of non-home based trip activity types is used to weight the person trips generated by the MPOD dataset. The NTEM generates trip purposes at the Middle Layer Super Output Area (MSOA) level, which we apportion to the LSOAs which constitute a particular MSOA. This is a potential weakness of our approach, if the end destination of trips vary markedly across the LSOAs comprising a MSOA. However, given that the LSOAs spanning town and city centres comprise settings with comparable characteristics (see

The characteristics of settings below), it is unlikely that this strategy will hold significant effect.

[2] The NTEM datasets are derived from the National Travel Survey, which is based on a face-to-face interview and a 7-day self-completed travel diary. Approximately 16,000 individuals, in 7,000 households, participate in the survey each year (Department for Transport 2019) https://www.gov.uk/government/collections/national-travel-survey-statistics Accessed 08 May 2019.

### *The characteristics of settings*

Ordnance Survey (OS) Points of Interest® (POI) data is categorised according to the activity classes derived from the NTEM dataset (work, education, shopping, personal business, recreation and leisure) and aggregated at the LSOA level as a count (Siła-Nowicka et al. 2016). There are 129,275 POIs across GM, with LSOAs exhibiting significant distinction in their POI profile. That being said, town and city centre LSOAs possess the greatest concentration of work, shopping and leisure POIs. A shortcoming in the POI data is that it does not reflect the authority constraints, or temporal function, of POIs, i.e. when POIs are open and accessible.

## 4. Analytical strategy

In order to assess the influence of the time variant activities of the exposed population-at-risk and the characteristics of settings upon the spatial and temporal patterning of violent crime in public spaces a negative binomial regression model (NBM) is deployed controlling for spatial lag effects. The decision to utilise a NBM followed an assessment of the over-dispersion of violent crime in public spaces on weekdays, which found variance-to-mean ratios ranging from 1.47 to 11.72 across the four time periods studied. NBMs are best suited to manage data exhibiting significant over-dispersion (Kim 2018; Osgood 2000). The NBM uses offset terms to adjust for the varied size of the exposed population-at-risk across the LSOA geography of GM, and in differing time periods, in order to calculate rates of violent crime in public spaces. Finally, the model controls for spatial lag effects, i.e., the potential of the characteristics of neighbouring spatial units to influence the focal spatial unit (Wenger 2018). To do so, the model includes a spatially lagged dependent variable, the average violent crime in public spaces rate in adjacent spatial units in different time periods (see Kearns et al. 2019). Moran's I (Anselin 1988; Moran 1950) is used to assess the spatial autocorrelation of the model's residual value.

Prior to the final models being constructed, an assessment of the degree of multi-collinearity between the independent variables was undertaken (Belsley 1991). This task identified that working activity trips held a high variance inflation factor (VIF) with settings identified as possessing a concentration of work places, i.e., the VIF was greater than 10. The most likely explanation for this finding is that working activity trips can be regarded as obligatory (Ratcliffe, 2006) and are made to settings in which work places concentrate, i.e., there are tight coupling constraints. As a consequence, these variables were excluded from the final models. The model specifications can be expressed as follows: While $V_{iT} \sim \lambda(\mu_{iT})$ denotes the violent crime in public spaces count $V$ exhibiting a Poisson distribution $\lambda$ at location $i$ in specific time-periods $T$, where $T$ =1 to 4.

- ***Model 1****: Settings* - the reference model, $\log(V_{iT}) = X'\beta + \log(E_{iT})$, where $E$ is the exposed population-at-risk offset, $\exp(\beta)$ yields the percentage change in the crime rate derived from a 1 unit change in the explanatory variable $X$, the characteristics of settings, in each LSOA. This can be rewritten as $\log(V_{iT}/E_{iT}) = X'\beta$, where our dependent variable, $\log(V_{iT}/E_T)$, denotes the rate of violent crime in public spaces, calculated with reference to the spatially and temporally variant exposed population-at-risk.
- ***Model 2****: Settings and activities* – here the explanatory variable $X$ incorporates the attributes

of both settings and activities.

- ***Model 3****: Settings, activities and spatial lag effects* **-**The NBM with spatial lag is $\log(V_{iT}) = X'\beta + WV_{iT} + \log(E_T)$.

# 5. Results

This section commences by outlining a set of descriptive statistics, capturing key aspects of the variables deployed in the study, serving to support the interpretation of the NBM. Thereafter, the model performance and its findings are reported. Fig 2 presents a set of time variant kernel density maps. Using Kernel density estimation (KDE) enables assessment of the continuous distribution of violent crime in public spaces from a defined point (Rosser et al., 2017), in our case the centroid of GM LSOAs. KDE produces a smooth surface to fit a two-dimensional spatial probability density function (Gerber, 2014) allowing clear visualisation of the spatial concentration of violent crime in public spaces in and around town and city centres (see Song et al., 2018, for a comparable example of this approach). Table 1 details the spatial and temporal variance of the count of violent crime in public spaces, the exposed population-at-risk (by activity type) and the characteristics of settings (Points of Interest). Finally, Fig 3 presents the proportion of activities (by activity type) undertaken by the exposed population-at-risk in each of the four time periods examined in the study. For reference only, given the analytical strategy adopted, data on work-related activities are also presented in these figures and table.

**[Insert Fig 2, Table 1, and Fig 3 here]**

Examining the spatial and temporal patterning of violent crime in public spaces, two observations stand out. Firstly, and in T4, the kernel density map of the count of violent crime in public spaces holds sharper delineation than in T1-T3. Secondly, the mean and maximum count of violent crime in public spaces is significantly higher in T4 than in T1-T3. Thus, violent crime in public spaces is of a greater scale and spatial concentration in T4 in comparison to T1-T3, when and where it is relatively sparse and dispersed. The exposed population-at-risk, by activity type, also exhibits distinct spatial and temporal variation. Thus, and in comparison to T1-T3, the scale of the exposed population-at-risk and the mean number of education, shopping and personal business activities undertaken are smaller in T4. Whilst the mean number of recreation and leisure activities undertaken are higher in T4 than in T1 and T2, they are substantially lower than in T3. Expressed as proportions, recreation and leisure activities dominate T4, as might be expected given the daily rhythms of the city. Finally, the characteristics of settings vary markedly across space, though not (of course) through time, implying that facilities supporting particular activity types cluster in certain settings. Thus, and for example, the spatial variance in the presence of leisure facilities is far greater than that of recreation facilities.

## *Model performance*

Table 2 presents the results of the various criteria that were used to assess and compare the performance of each model, in each time-period (T1-T4). The smaller log-likelihood (LL), Akaike Information Criterion (AIC) and Bayesian information criterion (BIC) scores achieved by model 3 indicate that it offers the best fit (Hilbe 2011; Lucy W. Mburu and Helbich 2016). The dispersion

parameter (i.e., θ theta) illustrates that the final models are not over-dispersed (0.87 to 1.27, p<0.001), serving to validate the appropriateness of deploying the NBMs (Zuur and Hilbe 2013; Vandeviver et al., 2015). Model 3, which combines setting and activity data with the spatial lagged covariate, exhibits differing performance across T1-T4. Whilst morning peak hours (07:00-10:00) shows the best model fit (i.e., AIC = 2405.42, LL =-1189.71, θ = 1.27, p 0.001), inter-peak hours (10:00-16:00) achieves the best goodness-of-fit (McFadden R2 = 0.079).

Table 2 also displays the incidence-rate ratios (IRR), the exponential form of the regression coefficient generated by the three NBMs, in each of the four time periods studied. The value of the IRR denotes the corresponding multiplicative change of influence arising from a one-unit change in the explanatory variable (Mburu and Helbich, 2016). Thus, an IRR value of 1.5 would imply that an explanatory variable is associated with a 50% increase in the risk of violent crime in public spaces, whilst an IRR value of 0.5 would imply that an explanatory variable is associated with a 50% decrease in the risk of violent crime in public spaces.

**[Insert Table 2 here]**

## *The influence of intra-daily activities and settings upon weekday violent crime in public spaces*

Given that Model 3 affords the best overall fit, the reporting of the key findings of the research is confined to this model. In overview, the activities of the exposed population-at-risk, in different time periods, hold statistically significant associations with weekday violent crime in public spaces. Thus, the nature of the activity being undertaken, remembering that these vary in scale and proportional distribution, serves to either decrease or increase the likelihood of crime. Focussing on the most statistically significant findings, the exposed population-at-risk undertaking education (in T1-T4, p<0.001), shopping (in T1 and T2, p<0.001) and recreation (in T4 p<0.001) activities diminish the risk of weekday violent crime in public spaces. In T4, the presence of those people undertaking education and recreation activities decrease likelihood of violent crime in public spaces by 44% and 39% respectively. In sharp contrast, the presence of the exposed population-at-risk undertaking leisure activities in T4 increase the likelihood of violent crime in public spaces by 59%.

In overview, the characteristics of settings (Points of Interest) hold limited association with the time variant incidence of weekday violent crime in public spaces. In the four time periods studied, statistically significant associations were only found between the presence of shopping facilities (in T2, p<0.001 and T3, p<0.01), personal business facilities (in T2, p<0.01), leisure facilities (in T4, p<0.001) and violent crime in public spaces. Of the more robust associations, the presence of shopping facilities (in T2) and leisure facilities (in T4) increased the likelihood of violent crime in public spaces by 40% and 63% respectively. The spatial lag variable exhibits a positive and statistically significant effect, particularly in T2-T4, i.e., it displays significant positive spatial autocorrelation. In effect, a 1% increase in violent crime in public spaces in any given spatial unit is associated with a 30% to 41% increased likelihood of violent crime in public spaces occurring in adjacent spatial units.

# 6. Discussion

The most striking results of Model 3 occur in T4 (19:00 to 07:00) when leisure activities and leisure settings hold strong and independent influence on the likelihood of weekday violent crime in public spaces, though they are bound by coupling constraints. It is in this period that the count of violent crime in public spaces is at its highest and most spatially concentrated (see Fig 2), a period also in which the exposed population-at-risk is significantly lower than at other times of the day (see Fig 1). In T4, leisure (and recreation) activities dominate, though the scale of the exposed population-at-risk undertaking these activities is smaller than earlier in the day, and are serviced by facilities that cluster in particular settings. Whilst previous literature has highlighted the importance of the scale and trip purpose of the transient population on crime (Boivin 2018; Boivin and D'Elia 2017; Boivin and Felson 2018; Felson and Boivin 2015), we believe that this is the first study to demonstrate the *time variant* nature of its influence.

The results evidence the claims made in existing research exploring the relationship between the NTE and violent crime. Alcohol consumption is the principal leisure activity of the NTE (Hadfield et al. 2009), occurring in a social environment that induces cumulative alcohol consumption (Bellis et al. 2010; Moore et al. 2007). Alcohol consumption is associated with heightened aggression and an increased likelihood of being involved in violence (Finney 2004; Schnitzer et al. 2010), making it plausible that a smaller population denominator is responsible for a higher crime count. The evidence gathered here appears compelling in this regard. Over the duration of a weekday evening, the exposed population-at-risk undertaking leisure activities exhibit an increased propensity to perform the roles of offender and / or victim and a decreased propensity to perform the role of guardian. Further, it is plausible that the absence of population groups undertaking other activities, who might play an active or passive role as a guardian (Felson and Boivin 2015), serves to further heighten the likelihood of violent crime in public spaces. The research found the presence of those undertaking education and recreation activities served to temper violent crime in public spaces in T4. It would appear worthwhile, from a policy perspective, to consider ways to increase the scale of those undertaking these activities in the later evening in city centre areas.

The results confirm the influence of environmental features on crime patterning (Brantingham and Brantingham, 1995; Kinney et al. 2008; Montoya 2015), specifically the role that drinking establishments (e.g., pubs, restaurants and nightclubs) or *risky facilities* (Bowers 2014) when clustered in settings or *magnetic places* (Boivin and D'Elia 2017) hold on the spatial concentration of violent crime in public spaces (Gmel et al. 2016). It is noteworthy, given the discussion of leisure activities associated with the NTE, that the authority constraints (Hägerstraand 1970; Miller 2005) governing access to drinking establishments do not prohibit this activity taking place in other time periods. This being said, premises such as pubs, restaurants and nightclubs tend, reflecting coupling constraints (Hägerstraand 1970; Miller 2005), to upscale their operation in the NTE.

In overview, through adopting a theoretically informed definition of the exposed population-at-risk of violent crime in public spaces, taking the transient population as the best available measure of this, and integrating both intra-daily activity and setting characteristics data, this research delivers substantive contributions to the existing literature. It demonstrates that population scale does not hold a direct relation with crime patterning. Rather, crime patterning (spatial and temporal) is a

function of the routine activities of the transient population and of the characteristics of the settings in which such routines take place. In contrast to previous studies that have been unable to distinguish intra-daily activity patterns, this paper illustrates that weekday violent crime in public spaces is reflective of the time sensitive and independent influence of, and interaction between, the coupling constraints shaping intra daily activities (scale and type) and land use features. The scale and mix of the transient population activities are evidenced to either heighten or lessen exposure to weekday violent crime in public spaces. When leisure activities dominate the use of settings, though smaller in scale than in other moments of the day, exposure to weekday violent crime in public spaces is at its greatest. At these times and in these settings, it is plausible that the balance between those capable of performing the role of victim, offender or guardian shifts, with people likely to hold an increased propensity to perform the roles of victim and/or offender and a decreased propensity to perform the role of guardian. That criminogenic settings, understood as a combination of crime attractors and population generators, also exhibit clustering and / or people pass through neighbouring spatial units to access these settings is no doubt influential in the higher levels of weekday violent crime in public spaces in adjacent spatial units.

# 7. Conclusion

This paper contributes to the emergent body of research examining the influence of the transient population on crime (Boivin 2018; Boivin and Felson 2018; Felson and Boivin 2015; Song et al. 2018). In contrast to these studies, however, it demonstrates that the activities undertaken by the transient population hold intra-daily distinction in their scale and influence on the likelihood of crime. Exploring the influence of intra-daily activities and settings upon weekday violent crime in public spaces, it found leisure activities and settings characterised by leisure facilities to significantly increase the likelihood of crime on weekday evenings but not at other times of the day. In these terms, weekday violent crime in public spaces is a function of what people do, with and without others, where and when. Cumulatively, these elements shape the mix of *active* offenders, victims and guardians in a given spatial unit at a given time. The research was founded on the integration of novel and fine-grained data, enabling quantification of a theoretically informed crime specific exposed population-at-risk (in this instance the transient population), qualification of their activities and of the characteristics of the settings they visited. These data are not without their limitations. Significantly, it was not possible to determine the socio-demographic characteristics of the exposed population-at-risk, recognising that these serve to influence where people go, what they do and how long they take to do it, as well as their likelihood of performing offending, victimisation and guardianship roles. Accessing such data would serve to significantly enhance this research field.

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# Tables and Figures

**Table 1. Weekday violent crime in public spaces, the activities of the exposed population and the characteristics of settings**

| Variable | T1 (morning peak hours: 7:00-10:00) | | | | T2 (inter-peak hours: 10:00-16:00) | | | | T3 (evening peak hours: 16:00-19:00) | | | | T4 (non-peak hours: 19:00-07:00) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Min. | Mean | Max. | SD | Min. | Mean | Max. | SD | Min. | Mean | Max. | SD | Min. | Mean | Max. | SD |
| **Violent crime counts in public spaces** | 0.00 | 0.33 | 9.00 | 0.78 | 0.00 | 1.70 | 56.00 | 3.62 | 0.00 | 1.39 | 61.00 | 2.71 | 0.00 | 3.63 | 222.00 | 9.00 |
| **Exposed population** | | | | | | | | | | | | | | | | |
| **Work** | 4.03 | 143.05 | 4,619.42 | 250.97 | 1.78 | 35.23 | 1,445.35 | 58.62 | 7.75 | 141.83 | 2,636.88 | 163.82 | 1.39 | 33.78 | 1,093.72 | 47.45 |
| **Education** | 5.14 | 121.82 | 1,379.05 | 126.09 | 3.51 | 91.23 | 842.21 | 90.3 | 2.18 | 38.04 | 394.49 | 34.93 | 0.05 | 1.24 | 12.84 | 1.17 |
| **Shopping** | 0.74 | 35.66 | 2,046.86 | 67 | 2.48 | 115.23 | 6,932.13 | 231.47 | 2.83 | 86.14 | 5,835.36 | 190.32 | 0.41 | 14.16 | 888.72 | 25.95 |
| **Personal business** | 0.75 | 21.59 | 330.98 | 29.57 | 1.88 | 45.6 | 798.2 | 54.79 | 1.91 | 34.22 | 720.07 | 41.26 | 0.29 | 5.67 | 56.25 | 5.8 |
| **Recreation** | 0.06 | 8.79 | 331.05 | 18.89 | 0.43 | 27.61 | 1,289.19 | 58.96 | 1.35 | 56.23 | 3,425.7 | 144.47 | 1.65 | 35.56 | 1,462.19 | 52.86 |
| **Leisure** | 0.35 | 9.11 | 292.19 | 13.5 | 1.1 | 23.53 | 628.72 | 29.55 | 3.27 | 63.22 | 1,884.25 | 85.56 | 1.52 | 32.55 | 504.15 | 32.16 |

| Variable | Min. | Mean | Max. | SD |
|---|---|---|---|---|
| **Settings** | | | | |
| **Work** | 3.00 | 34.58 | 899.00 | 47.57 |
| **Education** | 0.00 | 2.15 | 23.00 | 2.16 |
| **Shopping** | 0.00 | 8.02 | 545.00 | 23.28 |
| **Personal business** | 0.00 | 5.90 | 149.00 | 8.78 |
| **Recreation** | 0.00 | 2.85 | 41.00 | 3.19 |
| **Leisure** | 0.00 | 5.51 | 241.00 | 11.29 |

**Table 2. IRRs (Incident rate ratios) and model fit for the negative binomial regression models.**

| Variable | T1 (AM peak 07:00 -10:00) | | | T2 (Inter-peak 10:00-16:00) | | | T3 (PM peak 16:00-19:00) | | | T4 (Non-peak 19:00-07:00) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) | Model 1 IRR (SE) | Model 2 IRR (SE) | Model 3 IRR (SE) |
| **Settings** | | | | | | | | | | | | |
| **Education** | 0.96 (0.06) | 1.00 (0.06) | 0.99 (0.06) | 1.00 (0.04) | 1.05 (0.04) | 1.05 (0.04) | 0.97 (0.04) | 1.03 (0.04) | 1.03 (0.04) | 0.98 (0.04) | 1.04 (0.04) | 1.02 (0.04) |
| **Shopping** | 0.86 (0.07) | 1.08 (0.10) | 1.08 (0.10) | **1.18 (0.07)**** | **1.50 (0.10)***** | **1.40 (0.09)***** | 1.10 (0.07) | **1.29 (0.09)***** | **1.23 (0.08)**** | 0.91 (0.05) | 1.09 (0.07) | 1.08 (0.07) |
| **Personal business** | **1.39 (0.14)***** | 1.06 (0.11) | 1.04 (0.11) | **1.63 (0.11)***** | **1.22 (0.08)**** | **1.20 (0.08)**** | **1.44 (0.10)***** | 1.08 (0.08) | 1.05 (0.07) | **1.53 (0.09)***** | 1.14 (0.07)* | 1.12 (0.07) |
| **Recreation** | 0.94 (0.07) | 1.03 (0.07) | 1.03 (0.07) | **0.89 (0.04)**** | 0.96 (0.04) | 0.96 (0.04) | 0.91 (0.04)* | 1.01 (0.05) | 1.02 (0.04) | **0.90 (0.04)**** | 0.93 (0.04) | 0.95 (0.04) |
| **Leisure** | 1.02 (0.10) | 1.18 (0.11) | 1.18 (0.11) | **0.83 (0.06)**** | 0.98 (0.07) | 1.00 (0.07) | 0.90 (0.07) | 1.07 (0.08) | 1.11 (0.08) | **1.31 (0.09)***** | **1.79 (0.11)***** | **1.63 (0.10)***** |
| **Exposed population** | | | | | | | | | | | | |
| **Education** | - | **0.84 (0.05)**** | **0.84 (0.05)**** | - | **0.72 (0.04)***** | **0.74 (0.04)***** | - | **0.62 (0.04)***** | **0.65 (0.04)***** | - | **0.51 (0.03)***** | **0.56 (0.04)***** |
| **Shopping** | - | **0.72 (0.08)**** | **0.73 (0.08)**** | - | **0.80 (0.04)***** | **0.83 (0.05)***** | - | 0.98 (0.07) | 0.98 (0.07) | - | 1.16 (0.08)* | 1.18 (0.08)* |
| **Personal business** | - | 1.00 (0.05) | 1.00 (0.05) | - | 0.98 (0.04) | 0.99 (0.04) | - | 0.98 (0.05) | 0.99 (0.05) | - | **0.86 (0.04)**** | 0.90 (0.04)* |
| **Recreation** | - | 1.03 (0.06) | 1.03 (0.06) | - | 1.02 (0.05) | 1.02 (0.05) | - | 0.87 (0.07) | 0.88 (0.06) | - | **0.65 (0.05)***** | **0.71 (0.05)***** |
| **Leisure** | - | 0.89 (0.04)* | 0.89 (0.04)* | - | 1.05 (0.05) | 0.98 (0.04) | - | 1.14 (0.10) | 1.08 (0.09) | - | **1.97 (0.15)***** | **1.59 (0.12)***** |
| **Spatial lag** | | | | | | | | | | | | |
| **Average violent crime rates in adjacent areas** | - | - | 1.13 (0.06)* | - | - | **1.30 (0.04)***** | - | - | **1.41 (0.04)***** | - | - | **1.40 (0.04)***** |
| **N** | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 | 1673 |
| **Log Likelihood** | -1221.76 | -1192.21 | -1189.71 | -2805.95 | -2737.4 | -2701.3 | -2696.74 | -2619.42 | -2568.53 | -3818.5 | -3843.96 | -3723.97 |
| **Deviance** | 1092.63 | 1109.83 | 1110.56 | 1720.33 | 1714.94 | 1610.04 | 1701.32 | 1717.73 | 1723.13 | 1851.45 | 2087.98 | 1824.42 |
| **AIC** | 2457.52 | 2408.41 | 2405.42 | 5625.9 | 5498.8 | 5428.6 | 5407.49 | 5262.83 | 5163.07 | 7650.99 | 7711.92 | 7473.95 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **BIC** | 2495.48 | 2473.48 | 2475.91 | 5663.85 | 5563.87 | 5499.09 | 5445.44 | 5327.9 | 5233.56 | 7688.95 | 7776.98 | 7544.44 |
| **Dispersion parameter (θ)** | 1.66 | 1.30 | 1.27 | 1.16 | 0.98 | 0.89 | 1.33 | 1.00 | 0.87 | 1.20 | 0.97 | 0.90 |
| **Moran's I of residuals** | 0.18 | 0.17 | 0.14 | 0.23 | 0.23 | 0.12 | 0.26 | 0.26 | 0.12 | 0.28 | 0.30 | 0.18 |

**Note: *** (p<0.001), **(p<0.01), and * (p<0.05), IRRs whose p-values are less than 0.01 are marked in bold**.

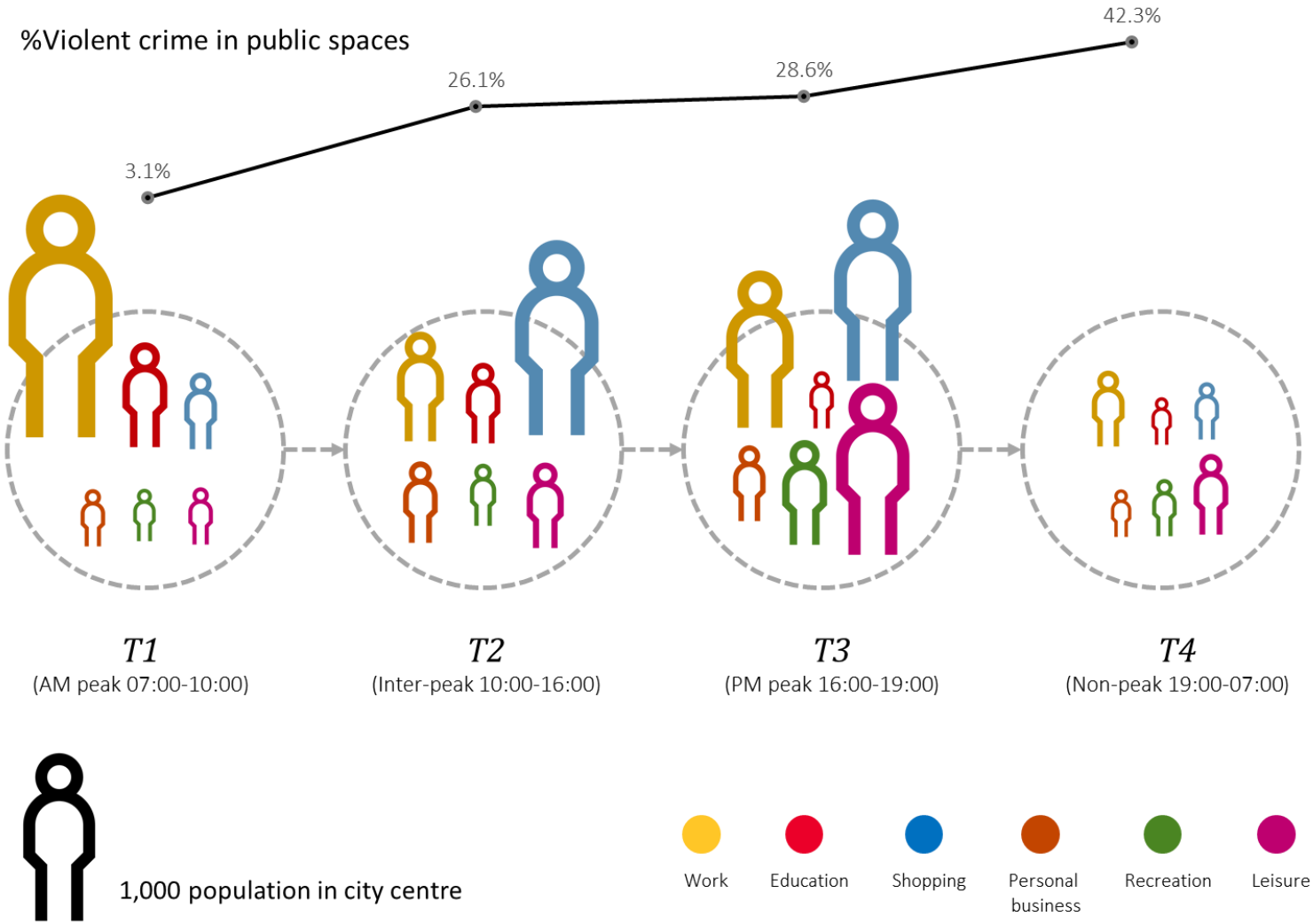
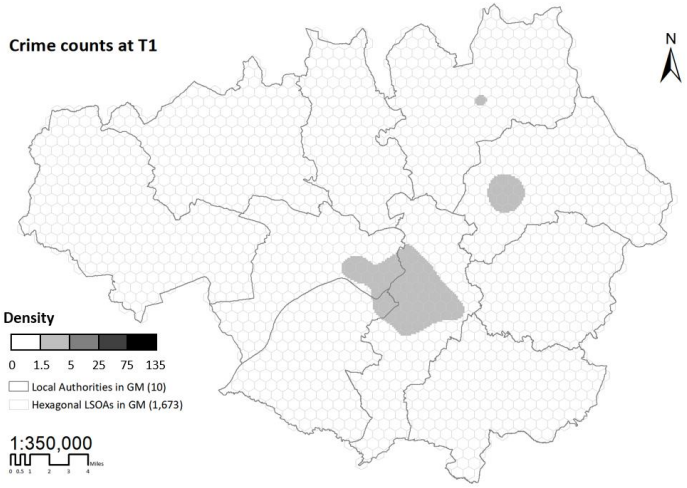
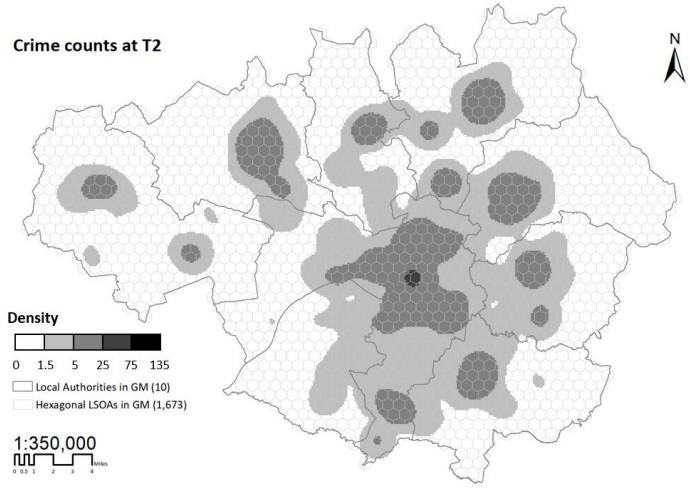


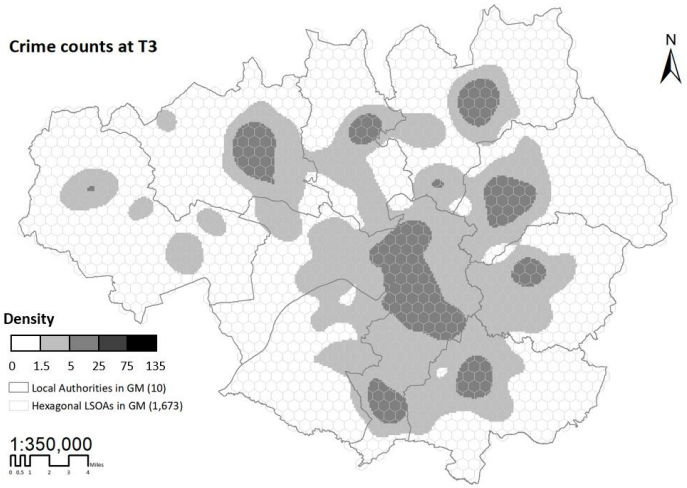

**Fig 1. Illustration of the time-variant scale and activity mix of the exposed population-at-risk in a city centre, and its association with violent crime in public spaces.**



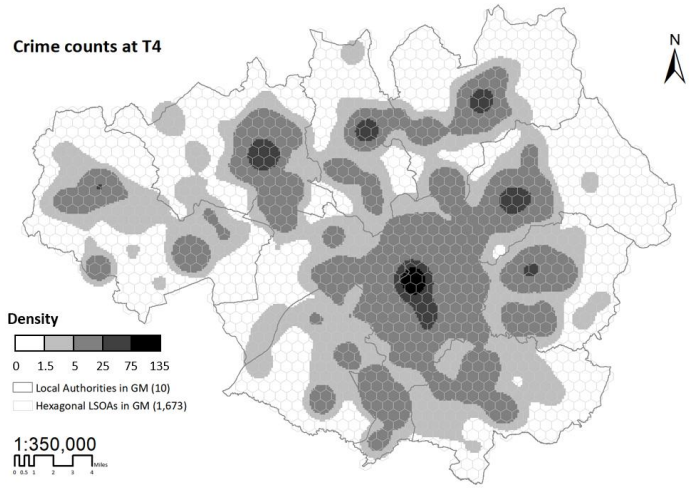

a: Crime counts at T1




b: Crime counts at T2




c: Crime counts at T3




d: Crime counts at T4

**Fig 2. The kernel density estimation of violent crime in public spaces in different time periods**
**(Source: Contains Ordnance Survey Boundary Line; Ordnance Survey data © Crown copyright and database right 2018)**

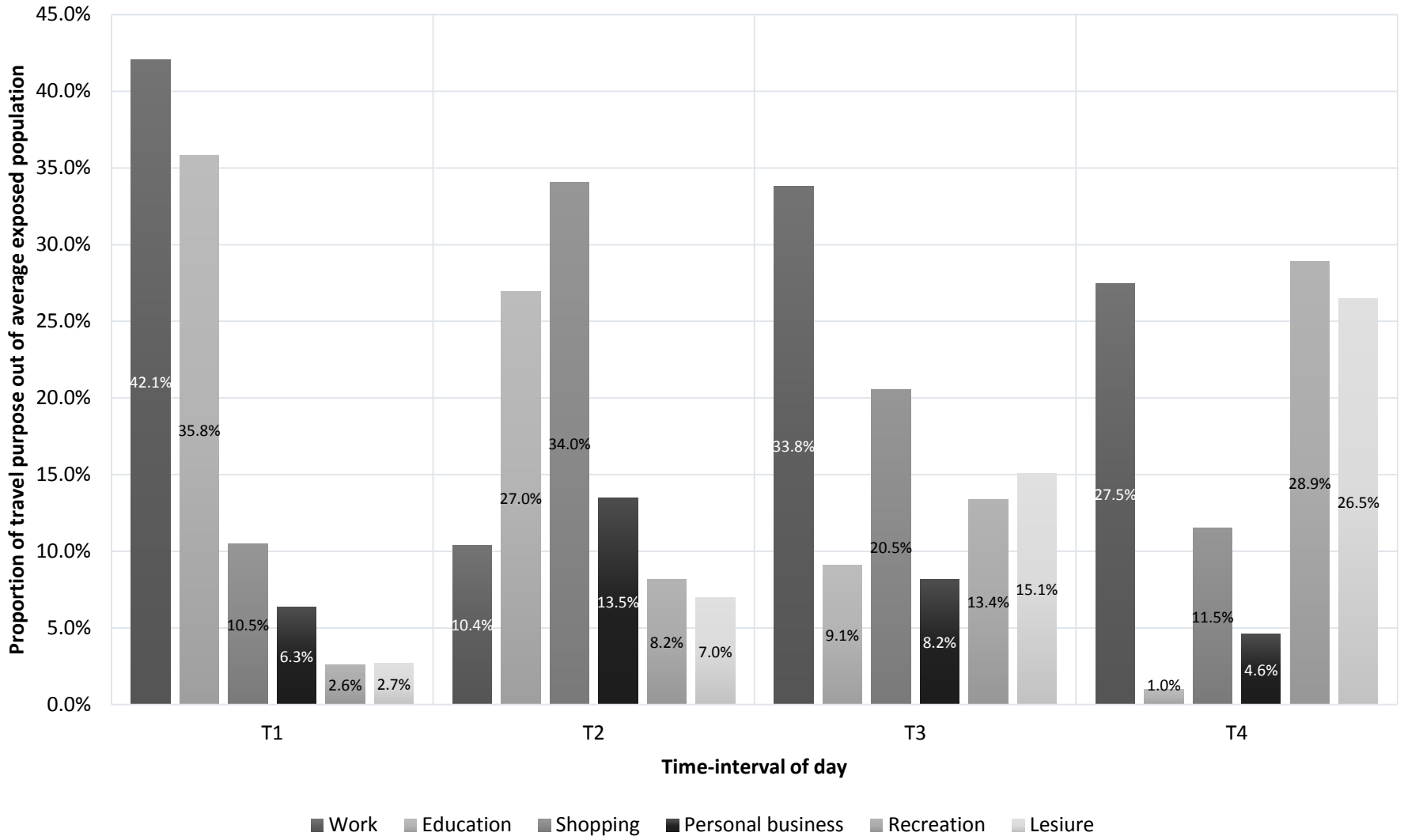



**Fig 3. Average exposed populations by major activity types at time-intervals of day across Greater Manchester.**
**(Source: National Trip End Model data set, TEMPro (The Trip End Model Presentation Program) v.7.2 provided by Department for Transport)**