STUDY OF CRIME PATTERNS WITHIN THE BUILT ENVIRONMENT – A SYSTEMATIC REVIEW AND META-ANALYSIS

Meha Shukla[1], Shane Johnson[2], Peter Jones[3]

Abstract

This research explores the academic literature to understand how the criminogenic properties in micro places of various urban elements, such as the configuration of the street network, parks, bus stops and schools have been found to influence crime through a systematic review and a statistical meta-analysis. The meta-analysis provided a baseline of the quantified criminogenic effect of urban elements found in the street environment, the purpose of which was to anticipate the impact of changes. It was found that despite differences in studies, urban elements in the built environment shape the spatial and temporal distribution of urban crime in a consistent manner. While the findings from this chapter need to be treated with caution, due to the low number of data points and studies included for some of the analyses, they highlight how the design of urban environments can influence patterns of crime. As a standalone exploratory study, this article contributes to academic literature to present the state of the art regarding the effects of traditional physical urban elements on crime.

Keywords: criminogenic properties of urban elements, crime and place, built environment, meta-analysis, crime patterns in built environment, risky facilities

[1] Dr. Meha Shukla- Researcher at UCL, Email: uctzshu@ucl.ac.uk, ORCID iD: 0009-0006-3651-8129.
[2] Dr. Shane Johnson – Director, Dawes Centre for Future Crime at UCL, Email: uctcsjo@ucl.ac.uk.
[3] Dr. Peter Jones - Professor of Transport and Sustainable Development at UCL, ucespmj@ucl.ac.uk.

1. Introduction

Studies of Environmental Criminology suggest that crime is not random but clusters in time and space (Brantingham & Brantingham, 1995; Sherman et al., 1989), among victims (Pease, 1998) and among facilities (Eck et al., 2007). Motivated by this finding, theories of Environmental Criminology consider the crime event as the object of central interest and place the focus of enquiry on the dynamics of crime events rather than the dispositions of offenders. An important principle of this perspective is that all criminal behaviour results from a person–situation interaction. The immediate environment is not just a passive backdrop for criminal behaviour, but rather it plays a fundamental role in making crime possible and shaping its course.

Routine Activity Theory (Cohen & Felson, 1979b) states that crime is most likely to occur when a motivated offender and vulnerable victim converge in time and space, absent a capable guardian (Cohen & Felson, 1979; Clarke, 1983). This convergence is proposed to be determined by the everyday movements of victims and offenders and hence, according to the theory, crime will concentrate where the routine movements of victims and offenders overlap. For example, research on routine activities has found that the core daily activities of people, such has hanging out with friends at night clubs, where there is a lack of social control and there is an absence of authority figures, is positively associated with assault and drug crimes (Miller, 2012). These associations between routine activities and offenses vary by offence type (Miller, 2012).

Research on crime and place consistently suggests that crime is strongly concentrated at the micro-level of place – such as street segments and census blocks – and that these concentrations are stable over time (Groff, Weisburd, & Yang, 2010; Weisburd, Bernasco, & Bruinsma, 2009). Such findings raise the question of specifically what factors influence routine activities and crime concentration and suggest that analyses intended to address this question should be conducted at the micro level. Empirical research suggests that the choice and placement of land use elements such as roads, bridges, tunnels, buildings and walk ways play an important role in shaping how people move as well as how they interact within urban spaces (Wuschke & Kinney, 2018; Kinney et al., 1978). Research has also found that specific land use types are more criminogenic than others due to their physical and social characteristics (Eck & Weisburd, 1995; Irvin-Erickson, 2015; Kennedy, Caplan, & Piza, 2011). For example, the use of permeable street network designs in mixed land use areas can facilitate varied movement patterns and hence can be associated with higher levels of crimes (Sohn, 2015). Connected streets and areas with higher accessibility, high traffic and those that are frequently travelled have been found to be associated with a higher concentration of targets and increased offender awareness; and hence higher crime (Newman, 1972; Beavon et al., 1994). In contrast to through roads, cul-de-sacs have lower connectivity and hence are less likely to be used (Johnson & Bowers, 2010a).

In addition to identifying the factors associated with the spatial concentration of crime, it is equally important to assess the magnitude of these associations—namely, their effect sizes(Groff et al., 2010). Such analysis contributes to both theoretical advancements in criminology and the development of more effective crime prevention strategies. In recent decades, an increasing number of studies have examined these issues at the micro-geographic level. Accordingly, the present research seeks to synthesize the existing empirical evidence through a systematic review. To more precisely estimate the criminogenic impacts of various factors, a meta-analytic approach was employed. Meta-analysis provides a statistical framework for calculating a single, aggregated estimate of effect size across multiple studies (Michael et al., 2011).

The overarching research questions to be addressed in this article are thus "which urban elements (such as the configuration of the street network, parks, shopping malls, restaurants, and schools) have been quantitatively analyzed for their influence on crime using micro spatial units, and what is their estimated overall effect on crime?" The remainder of the article is organised as follows. The next section describes the inclusion criteria, search strategy and search results for the review, Section 3 details the methodology for a meta-analysis of the data extracted from the studies identified, and Section 4 presents the results. Section 5 provides a discussion of the overall findings.

2. Study design – systematic literature review

Different approaches to reviewing literature exist. While useful, ad-hoc or standard literature reviews are known to lead to the identification of biased samples of studies (Shuster, 2011). As such, two different reviewers conducting the same search may come to different conclusions. For this reason, Systematic Reviews (SRs) have emerged as a method of synthesizing evidence in a reproducible and unbiased way (Higgins et al., 2019) and it is this methodology that is used here.

2.1 Inclusion criteria

The following eligibility criteria were used to decide whether to include or exclude studies:

1. Studies must be from a credible source or peer-reviewed and in English: All peer-reviewed academic papers and conference proceedings were included. Grey literature, such as organizational reports, were included if they were authored by a credible source. This included, for example, Transport for London (UK) and the UK Home Office. Magazine studies (except for Research*eu magazine) and online blogs were not included as these are not credible sources for quantitative analysis and are rarely subjected to quality assurance (such as peer review).

2. Studies must have conducted quantitative analysis using micro spatial units: To be included, the authors had to clearly examine the effect of a specific urban element (e.g. parks, schools) on crime and the spatial units employed had micro spatial units such as street segments, 400-500 feet buffer zones around a place (the average length of a street block), or $500ft^2$ grid cells. Block faces are the smallest units of Census geography in the USA (Roberto, 2018), and so the decision was taken to include studies that used this unit of spatial analysis too. Studies that did not define the spatial unit of analysis employed or had a very large spatial unit, such as census tracts, dissemination areas (which are often used in Canada) or large neighbourhoods were excluded.

3. Studies must focus on urban areas and must analyze crimes that occur in urban environments: Studies that focused on micro places within urban areas such as cities, towns and suburbs were included. For example, studies conducted for a self-contained university campus were excluded, but those conducted using data for a university town (e.g., Cambridge and Oxford in the UK) were included. Studies that analyzed crimes occurring in urban areas such as residential burglary were included.

4. Studies must analyze crime patterns quantitatively: Studies that did not report empirical findings were excluded.

5. Studies must analyze crime patterns using precise data: Studies that used data that lacked spatial accuracy were excluded. For example, data directly provided by police departments (which is usually accurate to a resolution of one metre, or similar) were included, but data provided by (for example) police.uk and public websites were excluded as these data are known to lack the spatial accuracy necessary for the analysis of crime at micro places (Tompson et al., 2014).

6. Studies must not analyze crime patterns using data from the Covid-19 pandemic period – 2020 to 2022: Studies that used data for the period of the Covid pandemic were excluded as crime patterns were very different to other periods of time due to the “stay at home” mandates imposed on people by Governments world-wide (Abrams, 2021; Díaz et al., 2022; Zhang & Chen, 2023).

2.2 Search strategy

A comprehensive search strategy was employed, utilizing a combination of keywords to identify studies that met the predefined inclusion criteria across various academic databases. In addition to peer-reviewed literature, relevant grey literature was also included, provided it aligned with the inclusion criteria. A systematic review protocol outlining the search methodology was developed and independently reviewed by two researchers. Based on their feedback, adjustments were made to incorporate spelling variations of the search keywords (e.g., "neighborhood" and "neighbourhood") to enhance the inclusivity and comprehensiveness of the search.

The databases searched were chosen to provide coverage of a wide range of disciplines (e.g. criminology, urban planning, transport, social sciences, criminal justice, policing, and Government policies):

1. ProQuest: a multidisciplinary database that covers Australian Education Index , Avery Index to Architectural Periodicals, Digital National Security Archive (39 databases) , EBook central, Humanities Index, ProQuest Central (61 databases) and Social Science Premium collection (17 databases) (Proquest LLC., 2020).
2. SCOPUS: one of the largest and most prestigious databases for peer-reviewed literature which covers multi-disciplinary globally sourced articles from fields such as Science, Technology, Medicine, Social sciences, and Arts and humanities (Elsevier B.V., 2020b).
3. Geobase: a database that allows access to international geoscience literature that covers 2,772,739 abstract records (Elsevier B.V., 2020a).
4. JSTOR: a database that allows access to “12 million journal articles, books, images, and primary sources in 75 disciplines” (Ithaka, 2020).
5. Campbell collaboration: a leading source of world-wide research literature that informs policy makers (Campbell Collaboration, 2020).

Additional data sources were identified from the grey literature by hand searching for publications produced by:

1. **Reports from relevant organizations in the UK**: Reports and websites from the following organizations were hand searched: The Home office, Transport for London, the UK College of Policing, the Office for the Deputy Prime Minster (ODPM), the Department of the Environment, Transport and the Regions, the Ministry of Housing and Communities & Local Government.
2. **Reports from relevant organizations in the US**: Reports and websites of the following organizations were hand searched: the National Institute of Justice, The Police Foundation and the Department of Homeland security.
3. **Reports from relevant organizations in Australia:** Reports and websites of the following organization were hand searched: the Australian Institute of Criminology and the Australian Urban Design Research Centre
4. **Reports from relevant organizations in New Zealand:** Reports and websites of the following organization were hand searched: the Ministry for the Environment, and the Ministry for Justice
5. **Other:** The following were also hand searched: Research*eu magazine, United Nations Interregional Crime and Justice Research Institute (UNICRI) publications, and International CPTED Association (ICA) – CPTED Journal publications.

<u>Search terms</u>

The databases were searched using search terms identified through an initial scoping of the literature.

The keywords used represented four dimensions of the search - elements of street Design and urban planning, crime patterns, specific crime types, and the type of (quantitative analysis) employed. The search terms used for ProQuest were based on the following themes (See Appendix 1 for details):

a) Elements of street Design and urban planning – Thematic keywords within this filter relate to physical urban environments, the design of the built environment, street characteristics, smart city elements and land use – e.g., “built environment, “neighbourhood”.
b) Crime patterns and impacts – Thematic keywords within this filter relate to crime analysis, and changes to crime – e.g., “correlation”, “spatiotemporal”.
c) Crime types – Thematic keywords within this filter relate to possible physical crimes that occur in the built environment – e.g., “burglar”, “arson”.

d) Quantitative analysis - Thematic keywords within this filter are used to exclude studies that used only qualitative analyses or did not report any analyses – e.g., "coefficient", "regression".

Due to differences in the syntax available, variations of this search string were used for the other search engines. Backward searches were also conducted by examining the bibliographies of articles identified and subsequently included in the review if the inclusion criteria was met.

2.3 Search results

Searches were conducted in January 2020 and updated in August 2024.

2.3.1 Screening of search results

The search results yielded 721 studies, while 7 other studies were identified manually, resulting in a total of 728 studies. These were imported into the web-based tool *Covidence.* 224 duplicate studies were automatically removed and a further six duplicate studies were identified and removed manually (see Figure 1). In line with PRISMA guidance (Selçuk, 2019), articles were first screened on the basis of their titles and abstracts, after which the full-text of the remaining articles were thoroughly read. Of the 498 non-duplicate articles, 323 were excluded as the screening of their title and abstracts indicated that they discussed non-urban entities, crimes that were out of scope (e.g., corporate crime) or did not conduct a quantitative analysis of the impact of urban elements on crime. Full text screening of the remaining 175 studies resulted in the removal of a further 81 studies (94 studies remained). Of those that were removed:

a) 21 study were not written in English (although the abstract was)
b) 15 studies did not use data with sufficient spatial accuracy (e.g. the crime data was downloaded from public websites rather than being provided by police departments)
c) 27 studies did not assess the influence of urban elements on crime, did not assess these quantitatively or did not report an effect size that was suitable for statistical meta-analysis
d) 3 studies assessed crimes associated with the internal features of urban elements
e) 14 studies included data from Covid-19 pandemic period
f) 1 study discussed specific scenarios such as dissident Republican violence in Belfast

Of the 94 studies that remained, 65 were excluded as they used large spatial units. Five of these did not define the spatial unit of analysis (one of which was a systematic literature review that assessed various models that measured the spatial effect of alcohol consumption on crime). Ultimately, 29 studies that used micro spatial units were included.

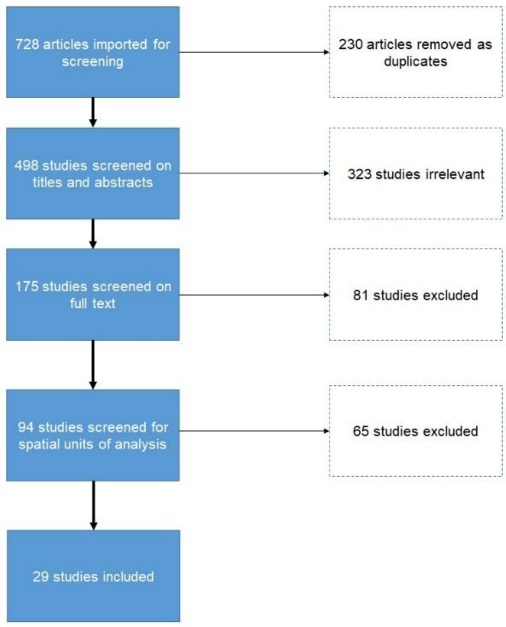

Figure 1 Prisma Chart of search process for systematic review

To assess Inter-rater reliability (IRR), two reviewers screened the titles and abstracts of 20% of the studies, applying the inclusion criteria described above, and the degree of agreement was assessed based on two parameters, inclusion and exclusion (Virta, 2013). The computed Prevalence-Adjusted Bias-Adjusted Kappa (PABAK) statistic of 0.78 indicated that there was high agreement between the reviewers, and consequently one reviewer screened the remainder of the studies.

2.3.2 Data extraction

A spreadsheet was used to manually extract information from the articles that met the inclusion criteria. A pilot exercise was completed for a sample of articles to ensure that data was captured in a reliable manner. The following details were extracted from articles that met the eligibility criteria:

- Title of the article
- Authors
- Year of study
- Brief description of the study
- Type of publication (e.g., journal, grey literature)
- City and country where the study was conducted
- Urban element (e.g., trees, bicycle parking, bus stop)
- Crime type examined (e.g., antisocial behaviour, burglary)
- Data sources and time-period

- Spatial unit of analysis
- Study design (e.g. longitudinal study, cross sectional study)
- Type of the statistic and statistical model used to examine association between crime and street element (e.g., Regression coefficient, bivariate association, hierarchical linear models, single level models)
- Type of study design (cross sectional, time series, experiment)
- Description of quantitative result (e.g. associated findings, context specific dependencies)
- Association of urban Street element with crime as found in the study (e.g., bus stop increases crime, decreases crime, or has no impact)
- Statistic value and precision (number)
- Comment (e.g., any additional findings, constraints of the model)

The extracted data from 29 studies that met the inclusion criteria are listed in Appendix 2.

2.3.3 Characteristics of included studies

Studies included in the SR were conducted across eight countries –Brazil, Canada, China, Israel, Italy, Mexico, UK, and USA. The urban elements examined are listed in Table 1.

Table 1 Urban Elements found in studies included in SR

Urban elements	Number of assessments	Studies
Street Network, Configuration and other features	12	(Bernasco & Block, 2011), (Clutter et al., 2019), (Davies & Johnson, 2015), (Groff & Lockwood, 2014), (Vilalta & Fondevila, 2019), (Beavon et al., 1994), (Johnson & Bowers, 2010), (Summers & Johnson, 2017), (Kim & Hipp, 2019), (Kim & Wo, 2023), (Favarin, 2018), (Xie et al., 2022)
Public Transit	10	(Bernasco & Block, 2011), (Hsu & Miller, 2017), (Clutter et al., 2019), (Amram et al., 2024), (Soohyun & Yongjei, 2016), (Favarin, 2018), (Liggett et al., 2003), (Groff & Lockwood, 2014), (Haberman & Ratcliffe, 2015), (Newton et al., 2014)
Retail land use	11	(Bowers, 2014), (Clutter et al., 2019), (Soohyun & Yongjei, 2016), (De Souza & Miller, 2012), (Favarin, 2018), (Haberman & Ratcliffe, 2015), (Kim & Hipp, 2019) , (Kim & Wo, 2022), (Bernasco & Block, 2011), (Hsu & Miller, 2017), (Vilalta & Fondevila, 2019),
Alcohol outlets	10	(Bernasco & Block, 2011), (Clutter et al., 2019), (Favarin, 2018), (Groff & Lockwood, 2014), (Haberman & Ratcliffe, 2015), (Vilalta & Fondevila, 2019), (Liggett et al., 2003), (Groff, 2014), (De Souza & Miller, 2012), (Ratcliffe, 2012)
Schools	7	(Clutter et al., 2019), (Soohyun & Yongjei, 2016), (Favarin, 2018), (Groff & Lockwood, 2014), (Haberman & Ratcliffe, 2015), (Wo & Park, 2020), (Kim & Wo, 2022)
Parks	5	(Groff & Mccord, 2012), (Haberman & Ratcliffe, 2015), (Clutter et al., 2019), (Hsu & Miller, 2017), (Boessen et al., 2018)
Drug treatment centers	3	(Clutter et al., 2019), (Groff & Lockwood, 2014), (Haberman & Ratcliffe, 2015)
Bank branches and ATM	2	(Favarin, 2018), (Haberman & Ratcliffe, 2015a)
Hotels	2	(Clutter et al., 2019), (Kim & Wo, 2022)
Shopping malls	2	(Kim & Wo, 2022), (Vilalta & Fondevila, 2019)
Alley ways and windows onto street	2	(Beavon et al., 1994), (De Souza & Miller, 2012)
Trees	2	(Deng, 2015), (Xie et al., 2022)
Walkability	2	(Lee & Contreras, 2021), (Xie et al., 2022)
Police stations. Total units of public housing on each street segment	1	(Favarin, 2018)
Public libraries, recreation centers	1	(Clutter et al., 2019)
Abandoned buildings, vacant land, mailboxes, parking lots, Churches	1	(Hsu & Miller, 2017)
Halfway houses	1	(Groff & Lockwood, 2014)
Fire stations	1	(Ratcliffe, 2012)
road density in the areas surrounding the street segments, walkability, the proportion of grass in the streetscape, the greening rate and the number of - streetlamps, sidewalks, enclosure effects, fences, number of buildings in street scape, number of walls in streetscape and number of trees in streetscape	1	(Xie et al., 2022)
Physical boundaries between two sides of streets (Land use difference)	1	(Y.-A. Kim & Hipp, 2022)
Number of businesses, Percentage of buildings built in past 10 years, community center and educational building within 500m of center of street segment, garden within 150m of street segment	1	(Amram et al., 2024)

With respect to study design, two studies employed a matched case-control design, whereas the remaining 27 studies were cross sectional studies. None used a randomized controlled trial (RCT). Studies mainly included analyses of urban elements on violent crime, property crime, disorder offenses, and drug crime, with analyses conducted using Negative Binomial or similar regression models (see Table 2).

Table 2 Statistical models used by studies in SR

Statistical models used	Number of studies N=29
Negative Binomial or equivalent Regression models	16
Zero-inflated Negative Binomial (ZINB) model	3
ANOVA or equivalent model	2
Poisson Hierarchical Linear Model	2
Conditional Logistic Regression Model	2
Ordinary Least Square (OLS) fixed effect Linear Regression model	1
Multivariate Least Square (OLS) Regression model	1
Multivariate Linear Regression Analysis	1
Machine learning model	1

The spatial units of analysis used in the studies were mainly census blocks, street segments, 50x50 m grid cells, 500- ft^2 grid cells, or a buffer area[4] (distance in feet/ meters) around the urban elements studied (see in in Appendix 2).

3. Methodology for meta-analysis

This section outlines the methodology employed for conducting the meta-analysis. Studies typically estimate effect sizes using statistical regression models of various forms. Effect Sizes (ES) and Standard Errors (SE) were extracted from the included studies were extracted to calculate the combined effect size where possible. Different statistics reported by the study authors could include an Incident Rate Ratio (IRR) or a raw regression coefficient. Hence, to combine effect sizes for the meta-analysis, it was necessary to convert them to a common metric. Here, IRRs were converted to coefficients by taking their natural logarithm.

Where the precision of a coefficient estimate (i.e., the standard errors) was not directly reported in a study, the approach to estimating them varied according to what data were reported and which type of test statistic was available. For example, where a z-value was reported, the SE of the coefficients were calculated using this (Kulinskaya, Morgenthaler, & Staudte, 2007 ; Lipsey & Wilson, 1961). Where a z value was not provided, the z value was estimated using the p-value reported (Kulinskaya et al., 2007; Lipsey & Wilson, 1961). Where an exact p-value was not provided, the highest value of p based on the significance level indicated was assumed (For example, for $p<0.01$, a value of $p=0.009$ was taken). This approach is not perfect but represents the most justifiable one. Where the SE of a coefficient was not provided, but an IRR

[4] Note: the number of facilities were regressed from each grid cell/ buffer area

and the SE of the IRR were, the SE of the coefficient – and the confidence intervals – were estimated using standard formulae (Kulinskaya et al., 2007; Lipsey & Wilson, 1961).

Two approaches can be used to compute combined effect sizes across multiple studies – the fixed effects and random effects models (Lipsey & Wilson, 1961). The fixed-effects model assumes that the true effect size is the same across the entire population of studies, and any variance is due to sampling error (Lee et al., 2016;Lipsey & Wilson, 1961). A random-effects model assumes that the true effect size varies across the population of studies and the studies in the analysis represent a random sample of these effect sizes (Lee et al., 2016;Lipsey & Wilson, 1961). The summary effect size is the estimation of the mean of a distribution of these effect sizes (Borenstein et al., 2010). As the random-effects model assumes that the effect can vary across studies, the weighted average combined effect size is computed using between-study as well as within-study variance. This gives a more conservative estimate of the overall effect size, and – compared to the fixed-effect model – a larger overall standard error (Lee et al., 2016; Lipsey & Wilson, 1961). This estimate is likely to be less biased and more accurate than the fixed-effect alternative. Hence, a random-effects model is used here. This was estimated using Maximum Likelihood estimation and computed using the meta commands in STATA/MP 16.0.

To visualize the findings that follow, Forest plots were used to show the individual effects from each study as well as the overall mean effect across them. Research on Situational Crime Prevention (SCP) suggests that situational factors influence different crime types in different ways making it important to analyse crime patterns separately for each crime type (Amram et al., 2024; Andresen et al., 2017; Chainey et al., 2008; Cornish & Clarke, 2003). Consequently, studies that met the inclusion criteria were grouped based on the type of crime examined and the predictor variables used. Where necessary, the lowest and highest effect sizes from this study were used to compute a combined effect size (to present the best-case and the worst-case scenarios) – for example, when spatio-temporal analysis was conducted across various time periods or when lowest and highest p values are assumed due insufficient data in the studies. When there was only one study for a particular combination, a meta-analysis could not be conducted, but the data for that study is still shown in a Forest plot.

4. Results

In the sections that follow, we first present a narrative review of the findings that met our inclusion. Next, we present forest plots constructed using the approach described above for each urban element for those studies for which suitable data were available.

4.1 Features of the street network

Twelve studies assessed the impact of different types of street layout, networks, connectivity, and permeability on crime. A positive association between street accessibility (however it was measured) and property & violent crimes was found across these studies.

Three studies (Bernasco & Block, 2011; Groff & Lockwood, 2014; Vilalta & Fondevila, 2019) analysed the effect of main roads on crime, all finding a possitive association. Analysing patterns of crime at the street segment level for Philadelphia (USA), Groff & Lockwood (2014) found that counts of violent, property crime and disorder were higher on major roads (expressways, major arterials, and minor arterials). Groff & Lockwood (2014) studied the influence of major roads on crime in buffers around them that were up to 400, 800 or 1200 feet away. In the meta-analysis reported here, we use their analyses for the 400ft buffers, as these are the smallest unit of analysis for which results were reported. Vilalta & Fondevila (2019) studied crime risks in the Santa Fe neighbourhood, Mexico City (Mexico) and found a high positive association between crimes in a block on the main avenue compared to the blocks on smaller streets (Vilalta & Fondevila, 2019). Bernasco & Block (2011) studied robberies in Chicago (USA). They concluded that the risk of robbery was elevated when a block was located along a main road, which facilitated accessibility across crime attractors and crime generators (Bernasco & Block, 2011).

Beavon et al. (1994) studied property crimes (bicycle theft, auto theft, theft from auto, burglary, wilful damage, break and enter, other property theft) in Maple Ridge and Pitt Meadows, British Columbia (Canada). They used street segments as the unit of analysis and found crime risk to be higher on accessible street segments (those with more connections) (Beavon et al., 1994). However, Beavon et al. (1994) did not provide estimates of effect size and precision, and hence this study could not be included in the meta-analysis. Johnson & Bowers (2010) conducted a study in Merseyside (UK) to analyze the influence of the accessibility of the street network on burglary risk using street segments as the unit of analysis. They found that the risk of residential burglary was higher with increased accessibility, and when a street segment was classified as being part of a major road. The risk of burglary was found to be lower on street segments classified as private roads and on cul-de-sacs (particularly those that were sinuous — or bendy — in nature) (Johnson & Bowers, 2010).

Summers & Johnson (2017) studied the influence of betweenness on serious violent crimes (i.e., crimes including homicides, attempted murders, and assaults) in one London borough (UK). Betweenness measures how frequently street segments feature in the shortest paths between all of the origins and destinations in a network and provides an estimate of how likely these street segments are used by people in journeys through the street network (Davies & Johnson, 2015). The measures of connectivity used by Summers & Johnson (2017) examined estimated through movement and to-movement potential for both pedestrian and vehicle journeys. The risk of violence was found to be higher on roads with higher estimated to-movement and higher estimated through-movement, an effect which also spilled over to nearby segments (Summers & Johnson, 2017).

Davies, & Johnson (2015) studied crime patterns in Birmingham (UK) using street segments as the unit of analysis. The study found that betweenness was associated positively with counts of burglary. As with Johnson & Bowers (2010), burglary was negatively associated with the linearity of streets – linearity arguably provides better visibility (Davies, & Johnson, 2015).

Using data for violent crimes (robbery, and aggravated assault) and property crimes (burglary, larceny, and Motor Vehicle Theft (MVT)) in San Francisco (USA), Kim & Wo (2023) studied the association between crime, physical land surface and the network of street segments using four predictor variables (elevation, slope i.e. steepness, differences in elevation – i.e. hilliness and betweenness i.e. Connectivity). Betweenness and differences in elevation in the ¼ mile radius surrounding the focal segment were measured. Burglary was found to be negatively associated with all four predictor variables (Kim & Wo, 2023). MVT was negatively associated with elevation and slope of street segments; however, MVT was found to be associated positively with betweenness and elevation differences in the surrounding ¼ mile radius (Kim & Wo, 2023). Larceny was found to be associated negatively and significantly with all predictor variables except betweenness for which there was a positive association (Kim & Wo, 2023). The association between aggravated assault and all predictor variables was positive. Robbery was positively associated with elevation and betweenness; and negatively with slope (%) and differences in elevation (Kim & Wo, 2023). It was found that the criminogenic effects of betweenness were "dampened by hilliness" in line with the least effort principle (Eck et al., 2007) wherein offenders tend to choose locations/targets where least effort is involved. When the elevation difference is high, street segments with high betweenness were found to have a robbery rate that was 16% larger in comparison to street segments with low betweenness (compared to 67% if the elevation difference was low) (Kim & Wo, 2023). Although slope (i.e. steepness) was associated with lower rates of crime, the change in the criminogenic effect sizes on a street segment was found to be low compared to other street typology measures (Kim & Wo, 2023). This could be because slope can hinder the visibility of victims and offenders (Kim & Wo, 2023).

Favarin (2018) also used street segments as their unit of analysis in Milan (Italy) and found that streets with limited access had lower levels of burglary, however, the effect was non-significant for robbery offenses (Favarin, 2018). However, the authors did not provide a definition of what streets with limited access were and what was being measured, hence this study was excluded from the meta-analysis below. Xie et al. (2022) studied the effect of three variables - the number of pedestrians on the street, street length, and road density on property crime in XG (China). Their findings indicated that while all three variables were positively associated with property crime, the number of people on the streets had the most significant association (Xie et al., 2022). The study was carried out using machine learning models and the SHAP (Shapley additive explanation) framework (Xie et al., 2022). Unfortunately, this method of estimating effect sizes was not comparable with the other studies and hence the findings were excluded from the meta-analysis.

Clutter et al. (2019) analysed street segments in the Business Improvement District (BID) of Cincinnati (USA) and found that betweenness was positively associated with higher counts of robbery. Kim & Hipp (2019) used betweenness centrality measures in Southern California (USA) and assessed their association with violent and property crime. They calculated both local and non-local betweenness values (using radii of ¼ mile and 1 mile, respectively). The former provides into insight shorter local journeys which are more likely to be made by pedestrians who have routine activities in the area and who act as guardians out of a sense of responsibility (Kim & Hipp, 2019). In contrast, the latter provides insight into the movements of vehicles by non-local people passing through the area; those less likely to act as guardians due to lack of perceived ownership (Kim & Hipp, 2019). They found that street segments that are more likely to be used (i.e., had higher betweenness) were associated with increased violent (aggravated assault, robbery) and property (burglary, motor theft, larceny) crimes; however, after reaching a threshold, property crime was found to decrease with increased betweenness at non-local distances (Kim & Hipp, 2019). As noted above, betweenness estimates how likely it is for a street segment to be used. In their study, the authors weighted their betweenness by population and the number of employees for four types of business (retail areas (more travellers), service, restaurants and stores) (Kim & Hipp, 2019). They also used a non-linear model that included squared and cubic terms to estimate the influence of street activity on crime. While valuable, this represents a departure from the general approach taken in other studies and makes it difficult to combine the data in a meaningful way. Consequently, this study was also excluded from the meta-analysis below.

Meta analysis

All the studies discussed used a cross-sectional design that estimated levels of crime for a fixed period but varied in terms of how they measured the influence of the street network, and which crime types were examined. In what follows, violent and property crimes are assessed separately due to differences in their opportunity, and the nature of these offences. In their study, Kim & Wo (2023) provided main effects for three types of property crimes (burglary, larceny and motor vehicle theft) and two types of violent crimes (robbery, aggravated assault). To deal with this, the analysis for each offense type is reported twice using the lowest or highest main effect sizes to represent the best- and worst-case scenarios.

The results of the meta-analysis are shown in Figure 2a, 2b and 2c. For each crime type, the findings from the individual studies are shown along with the overall weighted mean effect sizes. Findings are colour coded by crime type and independent variable considered.

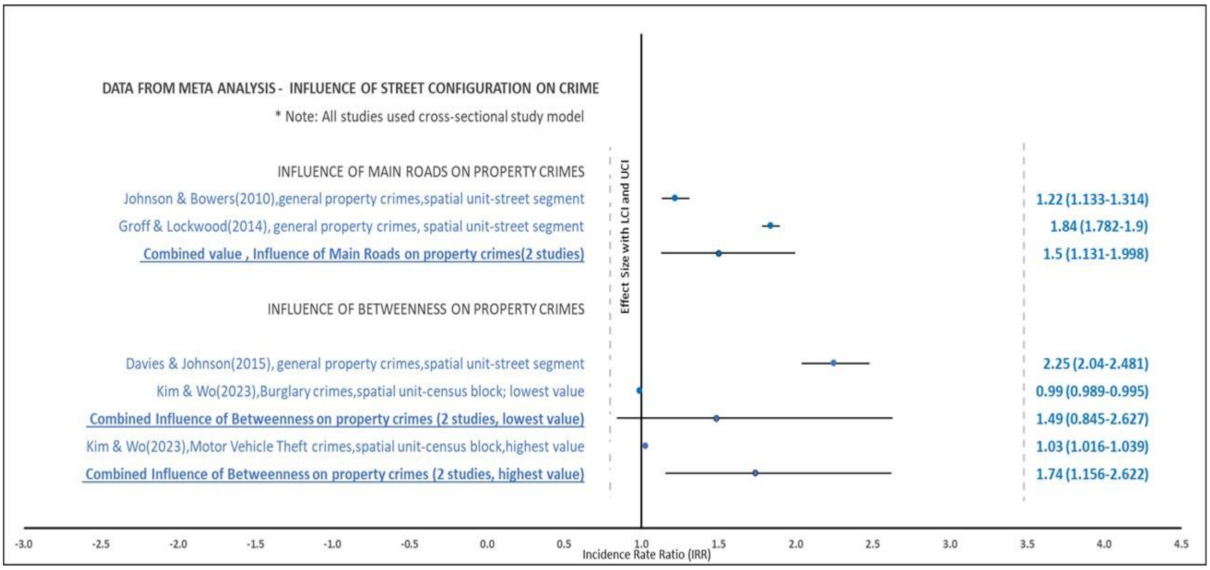

Figure 2 a Forest plot – Influence of Street Configuration on property crimes

The combined effect size of main roads (IRR = 1.5) on property crimes across the two studies for which data were available was positive and statistically significant. For the betweenness-property crime association, the overall effect size was computed twice due to the way Kim & Wo (2023) reported their results (see above). The lowest value (IRR=1.49) was not statistically significant, but the highest value (IRR = 1.74) was statistically significant.

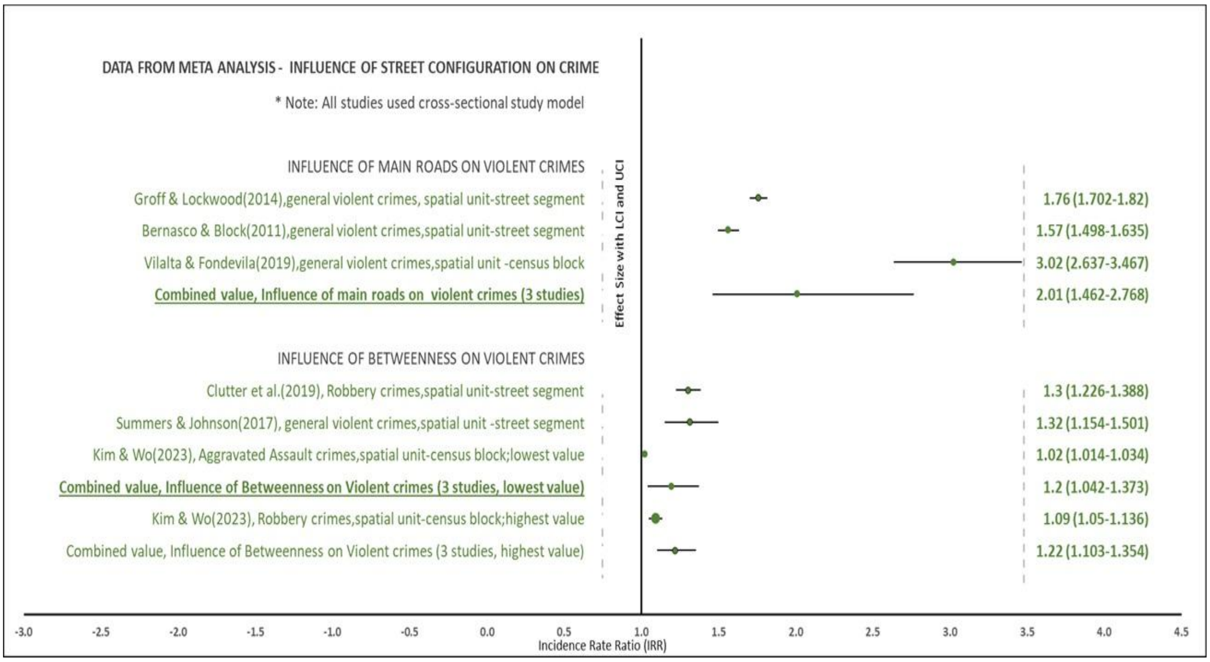

Figure 2 b Forest plot – Influence of Street Configuration on violent crimes

For violent crime and main roads, the effect size (IRR=2.01) was statistically significant and slightly higher than for property crimes. For the effect of betweenness, high and low estimates were calculated due to the inclusion of the Kim & Wo (2023) study. However, the two estimates were very similar (IRRs= 1.2 and 1.22) and both were statistically significant.

All of the combined effect sizes for the influence of the street network, configuration and other features of the street network were positively associated with crime, and in most cases, these were statistically significant. Considering the effect sizes for the 18 data points that could not be included in the meta-analysis, these mostly related to the slope or elevation of the street network. The findings suggest steepness or hilliness are negatively associated with crime. The remaining data point, taken from Groff and Lockwood (2014), provided an estimate of the effect of main roads on disorder. This was not included in the property or violent crime analyses due to the nature of this type of offense, but the estimated effect is consistent with them.

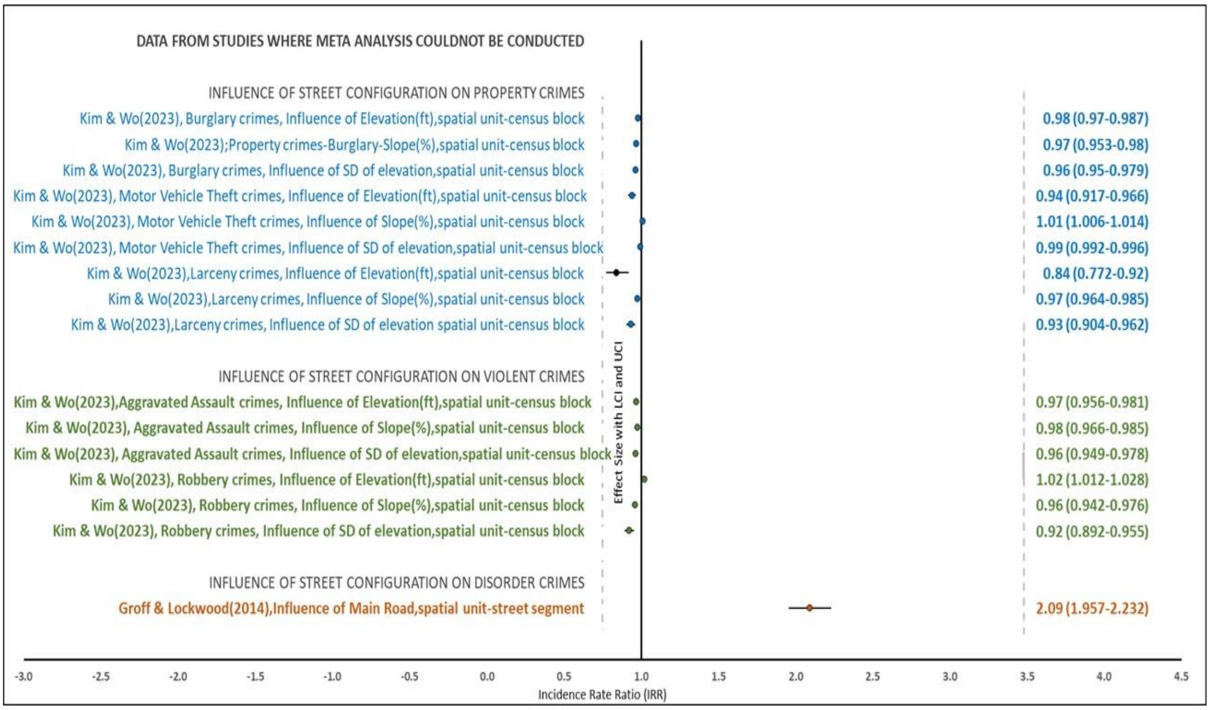

Figure 2 c Forest plot – Influence of Street Configuration on crimes - Meta-analysis could not be conducted

Overall, when combined meta-analytically, the findings from the studies suggest a positive association between crime and street network configurations that encourage the movement of people and crime. This was true regardless of crime type, study location, time periods studied, the precise statistical models used, and the independent (predictor) variables included in the model specification.

4.2 Public transit

Ten studies analysed the influence of bus stops (N=6), underground / subway transit stops (N=3), tram stops (N=1) and rail stations (N=1) on crimes including violence, property, and drug-related offences. Overall, these studies suggest that the presence of public transit is criminogenic, and the overall effects on types of crime change depending on the location and characteristics of the environments.

Bus stops and tram stops

Six studies that examined bus transit stops found mixed results for the association with property and violent crimes, whereas overall crimes and drug crimes were positively associated with bus stops. Hsu&Miller (2017) studied the relationship between bus stops and drug dealing in Newark NJ (USA) using a case-control study design. Their findings indicated that although bus stops were positively associated with crime, contrary to expectation, in terms of the crime generating capability of bus stops, the association between drug dealing and bus stops was not higher when located on intersections compared to street segments (Hsu & Miller, 2017). This study used a Conditional Logistic Regression Model which was not comparable with other studies and hence was excluded from the meta-analysis. Clutter et al.(2019) analysed the influence of bus stops on spatial crime patterns within BIDs of Cincinnati (USA). The authors found that street robbery was positively associated with the presence of bus stops on street segments (Clutter et al., 2019). A study in Israel found that the number of bus stops on a street was associated with property and violence offenses (Amram et al., 2024). Soohyun & Yongjei (2016) employed 6975 five-ft^2 grid cells as the spatial unit of analysis in Pittsburgh (USA) and found a positive association between presence of bus stops and aggregated crime levels (Soohyun & Yongjei, 2016). However, the multivariate linear regression model used in this study was not comparable with other studies (most used a count model, such as a negative binomial regression) and hence this study was not included in the meta-analysis.

Favarin (2018) measured the effect of the presence of bus and tram stops in Milan (Italy) on burglary and reported a negative effect size (insignificant) for the influence of transit stops on burglary. There are various reasons why the findings of this study may differ to the others. Burglaries were, however, higher when bus/tram stops were located in residential areas (Favarin, 2018). Liggett et al. (2003) studied crime around bus stops in Los Angeles (USA) using ridership data within a 150ft radius of intersections where bus stops were located. They focussed on the crime rate for the bus stop microenvironment and calculated the effect size for only four key variables near bus stops – liquor stores, litter, the visibility of bus stops and the wait time for buses. A significant positive association was found between overall counts of crime if there was a liquor store and litter around the bus stops, but the association was negative if there was sufficient pedestrian visibility in the bus stop environment (Liggett et al., 2003). This paper was not comparable with other studies and hence was excluded from meta-analysis.

Subway and Rail stations

The findings from four studies indicate that subway, underground stops and rail stations were associated with higher crime. Groff & Lockwood (2014) studied the influence of the presence of subway stations on crime using data for 40,371 street segments in Philadelphia (USA). The presence of subway stations was positively associated with violent, property, and disorder crime at various distance thresholds from each street segment to surrounding facilities within 400 ft, 800 ft and 1200 ft of street segments (Groff & Lockwood, 2014). As discussed in Section 4.1, the results reported which used a distance of 400 feet was included in meta-analysis as it was the smaller unit. Moreover, Groff & Lockwood (2014) found that the effect of subway stops on crime was reduced as the distance from the stop increased. Haberman & Ratcliffe (2015) conducted a temporal analysis using the census block as a spatial unit and demonstrated that subway stops in Philadelphia (USA) subway stations were positively associated with higher counts of street robbery during the daytime, evening and late at night but had no influence in the morning. Robberies were also higher when the census blocks had more residents (Haberman & Ratcliffe, 2015). Newton et al. (2014) conducted an analysis of the association between street configuration within a 400-meter buffer zone of underground transit stops in London, UK. They found that the risk of theft reduced with more domestic buildings nearby, and stations classified as terminus stations. However, the risk of theft increased with increased levels of accessibility and access to stations i.e., where there was a high percentage of roads and paths in the nearby environment (Newton et al., 2014). Newton et al. (2014) analysed theft at underground stations based on internal & external features of the station and the congestion of passengers – this was not comparable with other studies and hence was excluded from meta-analysis.

Bernasco & Block (2011) measured the influence of the Elevated (or El) rail stations (the rapid-transit system) in Chicago (USA) on street robberies. They found that census blocks with an EL rapid transit system station had over four times as many robberies as similar blocks without a public rail station (Bernasco & Block, 2011).

Meta analysis

The statistics that could be extracted from the studies were analysed to calculate overall combined effect sizes where possible. Favarin (2018) reported an IRR and a Coefficient but did not provide a SE or t or z statistics. Consequently, the only way to compute a SE was to use the p-value. However, the results were non-significant and consequently a specific p value was not provided. For this reason, two estimates of the overall effect size were computed using the potential highest ($p=0.51$, IRR = 1.93) and lowest values of p ($p=0.1$, IRR = 0.98) (see Figure 3a and 3b), and both were included in the forest plot. Haberman & Ratcliffe (2015) measured the influence of subway stops in Philadelphia (USA) on robbery across four time periods – morning, daytime, evening, and late night. The effect sizes varied marginally across all four time periods. The effect sizes were insignificant in the morning and in the evening. However, the effects were somewhat significant during daytime and highly significant during late night (Haberman & Ratcliffe, 2015b). Rather than use only one data point from this study, the overall effect size was computed for both the highest and lowest effect size values. Hence for violent crimes, effect sizes from six studies with comparable findings were combined in the meta-analysis.

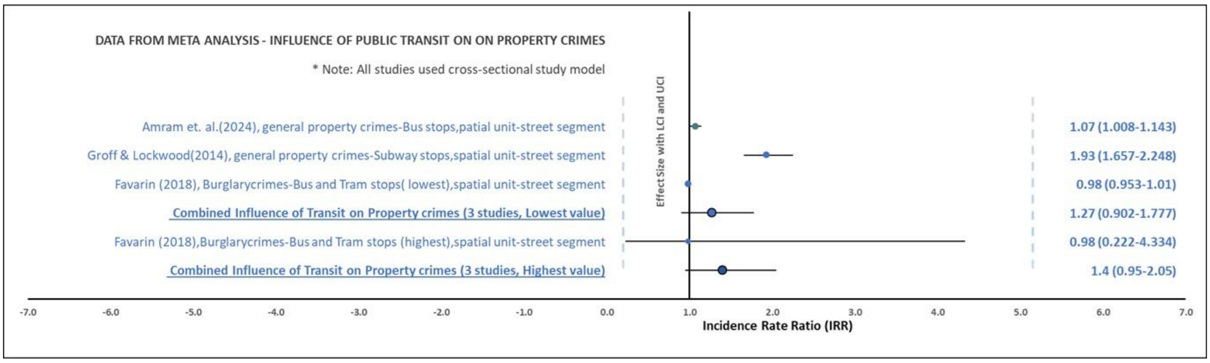

Figure 3 a Forest plot – Influence of Public Transit on property crimes

The results of the meta-analysis are shown in see Figure 3a and 3b. The combined effect sizes for the influence of public transit on property and violent crimes are positive. For property crimes, the combined effect sizes (combined values of IRR = 1.27 being the lowest and IRR=1.4 being the highest) were found to be positive but not statistically significant. Two estimates of the overall effect size for violent crime were computed due to the way Haberman & Ratcliffe (2015) reported results (see above). For violent crimes, the two mean effect sizes (measured in the morning and evening) that were computed in both cases were similar (least combined value of IRR = 1.90 and highest combined value of IRR=1.98) and were highly significant. Groff & Lockwood (2014) was the only study that analysed the influence of subway stops on disorder crimes (IRR=2.7), wherein the effect size was in the positive direction. Overall, the findings of the meta-analysis suggest that the effect of public transit stops on property crimes are lower than they are for violent and disorder crimes, regardless of public transit types (bus, tram, rail, and subway stops), time of travel and distance from public transit facilities.

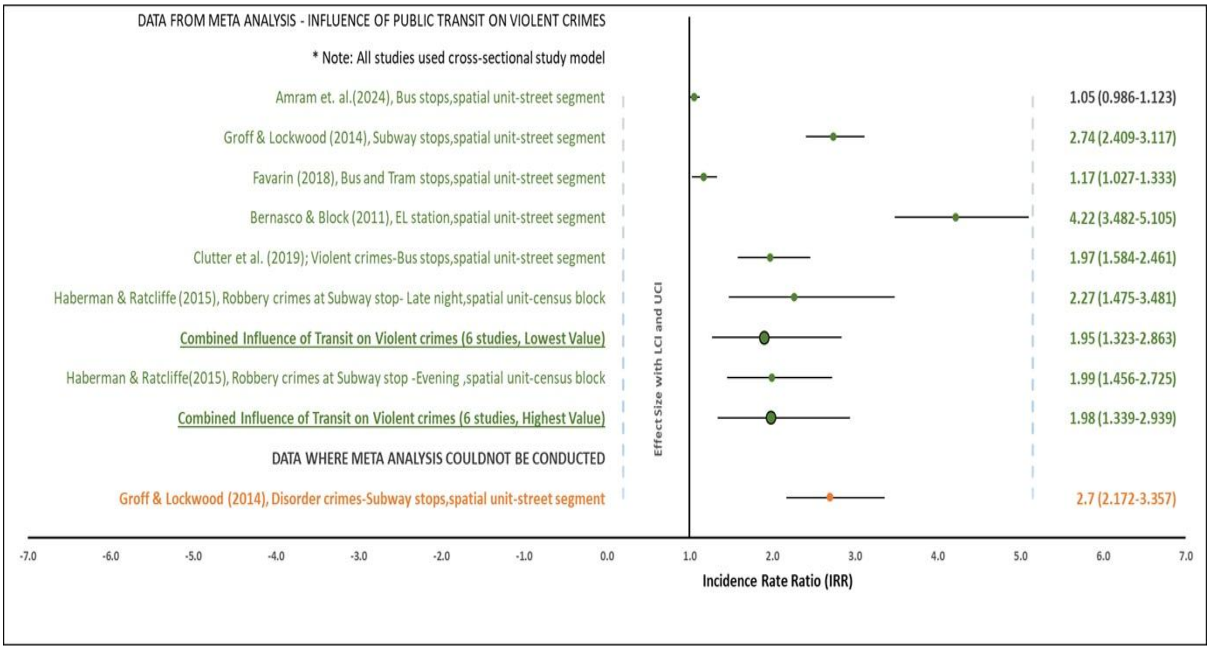

Figure 3 b Forest plot – Influence of Public Transit on violent crimes

4.3 Parks

Five studies assessed the influence of parks on violent, property, drug and disorder crimes within parks and the surrounding areas. Two studies indicated that the park environments were positively associated with crime, one study showed a negative association, one study showed no association, and one study showed mixed results.

Groff & McCord (2012) studied violent, property and disorder crimes in Philadelphia (USA) parks and found that crime counts in the parks and their surrounding streets were double that in other areas with disorder crimes being higher than violent and property crimes. Analysis of 400-1200 feet buffer areas surrounding the parks suggested that parks were associated with decreased crime in the immediate vicinity (0-400 feet) and far away (800-1200 feet) but that there was an increase in crime in the area 400-800 feet buffer area in between (Groff & Mccord, 2012). The built environment characteristics and activity generators within the park environment showed different associations for different types of crime. Parks with tennis courts and basketball courts were associated with reduced property and violent crime; basketball courts were associated with increased disorder and other courts were associated with increased violence. The presence of recreation centres and public transit stops were associated with reduced disorder crime but did not show any effect on violent or property crime. However, overall, activity generators were associated with lower levels of crime. Increased residential land use surrounding the parks was corelated with higher levels of crime (Groff & Mccord, 2012). This study examined crime in parks associated with the facilities within the parks which is not comparable to other studies and so was excluded from the meta-analysis.

One study reported the findings from a spatio temporal analysis and found a correlation between the presence of parks and higher counts of property and violent crimes in spring and summer seasons. In their study of street robbery patterns in Philadelphia (USA), Haberman & Ratcliffe (2015) found a significant positive association with neighbourhood parks and crime at the census block level at all times of the day. The neighbourhood parks were associated with crime across four time periods – morning, daytime, evening and late night (except the late-night hours) during the spring and summer seasons (Haberman & Ratcliffe, 2015). The effect sizes did not vary largely across the time periods; however, the effect size was higher in the daytime, but lower during mornings, evenings, and at night (Haberman & Ratcliffe, 2015). The nearby blocks experienced spillover effects during the late-night hours (Haberman & Ratcliffe, 2015). Aggravated assault and homicide were significantly and positively associated with the presence of a park in a block. Robbery, larceny, motor theft and homicide had a significant negative association with blocks that were within 400 feet of a park. Notably, the size of a park had no significant association with any predictor variables.

Clutter et al.(2019) studied patterns of robbery in the BID of Cincinnati (USA) using street segments as the spatial unit of analysis. This cross sectional study found a negative association between parks on street segments and the volume of robbery (Clutter et al., 2019).

Hsu & Miller (2017) analyzed the differences in situational factors between street segments and intersections that are associated with drug-dealing in Newark (USA). They found that public parks were not associated with drug markets across street segments and intersections (Hsu & Miller, 2017). This study used a Conditional Logistic regression model which is not comparable with the other studies (which used Negative Binomial Regression) and hence was excluded from the meta-analysis.

Boessen et. al (2018) analysed crime data for property (separately for burglary, motor theft and larceny) and violent crimes (separately robbery, aggravated assault, and homicide) using the census block as the spatial unit for nine cities in the USA (Chicago, Cleveland, Columbus, Dallas, Los Angeles, Milwaukee, Oakland, San Francisco, and Tucson). The predictor variables included the presence of a park in a block, the size of a park and proximity to parks. They found that residential areas in blocks with parks were associated with higher levels of crime, and that the effect did not depend upon the size of the park; however, the level of crime reduced as the distance from the park increased (Boessen et al., 2018). Blocks with commercial, industrial and office areas were associated with higher crime; however, the crime rates were lower compared to residential blocks (except for violence) and, the crime rate did not change due to proximity to a park (Boessen et al., 2018).

Meta analysis

Haberman & Ratcliffe (2015) conducted a spatio-temporal analysis, hence the lowest and highest effect sizes from this study were used to compute a combined effect size (to present the best-case and the worst-case scenarios).

Figure 4a and 4b show the results of the meta-analysis. Multiple data points for the effect of parks on specific crime types were plotted on the forest plot (Figure 4a and 4b). Only the effect sizes for robbery could be meaningfully combined (across three studies). In this case, the combined effect of parks on robbery was positive but the statistical significance appears to be unstable in that it was statistically significant in one scenario (IRR = 1.08) but not the other (IRR=1.19). The effect sizes of the remaining predictor variables for property and violent crimes were plotted for only one study - Bossen et al. (2018). for which the effect sizes were typically small (IRRs varied from

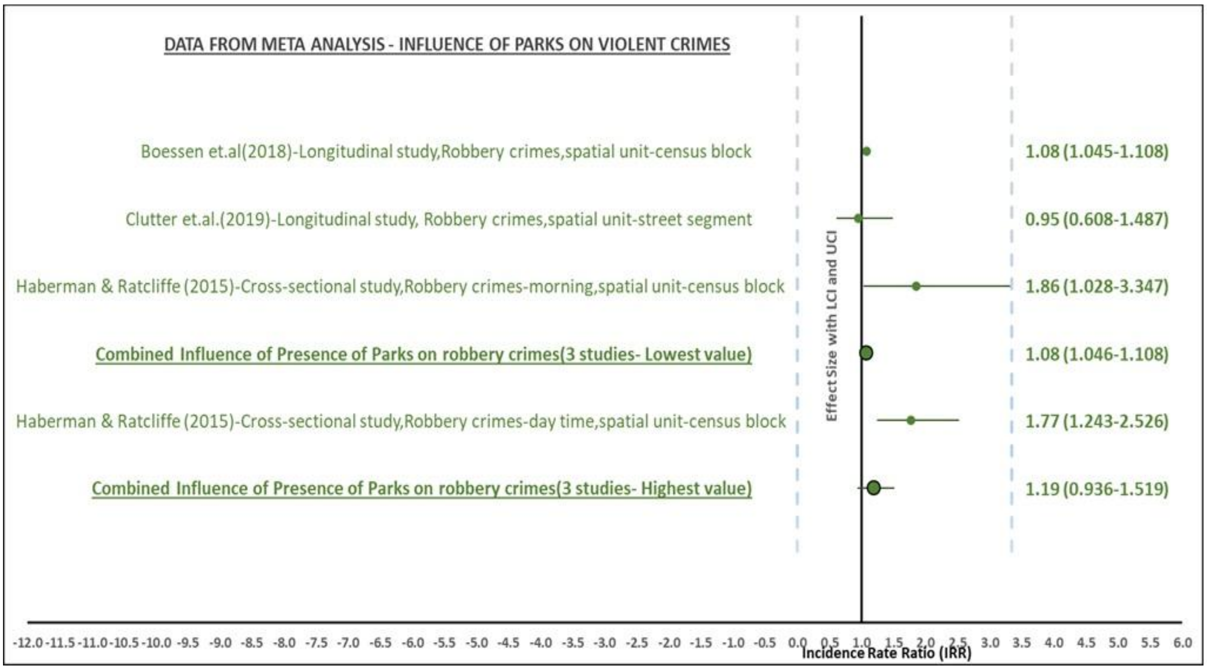

Figure 4 a Forest plot for Influence of Parks on violent crimes

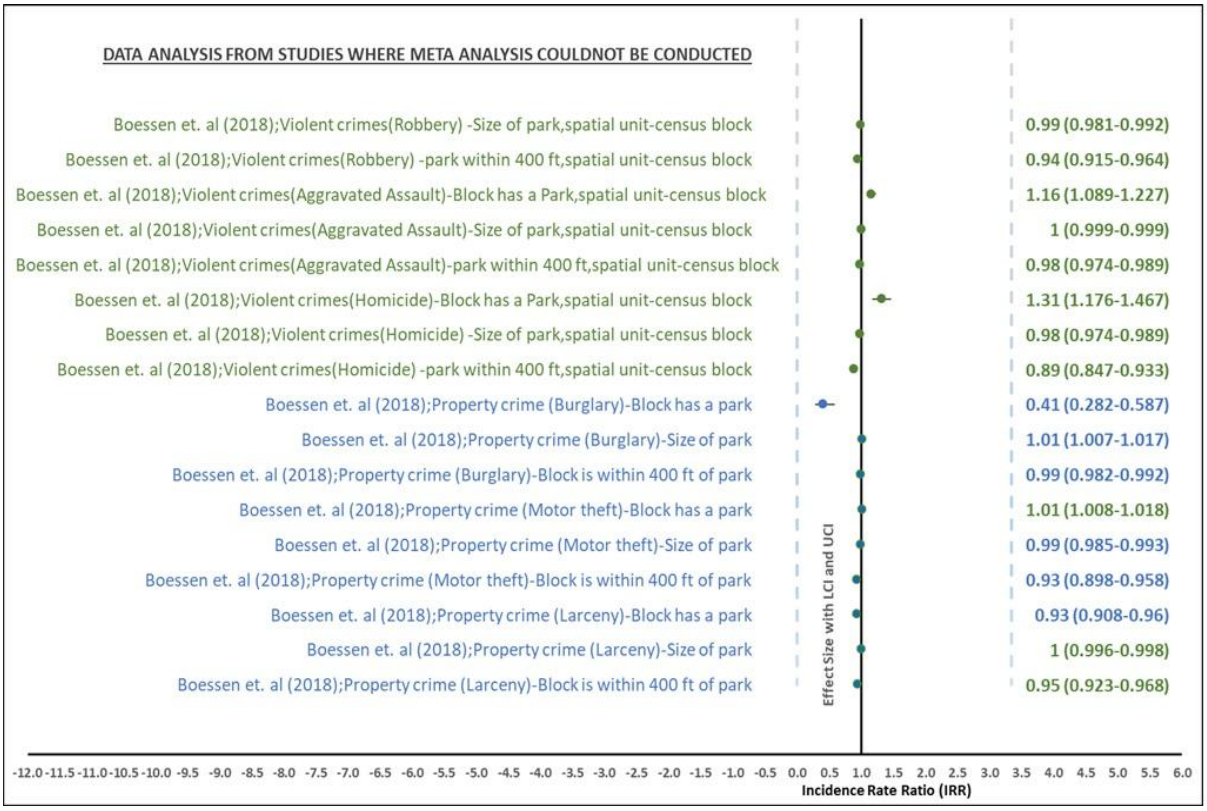

Figure 4 b Forest plot – Influence of Parks on crimes - Meta-analysis could not be conducted

.41 to 1.31). Overall, the results suggest a small effect of parks, but they need to be treated with caution due to the small number of data points available.

4.4 Schools

Seven studies analysed the association between various types of schools and crime for property, theft, and violent crime. All showed a positive association of schools with multiple crime types, however, levels of statistical significance varied.

In their study in Pittsburg (see above), Soohyun & Yongjei (2016) found a positive association between the count of schools with violence, property and aggregated crime levels considered. Clutter et al. (2019), discussed above, assessed the association between the location of high schools and higher education schools, finding both to correlate positively with levels of robbery. Groff & Lockwood (2014) studied the influence of non-elementary schools on crime at the street segment level. They found that such schools were significantly associated with disorder offenses, while the effect on violent and property crimes was positive but not statistically significant (Groff & Lockwood, 2014). In Favarin's (2018) study, the authors examined the association between the total number of schools and property crime in Milan (Italy). They found that schools that are on a street segment or intersect with street segments showed positive association with street robbery (Favarin, 2018). Wo and Park's (2020) study in Chicago (see above) found that the presence of any school in a block was positively associated with property and violent crimes (Wo & Park, 2020). For consistency with other studies, the results from Model 5 (which incorporated a range of socio-demographic and socio-economic characteristics in the block) in their article was included in the meta-analysis.

Two studies conducted a temporal analysis and found that the association was positive. In their analysis (see above), Haberman & Ratcliffe (2015) found that crime was higher in Philadelphia census blocks that contained schools not just during the time they were open but also during the times that they were "unofficially" not in use (Haberman & Ratcliffe, 2015). It was observed that the effect sizes were very similar across all times of the day. In their study, Kim & Wo (2022) found that in Orlando, crime in schools peaked during the summer and fall seasons where schools are not in session (Kim & Wo, 2022).

Soohyun & Yongjei (2016) and Kim & Wo (2022) used statistical models (Multivariate linear regression analysis and Logistic Regression respectively) that were not comparable to other studies and hence were excluded from meta-analysis.

Meta analysis

Figure 5a, 5b and 5c show forest plots of the individual and combined effects sizes. Only 3 data points were found for property crimes, and the IRRs varied quite substantially. The best- and worst-case scenarios were both positive but not statistically significant.

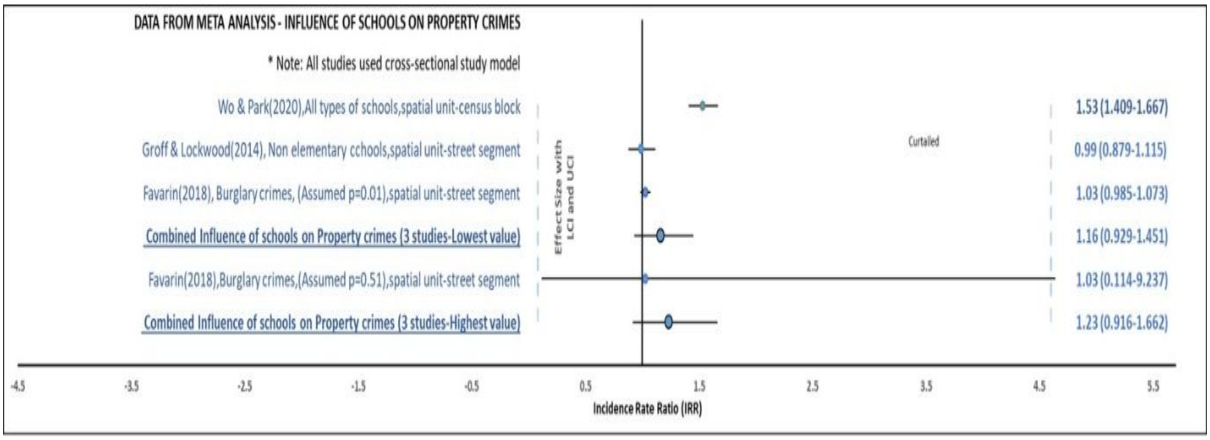

Figure 5 a Forest plot for Influence of schools on property crimes

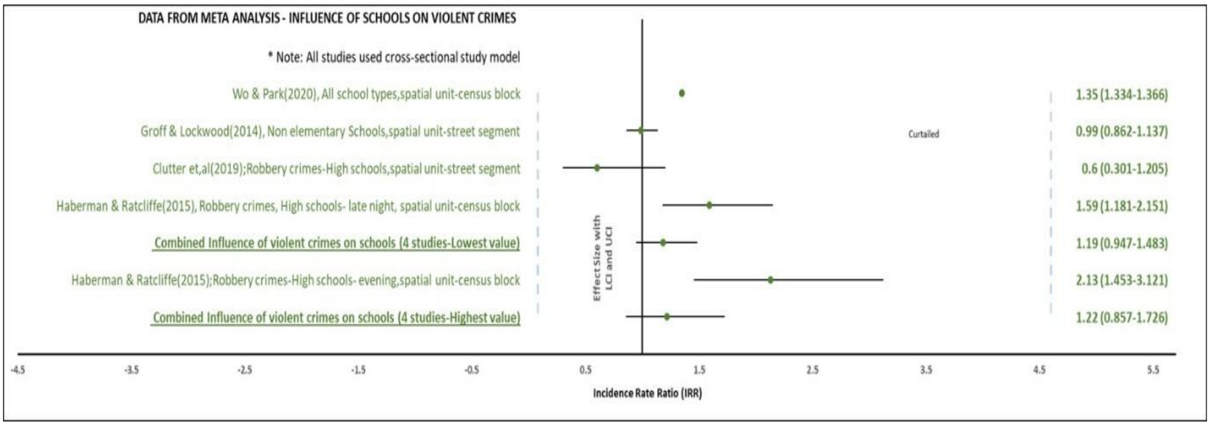

Figure 5 b Forest plot for Influence of schools on violent crimes

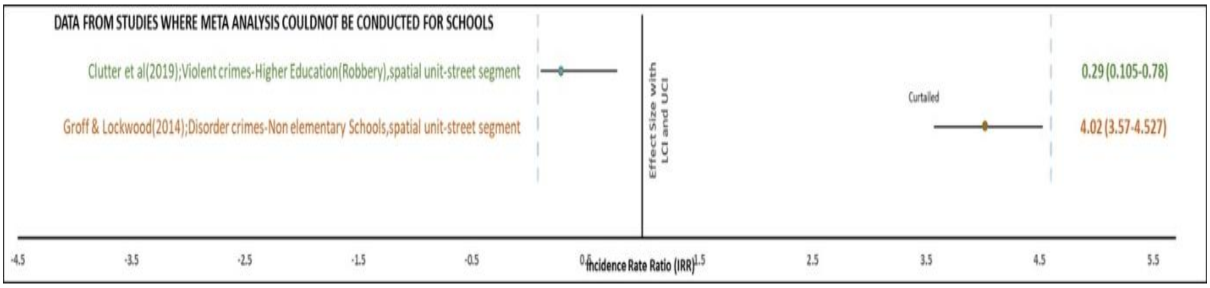

Figure 5 c Forest plot – Influence of Schools on crimes - Meta-analysis could not be conducted

For violent crime, data from four studies was suitable for meta-analysis. In this case, the best- and worst-case scenarios were also positive but not statistically significant. Groff & Lockwood (2014) assessed disorder and found a large and statistically significant criminogenic effect of schools (IRR=4.02). However, this finding is from only one study.

4.5 Alcohol outlets

Ten studies analyzed the relationship between crime and drinking establishments including alcohol outlets, eating & drinking establishments, liquor stores and bars. All studies revealed a positive association with violent crime and the effect was found to extend beyond the alcohol outlets.

In their study, Clutter et al. (2019) found that the count of alcohol establishments within a BID was positively associated with violent crime, however, the association was not significant (Clutter et al., 2019). In their study, conucted in Mexico city (see above), Vilaita & Fondevila (2019) found that violent crime was positively associated with the count of on-premises and off-premise alcohol outlets (Vilalta & Fondevila, 2019). Bernasco & Block (2011) found that the count of Liquor stores, as well as bars in Chicago, was positively correlated with the count of robberies at the census block level. Their findings suggest that the effect extended to adjacent blocks as well as those that were farther away. The association at greater distances was higher if crime attractors (such as places for illegal drug markets or prostitution) and crime generators (such as bus stops, parking places and supermarkets) were present on a block and decreased where there were relatively fewer numbers of crime attractors and crime generators on a block.

Liggett et al.'s (2003) study in Waterloo (Canada) found that the presence of liquor stores was within a bus stop micro-environment correlated positively with alcohol outlets when bus stops were positioned near street intersections. This was not comparable with other studies and hence this study was not included in the meta-analysis. Ratcliffe (2012) analysed the influence of bars at distance thresholds of 85, 420, and 540 feet and concluded that alcohol outlets were significantly correlated with violent crime within 85 feet of the outlets, but that this association was not statistically significant at greater distances. Effect sizes were not provided in this study and hence it is not included in the meta-anlaysis below.

Groff (2014) estimated the influence of alcohol facilities on violent crime on street segments using two approaches. For both, they found a positive association with violent crime, however, the two approaches were not comparable with other studies and hence this study was excluded from the meta-analysis.

Favarin (2018) analysed the association between the total number of licensed premises (bars, restaurants and night clubs) on street segments in Milan and counts of burglary and robbery and found a positive association. Groff & Lockwood (2014) studied the influence of bars on street segments for violent, property and disorder crimes, and found an association in all cases.

Two studies conducted a spatio-temporal analysis. Haberman & Ratcliffe (2015) found that the effect size for bars was positive and lowest in the evening, whereas the effect sizes for alcohol stores was negative and lowest in the morning; both bars and alcohol stores had the highest association with robbery during the daytime (Haberman & Ratcliffe, 2015b). Haberman & Ratcliffe argued that this was due to steady usage patterns. De Souza & Miller (2012) conducted a matched-case control study in Belo Horizante (Brazil)'s poor urban towns known as favelas studied the effect of bars on violent crimes during the day and night-time. Comparisons were made of the situational characteristics of a sample of 100 addresses where homicide had occurred and 100 control locations where it had not. Data on homicides in the favelas were gathered using field observations, documents, and interviews with police officers. To examine the influence of facilities, they examined what types of properties were found within 50 meters (min) and 100 meters (max) of the sample addresses. They found that the association was greater for homicides committed during the daytime and evening than at night-time (De Souza & Miller, 2012). However, De Souza & Miller (2012) used an Ordinary least square fixed effect Linear Regression model which is not comparable with other studies and hence this study was excluded from the meta-analysis.

Meta analysis

The predictor variables used in the studies included the number of licenced premises for alcohol consumption (such as bars, restaurants, clubs), number of liquor stores and distance of alcohol outlets from street segments. The aim of the meta-analysis was to compute the combined effect of the presence of all types of on-premises and off-premises alcohol outlets. Hence the data was not analysed further based on alcohol establishment type. Bernasco & Block (2011) measured two separate effect sizes for the influence of the number of licenced premises (bars and clubs) as well as the number of Liquor stores in Chicago (USA) on violent crimes (Bernasco & Block, 2011). The lowest and highest effect sizes from this study were included in meta-analysis. Figure 6a and 6b show the forest plot of the individual and combined effect sizes of alcohol outlets on property, and violent and disorder crimes.

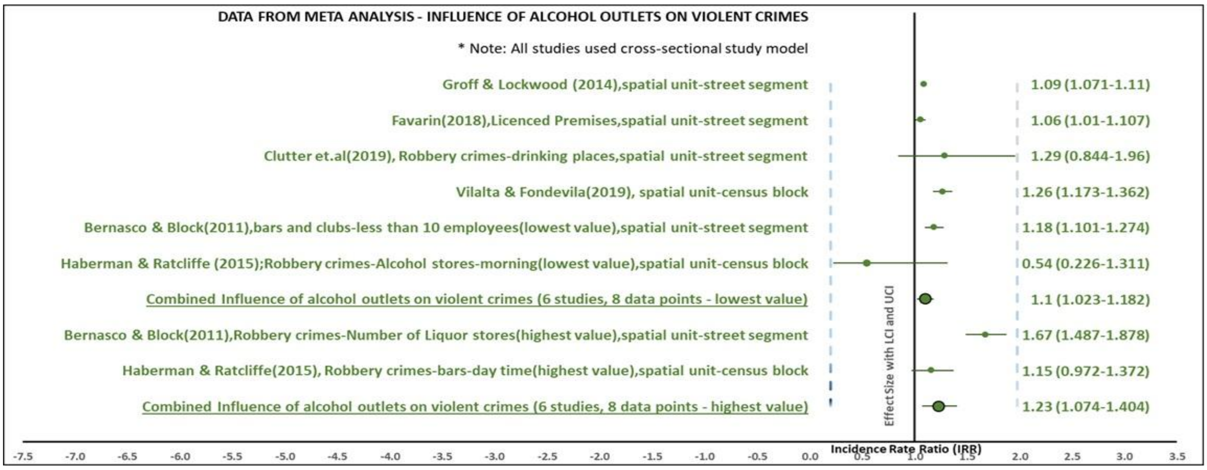

Figure 6 a Forest plot for Influence of Alcohol outlets on violent crimes

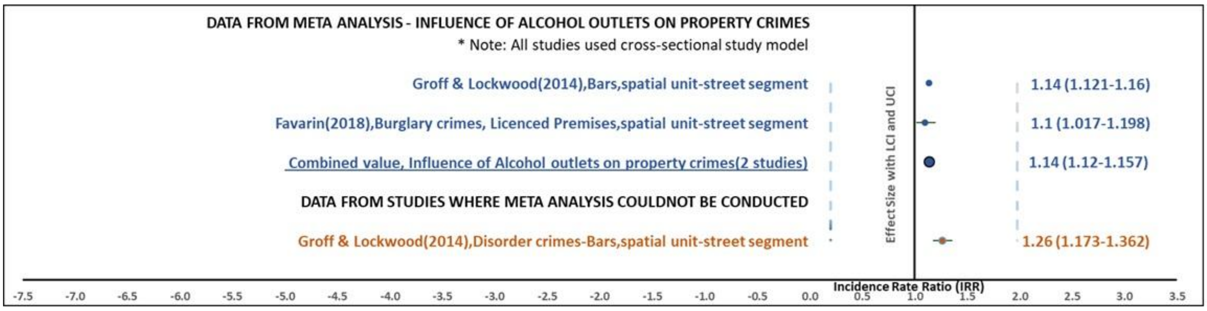

Figure 6 b Forest plot for Influence of Alcohol outlets on property crimes

The results for property crimes need to be treated with caution as the meta-analysis was done for data from only two studies. Groff & Lockwood (2014) was the only study that provided data for disorder crimes. Overall, the results of the meta-analysis indicated that the combined effect of alcohol outlets on property, and violent crimes were similar (IRR ranged from 1.14 to 1.23). This could be because the studies mainly assessed robberies as violent crimes. The results could have been different if other types of crimes such as assault and disorder were analysed by more studies. When combined meta-analytically, the results generally suggest that the presence of alcohol outlets is associated with crimes regardless of the type of outlet, location, methods used to estimate effect sizes, and the statistical models used for calculations. However, more studies are required to estimate the effect of alcohol outlets on crimes.

4.6 Retail land use

Eleven studies examined the effect of retail land use such as grocery, corner store (including restaurants, or takeaway outlets on crime. All studies co-related positively with the offences studied.

Bernasco & Block (2011) conducted a spatial analysis to understand if retail stores within census blocks were associated with robberies in Chicago (USA). A subset of nine types of shops and businesses were selected for which the proportion of cash transactions was likely to be high, and which had less than 11 employees. The nine types of retail businesses in Chicago included in the study were (1) bars and clubs, (2) restaurants, fast- food outlets and food stands, (3) barber shops and beauty salons, (4) liquor stores, (5) grocery stores, (6) general merchandise shops, (7) gas stations, (8) laundromats, and (9) pawn shops, currency exchange, and check- cashing services. They found that association between these urban elements and robbery (violence) within the focal block, in the adjacent blocks and farther away, i.e., the effects were not limited to the immediate block but "spilled over". The authors found that proximity to retail stores was associated with higher robbery counts. The association with robbery was found in adjacent blocks but the association weakened with increased distance from retail stores. The authors also observed that the crime risks of the block were elevated when a known offender was a resident of the block and, one or more incidents were recorded for drug dealing, prostitution, gambling, and gang-related activities. The crime risk in adjacent blocks was higher when crime attractors (such as places for illegal drug markets or prostitution) and crime generators (such as bus stops, parking places and super markets) were found in them (Bernasco & Block, 2011).

Bowers (2014) studied the influence of risky retail land parcels on the spatial distribution of theft in a large metropolitan area of the UK using 50x50 metre grid cells as the spatial unit of analysis. It was observed that for retail and recreation land use there was a positive non-linear association between the frequency of internal thefts in facilities and other commercial land uses and thefts on the street, after controlling for the on-street population

(Bowers, 2014). External theft was not found to influence internal thefts for retail and recreation land use, potentially due to perceived lack of opportunities (Bowers, 2014). The study suggests that criminogenic facilities act as "crime radiators" around which crime concentrates and, that as the number of these risky facilities increases, so too does crime. The number of retail land use parcels for external thefts considered in meta-analysis, showed positive but insignificant association with thefts.

Favarin (2018) and Vilalta & Fondevila (2019) found that retail shops co-related positively with property crimes and violent crimes respectively. Kim & Hipp (2019), as discussed in Section 4.1, used a non-linear statistical model which was not comparable with other studies and hence was excluded from meta-analysis. Clutter et al.(2019) analysed spatial robbery patterns using street segments as a spatial unit of analysis in the BID of Cincinnati (USA) for various land uses including Eating places, Entertainment places, hotels, retail stores, every day stores, grocery stores, pawn shops and Check cashing stores, Salons/barbers, Laundry, Body art parlors, recreation centers, public housing, drug treatment centers and Public libraries (parks, public transit and alcohol outlets are already mentioned earlier). Hotels, everyday stores, recreation centers, public housing and public libraries had a particularly significant positive association with robbery (Clutter et al., 2019). The authors found that street robbery increased whenever additional day stores opened in the BID.

Haberman & Ratcliffe (2015) conducted a temporal analysis to study the influence of banks, check-cashing stores, corner stores, fast-food restaurants, pawn shops and public housing on crime. in Philadelphia (USA) using census blocks as the spatial unit of analysis. They found an association between street robbery patterns across all four time periods and the presence of corner stores and fast-food restaurants. Robbery rates in areas with larger numbers of residents and larger concentrated disadvantages were higher in the morning, daytime, and lesser in the evening and night-time. In areas where residential mobility and racial heterogeneity was high, robberies were higher during the evening and late at night (Haberman & Ratcliffe, 2015).

Soohyun O & Yongje (2016) found a positive association between retail stores and violent, property and all crimes. However, this study was excluded in the meta-analysis due to the statistical models used not being comparable with the other studies. De Souza & Miller (2012) did not find association with retail stores during the daytime, evening, or night. The authors did find that situational factors played a large role in the occurrence of homicides. They found a positive association for convenience stores, bars/clubs, money loan shops and restaurants with violent crime as these places were central to the favela life, but the association was higher during day time and evening and comparatively lower at night (De Souza & Miller, 2012). However, as discussed in section 4.5, they used Ordinary least square fixed effect Linear Regression model which is not comparable with other studies and hence this study was excluded from the meta-analysis.

Kim & Wo (2022) analysed seasonal effects of blocks with stores and restaurants and found a non-linear association. Hsu & Miller (2017) studied the effect of drug-dealing crimes on street segments and intersections in Newark NJ using a matched-case control design. They found that retail facilities (stores, bars, and restaurants) were associated with higher crime on intersections than on street segments. The authors argued that the easy accessibility at intersections generate more crime (Hsu & Miller, 2017). Data from Hsu & Miller (2017) was not included in the meta-analysis due to the statistical models used not being comparable with the other studies.

Meta analysis

Studies analyzed retail land use in general or as a combination of various elements of retail land use such as commercial stores, convenience stores, bars/clubs, licensed premises, alcohol stores, fast food joints, restaurants, money loan shops, pawn shops, corner stores, general merchandise shops, gas station stores, laundromats, beauty salons, barbers, personal care shops, and check cashing stores. For each type of retail land use, the aim of the meta-analysis was to estimate the overall effect of that urban element on crime. Hence the effect sizes of each type of retail land uses were combined prior to conducting data synthesis across studies and the overall effect sizes were computed where data were comparable.

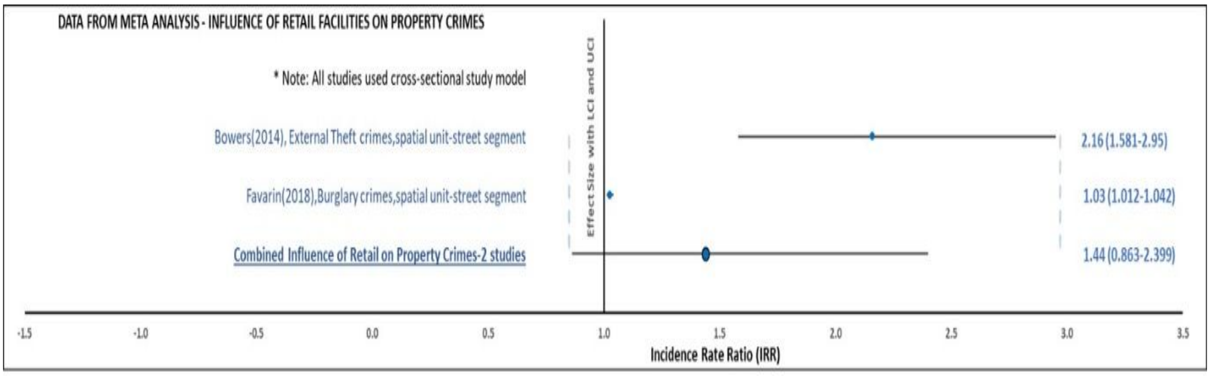

Figure 7 a Forest plot for Influence of Retail land use on property crimes

The individual IRRs, their confidence intervals, and the overall mean effect size, where appropriate were plotted on a forest plot (see Figure 7a and 7b). As seen in the forest plot, the mean effect size for property crimes is low (IRR=1.44) and it is statistically insignificant.

Bowers (2014) had a much higher IRR (2.16), more than double compared to the other two studies. This could be due to the difference in retail land use components included in these studies across different geographies.

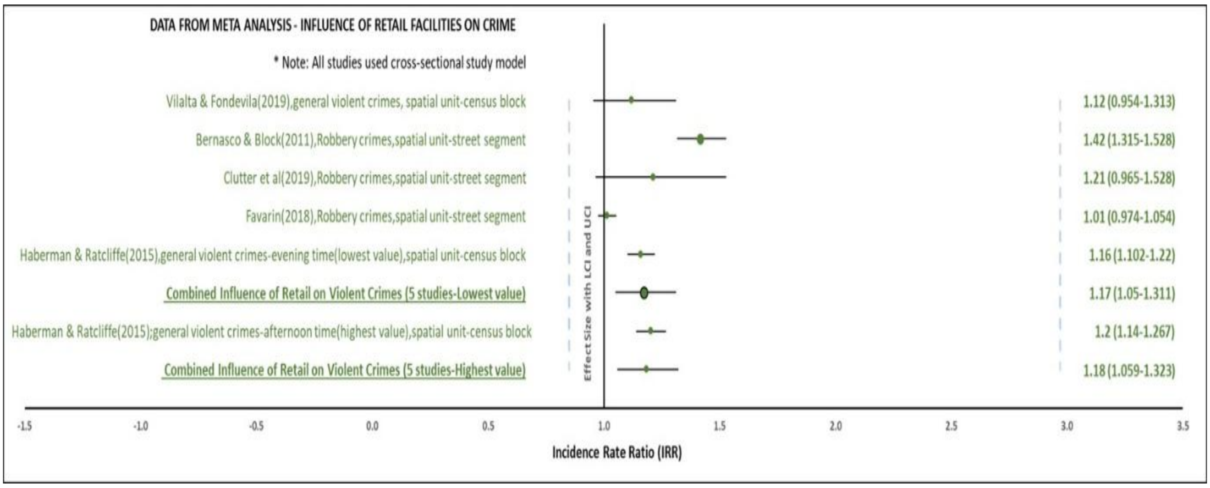

Figure 7 b Forest plot for Influence of Retail land use on violent crimes

For violent crimes, six data points were available. Two estimates of the overall effect size were computed due to the way that Haberman & Ratcliffe (2015) reported the results (see above). There was a marginal difference between the least overall mean effect size (IRR = 1.17, significant) and highest overall mean effect size (IRR = 1.18, significant) of retail land use on violent crimes.

Overall, the results of the meta-analysis suggest that despite being defined differently across studies, retail land uses appear to have positive association with both property and violent crimes.

4.7 Drug treatment centres

A smaller number of studies estimated the effects of the remaining urban features, and hence a shorter reporting format is adopted in the remaining results sections. Three studies discussed earlier – Clutter et al (2019), Haberman & Ratcliffe (2015) and Groff & Lockwood (2015) – analysed the effect of drug treatment centres on crimes. For violent crimes, Clutter et al. (2019) calculated IRR as 1.1702, Haberman & Ratcliffe (2015) calculated IRR at different times of the day for influence on robbery (1.512–morning, 1.372-daytime 1.537-evening, 1.175–late night), and Groff & Lockwood (2015) calculated IRR as 1.07 for robbery. Property and disorder crimes were analysed by Groff & Lockwood (2014) and the results reported had very similar IRR values – 1.25 and 1.28 respectively. Meta-analysis was conducted, and the results were presented on a forest plot (see Figure 8).

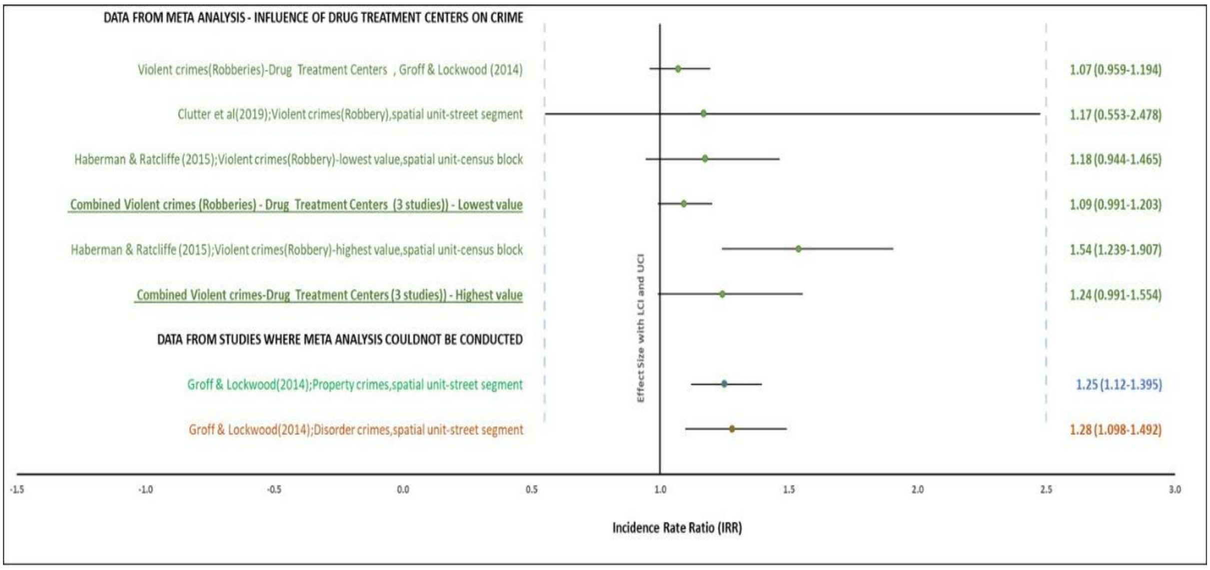

Figure 8 Forest plot for Influence of Drug treatment centres on crimes

The overall estimated effect sizes for the association between drug treatment centres and violent crime (least value IRR = 1.09 and highest value IRR = 1.24) were in the positive direction were significant.

4.8 Bank branches and ATMs

Two comparable studies – Favarin (2018) and Haberman & Ratcliffe (2015) – examined the effect of bank branches and ATMs on robberies. The IRR value provided by Favarin (2018) was 1.608. Haberman & Ratcliffe (2015) conducted a temporal analysis to calculate the effect sizes (morning (IRR=1.210), afternoon (IRR=1.344), evening (IRR=1.275) and late night (IRR=1.198)). The variations between effect sizes of these two studies could be due to the differences in geographies of the study areas. Meta-analysis for influence of banks & ATMs on violent crimes provided combined lowest effect size IRR=1.23 and highest effect size IRR=1.38 across two studies and both were statistically significant (see Forest plot – Figure 9).

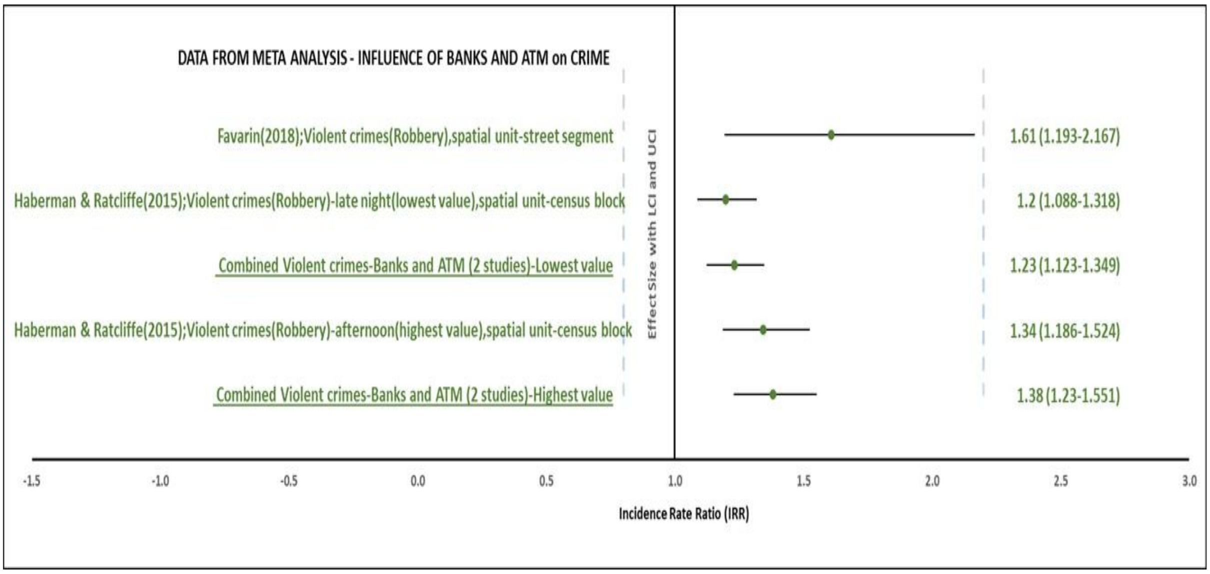

Figure 9 Forest plot for Influence of Bank branches and ATMs on crimes

4.9 Other urban elements

As was shown in Table 1, 40 urban elements were found to have been assessed quantitatively for association with crime. Meta-analyses have already been presented for eight of these elements (sections 4.1 to 4.8). Of the remaining 32 urban elements, six (Hotels, shopping malls, alley ways, windows onto streets, trees, and walkability) were assessed in more than one study, while 26 urban elements were assessed only in one study each. These urban elements are summarised below, along with a summary of how they have been found to correlate with crime (see Table 3).

A statistical meta-analysis could not be conducted for the data extracted for hotels, shopping malls, alley ways, trees, and walkability due to these studies using statistical models that were not comparable. Most urban elements in the included studies were associated positively with crime with a few exceptions. Windows onto the street, community and educational buildings within 500m of the centre of street segments, a garden (public or private garden, park, or landscaped area) within 150m of the centre of street segments, the percentage of buildings built in past 10 years all had a negative association with crime. Churches on street segments, the greening rate (i.e., the increase in vegetation or green spaces), fire stations and the number of buildings, walls and proportion of grass in the streetscape were not found to be criminogenic.

Table 3 Other urban elements and association with crime

Other urban elements found in SR	Number of assessments	Correlation with crimes
Hotels	2	Correlated positively with robbery (Clutter et al., 2019; Kim & Wo, 2022)
Shopping malls	2	Correlated positively with property and violent crimes (Kim & Wo, 2022; Vilalta & Fondevila, 2019)

Alley ways and windows onto street	2	Alleyways Correlated positively with homicide, Windows onto street correlated negatively (Beavon et al., 1994; De Souza & Miller, 2012)
Number of Trees in streetscape	2	Positive association with violent crimes (Deng, 2015) and no influence on property crimes (Xie et al., 2022)
Walkability	2	Positive association with property and violent crimes (Lee & Contreras, 2021; Xie et al., 2022)
Police stations. Total units of public housing on each street segment	1	Police stations correlated positively with robbery. Public housing correlated positively with burglaries and robberies (Favarin, 2018)
Public libraries, recreation centers	1	Correlated positively with robbery (Clutter et al., 2019)
Abandoned buildings, vacant land, mailboxes, parking lots, Churches	1	Churches - Not significantly associated with drug crimes on street segments, but associated significantly at intersections for drug crimes; all others - positive associations with drug crimes (Hsu & Miller, 2017)
Halfway houses	1	Positive correlation with property, violent crimes and disorder crimes (Groff & Lockwood, 2014)
Fire stations	1	Fire stations were not associated with crime (Ratcliffe, 2012)
the number of - sidewalks, streetlamps, enclosure effects, and fences - in the streetscape	1	Positive influence on property crimes (Xie et al., 2022)
the number of - buildings and walls– in streetscape, proportion of grass in the streetscape, and the greening rate	1	No influence on property crimes (Xie et al., 2022)
Physical boundaries between two sides of streets (Land use difference)	1	Positive association with property and violent crimes (Kim & Hipp, 2022)
Number of businesses, Percentage of buildings built in past 10 years, community center and educational building within 500m of center of street segment, garden within 150m of street segment	1	Positive association with property and violent crimes for number of businesses, the rest had negative association (Amram et al., 2024)

Two of the studies shown in Table 3 that have not been mentioned in any prior assessment are discussed here. Deng (2015) studied the association between different crime types and (configuration & composition of) trees across Milwaukee (USA) using census blocks as a spatial unit and by controlling for socio-economic variables such as age and ethnicity of the population. The findings of the study suggest that configuration as well as the composition of trees with varying heights co-related positively with property crime. Only the density of trees was positively associated with violent crimes, but the effects varied across the city (Deng, 2015). Lee & Contreras (2021) analysed the effects of neighbourhood walkability on property and violent crimes in city blocks of Los Angeles (USA) using a negative binomial regression model. The study found a strong influence of walkability with both property and violent crimes (Lee & Contreras, 2021) which was consistent with the crime pattern theory which suggests that the built environment plays a role in influencing criminal activities.

5. Discussion

This research provides a view of the state of art in terms of the available research and gaps in understanding how urban elements might influence physical crimes at micro spatial units. A total of 40 urban elements were evaluated for their effect on crime across 29 studies and it was found that most urban elements were associated with higher crime. The urban elements that were co-related with no or negative influence on crimes, were associated with features that increase the movement of people and/or increase guardianship. For only four of the urban elements examined (Windows onto the street, community and educational buildings within 500m of the centre of street segments, the presence of a garden within 150 meters of the centre of street segments, and the percentage of buildings built in past 10 years), a negative association observed was observed. The urban elements that were found to have no co-relation with crime were the greening rate (i.e., the increase in vegetation or green spaces), fire stations, community and educational buildings including schools (within 500m of the centre of a street segment), churches on street segments, the number of buildings and walls in the streetscape, and the proportion of grass in the streetscape. However, a meta-analysis could be conducted for only eight urban elements - street network configuration, public transit, parks, schools, alcohol facilities and bars, retail facilities, Drug treatment centers and bank branches & ATMs. To enable a direct comparison, Figure 10 shows a Forest plot of each of the overall estimated effect sizes for each element. For violent crime, the effect of main roads and public transit was found to be relatively higher than for the other urban elements. Public transit was more criminogenic in the surrounding areas, especially for bus stops, tram stops and subways. For property crime, the highest effect size of was associated with street configuration (using a measure of how likely a street is to be used). This was followed by the combined effect sizes of street configuration using main roads.

These results provide support for routine activity (Cohen & Felson, 1979b) and Crime Pattern Theory (Brantingham & Brantingham, 1995) which suggest that crime is more likely at locations where motivated offenders are likely to encounter crime opportunities. For example, street segments that are busier due to them being within more peoples' activity spaces are likely to facilitate more convergences of motivated offenders and vulnerable targets in the absence of capable guardianship/place management, which generates more crime opportunities (Brantingham & Brantingham, 1995; Davies & Johnson, 2015). Busier street segments tend to be those that are better connected, easily accessible, travelled frequently, and that have higher traffic (e.g., main roads) and pedestrian flows. It is precisely such street segments that appear to have the most crime on them.

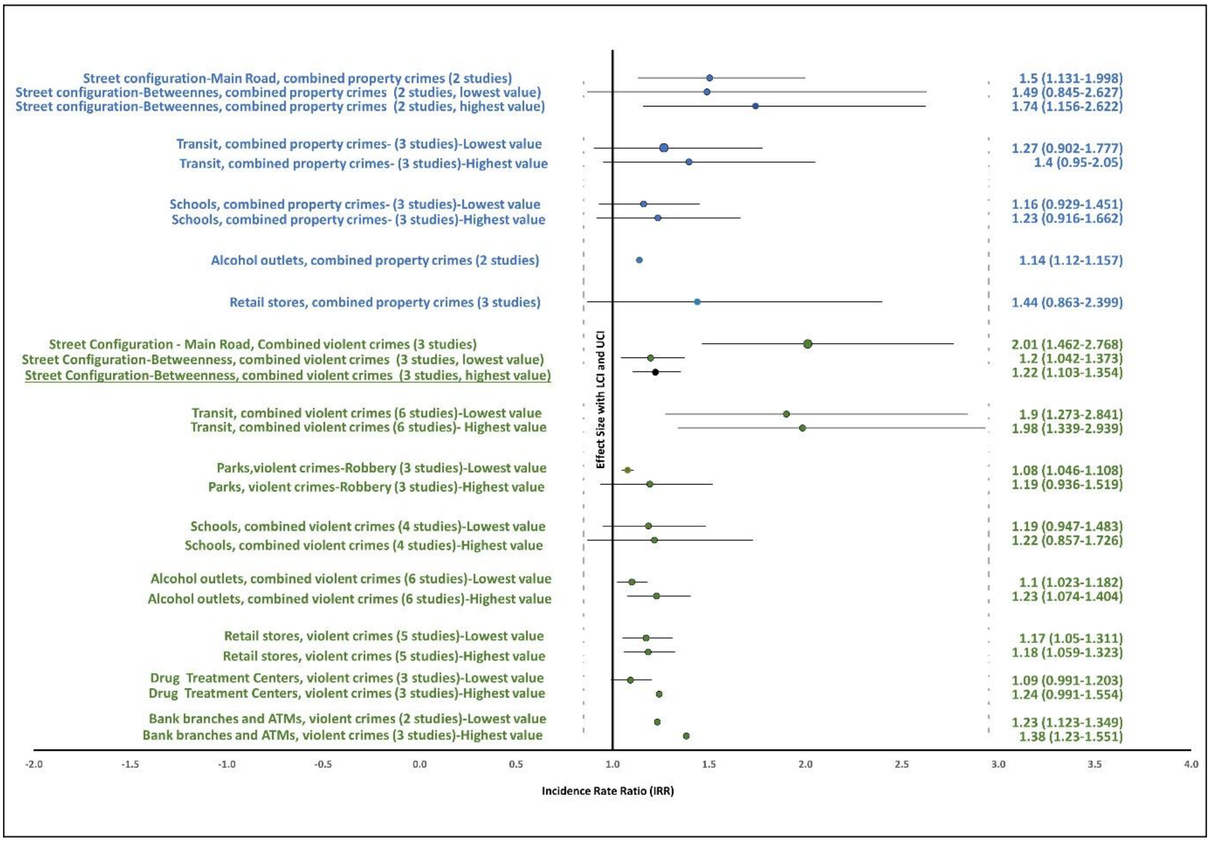

Figure 10 Forest plot – summary of the estimated Influence of Urban elements on crime

Different types of facilities exhibited different crime patterns depending on the crime type. The association between schools and property and violent crime was relatively low and non-significant with similar effect sizes that ranged from IRR=1.16 to IRR=1.23. In this case, the association may be more complicated and mediated by the wider geography, crime type and the type of school (e.g. public or private; higher education, or primary). Unfortunately, too few studies met the inclusion criteria, which meant that the moderating effect of such factors could not be explored meta-analytically.

For property crime, three urban elements (other than street configuration and schools) were meta-analyzed – retail stores, public transit and alcohol outlets. Overall, retail stores and public transit were positively but reliably associated with the property offenses studied. One reason for the mixed results may be that the association may depend on the location of transit stops, the frequency of transport, the number of people taking journeys, the time of the day, the level of accessibility near to transit stops, the spatial unit of analysis and the land-use characteristics of the street segment level (Block & Block, 2000; Ridgeway & Macdonald, 2017). More people completing journeys and high levels of accessibility near transit stops may result in more theft due to an increase in the availability of opportunities (Newton et al., 2014c; Zahnow & Corcoran, 2019), however, property crimes could be lower (at micro places) as the victim might report the crime after the theft and might not be aware of the location that the offense took place (Newton et al., 2014b).

For violent crime, six urban elements (other than street configuration and schools) were found to be significantly criminogenic – public transit, parks, alcohol outlets, retail stores, drug treatment centres and Banks & ATMs. Research suggests that such facilities encourage the convergence of offenders and potential targets because they attract those not familiar with a locality as well as people with recurring routine activities patterns. Put differently, these types of facilities spatially structure human activity and in doing so generate (e.g. Brantingham and Brantimgham, 1995) crime opportunities (Haberman & Kelsay, 2021; Wortley & Townsley, 2016). The lowest significant effect size for violent crime observed was for parks. Research suggests that parks could be crime generators (Groff & Mccord, 2012), but that the crime patterns are shaped by multiple features of parks and the activity that they encourage. Such features include secure fencing, the number of trees clustering, park furniture such as benches, the presence of a playground, the level of maintenance, whether there is lighting after dark, recreation centres, and if there is a main road or transit stop close to a park (Groff & Mccord, 2012; Taylor et al., 2019; van Vliet et al., 2021).

The estimates of the influence of urban elements on crime reported here are for the estimated effects after controlling for the influence of other socio-economic, socio-demographic, temporal and land use variables, urban features of the study area, and type of crime examined. Moreover, despite the differences in studies, with only a few exceptions, the urban elements examined in this SR consistently suggest a positive association with one or more types of crime. This was regardless of research design, crime type, independent (predictor) variables, the time periods for which data were collected, physical & social characteristics of the study locations, and the statistical models used for quantitative analysis. The common approach to analysis that facilitated meta-analysis was the use of Negative Binomial or Poission regression, but that many studies did not use this approach, We would encourage authors to report such analyses in the future where possible to facilitate meta-analysis.

The findings from this study can potentially help understand where interventions within urban designs might best be targeted for crime to limit the criminogenic impacts. That bus stops were found to be more criminogenic at street intersections than those located along street segments might suggest that removing bus stops from intersections would be a good idea. Alternatively, installing CCTV cameras at or near bus stops at intersections might help to monitor and ideally deter criminal activity more effectively. Preventing the clustering of alcohol outlets near sensitive locations—such as schools and residential areas—and ensuring the installation of bright, uniform lighting on surrounding pavements and parking areas can help reduce the risk of alcohol-related crimes. However, as already noted, surprisingly few studies met the inclusion criteria, and hence some caution is necessary, and it may not be appropriate to generalize from the findings for those urban elements discussed for which available data were limited.

Limitations

While there was a sizeable literature concerned with the association between urban elements and crime, many studies did not meet our inclusion criteria. Many authors conducted analyses using units of analysis that were too large. Other studies used analytic approaches that helped to test theory but were too different to those used in other studies to enable their synthesis meta-analytically. As a result, only a fraction of the studies identified in our searches could be included in the meta-analyses presented. This limits the generalizability of the findings and statistical power. As such, some caution should be exerciswed when interpreting the results presented here.

The studies included in this SR mainly used data directly reported to and recorded by the police. Hence, this analysis inherits the limitations associated with official crime data – chief amongst these being the under reporting of crime, which may mean that the findings are not representative of the risk encountered by the entire population.

Future research

It was somewhat surprising that so few studies used comparable statistical models. One solution to this would be that when authors conduct more sophisticated analyses (e.g. use of machine learning model (Xie et al., 2022)), they also report the findings for simpler models, such as a negative binomial or Poisson model, perhaps in an appendix. Another solution would be for authors to embrace the principles of open science and to publish anonymised versions of their data (aggregated to suitable spatial units of analysis) to facilitate the inclusion of their data in meta-analysis.

Urban elements are transforming, with many (e.g. digital kiosks, CCTV, connected car parks, connected charging stations) becoming internet connected (Laufs et al., 2020; Shukla et al., 2025). No studies identified in the systematic review analysed the influence of such elements, but it will be important for future studies to do so. More generally, internet connected information flows lead to “connected places” which are a mixture of physical and virtual built environments (Shukla, 2024). It will be important to study how such cyber-physical connectivity might change the activities of people, movement patterns, the operations of infrastructure and the way services are consumed by people in urban environments. The crime opportunities that might be facilitated by such cyber-physical connectivity could lead to significant changes in criminal trends across different types of developing urban environments. As such, there is an urgent need for research to examine if and how crime types are changing, and what the association is between crime and urban elements for both urban and online crime.

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APPENDIX 1

Search keywords and strings for systematic literature review (Section 2.2)

ProQuest:

("built environment") OR (neighbourhood*) OR (“neighbourhood*) OR ("physical environment") OR ("urban place") OR (urban NEAR/5 space) OR (urban NEAR/5 area*) OR (public NEAR/5 realm) OR (micro* NEAR/5 place) OR (street NEAR/2 urban) OR (street NEAR/2 Network) OR (road NEAR/2 network) OR ("Street Segment") OR ("Street configuration") OR (street NEAR/5 ecosystem) OR (street NEAR/5 traffic) OR (street NEAR/5 one-way) OR (Street NEAR/5 Two-way)

OR (street NEAR/5 tree) OR (street NEAR/5 green) OR (street NEAR/5 furniture) OR (micro NEAR/5 facilit*) OR (urban NEAR/2 facilit*) OR (super NEAR/5 facilit*) OR (street NEAR/5 facilit*) OR (urban NEAR/5 transport*) OR (Street NEAR/5 Transport*) OR (Street NEAR/5 Transit*) OR (road NEAR/5 transport*) OR (rail* NEAR/2 Station*) OR (bus NEAR/2 Station*) OR (bus NEAR/2 stop*) OR (park*) OR (underground NEAR/5 rail) OR (underground NEAR/5 station) OR (station NEAR/5 Transit*) OR (system NEAR/5 Transit*) OR (street NEAR/5 walk*) OR (street NEAR/5 pedestrian*) OR (street NEAR/5 freight*)

OR (Neighborhood* NEAR/5 design) OR (Neighbourhood* NEAR/5 design) OR (urban NEAR/2 design) OR (building NEAR/5 design) OR (urban NEAR/2 planning) OR ("land use") OR (street NEAR/2 design) OR (CRIME NEAR/5 “street light*”) OR (intervention NEAR/5 “street light*”) OR (intervention NEAR/5 CCTV) OR (crime NEAR/5 CCTV) OR ("crime generat*") OR ("crime attract*")

OR ("smart city") OR ("smart street") OR (drone) OR (wifi) OR ("smart phone") OR (smart NEAR/5 transport) OR ("mobile Phone") OR ("cell phone") OR (building NEAR/5 sensor*) OR (IoT NEAR/5 device) OR (IoT NEAR/5 urban) OR ("big data") OR ("cyber") OR ("virtual")

AND (influ* NEAR/5 crime) OR (crime NEAR/5 correlation) OR (crime NEAR/5 spati*) OR (crime NEAR/5 tempo*) OR (crime NEAR/5 spatiotemporal) OR ("crime pattern*") OR (Crime NEAR/5 predict*) OR (Crime NEAR/5 forecast*) OR (crime NEAR/2 impact*) OR (crime NEAR/2 affect*) OR (Crime NEAR/2 risk*) OR (Crime NEAR/5 GIS) OR (Distribut* NEAR/5 crime)

AND (coefficient) OR (Regression*) OR (quantitative* NEAR/2 Analysis) OR (analysis* NEAR/5 regression) OR (econometric NEAR/2 analyses)

AND ((abduct*) OR (arson*) OR (assault*) OR (blackmail) OR ("bodily harm") OR (burglar*) OR (firearm) OR (weapon) OR (fraud) OR (homicide) OR (kidnapping) OR (manslaughter) OR (murder) OR (prostitut*) OR (“public disorder") OR (robber*) OR (shoot*) OR (shoplift*) OR (theft*) OR (vandalism) OR (violen*) OR (terrori*) OR (rape) OR (riot*) OR (anti*social NEAR/2 behavio*) OR (knife NEAR/2 crim*) OR (money NEAR/2 laundering) OR (drug NEAR/2 misuse) OR (drug NEAR/2 use) OR (drug NEAR/2 possess*) OR (drug NEAR/2 deal*) OR (drug NEAR/2 traffick*) OR (drug NEAR/2 supply) OR (drug NEAR/2 market) OR (drug NEAR/2 abuse) OR (cyber NEAR/5 crime) OR (cyber NEAR/5 fraud) OR (cyber NEAR/5 security) OR (cyber NEAR/5 abuse) OR (Cyber NEAR/5 stalk*) OR (Digi* NEAR/5 security) OR (digi NEAR/5 intervention) OR (DDOS)OR (Ransom*))

APPENDIX 2

Data extracted from studies included in the Systematic Literature Review (Section 2.3.2)

Study (N=29)	Urban elements	Crime types	Spatial unit	Country	Type of study	Statistical model
Amram et. al. (2024)	number of bus stops (2006), number of businesses (2012), percentage of buildings built in past 10 years, new residential property transactions, community center and educational building within 500m of center of street segment, garden within 150m,	Property and Violence	Street segment	Israel	Cross-sectional study	Zero-inflated negative binomial (ZINB) regression
Beavon et al. (1994)	Street Network & Configuration, Alleyways and drug areas	Property	Street segment	Canada	Matched case–control design	MANOVA
Bernasco & Block (2011)	Street Network & Configuration, Public Transit, Alcohol outlets, Retail land use, barbers' shops and beauty salons, gas stations, laundromats, pawn shops and check cashing services	Violence	Street segment	USA	Cross-sectional study	Negative Binomial Regression Models
Boessena et. al. (2018)	Parks	Property and violence	Census block	USA	Longitudinal study	Negative Binomial Regression Models
Bowers (2014)	Risky facilities – Retail facilities (such as shops and café) and recreational facilities (such as movie theatres and large clubs)	Property	50x50 metre grid cells	UK	Cross-sectional study	Spatial Regression model
Clutter et. al. (2019)	Street Network & Configuration, Public Transit, Parks, Schools, Alcohol outlets, Retail land use, public housing, public libraries, drug treatment centers, hotels, and recreation centers	Violence	Street blocks (segments)	USA	Cross-sectional study	Negative Binomial regression model
Davies & Johnson (2015)	Street Network & Configuration	Property	Street segment	UK	Cross-sectional study	Poisson Hierarchical Linear Model
De Souza & Miller (2012)	Alcohol outlets, Retail land use, alley ways	Violence	50 m to 100-meter area from homicide address	Brazil	Matched case–control design	Ordinary least squares fixed effect Linear Regression model
Deng (2015)	Trees	Violence	Street segment	USA	Cross-sectional study	Multivariate Ordinary Least square Regression Analysis
Favarin (2018)	Street Network & Configuration, Public Transit, Alcohol outlets, Retail land use, Residential land use, mixed land use, public housing, bank branches/ATM, personal care shops, licensed premises, and police stations	Property	Street segment	Italy	Cross-sectional study	Negative Binomial regression model
Groff (2014)	Alcohol outlets	Violence	Street segment (distance of 400 feet)	USA	Cross-sectional study	Zero-inflated Negative Binomial (ZINB)
Groff & Lockwood (2013)	Street Network & Configuration, Public Transit, Schools, Alcohol outlets, drug treatment locations and halfway houses	Violence, property, disorder	Street segment	USA	Cross-sectional study	Negative binomial regression model

Study (N=29)	Urban elements	Crime types	Spatial unit	Country	Type of study	Statistical model
Groff & Mccord (2012)	Parks	Violence, property, disorder	50foot buffer around the park	USA	Cross-sectional study	ANOVA
Haberman & Ratcliffe (2015)	Public Transit, Parks, Schools, Alcohol outlets, Retail land use public housing communities, check-cashing stores, drug treatment centers and pawn shops	Violence	Census block	USA	Cross-sectional study	Binomial Regression analysis
Hsu & Miller (2017)	Public Transit, Parks, Retail land use, Abandoned buildings, vacant land, mailboxes, parking lots, churches	Drug	Street segments	USA	Matched case–control design	Conditional Logistic Regression Model
Johnson & Bowers (2009)	Street Network & Configuration	Property	Street segment	UK	Cross-sectional study	Poisson Hierarchical Linear Model
Kim & Hipp (2019)	Street Network & Configuration, Retail land use	Property and Violence	Street segment	USA	Cross-sectional study	Negative Binomial regression model
Kim & Hipp (2022)	Physical boundaries (as land use difference – residential, retail, office, industry and other between the two sides of the street)	Property and Violence	Street segments within a 20-m (65 feet) bufer	USA	Cross-sectional study	Negative Binomial Regression model
Kim & Wo (2023)	Physical topological features of street segments (effects of elevation, slope, and street connectivity i.e. betweenness within 1/4rth mile on crime)	Property and Violence	Street segment	USA	Cross-sectional study	Negative Binomial Regression
Kim & Wo (2022)	Retail (stores, shopping mall, restaurant), hotel, school	Property and Violence	Census Block	USA	Cross-sectional study	Logistic Regression
Lee & Contreras (2021)	Walkability	Property and Violence	Census Block	USA	Cross-sectional study	Negative Binomial Regression
Liggett et al. (2003)	Public Transit, Alcohol outlets	Violence, disorder, property and drug	46m (150ft) radius of intersections where bus stops were located	USA,	Cross-sectional study	Regression analysis
Newton (2014)	Public Transit	Property	400m buffer zone around stations	UK	Cross-sectional study	Negative Binomial Poisson regression model
Ratcliffe (2012)	Public Transit, Schools, Alcohol outlets, fire stations	Violence	85 feet from centroid of the bars	USA	Cross-sectional study	Change point Poisson regression
Soohyun & Yongjei (2016)	Public Transit, Schools, Retail land use	Property, Violence, Disorder and all crimes	500-ft^2 grid cells	USA	Cross-sectional study	Multivariate Linear Regression Analysis
Summers & Johnson (2016)	Street network & configuration	Outdoor serious violence	Street segment	UK - England	Cross-sectional study	Zero-inflated Negative Binomial (ZINB)
Vilalta & Fondevila (2019)	Street network & configuration, Alcohol outlets, Retail land use	Violence	Census block	Mexico	Cross-sectional study	Geographically weighted Poisson regression model
Wo & Park (2020)	Schools	Property and Violence	Census Block	USA	Cross-sectional study	Negative Binomial Regression
Xie et al. (2022)	road density in the areas surrounding the street segments, walkability, the greening rate and the number of - streetlamps, sidewalks, enclosure effects, fences, buildings, grass, walls and trees – in streetscape	Property	Street segment	China	Cross-sectional study	Machine learning model

Study (N=29)	Urban elements	Crime types	Spatial unit	Country	Type of study	Statistical model
Haberman & Ratcliffe (2015)	Public Transit, Parks, Schools, Alcohol outlets, Retail land use public housing communities, check-cashing stores, drug treatment centers and pawn shops	Violence	Census block	USA	Cross-sectional study	Binomial Regression analysis
Hsu & Miller (2017)	Public Transit, Parks, Retail land use, Abandoned buildings, vacant land, mailboxes, parking lots, churches	Drug	Street segments and interactions	USA	Matched case–control design	Conditional Logistic Regression Model
Johnson & Bowers (2009)	Street Network & Configuration	Property	Street segment	UK	Cross-sectional study	Poisson Hierarchical Linear Model
Kim & Hipp (2019)	Street Network & Configuration, Retail land use	Property and Violence	Street segment	USA	Cross-sectional study	Negative Binomial regression model
Kim & Hipp (2022)	Physical boundaries (as land use difference – residential, retail, office, industry and other between the two sides of the street)	Property and Violence	Street segments within a 20-m (65 feet) bufer	USA	Cross-sectional study	Negative Binomial Regression model
Kim & Wo (2023)	Physical topological features of street segments (effects of elevation, slope, and street connectivity i.e. betweenness within 1/4rth mile on crime)	Property and Violence	Street segment	USA	Cross-sectional study	Negative Binomial Regression
Kim & Wo (2022)	Retail (stores, shopping mall, restaurant), hotel, school	Property and Violence	Census Block	USA	Cross-sectional study	Logistic Regression
Lee & Contreras (2021)	Walkability	Property and Violence	Census Block	USA	Cross-sectional study	Negative Binomial Regression
Liggett et al. (2003)	Public Transit, Alcohol outlets	Violence, disorder, property and drug	46m (150ft) radius of intersections where bus stops were located	USA,	Cross-sectional study	Regression analysis
Newton (2014)	Public Transit	Property	400m buffer zone around stations	UK	Cross-sectional study	Negative Binomial Poisson regression model
Ratcliffe (2012)	Public Transit, Schools, Alcohol outlets, fire stations	Violence	85 feet from centroid of the bars	USA	Cross-sectional study	Change point Poisson regression
Soohyun & Yongjei (2016)	Public Transit, Schools, Retail land use	Property, Violence, Disorder and all crimes	500-ft^2 grid cells	USA	Cross-sectional study	Multivariate Linear Regression Analysis
Summers & Johnson (2016)	Street network & configuration	Outdoor serious violence	Street segment	UK - England	Cross-sectional study	Zero-inflated Negative Binomial (ZINB)
Vilalta & Fondevila (2019)	Street network & configuration, Alcohol outlets, Retail land use	Violence	Census block	Mexico	Cross-sectional study	Geographically weighted Poisson regression model
Wo & Park (2020)	Schools	Property and Violence	Census Block	USA	Cross-sectional study	Negative Binomial Regression
Xie et al. (2022)	road density in the areas surrounding the street segments, walkability, the greening rate and the number of - streetlamps, sidewalks, enclosure effects, fences, buildings, grass, walls and trees – in streetscape	Property	Street segment	China	Cross-sectional study	Machine learning model