Investigating the Crime Recovery Patterns in Nottingham in the Post-lockdown Period Using Social Disorganization Theory

DEPARTMENT OF GEOGRAPHY

BA/BSc Geography

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Abstract

Exceptional events have long been considered as the catalyst of social disorder and crime. However, the link between exceptional events and crime has been underdeveloped due to the limited number of exceptional events and the limited number of available datasets. The introduction of the covid lockdown measures provides an excellent opportunity to examine the variation of crime after the exceptional event. More research starts focusing on the effect of lockdown policies on crime. The results turned out that most of the crime types, including theft and property crime, experience a decreasing crime rate during the lockdown periods. However, only a few studies have focused on the crime recovery pattern after the lockdown ended. To fill this research gap, this study aims to investigate the crime recovery pattern in Nottingham where crime patterns are underexplored within the context of Covid lockdowns (1st lockdown, 2nd lockdown, 3rd lockdown). As the crime patterns vary across crime types, this study mainly focuses on two crime types – anti-social behavior and violence & sexual offences.

Within the ecological framework, a longitudinal study is conducted on both city and LSOA levels using generalized additive models. This study examines whether there was a statistically significant crime pattern before, during, and after the covid lockdown. The results suggest that after lockdowns, the rate of anti-social behavior experienced an inverted U-shaped recovery pattern, especially in the LSOAs close to Nottingham's city center. Though the rate of violence & sexual offences experienced a possible U-shaped recovery pattern after the 1st lockdown, similar patterns are not found after the 2nd and the 3rd lockdowns.

To further quantify the effect of lockdown on crime, generalized linear models and generalized additive models are carried out. The model output shows that the effect of lockdown on anti-social behaviors is greater than its effect on violence & sexual offences. That helps to explain the reason why the recovery pattern of anti-social behaviors is more significant than the one of violence & sexual offences. In the modeling process, social disorganization theory has been tested as well. The model output suggests that the crime pattern in Nottingham is not consistent with what social disorganization theory suggested – for example, low-income LSOAs do not experience high crime rates compared to their more affluent counterparts.

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List of Acronyms

ASB: Antisocial Behavior

VSO: Violence and Sexual Offences

SDT: Social Disorganization Theory

GST: General Strain Theory

SCT: Social Cohesion Theory

RAT: Routine Activity Theory

GAM: Generalized Additive Model

GLM: Generalized Linear Model

KDE: Kernel Density Estimation

LSCV: Least-square Cross-validation

LSOA: Lower Layer Super Output Area

CDRC: Consumer Data Research Centre

PTAI: Public Transport Accessibility Index

NNVRU: Nottingham City & Nottinghamshire Youth Violence Reduction Unit

Chapter 1: Introduction

This study is based in Nottingham. It aims to investigate the crime recovery patterns after covid lockdowns for two particular crime types – antisocial behavior (ASB) and violence & sexual offences (VSO). This section introduces the study background from four aspects: 1) crime recovery patterns after covid lockdowns, 2) lockdown policies introduced in the UK, 3) defining ASB and VSO, 4) characteristics of Nottingham. Based on the study backgrounds, three research questions are introduced in the latter section.

1.1. Crime recovery patterns after covid lockdowns

Routine Activity Theory (RAT) suggests that crime can be conceived as the confluence of three components – suitable victims, absence of guardians, and potential offenders (Miró, 2014). COVID lockdown has affected crime patterns by reshaping the interactions between these three components (Campedelli, Aziani and Favarin, 2021). During the lockdown periods, it is expected to have an increasing number of day guardians in the residential areas (Miró, 2014). Meanwhile, in public spaces, it is expected to observe fewer interactions between motivated offenders and potential victims (Miró, 2014). Consequently, most of the crime types experience a crime reduction. In Los Angeles, recorded robbery cases decreased by 23% after the containment policy came into force (Campedelli, Aziani and Favarin, 2021). In England and Wales, recorded VSO cases decreased by 24% during the first national lockdown (Langton, Dixon and Farrell, 2021). However, there are a few exceptions. In England and Wales, ASB increased sharply during the first national lockdown (Bade *et al.*, 2021). In Mexico, domestic violence cases increased as well mainly due to the increasing time spent at home (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021).

After the lockdown measures were relaxed, most of the people returned to their routine activities; therefore, crime rates are expected to return to the pre-lockdown levels (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021). In Mexico, theft and property crime cases followed a U-shaped recovery pattern – decreasing in the lockdown period and then increasing in the post-lockdown period (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021). However, there is lacking empirical evidence supporting crime recovery patterns in other countries or cities. This study, therefore, aims to fill this gap through investigating the crime recovery patterns of ASB and VSO.

These two crime types are selected for investigation because they are expected to have opposite recovery patterns. While the VSO rate is expected to follow a U-shaped recovery pattern – decreasing in the lockdown period and then increasing in the post-lockdown period, the ASB rate is expected to follow an inverted U-shaped recovery pattern – increasing in the lockdown period and then decreasing in the post-lockdown period.

1.2. Lockdown Policies Introduced in the UK

In the UK, the first national lockdown came into force in March 2020 with the closures of non-essential businesses and schools (Halford, Dixon and Farrell, 2022). Two-meter social distancing was required in the public space, and outdoor exercise was restricted to one hour per day. In May 2020, the lockdown policy was relaxed, and people were allowed to meet outdoors (Halford, Dixon and Farrell, 2022). After that, the first lockdown officially ended at the end of June.

With the increasing number of covid cases in the late summer of 2020, the “rule of six” was introduced in September 2020. Then, the second national lockdown was introduced, which lasted from November 2020 to December 2020 (Halford, Dixon and Farrell, 2022). During the second lockdown, most people returned to “work from home”, but schools remained open (Institute for Government, 2022).

The third lockdown was introduced in January 2021 and ended in March 2021. This lockdown is similar to the first lockdown in terms of the measures introduced during the lockdown period. However, with the “support bubble” program, two-household meetings were allowed during the third lockdown (Institute for Government, 2022). Overall, in terms of the measures introduced during the lockdown period, the first lockdown is considered to be the most restrictive one.

1.3. Defining ASB and VSO

In the 1861 Offences Against the Person Act issued in England and Wales, violence is broken down into three subcategories, with an increasing level of severity from category one to category three: 1) assault causing actual bodily harm; 2) malicious wounding and infliction of bodily harm; 3) wounding and causing grievous bodily harm intentionally (Lewis Nedas Law, 2023). Descriptions of the subcategories are shown in Table 1. Referring to Table 1, assault is described as the behavior that causes psychiatric or physical harm to someone, and sexual assault is included in this category (Lewis Nedas Law, 2023). According to the 2003 Sexual Offences Act issued in England and Wales, sexual offences happen “when somebody touches another person intentionally in a sexual way, without that person’s consent” (RCEW, 2023). It could include kissing without consent and touching somebody’s genitals and breasts without consent (RCEW, 2023).

Table 1: Legal Definition of Violence (Lewis Nedas Law, 2023)

Types of Violence	Description
Assault occasioning actual bodily harm	When an individual’s conduct causes physical or psychiatric harm on a victim. It covers a wide range of conduct, from causing someone to lose consciousness for even a small period of time to causing someone to suffer shock.
Malicious wounding or infliction of grievous bodily harm	The offence relates to an individual either having planned to inflict injury or did not care that a victim would suffer damage by their actions. The offence also involves two different kinds of damage: -- wounding and grievous bodily harm.
Wounding or causing grievous bodily harm with intent	The offence requires that a victim is either wounded or suffers grievous bodily harm. The main difference between this offence and all other offences listed above is that this offence requires that there be intent to cause wounding or grievous bodily harm.

In the 2003 Antisocial Behavior Act, ASB is defined as "the behavior that causes distress, alarm or harassment to persons not of the same household as the person" (Metropolitan Police, 2023). Traditional ASB includes vehicle abandoned, rowdy behavior, vehicle nuisance, rowdy neighbors, animal problems, littering, trespassing, nuisance calls, and prostitution-related activity (Metropolitan Police, 2023). With the introduction of Covid-19 regulations, a new form of ASB emerged in 2020. This covid-related ASB includes breaking the "rule of six", breaking the quarantine regulation, and breaking the other covid-related regulations (Halford, Dixon and Farrell, 2022).

1.4. Characteristics of Nottingham

Focusing on ASB and VSO, this study aims to investigate the crime recovery pattern in Nottingham. Nottingham locates in southwestern Nottinghamshire, and it has a young population structure. In 2021, it has a population size of 323,700, with 66,000 of the population below the age of 18 (ONS, 2021). Those young people have been disproportionately involved in criminal activities, as stated in the Profile of Youth Crime in Nottingham City (Warburton and Hough, 2009).

Additionally, Nottingham has a high crime rate compared to the other cities in Nottinghamshire. Among 26 population centers in Nottinghamshire, Nottingham has the highest crime rate in 2021, which is 114 cases per 1,000 residents (CrimeRate, 2023). Meanwhile, VSO and ASB are the most common crime types in Nottingham, with VSO accounting for 27.35% of the total crime and ASB accounting for 30.33% (CrimeRate, 2023). Though VSO and ASB account for a large portion of Nottingham's total crime, only a few research has made a comparison between ASB and VSO. To the author's knowledge, no study has investigated and compared these two crime types within the context of crime recovery. Therefore, this Nottingham-based study attempts to fill this gap following the research questions and objectives listed below:

Research Questions:

1. Does Nottingham's crime pattern change before, during, and after the first lockdown?
2. Does the crime recovery pattern of VSO and ASB vary across Lower Layer Super Output Areas (LSOAs)?
3. Does Social Disorganization Theory help to explain the crime pattern in Nottingham?

Objectives:

For RQ1: Mapping the ASB and VSO patterns in Nottingham in May 2019, May 2020, May 2021, and May 2022

For RQ2: Using generalized additive models to test whether there is a statistically significant crime recovery pattern in Nottingham in terms of ASB and VSO

For RQ3: Using generalized additive models and generalized linear models to examine the effect of crime-related variables on ASB and VSO.

Chapter 2. Literature Review

This section reports the findings from past literature, and it is divided into three subsections. First, crime recovery patterns are discussed using empirical and theoretical proof. Second, criminology theories are critically examined through the lens of VSO and ASB. Third, research gaps are addressed based on the literature review.

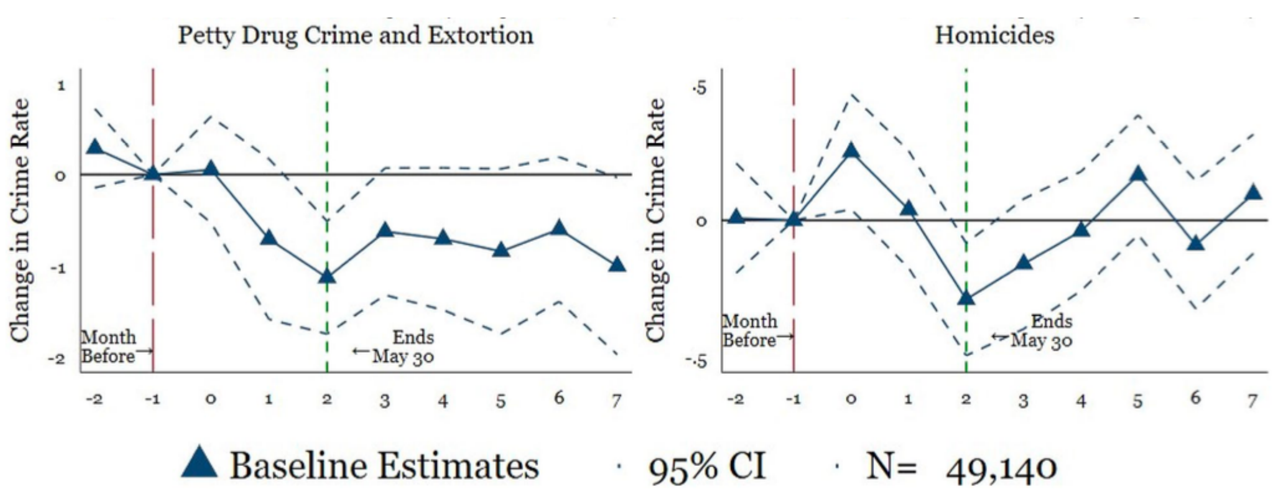
2.1. Crime recovery pattern in the post-lockdown period

2.1.1. Empirical Evidence

The effect of lockdown policy on crime has been widely investigated across literatures(Lewis Nedas Law, 2023); however, crime recovery patterns have been underexplored. A study done in Buenos Aires suggested that the number of reported theft decreased by 80% after the first mandatory lockdown introduced in March 2020, and then this number increased steadily after the lockdown policy was relaxed in April 2020 (Perez-Vincent, Schargrodsky and García Mejía, 2021). However, the number of reported theft had not recovered to its pre-lockdown level by December 2020 (Perez-Vincent, Schargrodsky and García Mejía, 2021).

A study done in Mexico suggested that after the first national lockdown introduced in Mexico in March 2020, a statistically significant U-shaped recovery pattern can be found in three crime types – assault & battery, theft & battery crime, and fraud (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021). Meanwhile, as Figure 1 shown, no statistically significant crime recovery patterns can be observed in petty drug crime & extortion and homicides, as the horizontal zero-line falls between the 95% confidence interval (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021). Based on the empirical evidence provided in these two studies, one can conclude that crime recovery patterns, as well as the significance level of crime recovery patterns, differ across crime types.

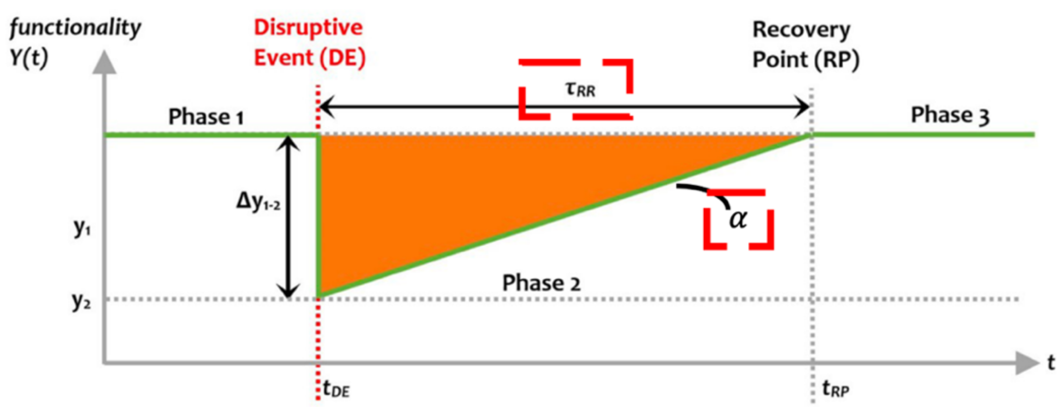
Figure 1: Mexico Crime recovery patterns (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021)



2.1.2. Theoretical Models

The U-shaped recovery pattern found in previous studies can be explained by the resilience model suggested by Bruneau et al (2003). Evolved from earthquake hazards, this model reflects how the functionality of a social system can be restored to its normal level after exceptional events (Bruneau *et al.*, 2003). As Figure 2 shown, social functionality is expected to change sharply at the point of the exceptional event; then, it would bounce back to its baseline level after the event ended. In this process, two key metrics are utilized for the quantification of resilience — Trr measures the recovery time, and α measures the recovery speed (Bruneau *et al.*, 2003). In the criminology context, these two metrics can be used to assess the ability of a criminogenic system to bounce back after an exceptional event (Borrion *et al.*, 2020).

Figure 2: Resilience Model suggested by Bruneau et al. (2003)



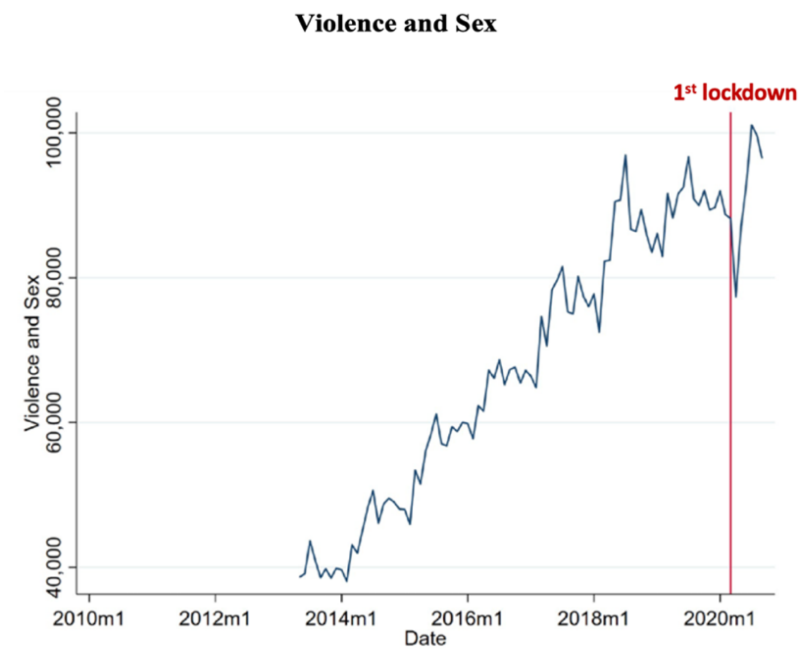
Unlike the recovery activities carried out intentionally by people after natural disasters, crime recovery occurred naturally when people returned to their routine activity (Borrion *et al.*, 2020). When the crime rate is gradually returning to its baseline level, it is possible for the criminogenic system to find a new equilibrium with a higher or lower crime rate (Borrion *et al.*, 2020). In the context of lockdown policy, the construction of the new equilibrium can be explained by two possible reasons. The first reason is that lockdown policies can influence individuals' lifestyles and individuals' routine activities in terms of shopping behavior, ways of working, and commuting behavior (de Palma, Vosough and Liao, 2022). That can eventually influence crime rates. The second possible reason is that lockdown policies can influence the determinants of crime. For example, people can keep suffering from loneliness and financial distress after lockdowns (Bade *et al.*, 2021). Referring to General Strain Theory (GST) and RAT, those stressors can act as the motivations for the potential offenders, which eventually increase the likelihood of crime in the post-lockdown period (Bucher, Manasse and Milton, 2014).

2.2. Criminology Theories and VSO

2.2.1. RAT and VSO

In England and Wales, the number of VSO cases decreased from 90,000 to 75,000 during the first lockdown; then, it bounced back to 100,000 as Figure 3 shown:

Figure 3: Changing crime count (Kirchmaier and Villa-Llera, 2020)



RAT helps to explain this recovery pattern. As mobility decreased sharply during the lockdown period, it was expected to have fewer opportunities for the offenders with fewer interactions between motivated offenders and potential victims in public spaces (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021). However, after the lockdown measure was relaxed, most of the people were returning to their routine activities. That provides more opportunities for the motivated offenders and eventually increases the likelihood of VSO, especially in Nottingham's city center where is teeming with commuters, shoppers, and drinkers (Balmori de la Miyar, Hoehn-Velasco and Silverio-Murillo, 2021).

2.2.2. Social Disorganization Theory (SDT) and VSO

With the emergence of the night-time economy, the number of drinkers increased substantially in Nottingham's city center (Hollows *et al.*, 2014). That can eventually give rise to social disorder and violent crime. Therefore, it provides an excellent chance to examine SDT. SDT suggested that social organization is crucial to combat crime (Bellair, 2017). Socially organized communities tend to have a high-level solidarity (internal consensus on establishing a safe community), a high-level cohesion (strong bond between neighbors), and a high-level integration (sense of belonging and social interaction) (Kubrin, 2009). On the other hand, socially disorganized communities are lacking in these aspects (Kubrin, 2009).

According to SDT, socially disorganized neighborhoods share five common characteristics: ethnic heterogeneity, low economic status, residential mobility, urbanization, and family disruption (Kubrin, 2009). First, ethnic heterogeneity could hinder communications among neighbors, thus making it difficult for the community to achieve common goals (creating a crime-free neighborhood) (Kubrin, 2009). A study done in Stockholm provided empirical evidence to support this idea. It suggested that ethnically diverse communities can suffer from a high violent crime rate among youths, as people share different norms and values (Pettersson, 2003). However, a study in Philadelphia suggested the opposite

– ethnically homogenous communities can encourage co-offender interactions among people from the same ethnic background (Pettersson, 2003).

Second, people from high-economic-status communities are likely to share a consensus on the social control (Kubrin, 2009). On the other hand, people from low-economic-status communities are prone to perform illegal behavior for a living (Kubrin, 2009).

Third, low residential mobility can encourage the establishment of community networks among neighborhoods (Barnett and Mencken, 2002). On the other hand, high residential mobility can have an adverse effect on community stability, as it takes time for the newcomers to assimilate into the community (Barnett and Mencken, 2002). A study done in the US supported this argument. It provided empirical evidence suggesting that high residential mobility can have a negative effect on collective efficacy, and that can eventually give rise to a higher violent crime rate (Sampson, Raudenbush and Earls, 1997).

Fourth, family disruption can lead to weak parental supervision, which negatively affects children's emotional problems and results in a high-level youth crime (Wong, 2012). Additionally, unstable families can increase the likelihood of crime by weakening informal social controls, with fewer people supervising children and watching over strangers in the neighborhoods (Wong, 2012). A few studies showed that a higher VSO rate can be found in places that have a higher proportion of single-parent family (Roncek, 1981; Rose and Clear, 1998).

Fifth, Groves and Sampson (1989) suggested that urbanization tends to limit the capacity for social control. With the busy nature of urban communities, people tend to have less personal interactions with their neighbors; thus, it could become difficult to control crime by maintaining social networks and controls (Bruinsma and Johnson, 2018). Urbanization is also found to be positively associated with high crime rates; however, Jones (1984) suggested that violent crime only increases in the initial stage of urbanization. After the urbanization process makes the city more institutionalized, that city is expected to experience a crime reduction in VSO rate (Jones, 1984).

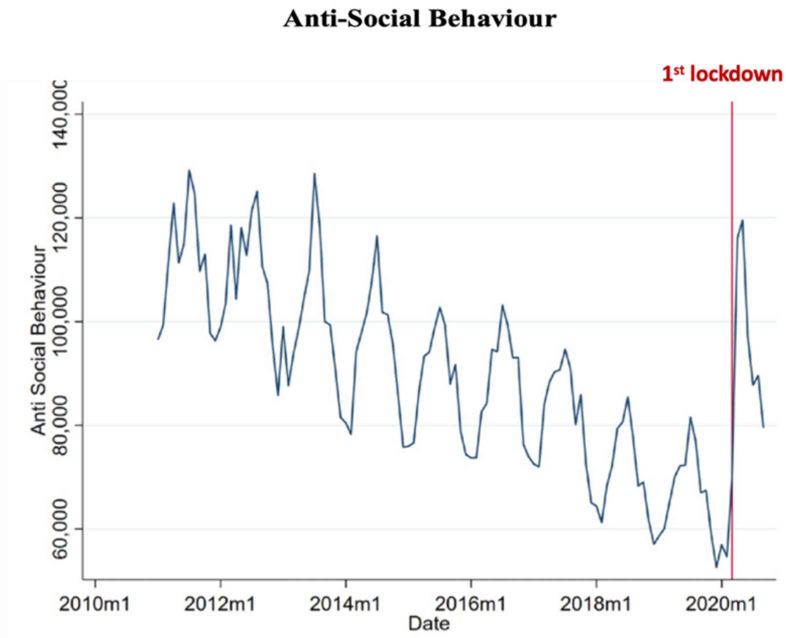
Theoretical and empirical evidence suggested that real-life scenarios are not consistent with what SDT suggested. Therefore, socially disorganized communities suggested in SDT may not necessarily experience a high VSO and ASB rate. Therefore, this study aims to combine SDT with the crime recovery process to investigate the effect of social-disorganization factors on crime.

2.3. Criminology Theories and ASB

2.3.1. RAT, Optimistic Bias and ASB

In England and Wales, the number of ASB cases increased from 40,000 to 120,000 during the first lockdown. Then, it decreased sharply to 80,000 as Figure 4 shown. Using the natural language processing technique, Halford, Dixon and Farrell (2022) found that both traditional and covid-related ASB increased during the lockdowns. A survey-based study done in Mexico also has similar findings. It suggested that during the lockdown period, there was an increase in traditional ASB, especially in the categories of "unruly children", "garbage dispute", and "gossip and misunderstanding" (Halford, Dixon and Farrell, 2022).

Figure 4: Changing crime count (Kirchmaier and Villa-Llera, 2020)



The recovery pattern of ASB can be explained by RAT. With the residential population spending more time in the residential areas during the lockdown periods, the likelihood of conflict increased among neighbors, leading to an increase in the number of ASB cases (Halford, Dixon and Farrell, 2022). After the lockdown measure was relaxed, some people are going back to work, which provides fewer opportunities for conflicts among neighbors, especially in the residential areas in Nottingham.

The initial increase in covid-related ASB can also be explained by optimism bias. Optimism bias describes a situation in which "people tend to think they are invulnerable, and they expect others to be victims of misfortune, not themselves" (Druică, Musso and Ianole-Călin, 2020). This underestimation of disease transmission can encourage potential offenders to break epidemic prevention policies and perform covid-related ASB (Druică, Musso and Ianole-Călin, 2020). For example, Nottinghamshire council officers found that during the lockdown periods, a few pubs and restaurants were breaking the lockdown restriction by allowing customers to drink alcohol inside (BBC, 2021).

2.3.2. GST and ASB

GST can be used to explain the crime recovery pattern of ASB. Robert Agnew's GST suggested that strains can trigger negative emotions and thus encourage crime commitments (Broidy, 2001). Referring to GST, there are three primary types of strains: 1) failure to achieve a positively valued goal, 2) exposure to negative stimuli, 3) losing positively valued stimuli (Broidy, 2001). During the lockdown periods, people could expose to negative stimuli such as financial distress and psychological distress; meanwhile, they could lose positively valued stimuli from weakening social bonds (Campedelli, Aziani and Favarin, 2021).

In Nottingham, financial strains could be a big problem, especially in Aspley Ward and Bulwell Ward where 12% of the population was suffering from unemployment in 2020 (Hennessy, 2020). This situation can even be worsened as some unemployed people are not qualify for Universal Credit (Hennessy, 2020). As a result, the magnitude of strains increased during the lockdowns, with an increased likelihood of ASB (Campedelli, Aziani and Favarin, 2021). Additionally, there is evidence suggesting the pandemic can exacerbate miserable childhood memories and thus encourage ASB committed by youths (Campedelli, Aziani and Favarin, 2021). When the lockdown policy relaxed, people would receive more positively valued stimuli such as hanging out with friends, with less negative stimuli such as staying at home alone. That would eventually decrease the likelihood of crime. According to GST, many socioeconomic characteristics can be classified as negative or positive stimuli; thus, it is difficult to test GST because of its broadness (Agnew, 2001). This study, therefore, would mainly focus on SDT in the modeling process.

2.2.3. Social Cohesion Theory (SCT) and VSO & ASB

SCT believes that exceptional events can encourage people to come together to fight against the crisis; therefore, crime rates are expected to decrease with stronger social cohesion (Andresen and Hodgkinson, 2020). A study done in Quebec further pointed out that altruism was prevalent in the urban communities during the 1998 power failure crisis, and that eventually led to a lower violent crime rate (Lemieux, 2014).

Some people, however, argued that strong cohesion may not lead to a lower crime rate (Forrest and Kearns, 2001). It is because strongly cohesive neighborhoods may be in conflict with other strongly cohesive neighborhoods, and that would eventually contribute to the problem of fragmented cities (Forrest and Kearns, 2001). For example, a strongly cohesive LSOA can share a notion that supports the introduction of lockdown policy, while another LSOA can share the notion against lockdowns. These two LSOAs can be in conflict because they share different common values. Therefore, the level of social cohesion can be different at different spatial scale (Forrest and Kearns, 2001).

2019 Tackling Anti-Social Behaviour and Crime Strategy further pointed out that social cohesion can have a positive impact on ASB. To promote social cohesion, Nottingham Together and Neighbourhood Development Teams collaborated with the Nottingham City Council's Cohesion Board to assimilate new immigrants (Nottingham City Home, 2019). If the level of social cohesion increased, it is expected to find a crime reduction in both VSO and ASB rates. However, it is not the case in England and Wales, implying that social cohesion may not have a substantial effect on VSO and ASB.

2.4. Research Gap

Exceptional events include epidemic outbreaks, natural disasters, and financial crises. Those events have long been considered a catalyst of social disorder and crime because they can have an adverse effect on people's safety, health, and property (Zahran *et al.*, 2009). However, the empirical link between exceptional events and crime has been underdeveloped due to the limited number of exceptional events and the limited available datasets (Zahran *et al.*, 2009). This study, therefore, investigates the effect of lockdown and the effect of social disorganization on crime in the context of crime recovery in Nottingham.

Though there are many studies focusing on the spatial-temporal variations in crime during the lockdown periods, there is lacking empirical evidence supporting the crime recovery patterns, especially in England and Wales. Meanwhile, it remains obscure whether the crime recovery pattern in England and Wales is similar to the seismic recovery pattern suggested by Bruneau et al. Therefore, this study attempts to fill this gap by investigating the crime recovery pattern of VSO and ASB.

Additionally, covid-19 pandemic has been described as the greatest criminological experiment in the history (Stickle and Felson, 2020). It allows criminology theories to be tested as never before (Stickle and Felson, 2020). Therefore, SDT and GST are included in the modeling process to investigate whether crime variation in Nottingham is matched to what criminology theories suggested. Moreover, as a particular area can contribute to a large proportion of crime, it is important to examine the criminology theories at a micro-geographic level (Weisburd, 2018). This study, therefore, examines the crime variation on the LSOA level.

2.5. Who are the beneficiaries?

As crime patterns vary across crime types, places, and time, it is important to deliver place-based research focusing on a particular crime type, which can provide insights for the development of place-based crime prevention techniques (Stickle and Felson, 2020). By researching and comparing the crime recovery patterns of VSO and ASB, new knowledge can be developed for the implementation of policy.

Through investigating the spatiotemporal variation in VSO and ASB, this study hopes to provide some Nottingham-based evidence for future criminology studies, and also for Nottingham's local authorities. For the crime-prevention purpose, the findings of this study can be used as a reference for the Nottinghamshire Police Force and the Nottingham City & Nottinghamshire Youth Violence Reduction Unit (NNVRU). As NNVRU always aims to tackle the root cause of VSO, this study hopes to address the socioeconomic factors that can possibly lead to VSO, by incorporating crime variation with criminology theories. Though the Covid-19 lockdown is unlikely to happen again, this crime-recovery study could still provide valuable insights into how to allocate resources before, during, and after exceptional events.

Chapter 3. Methodology

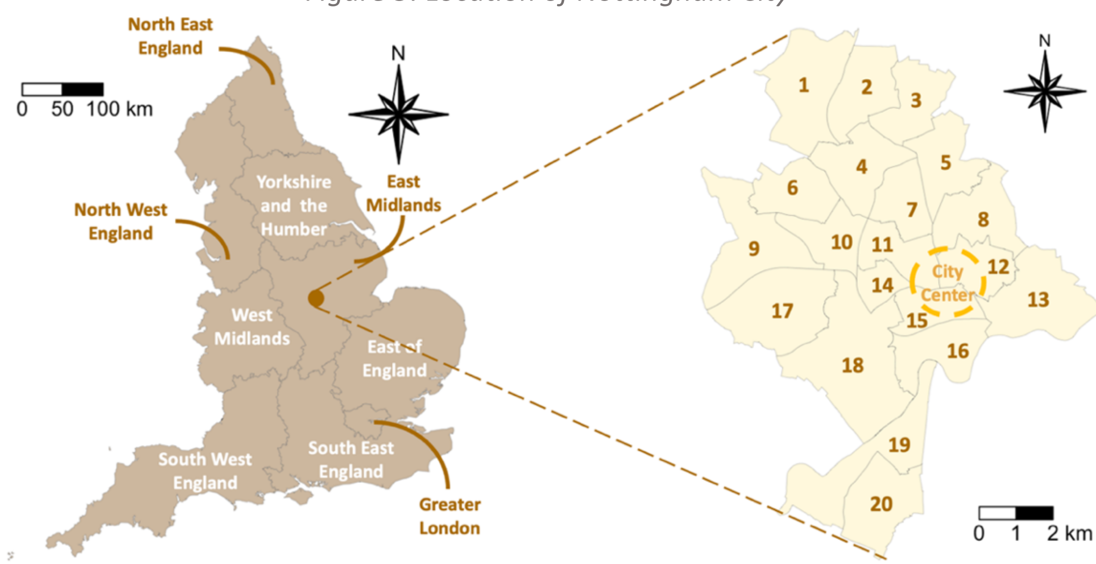
Within the ecological framework, this study examines the crime recovery pattern and investigates the impact of lockdown on crime as well as the impact of social-disorganization factors on crime. This section provides a description of the methods used in this study. Beginning with an introduction of the study area, data sources and data cleaning process are elaborated in the latter section.

3.1. Study area

3.1.1. Nottingham Characteristics

Nottingham city locates in southwestern Nottinghamshire in East Midlands (Nottingham Insight, 2023). As Figure 5 shown, Nottingham constitutes 182 LSOAs nested within 20 wards. According to the 2011 Rural-urban classification, all LSOAs in Nottingham are classified as minor conurbations, indicating that all the LSOAs are predominantly urbanized with less than 26% of the population living in rural settlements (ONS, 2011). Its city center locates in eastern Nottingham city. This mixed-used city center includes entertainment infrastructures, retail stores, and office buildings (Oc and Tiesdell, 1998).

Figure 5: Location of Nottingham City



Ward Name in Nottingham City			
1	Bulwell	2	Bulwell Forest
3	Bestwood	4	Basford
5	Sherwood	6	Aspley
7	Berridge	8	Mapperley
9	Bilborough	10	Leen Valley
11	Arboretum	12	St Ann's
13	Dales	14	Radford
15	Castle	16	Meadows
17	Wollaton West	18	Lenton & Wollaton East
19	Clifton West	20	Clifton East

3.1.2. Crime in East Midlands

East Midlands includes Nottinghamshire, Leicestershire, Derbyshire, Rutland, Northamptonshire, and Lincolnshire (Barberet and Fisher, 2009). In East Midlands, the VSO rate gradually increased from 26 cases per 1,000 residents to 37 cases per 1,000 residents from 2018 to 2021, implying that the situation is getting worse (CrimeRate, 2023). Additionally, many forms of serious violent crime, including knife crime and gun crime, have increased since 2014 (Hopkins, Floyd and Davis, 2020). To tackle the rising VSO rate, various forms of interventions have been implemented by the East Midland NNVRU. Police offices and schools have delivered mentoring programs and educational workshops to support positive behaviors, especially for people who were involved in violence before and people who are living close to the crime hotspots (Hopkins, Floyd and Davis, 2020).

From 2018 to 2021, the ASB rate gradually decreased from 25 cases per 1,000 residents to 24 cases per 1,000 residents, implying that the situation is getting better (CrimeRate, 2023). However, Nottinghamshire local news reported that the number of recorded ASB cases in 2021 could be underestimated, as the 101 line and the council's phone services failed to handle the rising calls during the lockdown periods (Malcolm, 2021). Therefore, whether the ASB rate experienced a decreasing trend remains obscured.

Overall, ASB and VSO cases account for over half of the total crime cases in East Midlands; therefore, it is worth investigating the crime variations of these two crime types. Based on the temporal crime trend, a seasonal variation can be found in both VSO and ASB rates, with an increasing crime rate in summer and a decreasing crime rate in winter (CrimeRate, 2023). This seasonal variation can be explained by the changing temperature. According to a study done by Field (1992), temperatures can influence crime rates by directly affecting people's physiological and psychological responses and indirectly affecting people's frequency of going out at night.

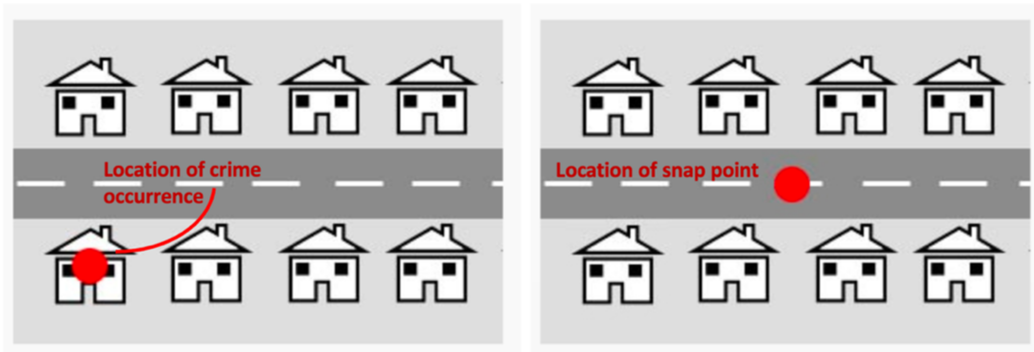
3.2. Data sources

3.2.1. Crime Data

To calculate the VSO rate and the ASB rate in each LSOA, longitudinal crime data was collected from police.uk, with 14 recorded crime types. To protect victims of crime, geomasking technique is utilized with the snap-point approach (Tompson *et al.*, 2015). This approach allows the coordinate of crime to be compared with a list of snap points; then, the coordinate of crime would be replaced by the coordinate of the nearest snap point (Tompson *et al.*, 2015).

Figure 6 further demonstrates how the snap point approach is utilized to hide the location of crime occurrence. This snap-point approach, however, compromises the accuracy of the maps (Smith, 2014). Additionally, one snap point can be assigned to multiple crime cases; therefore, it is necessary to aggregate crime by its Crime ID before carrying out data analysis. This will be further explained in section 3.3.1.1.

Figure 6: How snap point is assigned (Smith, 2014)



To ensure the accuracy of crime data, a rigorous internal validation process is undertaken by multiple offices (Tompson *et al.*, 2015). This data, however, can still be inaccurate from several aspects. First, victims may not remember the exact location of crime occurrence (Tompson *et al.*, 2015). Second, crime types are not further divided into some detailed categories. For example, ASB is not further categorized into Covid-related ASB and traditional ASB. VSO is not further categorized into malicious wounding and sexual assault. Third, some victims may not report crimes, or they may not report crimes directly to the regional police office. As a result, crime counts can be underestimated. Fourth, the problem of "double counting" can occur especially in a situation where two officers were dealing with the same case and both of them need to complete a record (Quinton *et al.*, 2020). From this perspective, crime counts can be overestimated. However, from the police.uk website, it is difficult to distinguish how many officers were dealing with the same case and how many crime cases had not been reported directly to the regional police office, so the number of recorded cases, as well as the calculated crime rate, can be biased.

3.2.2. Public Transport Accessibility Index

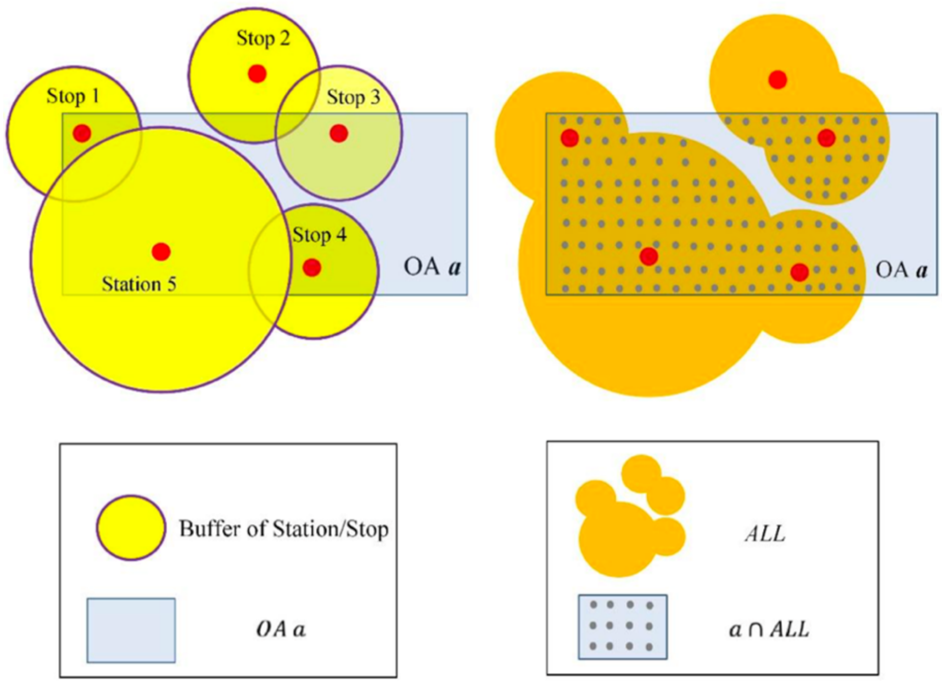
Public Transport Accessibility Index (PTAI) quantifies transport accessibility on the LSOA level. PTAI value is calculated based on the acceptable maximum walking distance to the bus stops, tram stops, rail stations, and ferry stations (UBDC, 2016). First, Stop-level and Station-level PTAIs are calculated by weighting the hourly number of trips passing a station or a stop on workdays (from Monday to Friday), following Formula 1:

$$PTAI(i) = \sum_{1}^{5} \text{cnt\_trip}(\text{i}, \text{t}) \ * \ \text{w}(\text{t}) \qquad (1)$$

In equation (1), the parameter $PTAI(i)$ is the total count of trips passing through the stop (station) *i* during the weighted one-hour period $w(t)$ on five workdays.

Second, a circular buffer is placed around each station and stop, as shown in Figure 7. The buffer radius is determined by the acceptable maximum walking distance. According to a travel survey, the acceptable distance differs across public transport modes; therefore, the radius of the buffer differs across public transport modes: 1) the acceptable maximum walking distance for the bus stops is 400 meters; 2) the one for the tram stops is 400 meters; 3) the one for the rail stations is 800 meters; 4) the one for the ferry stations is 800 meters (UBDC, 2016). Third, the services area of public transportation (the buffer) is overlapped with the LSOA, as shown in Figure 7. Based on Figure 7, the *PTAI(LSOA)* is calculated following equation (2), with a large PTAI value reflecting a high level of accessibility.

Figure 7: Aggregating Stop-level PTAI to LSOA-level PTAI (UBDC, 2016)



$$PTAI(LSOA) = \sum_{1}^{n=i} PTAI(i) * \frac{Area\ (i \cap LSOA)}{Area(LSOA)} \qquad (2)$$

In equation (2), the parameter $PTAI(i)$ is the Stop-level PTAI. This parameter is adjusted by $\frac{Area\ (i \cap LSOA)}{Area(LSOA)}$ which measures the proportion of service area within each LSOA.

3.2.3. Income Deprivation Index

In Income Deprivation Index, three variables are used for modeling: 1) health deprivation and disability decile; 2) education, skills and training decile; 3) income decile. For each decile, the value ranges from 1 to 10, with 1 denoting the most deprived LSOA and 10 denoting the least deprived LSOA. The underlying indicators of these three variables have been checked to ensure they do not share the same underlying indicators. This helps to avoid the double counting problem in the modeling process.

3.2.4. Ethnicity Data

CDRC Ethnicity data measures the proportion of people in each ethnicity group on the LSOA level. This dataset contains 11 ethnic groups, as shown in Table 2:

Table 2: Ethnicity Group in CDRC Ethnicity Data

1	Asian/Asian British: Bangladeshi	2	Asian/Asian British: Chinese
3	Asian/Asian British: Indian	4	Asian/Asian British: Pakistani
5	Asian/Asian British: Any Other	6	Black/Black British: African
7	Black/Black British: Caribbean	8	White: British
9	White: Irish	10	White: Any Other
11	OXX - Any Other Mixed Ethnic Group		

3.2.5. Other Data

For the geospatial analysis, datasets utilized in this study are listed in Table 3.

Table 3: All the data used in this study

Data	Data Source	Description
Crime Counts	Crime datasets from Police.uk	Crime counts from May 2019 to Oct 2022
Population Density Per Square Kilometer	2022 Population Density Dataset from the Office for National Statistics	The number of people per square kilometer in LSOA areas
% of Divorced Household	2011 Household Census from the Office for National Statistics	Percentage of divorced household on the LSOA level
Health Deprivation and Disability Decile	2019 Income Deprivation Index from the Office for National Statistics	Ranging from 1 (most deprived) to 10 (least deprived).
Education, Skills and Training Decile	2019 Income Deprivation Index from the Office for National Statistics	Ranging from 1 (most deprived) to 10 (least deprived).
Income Decile	2019 Income Deprivation Index from the Office for National Statistics	Ranging from 1 (most deprived) to 10 (least deprived).
Ethnicity Proportions	2020 Modelled Ethnicity Proportions from the Consumer Data Research Centre (CDRC)	Contains 11 ethnicities category
PTAI LSOA value	2016 Public Transport Accessibility Index	A higher PTAI value reflects a higher level of accessibility

3.3. Data Manipulation

Using the dataset listed above, geospatial analysis is carried out. However, some datasets need to be cleaned or transformed into a particular format before conducting the analysis. This data manipulation process contains 3 steps: 1) Data transformation, 2) Geocoding, 3) Geospatial Analysis.

3.3.1. Data Transformation

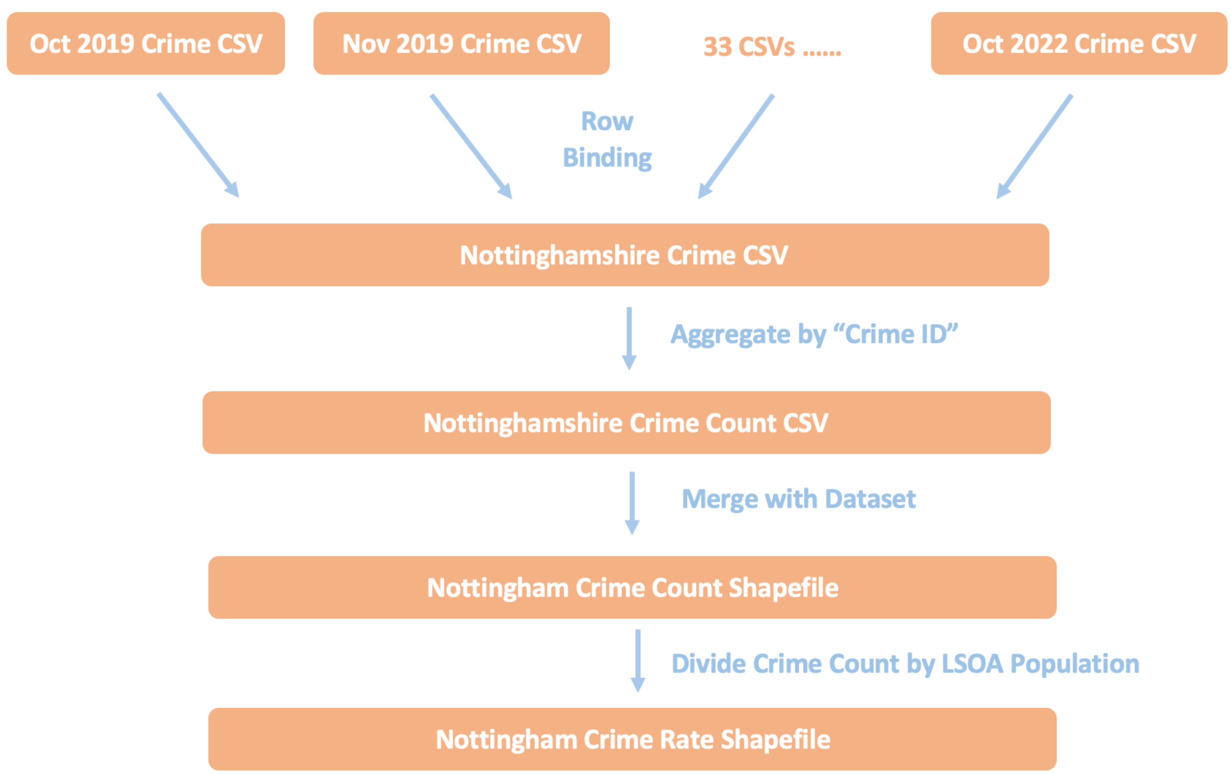
3.3.1.1. Crime Data

In the crime datasets, each case is assigned to a month, an LSOA code, and a geospatial coordinate (longitude and latitude). For this dataset, two transformations are conducted: 1) adding a lockdown variable, 2) transforming crime counts to crime rates.

For the first transformation, a new variable is constructed to demonstrate the lockdown period. If the data was collected from a lockdown period (month), the lockdown variable is denoted as 1. If the data was collected from a non-lockdown period, the lockdown variable is denoted as 0. This transformation allows us to test the effect of lockdown on crime in the modeling process.

For the second transformation, crime counts are adjusted to the population, with the crime count being the numerator and the LSOA residential population being the denominator. This process is shown in Figure 8.

Figure 8: Crime Data Cleaning Process



3.3.1.2. Ethnicity Data

Simpson's Index was used to calculate the level of ethnic diversity. Using the CDRC ethnicity dataset, the proportion of people within each ethnicity group is first adjusted to the LSOA population. This gives us the number of people within each ethnic group in each LSOA. Then, Simpson's Index is applied for the calculation of diversity, following equations 3 and 4:

$$\lambda = \sum_{1}^{n=i} \frac{n_i(n_i - 1)}{N(N-1)} \qquad (3)$$

$$D_{simpson} = 1 - \lambda \qquad (4)$$

In equation (3), the parameter λ is the probability that two individuals randomly drawn from the population N will belong to the same ethnic group n. In equation (4), the parameter $D_{simpson}$ is the probability that two individuals randomly drawn from a LSOA will belong to different ethnic groups.

As a probability, Simpson's index value ranges from 0 to 1. A large probability represents a high level of ethnic diversity (Murray, 2010). In the final ethnicity dataset, each LSOA was assigned to a Simpson's index value.

3.3.2. Geocoding

After data transformation, datasets are merged into the final data frame according to the same LSOA code they shared, as Figure 9 shown. However, for the spatial analysis, this dataset is required to be geocoded into spatial coordinates. This process can be simply carried out in R studio by merging the final data frame with the LSOA spatial data frame, as Figure 10 shown. The analysis approaches used in this study are also summarized in Figure 10 as well.

Figure 9: Combining all datasets into a single data frame

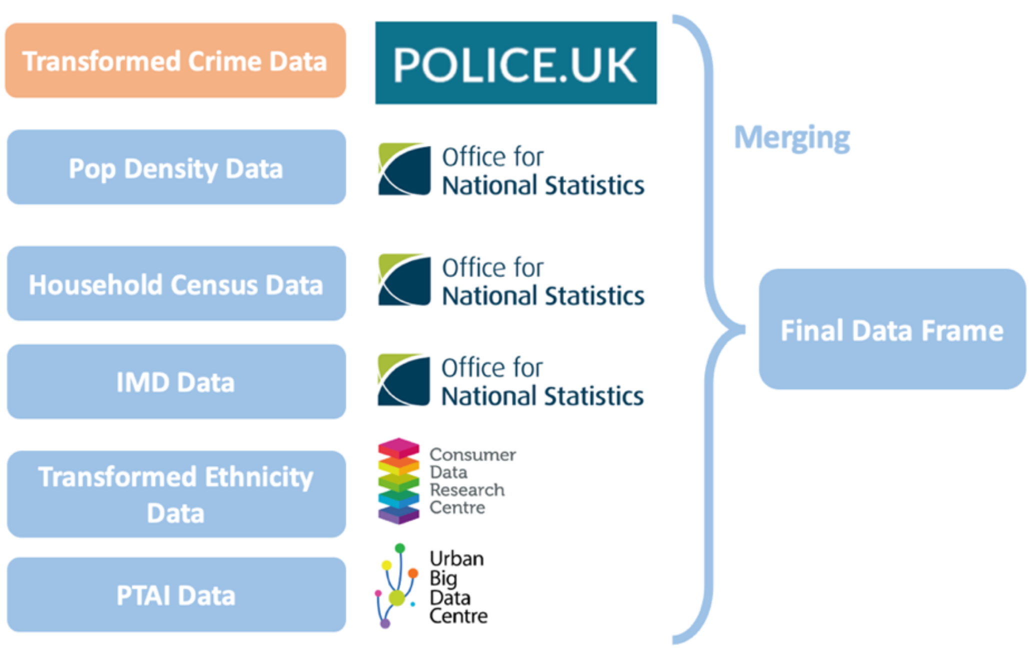
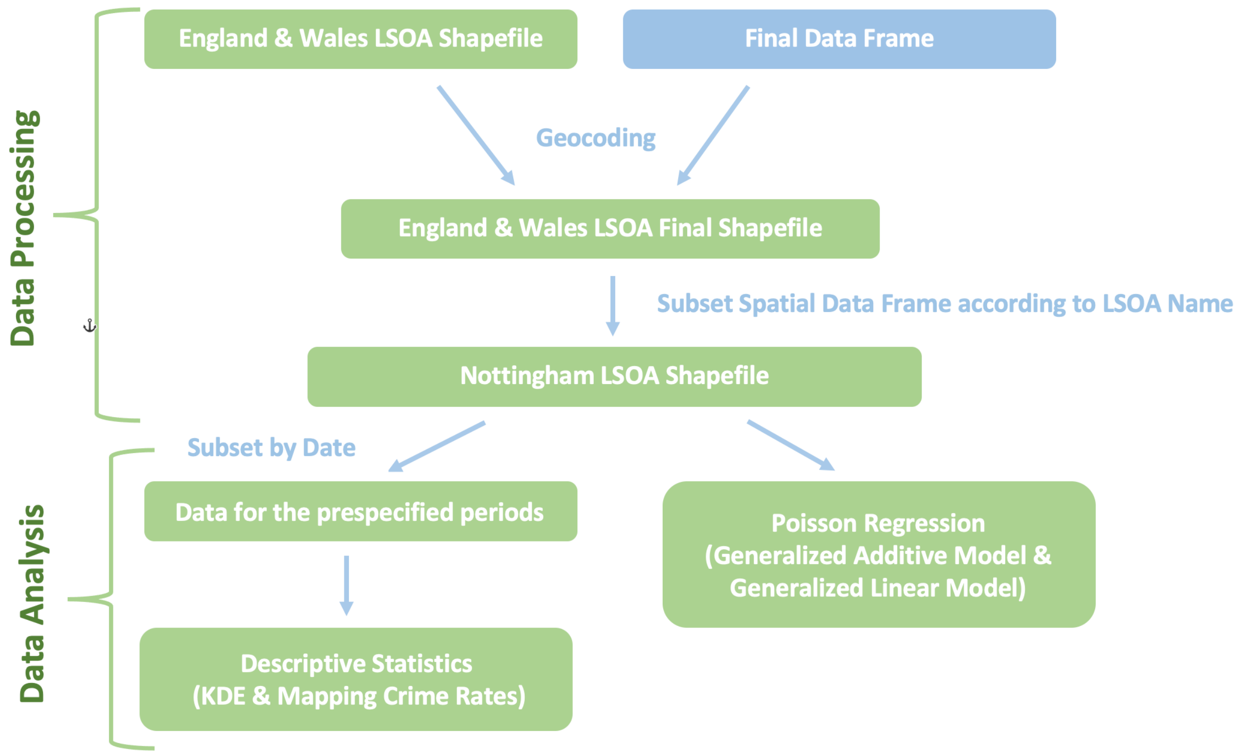


Figure 10: Data Processing & Data Analysis



3.4. Descriptive analysis

3.4.1. Mapping Crime Rate

Using the final Shapefile, the crime recovery pattern would be visualized by mapping the crime rates for four prespecified periods – May 2019, May 2020, May 2021, and May 2022. As Table 4 shown, May 2020 is used to represent the first Lockdown Period. To avoid the seasonal variation in crime, May 2019 is used as the Baseline Period. For the crime recovery pattern, May 2021 and May 2022 are chosen to be the recovery periods. As a result, 4 maps are produced for the VSO rate and four maps are produced for the ASB rate.

Table 4: Period used for descriptive statistics

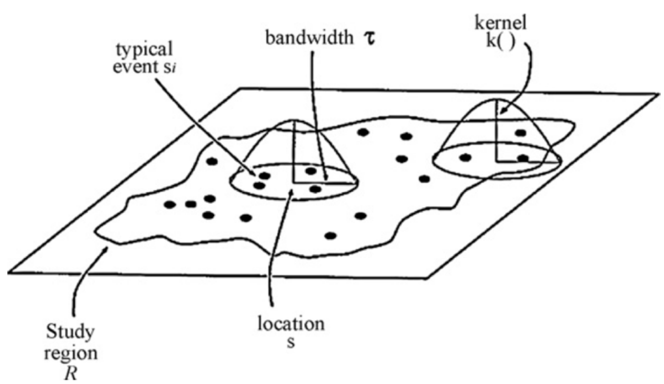
Period	Crime Data
1st Lockdown (From March 2020 to July 2020)	May 2020
Pre lockdown Period (Same period in 2019 as LD1)	May 2019
Recovery Period 1 (Same period in 2021 as LD1)	May 2021
Recovery Period 2 (Same period in 2022 as LD1)	May 2022

3.4.2. Descriptive analysis – Kernel Density Estimation

Kernel Density Estimation (KDE) is used for hotspot mapping to further demonstrate the temporal variation of crime rates. Across crime-related literature, KDE has been commonly used for the detection of crime hotspots and the forecast of crime hotspots (Hu *et al.*, 2018). As a smoothing technique, KDE helps to convert spatial points into a continuous density surface that reflects the distribution of the points (Hu *et al.*, 2018). Additionally, KDE helps to mitigate the Modifiable Areal Unit Problem, as density would not change abruptly at the regional boundary (Yin, 2020).

Assuming there is a grid map placed over Nottingham city, the density of each grid cell can be calculated following three steps: 1) placing a predefined kernel over the target area, 2) assigning more weights to the points that are close to the grid cell center based on the distance decay theory, 3) summing up the weighted value of each point lying under the kernel as shown in Figure 11 (Hu *et al.*, 2018).

Figure 11: Kernel Density Estimation (Hu et al., 2018)



The weights of each grid cell can be influenced by the predefined kernel bandwidth and the method of interpolation (Yin, 2020). While the kernel bandwidth determines the length of the radius, the method of interpolation determines the shape of the kernel. Compared to the method of interpolation, kernel bandwidth has a greater impact on the estimated density values, as small bandwidth can possibly lead to an under-smooth density map, and large bandwidth can possibly lead to an over-smooth density map (Yin, 2020).

A study done on the Northern American Elk suggested that spatial autocorrelation can distort estimated density values (Kie, 2013). Ad hoc bandwidth can help to mitigate this distortion. However, unlike least-square cross-validation (LSCV) bandwidth, ad hoc bandwidth cannot optimize estimated density values by reducing the square errors (Kie, 2013). Therefore, the autocorrelation level of crime would first be evaluated using global Moran's I. If Moran's I value suggests a spatially autocorrelated pattern of criminal cases, ad hoc bandwidth would be adopted to mitigate the distortion of KDE values. If the criminal cases were not spatially autocorrelated, LSCV bandwidth would be adopted instead. As a technique of spatial autocorrelation, Global Moran's I value ranges from -1 (perfectly dispersed) to 1 (perfectly clustered), and this value is calculated following equation 5:

$$I = \frac{1}{s^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n}(w_{ij})} \qquad (5)$$

In equation 5, parameter s^2 is the sample variance. n is the number of observations. $\bar{y}$ is the mean of variable y. y_i is the variable value of y for spatial unit i, and y_j is the variable value of y for spatial unit j. w_{ij} is the distance-based weight assigned to each pair of j and i.

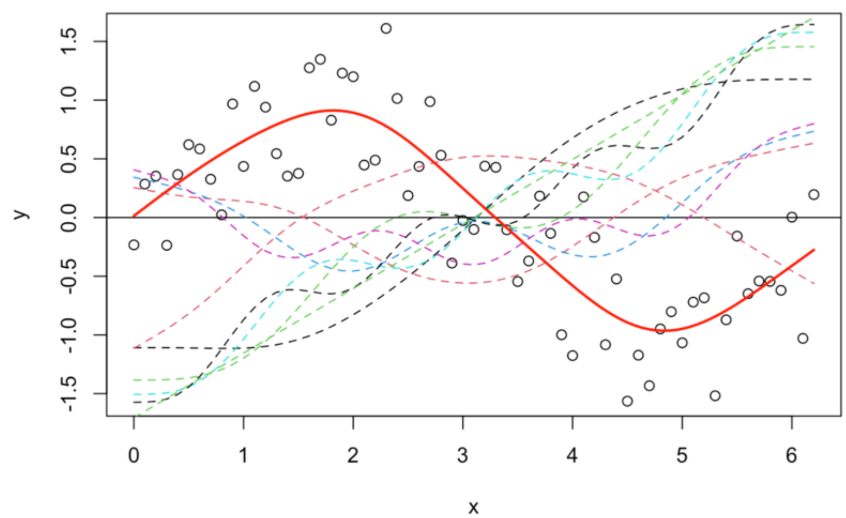
3.5. Statistical Analysis

3.5.1 Generalized Additive Model

In this study, Generalized Additive Model (GAM) is used for three purposes: 1) examining the crime recovery pattern; 2) testing the effect of lockdown on crime; 3) testing the effect of social-disorganization factors on crime.

GAM assumes the relationship between dependent and independent variables follows a smooth pattern which can be either linear or nonlinear. Therefore, GAM can have a combination of smooth terms and linear terms. For the smooth terms, it is impossible to interpret how a unit change in an independent variable can lead to a corresponding change in a dependent variable, because the smooth term is the sum of a set of basic functions, and each basic function has its own estimated coefficient (Lyons, 2017). As shown in Figure 12, dashed lines represent basic functions, and the red line represents the smooth term.

Figure 12: The basic functions of smooth terms (Lyons, 2017)



3.5.2 Examine Crime Recovery Pattern on City and LSOA Levels

To examine the temporal changes in VSO and ASB rates on both city and LSOA levels, Poisson regression is adopted within the GAM framework. First, the monthly averages of VSO and ASB rates are calculated at the city level. Then, a GAM regression is carried out for the estimation of the VSO rate and a GAM is carried out for the estimation of the ASB rate. Both GAMs follow the equations:

$$y \sim Poisson\ (\lambda) \qquad (5)$$

$$l\,n(\lambda) = \beta_0 + s(t) \qquad (6)$$

In equation (6), model parameter $l\,n(\lambda)$ is a link function that links the smooth term $s(t)$ with the parameter y for Poisson distribution probability. For the estimation of the VSO rate, parameter y is the monthly average VSO rate. For the estimation of the ASB rate, parameter y is the monthly average ASB rate. For the estimations of both VSO and ASB rates, t represents the months ranging from 1 (May 2019) to 42 (Oct 2022).

To visualize whether there is a statistically significant crime trend, t is further divided into 5 periods of time, as shown in Table 5. Lockdown 2 was from November 2020 to December 2020. Lockdown 3 was from January 2021 to March 2021. These two lockdowns are combined into a single period, because the time window between lockdown 2 and lockdown 3 is less than one month which is relatively short.

Table 5: Prespecified time periods used for GAM

Period	Duration
Pre Lockdown	From May 2019 to March 2020
Lockdown 1	From March 2020 to July 2020
Post Lockdown 1	From July 2020 to November 2020
Lockdown 2 & 3	From November 2020 to March 2021
Post Lockdown 2 & 3	From March 2021 to October 2022

The Poisson regressions shown in equations (5) and (6) are repeated on the LSOA level to see whether there is a statistically significant recovery pattern within each LSOA. In this case, parameter y is the monthly average ASB rate or the monthly average VSO rate for each LSOA. parameter x_1 is the month.

3.5.3 Examining SDT

To investigate the effect of lockdown and the effect of social-disorganization factors on crime, two Poisson regressions are conducted to estimate the VSO rate and the ASB rate, following the equations listed below:

$$y \sim Poisson\ (\lambda) \qquad (6)$$

$$l\,n(\lambda) = \beta_0 + \sum_{1}^{i=8} \beta_i\, x_i \qquad (7)$$

$$l\,n(\lambda) = \beta_0 + \sum_{1}^{i=8} \beta_i\, x_i + s(t) \qquad (8)$$

In equation (7), a Poisson regression is conducted within the Generalized Linear Model (GLM) framework. Model parameter $ln(\lambda)$ is a link function that links the independent variables x_i with the parameter y for Poisson distribution probability. The parameter y is the monthly average VSO rate or the monthly average ASB rate in each LSOA. The independent variables. β_0 is the intercept. β_i is the estimated coefficient for independent variable i.

In this model, independent variables include social-disorganization factors, general-strain factors, season factor, and lockdown factor, as shown in Table 6:

Table 6: Independent variables in equation 7 and equation 8

Types of Independent Variable	Variables	Variable Abbreviations
Social-disorganization Factors	Population density	V_{pop}
	Income decile	V_{income}
	Divorce rate	$V_{divorce}$
	PTAI value	V_{ptai}
	Simpson’s diversity index value	$V_{simpson}$
General-strain Factors	Health decile	V_{health}
	Education decile	V_{edu}
Lockdown Factor	Categorical lockdown variable	$V_{lockdown}$
Seasonal Factor	Month	V_{month}

In equation (8), a smooth term is added to equation (7). $s(t)$ is the smooth term that represents the month. This term is added to account for the seasonal variation of crime. In both equation (7) and equation (8), the effect of lockdown and the effects of social-disorganization factors are tested with general strain control. As the main variable, the lockdown variable is included as a two-level categorical variable with 1 denoting the lockdown month and 0 denoting the non-lockdown month.

As previously mentioned, five crime-related factors are suggested in SDT. Those factors are ethnic heterogeneity, low economic status, residential mobility, urbanization, and family disruption. Referring to Table 6, the divorce rate is used as a proxy for family disruption; income decile is used as a proxy for economic status; Simpson’s diversity index value is used as a proxy for ethnic heterogeneity; PTAI value is used as a proxy for residential mobility; population density is used as a proxy for urbanization. Two subjective strains are added into equations as well, which are education and health. Though it is difficult to test the GST because of its broadness, it is worthwhile to add strain-related factors to enhance the internal validity.

Chapter 4. Result

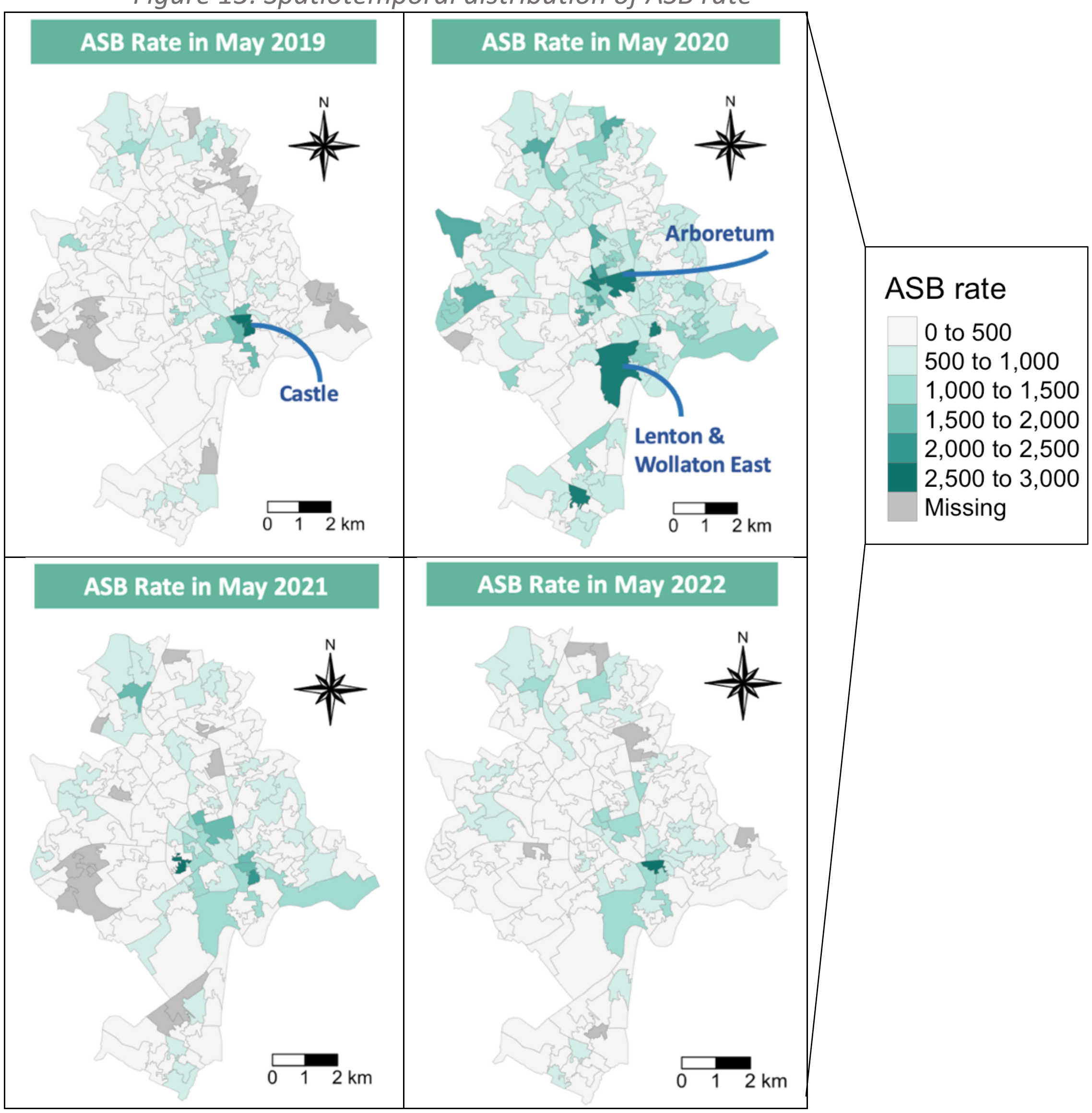
This section provides the visualizations and the statistical outputs listed in the methodology part. The findings are divided into three categories. First, descriptive statistics provide a general view of the spatiotemporal variation in ASB and VSO rates. Second, GAMs are utilized to demonstrate the significance level of crime recovery patterns on both city and LSOA levels. Third, GLM and GAM are utilized to test the effect of lockdown policy and the effect of social-disorganization factors on crime.

4.1. Descriptive analysis

4.1.1 Mapping ASB rate

The spatiotemporal distribution of the ASB rate between May 2019 to May 2022 is shown in Figure 13:

Figure 13: Spatiotemporal distribution of ASB rate



The ASB rate shown in the first map only accounts for traditional ASB rates, as the lockdown policy had not been implemented in May 2019. In the first map, over half of the LSOAs are marked in gray, indicating that they have an ASB rate below 500 cases per 100,000 people. However, a relatively high ASB rate could be found in the LSOAs located in the city center. For the LSOA marked in the first map, the ASB rate had even gone above 2,500 cases per 100,000 people.

The second map accounts for both traditional ASB cases and Covid-related ASB cases. Comparing the first and the second maps, it shows that most of the LSOAs experienced an increasing ASB rate during the first lockdown. For the LSOAs in Arboretum Ward and Lenton & Wollaton East Ward, the ASB rate had gone above 2,500 cases per 100,000 people. This increasing crime trend can also be found in some of the LSOAs located at the edge of the city.

In the third map, ASB rates seem to recover to the pre-lockdown level in May 2021. However, a few LSOAs in the city center still had an ASB rate higher than the pre-lockdown level. This observation can possibly be justified by the increasing number of covid-related ASB that emerged from the third lockdown (from January 2021 to March 2021). The crime distribution shown in the last map is similar to the distribution shown in the first map, indicating that the ASB rate has returned to the pre-lockdown level in May 2022 and Covid-related ASB may no longer exist.

4.1.2 Mapping ASB Hotspots

Before conducting the hotspot analysis using KDE, Global Moran's I statistics is used to assess the autocorrelation level of the ASB rate across LSOAs, and it would determine whether ad hoc bandwidth would be adopted to mitigate the distortion caused by the spatial autocorrelation.

As shown in Table 7, p-values are all below the significance level of 0.05. Therefore, one can reject the null hypothesis that points are distributed randomly. Additionally, Global Moran's I statistics are all positive, indicating that LSOA's ASB rate is positively autocorrelated. In other words, ASB is spatially clustered across LSOAs with high-crime LSOAs located close to the high-ASB LSOAs and low-ASB LSOAs located close to the low-ASB LSOAs. As the ASB rate is expected to be spatially autocorrelated across LSOA, ad-hoc bandwidth is adopted for KDE mapping.

Table 7: Global Moran I for the ASB rate

Period	Moran I Statistic	P value
May 2019	0.319	1.050e-15
May 2020	0.127	0.002
May 2021	0.267	7.489e-10
May 2022	0.209	2.855e-08

The spatiotemporal distribution of ASB cases between May 2019 to May 2022 is shown in Figure 14:

Figure 14: Hotspots of ASB Cases

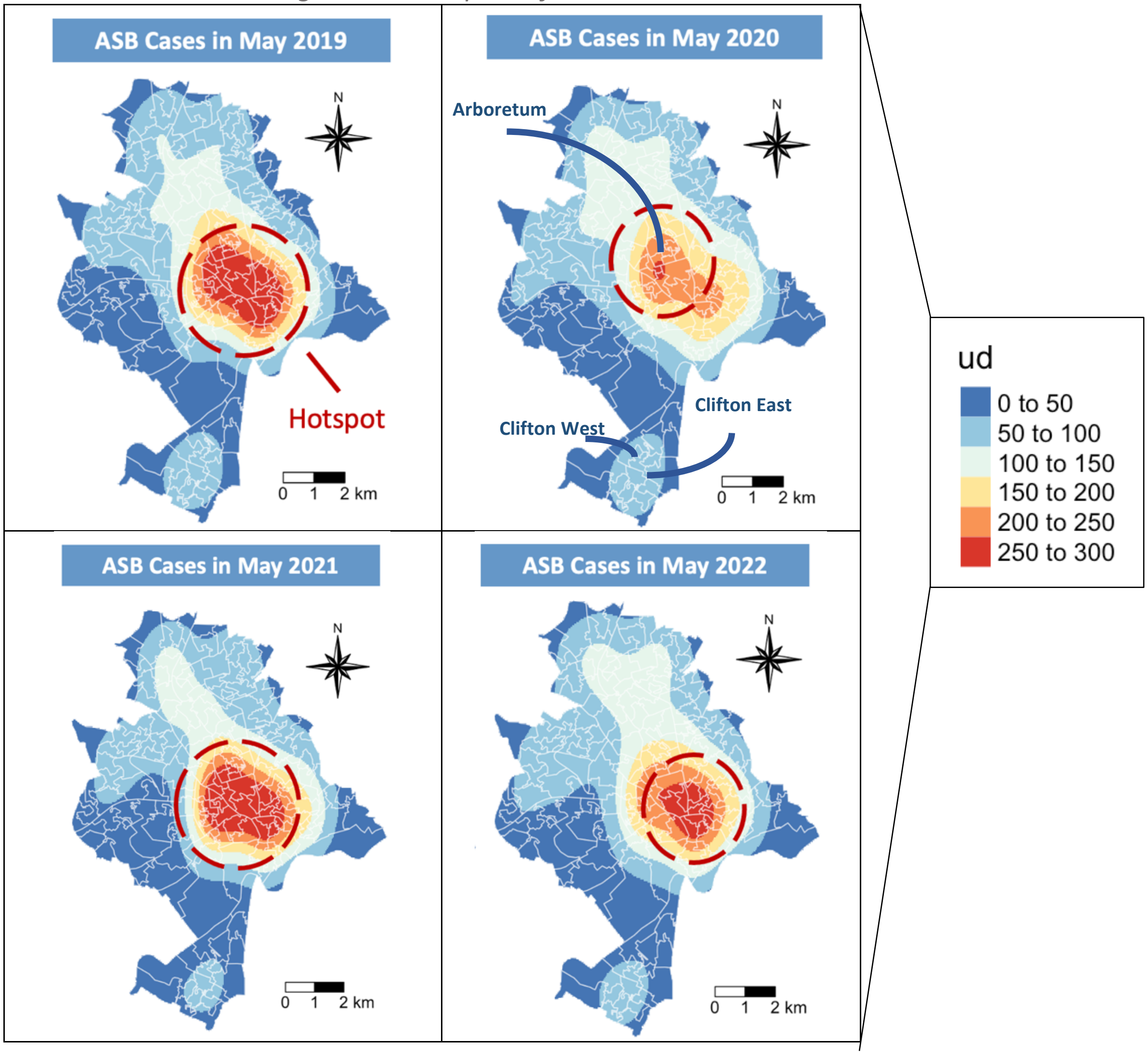


Figure 14 shows that ASB hotspot is mainly concentrated in the city center including Castle Ward, St Ann's Ward, and Arboretum Ward. UD refers to the probability density of ASB cases. If the UD is high, the distribution of ASB cases is expected to be more clustered. As Figure 14 shown, the UD of ASB gradually decreased from the city center to the edge of the city, indicating that the distribution of ASB cases is more dispersed at the edge of the city, especially at the southwestern edge. Though Clifton East Ward and Clifton West Ward are in the southwestern part of the city, the densities they have are higher than the ones in the surrounding areas. It can be explained by the Universities located in this area including the University of Nottingham and Nottingham Trent University. As international universities, these two universities have a high-level ethnic heterogeneity. That can increase the likelihood of ASB according to SDT. The second map shows that the hotspot is mainly located in Arboretum Ward, instead of Castle Ward and St Ann's Ward. Meanwhile, the hotspot seems to shift away from the city center. The third map shows that the distribution of VSO is almost returning to the pre-lockdown level in May 2021. The last map shows that the hotspot is shifting back to the city center. Overall, this descriptive statistic suggests two key findings: 1) the ASB hotspot is overlapped with the city center 2) the ASB hotspot slightly shift away from the city center during the first lockdown.

4.1.3 Mapping VSO rate

The spatiotemporal distribution of the VSO rate between May 2019 to May 2022 is shown in Figure 15:

Figure 15: Spatiotemporal distribution of VSO rate

The first two maps show that the VSO rate decreased during the first lockdown, especially in the LSOAs at the city center. For the LSOA marked in the first map, the VSO rate decreased from over 2,000 cases per 100,000 people to below 500 cases per 100,000 people. The third map shows that the VSO rate remains low in May 2021; however, there are a few exceptions. Some LSOAs in Bulwell experienced an increasing VSO rate. The last map shows that the VSO rate almost returned to the pre-lockdown level, with a relatively high VSO rate being found at the city center.

4.1.4 Mapping VSO Hotspots

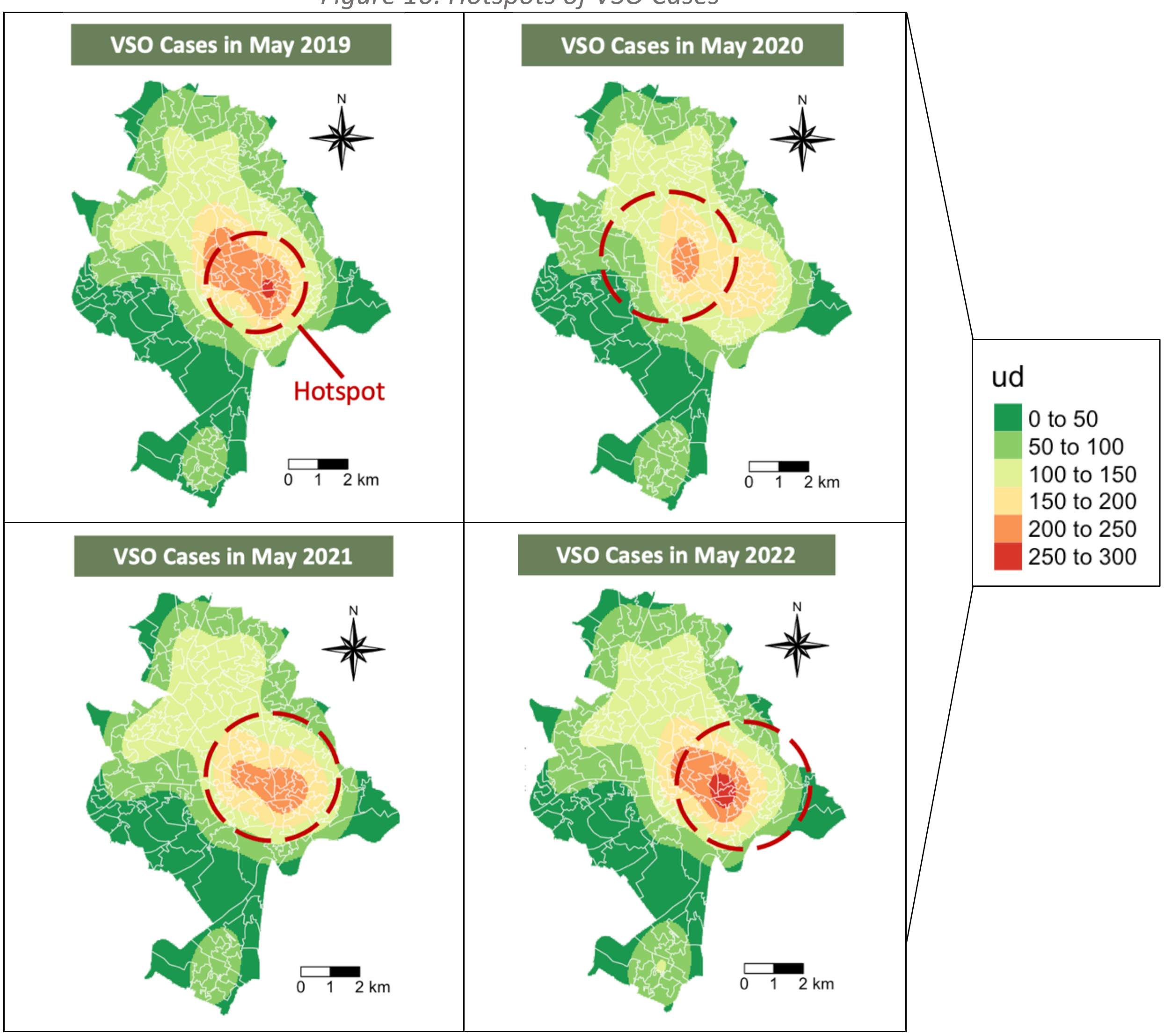
As Table 8 shown, the VSO rate in May 2020 has a relatively low Moran I Statistic and a relatively high p-value, indicating that there is evidence supporting the null hypothesis that points are distributed randomly. However, all the other p-values are below the significance level of 0.05. Therefore, for the other time periods, one can reject the null hypothesis. Meanwhile, all the Moran I Statistics are positive, indicating that the VSO rate is positively autocorrelated across LSOAs. As most of the p-values are statistically significant at the 0.05 significance level, ad hoc bandwidth is adopted for the KDE mapping.

Table 8: Global Moran's I for the VSO rate

Period	Moran I Statistic	P value
May 2019	0.208	1.025e-06
May 2020	0.041	0.158
May 2021	0.131	0.001
May 2022	0.187	0.002

The spatiotemporal distribution of VSO cases between May 2019 to May 2022 is shown in Figure 16:

Figure 16: Hotspots of VSO Cases



Though VSO and ASB rates follow an opposite recovery pattern, they both experienced a displacement of hotspots. During the first lockdown, crime hotspots shifted away from the city center towards the northwestern area, as shown in the first and second maps. Two years after the first lockdown, crime hotspots shifted back to the city center, as shown in the last map. Overall, this descriptive statistic suggests two key findings, 1) the VSO hotspot is overlapped with the Nottingham city center 2) the VSO hotspot slightly shift away from the city center during the first lockdown.

4.2 GAM

4.2.1 Examine Crime Recovery Pattern on the City Level

In this section, GAM is utilized to test the crime recovery pattern in Nottingham in 5 prespecified periods, as shown in Figure 17:

Figure 17: Timeline used for the examination of crime recovery pattern

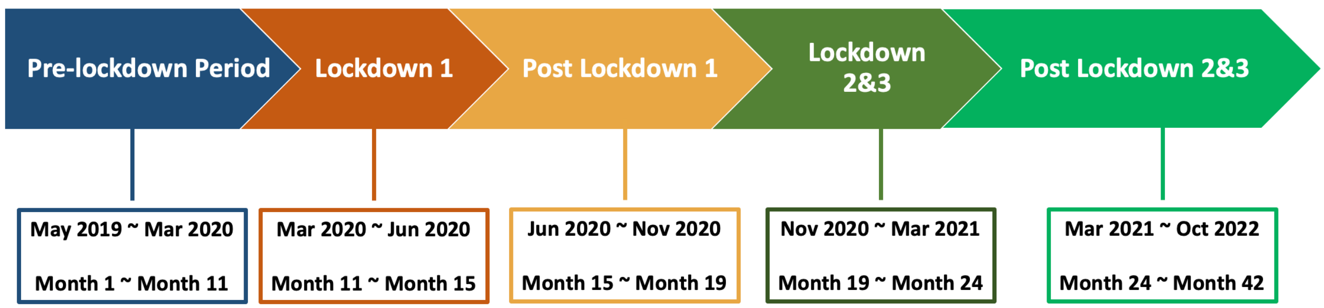
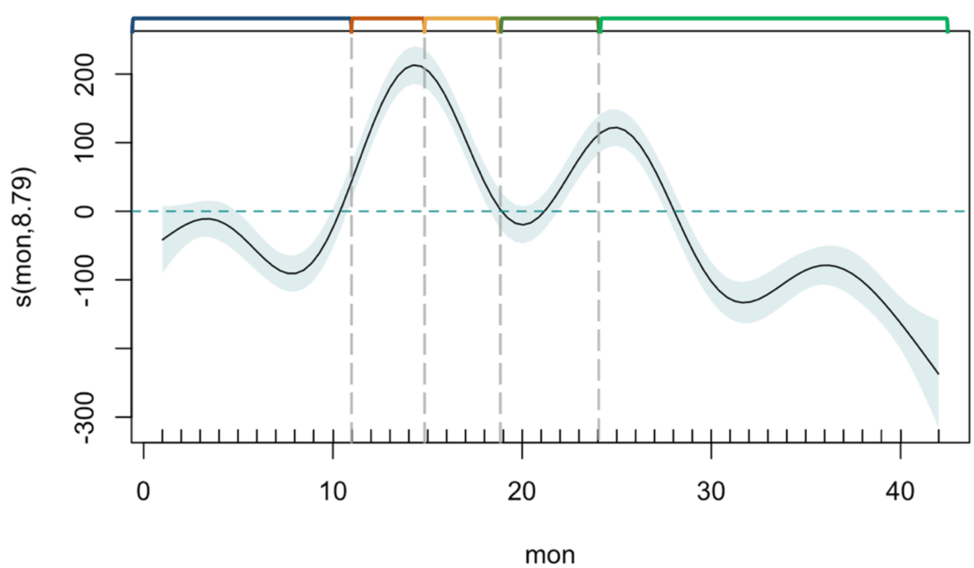


Figure 18 shows the temporal change in ASB rate, with the prespecified periods marked in corresponding colors:

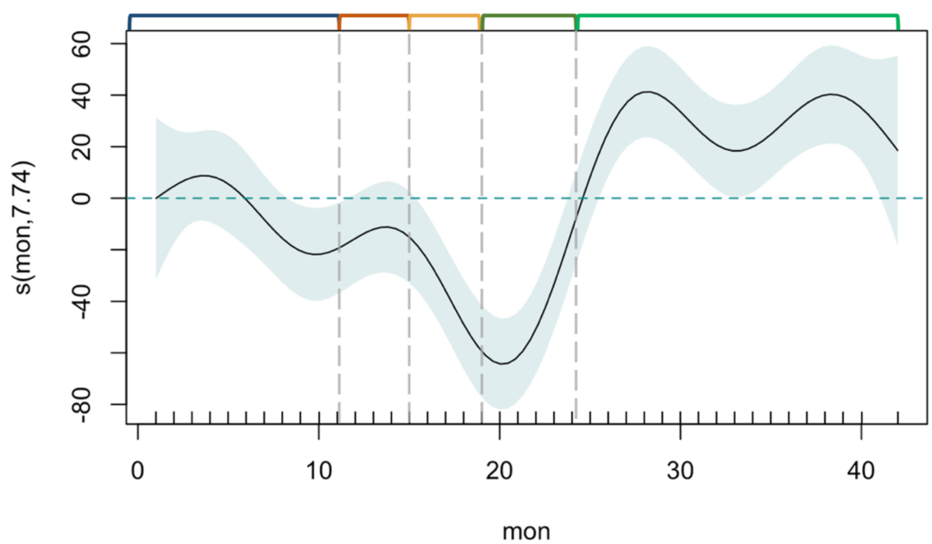
Figure 18: temporal change in ASB rate



During the pre-lockdown period, the ASB rate initially experienced a statistically insignificant trend with the zero-line passing through the 95% confidence interval. During the first lockdown, the ASB rate experienced a statistically significant increase. After the first lockdown ended, the ASB rate experienced a statistically significant decrease. This finding demonstrates that the ASB rate follows an inverted U-shaped recovery pattern. Similar recovery trends can be found in the second and third lockdown period with a lesser magnitude. This is reasonable, as the first lockdown is more restrictive than the second and the third lockdowns.

Figure 19 shows the temporal change in the VSO rate, with the prespecified periods marked in corresponding colors:

Figure 19: temporal change in VSO rate



During the pre-lockdown period, no statistically significant trend was observed in the VSO rate. During the first lockdown, no statistically significant pattern was observed as well, as the horizontal zero line is passing through the 95% confidence interval. However, a statistically significant decreasing trend could be found after the first lockdown ended, implying that lockdown policy can have a delayed effect on the VSO rate. The second and third lockdown period experienced a statistically significant increasing trend in the VSO rate. Those findings suggest that no consistent recovery pattern can be observed after the lockdown periods.

In Figure 19, there is a U-shaped recovery pattern after the first lockdown. However, it is difficult to tell whether this recovery pattern is mainly driven by the first lockdown, as the second and the third lockdowns intersect with the “recovery trend” (the increasing trend). Overall, Figure 18 and Figure 19 suggest three key findings: 1) ASB rate follows an inverted U-shaped recovery pattern. 2) No clear recovery pattern could be found in the VSO rate. 3) Different crime types respond differently to lockdown policies.

4.2.2 Examine Crime Recovery Pattern on the LSOA Level

The spatiotemporal change in ASB and VSO rates are shown in Figure 20 and Figure 21:

Figure 20: Changing ASB pattern across LSOAs

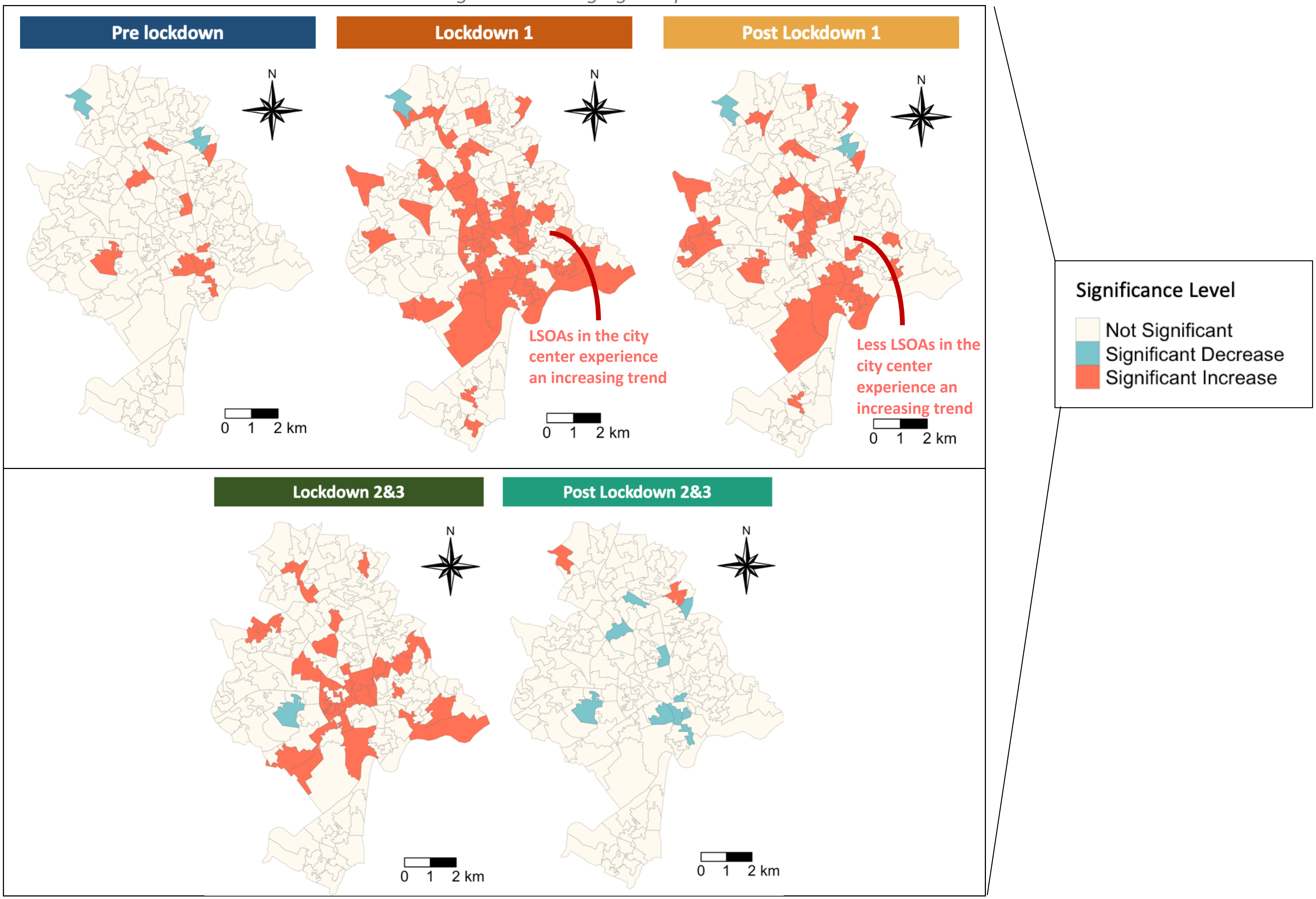
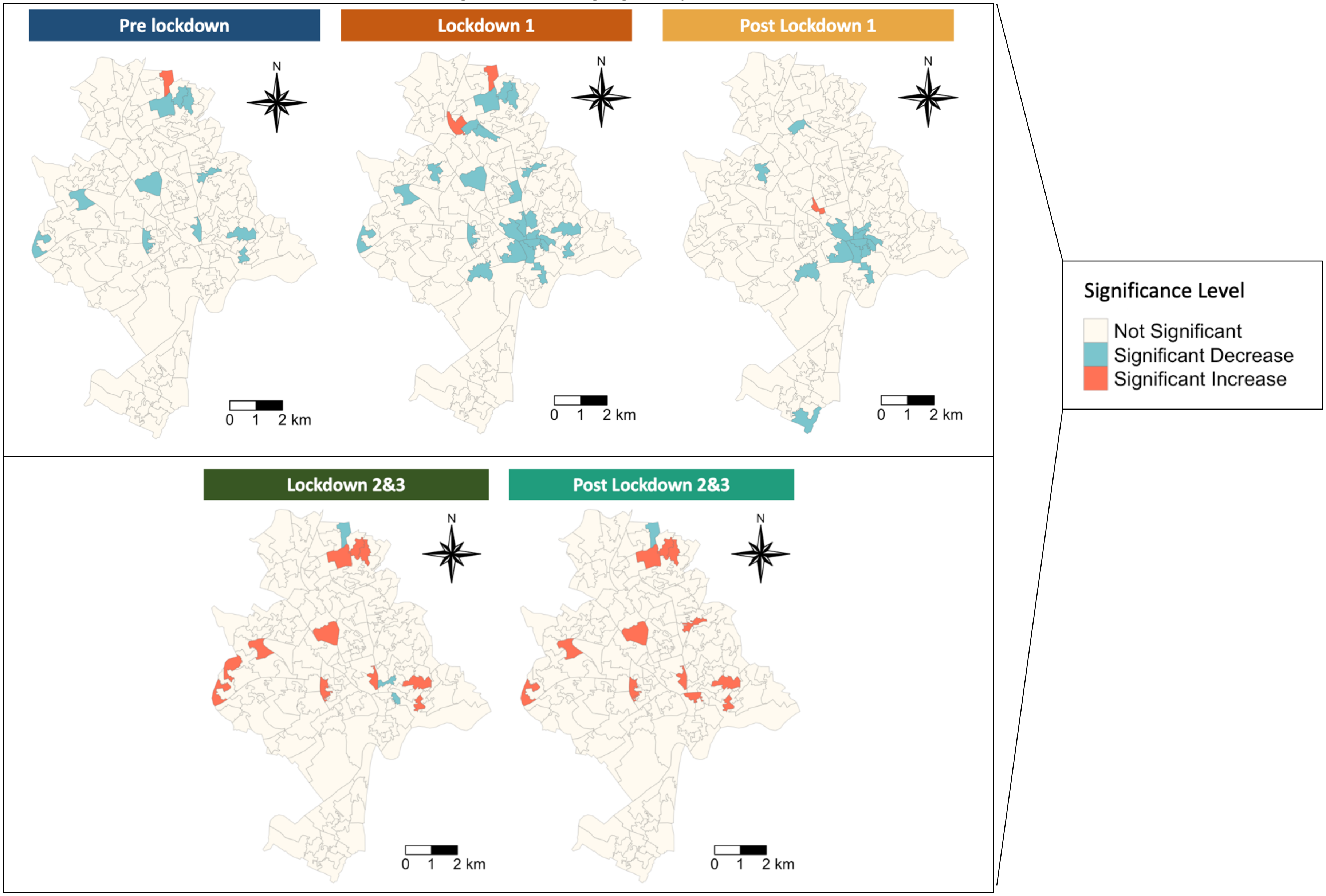


Figure 21: Changing VSO pattern across LSOAs



As Figure 20 shown, in the lockdown periods, some LSOAs experienced a statistically significant increasing trend in ASB rate. This increasing pattern is mainly concentrated in the wards close to the city center including Lenton & Wollaton East Ward, Meadows Ward, and Arboretum Ward. In the post-lockdown-one phase, over half of the LSOAs experience an insignificant trend in the ASB rate.

Compared to the crime pattern in the lockdown-one phase, the patterns shown in the post-lockdown-one phase demonstrate that fewer LSOAs experience an increasing trend, with two LSOAs experiencing a decreasing trend. It implies that crime recovery may occur with more LSOAs start experiencing a decreasing ASB rate. A similar pattern can be found after the second and the third lockdowns. After the second and third lockdowns, 10 LSOAs started experiencing a statistically significant decreasing trend, with two LSOAs experiencing a statistically significant increasing trend. However, the changing ASB pattern remains statistically insignificant in the LSOAs located at the edge of the city. Therefore, though a possible ASB recovery pattern can be found in the LSOAs close to the city center, it is difficult to find a statistically significant ASB recovery pattern at the LSOAs located at the edge of the city.

As Figure 21 shown, the VSO rate experienced an opposite crime trend compared to the ASB rate. In the pre-lockdown period, a few LSOAs had already experienced a statistically significant decreasing trend in VSO rate. In the lockdown-one phase, more LSOAs started experiencing a decreasing trend. This decreasing crime trend is mainly concentrated in the LSOAs close to the city center. In the post-lockdown-one phase, fewer LSOAs experienced a decreasing trend, with the majority of the LSOAs experiencing an insignificant crime trend. This implies that there can be a possible crime recovery pattern after the first lockdown, with fewer LSOAs experiencing a statistically significant decreasing trend.

However, during the second and third lockdowns, only three LSOAs experienced a decreasing trend, while 11 LSOAs experiences an increasing trend, with the rest of the LSOAs experiencing an insignificant crime trend. This finding suggests that the second and the third lockdowns can possibly encourage people to perform VSO. It also implies that VSO could respond differently to different lockdown policies. In addition, after the second and third lockdowns, a statistically significant increasing trend could still be found in a few LSOAs, though the crime trend remains insignificant in the majority of the LSOAs. Therefore, though there is a possible VSO recovery pattern after the first lockdown, it is difficult to find a recovery pattern after the second and third lockdowns.

Overall, four key findings could be concluded from this section: 1) There is evidence to support the ASB recovery pattern in the LSOAs that are close to the city center. 1) There is evidence to support the VSO recovery pattern after the first lockdown in the LSOAs that are close to the city center. 3) There is no evidence to support the VSO recovery pattern after the second and third lockdowns. 4) There is no evidence to support the VSO and ASB recovery patterns in the LSOAs located at the edge of the city.

4.2.1 GAM & GLM

4.2.1.1 Modelling ASB Rate

In this section, the ASB rate is estimated with multiple crime-related factors in order to investigate the effect of lockdown on the ASB rate, as well as the effect of social-disorganization factors on the ASB rate. A Poisson regression model is first conducted within the GLM framework, as shown in Model 1 in Table 9:

Table 9: Estimating ASB rate with crime-related factors (GLM)

Model 1: Modelling ASB Rate with General Strain Control				
Linear Terms:				
	Estimated Coefficient	*Standard Error*	*T-value*	*P-value*
Intercept	542.300	8.064	67.244	<2e-16
V_{health}	-80.390	1.039	-77.397	<2e-16
V_{edu}	3.094	0.769	4.022	5.76e-05
$V_{simpson}$	0.665	0.074	8.943	<2e-16
$V_{divorce}$	-11.110	0.524	-21.206	<2e-16
V_{ptai}	0.049	0.004	13.984	0.039
V_{income}	15.930	0.884	18.081	<2e-16
V_{pop}	0.005	0.000	-20.728	<2e-16
$V_{lockdown}$	140.300	2.008	69.856	<2e-16

All the p-values are below the significance level of 0.05, indicating that one can reject the null hypothesis that coefficients are equal to zero. In other words, all variables have a statistically significant relationship with the ASB rate. Across all variables, $V_{lockdown}$ has the strongest correlation with the ASB rate. Assuming all the other variables are fixed, the estimated ASB rate in the lockdown period is 140.300 (cases per 100,000 people) higher than the estimated ASB rate in the non-lockdown period. This helps to why the ASB rate is expected to increase during the lockdown periods and recover when the lockdown ended.

In terms of the social-disorganization factors, V_{income} has the greatest effect on crime. With a unit increase in the income decile, the ASB rate increases by 15.930 (cases per 100,000 people). This finding is not consistent with what SDT suggested, as SDT suggested that people living in high-economic-status communities are likely to have a consensus on the social control (Kubrin, 2009). The coefficient of $V_{divorce}$ is -11.110, indicating that the ASB rate decreased by 11.110 (cases per 100,000 people), with a percentage increase in divorced households in the LSOA. This is finding is not consistent with what suggested in SDT as well, as SDT believes that family disruption can increase the likelihood of crime.

The correlation coefficients of $V_{divorce}$ and V_{income} are not consistent with what SDT suggested, but the correlation coefficients of V_{pop}, $V_{simpson}$ and V_{ptai} are consistent with what suggest in SDT. The coefficient of V_{pop} is 0.005, indicating that the ASB rate is expected to increase by 0.005 (cases per 100,000 people), with a unit increase in population density in the LSOA. The coefficient of $V_{simpson}$ is 0.665, indicating that the ASB rate is expected to increase by 0.665 (cases per 100,000 people), with a unit increase in Simpson's index value (the probability that two individuals randomly drawn from a LSOA will belong to different ethnicity groups). The coefficient of V_{ptai} is 0.049, indicating that the ASB rate is expected to increase by 0.049 (cases per 100,000 people), with a unit increase in PTAI value (transport accessibility value).

After adding the seasonal control in Model 2, a Poisson regression model is conducted within the GAM framework, as shown in Table 10:

Table 10: Estimating ASB rate with crime-related factors (GAM)

Model 2: Modelling ASB Rate with General Strain Control and Month Control				
Linear Terms:				
	Estimated Coefficient	*Standard Error*	*T-value*	*P-value*
Intercept	536.100	5.622	59.684	<2e-16
V_{health}	-81.21	0.726	-68.568	<2e-16
V_{edu}	2.740	0.538	-31.631	0.00029
$V_{simpson}$	0.688	0.052	27.534	<2e-16
$V_{divorce}$	-11.210	0.366	31.903	<2e-16
V_{ptai}	0.005	0.002	2.046	<2e-16
V_{income}	16.260	0.618	42.449	<2e-16
V_{pop}	0.006	0.000	-20.766	<2e-16
$V_{lockdown}$	165.900	2.159	76.839	<2e-16
Smooth Terms:				
	Degree of Freedom	*Reference Df.*	*F statistic*	*P-value*
V_{month}	8.962	9	760.5	<2e-16

The directions of the coefficients shown in Model 1 are the same as the ones shown in Model 2, with all the p-values below the significance level of 0.05. The magnitude of the coefficients, however, changes slightly. For example, the coefficient of $V_{lockdown}$ increases from 140.300 in Model 1 to 165.900 in Model 2, indicating that $V_{lockdown}$ has a greater effect on the ASB rate when seasonal variation in crime is controlled. In addition, V_{month} accounts for the seasonal variation in crime, and it has 8.962 degrees of freedom, indicating that the smooth term of the month is wiggly.

4.2.1.2 Modelling VSO Rate

In this section, the VSO rate would be estimated with multiple crime-related factors in order to investigate the effect of lockdown on VSO in Nottingham, as well as the effect of social-disorganization factors on VSO. A Poisson regression model is first conducted within the GLM framework, as shown in Model 1 in Table 11:

Table 11: Estimating VSO rate with crime-related factors (GLM)

Model 3: Modelling VSO Rate with General Strain Control				
Linear Terms:				
	Estimated Coefficient	*Standard Error*	*T-value*	*P-value*
Intercept	337.00	5.638	59.779	<2e-16
V_{health}	-49.840	0.726	-68.634	<2e-16
V_{edu}	-16.99	0.538	-31.590	<2e-16
$V_{simpson}$	1.432	0.052	27.563	<2e-16
$V_{divorce}$	11.690	0.366	31.914	<2e-16
V_{ptai}	5.063	0.002	2.064	0.039
V_{income}	26.270	0.618	42.486	<2e-16
V_{pop}	-0.005	0.000	-20.728	<2e-16
$V_{lockdown}$	-5.319	2.008	-3.789	<2e-16

P-values are all below the significance level of 0.05, indicating that one can reject the null hypothesis that the coefficients are equal to zero. The coefficient of $V_{lockdown}$ is -5.319, indicating that the VSO rate in the lockdown period is 5.319 (cases per 100,000 people) lower than the VSO rate in the non-lockdown period, assuming all other variables are fixed. This helps to explain why the VSO rate is expected to decrease during the lockdown periods and increase after the lockdown ended.

The coefficient of V_{income} is 26.270, indicating that the VSO rate increases by 27.270 (cases per 100,000 people), with a unit increase in income decile. The coefficient of V_{pop} is -0.005, indicating that the VSO rate decreases by 0.005 (cases per 100,000 people), with a unit increase in population density. These two findings are not consistent with what SDT suggested, as SDT believes that socially disorganized neighborhoods have the characteristic of low economic status and high urbanization level, and those characteristics can increase the likelihood of crime.

V_{ptai}, and $V_{simpson}$ are consistent with what SDT suggested. The coefficient of V_{ptai} is 5.063, indicating that the VSO rate increases by 5.063 (cases per 100,000 people), with a unit increase in PTAI value. The coefficient of $V_{divorce}$ is 11.690, indicating that the VSO rate increases by 11.690 (cases per 100,000 people), with a percentage increase in divorced households. The coefficient of $V_{simpson}$ is 1.432, indicating that the VSO rate increases by 1.432 (cases per 100,000 people), with a percentage increase in Simpson Index value.

After adding the seasonal control in Model 3, a Poisson regression model is conducted within the GAM framework, as shown in Table 12:

Table 12: Estimating VSO rate with crime-related factors (GAM)

Model 4: Modelling VSO Rate with General Strain Control and Month Control				
Linear Terms:				
	Estimated Coefficient	*Standard Error*	*T-value*	*P-value*
Intercept	337.100	5.640	59.773	<2e-16
V_{health}	-49.780	0.726	-68.548	<2e-16
V_{edu}	-16.980	0.538	-31.569	<2e-16
$V_{simpson}$	1.430	0.005	27.524	<2e-16
$V_{divorce}$	11.690	0.366	31.911	<2e-16
V_{ptai}	0.005	0.002	2.047	0.040
V_{income}	26.230	0.618	42.428	<2e-16
V_{pop}	-0.005	0.000	-20.764	<2e-16
$V_{lockdown}$	-5.234	1.517	-3.450	0.001
Smooth Terms:				
	Degree of Freedom	*Reference Df.*	*F statistic*	*P-value*
V_{month}	6.979	8.065	4.658	8.09e-06

The directions of the coefficients shown in Model 4 are the same as the ones shown in Model 3, with all the p-values below the significance level of 0.05. In Model 4, the coefficient of $V_{lockdown}$ does not change too much. The coefficient of V_{ptai} , however, decreased from 5.063 in Model 3 to 0.005 in Model 4, indicating that the PTAI value has less effect on the VSO rate when seasonal control is added. V_{month} has 6.979 degrees of freedom, indicating that the smooth term of smooth is wiggly.

Overall, 3 key findings could be concluded from this section: 1) Lockdown variable has a positive correlation with the ASB rate, while it has a negative relationship with the VSO rate. It implies that in the lockdown periods, it is expected to observe an increasing ASB rate and a decreasing VSO rate. When the lockdown measure is removed, it is expected to find a decreasing ASB rate and an increasing VSO rate. 2) Comparing the coefficient of $V_{lockdown}$ across models, lockdown policies have a greater effect on the ASB rate compared to its effect on the VSO rate. 3) For the estimation of ASB rate, statistical outputs are consistent with what SDT suggested in terms of the coefficients of V_{pop}, $V_{simpson}$ and V_{ptai}. 3) For the estimation of VSO rate, the statistical outputs are consistent with what suggested in SDT in terms of the coefficients of V_{ptai}, $V_{divorce}$ and $V_{simpson}$.

Chapter 5. Discussion

This section discusses the findings of this research, and it is divided into five parts. First, it summarizes the findings of this study. Second, it compares the findings of this study with past literature to provide some possible interpretations for the findings. Third, it addresses the implication of findings on policy for the stakeholders. Fourth, it provides an evaluation of the research design from the perspective of internal and external validity. Lastly, it discusses the merits and limitations of this study.

5.1. Summary of key findings

This study provides a few insights into the crime recovery pattern in Nottingham. In terms of descriptive statistics, it shows that the hotspots of VSO and ASB concentrate in Nottingham city center in both pre-lockdown and post-lockdown periods. During the first lockdown period, the hotspot slightly shifted away from the city center towards the northwestern part of Nottingham where has more residential populations. Additionally, Moran's I statistics show that both VSO and ASB rates are positively autocorrelated across LSOAs, though it is noticeable that both VSO and ASB rates are less spatially autocorrelated during the first lockdown period.

Referring to the GAM outputs produced on the city level, it shows that the ASB rate follows an inverted U-shaped recovery pattern after lockdowns. This recovery pattern is statistically significant on the city level. However, it is difficult to observe a statistically significant recovery pattern in the VSO rate, as lockdown policy may have a delayed effect on the VSO rate.

Referring to the GAM outputs produced on the LSOA level, it shows that a possible crime recovery pattern can be found in both VSO and ASB rates after the first lockdown, especially in the LSOAs located in the city center. For the VSO rate, a possible U-shaped recovery pattern can be observed in the city center after the first lockdown. For the ASB rate, a possible inverted U-shaped recovery pattern can be observed in the city center. This statistically significant recovery pattern, however, can rarely be found in the LSOAs located on the southern or northern edge of the city.

Using GAM and GLM, the effect of lockdowns on crime is further quantified with the effect of social-disorganization factors. The model output shows that the lockdown variable has a positive correlation with the ASB rate, while it has a negative relationship with the VSO rate. It implies that the VSO rate is expected to increase when the lockdown is ended and the ASB rate is expected to decrease when the lockdown is ended. This helps to explain the crime recovery pattern.

Meanwhile, the VSO rate has positive correlations with ethnic diversity ($V_{simpson}$), family disruption ($V_{divorce}$), residential mobility (V_{ptai}) and economic status (V_{income}). It also has a negative correlation with urbanization (V_{pop}). On the other hand, the ASB rate has positive correlations with ethnic diversity $\left(V_{simpson}\right)$, residential mobility (V_{ptai}), urbanization (V_{pop}) and economic status (V_{income}). It also has a negative correlation with family disruption ($V_{divorce}$). The estimation of VSO and ASB rates shows that both ASB and VSO rates have a positive relationship with income, and this finding is not consistent with what SDT suggested.

5.2. Explanations of findings

VSO and ASB hotspots are mainly concentrated in Nottingham's city center. This is because Nottingham's city center is one of the busiest areas in Nottingham. It has many pubs and nightclubs which attract a large number of drinkers, especially on Saturday and Friday night (Hopkins, 2004). That can eventually give rise to alcohol-related VSO and alcohol-related ASB (Hopkins, 2004). That is also the reason why Nottingham city center was described as the most dangerous area by the local residents according to the news published by Nottinghamshire Live (Thurlow, 2022).

In the lockdown period, VSO and ASB hotspots were shifting towards Arboretum Ward where there has a larger residential population (18,241) compared to Castle Ward (13,413) and St Ann's Ward (14,638). Additionally, the VSO rate and ASB rate are less spatially autocorrelated in the first lockdown period. This could be explained by the decreasing mobility during the lockdown periods. As Perez-Vincent, Schargrodsky and García Mejía (2021) stated, when mobility is restricted, criminal activities become "more local". A study done in London has similar findings. A negative autocorrelation has been found in robbery rates across districts during the first lockdown, implying that robbery rates could have a dispersed distribution across districts during the first lockdown (Sun *et al.*, 2021).

In terms of VSO rate and ASB rate, a possible crime recovery pattern could be found in the LSOAs located in the city center but not in the LSOAs located at the edge of the city. This finding can be explained by the patterns shown in the descriptive statistics (See figure 11 and 13 in section 4.1. on page 32 and 35). As VSO and ASB rates remain low in the LSOAs located at the edge of the city, it is unlikely to find a statistically significant trend there. On the other hand, as VSO and ASB rates changed drastically in the LSOAs located in the city center, it is likely to find a statistically significant trend there. To the author's knowledge, no study has examined crime recovery patterns using GAM at a micro-geographic level. Therefore, it is difficult to tell whether the city center of the other cities also experienced a statistically significant crime recovery pattern. This paucity in consensus of results warrants further investigation.

The GAM and GLM results show that income has a positive correlation with both VSO and ASB rates, which is not consistent with what SDT suggested. This is because economic disadvantage may not necessarily lead to an increasing crime rate, especially in the rural area (Sunghoon and Choo, 2008). As poverty can prevent residents from moving to other places, poor communities tend to be more stable than their more affluent counterparts (Sunghoon and Choo, 2008). This increasing level of stability would eventually lead to a lower crime rate in the less affluent regions (Sunghoon and Choo, 2008).

5.3. Implication of findings on policy

In this study, the visualizations of crime help to demonstrate the dynamic distribution of crime before, during, and after exceptional events. Using GAM and GLM techniques, this study further investigates the LSOAs that are most affected by the lockdown policy and examines the social-disorganization factors that can possibly contribute these dynamic crime patterns. This finding helps to understand the impact of lockdown on crime on the LSOA level.

From the perspective of crime prevention, this study can be used as a reference for Nottinghamshire Police Force and NNVRU to prepare for the possible hotspot displacement that happened after exceptional events. With the hotspot shifting away from Castle Ward and St Ann's Ward towards Arboretum Ward, police officers can focus their resources on the new crime hotspot through increasing the amount of patrol time and increasing the number of police officers at Arboretum Ward. This place-oriented strategy normally refers to "hotspot policing", and it is proven to have a significant effect on crime reduction (Weisburd, 2018; Braga *et al.*, 2019).

From the perspective of urban planning, this study can be used as a reference for Nottingham City Council to prepare for the possible surge of ASB cases during the exceptional event and the possible surge of VSO cases after the exceptional event. This preparation can be delivered through a strategy called "crime prevention through environmental design". This strategy is developed from the idea of creating an unattractive environment for motivated offenders. Based on this idea, Nottingham City Council can either demolish the abandoned buildings where are the preferred sites for criminal activities or clean up the graffiti to create a safe atmosphere in the neighborhood (Cozens, Saville and Hillier, 2005).

5.4. Internal & External Validity

For the evaluation of internal validity, the author argues that this study has high internal validity for several reasons. First, this study is mainly conducted based on the crime data collected from May 2019 to Oct 2021. This longitudinal dataset contains 119,621 ASB cases and 129,999 VSO cases. With this large sample size, the statistical output is expected to be more sensitive to the spatiotemporal variation in crime. Second, this study is conducted on both city and LSOA levels. This design allows the crime recovery pattern to be captured on multiple geographical scales. Lastly, in the modeling process, the lockdown variable is tested with the other crime-related variables being controlled to reduce systematic errors.

In the modeling process, crime data is recorded longitudinally every month, but the other data are not longitudinal because of the limited available datasets. This study, therefore, cannot address how lockdown policy affected crime through the channel of socioeconomic factors. That can negatively affect internal validity. Fortunately, this problem is offset by the application of GAM which demonstrates the time dependency of lockdown on crime.

For the evaluation of external validity, the author argues that this study has a relatively low external validity for several reasons. First, different countries have different police systems in which crime types are classified differently. For example, while Mexico classified theft into the category of "theft & battery crime", police.uk classified theft into the categories of "theft from a person", "bicycle theft" and "other theft". Therefore, it becomes difficult to compare the crime recovery pattern across countries, and the findings of this study can be difficult to be generalized to other countries.

Additionally, different countries can have different lockdown measures. In China, the first lockdown policy was introduced in January 2020 in Wuhan where the Covid-19 virus is first identified. This policy came into force with the closure of public spaces, schools, and universities (Lau *et al.*, 2020). A permission card was given to everyone, which restricted outdoor activities to 30 minutes per two days

(Lau *et al.*, 2020). In the UK, the first lockdown also came into force with the closure of non-essential businesses and schools, but outdoor exercises were restricted to one hour per day, which was less restrictive compared to the one in Wuhan. As the lockdown policies differ across places, the findings of this study can be difficult to be generalized to other countries.

Overall, this study can have a relatively low external validity, as the findings of this study may not be applicable to other cities or countries. According to the classification of crime and the magnitude of the lockdown policies, this study could possibly be generalized to other cities in the UK. This study, therefore, can be repeated in other cities in the UK to test whether a similar recovery pattern can be found in VSO and ASB rates.

5.5. Merits & Limitations

One of the merits of this study is that it has high internal validity, as mentioned in section 5.4. From the perspective of methodology, another merit of this study is that it demonstrates how GAM results can be mapped in the context of crime. The maps (See figure 18 and 19 in section 4.2.2. on page 39 and 40) show that this visualization of GAM results is effective in capturing the LSOAs that are most affected by the lockdown policies. To the author's knowledge, no study has mapped GAM results in the context of crime; therefore, this study hopes to provide insights for future criminology studies.

However, this study has some limitations related to data. First, as mentioned in section 1.2., the lockdown policies introduced in the UK are slightly different from one another, with the first lockdown being the most restrictive one. However, the lockdown variable ($V_{lockdown}$) used in this study does not reflect this difference in policies, as it coded all lockdown periods into 1 and all non-lockdown periods into 0. Second, as an ecological study, this study is developed based on the data collected on the LSOA level instead of the data collected on the individual level. As a result, "ecological fallacy" can occur, as the findings of this study may not be applicable to a finer scale.

Chapter 6. Conclusion

On reflection of the summary findings, this study explored the crime recovery pattern in Nottingham after Covid-19 lockdowns. The temporal variation of crime suggested that the ASB rate follows an inverted U-shaped recovery pattern on the city level while no statistically significant recovery pattern can be observed in the VSO rate. On the LSOA level, the temporal variation of crime further suggests that the LSOAs located in city center are most affected by the lockdown policies.

The Poisson regressions quantify the effect of lockdown on crime, as well as the effect of the social-disorganization factor on crime. The estimated coefficients show that lockdown is negatively associated with the VSO rate while it is positively associated with the ASB rate. Additionally, the lockdown policy is expected to have a greater effect on the ASB rate compared to its effect on the VSO rate. Referring to the estimated coefficients of the social-disorganization factors, it suggests that the ASB rate and VSO rate in Nottingham do not necessarily follow what SDT suggested. For example, low-income LSOAs do not experience a high VSO rate or a high ASB rate compared to their more affluent counterparts.

The findings of this study hope to provide crucial insights for future criminology research. Possible research includes:

- Conducting crime recovery analysis on the other crime types to obtain a more comprehensive understanding of the crime recovery pattern in Nottingham
- Repeating this study in other cities in the UK to investigate whether this crime recovery pattern is applicable to the other context
- Examining the recovery pattern of VSO rate in other countries, given the time window between the first and the second lockdown in the UK may not be long enough to capture the whole recovery process of VSO

From the methodological aspect, there are some recommendations for future research. Referring to the limitations of this study, recommendations are listed as follows:

- Quantifying the level of lockdown policies based on the specific rules introduced in the lockdown periods
- Incorporating more predictors in the examination of SDT, given the results shown in this study is not fully consistent with SDT

Chapter 7. Autocritique

This dissertation aims to investigate the crime recovery pattern in Nottingham following three research questions. As a refresher, the research questions are shown as follows:

1. Does Nottingham's crime pattern change before, during, and after the first lockdown?
2. Does the crime recovery pattern of VSO and ASB vary across LSOAs?
3. Does Social Disorganization Theory help to explain the crime pattern in Nottingham?

Those research questions have been clearly addressed in the dissertation. However, the author encountered several challenges in this process. Initially, the research plan was to demonstrate the crime recovery pattern in Nottingham using segmented regression, because segmented regressions can better demonstrate the recovery speed of crime. The statistical results, however, turned out that segmented regression does not produce a well-fitted model that clearly demonstrates the crime recovery pattern. So, GAM is used instead to depict the curvilinear relationship between time and crime rate, though this approach compromises the statistical findings of recovery speed.

The second challenge is about the time windows between lockdowns. As mentioned in section 3.4.2.1.1, the time window between the second and the third lockdowns is relatively short, and that is the reason why these two lockdowns are combined in this research. Additionally, the time window between the first and the second lockdowns is not long enough to observe the full recovery process of the VSO rate. This scenario becomes even worsened as there is a possible delayed effect in the recovery of the VSO rate.

Despite those challenges, this study allows a deeper understanding of the crime recovery pattern after exceptional events. According to the hotspot analysis and the GAM & GLM analysis, this study hopes to offer valuable policy implications for crime reduction purposes. It also hopes to offer theoretical insights for future criminology research.

Chapter 8. Appendices

Appendix 1:

Link to the reproduceable codes and the datasets: shttps://github.com/qghuihuihui/Dissertation-2023

Appendix 2:

Link to all the LSOA GAM plots – it contains 182 plots for ASB and 182 plots for VSO: https://github.com/qghuihuihui/GAM-plots

Appendix 3: Datasets used in this study

Data	Data Source	Description
Crime Counts	Crime datasets from Police.uk	Crime counts from May 2019 to Oct 2022
Population Density Per Square Kilometer	2022 Population Density Dataset from the Office for National Statistics	The number of people per square kilometer in LSOA areas
% of Divorced Household	2011 Household Census from the Office for National Statistics	Percentage of divorced household on the LSOA level
Health Deprivation and Disability Decile	2019 Income Deprivation Index from the Office for National Statistics	Ranging from 1 (most deprived) to 10 (least deprived).
Education, Skills and Training Decile	2019 Income Deprivation Index from the Office for National Statistics	Ranging from 1 (most deprived) to 10 (least deprived).
Income Decile	2019 Income Deprivation Index from the Office for National Statistics	Ranging from 1 (most deprived) to 10 (least deprived).
Ethnicity Proportions	2020 Modelled Ethnicity Proportions from the Consumer Data Research Centre (CDRC)	Contains 11 ethnicities category
PTAI LSOA value	2016 Public Transport Accessibility Index	A higher PTAI value reflects a higher level of accessibility

Chapter 9. References

Agnew, R. (2001) ‘Building on the Foundation of General Strain Theory: Specifying the Types of Strain Most Likely to Lead to Crime and Delinquency’, *Journal of Research in Crime and Delinquency*, 38(4), pp. 319–361.

Andresen, M.A. and Hodgkinson, T. (2020) ‘Somehow I always end up alone: COVID-19, social isolation and crime in Queensland, Australia’, *Crime Science*, 9(1), pp. 1–20. Available at: https://doi.org/10.1186/s40163-020-00135-4.

Bade, R. *et al.* (2021) ‘Changes in alcohol consumption associated with social distancing and self-isolation policies triggered by COVID-19 in South Australia: a wastewater analysis study’, *Addiction*, 116(6), pp. 1600–1605. Available at: https://doi.org/10.1111/add.15256.

Balmori de la Miyar, J.R., Hoehn-Velasco, L. and Silverio-Murillo, A. (2021) ‘The U-shaped crime recovery during COVID-19: evidence from national crime rates in Mexico’, *Crime Science*, 10(1), p. 14. Available at: https://doi.org/10.1186/s40163-021-00147-8.

Barberet, R. and Fisher, B.S. (2009) ‘Can security beget insecurity? Security and crime prevention awareness and fear of burglary among university students in the East Midlands’, *Security Journal*, 22(1), pp. 3–23. Available at: https://doi.org/10.1057/sj.2008.9.

Barnett, C. and Mencken, F.C. (2002) ‘Social Disorganization Theory and the Contextual Nature of Crime in Nonmetropolitan Counties*’, *Rural Sociology*, 67(3), pp. 372–393. Available at: https://doi.org/10.1111/j.1549-0831.2002.tb00109.x.

BBC (2021) ‘Covid: Pub and restaurant fined after drinkers found inside’, *BBC News*, 29 January. Available at: https://www.bbc.com/news/uk-england-nottinghamshire-55855711 (Accessed: 13 March 2023).

Bellair, P. (2017) *Social Disorganization Theory*, *Oxford Research Encyclopedia of Criminology and Criminal Justice*. Available at: https://doi.org/10.1093/acrefore/9780190264079.013.253.

Borrion, H. *et al.* (2020) ‘Measuring the resilience of criminogenic ecosystems to global disruption: A case-study of COVID-19 in China’, *PLOS ONE*. Edited by I. Linkov, 15(10), p. e0240077. Available at: https://doi.org/10.1371/journal.pone.0240077.

Braga, A.A. *et al.* (2019) ‘Hot spots policing and crime reduction: an update of an ongoing systematic review and meta-analysis’, *Journal of Experimental Criminology*, 15(3), pp. 289–311. Available at: https://doi.org/10.1007/s11292-019-09372-3.

Broidy, L.M. (2001) ‘A Test of General Strain Theory*’, *Criminology*, 39(1), pp. 9–36. Available at: https://doi.org/10.1111/j.1745-9125.2001.tb00915.x.

Bruinsma, G. and Johnson, S.D. (2018) *The Oxford Handbook of Environmental Criminology*. Oxford University Press.

Bruneau, M. *et al.* (2003) ‘A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities’, *Earthquake Spectra*, 19(4), pp. 733–752. Available at: https://doi.org/10.1193/1.1623497.

Bucher, J., Manasse, M. and Milton, J. (2014) ‘Soliciting strain: examining both sides of street prostitution through General Strain Theory’, *Journal of Crime and Justice* [Preprint]. Available at: https://www.tandfonline.com/doi/full/10.1080/0735648X.2014.949823 (Accessed: 29 January 2023).

Campedelli, G.M., Aziani, A. and Favarin, S. (2021) ‘Exploring the Immediate Effects of COVID-19 Containment Policies on Crime: an Empirical Analysis of the Short-Term Aftermath in Los Angeles’, *American Journal of Criminal Justice*, 46(5), pp. 704–727. Available at: https://doi.org/10.1007/s12103-020-09578-6.

Cozens, P.M., Saville, G. and Hillier, D. (2005) ‘Crime prevention through environmental design (CPTED): a review and modern bibliography’, *Property Management*, 23(5), pp. 328–356. Available at: https://doi.org/10.1108/02637470510631483.

CrimeRate (2023) *Nottingham Crime and Safety Statistics*. Available at: https://crimerate.co.uk/nottinghamshire/nottingham (Accessed: 4 February 2023).

CrimeRate, 20 (2023) *East Midlands Crime Safety Statistics | CrimeRate*. Available at: https://crimerate.co.uk/east-midlands (Accessed: 4 February 2023).

Druică, E., Musso, F. and Ianole-Călin, R. (2020) ‘Optimism Bias during the Covid-19 Pandemic: Empirical Evidence from Romania and Italy’, *Games*, 11(3), p. 39. Available at: https://doi.org/10.3390/g11030039.

Field, S. (1992) ‘The Effect of Temperature on Crime’, *British Journal of Criminology*, 32(3), pp. 340–351.

Forrest, R. and Kearns, A. (2001) ‘Social Cohesion, Social Capital and the Neighbourhood’, *Urban Studies*, 38(12), pp. 2125–43.

Halford, E., Dixon, A. and Farrell, G. (2022) *Anti-social behaviour in the coronavirus pandemic | Crime Science | Full Text*. Available at: https://crimesciencejournal.biomedcentral.com/articles/10.1186/s40163-022-00168-x (Accessed: 31 January 2023).

Hennessy, P. (2020) *How unemployment rate in Nottingham has increased this year*, *NottinghamshireLive*. Available at: https://www.nottinghampost.com/news/local-news/unemployment-rate-nottinghamshire-2020-coronavirus-4772896 (Accessed: 13 March 2023).

Hollows, J. *et al.* (2014) ‘Making sense of urban food festivals: cultural regeneration, disorder and hospitable cities’, *Journal of Policy Research in Tourism, Leisure and Events* [Preprint]. Available at: https://www.tandfonline.com/doi/full/10.1080/19407963.2013.774406 (Accessed: 13 March 2023).

Hopkins, M. (2004) 'Targeting Hotspots of Alcohol-related Town Centre Violence: A Nottinghamshire Case Study', *Security Journal*, 17(4), pp. 53–66. Available at: https://doi.org/10.1057/palgrave.sj.8340183.

Hopkins, M., Floyd, K. and Davis, C. (2020) 'Reducing Public Space Violence across the East Midlands: Mapping the Interventions'.

Hu, Y. *et al.* (2018) 'A spatio-temporal kernel density estimation framework for predictive crime hotspot mapping and evaluation', *Applied Geography*, 99, pp. 89–97. Available at: https://doi.org/10.1016/j.apgeog.2018.08.001.

Institute for Government (2022) *Timeline of UK government coronavirus lockdowns and restrictions*, *Institute for Government*. Available at: https://www.instituteforgovernment.org.uk/data-visualisation/timeline-coronavirus-lockdowns (Accessed: 6 February 2023).

Jones, T.A. (1984) 'Review of Crime and Modernization: The Impact of Industrialization and Urbanization on Crime.; Readings in Comparative Criminology., Louise I. Shelley', *Social Forces*, 62(4), pp. 1117–1119. Available at: https://doi.org/10.2307/2578585.

Kie, J.G. (2013) 'A rule-based ad hoc method for selecting a bandwidth in kernel home-range analyses', *Animal Biotelemetry*, 1(1), p. 13. Available at: https://doi.org/10.1186/2050-3385-1-13.

Kirchmaier, T. and Villa-Llera, C. (2020) 'COVID-19 and Changing Crime Trends in England and Wales'. Rochester, NY. Available at: https://doi.org/10.2139/ssrn.3700329.

Kubrin, C.E. (2009) 'Social Disorganization Theory: Then, Now, and in the Future', in M.D. Krohn, A.J. Lizotte, and G.P. Hall (eds) *Handbook on Crime and Deviance*. New York, NY: Springer (Handbooks of Sociology and Social Research), pp. 225–236. Available at: https://doi.org/10.1007/978-1-4419-0245-0_12.

Langton, S., Dixon, A. and Farrell, G. (2021) 'Six months in: pandemic crime trends in England and Wales', *Crime Science*, 10(1), p. 6. Available at: https://doi.org/10.1186/s40163-021-00142-z.

Lau, H. *et al.* (2020) 'The positive impact of lockdown in Wuhan on containing the COVID-19 outbreak in China', *Journal of Travel Medicine*, 27(3), p. taaa037. Available at: https://doi.org/10.1093/jtm/taaa037.

Lemieux, F. (2014) 'The impact of a natural disaster on altruistic behaviour and crime', *Disasters*, 38(3), pp. 483–499. Available at: https://doi.org/10.1111/disa.12057.

Lewis Nedas Law (2023) *Violent Crime - Lewis Nedas Law*. Available at: https://lewisnedas.co.uk/legal-services/criminal-litigation/violent-crime.html (Accessed: 30 January 2023).

Lyons, M. (2017) *Generalised Additive Models (GAMs) :: Environmental Computing*. Available at: https://environmentalcomputing.net/statistics/gams/ (Accessed: 19 March 2023).

Malcolm, R. (2021) *Fears over rise in anti-social behaviour during pandemic*, *NottinghamshireLive*. Available at: https://www.nottinghampost.com/news/local-news/fears-over-rise-anti-social-5645365 (Accessed: 4 February 2023).

Metropolitan Police (2023) *What is antisocial behaviour?* Available at: https://www.met.police.uk/advice/advice-and-information/asb/asb/antisocial-behaviour/what-is-antisocial-behaviour/ (Accessed: 31 January 2023).

Miró, F. (2014) 'Routine Activity Theory', in *The Encyclopedia of Theoretical Criminology*. John Wiley & Sons, Ltd, pp. 1–7. Available at: https://doi.org/10.1002/9781118517390.wbetc198.

Murray, L. (2010) *Tutorial 13.2 - Species richness and diversity*. Available at: https://www.flutterbys.com.au/stats/tut/tut13.2.html (Accessed: 7 February 2023).

Nottingham City Home (2019) *Tackling Anti-Social Behaviour and Crime Strategy 2019-2022*. Available at: https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjqhbn199j9AhXVNMAKHV5CArUQFnoECBIQAQ&url=https%3A%2F%2Fdocuments.nottinghamcity.gov.uk%2Fdownload%2F7874&usg=AOvVaw1s0jP3rnkVP4jYIR1p9tnQ (Accessed: 13 March 2023).

Nottingham Insight (2023) *Home - Nottingham Insight*. Available at: https://www.nottinghaminsight.org.uk/ (Accessed: 3 February 2023).

Oc, T. and Tiesdell, S. (1998) 'City centre management and safer city centres: approaches in Coventry and Nottingham', *Cities*, 15(2), pp. 85–103. Available at: https://doi.org/10.1016/S0264-2751(97)10016-6.

ONS (2011) *Rural/urban classifications - Office for National Statistics*. Available at: https://www.ons.gov.uk/methodology/geography/geographicalproducts/ruralurbanclassifications (Accessed: 9 February 2023).

ONS (2021) *How the population changed in Nottingham, Census 2021 - ONS*. Available at: https://www.ons.gov.uk/visualisations/censuspopulationchange/E06000018/ (Accessed: 15 March 2023).

de Palma, A., Vosough, S. and Liao, F. (2022) 'An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak', *Transportation Research Part A: Policy and Practice*, 159, pp. 372–397. Available at: https://doi.org/10.1016/j.tra.2022.03.024.

Perez-Vincent, S.M., Schargrodsky, E. and García Mejía, M. (2021) 'Crime under lockdown: The impact of COVID-19 on citizen security in the city of Buenos Aires', *Criminology & Public Policy*, 20(3), pp. 463–492. Available at: https://doi.org/10.1111/1745-9133.12555.

Pettersson, T. (2003) 'Ethnicity and Violent Crime: The Ethnic Structure of Networks of Youths Suspected of Violent Offences in Stockholm', *Journal of Scandinavian Studies in Criminology and Crime Prevention*, 4, pp. 143–161. Available at: https://doi.org/10.1080/14043850310021567.

Quinton, P. *et al.* (2020) *Police use of force: Tactics, assaults and safety. Exploratory analysis of police recorded data 2017/18*.

RCEW (2023) *What is sexual assault?*, *Rape Crisis England & Wales*. Available at: https://rapecrisis.org.uk/get-informed/types-of-sexual-violence/what-is-sexual-assault/ (Accessed: 30 January 2023).

Roncek, D. (1981) *EBSCOhost | 5287421 | Dangerous Places: Crime and Residential Environment.* Available at: https://web.p.ebscohost.com/abstract?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=00377732&asa=Y&AN=5287421&h=cA2yreJCQcPhkYGH%2bSJ9fWesXfHj5hnf3YpYoAE%2fLjW7ytbHDOi8TN060%2fdBVXJsaWHStmyNgMqkHGeIv8nugg%3d%3d&crl=c&resultNs=AdminWebAuth&resultLocal=ErrCrlNotAuth&crlhashurl=login.aspx%3fdirect%3dtrue%26profile%3dehost%26scope%3dsite%26authtype%3dcrawler%26jrnl%3d00377732%26asa%3dY%26AN%3d5287421 (Accessed: 1 February 2023).

Rose, D.R. and Clear, T.R. (1998) 'Incarceration, Social Capital, and Crime: Implications for Social Disorganization Theory*', *Criminology*, 36(3), pp. 441–480. Available at: https://doi.org/10.1111/j.1745-9125.1998.tb01255.x.

Sampson, R.J., Raudenbush, S.W. and Earls, F. (1997) 'Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy', *Science*, 277(5328), pp. 918–924. Available at: https://doi.org/10.1126/science.277.5328.918.

Smith, A.M. (2014) 'Police.uk and Data.police.uk: Developing Open Crime and Justice Data for the UK.', *JeDEM - eJournal of eDemocracy and Open Government*, 6(1), pp. 87–96. Available at: https://doi.org/10.29379/jedem.v6i1.326.

Stickle, B. and Felson, M. (2020) 'Crime Rates in a Pandemic: the Largest Criminological Experiment in History', *American Journal of Criminal Justice*, 45(4), pp. 525–536. Available at: https://doi.org/10.1007/s12103-020-09546-0.

Sun, Y. *et al.* (2021) 'Spatial Patterns of COVID-19 Incidence in Relation to Crime Rate Across London', *ISPRS International Journal of Geo-Information*, 10(2), p. 53. Available at: https://doi.org/10.3390/ijgi10020053.

Sunghoon, R. and Choo, T.M. (2008) *EBSCOhost | 34156706 | Looking Inside Zone V: Testing Social Disorganization Theory in Suburban Areas.* Available at: https://web.p.ebscohost.com/abstract?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=10964886&AN=34156706&h=fufbHJPaSJ47njLtpobypx1qXXyGzPgCj5hF9HthRgTARdCV2dL3r%2fd08USNtw1r%2fPSIwrYepaoa3mIYAF8Jag%3d%3d&crl=c&resultNs=AdminWebAuth&resultLocal=ErrCrlNotAuth&crlhashurl=login.aspx%3fdirect%3dtrue%26profile%3dehost%26scope%3dsite%26authtype%3dcrawler%26jrnl%3d10964886%26AN%3d34156706 (Accessed: 25 January 2023).

Thurlow, J. (2022) *‘Real shame’ as Nottingham city centre named most dangerous area of county - Nottinghamshire Live*. Available at: https://www.nottinghampost.com/news/nottingham-news/real-shame-nottingham-city-centre-6929057 (Accessed: 4 February 2023).

Tompson, L. *et al.* (2015) ‘UK open source crime data: accuracy and possibilities for research’, *Cartography and Geographic Information Science*, 42(2), pp. 97–111. Available at: https://doi.org/10.1080/15230406.2014.972456.

UBDC (2016) *Public transport availability indicators (PTAI) - UBDC Data Portal*. Available at: http://ubdc.gla.ac.uk/dataset/public-transport-availability-indicators-ptai (Accessed: 9 February 2023).

University of Mary Washington and Yin, P. (2020) ‘Kernels and Density Estimation’, *Geographic Information Science & Technology Body of Knowledge* [Preprint], (Q1). Available at: https://doi.org/10.22224/gistbok/2020.1.12.

Warburton, H. and Hough, M. (2009) *A profile of youth crime in Nottingham City*. London, UK: Institute For Criminal Policy Research. Available at: http://www.kcl.ac.uk/schools/law/research/icpr/pubs/houghm/pubs2009.html (Accessed: 15 March 2023).

Weisburd, D. (2018) ‘Hot Spots of Crime and Place-Based Prevention’, *Criminology & Public Policy*, 17(1), pp. 5–25. Available at: https://doi.org/10.1111/1745-9133.12350.

Wong, S.K. (2012) ‘Youth crime and family disruption in Canadian municipalities: An adaptation of Shaw and McKay’s social disorganization theory’, *International Journal of Law, Crime and Justice*, 40(2), pp. 100–114. Available at: https://doi.org/10.1016/j.ijlcj.2011.09.006.

Zahran, S. *et al.* (2009) *Natural Disasters and Social Order: Modeling Crime Outcomes in Florida*. Available at: https://doi.org/10.1177/028072700902700102.