Seasons of Crime in London

Shiode N[*1], Shiode S[†2], Nishi H[‡3] and Hino K[§3]

[1]Department of Geography, King's College London
[2]Department of Geography, Birkbeck, University of London
[2]Department of Urban Engineering, University of Tokyo

February 15, 2021

Summary

This paper investigates whether different types of crime share common traits in their seasonal fluctuation. Specifically, we examine the similarity and difference in the patterns of their trend, the amplitude of the seasonal fluctuation and the peak and the trough seasons to see whether they share common underlying factors. Results show that most seasonal crimes peak in the summer, while some had non-seasonal fluctuation; regardless of the amplitude of their fluctuation. Principal component analysis suggests the presence of the intensity of the seasonality of crime, and reflection of the peak season of the respective crime.

KEYWORDS: crime, trend analysis, principal component analysis, seasonality

1. Introduction

The presence of temporal fluctuation in the volume of crimes has been known for some time (Block, 1984). Its studies are often motivated by the need to understand the relevant criminalistic behavior, or to predict the changes in their volume to raise awareness and manage policing resource efficiently. Some have explored the temporal changes across different crimes (Hird and Ruparel, 2007; McDowall *et al*., 2012; Andersen and Malleson, 2013; ONS, 2013; Linning *et al*., 2016), while others focused on simulating the fluctuation of specific crime types in each season (Dong *et al*., 2017; Stalidis *et al*., 2018). However, hardly any study has investigated the similarity and difference in the temporal patterns of different crime types. Among few exceptions is a report by Hird and Ruparel (2007) which reviewed monthly data between 2000 and 2005, and concluded that crimes in UK can be classified into three categories:

(1) those with peaks in the summer months and troughs in the winter months;
(2) those with peaks in the winter months and troughs in the summer months; and
(3) those with regular peaks and troughs each year which are not led by the seasons.

However, their study fell short of identifying those categories systematically and exploring their underlying factors. This study investigates which types of crimes show seasonality, which pattern of seasonality they share with other crimes, and what may be causing these temporal changes. Findings are expected to improve our understanding of the frequency and seasonality of different crimes and, thereby, raise awareness and help manage resources efficiently by the local police force.

2. Methodology

2.1. Trend-Seasonality Decomposition

The temporal fluctuation in the volume of crime mainly consist of the short-term, recuring seasonality of crime, and the long-term trend of the criminal activities. For instance, the overall number of crime

* naru.shiode@kcl.ac.uk
† s.shiode@bbk.ac.uk
‡ h.nishi@ua.t.u-tokyo.ac.jp
§ hino@ua.t.u-tokyo.ac.jp

in London has been on the decline for the last 20 years, yet the seasonal fluctuation persists across different crimes, and their patterns vary by the crime type.
In this study, we will use a non-Gaussian state-space model to separate the temporal changes of crimes into the recuring seasonality and the long-term trend. The model can be described as

System Model (t: Time Stamp, ε_t^*: Gaussian noise)

$$Trend\ Component: \ \alpha_t = 2\alpha_{t-1} - \alpha_{t-2} + \varepsilon_t^{\alpha} \tag{1}$$

$$Seasonal\ Component: \ s_t = -\sum_{d=1}^{11} s_{t-d} + \varepsilon_t^{s} \tag{2}$$

Observation Model (y_t: Crime count, u_t: number of days at the tth month)

$$y_t \sim \text{Poisson}\big(y_t \mid u_t \exp(\alpha_t + s_t)\big) \tag{3}$$

The mean values in the state space model are then smoothed and simulated using a Kalman-filtering package KFAS (Helske, 2017).

2.2. Clustering Analysis

In order to measure the degree of similarity in the temporal footprints of different crimes, we will derive the dissimilarity matrix between crime types. Two separate methods are used for deriving similarities and differences of their time-series: (1) L_1-distance which retains the timing of the peaks/troughs when comparing their seasonality, and (2) Dynamic Time Warping (DTW) (Müller, 2007) which focuses on the time-series wave form. The components are standardised to account for the difference in amplitude. After grouping the crimes based on the dissimilarity matrix and Ward's method, we further investigate their seasonal characteristics by applying principal component analysis (PCA) to their seasonal fluctuation and the peak seasons.

3. Results

Figure 1 Grouping by the long-term trend.

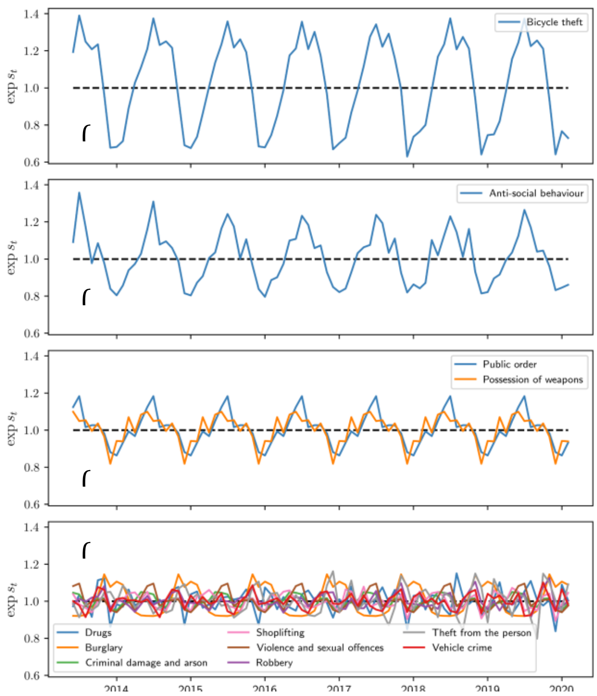

Figure 2 Grouping by the amplitude of the seasonal fluctuation.

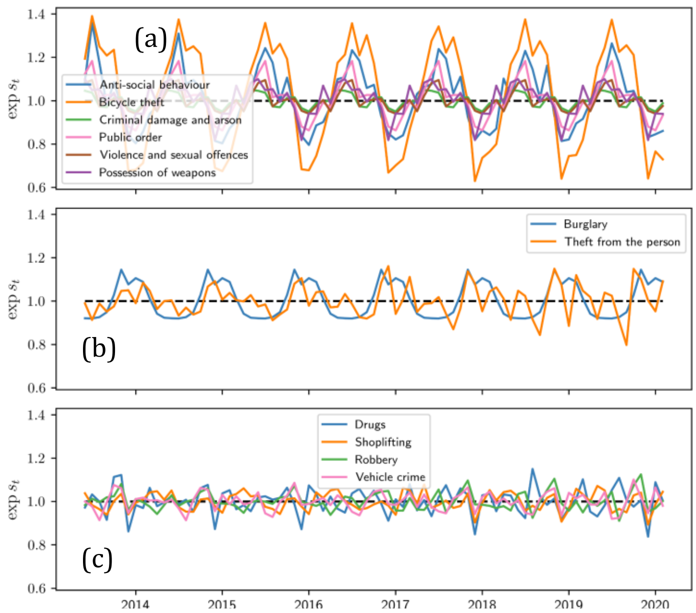

Figure 3. Grouping by the peak and the trough seasons.

Our study used the monthly crime counts of 12 types of crime recorded across Greater London, U.K. recorded between June 2013 and February 2020. They are anti-social behavior (ASB), bicycle theft, burglary, criminal damage and arson, drugs, robbery, possession of weapon, public order, shoplifting, theft from the person, vehicle crime, and violence and sexual offence.

Figure 1 shows the results of the clustering analysis by the long-term trend. They were classified into four groups: (1) fluctuation: crimes exhibiting fluctuations but no long-term changes; (2) decline-increase: those with initial decrease followed by recent increase but no long-term growth; (3) steady-increase: those increasing steadily; and (4) decline-steady-increase: those with initial decrease followed by recent increase and show long-term growth in their volume.

The seasonality of crimes was categorised initially by their magnitude, ranging from (1) very high fluctuation (e.g. bike theft), (2) high fluctuation, (3) medium fluctuation, to (4) low fluctuation (**Figure 2**). They were then classified with respect to their peak season (**Figure 3**), which resulted in three different groups: (1) Peaks in summer, (2) Peaks in winter, and (3) unclear or weak seasonality. For instance, bike-theft and ASB had high peaks in summer, while burglary and theft-from-the-person showed moderate increase in winter. These results confirm those reported by Hird and Ruparel (2007).

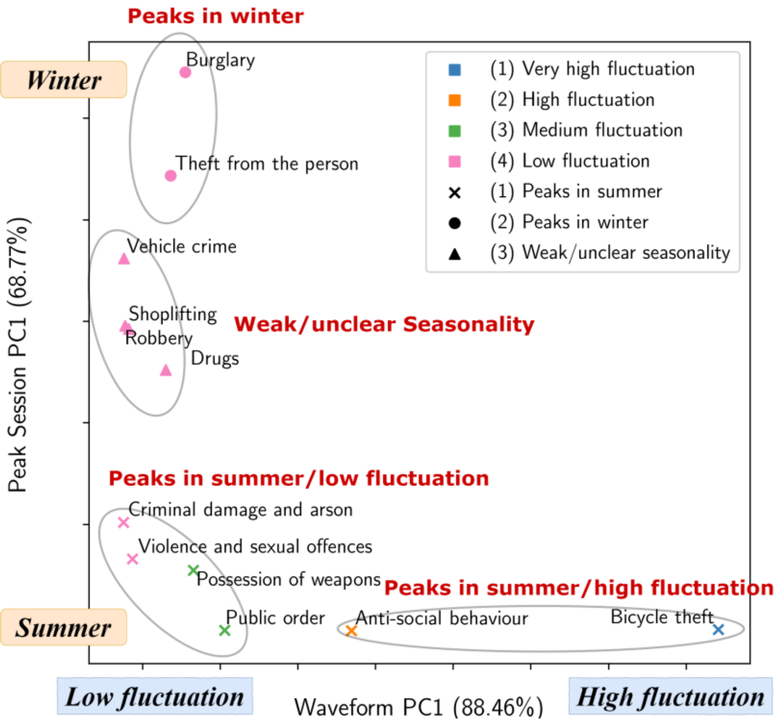

Figure 4. Scatter plot of the distribution of the seasonal fluctuation and peak seasons.

Figure 4 shows a scatter plot that reflects the outcome of the PCAs carried out against the magnitude of seasonal fluctuation and that of the peak seasons. It shows that the magnitude of the seasonal fluctuation played a key role in explaining 88.46% of the variance in their wave forms. It can be interpreted as "the intensity of the seasonality" of crime. Similarly, the peak and the trough of the seasons were found to explain 68.77% of the variance in their seasonal trend which can be interpreted as "reflection of the peak season" of the respective crime.

4. Discussion

Outcomes from the seasonality analyses revealed several interesting patterns:

(1) Crimes with high to medium fluctuation have peaks in the summer months, possibly because the offenders are spending more time outdoor (warm weather/longer day). These crime types are likely to occur unplanned (e.g. bicycle theft, anti-social behavior) and may be affected by the weather.

(2) Burglary and thefts from the person peak in the winter months, especially November. This is because of the dimmer/shorter days, less witnesses on road, as well as people likely to be carrying around more cash in the run-up to Christmas.

(3) Crimes with unclear or weak seasonality show low fluctuation (but with a dip in December). These crimes (shoplifting, robbery, drugs and vehicle crimes) are habitual and persistent in nature.

These findings indicate that the types of crimes sharing similar seasonal fluctuations are linked by the criminalistic behaviour rather than the nature of the crime. Results from PCAs also confirm the grouping of crime types that are brought together by the offenders' motivation and behaviour, some of which are prone to the weather condition while others are more robust and persistent. Further interpretation of how they map against the existing criminological theory could help add more evidence to the understanding of the patterns of crime across time. Seasonal fluctuations in the volume of crime have been studied for several different crime types, especially those that exhibit clear seasonality; e.g. burglary, arson and violent crimes. However, similarities and differences between these crimes have not been studied systematically until now, and this study offers fresh insights into their association in that respect.

5. References and Citations

Andersen M A and Malleson N (2013). Crime seasonality and its variations across space. *Applied Geography*, 43, 25-35.

Block C R (1984) Is crime seasonal? *Illinois Criminal Justice Information Authority*.

Dong K, Cao Y, Siercke B, Wilber M and McCalla S G (2017). Advising caution in studying seasonal oscillations in crime rates. *PLoS ONE*, 12(9) (https://doi.org/10.1371/journal.pone.0185432).

Helske J (2017). KFAS: Exponential family state space models in R. *Journal of Statistical Software* 78(1), 1–39.

Hird C and Ruparel C (2007). Seasonality in recorded crime: Preliminary findings. *UK Home Office Online Report*, 13pp.

Linning A J, Andresen M A and Brantingham P J (2016). Crime seasonality: Examining the temporal fluctuations, *International Journal of Offender Therapy and Comparative Criminology* 61: 1866-91.

McDowall D, Loftin C and Pate M (2012). Seasonal cycles in crime and their variability. *Journal of Quantitative Criminology*, 28(3), 389-410.

Müller M 2007. *Information Retrieval for Music and Motion*, Berlin: Springer Verlag.

Office of National Statistics (2013). Analysis of seasonality in police recorded property crime. *Office of National Statistics: Methodological Note*.

Stalidis P, Semertzidis T and Daras P (2018). Examining deep learning architectures for crime classification and prediction. *ArXiv* abs/1812.00602, n. pag.

Biographies

Narushige Shiode is Reader in Geocomputation and Spatial Analysis with Department of Geography, King's College London and the Centre for Urban Science and Progress, London. He has worked mainly in the fields of urban geography, spatial analysis and GIS to identify patterns of changes in areas of built and natural environment.

Shino Shiode is Senior Lecturer in Geographic Data Science at Birkbeck, University of London where she serves as Director of the GIS programme. Her area of expertise extends to geography of crime, spatial epidemiology, as well as development of theory and methods for spatial analysis.

Hayato Nishi is a PhD student with Department of Urban Engineering, University of Tokyo. He works on the development of statistical methodologies for interpreting geo-spatial data on housing market, crimes and traffic accidents.

Kimihiro Hino is Associate Professor with Department of Urban Engineering, University of Tokyo. His current research interests include crime prevention through environmental design (CPTED) and citizen participation in crime prevention activities.