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Crime volume and severity: a numerical and geospatial study

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The necessity of uniting in society being granted, together with the conventions, which the opposite interests of individuals must necessarily require, a scale of crimes may be formed, of which the first degree should consist of those which immediately tend to the dissolution of society, and the last, of the smallest possible injustice done to a private member of that society.

—Cesare Beccaria*, On Crimes and Punishments and Other Writings, 1764*

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Abstract

The default position of crime volume as the metric for the allocation of policing resources has recently been challenged with the creation and implementation of several indices that purport to measure the severity of crime through the use of either actual, or guideline, sentencing data. However, the literature regarding these indices is still sparse, with the question as to whether severity offers any useful insight over and above crime volume remaining unanswered. This study aims to numerically and geospatially investigate the relationship between crime volume and two of these indices, the Cambridge Crime Harm Index (CHI) and the Office for National Statistics Severity Index (ONSI), with the intention of addressing the above question.

Detailed crime volume data for three financial years (2014/15, 2015/16 and 2016/17), totalling 157,579 crimes, were obtained from Derbyshire Constabulary and converted to a population normalised severity scale using both the CHI and ONSI. The data for both indices were aggregated to Lower Layer Super Output Areas (LSOAs) and subjected to both numerical and geospatial analysis, with bivariate linear least squares regression models being developed. For both the CHI and ONSI, there was found to be a strong positive linear relationship with crime volume, with little observed variability for LSOAs with either low or high crime volumes, suggesting that that there will always be the same proportion of severity within an area irrespective of the volume of crime experienced within that same area.

This study represents the first of its type within the published literature that examines the relationship between crime volume and crime severity at a geospatial scale smaller than that of entire police force areas. The discovery that crime volume and crime severity are linearly scaled fundamentally calls into question the benefits of adopting a severity based policing model over a more traditional crime volume based approach.

1 Introduction

The use of crime volume to determine the impact of crime upon the public has recently been called into question by several authors who note that all crime is not created equally (Ignatans and Pease 2016; Sherman, Neyroud and Neyroud 2016). It follows therefore, the impact of individual crime types upon the very same public must also be unequal. Despite this, crime volume is the primary metric utilised by the United Kingdom Home Office for measuring the performance of individual police forces within England and Wales, even though significant efforts to develop alternative, more robust, approaches have been attempted over the years that focus upon an attempt to measure the severity[1] of crime (Pease, Billingham and Earnshaw 1977; Pease et al. 1977; Pease 1988).

Recent work by Sherman, Neyroud and Neyroud (2016) on the Cambridge Crime Harm Index (hereafter CHI) and Bangs (2016) on the Office for National Statistics Severity Index (hereafter ONSI), indices that both purport to measure and reflect the severity of crimes, has resulted in significant interest in readdressing the shortcomings of crime volume as a metric for the impact of crime on the public. In fact, the use of these severity indices to inform the allocation of decreasing police resources has already begun by several police forces within the East Midlands Policing Collaboration Region (Travis and Dodd 2015; The Economist 2016) despite there not having being any form of evaluation (either from the public or through academia) of the validity of the use of these indices for such a purpose. Recent work by Ashby (2017) has critically examined and compared these severity indices, but the question still remains

[1] Harm and seriousness are referred to almost interchangeably within the literature despite the terms conveying different subjective meanings. For a more in-depth discussion of this issue please see Tanner (2017).

unanswered as to whether resource allocation informed by crime severity offers any benefit over that based upon more traditional crime volumes.

As noted by Curtis-Ham and Walton (2017a), the move towards a severity based policing model offers an opportunity to review how both crime and severity spatially interact, as the criminology of place is still poorly understood (Weisburd 2015). Recently, an emphasis on crime "hot spots" has permeated the literature (Braga, Papachristos, and Hureau 2014), although "harm spots" are garnering further interest (Weinborn et al. 2017); macroscopic[2] rather than microscopic geospatial studies of severity and the criminality of place were, up until recently, non-existent. In their recent ground-breaking paper, Curtis-Ham and Walton (2017a) addressed the shortage of this available research by publishing the first macroscopic geospatial analysis of crime severity using their newly developed New Zealand Crime Harm Index (Curtis-Ham and Walton 2017b), although they concentrated on determining whether their index was comparable with another metric (the New Zealand Priority Locations Index) rather than addressing the unanswered question concerning crime volumes noted above.

Given the that this problem is still unresolved, it is obvious that there is an opportunity for original research that addresses a macroscopic geospatial evaluation of the impact of the move towards a severity based policing model within the United Kingdom, with the aim of ultimately determining what value (if any) this method offers over a more traditional crime volume based approach.

The purpose of this study is therefore threefold. Firstly, crime data obtained from a single police force within England and Wales (Derbyshire Constabulary) will be transformed onto a severity scale (using both the CHI and ONSI indices) to determine

[2] Macroscopic here is taken to mean at geographies less than an individual police force area in size, but greater in size than street segments and intersections.

the numerical relationship between crime volume and crime severity. Secondly, geospatial analyses of the same data will be performed at a macroscopic level to determine the validity of any relationship between crime volume and crime severity discovered above. Finally, the findings of this study will be discussed in depth and opportunities for further research based upon these findings will be proposed.

2 Literature Review

As previously discussed, recent work by Sherman, Neyroud and Neyroud (2016) and Bangs (2016) has resulted in significant interest in readdressing the shortcomings of crime volumes as a metric for the impact of crime, favouring instead a severity based approach. Beccaria, in his seminal work of 1764 (Williams and McShane 2010), discussed the need to differentiate between crime types based upon severity in order to ensure the correct apportionment of punishment. It took almost two hundred years before the work of Sellin and Wolfgang (1964) created the first published crime severity index, with variations on this work developed over the following decades.

In 2005, Francis et al. created a crime severity index that used the actual sentence handed down by the courts as a metric for crime severity, suggesting that the punishment handed down by a nation state is directly proportional to the impact of crime upon the victim and the public at large. This methodology quickly gained traction with national statistics and criminal justice bodies such as Statistics Canada (Babyak et al. 2009), the United Kingdom Office for National Statistics (Bangs 2016), and the New Zealand Ministry of Justice (Sullivan, Su-Wuen, and McRae 2017), who each created their own severity indices based upon actual sentence data.

The development of crime severity indices was not however limited to national bodies. Ratcliffe (2015) suggested that the use of gravity scores (i.e. a guideline for the courts to determine the appropriate penalty for a guilty individual) would provide a robust and straightforward metric of severity, whilst Sherman, Neyroud and Neyroud (2016) argued for the use of sentencing guidelines, an approach later adopted by Curtis-Ham and Walton (2017b) for use within New Zealand.

The recent work by Ashby (2017) examined in depth both the ONSI (referred to by them as the CSS) and CHI, and found that significant differences existed between them. These differences were found to primarily relate to the variability in the severity scores between each of the indices, originating in the method chosen to determine those scores: actual sentence data for the ONSI and sentencing guidelines for the CHI. In addition, the resolution of each index was also deemed to be responsible for the noted variability, with the CHI using Home Office codes (739 in total), whereas the ONSI uses a smaller number of Home Office classes (259 in total). In general, the ONSI was found to produce higher severity scores with less resolution, suggesting that whatever method is chosen to determine severity, it will be limited by the underlying methods used for its production. This was clearly demonstrated when a comparison was made by them between the crime severity scores, from each of the indices, calculated for each police force area within England and Wales during the financial year 2015/16. With very few exceptions, the severity rank of each individual police force was different depending on whether the CHI or ONSI was adopted to perform the overall severity calculation. This led them to reach the conclusion that each method would have resulted in significantly different resource allocation if used for that purpose by police forces. In drawing their conclusions, the author remained silent as to which method should be adopted more broadly, although they did assert that resources should be targeted where they are needed most using a severity based approach.

Weinborn et al. (2017) took the work of Sherman, Neyroud and Neyroud (2016) and applied it to the geospatial theory of crime "hot spots" (Braga, Papachristos, and Hureau 2014), theorising that a greater emphasis should be placed on "harm spots" generated using crime severity indices. Weinborn et al. (2017) asserted that this approach would have the greatest impact on the wellbeing of the public (whilst simultaneously saving "…system costs…"), although they acknowledged that the geospatial distribution of crime severity is poorly understood when compared to crime volumes. In their study, the authors performed analyses across multiple council areas within the United Kingdom at the level of street segments (i.e. geospatially microscopic) to determine the level of geospatial clustering (or otherwise) of crime severity and crime volume. The conclusions of their study are interesting, as the authors find that crime severity has a geospatial concentration that is approximately three times greater than crime volume, with "harm spots" not necessarily being co-located with "hot spots"; this would suggest that the resources police forces would again be allocated to different areas depending on the metric adopted if used for such an approach.

Curtis-Ham and Walton (2017a) adopted a different approach to that of Weinborn et al. (2017) above, favouring a geospatially macroscopic study of crime severity using their New Zealand Crime Harm Index (Curtis-Ham and Walton 2017b). A geospatial analysis of crime severity was conducted for census units within New Zealand, similar to Lower Layer Super Output Areas (LSOAs) within the United Kingdom, with the intention of determining if there was any correlation (or lack thereof) between crime severity and the vulnerability of communities using another metric rather than crime volume (the New Zealand Priority Locations Index). The authors found that the vulnerability of a community, and the severity of crimes suffered therein, were not necessarily correlated as is widely accepted (see Breetzke and Pearson 2015 for an in-depth review), and that population size, deprivation, and rural/urban classification accounted to some extent for the geospatial variability observed in crime severity.

Despite the work of Weinborn et al. (2017) and Curtis-Ham and Walton (2017a) remaining silent as to the question of the correlation (or lack thereof) between crime severity and crime volume, these studies can be considered to be the state of the art in terms of a geospatial approach towards the analysis of crime severity, and represent the first published efforts towards the mapping of crime severity using geospatial information systems (GIS).

3 Methodology

3.1 Data Collation and Reduction

In order to determine if there is a numerical and/or geospatial relationship between crime volume and crime severity, crime data were sourced from Derbyshire Constabulary for the period of the financial years 2014/15, 2015/16, 2016/17[3]. The crime data contained all crimes recorded in these financial years (irrespective of whether the crime was committed in these years) and included details for each individual crime type by Home Office class and code, as well as the latitude/longitude of the crime location.

In total, data for 158,350 crimes were provided which required a quality assessment prior to any subsequent reduction and analyses being performed. It was noted that a significant number of crimes either had no location recorded, were from a date that was prior to the period covered by the three financial years above (i.e. historical crime reports), or did not possess a Home Office class or code. As such, these data were removed resulting in 157,759 crimes for subsequent reduction and analyses i.e. a

[3] Please see Appendix A for the decision by the Ethics Committee regarding this data access.

reduction of 591 crimes or approximately one third of one percent of the overall number of crimes originally sourced from Derbyshire Constabulary.

Severity data were sourced for the CHI (University of Cambridge Institute of Criminology 2017) and the ONSI (Bangs 2017) and combined into a severity reference file which was subsequently used to perform a cross reference for each of the 157,759 crimes (using either the Home Office class or code), allowing each crime to be assigned a severity from both of the indices. Once each crime had been assigned a severity from both of the indices, the data were imported into ESRI ArcGIS (ESRI 2016) and georeferenced (using latitude/longitude) creating a point based vector shapefile.

In order to ensure that privacy concerns regarding the location of individual victims and offences were addressed (Information Commissioner's Office 2014), and to allow for subsequent use of the data in future research (see Section 6 below), the data were aggregated to polygons representing LSOAs based upon the geographies used within the 2011 United Kingdom Census (Office for National Statistics 2017), with each crime being assigned a code representing the LSOA in which it was located. In total, 642 LSOAs were found to be present within the county boundary of Derbyshire, England.

This data was then analysed to determine the number of crimes for each of the individual Home Office classes or codes within each of the LSOAs using a pivot table. The severity for each crime type within each of the indices were then applied (i.e. by multiplying each severity value by the number of crimes for that severity value), with the results being summed to determine an overall severity score for each of the indices within each of the LSOAs.

Finally, population estimates for mid-2016 (i.e. the latest data at the time of publication of this study) were obtained for each of the LSOAs (Park 2017) and combined with the above data to provide a master reference file for further data analyses. The resultant master reference file contained the following data for each of the 642 LSOAs within the county boundary of Derbyshire: LSOA code, population estimate, total number of crimes, CHI severity, and ONSI severity.

3.2 Population Normalisation

LSOAs were designed to ensure that they represented a geospatial unit in which an approximately uniform population resided i.e. between 1,000 and 3,000 persons (Office for National Statistics 2017). For the 642 LSOAs within Derbyshire, the population ranged from 1,032 to 3,461 persons, meaning that a direct comparison between the number of crimes and the severity scores for each of the indices was not possible without normalising the data for variance of population. Typically, crime data is normalised to a rate of crimes per 1,000 persons (Santos 2017). As such the total number of crimes, CHI severity, and ONSI severity from the master reference file were normalised using the population estimate for each of the LSOAs, with the resultant data being recorded in the master reference file.

3.3 Data Transformation

In order to determine if there is a numerical and/or geospatial relationship between crime volume and crime severity, various statistical methods were utilised including bivariate linear least squares regression (numerical), and Global/Anselin Local Moran's I (geospatial); these techniques will be discussed in further detail in Section 4 below.

The above statistical methods assume that the data that is being analysed has been drawn from a population where the values of interest have a normal distribution i.e. the data themselves are normally distributed (Burt, Barber and Rigby 2009). The normality of the total number of crimes, CHI severity, and ONSI severity were tested using the JMP software package (SAS Institute Inc. 2016) and were all found to deviate from normality with a positive skewness. As such, a statistical transformation was performed to ensure the assumption of normality was met (Burt, Barber and Rigby 2009). The logarithm at base ten (hereafter Log_{10}) was obtained for each of the data, with the resultant values being recorded in the master reference file for subsequent analyses. It is worth noting that the transformed data showed no significant deviation from normality meaning the above statistical methods could be utilised with the certainty that any findings would be statistically robust.

4 Results

4.1 Numerical Analysis

The data for the ONSI and CHI contained in the master reference file (discussed in Section 3 above) were imported into the JMP software package (SAS Institute Inc. 2016) for further analyses.

Figure 1 below shows an XY-scatterplot of crime volume versus ONSI (transformed as discussed in Section 3.3 above) for each of the 642 LSOAs within the county boundary of Derbyshire during the financial years 2014/15, 2015/16, and 2016/17 normalised for population variance. On the XY-scatterplot is superimposed a bivariate linear regression model (solid dark blue line), with corresponding prediction interval (shaded blue area with $\alpha = 0.05$ being roughly equivalent to $\pm 2\sigma$), as well as a bivariate normal ellipse (red dashed line $P = 0.95$).

Crime volume and ONSI are highly positively correlated (0.91 $p < 0.0001$) with the bivariate linear regression model yielding a large coefficient of determination ($R^2 = 0.82$) thereby indicating a strong quality of fit with 82% of the variance in Log_{10} ONSI being explained by Log_{10} Crimes. This is confirmed by visual examination of the model, with particular attention being drawn to the prediction interval; the model explains the majority of the data with the exception of a small number of expected statistical outliers. In order to ensure the validity of the regression model, the homoscedasticity and normality of the residuals between the predicted and actual data were analysed using the same software package and found to be compatible with the requirements of the Gauss–Markov theorem (Schumacker 2014).

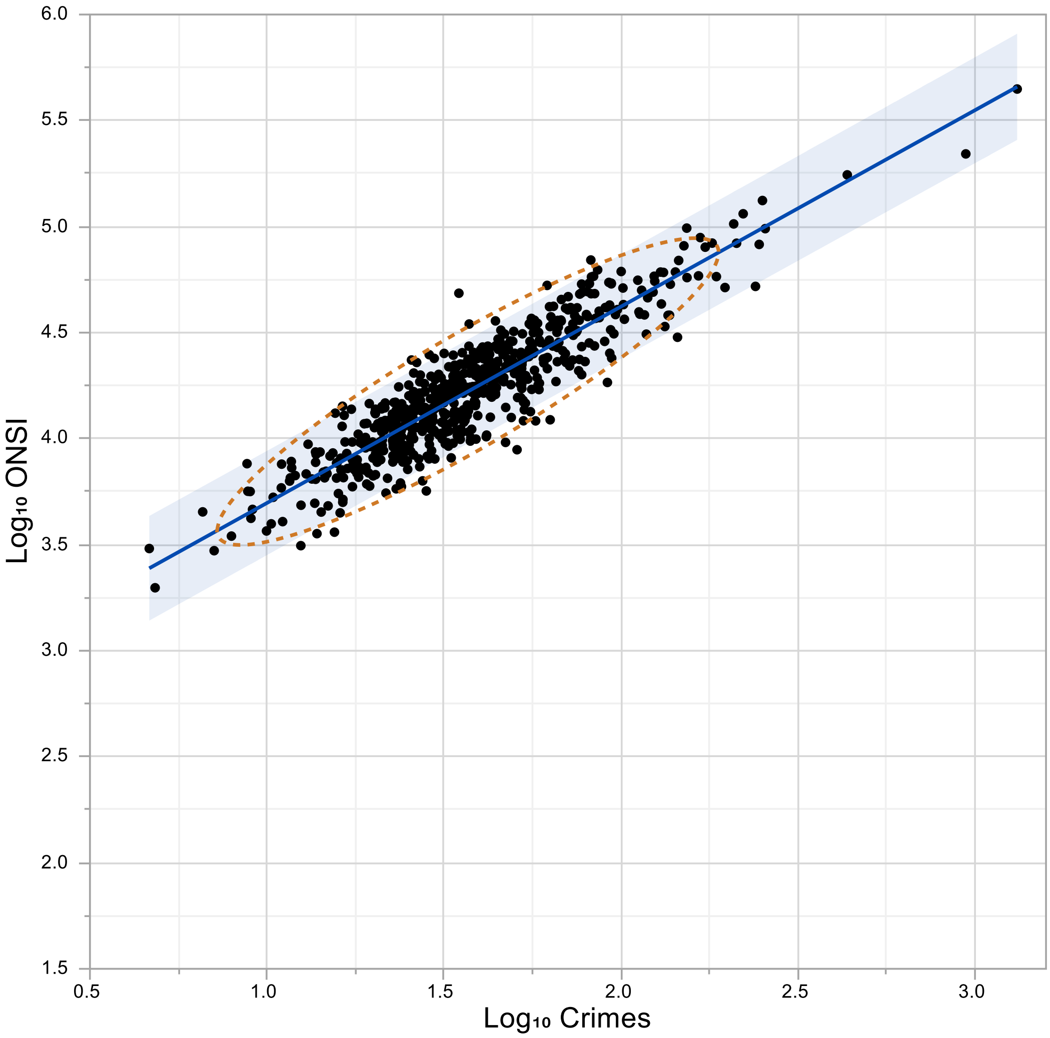

Figure 1: Log$_{10}$ Crimes versus Log$_{10}$ ONSI for each of the 642 LSOAs within the county boundary of Derbyshire during the financial years 2014/15, 2015/16, and 2016/17 normalised for population variance.

The bivariate linear regression model follows the specification shown in Equation 1 below. In this specification, β_1 is defined as being the elasticity of the model and provides a measure for the percentage change in ONSI for a defined percentage change in crime volume.[3][4] For the above model (Log_{10} Crimes versus Log_{10} ONSI,) the elasticity is found to be 0.93 with a standard error of 0.02, i.e. for every 1% increase in crime volume there is a corresponding increase in ONSI of 0.93%. Whilst this result in non-linear, it is only fractionally so, suggesting that for all values of crime volume within this study, the relationship with ONSI is practically linear.

$$\widehat{Log_{10}(Y_i)} = \beta_0 + \beta_1 \cdot Log_{10}X_i + \epsilon_i$$

Equation 1: Specification for the bivariate linear regression model between X_i (crime volume) and Y_i (either ONSI or CHI).

Figure 2 below shows an XY-scatterplot of crime volume versus CHI (transformed as discussed in Section 3.3 above) for each of the 642 LSOAs within the county boundary of Derbyshire during the financial years 2014/15, 2015/16, and 2016/17 normalised for population variance. The elements of the XY-scatterplot are the same as those contained within Figure 1 above. Crime volume and CHI are highly positively correlated (0.82 $p < 0.0001$) with the bivariate linear regression model yielding a moderate coefficient of determination ($R^2 = 0.67$) thereby indicating a reasonable quality of fit with 67% of the variance in Log_{10} CHI being explained by Log_{10} Crimes. This is confirmed by visual examination of the model, with low value outliers (i.e. low values of Log_{10} CHI for a given Log_{10} Crimes) being noted, but being expected due to the greater resolution of the CHI (Ashby 2017). Again, in order to ensure the validity of the regression model, the homoscedasticity and normality of the residuals between the predicted and actual data were analysed and found to be compatible with the requirements of the Gauss–Markov theorem (Schumacker 2014).

[4] The variables β_0 and ε_i are also defined within this specification but are not relevant to this analysis.

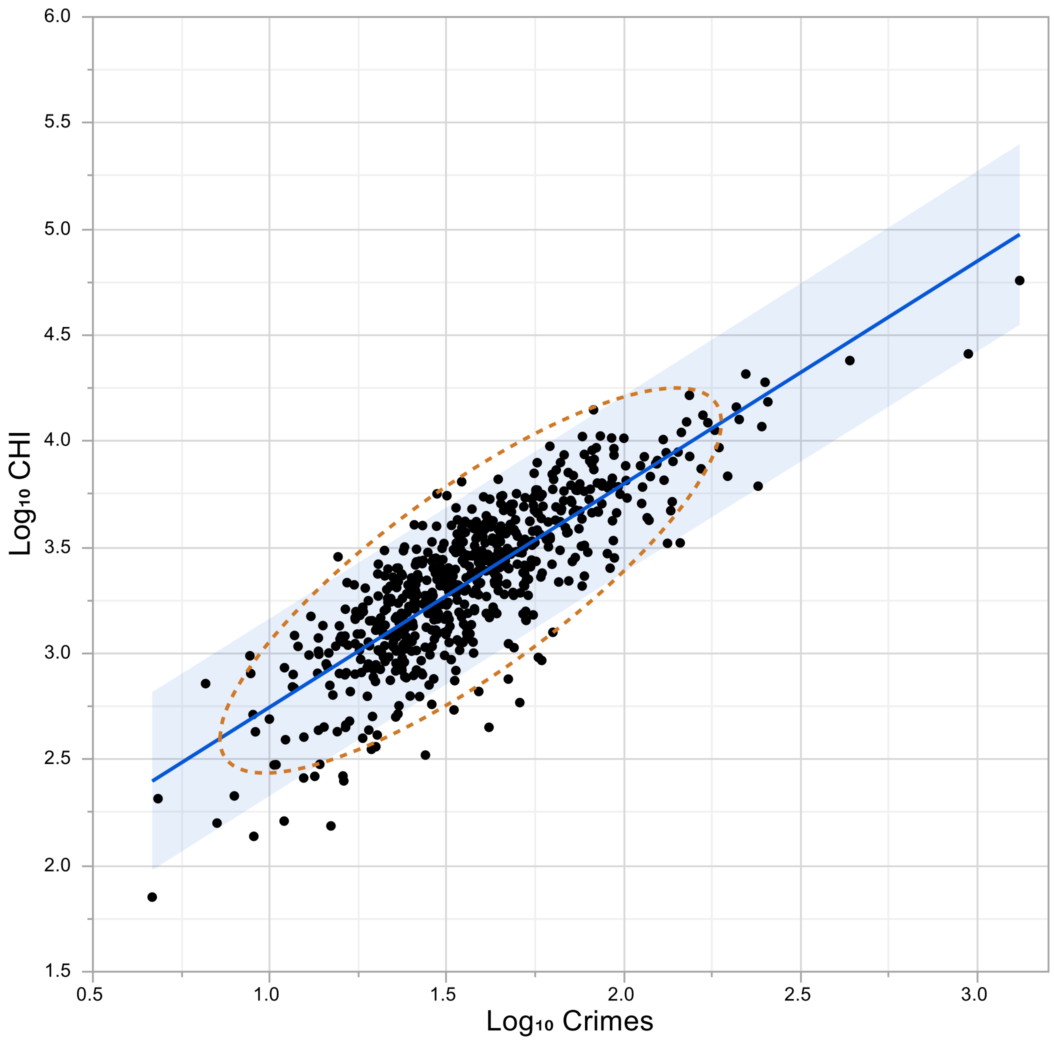

Figure 2: Log_{10} Crimes versus Log_{10} CHI for each of the 642 LSOAs within the county boundary of Derbyshire during the financial years 2014/15, 2015/16, and 2016/17 normalised for population variance.

The bivariate linear regression model again follows the specification shown in Equation 1 above. For the above model (Log_{10} Crimes versus Log_{10} CHI) the elasticity is found to be 1.05 with a standard error of 0.03, i.e. for every 1% increase in crime volume there is a corresponding increase in CHI of 1.05%. Whilst this result in non-linear, it is only fractionally so, suggesting that for all values of crime volume within this study, the relationship with CHI is practically linear, a result similar to that for the ONSI.

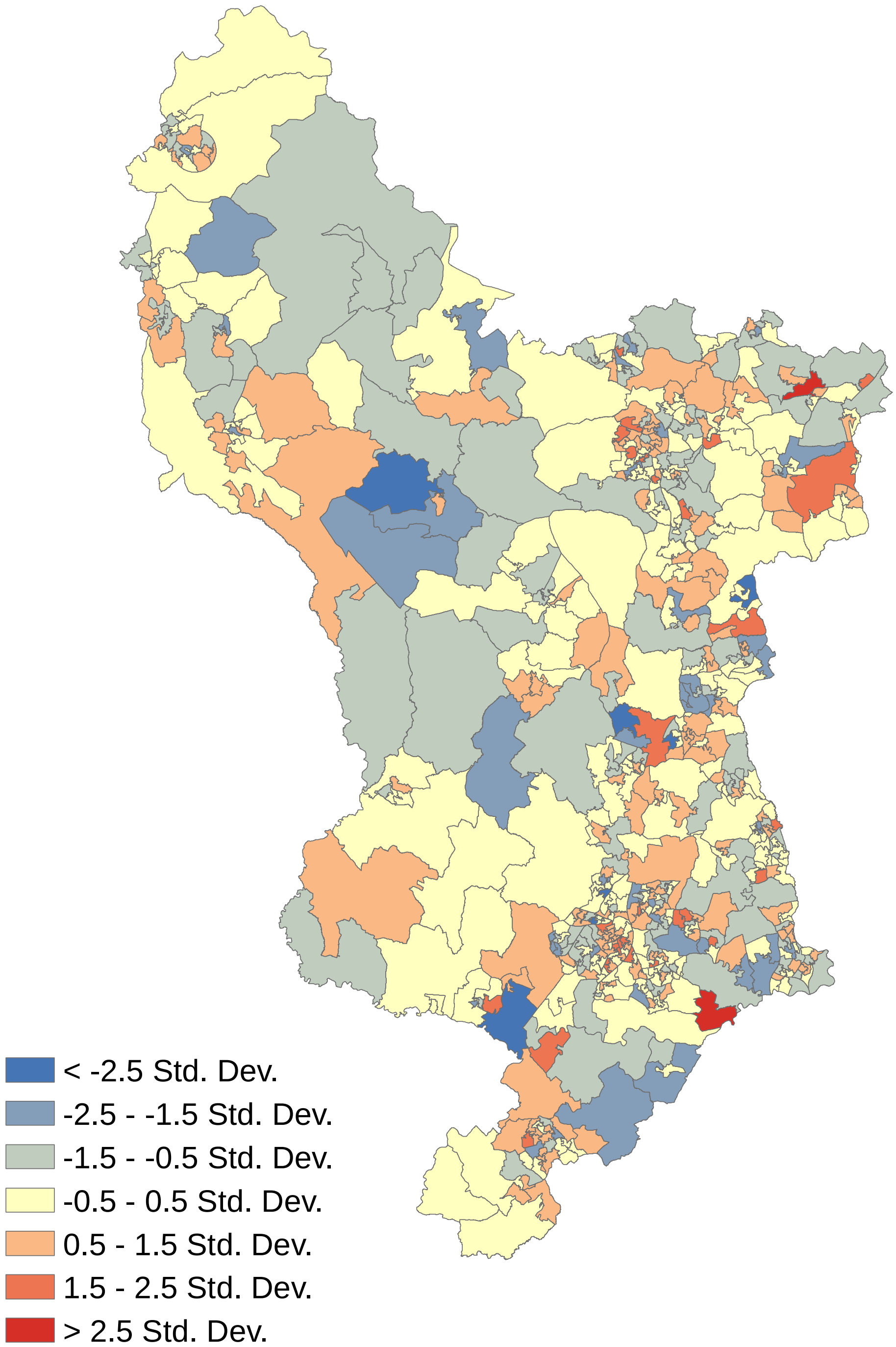

Figure 3: Choropleth map showing residuals (as standard deviations) from the bivariate linear regression model of Log_{10} Crimes versus Log_{10} ONSI for each of the 642 LSOAs within the county boundary of Derbyshire during the financial years 2014/15, 2015/16, and 2016/17 normalised for population variance.

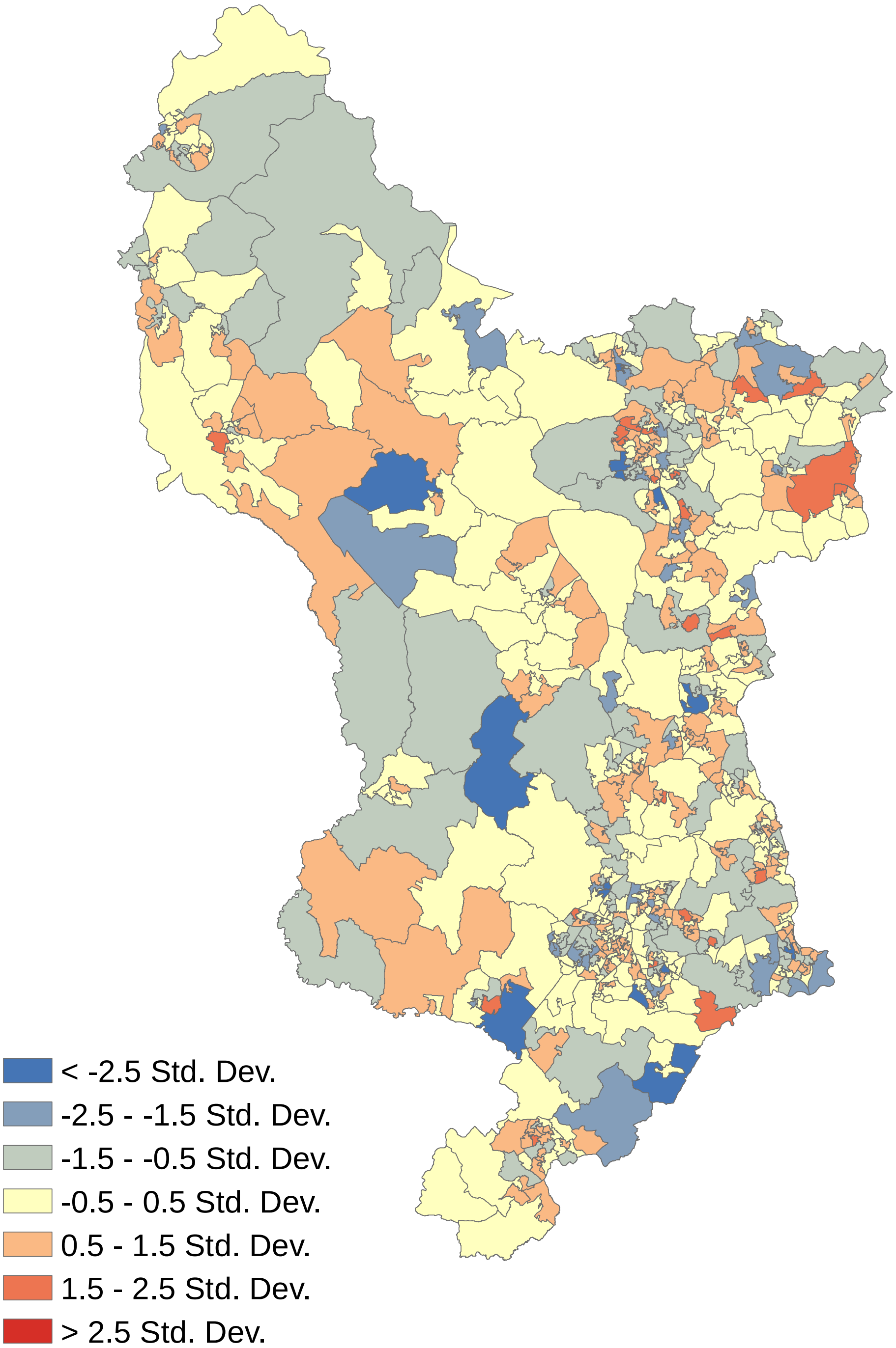

Figure 4: Choropleth map showing residuals (as standard deviations) from the bivariate regression model of Log_{10} Crimes versus Log_{10} CHI for each of the 642 LSOAs within the county boundary of Derbyshire during the financial years 2014/15, 2015/16, and 2016/17 normalised for population variance.

4.2 Geospatial Analysis

The data for the ONSI and CHI (discussed in Section 3 above) were imported into ESRI ArcGIS (ESRI 2016) and spatially joined with a vector shapefile containing polygons for the 642 LSOAs within the county boundary of Derbyshire, based upon the geographies used within the 2011 United Kingdom Census (Office for National Statistics 2017).

In order to investigate the above discovery that the relationship between crime volume and severity (using either using the CHI and ONSI severity indices) is practically linear, choropleth maps of the residuals (as standard deviations) from the bivariate linear regression model of Log_{10} Crimes versus Log_{10} ONSI (Figure 3 above) and Log_{10} Crimes versus Log_{10} CHI (Figure 4 above) were produced.

Whilst it is not immediately apparent from visual inspection that similarly valued residuals (as standard deviations) are clustered within each set of the data, it may be the case that spatial autocorrelation is present for both the Log_{10} Crimes versus Log_{10} ONSI and Log_{10} Crimes versus Log_{10} CHI model residuals. Spatial autocorrelation follows from Tobler's first law of geography which states "…everything is related to everything else, but near things are more related than distant things…" (Tobler 1970). It is generally accepted that a small degree of positive spatial autocorrelation will be present in the analysis of crime data as crime in one area will tend to diffuse into another (Andresen 2011). However, in order to be compatible with the requirements of the Gauss–Markov theorem (Schumacker 2014), the residuals between the predicted and actual data must be independent of each other. If significant spatial autocorrelation is present in the residuals, then any linear regression model (bivariate or otherwise) may be biased, which could lead to incorrect conclusions being drawn (Haining 1991).

In order to test for spatial autocorrelation, a Global Moran's I value (Cliff and Ord 1973) was calculated using ESRI ArcGIS (ESRI 2016) for both sets of residuals implementing *row standardisation* and *contiguity edges corners* to conceptualise the spatial relationships of the LSOAs. For the Log_{10} ONSI model residuals, the Global Moran's I value was found to be 0.09 ($Z = 4.03$ $p < 0.0001$) which, whilst statistically significant, is only fractionally greater than zero. For the Log_{10} CHI model residuals the Global Moran's I value was found to be 0.12 ($Z = 5.32$ $p < 0.0001$) which, again, is only fractionally greater than zero but a statistically significant result nonetheless. Given that the Global Moran's I value ranges from -1 (dispersed), through 0 (random), to +1 (clustered), it is apparent from these results that the level of spatial autocorrelation observed is consistent with that expected for the analysis of crime data i.e. positive but close to zero (random).

The lack of clustering of the residuals was further investigated using the Local Moran's I method (Anselin 1995) within ESRI ArcGIS (ESRI 2016) for both sets of residuals implementing *row standardisation* and *contiguity edges corners* to conceptualise the spatial relationships of the LSOAs, and a *false discovery rate* (499 permutations) to account for multiple testing and spatial dependency. No statistically significant clusters were found for either set of residuals, further confirming that spatial autocorrelation was of a level that would be insufficient to cause biases to be present within either of the bivariate linear regression models.

5 Discussion

The results from Section 4 above are surprising, as it would appear that there is a strong positive linear relationship between crime volume and crime severity for both the ONSI and CHI indices. Whilst there is some variability observed between adopting a crime volume or crime severity approach (as represented by the spread in the data observed in Figure 1 and Figure 2 above), this does not represent meaningful variability in the data i.e. the rank of an individual LSOA may change when using a crime volume or crime severity approach, but not in any statistically significant way. As such, one is drawn to the inevitable conclusion that there is no benefit to adopting a crime severity based model; crime volume provides an equivalent result that is considerably less complicated to calculate. Given that the ONSI and CHI indices are non-linear by design (Ashby 2017), and that they were both formulated on the assertion that all crime is not created equally (Ignatans and Pease 2016; Sherman, Neyroud and Neyroud 2016), an explanation as to this discovery should be sought.

A common issue when dealing with data that has been aggregated from point sources into polygons (areals) is the so-called modifiable areal unit problem (Fotheringham and Wong 1991). As data can be aggregated to differing spatial scales, and to within differing boundaries, the impact of this aggregation has a profound impact upon the detection of subtle differences in the variables under study; the effects of a spatial study are smoothed with increasing areal unit size. It is therefore inevitable that the modifiable areal unit problem will have impacted upon this study, but the need to ensure privacy (see Section 3.1 above) means that the use of spatially smaller census areas is not possible. Regardless of this, the areas normally used by the police for the allocation of resources are either comparable to, or larger than, the 642 LSOAs used within this study, rendering the limitations imposed by the modifiable areal unit problem meaningless in a practical sense.

Finally, another possible issue worth noting is the use of three years of combined data taken from a single county police force. It cannot be ruled out by this study alone that the use of data from a single source and/or the combination of three years of data did not yield the above discovery. However, national crime data (Flatley 2018) suggests that Derbyshire as a county does not possess an unusual crime profile, and that this has remained fairly consistent over the three years in question, leading to the conclusion that the above discovery is not geographically unique or an analytical anomaly.

6 Proposed Future Research

From the discussion in Section 5 above it is clear that there is considerable scope for additional research to determine whether the discovery that the use of severity indices to inform the allocation of ever dwindling police resources truly offers no benefit over an approach based upon more traditional crime volumes.

As such, it is proposed that a further study is conducted that addresses the following questions. Firstly, what impact would the analysis of crime data from another police force (or forces) have upon the numerical and geospatial relationship between crime volume and crime severity; would it also be linear as discovered here? Secondly, if the relationship is determined to be non-linear, what particular set of circumstances led to the results for the county of Derbyshire being linear?

The author of this study has already secured crime data for the period of the financial years 2014/15, 2015/16, 2016/17 for the South Yorkshire policing area. As such, the first question posed above could be answered quickly using the already well established workflows as discussed in Section 3 above; subsequently, it would also be determined if the second question was relevant or not. If it was determined to be relevant, then further consideration would need to be given as to whether the differences observed between police forces is due to socio-environmental factors. Curtis-Ham and Walton (2017a) went some way towards looking at these factors when they compared their newly developed New Zealand Crime Harm Index (Curtis-Ham and Walton 2017b) against another metric (the New Zealand Priority Locations Index), discovering that their bivariate linear regression model was improved by changing the specification to a multivariate model with deprivation and land use included. Again, the author of this study has secured deprivation data for the United Kingdom in the form of the English Indices of Deprivation (Ministry of Housing, Communities & Local Government 2015) and land use data in the form of CORINE (Rae 2017), and as such this analysis could be conducted quickly for the ONSI and CHI. It is worth noting that the Derbyshire and the South Yorkshire policing areas are markedly different in terms of socio-environmental factors. For example, Derbyshire is predominantly rural with only one city (Derby) and approximately one third of the entire county within a national park (The Peak District), whilst South Yorkshire is an expansive urban conurbation with four cities (Barnsley, Doncaster, Rotherham and Sheffield) and relatively little settled land within the same national park. In light of this, it would certainly be a surprising result to find that any relationship between crime volume and crime severity is not in some way impacted upon by deprivation and land use.

This proposed study would represent a significant increase in our knowledge of the impact of implementing a severity based policing model, and would finally answer the question: What is the numerical and geospatial relationship between crime volume and crime severity?

7 Conclusion

The purpose of this study was to address the unanswered question as to how crime volume and crime severity (using the newly developed ONSI and CHI severity indices) are related, and if a severity based policing model offers any benefits over that of one based upon a more traditional crime volume based approach. It is the first study of this type in the published literature to address this question, despite the fact that a severity based approach is already being used to inform the allocation of ever decreasing police resources by several police forces within the East Midlands Policing Collaboration Region.

Crime volume and crime severity have been shown to scale linearly, such that there will always be the same proportion of severity within an area (LSOA for this study) irrespective of the volume of crime experienced within that same area. The bivariate linear regression models, developed using numerical and geospatial analysis techniques, are so well specified that there is little room to doubt their validity. As such, the findings of this study fundamentally call into question the benefits of adopting a severity based policing model over a more traditional crime volume based approach, and also challenge the assertion, originally made over two hundred years ago by Cesare Beccaria, that crime should be differentiated on the basis of severity.

Word count: 5,035

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Appendix A – Notification of Ethics Committee Decision

NOTTINGHAM TRENT UNIVERSITY

College of Business Law and Social Sciences
School of Social Sciences

School of Social Sciences Research Ethics Committee (SREC)

Notification of Decision

Student's Name	John Tanner
Supervisor's Name	J Hunter
NTU ID	N0759823
Course	PG Cert Policing
Date of SREC meeting	23/11/17
Date Notification sent to student	30/11/17

At the Social Sciences Research Ethics Committee meeting the following decision was made in respect of your application for Ethical Approval of a Research Project:

Approved - you may commence your research as outlined in your application

If at any stage of the application process it has been decided that your project requires a **Disclosure and Barring Service Check** (DBS Check) or an Overseas Police Check you may **not** commence research until this check has been completed and considered as satisfactory. Please note a DBS check might not be listed as an additional condition/recommendation identified by SREC as we might be satisfied that your Project Supervisor has already identified this as a requirement on your application form.

If you need to enter an ethical approval code for the research participation scheme, then use the date of this notification as that code.

If you have any queries please do not hesitate to contact your project supervisor or alternatively e-mail SOC.ethics@ntu.ac.uk.

Further information and guidance can be found on the ethics module (XXSOC10002) on NOW.

School Research Ethics Committee