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Buil-Gil, D, Brunton-Smith, I, Pina Sanchez, J orcid.org/0000-0002-9416-6022 et al. (1 more author) (2022) Comparing measurements of violent crime in local communities: a case study in Islington, London. Police Practice and Research, 23 (4). pp. 489-506. ISSN 1561-4263

https://doi.org/10.1080/15614263.2022.2047047

Comparing Measurements of Violent Crime in Local Communities: A Case Study in Islington, London

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Funding details

This work is supported by the Secondary Data Analysis Initiative of the Economic and Social Research Council (Grant Ref: ES/T015667/1).

Abstract

Police-recorded crime data are prone to measurement error, affecting our understanding of the nature of crime. Research has responded to this problem using data from surveys and emergency services. These data sources are not error-free, and data from different sources are not always easily comparable. This study compares violent crime data recorded by police, ambulance services, two surveys and computer simulations in Islington, London. Different data sources show remarkably different results. However, crime estimates become more similar, but still show different distributions, when crime rates are calculated using workday population as the denominator and log-transformed. Normalising crime rates by workday population controls for the fact that some data sources reflect offences' location while others refer to victims' residence, and log-transforming rates mitigates the biasing effect associated with some multiplicative forms of measurement error. Comparing multiple data sources allows for more accurate descriptions of the prevalence and distribution of crime.

Keywords

Police data; Crime surveys; Crime mapping; Measurement error; Official statistics

Introduction

Crime data recorded from various sources are widely used for a range of purposes. Police forces use data about calls for police services and police-recorded offences to identify geographic areas with high crime rates and design targeted policing strategies (Herchenrader and Myhill-Jones, 2015; Weisburd and Lum, 2005). Policymakers use estimates of crime obtained from victim surveys and police records to evaluate the impact of crime prevention policies and other legal and socio-economic changes (Langton et al., 2017; Office for National Statistics, 2021). Economic actors rely on open data platforms that share police records to estimate housing prices or determine insurance premiums (Tita et al., 2006). And researchers use all these data sources to develop and evaluate theories of crime (Tilley and Tseloni, 2016). These are just some examples of the uses of crime data, with the variety of applications of crime statistics likely much wider.

Police-recorded crime statistics and victim surveys, such as the National Crime Victimization Survey and the Crime Survey for England and Wales (CSEW), remain the main sources of crime data, but the growing need for information about crime has led to an increasing number of data sources about offending and victimisation. These include calls for police services, probation statistics, incidents recorded by health emergency services, social media data and self-report crime surveys (Hibdon et al., 2021; Koziarski et al., 2022; Sutherland et al., 2021; Williams et al., 2017). Researchers have even begun to simulate crime data, highlighting potential future crime hotspots (Mohler et al., 2011) and exploring the dynamics of crime risk at small spatial scales (Buil-Gil et al., 2021). All these data sources are used to obtain information about crime, but they measure slightly different phenomena and some of them capture crime incidence more successfully than others. For example, whilst some data sources allow analysis into the individual risk of victimisation (e.g., victim surveys), others capture information useful to assess offending risk (e.g., self-report surveys, probation and court data), and some of them provide spatial information which is used to analyse the geographic concentration of crime as well as the activities of the police (e.g., police-recorded crime, calls for police services).

Moreover, some data sources are more adequate than others to study certain crime types. While police-recorded crime statistics, ambulance data and death registry data can be used to study homicides, violence resulting in death cannot be measured using survey data. By contrast, surveys offer valuable information about highly underreported crimes such as theft, hate crime or harassment. So-called 'victimless' crimes, such as drug crime and tax fraud, cannot be adequately probed in victim surveys, but self-report offending surveys offer valuable information about them (Thornberry and Krohn, 2000). The epistemological value of each crime data source is different: while all of them record information about crime, different sources reflect different conceptualisations of crime.

Aside from this, some sources of crime statistics are more useful than others to estimate the total volume of crime in society. Police-recorded crimes, for instance, capture more offences than crimes prosecuted and sentenced, thus being closer to the 'dark figure of crime' (i.e., all crimes that remain hidden from statistics; Skogan, 1977). Police records, however, are affected by measurement error associated with victims' reporting and police forces' recording inconsistencies. By focusing on the experiences of victims of crime, victim surveys can be used to obtain estimates of crimes known and unknown to the police (Buil-Gil et al., 2021), but these are affected by error arising from sampling biases and small samples in geographic areas (Rosenbaum and Lavrakas, 1995). Victim surveys also pick up a range of incidents that, whilst meeting official definitions of criminal activity, would typically be dealt with informally by the police rather than officially recorded.

Different data sources not only reflect different conceptualisations of crime, but they are also affected by different types of measurement error, which can affect our understanding of the prevalence and distribution of crime, and its causes and consequences. For instance, the relationship of crime with certain socioeconomic variables, such as inequality, perceived disorder and gun ownership, may be severely biased by the presence of measurement error in crime records (Gibson and Kim, 2008; Levitt, 1998; Martin and Legault, 2005; Pepper et al., 2010; Pina-Sánchez et al., 2021). Sutherland et al. (2013) observed that the relationship between *collective efficacy* (i.e., shared values and shared propensities for action against crime; Sampson et al., 1997) and crime may vary depending on the crime data source used. Neither of these points is always recognised by crime data users, but it can severely affect our understanding of crime and the design and evaluation of crime prevention strategies used by police forces and other actors (Brantingham, 2017; Taylor and Gassner, 2010).

However, the increasing availability of crime data sources also creates new opportunities for comparing and combining crime estimates obtained from different sources, thus allowing researchers and practitioners to explore their measurement properties and shed light on their pros and cons. With the purpose of assessing the extent to which multiple data sources provide complementary information about crime in local communities and its geographical patterning, this study compares five sources of violent crime data in Islington, London. Data from two local surveys, police statistics, ambulance registers, and synthetic crime estimates generated from computer simulations are used to obtain alternative estimates of crime rates in geographic areas. We examine the consistency of descriptive statistics and results from bivariate analyses across these data sources. Since previous research has found that the accuracy of crime rates is not only dependent on the data source used, but also the way crime rates are calculated, in terms of the denominator used (Malleson and Andresen, 2015) and whether these are log-transformed or not (Pina-Sánchez et al., 2021), we also assess if the way in which we calculate crime rates affects the consistency of results across data sources. The aim of this paper is thus two-fold: examine the comparability and consistency of violent crime rates computed from different sources, and assess if the way we calculate crime rates affects this comparability and consistency.

Literature Review

Researchers have criticised the lack of reliability of official crime statistics since the early nineteenth century. A few years after the publication of the first judiciary statistics in France, which recorded data of persons sentenced at the regional level, de Candolle (1987 [1830]) argued that these records were affected by several factors external to crime which could vary in space and time: victims may be unaware of crime or may not report it, the police may fail to identify or arrest the offender, and the court may fail to convict the person arrested. For these reasons, the number of crimes known to the police is argued to be a better indicator of crime incidence than the number of persons accused or convicted, since the former is closer to the crime event in terms of legal procedure. This is the rationale of "Sellin's dictum", which argues that "the value of a crime rate for index purposes decreases as the distance from the crime itself in terms of procedure increases" (Sellin, 1931: 346). This is also known as the 'funnel' of crime statistics, visualised in Figure 1, which assumes that there is a ‘true’ score of crime and illustrates how the number of crimes recorded decreases with the stages of the criminal justice system.

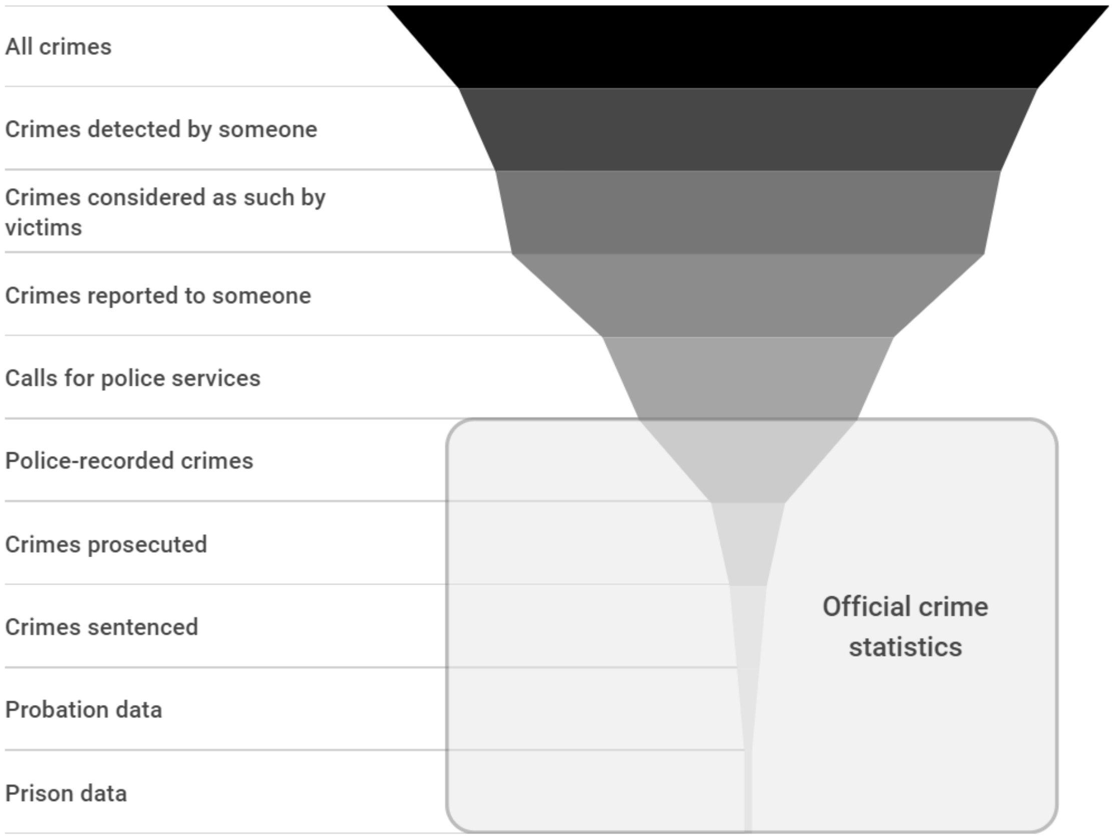


Figure 1. *The ‘funnel’ of crime data.*

However, while police-recorded incidents and calls for police services are closer in distance to the criminal incident than any other source of official statistics, they are also affected by inconsistencies in crime reporting and recording (Skogan, 1977). Crime reporting rates vary across demographic groups, crime types and geographic areas (Hart and Rennison, 2003; Xie and Baumer, 2019). Moreover, the rules and practices followed by the police to count crimes vary across countries (Aebi, 2010) and police forces (UK Statistics Authority, 2014). There is also evidence of deliberate manipulation of crime data by some police forces and government agencies (Eterno et al., 2016; Mosher et al., 2011). Thus, crime prevention efforts based solely on police-recorded crime data, for example to identify hot spots of crime and design targeted policing strategies, may fail to accurately identify crime levels in areas with particularly low crime reporting rates, where police officers do not engage with crime recording practices, or where crime records have been lost or deliberately manipulated. In the UK, after a public inspection of the factors affecting the 'integrity' of police records, UK Statistics Authority (2014: 2) concluded that "there is accumulating evidence that suggests the underlying data on crimes recorded by the police may not be reliable". Consequently, crime statistics were removed from the official designation of National Statistics. Since crime data known to public authorities are thought to be severely affected by measurement error, a growing number of alternative data sources are used to estimate crime and applied in research and practice.

The main alternative source of crime data is victim surveys. This data records information from samples of respondents who inform about their experiences with crime, both reported and unreported to the police. This has the benefit of being unaffected by differential recording practices across police forces, whilst also providing insight into those crimes that do not reach the attention of the police or are not deemed serious enough to be recorded. However, whilst unaffected by recording practices, estimates of crime obtained from surveys may be affected by measurement error arising from interviewer effects, sampling error and non-response bias, memory failures, question wording, and social desirability bias (Brunton-Smith et al., 2020; Schneider, 1981). Moreover, crime surveys tend to have limited sample sizes at the level of small areas (Rosenbaum and Lavrakas, 1995), and Cernat et al. (2021) highlight that most crime surveys do not record information about places where crimes happen ('area offence'), but only about places where victims live ('area victimisation'). This means they are less suited to explore the geographical distribution of crime, which complicates their comparability with crime estimates from other sources and their use to identify places that concentrate high density of crimes.

Other sources of crime data have also gained traction during the last twenty years. Two examples are calls for police services data – which may also be affected by residents' willingness to cooperate with the police, mental health-related calls, and police officers' counting practices (Klinger and Bridges, 1997; Koziarski et al., 2022), and emergency medical services data – which typically show different spatial and temporal patterns to police records (Hibdon et al., 2017, 2021; Sutherland et al., 2021). Health emergency services data only capture crimes that result in physical injuries or health damages, and as such only represent a minority of offences. Crowdsourced and social media data are also used to obtain information about crime, but these are affected by biases associated with the use of non-probability samples (Solymosi and Bowers, 2018). Researchers are also developing new approaches to generate synthetic datasets of crime which simulate real-world parameters and aim to overcome some of the limitations of more traditional sources of crime data (Akpinar et al., 2021; Buil-Gil et al., 2021).

With the growing availability of crime data sources, researchers and practitioners are increasingly comparing multiple sources with two main aims: to better understand the measurement properties of each data source, and to calculate more accurate estimates of crime in geographic areas. Bottoms et al. (1987) collated official police records, victim surveys and self-report surveys in seven neighbourhoods in Sheffield, England, and concluded that while different datasets found similar patterns across areas with similar housing styles, police data underestimated crime in high-rise housing areas. Aebi et al. (2002) compared data recorded by the International Crime Victim Survey, the European Sourcebook of Crime and Criminal Justice Statistics and Interpol Statistics at the national level in Europe, concluding that while unchecked police data should not be used for comparative cross-national studies, screening the recording rules followed in each place allows for adjustments to make survey and police statistics more similar. Hibdon et al. (2017) compared calls for emergency medical services and police services in Seattle, observing some dissimilarities with regard to places with high concentrations of emergency calls, as well as some changes over time. Messner (1984) compared police records and survey estimates in twenty-six US cities and concluded that while correlations between them showed very dissimilar patterns, the two datasets could be equated by including homicides in the study and applying differential weights to particular crime types. Comparisons of survey and police-recorded crime data have also been conducted in France (Aubusson de Cavarlay, 2009), Germany (Obergfell-Fuchs, 2009), Netherlands (Wittebrood and Junger, 2002), Switzerland (Haymoz et al., 2009) and other countries. Other researchers have analysed the divergence between temporal trends calculated from crime surveys or police records (Enzmann and Podana, 2010; Lynch and Addington, 2006).

It is key to note, however, that differences observed across crime data sources will not be solely due to measurement errors. How crime is conceptualised is also central, with different sources of crime data actually measuring distinct, but related, phenomena. For instance, police statistics record crimes that happen in an area, while estimates of crime obtained from surveys show crimes in places where victims live, thus systematically underestimating crime in places with a low residential population and a large 'ambient' population (Cernat et al., 2021). The crimes captured by the two sources may also be different, with many of the incidents identified in a victim survey unlikely to be reported to the police (perhaps because they are not deemed serious enough, or because of public distrust or fear of reprisals) and many of those incidents reported to the police not ultimately recorded (if they are less serious or details are ambiguous). Similarly, while the number of arrests in an area may vary depending on crime levels, these are also affected by police activity (Decker and Kohfeld, 1985). And ambulance data only capture instances in which someone was injured or physically affected (e.g., violence, drug overdose), not serving as a measure of 'all' crimes (Hibdon et al., 2017; Sutherland et al., 2021).

Moreover, researchers have shown that the way in which we calculate crime rates also affects the accuracy of descriptive and inferential results obtained from them. Malleson and Andresen (2015) highlight that crime rates computed from police records are sensitive to the denominator used, with some areas that are identified as 'crime hot spots' when using residential population as the denominator no longer being flagged when data about the number of people who spend their day in the area is used. More specifically, Malleson and Andresen (2016) argue that the workday population (i.e., the number of people who either work or live in an area) is the most suitable measure of 'population at risk' to be used to calculate crime rates. Although this may depend, in part, on the type of crime being examined, with resident population more conceptually relevant when household property crime rates are considered. Other researchers argue that static measures of population-at-risk fail to capture the ebb and flow of people and its impact on violent crime, and these should consider temporal variations in routine activities (Haleem et al., 2021). The impact of measurement error can also be affected by the way that crime is calculated, with Pina-Sánchez et al. (2021) showing that the biasing effect of measurement error in police records on some regression models can be mitigated by log-transforming crime rates.

While this body of research provides valuable information about the measurement properties of crime data and the comparability of different data sources, there are still some important gaps that this article will address. First, research aimed at comparing multiple crime data sources is often conducted at very large geographic scales, such as countries or regions/states. It is not yet known how choosing one data source instead of another may impact our understanding of crime patterns in local areas. Second, no research has yet analysed the effect of using different denominators and log-transformations on the comparability of crime rates obtained from different sources. This study expands research in this field by including the largest number of datasets ever explored in a study of this kind.

Gaining a better understanding of the measurement properties of crime data obtained from different sources, as well as approaches to mitigate the effect of measurement error on statistical analyses and to compare and combine multiple data sources, is not only crucial to advance our explanations of crime, but perhaps more importantly, it is key to accurately identify high crime areas where targeted policing approaches may be applied for crime prevention (Brantingham, 2017; Hutt et al., 2018).

In our study, we compare five data sources in sixteen wards in Islington, London. We examine if different sources of crime data show similar geographic crime patterns. The focus on Islington is due to the unique availability of a variety of data sources, made possible as a result of the historical focus placed in this borough by British criminological research. One of the first local crime surveys was conducted in Islington in the mid-80s and many researchers have analysed crime and policing in this borough (Crawford et al., 1990; MacLean, 1993; Matthews et al., 2016). Islington is one of the 32 boroughs of London. It is situated in Inner London and surrounded by Camden, Haringey, Hackney and the City of London. Since the 90s, several researchers have found particularly high levels of street crime in one of Islington's wards, Finsbury Park, which is defined by larger indices of deprivation than the rest of Islington (Harper et al., 1995; Mooney, 1992).

Data and Methods

We compare five sources of violent crime data: police-recorded crime data, ambulance call out data, victimisation data from the Metropolitan Police Public Attitudes Survey (METPAS), victimisation data from the Islington Crime Survey (ICS), and synthetic crime data derived from the CSEW and 2011 Census. Some of the data sources also record information about other crime types, and at smaller spatial scales and for other years, but violent crimes aggregated in wards represent the only crime type and area level shared by all five data sources. Whilst all these data sources are intended to capture variations in levels of violent crime, there are conceptual differences in the crimes that they measure. There are also differences in the incidents that fall within their definition of violence.

a) *Police data:* Police-recorded crime data provide a direct measure of police activity[1]. For an incident to be recorded, the police must be notified, define the incident as a crime, and then record it in the official record. Police statistics were downloaded from the police open crime data portal (https://data.police.uk/). As discussed by Tompson et al. (2015), data available from this portal is not accurate at the level of output areas (small areas with an average of 310 residents) due to the geomasking process applied by data administrators to protect location privacy. However, this data can be used at larger scales such as MSOAs (on average, 8,288 residents) and wards (in Islington, on average, 10,831 residents in 2011). Incidents recorded by the police cover assault with injury, common assault, murder, offensive weapon, wounding, other violence, robbery, rape, harassment and other sexual offences.

b) *Ambulance data:* The London Ambulance Service publishes data about violence-related ambulance dispatches, which can be related to knife, gun or weapon attacks, sexual injuries or other injuries due to violence. These represent the most serious forms of violent crimes experienced by individuals. This data refers to places where ambulance services were dispatched, which may vary from the offence location if the victim moved before contacting ambulance services. We do not have further information about the number of cases in which the offence location and the pickup point varied. The Greater London Authority's Ward Atlas (https://data.london.gov.uk/dataset/ward-profiles-and-atlas) publishes violence data aggregated at the ward level since 2006.

c) *METPAS:* While this survey is primarily designed to record information on attitudes and perceptions about the police, it also includes information about victimisation: "Have you been a victim of crime or antisocial behaviour in the last 12 months?". Those who report having

[1] We also requested access to data about calls for police services to the Metropolitan Police Service, but our request was not approved due to privacy considerations of data aggregated to low-level geographies.

suffered a crime, are then asked whether the most recent incident happened in the local area or elsewhere, and the type of incident (e.g., property crime, violent crime, hate crime, harassment, fraud). As such, it captures all incidents that an individual defines as criminal, whether or not they were reported to the police. However, respondents can only report a maximum of one incident. For comparative purposes, we only consider incidents that happened in the local area and were defined as either "violent crime (physical attacks which could include being punched, kicked, pushed or something worse)" or "harassment". In total, each year around 12,800 interviews are conducted with at least 100 respondents in each of the 32 London boroughs (Mayor's Office for Policing and Crime, 2019). In order to increase the effective sample size in Islington, we merge data from the 2015, 2016 and 2017 rounds, calculating the weighted mean of crimes in each ward times the population count in the area[2].

d) *ICS:* The ICS is also a victim survey based on a sample of 2,025 Islington residents contacted between April and June 2016. However, unlike the METPAS, the main objective of the ICS was to gain understanding of victimisation patterns in this borough, and as such the survey oversampled respondents who had suffered *at least* one crime in the last year. A quota-controlled sampling approach was used to select a purposive sample of 1,501 victims and 524 non-victims (Matthews, 2018). To qualify as 'victims', respondents were asked a series of questions about their experiences of victimization in the last year in a screener interview before completing the survey, and those who reported at least one incident were invited to complete the full questionnaire. No additional sample controls were used in the sampling design. All invited participants were asked "Have you been a victim of any of the following crimes over the past twelve months? Please indicate how many times this has happened" for a series of crime types, including burglary, violence, theft, vehicle crime, damage, sexual assault, hate crime, fraud and online crime. We focus on those who suffered either "violence or threats of

[2] Survey weights were calculated by METPAS administrators to compensate for unequal selection probabilities across London boroughs and people living in households, to compensate for differential response rates across boroughs, property types and household members, and to ensure quarterly samples are equally weighted (Mayor's Office for Policing and Crime, 2019). The characteristics of the weighted sample are representative of that of the target population, but weights do not adjust sample sizes to population totals.

violence, including violence when something was stolen" or "sexual assault or harassment". We obtain estimates of crime in each ward by calculating the weighted mean of crimes times the population count[3].

e) *Synthetic crime data:* We generate synthetic violent crime data – covering violence or sexual assault, wounding due to violence, and robbery in the local area – by mapping information from the CSEW (specifically the multivariate distributions of a set of socio-demographic variables and their associations with crime victimisation) onto population data from the UK Census. This provides us with an estimate of all violent crimes suffered by the resident population in each Islington ward, whether or not they were reported to the police. We follow the steps described by Buil-Gil et al. (2021) to generate our synthetic dataset of violent crimes: First, we obtain access to Census 2011 data about the age, sex, country of birth, ethnicity, income, marital status and education level of residents in each output area (https://www.nomisweb.co.uk/census/2011). Second, we generate a synthetic population following a multivariate truncated normal and binary distribution which replicates the empirical parameters of demographic variables recorded in the Census in output areas. Our synthetic population is highly similar to the population of each place. Third, we access the CSEW 2011/12 (Office for National Statistics, 2020) and estimate negative binomial regression models of crime victimisation for different crime types using the same demographic variables recorded in step 1. And fourth, we use the regression and dispersion parameters obtained in step 3 to generate the number of crimes suffered by individuals in our synthetic population following a negative binomial model. We then sum the output area estimates by Islington ward to generate our final ward-level estimates.

We calculated the rate of violent crimes per 1,000 people in each ward from each dataset, using both the resident population and the workday population as the denominator. The resident population refers

[3] Survey weights were calculated by ICS administrators to compensate for the non-probability sampling design and varying levels of non-response between demographic groups. Survey administrators used comparative data recorded by the Census and other sources to calculate weights that correct for the over-sampling of victims and different response rates across age groups, gender, ethnic groups, working status, tenure and areas of residence (Matthews, 2018). The weights equate the characteristics of the sample to the target population, but do not adjust sample sizes to population totals.

to the number of people who live in the area, while the workday population is the number of people who either live or work in the area. The latter is expected to be a better measure of 'population at risk' given that violent crimes in an area are not only suffered by residents (Malleson and Andresen, 2016). Both the residential population and the workday population were recorded in the Census 2011 and accessed from the website of the Office for National Statistics (https://www.nomisweb.co.uk/). Other indicators of *time-varying* population-at-risk have also been used in previous research to calculate crime rates, such as different measures of ambient population derived from mobile phone (Haleem et al., 2021) or social media data (Malleson and Andresen, 2015). Since three of our five data sources (i.e., METPAS, ICS and synthetic crime data) are only designed to allow for static estimates of crime each year, we calculate crime rates using the unvarying residential and workday population denominators recorded in the Census.

We also log-transformed crime rates ($\log(\hat{\theta}+1)$) to mitigate some of the multiplicative forms of measurement error affecting crime data (Pina-Sánchez et al., 2021). This has been shown to reduce the undue influence of areas with high crime prevalence, where more crimes are missed by police statistics. As shown in Figure A1 and Table A1, in the Appendix, log-transforming our crime rates also contributed to less skewed distributions, with the only exception of METPAS data (we return to this point in the Discussion). Thus, we calculate four estimates of violent crime rate from each data source.

To compare the scale, patterns and associations of the different estimates of violent crime obtained from the five data sources, we first present descriptive statistics of the average rate of crimes estimated across wards. Next, we calculate correlation matrices between estimates of crime obtained from different sources, before visualising the estimates with maps to assess if areas that concentrate many crimes in one dataset are also identified as 'hot spots' with other data sources. We also calculate the Moran's I index, a measure of spatial autocorrelation (i.e., the degree to which neighbouring observations are similar to each other), for each estimate of crime produced from each data source.

Results

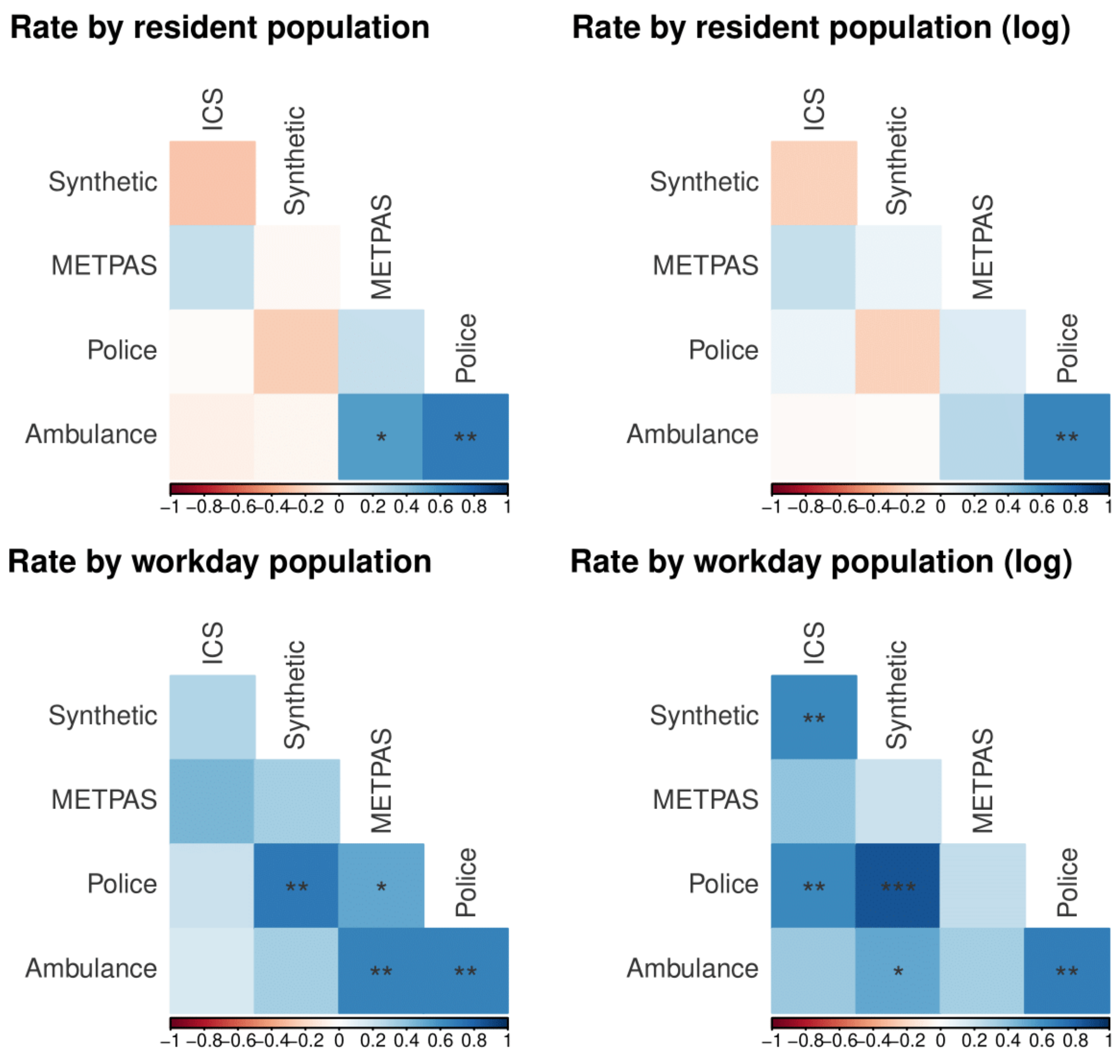
As shown in Table 1, there are substantial differences in the estimated crime rate depending on which source of data is being used. We find that the largest estimates are from the synthetic crime data. The second dataset with the largest crime rate estimate is police statistics, which records on average 52% fewer crimes than the synthetic dataset. The two crime surveys estimate lower crime rates, but METPAS estimates are slightly larger than ICS estimates. Unlike synthetic data, which is designed to generate information for all residents, these surveys are derived from smaller samples of residents. Both survey-based figures are likely to be under-estimates. In the case of the METPAS, this may, in part, reflect the fact that respondents can only report one incident, and therefore we do not pick up those individuals that suffer multiple violent crimes (Walby et al., 2016). However, this is unlikely to be the only reason for the low figures, with differences in the scope of offences considered, limitations in the question wording (when compared to the more comprehensive approach adopted by the CSEW used to generate the synthetic data), the context of the survey (conducted on behalf of the police) and sampling errors all likely playing a part. The small difference between the METPAS and ICS may reflect the non-probability sampling of the ICS, which is purposely designed to oversample residents who were victims of crime during the last year. The ICS sampling design may overrepresent victims of more common offences, such as fraud (suffered by 41.1% of the sample), motor vehicle or bicycle theft (9.2%) or personal theft (8.7%), while underrepresenting respondents who suffered incidents like violence that are less common. Ambulance data is the dataset which provides the lowest crime estimates, with approximately 91% fewer crimes than police-recorded statistics. We also note that all crime rates become smaller when the denominator used is the workday population, since more people spend their day in Islington than reside in the area.

Table 1. *Average sample sizes and violent crime rates in the 16 Islington wards.*

	Average sample size	Average crime rate by resident population	Average crime rate by workday population
Synthetic data	12882.81	99.80	84.50
Police data	-	47.64	38.48
METPAS	94.38	13.10	10.79
ICS	126.50	10.79	9.25
Ambulance data	-	4.62	3.67

However, differences in mean crime rates may be less problematic if the distribution of crimes across areas is consistent across datasets. To assess this, we calculate Pearson's correlation matrices and visualise them in Figure 2. We observe, first, that when we calculate crime rates using the resident population as the denominator, which is the most common practice in crime analysis (Andresen and Jenion, 2010), most correlations across datasets are non-significant and some of them are negative. In other words, the rates of violent crime obtained from one dataset may have very little in common with the rates calculated from other sources. Only two correlations are statistically significant: between police and ambulance records, and between METPAS and ambulance data. This may have severe implications for crime prevention. Areas identified as 'hot spots', and thus targeted for increased police presence, may vary extensively depending on the data source used. Log-transforming crime rates by residential population does not improve comparability across datasets.

However, the correlations between violent crime rates improve substantially when we calculate crime rates using workday population as the denominator. All correlations between data sources become positive, showing that the comparability across datasets improves substantially. We find the following statistically significant correlations: between ambulance data and METPAS ($\rho = 0.67$) and police data ($\rho = 0.67$), and between police and METPAS ($\rho = 0.51$) and synthetic data ($\rho = 0.70$). The only dataset that does not hold statistically significant correlations with any other source of data is the ICS. These correlations are slightly strengthened by log-transforming them. After log-transforming the rates by workday population, the correlations between the ICS estimates and synthetic ($\rho = 0.63$) and police data ($\rho = 0.63$), and between the synthetic and ambulance data ($\rho = 0.51$), become significant. The correlations of METPAS estimates with the police and ambulance data, nonetheless, become non-significant. Overall, using the workday population as the denominator appears to contribute to reduce the observed differences across data sources. Synthetic and police data are those that hold statistically significant correlations with more datasets (three out of four).



***p-value<0.001, **p-value<0.01, *p-value<0.05

Figure 2. *Correlation matrices of crime rates calculated from different data sources.*

To further illustrate the differences between patterns identified in each dataset, we visualise the rates in maps. Figure 3 includes maps of crime rates calculated using the residential population, while in Figure 4 we show the maps of log-transformed crime rates using the workday population as the denominator, since this was shown to have a markedly higher convergence validity. In order to allow direct visual comparisons across datasets, we re-scale all of them to 0-10 by calculating $\frac{\hat{\theta}_d - \min(\hat{\theta})}{\max(\hat{\theta}) - \min(\hat{\theta})} \times 10$, where $\hat{\theta}_d$ is the crime estimate in area d.

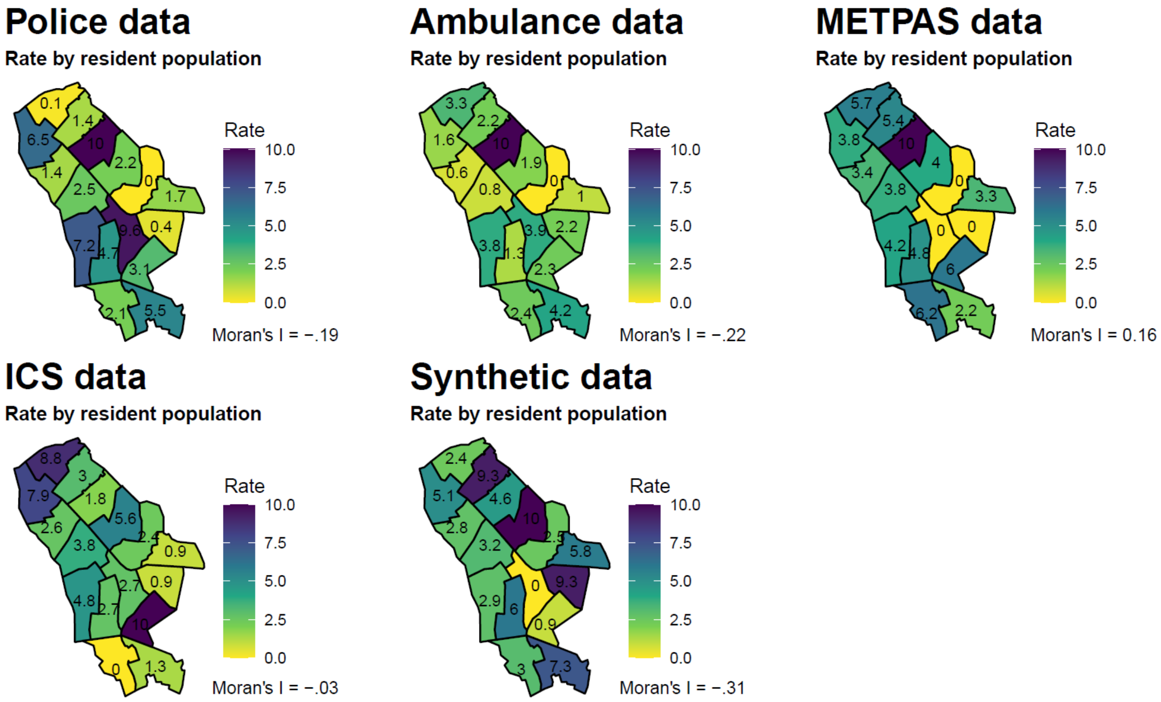


Figure 3. *Violent crime rates by resident population calculated from different data sources (re-scaled to 0-10).*

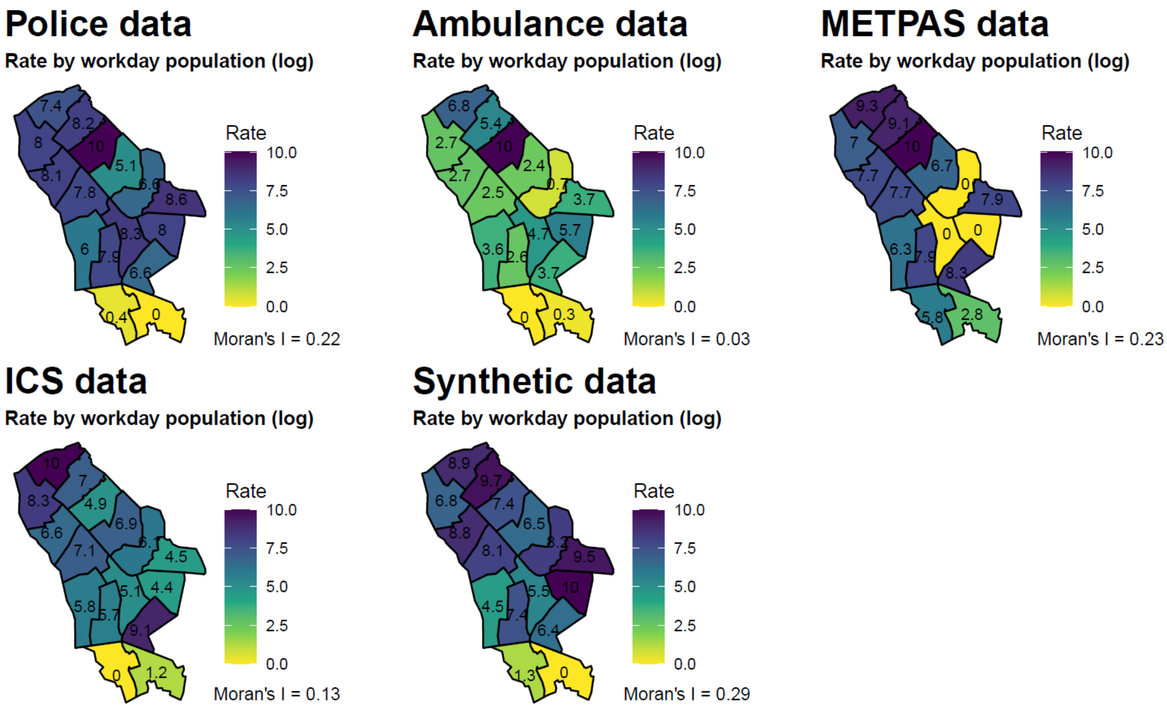


Figure 4. *Log-transformed violent crime rates by workday population calculated from different data sources (re-scaled to 0-10).*

In Figure 3 (rates by residential population), three out of five data sources highlight one ward in the upper-right part of the map, Finsbury Park, as the area with the highest crime rate. These three data sources (police, ambulance and METPAS) also identify that there is one area located two wards below this with very few crimes (Highbury East). Highbury East is the area in Islington where the relative difference between the residential and workday population is smallest. In other words, not many non-residents work in this area, and thus the 'population at risk' may be primarily those who live here. Aside from this, we observe remarkably little commonalities across datasets. Hence, areas identified as crime 'hot spots' for crime prevention strategies would vary extensively depending on the crime measure used. The measures of spatial autocorrelation (i.e., Moran's I) are remarkably different between data sources.

Contrarily, in Figure 4 (log-transformed crime rates by workday population), the visual inspection of the five maps shows that the distributions are much more similar than before, and the measures of Moran's I are also more closely aligned. Finsbury Park is still identified as a high crime area according to police, ambulance and METPAS data. However, Highbury East is only identified as a low crime rate area by METPAS and ambulance estimates. In four datasets, the two most southern wards have the lowest crime rates (Clerkenwell and Bunhill). This is because these two wards have the largest workday population in Islington. We also see that most data sources identify remarkably high crime rates in the most northern ward (Hillrise). Importantly, even after log-transforming crime rates we can still identify some clear differences in the crime distribution across the different datasets.

Discussion and Conclusions

The growing need for reliable information about crime has favoured an expansion in the number of available sources of crime data. This has had a positive effect on crime research and crime prevention, enabling evidence-oriented policing strategies and testing theories of crime in different contexts. But it has also allowed researchers to compare results across datasets, in turn exposing an overall lack of consistency across estimates of crime obtained from different sources (Bottoms et al., 1987; Brunton-Smith et al., 2020; Enzmann and Podana, 2010; Hibdon et al., 2017; Messner, 1984).

Two main reasons are used to explain why crime estimates obtained from different sources tend to show remarkably different results. First, different data sources pick up knowledge about different parts of the 'true score' of crime. Even if health emergency services records, victim surveys and police statistics captured all crimes they could possibly record, the three estimates would still be substantively different because they are measuring qualitatively different concepts. Ambulance data will always show lower estimates than police statistics because they only pick up the most serious forms of violent crime that require medical attention (Hibdon et al., 2021; Sutherland et al., 2021). Moreover, some victims may move before contacting ambulance services and the 'offence location' may vary from the ambulance 'pickup point' – but this has not been identified as a major issue when comparing the geographic distributions of crime. Police records tend to be concentrated on more serious forms of activity, with the police filtering out a range of activities that may not be judged as likely to generate a conviction. And estimates obtained from surveys do not record crimes suffered by outsiders, homicides or 'victimless' crimes, but do pick up a range of activities that victims may not deem serious enough to be reported to the police, or that members of the public may be reluctant to report (whether because of fear of repercussions, lack of trust in police, or because they were dealt with informally). Survey-based estimates of crime are also affected by the sampling design, the wording of questions and the cap of crimes recorded per respondent (Brunton-Smith et al., 2020; Schneider, 1981), as identified in this research. Second, different data sources are differentially affected by various sources of measurement error, and as a result each of them fail to capture an important part of the assumed 'true score' of crime.

This research has compared five sources of violent crime data in Islington to examine the extent to which different datasets show comparable results about the scale, patterns and distribution of crime. Moreover, given that previous research identified that it is not only the dataset we use to estimate crime that affects the accuracy of estimates, but also the method we use to calculate crime rates (Malleson and Andresen, 2015; Pina-Sánchez et al., 2021), we have computed crime rates using different populations as the denominator and log-transforming them.

Our analysis shows that synthetic crime data record, on average, the largest frequency of violent crimes. Generating synthetic crimes through computer simulations may contribute to obtaining estimates of crime that are closer in volume to the dark figure of crime (Akpinar et al., 2021; Buil-Gil et al., 2021). By contrast, estimates of violence using ambulance data show the smallest average crime rates, confirming that while these data may provide valuable information about crime (Hibdon et al., 2021), they only represent a small proportion of true crime levels. Survey data produce higher crime rates than ambulance data and lower rates than police statistics. This may, in part, be due to the small sample sizes that surveys record in small areas (Rosenbaum and Lavrakas, 1995), although it may also be explained by the design of both surveys analysed: the small rates obtained from the METPAS may be explained by the cap of one crime recorded per respondent, while the small rates computed from the ICS may be related to the non-random sampling design used to over-sample victims mostly of non-violent crime. These differences may also reflect the fact that while our survey-based estimates identify crimes where victims live, police data are more likely to represent the places where crimes happen (Cernat et al., 2021).

We also find that while different data sources show large differences in crime rates, these differences can be reduced by calculating crime rates using workday population as the denominator. The use of the right denominator explains a large extent of the disparities observed across data sources. As discussed by Malleson and Andresen (2015), the 'population at risk' in each area, at least for violent crime, is not only those who live in the area, but also persons who spend their day there but reside elsewhere. In our study, calculating violent crime rates using the workday population as the denominator results in several data sources converging to identify the same places as high crime areas. This confirms the expectation that Finsbury Park has the highest crime rate in the area. Moreover, it also controls for the fact that police and ambulance data tend to show higher crime rates by residential population in areas with low residential population and large workday population (where the 'population at risk' is larger than the denominator), and lower crime rates by residential population in areas where the residential and workday population are very similar (where the 'population at risk' is similar to the denominator). We note, however, that the observed difference between the residential and workday populations in Islington is uncharacteristically large when compared to other locations in the UK, which may limit the generalisability of our findings. Moreover, while Malleson and Andresen (2016) identified the workday population as the most appropriate measure of population-at-risk for theft, in this study we analyse violent crime, which is characterised by notably different causal mechanisms and temporal variation.

Crime estimates from different sources become more similar by log-transforming crime rates by workday population. Nonetheless, while log-transforming crime rates contributed to improving the correlations between datasets, it also resulted in all correlations with METPAS estimates becoming non-significant. This is primarily driven by the fact that METPAS recorded zero crimes in three wards, which remained the three areas with lowest rates regardless of the way we calculate crime rates. The METPAS recorded zero crimes in several wards due to the cap of one crime per respondent. Moreover, METPAS data was less skewed than all other data sources and log-transforming it increased its skewness (Figure A1 and Table A1 in the Appendix) – while log-transforming crime rates is advised to deal with measurement error and skewed data, this strategy may have its downsides when data is not skewed.

By comparing multiple crime data sources, we can identify those areas that consistently show relatively high or low crime rates across datasets, thus minimising the impact of measurement error or different crime conceptualisations, and allowing for more precise targeted crime prevention practices and policing strategies. At the same time, we can also identify those areas where one particular dataset shows a particularly high crime rate when others do not, potentially highlighting issues with the mode of production or sampling strategy used to record data. With multiple crime data sources, researchers can also benefit from advances in methodology to produce more robust 'multi-method' estimates of crime, derived by empirically combining crime rates from multiple data sources. For example, we can use Confirmatory Factor Analysis to calculate latent scores of crime rates from our five datasets (Figure 5). This represents the adjusted 'true' crime score, calculated as a reliability weighted mean of the separate crime estimates.

Figure 5. *Latent scores of violent crime rates in Islington from combining five data sources.*

After combining the existing sources of crime data, we can still identify one ward that is repeatedly highlighted as a high violent crime rate area: Finsbury Park. Since the early 90s, criminologists have found large crime rates in this area (Mooney, 1992). Harper et al. (1995) argued that during the late 19th century the poor condition of housing in this area, and particularly in Campbell Road, prompted middle class residents to move to other places. Gangs became dominant in the area throughout the 20th century and crime and prostitution increased, and while actions were taken to improve housing (Harper et al., 1995) and reduce prostitution (Matthews, 1990), it remains a high crime neighbourhood until today. On the other end, the two most southern areas show low crime rates by workday population. These two areas are defined by the largest workday population in Islington, where the potential ‘population at risk’ is larger, but where the actual rate of violent offences by those who live or work in the area is smaller.

Future research should also study time-varying levels of violent crime in each area in Islington, and whether these vary across data sources.

Our study has several implications for theory and practice. First, law enforcement and policymakers should always consider how the mode of production of crime data, and the way crime rates are calculated, may be affecting results and crime prevention efforts. Public authorities should compare multiple data sources where possible. By doing this, they will reduce the risk of mistakenly classifying certain areas as ‘crime hot spots’, and consequently avoid potentially severe negative impacts on local communities. Second, crime researchers should utilise multiple sources of crime data where possible to assess the robustness of their analyses. If different results are found in different datasets, researchers should consider whether their findings are explaining how data is recorded (e.g., propensity of crime reporting, police control over areas) instead of crime. In countries where fewer types of data are available, data analysts should consider findings of research conducted elsewhere to anticipate potential ways in which their data may be affected by different conceptualisations of crime and measurement error. And third, a potential avenue for equating multiple data sources, or at least conducting sensitivity analyses on our crime data, may be to use measures of workday population as the denominator when calculating crime rates (Malleson and Andresen, 2016).

Appendix

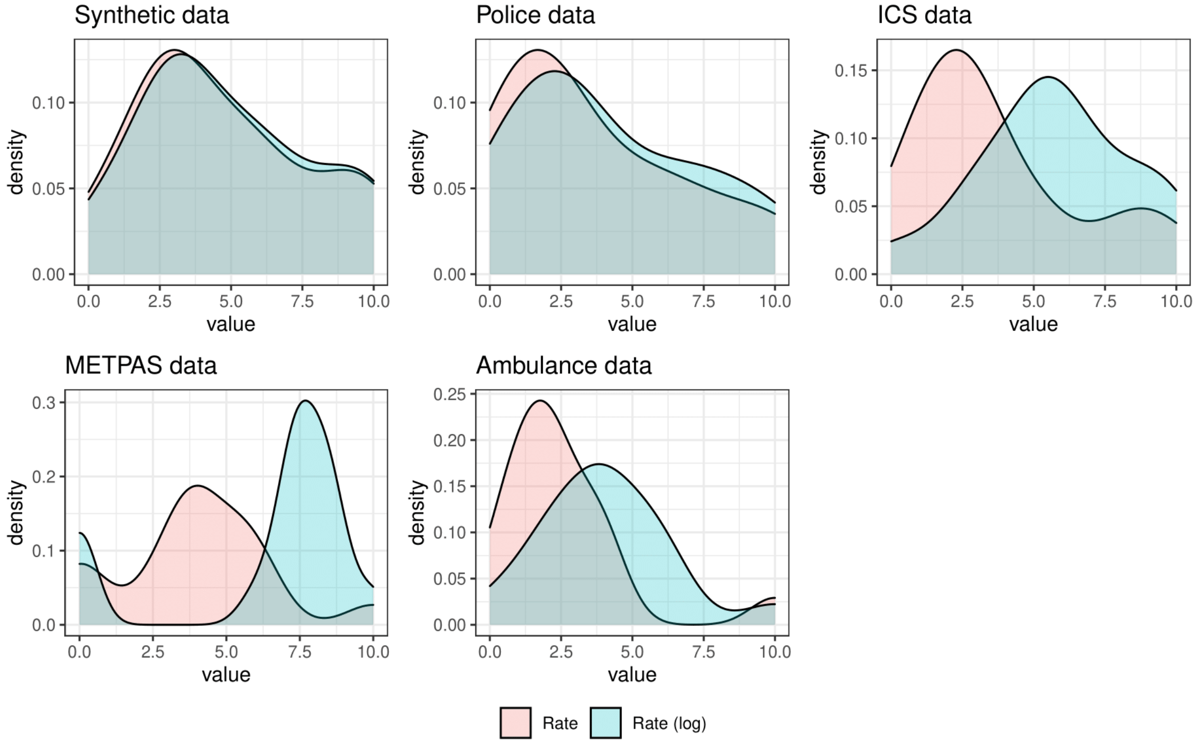


Figure A1. *Density plots of crime rates and log-transformed crime rates.*

Table A1. *Measures of skewness and Shapiro-Wilk tests of normality for crimes and log-transformed crime rates.*

Data source	Test	Rate	Log-transformed rate
Police data	Skewness	0.69	0.45
	Shapiro-Wilk test	0.89 (p-value = 0.06)	0.92 (p-value = 0.19)
Ambulance data	Skewness	1.89	0.63
	Shapiro-Wilk test	0.77 (p-value < 0.01)	0.95 (p-value = 0.54)
METPAS	Skewness	0.24	-1.20
	Shapiro-Wilk test	0.93 (p-value = 0.24)	0.76 (p-value < 0.01)
ICS	Skewness	0.82	-0.20
	Shapiro-Wilk test	0.89 (p-value = 0.06)	0.97 (p-value = 0.88)
Synthetic data	Skewness	0.37	0.29
	Shapiro-Wilk test	0.93 (p-value = 0.28)	0.94 (p-value = 0.36)

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