ESRC SDAI Application - Understanding domestic abuse using Big Data

1 Introduction

Domestic abuse is a complex phenomenon affecting people from all walks of life. It is increasingly recognised as a major public policy concern in many countries, including the UK (European Parliament, 2018). While anyone can become a victim of domestic abuse, women are disproportionately affected, with more than 25% of women, and 15% of men in England and Wales reported to have experienced some form of domestic abuse since the age of 16 (Office for National Statistics, 2018). The current legal definition in the UK aims to capture the multifaceted nature of domestic abuse, by recognising that domestic abuse encompasses a wide range of behaviours, including emotional, sexual, and physical abuse, threatening, intimidating, coercive and controlling behaviour (Home Office, 2018a).

Domestic abuse has substantial mental health implications, with an estimated three-quarter of survivors experiencing posttraumatic stress disorder symptoms, and are significantly more likely to report symptoms of anxiety and depression compared to the general population (Ferrari et al., 2016). The long lasting impacts of domestic abuse are not limited to the direct target of abuse. Witnessing domestic abuse at home can have severe developmental impacts on children, including an increased risk of mental and physical health problems, difficulties in interpersonal relationships in later life, worse educational attainment, and a higher likelihood of engaging in criminal behaviours (Callaghan, Alexander, Sixsmith, & Fellin, 2015).

As the legal definition reflects, one characteristic of domestic abuse that differentiates it from other violent crimes is its repeated nature. Estimates show that before getting effective help, on average, survivors live in the abusive relationship for 2.7 years, experiencing an estimated 50 cases of abuse (Safe Lives, 2015). The most reliable statistics on domestic abuse in the UK is the Crime Survey for England and Wales (CSEW; Office for National Statistics, 2018), a victimisation survey, which includes a self-completion module on domestic abuse. According to the CSEW, of those respondents who experienced any form of domestic abuse between April 2017 and March 2018, only 17% reported it to the police (Office for National Statistics, 2018). This extremely high level of underreporting is another characteristic that is specific to domestic abuse compared to other types of crimes.

In the most extreme cases, domestic abuse can culminate in domestic homicide. In the period between April, 2017 and March, 2018, 70 people in England and Wales were killed by their current or former partner, 90% of these victims were women (Office for National Statistics, 2019a), demonstrating that domestic abuse is a fundamentally gendered phenomenon. While the pervasive problem of underreporting poses a significant obstacle to deriving reliable estimates of the true extent of the problem, the economic cost of domestic abuse in England and Wales between April, 2016 and March, 2017 was estimated to be £66 billion (Rhys Oliver, Barnaby Alexander & Wlasny, 2019). The largest component of this cost is represented by the physical and emotional consequences of abuse, reflected in a reduced expected quality of life for survivors. In addition, lost economic output resulting from missed workdays and reduced productivity, as well as costs to the health care system also significantly contribute to the overall figure.

This research programme consists of four research projects aiming to deliver useful, policy-relevant insights about domestic abuse. First, we will explore the demographic and socio-economic characteristics of victims of domestic abuse, the reasons behind police mis-recording of domestic abuse cases, and victim's perception of the police after reporting an incident. Second, we will investigate the factors predicting suffering serious injury and the decision to report. Third, we will examine the long-lasting effects of being a victim of domestic abuse or witnessing domestic abuse at home as a child. Finally, we explore the association between exogenous, time-varying factors, such as changes in alcohol consumption and financial resources, and the prevalence of domestic abuse.

2 Data sources

The research projects detailed below draw on various data sources. All of the projects rely on the CSEW, an annual, cross-sectional representative survey collecting information on victims of crime across England and Wales, including 30,000–40,000 households every year (Office for National Statistics, 2019b). The survey has a self-completion module containing questions about the respondent's experiences of domestic abuse throughout their life (since the age of 16), and in the past 12 months in particular. Given the serious problem of underreporting, one of the unique characteristic of domestic abuse, the CSEW is the most reliable source of information on the prevalence of domestic abuse in England and Wales.

Some of the projects also benefit from a crime dataset provided by the West Midlands Police (WMP), which includes all crimes and incidents recorded by the police force in the period between January, 2010 and October, 2018. The WMP is the third largest police force in England, serving a population of 2.9 million (Home Office, 2018c). Crimes that have a domestic abuse marker indicate cases of domestic abuse that meet the criteria for notifiable offences in the UK, whereas domestic abuse incidents refer to cases that do not qualify as a crime. About 31% of all crimes and incidents have a domestic abuse marker. For each record in this dataset, we have rich information about the circumstances of the case, including exact location and time of the incident or crime, the gender, age and ethnicity of the offender and victim, **their address**, and the severity of the injury sustained by the victim, if any. The first and last occurrence of the offence, as well as the exact time of reporting is also recorded. Each person in this dataset has a unique person identifier, allowing us to follow people over time. ***Sentence about access to this dataset.***

These two datasets have different merits, and combining them allows us to gain a deeper understanding the characteristics and dynamics of domestic abuse, and deliver policy-relevant insights. A unique benefit of the CSEW is that it provides information on a control group (those who have not suffered domestic abuse), allowing us to investigate the causal effect of domestic abuse. In addition, the CSEW is more likely to give a better estimate of the true prevalence of domestic abuse, and contains rich demographic, socio-economic and geographic (LSOA level) information on the respondent (survivor). However, owing to the fact that it is a victimisation survey, it does not contain any information on the perpetrators, and has limited longitudinal information (respondents are asked about whether they suffered domestic abuse in the past 12 months, but the dates of those incidents are not specified). In contrast, the WMP crime dataset has information (age, gender, ethnicity) on both the victim and the offender, and records all reported incidents for the same victim-offender pair, allowing us to conduct a quantitative analysis of the dynamics of abusive relationships, and identify the predictors of escalation. Information on the exact timing of the abuse and the time of reporting will help us identify high-risk times of the year and understand the factors influencing the decision to report. Furthermore, the crime dataset provides us with information on other criminal behaviours of the offender. In all the analysis plans outlined below, we will not link the individuals in these datasets.

Our last proposed project will also rely on a transaction per row dataset containing credit card and current account spending of 20 million customers across the UK. We have access to this data as part of a data sharing agreement with a very large UK bank. As we know which neighbourhood (LSOA) the card owners live in, this data will allow us to construct a neighbourhood-level measure of spending on alcohol, gambling, and benefit payments throughout time. We will not use individual-level data or match people in this dataset with people in the WMP dataset.

In addition, in analyses that rely on neighbourhood-level characteristics, we will use the Incides of Multiple Deprivation (IMD; HM Government, 2015). The IMD ranks all 32,844 LSOAs in the UK based on their relative deprivation on various domains, including income, employment, education, health, crime, housing and living environment, providing us with a complex descriptor of the socio-economic characteristics of each neighbourhood in the country.

Research Programme

This research programme involves four research projects exploring different aspects of domestic abuse. Drawing on the extensive, rich respondent information in the CSEW, and the unique, temporal nature of the WMP, we aim to complement, extend and deepen our understanding of domestic abuse. In outlining the analysis plan for each of these projects, we will specify a set of statistical analyses we plan to conduct for the sake of clarity (including dataset, unit of analysis, outcome and explanatory variables, and statistical method). We will preregister all of our analysis plans using the Open Science Framework (OSF) ahead of beginning research. We will aim to complement all analyses with robustness checks, and further exploratory regressions as the data allows (see, ***Trendl Football***, for an example of this approach).

1. Understanding domestic abuse: survivor characteristics and police mis-recording

Short intro about aims, highlighting added value. In this research project, we will first use the CSEW to investigate the demographic and socio-economic characteristics of survivors of domestic abuse. Exploring the risk factors in domestic abuse victimisation is key in designing effectively targeted policy measures. We will also use the CSEW to explore the police's response to reported cases of domestic abuse. Increasing victim's trust in the police through improving law enforcement response to reported incidents is key in encouraging victims to report domestic abuse and prevent further harm.

Detailed plan First, using the CSEW data, we will extend our understanding of the demographic and socio-economic factors predicting domestic abuse victimisation. The CSEW provides a broad range of information on the characteristics of the respondent, including age, sex, marital status, number of children, ethnicity, education, employment, income, benefit history, physical and mental health, frequency of going out, house and car ownership, self-reported well-being, and frequency of drug and alcohol use. Previous research has identified a number of risk factors predicting domestic abuse victimisation (being female, young, unemployed, separated or divorced, living in single parent household and earning in the lowest income bracket), based on descriptive statistics derived from the CSEW data (Office for National Statistics, 2018). Building on what we know so far, we will explore the predictive power of a broader range of victim characteristics, using a logistic regression approach. Investigating the explanatory power of these characteristics within one statistical model will provide us with a deeper understanding of the relative importance of these factors in predicting domestic abuse victimisation, compared to a purely descriptive statistics approach. We are also interested in how the predictive power of victim characteristics vary with the type of abuse suffered (physical abuse, threats, sexual abuse).

However, given the complex nature of domestic abuse, it is likely that there are important interactions between various victim characteristics in predicting the risk of domestic abuse victimisation (for example, we would expect that not having stable employment is a more significant risk factor of domestic abuse victimisation for those who have young children). To uncover the structure of these interactions without having to a priori specify them – as is required in a logistic regression model – we will also use a random forest classification algorithm, a machine learning method that has the ability to detect non-linear relationships between variables, allowing us to identify particularly vulnerable subgroups of the population. Insights from both methods will provide us with the first extensive characterisation of the risk factors predicting domestic abuse victimisation in England, using a national-level, large representative sample like the CSEW.

Her Majesty's Inspectorate of Constabulary and Fires & Rescue Services (HMICFRS) oversees police forces in England Wales, and regularly inspects their responses to reported crime, including cases of domestic abuse. Their latest crime data integrity inspection of 32 police forces have found that 20 forces require significant improvements in their crime recording practices (Her Majesty's Inspectorate of Constabulary and Fires & Rescue Services, 2019). These concerns are especially pertinent in the context of domestic abuse, for example, the latest report found that the WMP have failed to record 25% of reported crimes that were domestic abuse-related.

We will explore whether the extent of crime mis-recording depends on victim characteristics (e.g., a crime reported by a victim with a mental illness, substance dependency or language difficulties might be less likely to be recorded as a crime by the police). Using the CSEW, we will be able to tell whether the domestic abuse reported by the respondent is likely to amount to a crime according to the list of notifiable offences (Home Office, 2018b). We will run a multinomial regression with police force fixed effects for each broad crime type (sexual, physical violence, harassment and stalking), predicting whether the police's response (no action, warning, arrest, charge) depends on the socio-economic characteristics of the victim. Using a fixed effects approach will help us tell the relative importance of police force and victim characteristics in crime mis-recording. To complement this analysis and explore potential interactions between our explanatory variables, we will also investigate this question with a mixed effects random forest with police force clustering. Second, using the same statistical model for each type of crime, we will also investigate how victim's satisfaction with the police, and their perception of their personal security after reporting a crime depends on the police action taken, and their socio-economic characteristics.

Table 1: Understanding domestic abuse: survivor characteristics and police mis-recording, analysis plan

Research question	**Dataset**	**Unit of analysis**	**Outcome variables**	**Explanatory variables**	**Model**
What are the characteristics of domestic abuse victims?	CSEW	Individual (respondent-level)	Domestic abuse victimisation; Victimisation by type (physical, sexual abuse, threats)	demographic and socio-economic characteristics	Logistic regression/random forest
How does the police response depend on victim characteristics?	CSEW (reported domestic abuse, by type of offence)	Individual (respondent-level)	Police action taken (no action, warning, arrest, charge)	demographic and socio-economic characteristics of the victim	Multinomial logistic regression with fixed effects/ mixed effects random forest
What predicts victims' trust in the police?	CSEW (reported domestic abuse, by type of offence)	Individual (respondent-level)	Satisfaction with police action, perception of security after reporting	police action taken, demographic and socio-economic characteristics of the victim	Multinomial logistic regression with fixed effects/ mixed effects random forest

Core outcomes

The first extensive investigation of the demographic and socio-economic predictors of domestic abuse victimisation. A deeper understanding of the characteristics of police mis-recording and its effect on victim's trust in the CJS.

2. Predicting serious harm and understanding the decision to report

Short intro about aims, highlighting added value. In this project, we will explore the victim and offender characteristics that predict serious harm and the factors determining the decision to report the abuse. Identifying high-risk victim-offender pairs is key in preventing serious harm. Understanding what affects the decision to report is particularly important, as underreporting represents the biggest obstacle to effectively tackling domestic abuse. Insights from these analyses can inform decisions about the optimal timing and target audience for domestic abuse awareness campaigns.

Detailed plan Drawing on the different strengths of the CSEW and the WMP datasets, we will explore the relative importance of the risk factors predicting serious harm. Previous studies investigating this question mostly relied on police data and focused on identifying high-risk offenders (Thornton, 2017). Using the CSEW, we will complement and extend this research by simultaneously considering the victim characteristics that are predictive of suffering serious injury. Specifically, using a multinomial logistic approach, we will explore the extent to which financial independence and resilience (income bracket, employment stability), mental health (self-reported well-being), drug and alcohol dependence (frequency of usage), social isolation (self-reported frequency of going out, living alone or with the perpetrator, family disputes), recent separation, and feeling frightened (increased home security, reporting feeling scared) are predictors of various levels of harm (threats, minor or serious injury). We will know the level of harm suffered, because the CSEW asks whether the respondent needed to see a doctor, nurse or other health worker, or needed to take time off work because of the abuse. While we cannot investigate causal relationships due to the cross-sectional nature of the CSEW, this analysis will nevertheless provide us with important insights about the characteristics of groups most vulnerable to domestic abuse.

Using the WMP data, we will also explore the risk factors associated with the perpetrator. The strength of the WMP data is that it has a temporal dimension, and we can follow the same perpetrator-victim pair over time. Our detailed crime dataset will allow to investigate the extent to which the perpetrator's previous recorded self-harm and suicide attempts, previous violent and drug offences, breaches of court orders and separation from the victim will predict causing serious harm, using each perpetrator-victim pair as a unit of analysis. From the detailed description of the incident, we will know if the perpetrator and the victim live together. We will explore this question using a multinomial logistic regression analysis with perpetrator-victim fixed effects, where we will use previously known information about the perpetrator to predict serious harm. Using a fixed-effects regression approach will allow us to disentangle the relative importance of our explanatory variables and perpetrator-victim specific factors in predicting serious harm.

We will also use both datasets to explore the predictors of the decision to report and escape the abuse. We are not aware of previous research exploring this question. Using the CSEW and logistic regression approach, we will investigate how the decision to report (or the decision to seek any form of external help) depends on the individual-level, time-invariant characteristics of the survivor, controlling for the severity and type of the abuse suffered. We are especially interested in exploring how trust in the Criminal Justice System (CJS), social ties (living with family, going out, length of living in the area, member of Neighbourhood Watch), financial independence (own income, employment status, car ownership), number of children, mental health, and alcohol and drug dependency affect the decision to report. Using the WMP data, we will explore time-varying factors affecting the decision to leave the abuser. Due to the high levels of underreporting, it is hard to distinguish between time periods when the number of domestic abuse incidents increase, and when the victims have a higher propensity to finally report the ongoing abuse. Here we are mainly interested in the latter case (and will explore the first case in more detail in the last research project), therefore we will focus on the subset of incidents where the victim for the first time reported a long history of abuse. We are interested in whether these reports are more likely to occur after certain days of the year (e.g., birthday of the victim or perpetrator, Christmas, Halloween, Easter, etc.), potentially reflecting cases where the abuse has suddenly escalated, or became known to outsiders.

Core outcomes

A deeper understanding of the victim and perpetrator characteristics that predict serious harm, and the time-invariant and time-varying factors affecting the decision to report the abuse to the police.

Table 2: Predicting serious harm and understanding the decision to report, analysis plan

Research question	**Dataset**	**Unit of analysis**	**Outcome variables**	**Explanatory variables**	**Model**
What victim characteristics predict serious harm?	CSEW	Individual (respondent-level)	Level of harm resulting from domestic abuse victimisation (no physical harm, minor, serious)	financial resources, mental health, dependence, social isolation, separation, feeling scared	Multinomial logistic regression
What perpetrator characteristics predict serious harm?	WMP	Perpetrator-victim pairs	Violent offences resulting in injury	previous self-harm and suicide attempts, previous violent and drug offences, breaching court orders, separation	Multinomial logistic regression with perpetrator-victim fixed effects
What time-invariant (victim) characteristics predict the decision to report?	CSEW	Individual (respondent-level)	Reported abuse to the police	severity/type of abuse, trust in CJS, social ties, financial status, children, mental health, dependencies	Logistic regression
What time-varying characteristics predict the decision to leave?	WMP	Perpetrator-victim pairs	Reported ongoing abuse to the police	time of year, specific holidays, length of abuse, severity of last occurrence	Logistic regression

3. The long-lasting effects of domestic abuse

Short intro about aims, highlighting added value. Domestic abuse has long-lasting adverse effects on victims and those close to them. In this research project, our is aim to explore some of these consequences on the direct victims of domestic abuse and the children who live in the same household. Gaining a deeper understanding of the tangible, far-reaching consequences of domestic abuse will help to design survivor support programmes and quantify the societal harm caused by it.

Detailed plan First, we will explore the causal effect of past experiences of domestic abuse on present socio-economic outcomes. First, using the CSEW, we will explore how witnessing abuse at home in childhood affects educational, employment and health outcomes in adulthood. The 2016 CSEW included a module asking respondents about whether they witnessed domestic abuse at home as a child. Descriptive statistics of this dataset revealed that those who reported to have witnessed abuse as a child were significantly more likely to report long-term health problems, and live in a single parent household as an adult (Office for National Statistics, 2016). However, due to the possibility of various confounders (e.g., those growing up in economically deprived areas are more likely to witnessing abuse, but economic deprivation also affects educational outcomes), these descriptive statistics do not reveal the causal effect of witnessing abuse as a child on socio-economic outcomes in adulthood. To overcome this difficulty in quantifying this causal relationship, we will use propensity score matching, a statistical approach that allows for causal inferences to be drawn about the effect of witnessing abuse on educational, employment, and mental and physical health outcomes, and the probability of experiencing domestic abuse in adulthood. In a similar vein, using propensity score matching and the CSEW, we will explore how past experiences of domestic abuse affect current health outcomes, by comparing people who have experienced domestic abuse in the past, but not in the last 12 months, with people who have never experienced domestic abuse, but otherwise have similar socio-economic characteristics.

Second, using both the CSEW and WMP, we will explore how children's behavioural problems are affected by witnessing domestic abuse at home. Using data from the 10-15 year old questionnaire of the CSEW (which can be linked to the adult questionnaire), we can examine the effect of domestic abuse on children living in such households. The children's questionnaire records information about experiences with bullying, carrying knives, gang membership, school truancy, learning difficulties and health outcomes, including drug use and drinking behaviour. Using this dataset and a propensity score matching approach, we will explore the causal effect of living in an abusive household on childhood behavioural outcomes.

We will complement this analysis using data on young offenders from the WMP. We will identify if young offenders' home addresses can be linked with a domestic abuse incident in the recent past, allowing us to explore whether living in a household with a domestic abuse problem predict the type of crime they will engage in (property-related, public order offence, violent), controlling for the socio-economic characteristics of the neighbourhood (using the IMD). We are especially interested if living in an abusive environment is predictive of knife crime-related offences.

Core outcomes The first UK-based quantitative exploration of the causal effect of domestic abuse and childhood abuse on socio-economic outcomes.

Table 3: The long-lasting effects of domestic abuse, analysis plan

Research question	**Dataset**	**Unit of analysis**	**Outcome variables**	**Explanatory variables**	**Model**
How does witnessing domestic abuse as a child affect socio-economic outcomes in adulthood?	CSEW	Individual (respondent-level)	Educational attainment, employment status and health-related outcomes, including domestic abuse victimisation	Witnessing domestic abuse	Propensity score matching
How does experiences of past (but not recent) domestic abuse affect socio-economic outcomes in adulthood?	CSEW	Individual (respondent-level)	Current health and employment outcomes	Degree and type of domestic abuse suffered	Propensity score matching
How does living a household with domestic abuse affect behavioural outcomes in childhood?	CSEW	Individual (respondent-level)	Bullying, involvement with gangs, school truancy, carrying knives, drugs and alcohol usage, learning difficulties, health	Degree and type of domestic abuse in household	Propensity score matching
Are young offenders from abusive households more violent?	WMP, IMD	Young offenders (individual)	Type of offence (property-related, public order offence, violent)	Household LSOA socio-economic characteristics, abusive household or not	Multinomial logistic regression

Environmental factors

Short intro about aims, highlighting added value. In this research project, we will investigate some of the environmental predictors of domestic abuse. While individual-level characteristics are likely to be the main predictors of domestic abuse victimisation, the environment around the victim can play a key role in either exacerbating or alleviating domestic abuse. Understanding how neighbourhood-level characteristics affect the prevalence of domestic abuse and reporting behaviour is crucial for the most effective distribution of resources to help victims and targeted awareness campaigns. We will also explore how time-varying, exogenous factors related to alcohol consumption and financial stability affect domestic abuse.

Detailed plan Using the CSEW, we will first explore whether neighbourhood characteristics are predictive of the prevalence of domestic abuse and the willingness to report. Previous literature has suggested various pathways, including reduced collective efficacy of neighbourhood, and normalisation and acceptance of violence through social norms, to explain the link between neighbourhood characteristics and domestic abuse, but the question has not been explored in a UK context yet. Fisrt, using a logistic regression, we will explore how the interviewer's perception of the street (signs of rubbish, vandalism, and the general condition of houses, member of Neighbourhood Watch) as well as the respondent's connection and attitude towards the neighbourhood (length of time living in the local area, noisy neighbours, rubbish lying around, teenagers hanging around, vandalism, drunken and anti-social behaviour, drug trafficking, abandoned cars, speeding traffic, police presence in the area, worries about crime levels) predict domestic abuse victimisation, after controlling for the socio-economic characteristics of the respondent. Second, we will explore how deprivation in a neighbourhood (LSOA level, measured by the IMD) affects the prevalence of domestic abuse (estimated from the CSEW), and the willingness to report, using a spatial regression framework. Using this statistical approach will alleviate the problem of spatial dependency in our dataset, and will allow us to derive a precise estimate of the effect. These analyses will extend our understanding of the neighbourhood-level predictors of domestic abuse victimisation, and complement our individual-level approach outlined in the first project to provide a comprehensive exploration of the factors affecting domestic abuse victimisation and willingness to report.

We are also interested in exploring how time-varying external factors, including alcohol consumption, and financial stress (measured by gambling expenditure and benefit dependency) affect the propensity to engage in abusive behaviours. In investigating this question, we will use the transaction dataset described earlier, which allows us to estimate a spending profile for each LSOA over time. This will allow us to identify time-specific changes in alcohol consumption, gambling expenses and benefit receipts in parts of the West Midlands, and investigate their effect on the number of reported domestic abuse cases in the area (from the WMP), using a spatial Poisson regression approach.

To explore the effect of alcohol consumption on domestic abuse, we will identify externals events that may affect alcohol consumption (e.g., local festivals, weather, bank holidays, sport tournaments) measured by spending on alcohol in an LSOA in a given time period, and investigate whether it affects the number of reported domestic abuse incidents in that area. Previously, we have found a 60% increase in alcohol-related domestic abuse when the England national football team won, highlighting the profound effect exogenous events can have on the propensity for violence.

To explore the effect of financial shocks on domestic abuse, we will be using the same estimation approach, but we will focusing on gambling and benefit payments. Gambling is increasingly recognised as a serious health concern across the UK, and can have a profoundly adverse impact on family finances. We will use our transaction data and WMP dataset to assess the link between changes in spending on gambling in a given LSOA and the prevalence of domestic abuse in that area. The recent reforms of the UK benefit system, in the form of the introduction of the Universal Credit (UC) had been criticised widely, due to the temporal financial strain it imposes on the least financially resilient people in society. Drawing on previous findings about the link between financial stress and domestic abuse, we will explore what effect the roll-out of the UC across the West Midlands had on the reported number of domestic abuse cases. The fact that the exact date of the roll-out varied across the seven metropolitan boroughs within the county allows for a more precise estimation of the effect of UC on the reported number of domestic abuse incidents in the West Midlands.

Core outcomes The first extensive analysis of the neighbourhood-level predictors of domestic abuse within the UK. An exploration of the exogenous, time-varying factors, including alcohol consumption and

Table 4: Environmental factors affecting domestic abuse, analysis plan

Research question	**Dataset**	**Unit of analysis**	**Outcome variables**	**Explanatory variables**	**Model**
How do environmental characteristics of the neighbourhood predict domestic abuse?	CSEW	Individual (respondent-level)	domestic abuse victimisation/willingness to report	Perception of neighbourhood, socio-economic characteristics	Logistic regression
How does neighbourhood deprivation predict domestic abuse?	IMD, CSEW	LSOA-level	domestic abuse victimisation/willingness to report (proportion of overall population)	Various measures of deprivation	Spatial Logistic regression
How do temporal changes in alcohol consumption and income affect domestic abuse?	WMP, Credit card data	LSOA, day/week-level	Number of reported domestic abuse cases	Spending on alcohol and gambling, changes in benefit receipts	Poisson/Negative binomial regression with spatial effects

financial stress (gambling, universal credit) affecting the reported number of domestic abuse cases in the West Midlands.

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